Multi-modal Building Energy Management

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Abstract

The energy transition from fossil energy carriers and centralized power plants towards renewable energy sources and distributed generation calls for suitable approaches and systems supporting this change. Due to the intermittent energy generation of renewables and limited capacities of economical electrical energy storage, the electrical energy systems are in need of a paradigm change from "supply follows demand" towards "demand follows supply". Demand side management will provide the means to adapt the electricity demand to the availability of renewable and thus sustainable energy and increase the efficiency of energy systems. To plan, assess, optimize, and ultimately operate future energy systems, there is a need for approaches and systems facilitating not only automated energy management in productive systems but also detailed and accurate simulations.

A promising way to gain additional flexibility in our energy systems is a *holistic energy management* approach to the provision, conversion, distribution, storage, and utilization of *all energy carriers*. The sectors of electricity, heating, cooling, fuels, and mobility are closely interconnected. Strengthening these links and using their respective advantages will support the energy transition and is likely to be the prerequisite of decarbonizing energy systems. However, enhancing the interlinking and interdependencies of energy systems leads to a higher overall complexity for automation, control, and scheduling. This stresses the necessity and thus importance of automated systems enabling the active and integrated energy management of all energy carriers: *multi-modal energy management*.

Smart buildings adapting their inbound and outbound energy provision, i. e., their demand from as well as supply to surrounding energy systems, will be an essential part of a multi-modal future energy system. On these grounds, this thesis canvasses multi-modal energy management and presents an *automated energy management system* that provides the means for *multi-commodity optimization* in future buildings. This system is used in detailed bottom-up simulations of smart buildings to evaluate the effects of multi-modal energy management and measures of demand side management. Furthermore, the system is deployed to real buildings, performing automated energy management in practice.

The major contribution of this thesis is the presentation of an *automated multi-modal building energy management system*. It is based on a systematic identification and analysis

of the *prerequisites for multi-modal energy management* in multi-energy systems. This thesis provides a definition of multi-energy systems, multi-modal energy management, and multi-commodity optimization and thus a consistent terminology that may be used in the future. It introduces the so-called energy-related degree of freedom in the optimization, extending the temporal degree of freedom, i. e., the deferral and interruption of devices, by a second dimension that allows for changing the utilized energy carrier.

The thesis provides the foundation of applied *building energy management and operating systems* and infers a consistent generic architectural framework. The presented modular *multi-energy simulation and heuristic multi-commodity optimization* is capable of optimizing the provision, conversion, distribution, storage, and utilization of all relevant energy carriers. This concept as well as the exemplary implementation of the building energy management system using the customizable architecture and modular structure are presented in detail. By means of suitable drivers and models, many exemplary devices are integrated into this system. The presented building energy management system is compared to similar systems and approaches, showing that none of them is providing a comparably extensive set of functionality in simulation as well as in practical application.

A detailed analysis of *smart residential and commercial buildings* provides the basis for bottom-up simulations. By means of such simulations, the building energy management system is used to analyze the effects of multi-commodity energy management of *interruptible and hybrid appliances* as well as *trigeneration systems* in different smart residential and commercial building scenarios. The results show that most of the effects of measures of demand side management which are limited to electricity are most probably smaller than given in the literature. However, the usage of hybrid appliances and multi-modal energy management is able to increase the effects. In addition to the usage in simulations, this thesis demonstrates the *deployment and operation of the building energy management system in a real building.*

In conclusion, this thesis contributes to the field of *Energy Informatics* by providing, firstly, theoretical foundations of multi-energy systems, multi-modal energy management, and multi-commodity optimization, secondly, the architectural design and exemplary implementation of an automated building energy management system performing multi-modal energy management by means of multi-commodity optimization, and, finally, the evaluation of exemplary smart buildings using multi-modal building energy management systems, quantifying the expected effects of automated energy management, hybrid home appliances, and measures of demand side management in exemplary multi-energy systems.

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List of Abbreviations

AC	Alternating Current
BEMS	Building Energy Management System
BESS	Battery Energy Storage System
BOS	Building Operating System
CAL	Communication Abstraction Layer
CCHP	Combined Cooling, Heat, and Power Plant
CHP	Combined Heat and Power Plant
CIM	Common Information Model
CO_2	Carbon Dioxide
COP	Coefficient of Performance
DC	Direct Current
DER	Distributed Energy Resource
DG	Distributed (Electricity) Generation
DHW	Domestic Hot Water
DR	Demand Response
DSM	Demand Side Management
EA	Evolutionary Algorithm
EAL	Entity Abstraction Layer
EDoF	Energy-related Degree of Freedom
EMP	Energy Management Panel
EMS	Energy Management System
ESC	Energy Simulation Core
ESHL	KIT Energy Smart Home Lab
ESS	Energy Storage System
FZI	FZI Research Center for Information Technology
GA	Genetic Algorithm
GHG	Greenhouse Gases
HAL	Hardware Abstraction Layer
HIL	Hardware-in-the-loop

HoLL	FZI House of Living Labs
HVAC	Heating, Ventilation, and Air-Conditioning
I^3	Interdependency and Interconnection Information
ICT	Information and Communication Technology
IEC	International Electrotechnical Commission
IEEE	Institute of Electrical and Electronics Engineers
IHE	Insert Heating Element
IoT	Internet of Things
IPP	Interdependent Problem Part
JoSchKa	Job Scheduling Karlsruhe
KIT	Karlsruhe Institute of Technology
LP	Linear Programming
microCHP	Micro Combined Heat and Power Plant
MILP	Mixed Integer Linear Programming
MINLP	Mixed Integer Non-linear Programming
O/C Architecture	Observer/Controller Architecture
O/C-layer	Observer/Controller Layer
O/C-unit	Observer/Controller-unit
OC	Organic Computing
OS	Operating System
OSGi	Open Services Gateway initiative
OSH	Organic Smart Home
PCM	Phase-change Material
PSO	Particle Swarm Optimization
PV	Photovoltaic
RES	Renewable Energy Sources
SCADA	Supervisory Control And Data Acquisition
SLP	Standard Load Profile
SuOC	System under Observation and Control
TDoF	Temporal Degree of Freedom
UML	Unified Modeling Language
VDE	*Verband der Elektrotechnik, Elektronik und Informationstechnik*
VDI	*Verein Deutscher Ingenieure*
VPP	Virtual Power Plant
XML	Extensible Markup Language
XSD	XML Schema Definition

Nomenclature

Symbols	Description	
Short symbols		**Unit**
A	Area	m^2
B	Bit string	–
b	Number of bits in a bit string $\mathcal{B}$	–
C	Costs	cent
c	Price signal	i.a. cent/kWh
E	Energy	J
f	Function	–
h	Specific heat capacity	$J/(kg \cdot K)$
J	Set of all devices	–
k	Selected profile	–
L	Load limit	W
m	Mass	kg
p	Number of time slots	–
P	Power	W, var
Q	Reactive power	var
r	Relation between entities	–
S	Complex power	VA
s	State	–
t	Time step, duration	s
U	Voltage, thermal transmittance	V, $W/(m^2 \cdot K)$
V	Volume	m^3
E	Set of all commodities	–
ε	Commodity	–
$\tilde{E}$	Set of all ancillary commodities	–
$\tilde{\varepsilon}$	Ancillary commodity	–

η	Efficiency	–
ρ	Volumetric mass density	kg/m^3
σ	Coefficient	–
θ	Temperature	°C
τ	Factor for additional penalty	–
$\mathcal{A}$	Agents in multi-agent simulation	–
$\mathcal{C}$	Control sequence	–
$\mathcal{E}$	Environment in multi-agent simulation	–
$\mathcal{F}$	Finite-state machine	–
$\mathcal{H}$	Optimization horizon	–
$\mathcal{I}$	Interdependency and Interconnection Information	–
$\mathcal{P}$	Additional penalty	–
$\mathcal{R}$	Set of all relations r	–
$\mathcal{S}$	State trajectory of agents in multi-agent simulation	–

Long symbols		**Unit**
COP	Coefficient of performance	–
EUF	Energy utilization factor	–
PER	Primary energy ratio	–

Subscript symbols	
a	Active power (electrical)
b	Baseload active power (electrical)
c	Cooling power
h	Heating power
i	In, into
n	Natural gas power
o	Out
p	Peak
r	Reactive power (electrical)
w	Waste power, e. g., waste heat
E	Set of all commodities
ε	Commodity
$\tilde{E}$	Set of all ancillary commodities
$\tilde{\varepsilon}$	Ancillary commodity

Superscript symbols	
d	Deadline (of an entity)
o	Operating time (of an entity)
r	Release time (of an entity)

avg	Average
max	Maximum
min	Minimum

Other (typographic) symbols

✓	Yes, possible, available
✗	No, not possible, not available
$\hookrightarrow$	*Continued*, e. g., from previous line
✍	Peer-reviewed
①	Best paper award

1 Introduction

This chapter provides the general motivation, identifies relevant problems, and states the research questions and hypotheses that are addressed in this thesis. Furthermore, it highlights the key contributions and outlines the structure of this thesis.

1.1 Motivation and Problem Statement

More services and thus people than ever before are relying on the ubiquitous and permanent availability of energy carriers, such as electricity, hot water, fossil fuels, and natural gas [246]. This increasing dependency is apparent as these energy carriers are used, e. g., to heat and air-condition buildings, to fuel transportation and individual mobility, to provide fresh potable water, and to treat sewage. This leads to a world energy consumption that is on an all-time high and expected to rise further in the years ahead [310, p. 53].

At the same time, energy systems all over the world are currently in a phase of transition from fossil energy carriers and centralized power plants, such as coal-fired and nuclear plants, towards Renewable Energy Sources (RES), because of economic, political, technical, and environmental reasons [311]. To date, most of the electrical energy generation and the fuel used for transportation is based on limited, quasi-finite fossil energy carriers, like coal, crude oil, and natural gas. They have to be extracted from earth by exploration and exploitation, which are getting—in particular in the case of crude oil and natural gas—more complex and more expensive than ever. Additionally, many of the reserves are located in already populated, politically sensitive, or environmentally critical regions [491].

Furthermore, the combustion of fuels emits Greenhouse Gases (GHG) and causes pollution of the air with toxic substances and particulates, leading to smog and contamination, harming nature as well as mankind and individuals' health. In addition to toxics and particulates, the emission of Carbon Dioxide (CO_2) when burning fossil fuels is adding more CO_2 to the atmosphere and already leading to an enhanced greenhouse effect on earth, both on land and at sea, causing climate changes [310, pp. 241 ff.]. In turn, climate changes have impacts on temperatures and precipitation [9], which influences the energy consumption. It is assumed that heating loads will decrease and cooling loads will increase in many climate zones [219, 326, 627, 631, 655]. From an economic perspective, fossil fuels often have volatile prices on global markets, causing fluctuations in government budgets and corporate earnings. Moreover, building big power plants is expensive and inflexible. Not to speak about financial risks that are associated with the exploitation of fossil resources, such as oil spills, e. g., the 2010 *Deepwater Horizon* spill, or with their utilization in power plants, particularly in nuclear power plants, such as *Three Mile Island*, *Chernobyl*, or *Fukushima-Daiichi*, and in lignite and coal-fired plants, causing smog and health risks [311, pp. 6 ff.].

The dangers and risks of climate changes, nuclear energy, and pollution from combustion processes to the public as well as the opposition of society to new power plants and power lines in highly populated areas or nature reserves put pressure on on politics and on politicians. All these reasons lead to a rise of RES, Distributed (Electricity) Generation (DG), and electric mobility [491]. RES comprise in particular Photovoltaic (PV) systems, wind turbines, and biomass plants, which are smaller than usual fossil- or nuclear-fueled power plants and therefore more distributed over the electricity grids. Significant additional DG is caused by small Combined Heat and Power Plants (CHPs) [311].

To support the transition from fossil energy carriers and centralized power plants towards RES, the European Union (EU) has defined ambitious goals for the year 2030: a reduction of GHG emissions by at least 40 %, an increase of the share of RES to at least 27 % of the final energy consumption, and an increase of energy efficiency by at least 27 %, all as compared to the year 1990 [198]. These goals by the EU have been devolved into national policies. For instance, the British government has decided to reduce the CO_2 emissions in the United Kingdom by at least 80 % by 2050 compared to 1990 [287, Part 1, Section 1]. Similarly, the German government has decided to increase the share of power generation from RES to at least 35 % by 2020 and to at least 80 % by the year 2050 [242]. Internationally, a broad consensus to reduce the risks and impacts of climate change, e. g., by the decarbonization of the energy systems, has been reached by the adoption of the *Paris Agreement* at the *2015 United Nations Climate Change Conference*.

The German path towards an economically efficient and a more self-sufficient, socially accepted, and—most importantly—environmentally sound energy policy—the German *Energiewende* (energy transition)—causes an increasing share of power generation from RES and an accelerated phase-out of nuclear-based power generation, which is scheduled to be completed by 2023 [242]. Since the nuclear power in Germany is not completely replaced by RES, the share of power generation by coal-fired power plants is rising and increasing GHG emissions. Unfortunately, the same holds mostly true for nuclear power world-wide, as many countries revised their policies in the wake of the 2011 tsunami in Japan and the resulting accident at the *Fukushima-Daiichi* nuclear power plant [310, p. 28] and due to the fact that "nuclear reactors are generally not an economically attractive option without some form of government support" [310, p. 47].

The intermittent generation by RES and the increasing power feed-in by DG are already leading to volatile electricity prices at the European Energy Exchange and problems in electricity grids, such as voltages problems and electrical overloads of power lines [666]. Reasons for these problems are the variable generation by spatially distributed RES with high generation peaks but rather low average generation. Additionally, their load is quasi non-dispatchable, because legislation often requires as much renewable energy as possible to be utilized. The electricity grid itself has been built with a centralized design, where electricity generation is done in relatively few large power plants, which is in strong contrast to DG by many small power plants that use RES.

To tackle these problems in electricity grids, *smart grids* and measures of Demand Side Management (DSM) promise to offer solutions. Smart grids allow for advanced monitoring, management, and optimization capabilities and provide the means for flexibility of the electricity consumption encompassing the grid as well as individual buildings. DSM is supposed to enable an economically efficient way of responding to intermittent and decentralized energy feed-in from renewables by making the consumers more flexible in their demand and responsive to external signals [469]. DSM is supposed to invert the conventional central paradigm of electricity distribution from "supply follows demand" to "demand follows supply". This is necessary, because at all times, the power plants have to generate as much electricity as consumed. Storage has to be used as a new resource to avoid imbalances that cause frequency deviations, voltage problems, or even power outages. Thus, the flexibilization of electricity consumption is of utmost necessity, given the fact that RES used for electricity generation are mostly intermittent and electrical energy storage is expensive, as in the case of batteries, or often faces heavy opposition by the population, as in the case of pumped-storage hydroelectricity.

To keep the control systems of energy grids and their complexity manageable, DSM requires not only appropriate control methods and communication systems but also most importantly buildings, systems, and devices that are able to react on external signals, e. g., variable tariffs. Energy Management Systems (EMSs) for energy grids and for individual buildings promise to enable the implementation of such methods and to provide systems that support optimization and communication in energy systems [152].

In 2012, 32 % of the final energy consumption and 53 % of the electricity consumption in the world was caused by buildings [311]. This fact underlines the relevance of buildings for energy management. Additionally, it has to be taken into account that energy consumption in buildings is caused by a multitude of different devices. Thus, as many devices as possible should be included in energy management. Therefore, this involves many different energy carriers, from electricity over hot water to natural gas.

Apart from new technologies and efficient utilization of RES, the optimization of existing systems is a promising factor to achieve the successful transition of energy systems. EMSs that manage and optimize not single devices but entire systems promise to ensure an efficient utilization of energy on all levels of our energy systems. This applies not only to electricity but to all energy carriers. As yet, the focus is mainly on the flexibilization of electricity consumption and the implementation of a smart electricity grid. This excludes a holistic view on the possibilities to shift energy consumption from one energy carrier to another. Optimizing the European energy system as a whole implies that all entities, i. e., buildings, systems, and devices, and all energy carriers have to be included in the transition process and in energy management. Thus, the narrow focus on smart electricity grids has to be broadened to smart energy systems and grids comprising *all energy carriers*.

Statement of Problems

The general motivation of this thesis is summarized in the following fundamental challenges and problems that arise in energy systems and energy management.

Energy Transition and Intermittent Generation Handling a rising energy consumption, more DG, the integration of RES, and the energy transition at the same time is an ambitious task. Increasing intermittent generation by RES without increasing the energy storage capabilities calls for the flexibilization of energy consumption.

Multiple Energy Carriers and Interdependencies Electricity is only one of many energy carriers. Most of the energy consumption in buildings is related to thermal energy services, i. e., heating and cooling, which calls for an approach that considers and integrates all energy carriers and utilizes the flexibilities that may be realized across them. Taking into account all energy carriers and their provision, distribution, conversion, storage, and utilization, leads to many interdependencies and relations that have to be handled successfully.

Distributed Flexibility and Automated Energy Management Single buildings and households have to provide flexibility, as they are a factor for flexibilization of the energy consumption as well as distributed energy generation. Optimization and flexibilization of future energy systems requires the usage of automated EMSs that optimize energy flows on all levels of the energy system and across all energy carriers autonomously without permanent user interaction.

Complexity, Functionality, and Adaptability of Energy Management Integrating, managing, and optimizing all energy-related devices and systems that are found in buildings, leads to a high complexity that has to be handled. Automated EMSs promise to offer solutions to these problems. Nevertheless, the required capabilities and the functionality are not clearly and completely stated, yet. The heterogeneous structure and capabilities of devices, buildings, and energy systems with different setups of devices for energy provision, conversion, distribution, storage, and utilization call for a flexible and modular approach towards energy management adapting to different environments.

Architectures of Energy Management Systems Reliable and robust EMSs call for suitable architectures that support configuration, management, monitoring, analysis, control, and optimization of energy systems in the sense of a building operating system.

Application Domain

This thesis aims at an automated energy management of all energy carriers in intelligent buildings, such as smart *residential and commercial buildings*, comprising DG, storage systems, and controllable systems and devices, such as Heating, Ventilation, and Air-Conditioning (HVAC) systems as well as home appliances. This energy management is facilitated and enabled using information and communication technologies and an *automated* EMS that is taking all relevant systems and devices and their interdependencies into account when *optimizing the building's energy provision, distribution, conversion, storage, and utilization* with respect to various objectives.

1.2 Research Questions and Hypotheses

This thesis provides answers to the following research questions in the domain of automated energy management of all energy carriers in intelligent buildings by investigating the corresponding hypotheses.

Research Question RQ 1

What is the contribution of an automated building energy management of all energy carriers to the flexibilization of energy demand and supply as well as to the energy efficiency?

Hypothesis H 1 A An automated energy management in buildings is able to increase the energy efficiency, diversify the energy utilization, and make the provision, distribution, and utilization of energy more flexible, leading to an increase of the self-consumption and self-sufficiency rates of locally generated energy.

Hypothesis H 1 B An integrated energy management of all energy carriers enables additional flexibilities with respect to the electricity demand and supply in buildings in comparison to an energy management that takes only electricity into account.

Hypothesis H 1 C Interruptible as well as so-called hybrid home appliances help to increase the flexibility of the energy demand of buildings.

Hypothesis H 1 D Electrical insert heating elements add flexibility to the energy demand in buildings and support the flexibilization provided by hybrid appliances.

Hypothesis H 1 E The efficiency of combined cooling, heat, and power plants may be optimized by an appropriate building energy management system.

Research Question RQ 2

How to realize the modular energy management and optimization of devices and systems in real and simulated buildings when taking multiple energy carriers into account?

Hypothesis H 2 A Energy management and optimization in simulated as well as real buildings requires the adaptability to different setups, which has to be provided by an adequate architectural approach.

Hypothesis H 2 B Energy management of multiple energy carriers requires a holistic and integrated approach to optimization that considers interdependencies in the energy generation and consumption of different devices.

Hypothesis H 2 C An integrated approach to energy management and optimization requires a suitable energy simulation of the building and its components in simulation as well as in real-world application.

Hypothesis H 2 D There is no publicly available energy management system or architectural framework that covers the requirements of an integrated, holistic energy management and takes all relevant energy carriers in buildings and their components into account while reflecting and respecting their interdependencies.

Research Question RQ 2.1 Which interdependencies in the provision, conversion, storage, and utilization of different energy carriers have to be considered in buildings to allow for the best response to intermittent availability of energy?

Hypothesis H 2.1 A There is no consistent terminology of devices and systems utilizing or providing multiple energy carriers.

Hypothesis H 2.1 B Hybrid appliances utilizing multiple energy carriers as well as cogeneration and trigeneration systems will cause interdependencies of the energy carriers in future buildings.

Research Question RQ 2.2 How to consider the utilization and provision of the same energy carriers by different devices in different qualities and prices?

Hypothesis H 2.2 A Energy carriers have to be categorized into different standardized commodities, e. g., active and reactive power, that are used in buildings and relevant for energy management.

Hypothesis H 2.2 B Commodities have to be distinguished into *ancillary commodities*, e. g., active power generated by a photovoltaic system, reflecting different origin, price, and quality, e. g., related emissions and feed-in tariffs, to facilitate optimization.

Research Question RQ 2.3 How to design the architecture of the automated energy management system, the energy simulation, and the integrated optimization in a way making them adaptable and flexible with respect to different scenarios, multiple energy carriers, and interdependencies?

Hypothesis H 2.3 A The energy simulation can be implemented as a separate system which is interlinked with the energy management system and the optimization module using standardized interfaces.

Hypothesis H 2.3 B Devices and systems in buildings can be represented in the energy simulation using physical-technical and optimization models having standardized interfaces, which abstract their behavior and controllability.

Research Question RQ 2.4 What kind of approach to optimization is suitable for this kind of optimization in integrated energy management in heterogeneous setups and scenarios?

Hypothesis H 2.4 A The utilization of heuristic optimization is a practicable way in energy systems, which are characterized by dynamic changes and uncertainties.

Hypothesis H 2.4 B Evolutionary Algorithms offer the required adaptability to different setups and scenarios and are able to cope with the complexity that arises in some of these setups and scenarios.

Assumptions and Delimitations

This thesis covers a wide range of topics, inevitably leading to some fundamental assumptions and delimitations. However, the assumptions are realistic because the required technologies are already available.

Intelligent Buildings It is assumed that future buildings are going to be equipped with information and communication technology enabling the communication between virtually all devices and systems in buildings and making the buildings "smart".

Connected Controllable Devices It is assumed that the used devices and systems are going to be capable of communicating their states and receiving control commands. However, there are still going to be many different communication media and protocols as well as abstract representations of the devices and systems.

Future Home Appliances It is assumed that future home appliances are going to be able to utilize multiple energy carriers when providing their energy services and thus become so-called hybrid appliances.

Single Buildings Although the concepts and the system presented in this thesis are designated to be used to simulate multiple buildings concurrently, the evaluation of the proposed energy management system in this thesis is limited to single buildings.

Residential and Commercial Buildings Although a major share of the energy consumption is related to industry and mobility, this thesis focuses on residential buildings, i. e., private dwellings, and commercial buildings, i. e., office buildings and small companies. Furthermore, this thesis focuses on buildings in Germany.

Focus on Automated Energy Management Systems Although energy management systems will always require some kind of user interface for configuration, visualization, and interaction, have to take security and data privacy concerns into account, and use methods of big data analysis, this thesis focuses on the very heart of energy management—the actual system that manages and optimizes energy provision, distribution, conversion, storage, and utilization.

Operational Costs This thesis focuses on the optimization of the operation of energy systems, i. e., the minimization of operational costs, and neglects investment costs. Nevertheless, the simulations of the proposed energy management system may be used in future evaluations to facilitate investment decisions.

1.3 Contributions

The major contribution of this thesis is the presentation, evaluation, and documentation of an *automated multi-modal building energy management system* that is based on a systematic identification and analysis of *prerequisites for energy management* in residential and commercial buildings. It is able to perform a *heuristic optimization* of the consumption and generation of *multiple energy carriers* utilizing the so-called *Energy Simulation Core* and *Interdependent Problem Parts* in a modular and customizable approach.

The building energy management system is compared to similar systems and approaches. In simulations, it is used for the *analysis of the effects of multi-commodity energy management* of *interruptible and hybrid appliances* as well as of *trigeneration systems* in different *smart residential and commercial building scenarios*. In addition, it is *deployed to real buildings* and thus applied in practice.

Parts of this thesis are based on work that has already been published. A list of all these publications is given in Table H.1 on pp. 485 f., explaining their relation to this thesis. In addition, the publications are referenced whenever parts of this thesis are based on them. However, for the first time, this thesis provides an exhaustive study of multi-modal building energy management and its realization in a prototypical implementation. Therefore, it provides the necessary fundamentals and links to the source code of the proposed building energy management system, which is a new version of the *Organic Smart Home* [10].

Prerequisites for Multi-modal Energy Management

This thesis investigates and provides:

- The background and basic concepts of the provision, conversion, distribution, storage, and utilization of multiple energy carriers.
- The definition and delimitation of multi-modal energy management and multi-commodity optimization as well as a terminology for multi-energy systems.
- The requirements of energy management, energy management systems, and integrated optimization of the behavior and utilization of devices, systems, and buildings in energy systems.
- An architectural and conceptual framework for the structuring and design of entities in a future energy information and control network with distributed intelligence.
- A suitable energy flow simulation that facilitates device abstraction and modular optimization of heterogeneous but interdependent devices using their temporal as well as energy-related degrees of freedom.

Multi-modal Building Energy Management System

This thesis presents a building energy management system that:

- Can be used in detailed bottom-up simulations as well as in real buildings.
- Realizes a suitable abstraction of each device for the optimization module.

- Optimizes the joint operation of all devices and systems concurrently.
- Respects interdependencies of devices and energy flows in buildings.
- Considers all energy carriers that are currently relevant in buildings and may easily be extended to consider additional ones.
- Distinguishes energy carriers into different so-called commodities and ancillary commodities to account for different origins, qualities, and costs as well as prices of each energy carrier.
- Facilitates the optimization of different objective functions with respect to device operation and other given constraints, such as user preferences.
- Is modular, customizable, and flexible with respect to the devices and systems that can be managed and the scenarios in which it may be used.
- Enables the increase of energy efficiency.
- Allows for the temporal flexibilization of energy consumption and generation as well as the flexibilization across energy carries.
- Exploits the flexibility of a building and its devices and systems with respect to changes of the provision, conversion, and utilization of energy.

Multi-energy Simulation and Heuristic Multi-commodity Optimization

To enable building energy management by the system, this thesis introduces a novel concept of energy simulation based on the so-called *Energy Simulation Core* and *Interdependent Problem Parts* that:

- Is utilized by the building energy management system to enable the integrated optimization of all devices and systems and facilitate bottom-up simulations of buildings.
- Respects interdependencies between devices and between energy carriers.
- Uses standardized interfaces that allow for the integration of other simulation tools.
- Is able to optimize different devices and energy carriers concurrently with respect to typical objectives by distinguishing commodities and ancillary commodities.

The introduction of the Energy Simulation Core and the Interdependent Problem Parts enables the concurrent optimization of a multitude of different devices and systems that utilize different energy carriers. The multi-commodity optimization is based on an Evolutionary Algorithm that is extended by:

- Novel encodings for the representation of devices.
- Standardized interactions with and interfaces to the Energy Simulation Core, making the optimization module interchangeable.

Evaluation of Smart Building Scenarios comprising Hybrid Devices and Systems

Finally, the presented building energy management system is used to:

- Analyze the load flexibility of single devices and of entire smart residential buildings that comprise multiple devices in detailed bottom-up simulations.
- Show for the first time the detailed impact and potential of home appliances that are interruptible and able to use multiple energy carriers interchangeably in their operation—so-called hybrid appliances.
- Demonstrate the optimization potential of a trigeneration system in a smart commercial building that consists of an adsorption chiller, a combined heat and power plant, and storage tanks for hot as well as for chilled water.

1.4 Structure

The following Chapter 2 provides definitions of relevant terms and basic information about energy systems, such as electricity grids, energy generation and consumption, as well as emerging problems and challenges. Chapter 3 gives an overview of various related work regarding multi-energy systems, smart buildings, DG, DSM, and Building Energy Management Systems (BEMSs). A detailed analysis of the requirements of building energy management, such as statistical data and models, as well as the selected approach regarding the management and optimization are given in Chapter 4. Chapter 5 provides a detailed view on the proposed architecture and the BEMS that is developed as part of the thesis. This system is then evaluated in Chapter 6 using several experimental setups of smart residential and commercial buildings. Finally, Chapter 7 concludes this thesis and gives an outlook to further work.

2 Background and Basic Concepts

This chapter provides background information and introduces basic concepts that ease the understandability and comprehensibility of the present thesis. It defines relevant terms and fundamentals about energy systems, carriers, generation as well as consumption, emerging problems and challenges, Information and Communication Technology (ICT) in energy systems, *Energy Informatics*, and related fields, such as *smart cities* and the *Internet of Things*. The very basics terms and concepts are defined and explained in Appendix A.1.

2.1 Provision, Distribution, Storage, and Utilization of Energy

The provision, distribution, and utilization of energy in energy systems have to cope with fluctuating demands and supplies as well as spatial differences, i. e., spatio-temporal imbalances in the energy system. Energy distribution grids and storage help to realize this balancing. The main energy carriers used by consumers in interconnected energy systems—electricity, gas, oil, hot water, and chilled water—differ heavily in their respective provision, distribution, storage, and utilization, which is outlined in the following sections.

2.1.1 Provision and Utilization of Energy

Every energy carrier that is utilized in an energy system to provide an energy service (see also Appendix A.1) has to be provisioned, i. e., introduced into the energy system. The utilization of energy carriers, i. e., consumption based on demand, removes them from the energy system. To obtain a stable system, provision and utilization have to be balanced. This task involves all energy carriers and solutions differ from one carrier to another.

This thesis considers energy generation as well as consumption always from the consumers' perspective. Consequently, positive values represent energy consumption, whereas negative ones represent energy generation.

Provision and Generation of Energy Energy provision is the task of importing an energy carrier (procurement) or generating some form of energy or energy carrier by transforming other carriers (conversion), i. e., energy provision introduces forms of energy into an energy system and makes them available. To enhance readability, *energy generation* is used throughout this thesis when referring to the provision of energy by using other forms of energy, i. e., a process that is actually conversion.

Utilization and Consumption of Energy Energy utilization is the usage of energy carriers to provide an energy service, such as lighting or heating. The consumption of energy carriers covers the overall energy demand, i. e., the *vector* or *signature* [131, p. 201] of demands for different energy carriers. The utilization of energy carriers removes them from the energy system. Although this is mostly also a conversion process into another form of energy, it is called *energy consumption*. The actually consumed energy carriers depend heavily on the accessibility, availability, and acceptability of energy carriers in the provisioning process.

Balancing Provision and Utilization of Energy

As described in Appendix A.1 in detail, energy demand consists of different forms of energy for which there is a usage incentive. The demand is the maximum required energy, whereas consumption is the actually used energy, which depends on the demand as well as the current generation and thus also on external conditions. [131, p. 153]

Balancing of Supply and Demand The balancing of energy demand and supply in an energy system, which is also called *supply and demand matching*, is realized to a large extent—depending on the time frame—by some energy market that clears demand and supply of an energy carrier according to a flexible price or other mechanisms enforcing an equilibrium. Thus, this term very often refers to the context of economics.

The energy demand is actually a vector of multiple energy carriers with interdependencies and possibilities to substitute some with others. Therefore, balancing demand and supply actually happens not only spatially and temporally but also across all energy carriers, leading to a certain generation of each energy carrier. Some energy markets are more flexible than others. For instance, the electricity markets are rather flexible when compared to the gas markets. This is caused by different price-elasticities and interdependencies with other markets and determines the balance of demand and supply. [49, 131] [308, p. 12]

Balancing of Generation and Consumption The balancing of generation and consumption in an energy system refers to a more technically oriented perspective. A stable energy system requires the generation, i. e., the inbound provision and conversion, to be equal to the consumption, i. e., the outbound provision and utilization. This may be realized in different ways: adapting the generation to the actual consumption, adapting the consumption to the generation situation, and storing energy to balance fluctuations. In doing so, intertemporal relations and path dependencies as well as spatial constraints have to be respected.

Temporal Imbalances in Energy Systems Imbalances in energy systems are often only temporary, because demand as well as supply is sometimes higher, sometimes lower. Energy storage is used to compensate temporal imbalances in energy systems that may be settled by matching a surplus in one period with a deficiency in another. The consideration of all energy carriers increases the number of possibilities and the capacity for avoiding imbalances.

Spatial Imbalances in Energy Systems Energy systems are usually made of spatially distributed sub-systems, i. e., balancing each of these systems depends on the scope of the particular system and the defined boundaries, which may be a single building, a larger facility, a local distribution grid, or even the whole interconnected energy grid. Energy grids are used to compensate imbalances of spatially distributed energy systems. To deal with spatial imbalances, the energy flow and its limitations have to be considered.

Self-consumption and Self-sufficiency The *self-consumption* rate (or *self-consumption with respect to local generation* [639]) denotes the share of locally generated energy that is also consumed locally. In contrast, the *self-sufficiency* rate (or *self-consumption with respect to load* [639], *grade of autarky* [626], *grade of autarchy* [212], *autonomy* [646]) is the share of locally consumed energy that has also been generated locally. The terms *self-reliance* or *autarky* (also *autarchy*) refer to the state of a system that is completely self-sufficient. Even then, the self-consumption rate may be still below 100 %. [386, 636]
Self-consumption is defined as:

$$\text{self-consumption} = \frac{\text{total generated energy - fed-in energy}}{\text{total generated energy}}\,.$$

Self-sufficiency is defined as:

$$\text{self-sufficiency} = \frac{\text{total generated energy - fed-in energy}}{\text{total consumed energy}}\,.$$

Metering of Energy Flows

An important prerequisite for monitoring and thus balancing energy in a system is to measure the energy flows—directly or indirectly—using some metering device. This includes electricity meters, gas meters, and heat meters. From a technical perspective, metering is done using different methods, such as measuring the mass flow, the volumetric flow, or the electric current. These methods have to take additional information into account for calculating the energy flow. For instance, natural gas has a varying calorific value that determines the energy flow when using the volumetric flow rate. Other examples are the voltage of electric currents and temperature differences between flow and return in heating circuits. From an economic perspective, metering is used for billing and accounting purposes, because the same energy carrier has often different prices or economic values that have to be respected, e. g., electricity generated by a PV system or a coal-fired power plant.

Pricing and Tariffs

There are many different pricing regimes that determine the price of energy commodities. The price may be fixed for all units that are consumed, fixed only up to a certain limit per billing period, differ from time period to time period, contain events that lead to special prices, and change every day or even every 15 minutes. In addition, some tariffs are related to the minimal and maximal power consumption, e. g., the monthly peak power, and introduce so-called demand rates. Typically, they aim at reducing consumption peaks and thus the required connected load (see also Section 4.8.2). Most tariffs fit into the following categories or are a combination of them. [19, 133, 541]

Flat Rate Pricing A flat rate refers to one of the two following pricing schemes. In the first type, there is a fixed fee that has to be paid, no matter how much energy is used. This kind of tariff is nowadays very rare with respect to energy and typical for mobile communication. More common is the second type of flat rate pricing: The price per unit is fixed, irrespective of time or total units consumed. [133, pp. 262 ff.]

Block Pricing Block pricing refers to a pricing scheme having a fixed price per unit of a certain number of units, i. e., a block. Thus, the price changes when reaching certain tiers of consumption. The price is called an increasing, inverted, or incline block tariff if it gets more expensive the more energy is used. Conversely, it is called a decreasing or decline block tariff. [133, p. 148]

Time-of-use Pricing Time-of-use (TOU) tariffs define periods having different prices, e. g., peak and off-peak periods. The periods are often based on average system loads—generation as well as consumption—and their typical imbalances. The term “peak period” results from the conventional problem of generating enough electricity to satisfy peak demand, which can be supported by this kind of tariff. Sometimes there is an even more partitioned structure that has several peak and off-peak periods as well as intermediate periods. The tariff may distinguish different prices per time of year, day of week, or even hour of day. Nevertheless, the price in each block is predefined, e. g., at the beginning of the year, and does not necessarily reflect the current market conditions. [19] [133, pp. 203 f.]

Critical or Variable Peak Pricing Critical peak pricing (CPP) or variable peak pricing refers to a pricing scheme having sporadic critical periods that lead to peak prices or rebate rates, which are announced at short notice, e. g., several minutes to hours in advance. The critical periods are anticipated, predicted periods of heavy imbalances, e. g., due to insufficient generation capacities or too much generation from RES, which results in significantly higher or lower prices. Usually, there is some kind of upper limit that defines the maximum number of critical periods per year or per month. [19]

Real-time or Dynamic Pricing Real-time pricing (RTP) or dynamic pricing[1] refers to a pricing scheme in which the prices vary dynamically with the current situations and conditions on energy markets, i. e., of demand and supply, or other variable prices that reflect the situation in the energy system. The prices are usually communicated at short notice, e. g., day-ahead, hour-ahead, or quarter-hour-ahead. Automated energy management opens a chance to monitor not only the local situation but also the variable prices and to react accordingly, using automated optimization and control. [19] [133, p. 204]

2.1.2 Distribution of Energy and Energy Distribution Grids

Usually, the distribution of energy is done using some kind of dedicated energy grid, e. g., the electricity grid, or transportation network, e. g., roads, railways, and waterways. The distribution of energy includes transporting, monitoring, controlling, and securing the energy flows [610]. This section introduces several generic concepts in the context of energy grids.

[1] Sometimes dynamic pricing refers to all pricing schemes that have unforeseen price changes, i. e., CPP and RTP, or even to all pricing schemes that have price changes.

Energy Distribution Grids and Networks

From a more global perspective, energy grids include electric power grids, gas grids, and heat grids, i. e., district heating and cooling. Locally, the energy is distributed using local supply grids, i. e., wires, pipes, and ventilation shafts. In addition to the mere operation of grids, ancillary services support the distribution of energy. Usually, the term ancillary service is used in the context of electricity and includes frequency, voltage, and reactive power control, phase balancing, and congestion management using redispatch.

Often, the term *distribution* is used to describe the transfer of energy within a system and in particular from a single point to many points of final energy usage, whereas the term *transportation* refers to the point-to-point transfer from one system to another. To distinguish between energy distribution and ICT networks, throughout this thesis, the term *grid* is used for interconnected energy systems, whereas the term *network* refers to interconnected communication and service systems.

Microgrids

Usually, the term *microgrid* is used in the context of electricity grids. There are two major definitions of microgrids that are widely used. The first definition is provided by the *Microgrid Exchange Group* of the *U.S. Department of Energy* and the second one has been given by the *Working Group C6.22 Microgrids* of the *International Council on Large Electric Systems* (CIGRÉ) [182]. These two as well as other common definitions emphasize certain distinguishing characteristics of microgrids [42, 127, 182, 400, 432, 590]. Therefore, this thesis proposes the following comprehensive definition of a microgrid:

> **Definition:** A microgrid is a small-scale distribution grid that is topologically interconnected and has a defined spatial boundary. Although it is usually connected to an external grid, it may be disconnected, resulting in an island-mode operation of the microgrid. Therefore, it must be controllable as a separate energy system providing all necessary ancillary services. Typically, microgrids aim at permanent net power island-mode operation and do not necessarily participate in external markets.

Typically, the main goal of operations in the microgrid is to enable supply demand matching within the microgrid, i. e., local balancing, resulting in *de facto* island-mode operation. Therefore, microgrids manage and coordinate their DG, storage, and consumption. This may be realized by using measures of DSM and a joint optimization of all participants, i. e., generators, storage systems, and consumers, which helps to match supply and demand within the microgrid. Furthermore, this calls for optimization and coordination methods. Local management and coordination requires monitoring, prediction, and control capabilities of local energy flows, requiring sensors, meters, and EMSs. [19, 127, 432]

Based on [127, 182, 400, 432, 470, 590], the advantages and benefits of microgrids can be summarized as follows:

> **Advantages of Microgrids:** Microgrids may reduce energy consumption, energy loss, and environmental impact by improving energy efficiency, integration of

> RES, system reliability, resilience, and power quality. In this way, microgrids facilitate the decentralized provision of ancillary services for the external grid, grid modernization, innovative approaches, energy independence, and self-reliance, while promoting customer and community acceptance and participation.

Typical use cases for microgrids are buildings, facilities, and small communities in remote areas and islands. As microgrids may serve as testbeds for novel technologies, methods, and concepts that may be used in future smart grids [19], they are sometimes called *smart microgrids* [21] or *micro smart grids* [226].

Cellular, Holonic, and Hybrid Grids

The concepts of cellular [101, pp. 200 ff.] [349,606], holonic [213,224,452], and hybrid [131,470] grids are very similar to those of microgrids and apply EMSs for decentralized control.

Cellular Grid In the concept of a cellular grid, each cell is "equipped with smart grid components (generators, consumers, energy storage and grid operating resources) [and] act in a self-optimizing manner, targeting [...] [on] energy balance" [349]. Multiple cells are communicating and collaborating as higher level cells. Nevertheless, the approach is originally limited to the electricity grid and does not respect interdependencies with other energy carriers. [101, pp. 200 ff.] [349, 606]

Holonic Grid The holonic approach emphasizes several principles and features of so-called holons [452]:

- Autonomy, self-management, intelligence, and communication.
- Recursive aggregation.
- Dynamic reconfiguration.

The holonic grid—the so-called holarchy—is aggregated and organized recursively in a bottom-up manner from cooperative holons that are self-managing and able to function autonomously. Communication and cooperation enables the holons to achieve common higher goals that may not be achieved independently. Dynamic reconfiguration enables the holarchy to adapt to changes in the environment. [213, 224, 452]

Hybrid Grid The term *hybrid* in hybrid networks refers to different notions. Firstly, an economic and resilient grid may be accomplished by combining measures of grid expansion and the integration of novel control methods, such as DSM [470]. Secondly, the resilience of the grid may also be improved by establishing many microgrids in the whole grid. In case of problems in the main grid, these microgrids may be operated in island-mode [470]. Finally, it refers to the combination of centralized and decentralized systems, i. e., large power plants and DG [615]. Furthermore, the term hybrid grids is used in the sense of hybrid AC/DC/HVDC electricity grids [205, 630] and hybrid energy systems comprising multiple energy carriers [131, p. 294]. These completely different notions are described in Sections 2.1.4 and 2.3.2 and analyzed in Section 4.7.

2.1.3 Storage and Buffering of Energy

Energy storage saves spare energy in a useful form for later usage, enabling a more flexible energy chain. Thus, energy storage is at first a consumer and a generator later, providing additional energy flexibility that may be used by EMSs. At the same time, energy management is often applied to reduce storage requirements or to avoid energy storage at all. The fundamental methods or classes of energy storage are chemical, electric, electrochemical, magnetic, mechanical, and thermal storage [131, p. 201] [573, p. 31 f.]. Examples for energy storage in the energy systems include fuel tanks, Battery Energy Storage System (BESS), supercapacitors, pumped hydroelectric energy storage, and thermal energy storage in water tanks [101, 131].

The duration, loss, capacity, and efficiency of storage depends on the particular technologies and thus the energy carriers used when storing energy as well as the energy carriers that can be retrieved from the storage system. Some technologies are used for seasonal storage of large quantities of energy for long periods, whereas others store energy only temporarily and are also characterized as *buffer*.

All ways of storing energy have their advantages and disadvantages, which have to be taken into account when realizing building energy management in real buildings that utilize Energy Storage Systems (ESSs). An EMS that is able to handle and optimize energy flows of all energy carriers concurrently may select the best way of storing energy depending on the current energy situation as well as predictions.

2.1.4 Electricity

The provision and distribution of electricity is actually the transmission of an energy carrier in many varieties having different qualities and properties. In general, electricity is available as Alternating Current (AC) or Direct Current (DC), both having their advantages and disadvantages that are briefly described below. Additionally, electricity is generated and consumed at different voltage levels. [623, pp. 49 ff.]

In case of AC, electricity may be separated into two basic commodities. Firstly, there is active power, which provides the energy that is actually consumed by energy services. Secondly, there is reactive power, which occurs only in AC electric circuits and which is utilized by energy services because of physical and technical reasons. [19, pp. 16 f.]

Alternating and Direct Current

Provision, distribution, and utilization of electricity is done using AC and DC electric circuits. Neither has become prevalent because both have their pros and cons. In AC circuits, voltage and current are alternating with a typical nominal frequency of 16.7 Hz, 50 Hz, or 60 Hz, i. e., the flow of electric charge is changing its direction periodically. This is leading to reactive power and thus technical limitations in grids due to this additional load. In DC circuits, voltage and current are not alternating, i. e., the flow of electric charge is unidirectional. [245, p. 13] [541, p. 306]

Historically, there has been a so-called *Battle of Currents* [623, p. 49] or *War of Currents* [205] in the late 19th century about whether to use AC or DC for electricity grids. The voltage of AC can easily and efficiently be converted by transformers that enable the transformation to high voltages for transmission, which reduces currents and thus transmission losses. At that times, this had not been possible for DC and it had to be generated and distributed at the same voltage as it was used, which eventually led to the usage of AC for electricity distribution. [205]

Nowadays, DC may also easily and efficiently be converted using DC-to-DC power converters, which enables the practical utilization of DC in buildings having appliances that require different voltage levels. Additionally, developments in power electronics enable converter stations that transform AC to DC and back, which is done in high-voltage direct current (HVDC) electric power transmission. Hence, EMSs should be able to handle both AC and DC electricity. [205]

Active, Reactive, Apparent, and Complex Power

Electricity consists of active power, which provides the energy that is consumed by energy services, and reactive power, which occurs in AC electric circuits due to reactance, i. e., inductance and capacitance. Both active and reactive power contribute to electrical losses and voltage drops in the electricity grid. Thus, EMSs have to consider them jointly—as complex or apparent power—as well as separately. The management of active power is mostly relevant for generation and consumption management, whereas the management of reactive power is important for local voltage control and reactive power compensation. [245, pp. 53 ff.] [623, pp. 66 ff.]

Active Power The active or real power is the power that is used by ohmic resistors. In DC circuits, there is only active power, which is the power that is actually doing work. Consumption of active power leads to voltage decrease and generation to increasing voltage. [131, p. 7] [623, pp. 68 ff.]

Reactive Power The reactive power is the additional power that is required when reactance is present, which is either capacitive reactance caused by alternating electrical fields, e. g., capacitors, or inductive reactance caused by alternating magnetic fields, e. g., electric motors. Capacitive reactance leads to *capacitive reactive power* and inductive reactance leads to *inductive reactive power*. This power is not used like the active power, because there is no work done in average, but required to alternate the electrical and magnetic fields. Inductive reactive power reduces the voltage increase caused by active power generation, capacitive reactive power increases the voltage. [131, p. 488] [623, pp. 68 ff.]

Apparent and Complex Power Both the apparent and the complex power are a combination of active and reactive power. In case of DC circuits and purely ohmic AC circuits, the apparent power is equal to the active power as there is no reactive power. In case of AC circuits with reactance, the vector sum of active and reactive power is the complex power and its magnitude is the apparent power. [131, p. 27] [623, pp. 68 ff.]

Generation, Consumption, and Balancing in Electricity Grids

In electricity systems, electrical energy has always to be generated and consumed at nearly the same rate because the electricity grid itself, i. e., the transmission lines and cables, have negligible storage capability. Imbalances between generation and end users have to be balanced using ESSs, such as pumped hydroelectric energy storage. The electricity system has become larger and more interconnected in the past decades because of technical and economic reasons, which include economies of scale and averaging effects that lead to better load factors, higher reliability, and smaller reserves. [623, pp. 144 ff.]

Generation Electricity generation is done by transforming other energy carriers into electrical energy in so-called power plants. Typical energy carriers that are used in this process are fuels, coal, lignite, natural gas, fissile material, mechanical work, e. g., wind, and electromagnetic waves, e. g., solar radiation. [131, p. 252]

Consumption Electricity consumption, i. e., "the amount of electrical energy actually used" [131, p. 153], is done by all devices and systems that provide energy services. In addition to the energy consumption, there are also losses, e. g., conversion and transportation losses, that arise in the electrical energy system. [131, p. 129]

Balancing In electricity grids, there are two fundamentally different values that measure imbalance: global grid frequency and local voltage. Additionally, balancing groups and accounting grids are virtual entities that are used in energy markets to facilitate balancing. In general, imperfect predictions and failures in generators, grids, and transformers cause deviations that have to be handled. [623]

The frequency of the grid is a value that is equal in the entire interconnected and synchronized electricity grid, regardless of the voltage level. Power generation increases the grid frequency and consumption decreases it. Hence, electricity generation and consumption have to be matched, including the matching of supply and demand. Naturally, the voltage differs not only across voltage levels but also from node to node on the same level: power generation and feed-in increase the voltage, power consumption decreases it locally. Thus, operating the grid in a stable state requires frequency as well as voltage control. Both are ancillary services that facilitate the operation of a grid (see the next section). [49]

In addition to that, there is another virtual value that is based on the structure of some energy markets and their regulation: the balance of so-called balancing groups and accounting grids. Their balance is virtual and has to be maintained by grid operators, requiring load prediction, metering, and settlement between different groups. [49]

Electricity Grids

Most of the electricity grids comprise *transmission grids* and *distribution grids* (see Figure 2.1) that have a radial, meshed, or ring structure. Traditionally, suppliers and consumers of electricity were separated. Power was generated in large power plants connected to the transmission grid, such as coal-fired or nuclear power plants, whereas the consumers were connected to the distribution grids. Thus, those grids had a downward energy flow from transmission grids using very high voltage down to distribution grids with medium and low voltage. Nowadays, DG is leading to major changes. Many suppliers, such as CHPs and PV systems, are now connected to the distribution grids, sometimes leading to an inversion of the energy flow from a grid on a lower hierarchy level to superordinate grids. [207, 409]

The hierarchy of the electricity grid comprises grid levels having different voltages and three or four phases. In Europe, the highest voltage level—the extra-high-voltage systems—

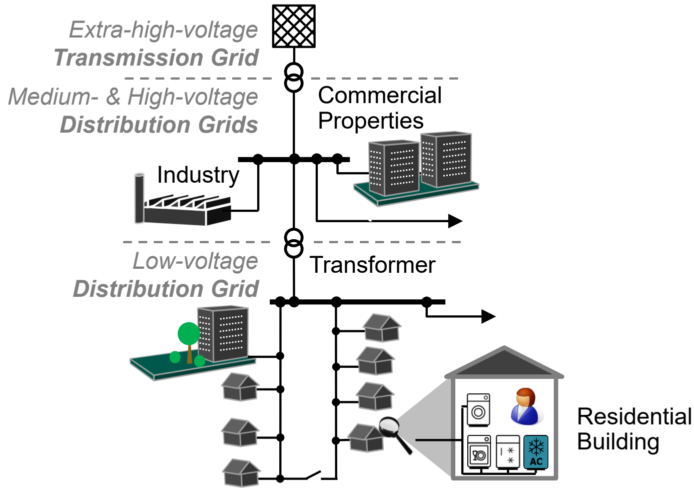


Figure 2.1: General topology of electricity grids

typically uses a voltage of 220 kV or 380 kV, the high-voltage systems use 60 kV or 110 kV, medium-voltage systems use 3 kV to 50 kV, and the lowest level—the low-voltage systems—has 230 V and 400 V. Usually, there is only a low-voltage system available in buildings and thus of importance for this thesis. [541, 610]

Transmission Systems and Grids The transmission systems or grids consist of lines, equipment, and facilities that enable the transfer of electrical energy over long distances from one point in the electrical system to another using high voltage to avoid losses. Many ancillary services are actually provided by the transmission system, which is operated by a transmission system operator. [19] [131, p. 611]

Distribution Systems and Grids The distribution systems or grids consist of lines, equipment, and facilities that enable transfer of electrical energy over short distances from one point to multiple points of final consumption by an end user. A distribution system or grid is operated by a so-called distribution system operator. [19] [131, pp. 166 f.]

Islanding / Island-mode Operation An island is a part of the energy system that is operating independently from the surrounding energy system in a disconnected state. The process of islanding leads to independent islands that are capable of island-mode operation. This is realized using, e. g., an uninterruptible power supply in backup energy systems or microgrids. [19] [131, p. 321]

Ancillary Services in Electricity Grids

Ancillary services are all services that support the operation of the electricity grid. They are necessary to achieve a reliable and robust electricity grid. Often, the following six services are distinguished [19, 69, 297, 352].

Frequency Control Frequency control maintains the grid frequency at about its nominal value, i. e., in a defined acceptable range. If generation becomes higher than consumption, the frequency increases and vice versa. Frequency control adapts generation and consumption to maintain the frequency. Usually, it comprises three basic types of control[2]: Firstly, the frequency containment or primary reserves. Secondly, the automated frequency restoration or secondary reserves that are activated automatically to supersede the primary reserve. Finally, the manual frequency restoration or tertiary reserves that are activated manually to supersede the primary and secondary reserve in case of major and long-term imbalances. BEMSs may facilitate primary reserve and contribute to secondary and tertiary reserves. [297, 352]

Voltage Control Voltage control maintains the local voltages at about their nominal values, i. e., in defined acceptable ranges around the voltage level of the particular grid. DG increases the voltage and may lead to severe problems and damage in grids because of violations of upper voltage limits. In contrast, the consumption decreases the voltage. Both, voltage increase and decrease, depend strongly on the grid structure and its properties. Voltage control is done using transformers with tap changers, managing reactive power, and applying measures of Demand Response (DR) (see also Section 2.3.4). [297, 352]

Reactive Power Control Reactive power control ensures that the grid is operated in a stable state. Consumers and grids require reactive power, due to technical and physical reasons. Therefore, reactive power has to be provided by some entity in the grid. Furthermore, reactive power causes additional losses in the grid. Thus, it is often compensated locally to reduce reactive power flow. [69, 297]

Phase Balancing In three and four phase AC grids, imbalances between the phases may occur because of unequal loads on their phases. Balancing the phases reduces transmission losses, required capacities, and voltage deviations. [297, 352]

Redispatch and Congestion Management Congestion in the grid, i. e., overloads of the infrastructure due to insufficient capacities, arises on a global level in the transmission grid as well as on the local level of distribution grids or even within buildings. Redispatch solves the problem on a global grid level whereas congestion management solves it locally. Both utilize modifications and adaptations of generation and consumption, such as curtailment, as well as of grid structures to ease congestion. The change or rescheduling of generation plans leads to additional costs that are added to the market price of electricity. For instance, in 2015, the costs of redispatch and congestion management in Germany have risen to more than one billion Euro per year. [19, 57, 297, 352]

Restoration after Power Outages Wide-range power outages require a controlled restoration of the electricity supply to avoid severe voltage problems and instabilities of the system. Thus, the restoration after power outages has to be handled carefully to avoid new outages in this process. [297]

Electrical Energy Storage

Examples for electrical energy storage include battery storage, compressed air storage, flywheel storage, pumped-storage, superconducting magnetic energy storage, and storage in supercapacitors. Bidirectionally connected electric vehicles, which are able to feed power

[2]The specific implementation depends heavily on the particular energy system.

back to the grid that has been stored in the battery, may provide additional storage capacity in the future. This concept is also called *vehicle-to-grid* [49, 144, 393].

In addition to electrical ESSs, which utilize electricity when charging and regain electricity when discharging, there is storage that uses electricity only in the charging process but retrieves another form of energy, e. g., thermal storage using heat pumps or electrical Insert Heating Elements (IHEs). These storage systems are thus using so-called *power-to-** technologies (see Section 2.2.1) [101, 131, 573]

2.1.5 Gas and Other Fuels

There are many different gases and other fuels that are widely used in our energy systems, such as natural gas, heating oil, and ethanol. They are used for electricity generation, heating, cooking, transportation and other energy services. Some of them are fossil fuels that are extracted from non-renewable fossil resources, such as natural gas and diesel, others are generated using renewable primary energy sources, e. g., methane, methanol, and ethanol.

Generation, Consumption, and Balancing

The generation, consumption, and balancing of gases and other fuels in energy systems are different from those of electricity. For instance, gas can be pressurized or liquefied and then stored in large quantities. Additionally, pipelines that distribute gas may have different pressures and thus inherently serve as a storage system. Liquid fuels can easily and efficiently be stored in storage tanks. [446, 623]

Gases, fuels, and alcohols that are widely used in our energy systems comprise different hydrocarbons and alcohols as well as other organic compounds and molecules. Examples for typical gases and liquid fuels that are used in energy systems include those mentioned in the following paragraphs.

Natural Gas Natural gas is actually a processed and blended mixture of several hydrocarbon gases and other gases that have been extracted from natural resources. Thus, its calorific values are not constant. Natural gas is transported using pipes in gas grids or tankers. To make transport of natural gas in tanks practicable, its volume is reduced through density increase by liquefaction or compression. Natural gas is used in cooking, heating as well as industrial and combustion processes, which includes DG by CHPs. [446, pp. 92 ff.] [448, pp. 11 ff.] [623, pp. 271 ff.]

Hydrogen Hydrogen is the chemically simplest and lightest one of all energy carriers. It can be generated by decomposing water using electrolysis, by the chemical reaction from methane and water into CO_2 and hydrogen using reforming or partial oxidation, by the decomposition of methane in a bubble column reactor made of tin, or by gasification processes from coal. The other way around, hydrogen can also be converted to methane in a process called methanation. The storage of hydrogen requires pressurization or liquefaction, which are both complex and expensive. [235] [446, p. 203] [507] [623, p. 273] [661]

Methane Methane is the chemically simplest and lightest hydrocarbon energy carrier. Typically, it is extracted from fossil gas sources and it is the main part of natural gas. Nevertheless, it can also be produced out of hydrogen in a process called methanation or from biomass using anaerobic digestion of bacteria. Storage of methane is easier than that of hydrogen. [446, pp. 71 ff., 180]

Ethane, Propane, and Butane Ethane, propane, and butane are light hydrocarbons and make up a small part of natural gas. They are extracted from natural gas and are a by-product of petroleum refining from crude oil. They can more easily be compressed and liquefied than methane. In particular, a mixture of propane and butane is used as liquefied petroleum gas (LPG) for cooking and off-grid refrigeration or in combustion processes, which includes DG by CHPs. [446, pp. 71 ff.]

Gasoline, Diesel, Kerosene, and Heavy Oil Gasoline, diesel, kerosene, and heavy oil are typical products of crude oil. All of them are used for cooking and heating purposes as well as in combustion processes for electricity generation and mobility. Often, DG is using gasoline or diesel for electricity generation. For instance, diesel generators are used in island grids, to serve as uninterruptible power supplies. [446, p. 87]

Methanol and Ethanol Methanol and ethanol are the two simplest alcohols and widely used as energy carrier. Methanol is generated from methane, from biomass using a gasification process, or from CO_2 and water using a process "of electrolytic cracking and catalytic synthesis" [446, p. 204]. Typical sources for ethanol include sugar cane, corn, other biomass, and waste. [70, pp. 254 ff.] [446, pp. 180, 204 ff.]

Balancing The balancing of supply and demand of gases and other fuels is rather slow, because consumers may not flexibly change their consumption at short notice, i. e., they are price-inelastic in their demand. Changing the consumption significantly requires switching to alternative energy carriers, because customers that are connected to a grid have usually only limited local storage capacities. In particular, in the case of natural gas, which is distributed using the gas grid, there are usually no storage capabilities of the customers at all. In case of domestic fuel oil, the storage tanks are big and usually only refilled once a year, which leads to the same effect of inelasticity.

Devices and systems that may use multiple energy carriers alternatively and allow for switching to other fuels are usually more expensive than single fuel technologies. Additionally, the prices of gas and other fuels are often heavily interdependent or linked to each other, i. e., a price increase of one energy carrier leads to increasing prices of the others as well. Adding generation capacity, such as additional wells, pipelines, and terminals, is expensive, too, and often requires several months to implement. Apart from that, gas consumption depends heavily on weather and season. [141, pp. 1 ff.] [308, p. 12]

Grids and Distribution Systems

Natural gas is the only gas that is widely distributed using dedicated gas grids with pipelines. Nevertheless, natural gas is also distributed as compressed natural gas (CNG) or liquefied natural gas (LNG), which enable the transportation using storage tanks and terminals. The natural gas grid is a hierarchically structured grid of pipelines with different pressure levels of usually up to 100 bar, which is obtained using compressor stations. It serves for transportation and storage at the same time, because a pipeline can have different gas pressures, which allow for a variation of the total amount of gas in the grid [448, pp. 4 ff.] [623, p. 260]. Other gases are also distributed using tanks and terminals, such as liquefied petroleum gas (LPG). In case of liquid energy carriers, crude oil is widely distributed using dedicated grids. All liquid fuels are transported using storage tanks, some are also distributed locally in small grids. [446, pp. 51 ff.]

From a local perspective, i. e., within a property or building, nearly all gases and other fuels are distributed in some kind of small local grid or using direct lines between the storage tanks and the consuming devices and systems. [448]

Storage and Storage Systems

The consumption of gas and other fuels depends strongly on climate, season, and weather, because a large share of them is used for heating. Supply and demand are both rather inflexible and inelastic: The supply is inflexible because generation capacities cannot be increased significantly without huge investments. The demand is in-elastic because devices and systems are usually only able to burn one energy carrier but no other carriers. Thus, storage is often done with a seasonal character. [141, p. 1]

In addition to storage handling seasonal and daily imbalances in demand and supply, there is also precautionary and strategic storage to handle risks of accidents or geopolitical problems and changes. These storages are often subject to governmental policies. [141, pp. 1 ff.]

Storage capabilities of natural gas include the gas grids, which is called linepack gas, storage tanks, e. g., at terminals, and underground storage reservoirs, such as salt caverns and aquifers. Gas grids provide a limited capability of storage, because pipelines in grids have different gas pressures that allow for a variation of the total amount of gas in the grid. Other gases and fuels are typically stored in storage tanks and terminals. [141, 448]

2.1.6 Thermal Energy

Typically, residential and commercial buildings need space heating and Domestic Hot Water (DHW), i. e., hot potable water, while industrial buildings need also steam for industrial processes, too. Another form of energy service that is often required in buildings is space cooling, which is provided by air-conditioning systems [309, pp. 36 ff.]. This thesis focuses on the following thermal energy carriers: DHW, hot water for space heating, and chilled water for space cooling, which are generated locally or provided externally by district a heating or cooling system. The potable water for DHW is provided by an external water supply.

Thermal Power

Thermal energy in form of water—more precisely the enthalpy of water—is the most important energy carrier in thermal heating and cooling systems. Often, water is mixed with some other substances improving its characteristics, such as antifreeze agents.

Potable Water and Domestic Hot Water Potable water is drinkable water. It is regarded in this thesis only in case of DHW, which is generated locally from potable water using some kind of heating device or system. DHW is potable water that has been heated up by some heating device or system. The term *domestic hot water* is used in this thesis to distinguish this kind of water from non-potable hot water, e. g., used in heating systems.

Hot and Heating Water Hot water and heating water are used synonymously in this thesis. They refer to water that has been heated up using some heating device in order to be used in some kind of heating cycle providing thermal energy. The term *hot water* is used in this thesis to distinguish this kind of water from potable DHW.

Cold and Chilled Water In order to avoid confusing cold potable water and cooling water, the term *chilled water* is used throughout this thesis for water that has been cooled down, i. e., chilled, to be used somewhere in buildings for an energy service. In contrast, *cold water* refers to simply cold water that has not explicitly been chilled.

Generation, Consumption, and Balancing

Thermal energy is generated locally in buildings as well as on a community level. This thesis focuses on the former, i. e., local generation of thermal energy. Nevertheless, local utilization may be based on a thermal energy carrier that is provided by an external district energy grid, i. e., district heating and cooling.

District Heating District heating is a collective heating system where heat is generated centrally and then distributed to the places where it is used for heating purposes. Typically, this kind of heating system is installed in large urban areas and feed-in is done using cogeneration, i. e., CHP plants, and heat-only boilers or waste heat recovery from incineration or industrial processes. One of the main reasons for the rising popularity of district heating is the spread of cogeneration, which offers a higher energy efficiency than the exclusive generation of electricity. District heating systems are often supplied from multiple plants using different energy carriers. [309, pp. 28 ff.]

District Cooling District cooling is very similar to district heating and is growing in popularity. In district cooling systems, cooling energy is generated centrally and then distributed to residential, commercial, and industrial buildings and plants. Typical energy services include air-conditioning, refrigeration, and process cooling. District cooling is generated using compressors and absorption as well as adsorption chillers. Absorption and adsorption chillers use heat to generate cooling, which enables the usage of district heating for district cooling. This is of interest in the summer because there is cooling instead of heating demand and thus a potential surplus heat generation. Usually, such technologies are combined with conventional compressors that provide peak generation. [309, pp. 37 ff.]

Heated and Chilled Air Heated and chilled air are the result of the energy services space heating and space cooling. Nevertheless, they may also be generated centrally and then distributed in buildings using air distribution ducts. Heated and chilled air is “consumed” because of thermal losses mainly due to convection and heat conduction through the building envelope and air exchange. Thermostats are used to condition the building with an air temperature around a temperature set point or within temperature limits.

Hot and Chilled Water Hot and chilled water are provided by some heating or cooling device or system. Typically, they are at least buffered in small tanks or even stored in large storage tanks that partially decouple generation from consumption, increase system efficiency, and decrease the number of operation cycles of heating devices and systems.

Domestic Hot Water DHW is heated up using some kind of heating device or system, such as a boiler or heat exchanger. Heat exchangers utilize another source of energy, e. g., hot water that has been stored locally or in a district heating system. DHW has special drinking water requirements, such as legionella protection. Provision and storage of potable water is usually done centrally, i. e., on a community level, except for DHW, which is sometimes stored in small quantities locally in water boilers or hot water storage tanks.

Thermal and Water Grids and Distribution Systems

Usually, the distribution of thermal energy is based on the usage of water, rarely on steam. Water and steam are mostly distributed in closed-loop circuits, i. e., having flow and return. The thermal energy is drawn from the circuit using radiators, heat exchangers, or simply by the conduction to surrounding material, such as the building's floor. The water or steam that is distributed through these systems has different flow and return temperatures. Thus, the transferred energy, including losses, is based on the flow rate and the flow and return temperature. In some cases, water or steam are transferred only unidirectional and leave the system at the energy service. Thus, they are replaced by fresh water from a water supply.

District Energy: Heating and Cooling In district energy, the thermal energy is transferred using a distribution grid of pipes that forms a closed circuit of flow and return in a wide area. Therefore, thermal grids that serve a wider area are usually called *district heating* and *district cooling*. To distinguish district heating that serves very large areas, for instance a whole city or region, from district heating that serves only small areas, e. g., a small village, a neighborhood, or several buildings of a property, the smaller grids are sometimes called *close-range* or *local district heating and cooling*. [309, pp. 36 ff.]

Heated and Chilled Air Heated as well as chilled air are mostly generated directly in the rooms or centrally in the building. However, they may also be generated outside of the building and distributed to buildings using air distribution ducts.

Steam, Hot, Cold, and Chilled Water Steam is sometimes used to transport thermal energy for process heat in industrial processes. Due to higher temperatures, the transportation losses in steam grids are usually higher than in grids using water as energy carrier. Thus, steam grids are quite rare in residential and commercial buildings. [610]
Hot water is distributed using pipes before being used by heating energy services, such as space heating. Usually, it is distributed in a closed circuit, meaning that it forms a loop where the flow has a higher temperature than the return.
Cold and chilled water are distributed using pipes before being used by cooling energy services, which include space cooling and cooling of devices and systems, e. g., data centers [142, pp. 193 ff.]. Typically, the water has a temperature range between 4 °C and 25 °C, which is often seasonally variable. Chilled water is usually distributed in a closed circuit. Cold water is sometimes distributed in open circuits, e. g., to an evaporative cooler. [610]

Domestic Hot and Cold Water Domestic hot and cold water has usually not a closed-loop system of pipes, i. e., water circuit, but is unidirectional. The potable water is used and then partly returned into a separate sewage pipe system. Thus, new potable water has to be provided by some potable water supply.

Thermal Energy Storage

Thermal energy storage is the storage of thermal energy, i. e., heat storage, by sensible, latent, or thermochemical heat to provide energy services, i. e., heating or cooling, at a later time [33] [131, p. 594]. The three main types of thermal energy storage technologies are sensible, latent and thermochemical heat storage.

Sensible Heat Storage in Tanks and Caverns Typically, thermal energy storage is done in tanks or caverns and utilizing fluids—mostly water—for sensible heat storage. The thermal energy increases or decreases the temperature of the fluid material without changing the phase, e. g., the state of being liquid. [131, p. 526]

Sensible Heat Storage in Solids Thermal energy storage is sometimes done using solid material, such as concrete, ceramics, pebbles, or rocks, for sensible heat storage. Although the thermal capacity is low when compared to other materials, such as water, heat storage in solid materials usually allows for a wider temperature range to be utilized. A typical device that uses this kind of storage is the domestic storage heater. [33]

Latent Heat Storage using Phase Change Materials Thermal energy storage in Phase-change Materials (PCMs) utilizes the phase change of a material, i. e., melting/freezing or boiling/condensing, at a constant temperature and pressure to store latent heat. Often, the storage in PCM utilizes both latent heat storage and sensible heat storage. Materials that are used as PCM include salts, paraffin, and water. In case of water, both phase changes are utilized: melting/freezing in ice storage and boiling/condensing in steam accumulators. [131, p. 445]

Thermochemical Heat Storage Thermochemical heat storage utilizes sorption processes, i. e., absorption or adsorption, or chemical reactions that are reversible to store thermal energy. Main advantages of thermochemical heat storage include high storage densities and lower heat losses. Typical examples of thermochemical heat storage are silica gel, zeolite, i. e., solid adsorption materials. [33]

Conversion of Different Types of Heat and Thermal Energy Carriers

Often, heat has to be transferred from one heating system to another, e. g., from heating hot water to potable DHW. This is realized using heat exchangers that transfer the thermal energy from one heating circuit to another or between a heating circuit and a storage tank. The transfer from water to air is done using radiators or via material, such as the building's floor in underfloor heating systems.

2.2 Interdependencies in Energy Systems

Energy systems are highly interdependent systems that have interrelations between the different forms of energy as well as between the systems and sub-systems. Figure 2.2 depicts these interdependencies in energy provision, conversion, and usage of the energy sources, carriers, and commodities that have been introduced in Figure A.10 and Figure A.11.

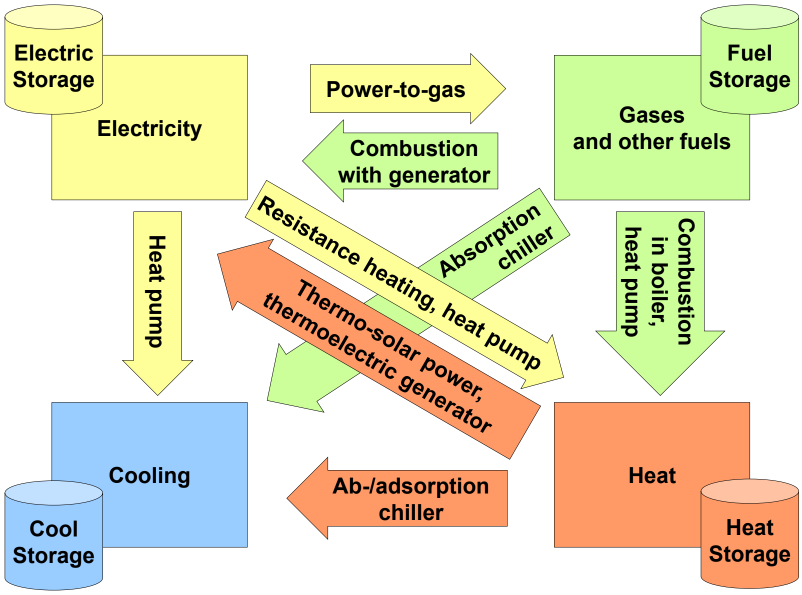


Figure 2.2: General framework of the interdependencies between electricity, cooling, heat, and gases and other fuels with typical conversion technologies

Historically, provision, distribution, and utilization of different energy carriers have been realized in different, dedicated energy systems with few interdependencies between these systems or without explicitly considering them. Recently, there is a change of this paradigm towards *energy systems integration* [520] and the *convergence of different energy sources* [606]. Several technologies are promoted to facilitate the integration of RES into the electrical energy system as well as of the energy systems with one another, e. g., power-to-gas, power-to-heat, and vehicle-to-grid. The main idea is to handle imbalances in the electrical energy grid better by integrating it more with heat and gas. This includes utilizing surplus electricity for other energy services, reducing electricity demand of energy services in case of electricity shortages, and integrating more electric storage intelligently into the grid, such as electric vehicles. [124, 201, 394]

The optimization of energy systems includes structural and economic, i. e., long-term, as well as operational, i. e., short-term, optimization on all levels. The long-term optimization determines possibilities and capabilities of the system that are optimized in their operation. Conversely, the short-term optimization influences the structural and economic optimization. Thus, both types of optimization have to be integrated [124, 394, 523]. In addition, interdependencies in energy systems are often complex and nontransparent for external entities. This is why decentralized EMSs that react to signals indirectly, such as load optimization with respect to price signals, promise to offer solutions for complexity and abstraction problems [340].

Multi-energy systems [394] or hybrid energy systems [131, p. 294] allow for a flexible selection of energy sources for provisioning, distribution, storage, and utilization for energy services as well as conversion processes. Although their selection and optimization has to respect the interdependencies as well as individual constraints, the integration enables to

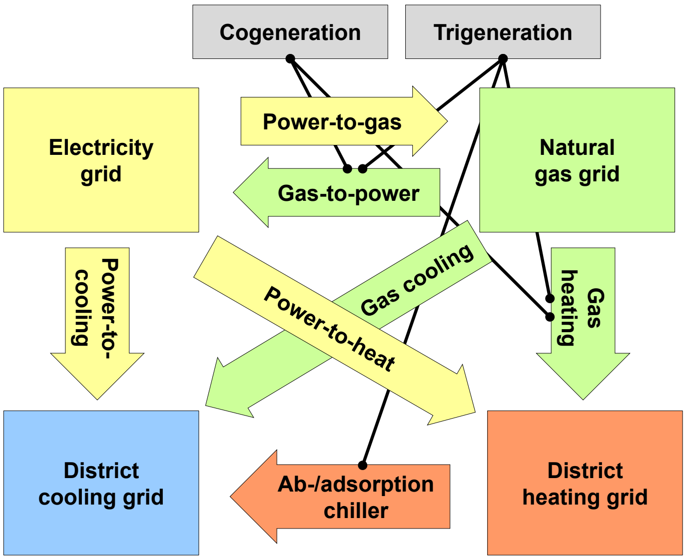


Figure 2.3: General framework of the interdependencies between the electricity, district cooling, district heating, and natural gas grids with typical conversion technologies and concepts

overcome individual availabilities, intermittencies, limitations, uncertainties, and risks of the energy carriers, while at the same time increasing the overall performance economically and environmentally. [201, 394]

The following sections describe typical interdependencies on different hierarchical levels of the energy system and technologies that cause or exploit interdependencies.

2.2.1 Technologies and Concepts

There are several technologies and concepts that focus on the linkage of different energy systems to increase efficiency and flexibility, e. g., cogeneration, trigeneration, and so-called power-to-* technologies. The most important ones are described in this section.

Cogeneration and Trigeneration

Broadly speaking, cogeneration technologies simply generate two energy carriers from one and trigeneration technologies generate even three carriers that are used by one or more energy services.

Cogeneration: Combined Heat and Power Cogeneration incorporates the principle of *energy cascading* into a single system, i. e., the usage of residual heat from one system in another for improving the overall efficiency. This system generates useful electricity and heat at the same time from a single fuel [131, p. 117, 197]. Typical cogeneration systems are combustion engines and fuel cells. For an analysis of CHP plants, see Section 4.5.4.

Trigeneration: Combined Cooling, Heat, and Power Trigeneration combines cogeneration of heat and electricity from a single fuel with the generation of a third one: cooling [131, p. 613]. Typical cooling devices include absorption and adsorption chillers, which use the heat to generate “negative” heat, i. e., realize cooling of an energy carrier such as chilled water or air. For an analysis of trigeneration, see Section 4.5.5.

Power-to-gas, Power-to-heat, and Power-to-cooling

Basically, the power-to-* or power-to-X technologies provide ways of using surplus electricity for the generation of other energy carriers and subsequently the provision of energy services that usually do not rely on electricity but on another energy carrier.

Power-to-gas Power-to-gas is typically realized as power-to-hydrogen or power-to-methane. The particular technologies generate gas utilizing electrical power and thus facilitate storage of surplus energy in form of gas fuels. Power-to-gas technologies generate heat as a secondary product that should be utilized as well, e. g., in a biogas plant for process heating or via district heating in buildings for space heating. The gas can later be converted back to electricity using, e. g., cogeneration or fuel cells, or used for heating. Nevertheless, the efficiency with respect to the required electricity is low, because each step in the conversion chain has losses that may not all be recaptured and used for other purposes. This is why this concept is not used to a large extent. [101, pp. 51 ff.] [232]

Power-to-heat Power-to-heat may be implemented locally using electric heaters or heat pumps. This way, electricity is used to substitute other fuels, such as natural gas. Therefore, this concept is sometimes also characterized as *virtual generation of gas* or *generation of virtual gas*, because the usage of electricity reduces the consumption of gas that would otherwise be utilized to provide the same energy services. In general, heat is stored more easily and cheaply than electricity in a distributed way and in large quantities. Buildings are actually some kind of thermal storage, too, which can be used to shift energy usage by slightly overheating the building. [385]

Power-to-cooling Power-to-cooling is similar to power-to-heat. As opposed to this, it is cooling that is utilized, which usually is done using electricity. Therefore, there is usually no other energy carrier that is substituted but the consumption of electricity is just shifted to other periods. [385]

2.2.2 System Boundaries, Spatial Scopes, and Networks

Interdependencies of energy carriers in energy systems depend on the chosen boundaries of the energy system at stake as well as the spatial scope. For instance, a trigeneration system can be regarded as a single integrated system or as the combination of an engine, a cooling and heating system, and an ab- or adsorption chiller. Some interdependencies are only valid for certain energy sub-systems or when the systems are interconnected to the trigeneration system. The trigeneration system may be part of a larger building energy system.

Spatial Scope and Perspective

To handle the complexity, different spatial scopes and perspectives show different levels of aggregation. The aggregation of devices to entities, i. e., systems, and the subsequent aggregation of systems to buildings, of buildings to areas, districts, regions, or even the whole energy system of states or continents enables different perspectives on energy systems using different levels of abstraction and thus consideration in evaluation and optimization [394]. A popular example of the graphic visualization of an energy system and some of its interdependencies of energy carriers are so-called *Sankey diagrams* [310, 529]. An exemplary Sankey diagram for a trigeneration system is depicted in Figure 2.4.

Scope: Energy System at Grid Level From an abstract overall energy system or grid level, the possible energy portfolios of carriers that are used for provision as well as for utilization of energy services show interdependencies of those carriers (see Figure 2.5). Some energy carriers in the input energy portfolio can be substituted for other carriers or may be transformed into each other (see also Figure 2.2). In particular, electricity can be used for the provision of different energy services, e. g., heating, lighting, or mechanical power.

Scope: Energy System at Building Level Buildings use a multitude of different devices and systems to provide energy services to its occupants and users. There are many possible combinations of different devices and systems to provide the same services. For instance, heating in a building can be provided by a gas-fired boiler, a heat pump, or a wood chip boiler. The set of devices and systems that is used in a building to provide a certain output energy portfolio determines the input portfolio. A certain input energy portfolio requires certain energy carriers and the output portfolio determines the possible energy services. This is visualized in Figure 2.6 and more closely described in Section 2.4.3.

Even simple technologies, such as boilers, which convert a fuel into heat by some kind of combustion process, lead to a relation of two energy carriers. Some of the technologies lead to interdependencies between multiple energy carriers, such as complex trigeneration systems, which include electricity, natural gas, hot water, and chilled water. Hence, all stages in the energy chain have interdependencies between energy carriers before they are finally used to provide an energy service. [201, 394]

The technologies that are used in a particular building depend on the energy carriers that are available for energy inbound provision. For instance, a building that has a connection to an electricity grid as well as one to a natural gas grid has a set of options and requirements that is different from a building having no connection to any grid at all but relying on some kind of fuel that is delivered periodically or solely on Distributed Energy Resource (DER).

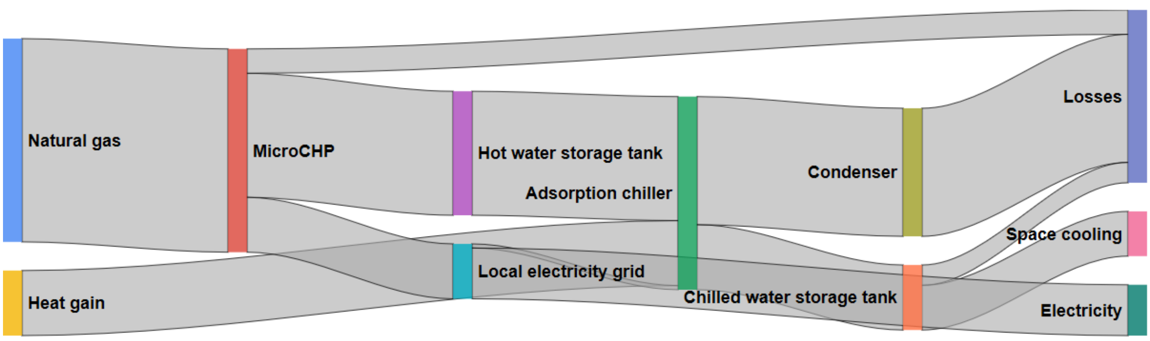


Figure 2.4: Sankey diagram of an exemplary trigeneration system (schematic energy flow)

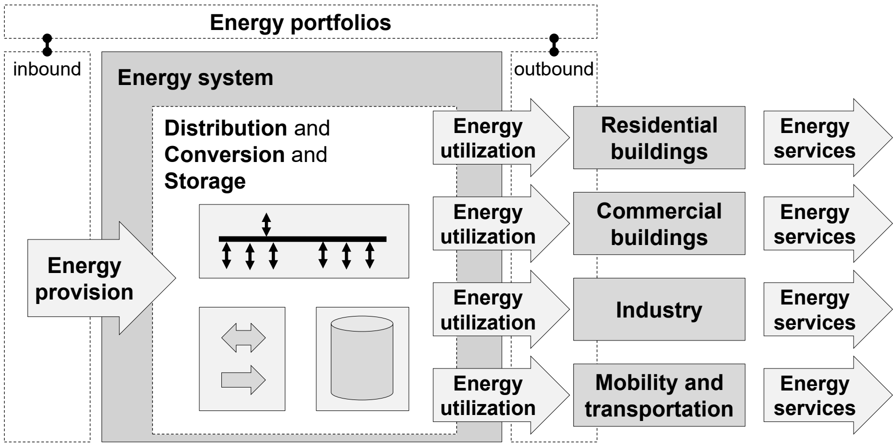


Figure 2.5: Abstract grid at the scope of the whole energy system including all grids

Scope: Single Systems and Devices The narrow scope of a single device of a small system, e. g., a gas-fired boiler or a gas-fired CHP, enables a detailed analysis and optimization of the device or system and the interdependencies of energy carriers that are used in the device or system (see Figure 2.7). At the level of single devices or devices that are combined into integrated systems, there are many individual options, operation modes, constraints, and limitations. For instance, hybrid devices having different heating components that enable them to run on different fuels offer a flexibility that is not met by conventional boilers using a single fuel (see also Section 4.7 for more information about hybrid devices).

Additionally, some devices have operation modes or configurations that enable them to alter the interdependencies of energy carriers. For instance, many CHPs have only a fixed rate of how much electricity and hot water they generate, whereas others can change the rate of hot water and electricity within certain limits. Often, the efficiency of a device and thus also the ratio of energy carriers depend on the device's load. [394, 482, 649]

Provision and Utilization

The interdependencies of energy carriers are in between the energy carriers that are used for energy provision, i. e., as energy input into the energy system, as well as the energy carriers that are finally used in energy utilization, i. e., as energy output leaving the energy system. Additionally, the energy portfolios of provision and utilization, i. e., the inbound and outbound energy carrier vectors, are usually interdependent (see Figure 2.5). [394]

2.3 Communication and Management in Energy Systems

To date, worldwide energy systems are heavily based on fossil and nuclear energy sources that are used to always generate as much energy as there is consumed. Mostly, these energy systems have been developed without bearing in mind that they may have unintended or even dangerous side effects and consequences, such as climate change and environmental pollution, or are subject to volatile prices in economic and political crises [51]. The communication

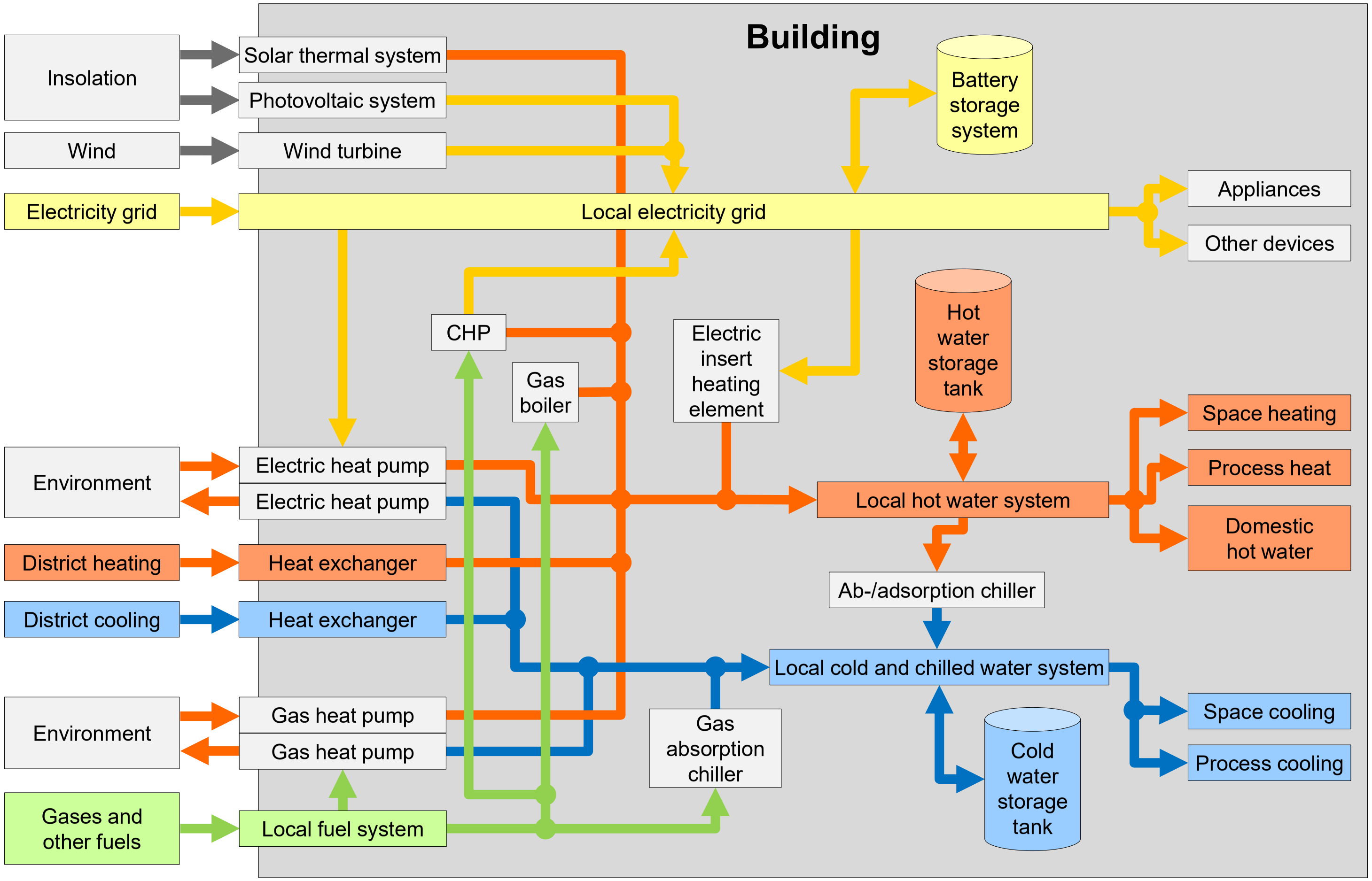


Figure 2.6: Interdependencies between electricity, cooling, heat, and other fuels in the provisioning process of different energy services at building level; arrows showing direction of energy flows

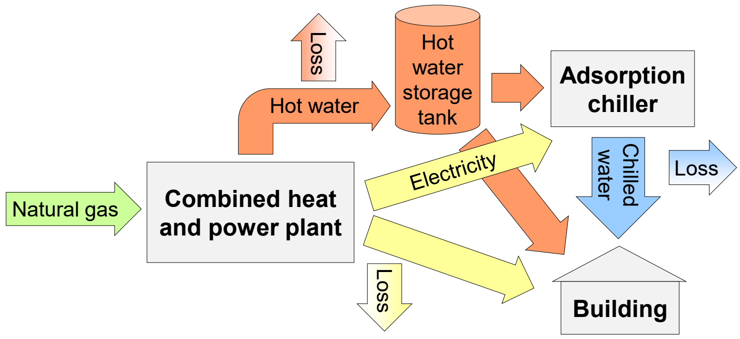


Figure 2.7: Interdependencies at system level: exemplary trigeneration system

and management technologies and concepts that are currently used in grids have been developed in this context. Nowadays, DG and RES call for several changes and adaptations to enable a successful transition to modernized grids and energy systems.

In particular, the paradigm change in the electrical energy system from “generation follows consumption” to “consumption follows generation” calls for novel concepts dealing with the challenges of DG that feeds into distribution grids and of intermittent generation from RES. Additionally, interdependencies between the grids and infrastructures of different energy carriers call for an increasing information exchange between different systems.

2.3.1 Current Control Structure of Grids

This section focuses on electricity, because electricity grids are subject to permanent disturbances that require sophisticated monitoring and control structures. Naturally, other grids are monitored and controlled, too.

Traditionally, electricity grids consist of two fundamentally different levels that are handled separately: the transmission grid that is closely monitored and controlled and the distribution grid that is rarely monitored and controlled. The transmission grids are spatially large grids but have only a limited number of nodes and degree of structural meshing, complexity, and diversity. The transmission grids are handled by transmission system operators that utilize Supervisory Control And Data Acquisition (SCADA) systems to acquire data and to control the grid. Typically, the SCADA systems are monitored manually by humans. Management and operation of distribution grids are in the responsibility of distribution system operators, which usually monitor and control only the medium and high voltage parts of the distribution grids. The extensive and diverse low-voltage distribution grids comprising a very large number of nodes are typically not closely monitored or controlled using sensing, automation, and remote control technologies (see also Figure 2.9 and below).

In the past, electricity has mainly been generated centrally, fed first into transmission grids before being delivered to the consumers using the distribution grids, i. e., the resulting energy flow was unidirectional. Nowadays, electricity generation by DG is leading to a large share of generation that is fed directly into the distribution grids and sometimes even flowing up into higher levels of the distribution grid, i. e., resulting in a reversed load flow and thus changing directions of energy flow. This new situation poses new risks, such as overvoltage due to power flow reversals, which did not have to be handled before. [206, 207, 346]

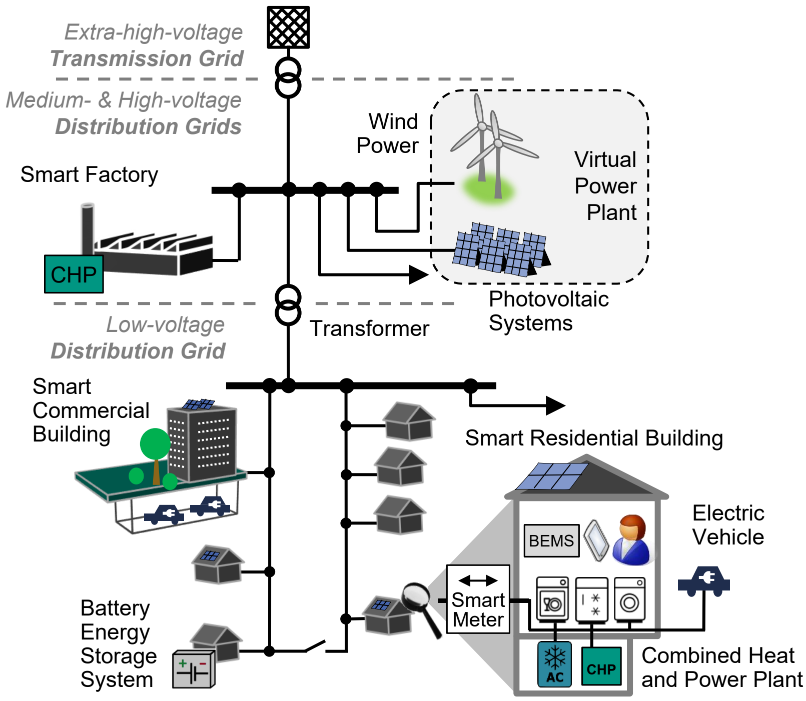


Figure 2.8: Components and topology of a future smart electricity grid, partly based on [409]

2.3.2 Smart Grid

The paradigm change in electricity grids towards a flexible and adaptive demand, which is a major part as well as result of changes in the electrical energy systems, such as the German *Energiewende*, calls for technologies that facilitate the flexibilization of electricity demand which is currently hardly controllable. *Smart grids*, which may be regarded as cyber-physical energy systems comprising heterogeneous interacting entities, offer a promising solution to these requirements. [338]

In a future energy system, the grid and the consumers must be able to adapt to intermittent and DG, enabling an efficient and stable grid operation. This is possible by flexibilizing the demand or by investing in infrastructure, i. e., grid reinforcement and new ESSs. As infrastructural investments are expensive and as it is hard to increase its capacities substantially, the focus is on the flexibilization of the demand side to use as much renewable energy as possible. In particular electricity storage, such as BESSs, is expensive or faces heavy opposition by the population, such as hydroelectricity. Consequently, the complexity of the infrastructure of grids is increasing as they will have to be operated in ways they had originally not been designed for. To ensure grid stability and reliability, advanced distributed control systems have to be designed that keep up with the changes and operate across organizational boundaries.

Smart grids comprise advanced monitoring, control, management, and optimization concepts that are facilitated by advanced technologies and methods, which provide the means for efficiency and flexibility of electricity provision, distribution, storage, and utilization. They include the flexibilization of the energy consumption as well as (distributed) generation

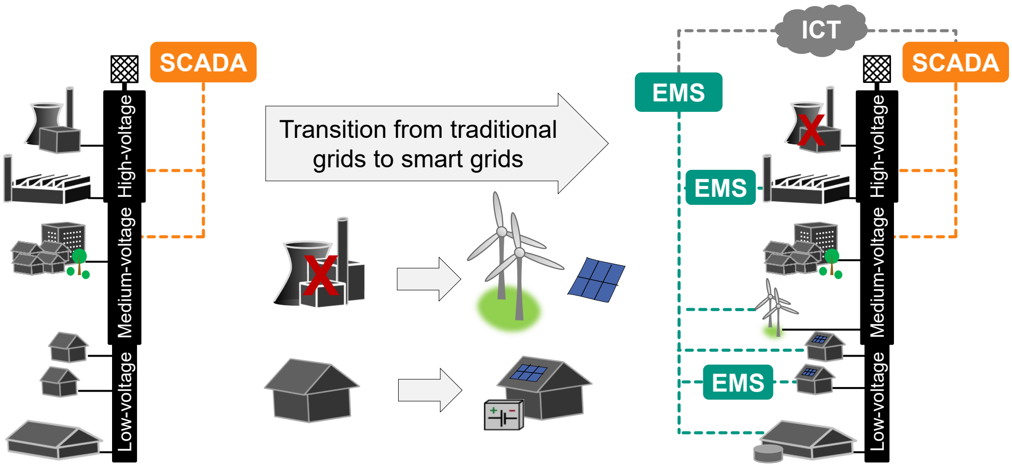


Figure 2.9: Transition from conventional electricity grids to smart grids using EMSs

encompassing the grid as well as individual buildings. An important concept is DSM (see also Section 2.3.4). It is supposed to enable an economically efficient way of responding to intermittent and decentralized energy feed-in from renewables by making the traditional demand side, i. e., the lowest levels of the electricity grid, responsive to external signals. [469]

The technologies that are used include in particular ICT that facilitates the communication between distributed sensors and actuators and enables remote monitoring and control of larger parts of the grids (see Figure 2.9). Thus, ICT will help to cope with the arising challenges and to limit investments into the physical infrastructure of the grid. Basically, it will provide an overlay infrastructure onto the physical grid that is necessary to make the grid smart (see Figure 2.8). Nevertheless, its architecture and structuring are likely to become very different and include various novel technologies, such as phasor measurement units, controllable smart transformers, and automated smart metering.

Smart grids will comprise numerous heterogeneous interacting entities blurring the historic distinction between different segments of the grid having separate dedicated entities: All kinds of smart buildings will adapt their consumption as well as generation and become so-called *prosumers*, i. e., producers and consumers, instead of sole consumers, while BESSs and electric vehicles will support the task of load balancing.

Traditionally, activities in electricity grids had been separated into the following segments that have separate entities and use dedicated technologies:

- Provision: electricity generation.
- Distribution: electricity transmission and distribution.
- Storage: electrical energy storage.
- Utilization: electricity consumption, metering, and billing.
- Supervision, control, and management: sensors, actuators, and SCADA systems.

The concept of a smart grid addresses in particular the following additional points:

- DER, RES, and DG and their management.

- Novel supervision, control, and management technologies and concepts for transmission and distribution grids.
- Facilitation of DSM and load flexibility.

The following two definitions of the term smart grid provide a general meaning of the term, before the developments and changes in electricity systems, the capabilities, concepts, features, and objectives of smart grids, as well as novel technologies and entities in smart grids are explained in more detail.

Common Definitions of Smart Grid Although there is a multitude of different definitions of the term smart grid, few of them are comprehensive. The following two definitions provide general definitions of the term smart grid without referring to dedicated technologies and concepts that may probably be applied in future electricity grids. A general definition has been provided by the *European SmartGrids Technology Platform* [199]:

> “A SmartGrid is an electricity network that can intelligently integrate the actions of all users connected to it – generators, consumers and those that do both – in order to efficiently deliver sustainable, economic and secure electricity supplies. A SmartGrid employs innovative products and services together with intelligent monitoring, control, communication, and self-healing technologies [...].
>
> SmartGrids deployment must include not only technology, market and commercial considerations, environmental impact, regulatory framework, standardization usage, ICT [...] and migration strategy but also societal requirements and governmental edicts.”

Another general definition is provided by the *Electric Power Research Institute* [197]:

> “[...] The term Smart Grid refers to a modernization of the electricity delivery system so it monitors, protects and automatically optimizes the operation of its interconnected elements – from the central and distributed generator through the high-voltage network and distribution system, to industrial users and building automation systems, to energy storage installations and to end-use consumers and their thermostats, electric vehicles, appliances and other household devices. The Smart Grid will be characterized by a two-way flow of electricity and information to create an automated, widely distributed energy delivery network. It incorporates into the grid the benefits of distributed computing and communications to deliver real-time information and enable the near-instantaneous balance of supply and demand at the device level.”

Both definitions provide only general definitions of the term smart grid without referring to dedicated technologies and concepts and explaining the capabilities and objectives. In addition, the definitions focus solely on electricity. Some of the upcoming capabilities and objectives that are part of the concept of a smart grid are briefly explained in the following paragraphs. [49, 197, 199, 400]

Active Distribution Networks, Microgrids, and Self-healing The distribution grids will be operated more actively and autonomously, which includes technologies such as DSM, substation automation, and the introduction of microgrids, enabling for instance self-healing functionality. The concept of DSM and DR is closely described in the following Section 2.3.4, microgrids are closely described in Section 2.1.2.

Prosumer Interaction and Participation The consumers will become prosumers that interact and participate more actively in the grid, which includes automated smart metering, DG, and variable tariffs. Additionally, the consumers will have more information about their energy consumption as well as the situation of the grid and will be able to interact with respect to choices, incentives, goals, and objectives.

Economic Efficiency and Cost Optimization Efficiency and cost optimization covers the transition from current energy grids to smart grids as well as the operation of the future energy system. Assets, infrastructures, and resources have to be utilized and operated effectively and efficiently while staying competitive.

Energy Security, Reliability, Resilience, Robustness, and Quality Making the grid smarter may help to sustain or even increase the energy security, reliability, resilience, and quality of service, e. g., power quality, despite intermittent RES. The smart grid will increase the grid's capacity and predict and react on system disturbances. Additionally, it is enhanced with respect to its resilience against natural disasters and attacks by internal and external entities, making it less vulnerable. A reliable energy system is the prerequisite for the digitization of our economy. Therefore, security issues of infrastructures have to be handled seriously and additional measures have to be taken in smart grids [140, 318, 350].

Greenhouse Gas Emissions, Pollution, and Safety Emissions of GHGs and other pollutants will be reduced. This will help to limit or even reduce the carbon footprint as well as the hazardous discharge of particles and substances into the environment.

Openness to New Technologies and Solutions Most importantly, the introduction of a smart grid will be open to all kinds of technologies, no matter whether they are old or new. This includes all generation and storage technologies but also ICT that will enhance the functionality and capabilities of conventional technologies.

Openness to New Markets, Products, and Services The smart grid will be open to new markets, changes and adaptations in existing markets, and novel products and services that are enabled by new technologies. This may include the introduction of *transactive energy*: This concept is based on the principle that all decisions in energy systems are being made based on their value, which depends on energy, price, emissions, comfort. Thus, it is the dynamic balancing of supply and demand across all parts of energy systems using economic control principles related to their valuation [262, p. 11].

Multiple Energy Carriers and Multi-energy Smart Grid The concept of a smart grid is not limited to electricity. A truly *smart* grid has to consider all energy carriers, as energy management and optimization are important in all energy grids. Technologies, such as smart metering, may be applied to all energy carriers. The integration of the different grids into a combined *multi-energy smart grid* provides additional opportunities. For instance, it facilitates a holistic view on all energy carriers and enables additional flexibilities, e. g., by shifting energy consumption and generation, respectively, from one energy carrier to another. This leads to the following proposed definition of a multi-energy smart grid:

> **Definition:** A *multi-energy smart grid* is an integrated energy grid comprising all energy grids that are used in the (distributed) generation, distribution,

> and consumption of energy using various energy carriers. It includes novel technologies and entities that enable the intelligent interaction of all entities to provide new services, facilitate new functionality, and increase energy efficiency. The main characteristic is a two-way flow of information to and from all entities.

This thesis emphasizes the importance of including all relevant energy carriers in a single multi-energy smart grid and optimizing them in an integrated manner.

2.3.3 Virtual Power Plant

Virtual Power Plants (VPPs) [101, 432] or virtual power stations [610, p. 33] are aggregated virtual entities comprising multiple distributed real entities in the grid. Although this concept had originally been limited to generators, it has later been extended to include energy storage and controllable loads, too. This enables a high flexibility and quick reactions to fluctuations of RES and imbalances in the energy grids. Nevertheless, a VPP is a complex system comprising heterogeneous entities that have to be linked using ICT and optimized using suitable methods. The communication with distributed systems that may also be located in residential buildings provokes additional privacy and security issues. [101, pp. 249 f.] [432]

The main idea of VPPs is the abstraction from heterogeneous entities, such as Micro Combined Heat and Power Plants (microCHPs), PV systems, BESSs, and controllable loads, into virtual entities. These virtual entities resemble the functionality and capabilities of conventional power plants as well as of operating reserves and participate in energy markets. A VPP may not only provide active power for frequency control but also other ancillary services, such as reactive power and voltage control. Thus, the concept of VPPs is similar to that of microgrids. The major difference is that microgrids are spatially constricted entities whereas VPPs may be distributed across the whole energy system. [42, 49]

Implementing VPPs requires ICT and algorithms that facilitate the abstraction and combination of subordinate entities, control and react to states of real entities, and enable the integrated optimization of heterogeneous and originally independent entities. The controlling system is actually a specific EMS that coordinates and optimizes subordinate entities while marketing products and services [42, 610]. Typical tasks of VPPs include [101, p. 249]:

- Monitoring and supervision of subordinate entities and of changing external conditions.
- Forecasting and prediction of the future states, behaviors, and capabilities of the subordinate entities.
- Optimization of schedules and actions, such as the market negotiation and sale of products and services.
- Coordination and control of the subordinate entities to execute schedules.

In case of intelligent subordinate entities, there may be problems of asymmetric information and strategic considerations. For instance, a subordinate entity might manipulate its communicated future capabilities to increase its profits and rewards to the disfavor of the other subordinate entities. To avoid such kinds of problems, effective mechanisms have to be implemented that control, track, and verify the actions of the entities. This may also include mechanisms for trustworthiness and reputation. [491]

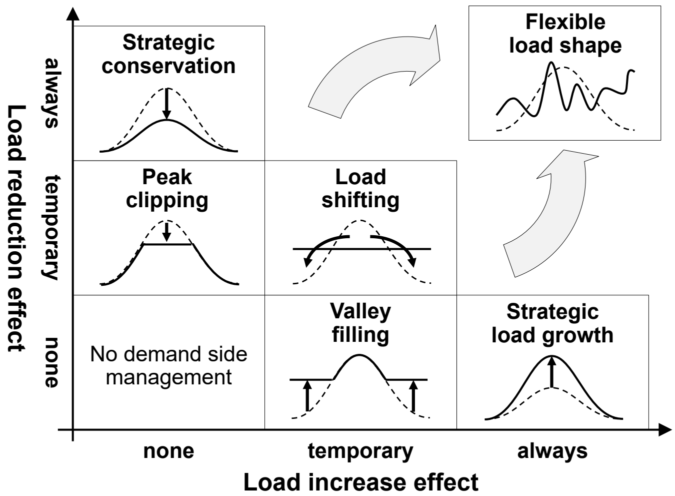


Figure 2.10: Types of demand side management, partly based on [240]

2.3.4 Demand Side Management and Demand Response

Although the idea of influencing the demand side of the energy system to balance the system more efficiently is used for decades [239], there is no consistent definition and nomenclature of DSM and DR in the literature.

Sometimes DSM and DR are used interchangeably [487, Chapter 9]. Sometimes DR is seen as a subset of DSM [469] or vice versa [49]. Sometimes measures of energy efficiency and conservation are included [469], sometimes they are specifically excluded [487, Ch. 9]. Sometimes DSM is defined as a top-down approach using a set of measures that is implemented by market roles, i. e., utilities and aggregators, to increase the efficiency, whereas DR refers to the bottom-up approach of customer reactions to monetary incentives and information, i. e., the realization of a distributed active energy management that leads to decentralized decision making [115]. Sometimes it is now named demand side integration [41, 128, 158]. Additionally, the term *demand* is misleading because nowadays the demand side is generating energy, too [148]. Thus, managing to define DSM is actually quite demanding.

Definition of Demand Side Management In this thesis, the term *demand side management* is used to describe all measures and methods that are applied at or influence the lowest level of the energy grids—the former demand side—for the benefit of the overall grid and energy system. This includes the reduction of energy consumption or the increase of energy generation as well as the other way round. Thus, all market roles as well as all stakeholders may participate in one way or another in DSM. Additionally, it covers different categories of measures, such as energy efficiency and conservation, operating reserve, physical, market, and other DR signals. Therefore, DR refers to all measures that incentivize the demand side to adapt their consumption and generation because of additional costs, benefits, information, and education. In contrast, energy efficiency and conservation is only targeting the consumption.

Due to the complexity of the demand side and the difficulty of abstracting its flexibility, the usage of market DR is getting popular, enabling distributed decision making that that does

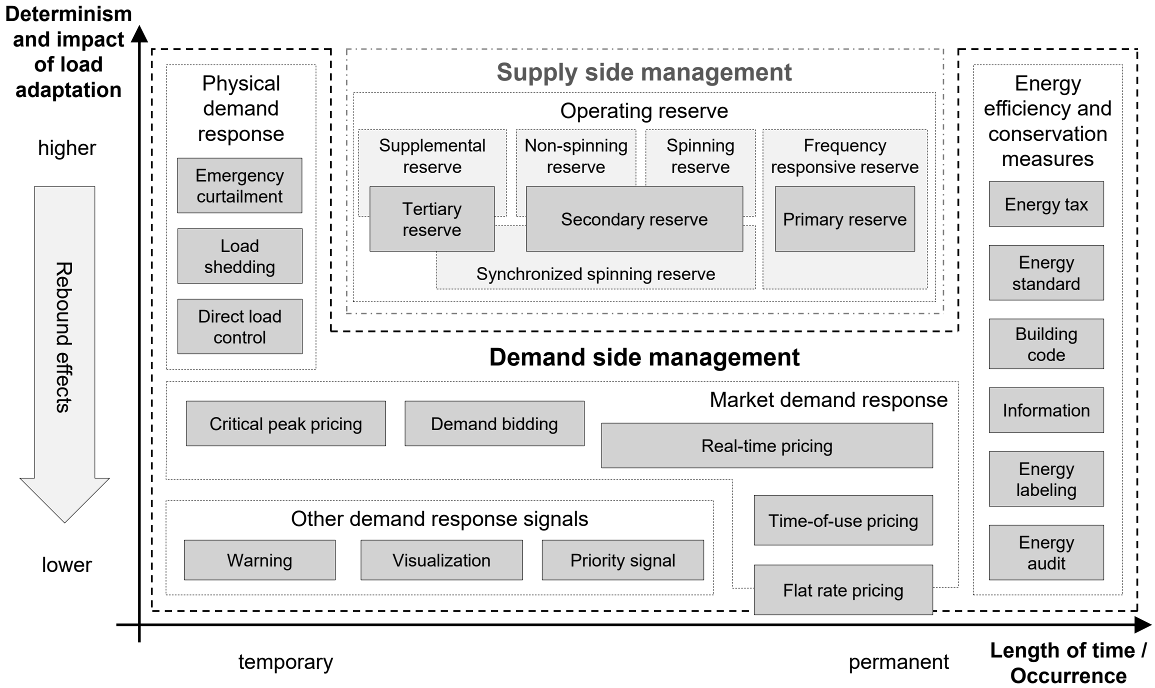


Figure 2.11: Categories of measures of demand side management and operating reserve, partly based on [190, 469, 471, 495]

not require such and abstraction but calls for a distributed automated energy management by means of EMSs. Importantly, DSM has to be realized across multiple energy carriers because of interdependencies between energy carriers when maintaining energy services, which cause substitution effects. Additionally, the different energy grids have individual characteristics, requirements, and constraints, which have to be respected. [49, 107, 398, 469]

Generally, DSM is supposed to enable an economically efficient way of responding to imbalances in the grid that are caused by intermittent and decentralized energy feed-in from DG and RES by making the consumers and their devices flexible in their consumption and responsive to external signals. Thus, DSM provides the means to invert the paradigm of energy provision, distribution, and utilization from "supply follows demand" to "demand follows supply". DSM is part of smart grids: ICTs, which are core components of smart grids, allow for advanced monitoring, management, and optimization capabilities and enable active DSM based on the distributed flexibility of the energy consumption and generation encompassing buildings as well as individual devices by achieving controllability or at least influenceability. [107, 148, 469]

It is important to note that DSM includes various types and objectives of load change [240]. These types and objectives are depicted in Figure 2.10. *Peak clipping* refers to a *temporary load reduction* of peak consumption that might otherwise cause overloads in the grid or exceed the maximum possible generation. By contrast, *valley filling* refers to a *temporary load increase* during times of low consumption that might otherwise lead to surplus generation. Combining both at different times, i. e., temporary load reduction and increase, leads to *load* *shifting* that improves efficiency and exploitation of energy provision. Additionally, it might be in the interest of a utility to achieve permanent *strategic conservation* or *strategic load growth* to cope with systematic imbalances. Finally, a *flexible load shape* may be realized by combining all types flexibly.

In Figure 2.11, several measures of DSM and types of operating reserves are categorized according to their determinism and impart of load adaptation as well as the occurrence, based on figures, definitions, and descriptions by [190, 469, 471, 495]. The so-called *rebound* or *fallback effects* reduce the determinism and impact of load adaptation [650], because people get accustomed to the measures and tend to react less on reoccurring measures. In contrast, automated energy management preserves the determinism and impact of the measures. The measures of supply side management depicted in Figure 2.11 describe neither exactly the European nor the American wording of these reserves.

Energy Efficiency and Conservation Measures Measures of energy efficiency and conservation include the introduction of energy taxes, e. g., CO_2 emission taxes, energy standards for devices and building codes, or the provision of information and education, such as display, energy labeling, and energy audits. [469]

Direct Physical Demand Response Measures of direct or physical DR include the realization of emergency curtailment, load shedding, and direct load control, i. e., disconnection of preselected loads, that enable a direct control in case of emergencies and critical situations as well as in ordinary situations. [487, Chapter 9] [469]

Indirect Market Demand Response Measures of indirect or market DR include pricing schemes, e. g., critical peak pricing, real-time pricing, and time-of-use pricing (see also Section 2.1.1), and demand bidding mechanisms, i. e., market participation of the consumers, that realize an indirect and thus often non-deterministic control of the demand side. [148, 469]

Other Demand Response Signals There is a multitude of other signals that may be used to influence the demand side, e. g., warning notices, visualization of the grid's state or the local energy consumption, and priority signals. [469]

Supply Side Management: Operating Reserve At the generation side, i. e., in contrast to the demand side, there are different types of operating reserve: primary, secondary, and tertiary reserve. The nomenclature of the different reserves is inconsistent, because the naming and concrete realization differs worldwide depending on the balancing region or group and the respective legal framework. [190, 469, 471, 495]

2.4 Buildings, Systems, and Devices

The terms *building*, *system*, and *device* are used in a variety of contexts. This section defines these terms the way they are used in this thesis before defining different types of *smart buildings* and describing typical devices and systems in buildings.

Building Simply put, a building is a structure of walls that has a roof on its top. However, there are many different types of buildings, e. g., residential, commercial, industrial, agricultural, public, and military buildings. This thesis focuses on residential and commercial buildings which typically have building services, such as a heating system, that are provided by the physical plant and which are equipped with additional energy consuming devices, such as home appliances. Although it is sometimes used for commercial buildings only [181], the term building refers in this thesis to both residential and commercial buildings.

System A system is an integrated set of components or parts, e. g., devices or—more generally—entities, that are interacting and usually interdependent. It has a defined spatial boundary and its surrounding is called environment [78]. Furthermore, it has an internal structure, i. e., state and transition mechanism, and shows a behavior, i. e., relationship between its input and output [659, pp. 3 ff.]. This thesis uses the term system in two contexts: firstly, in the context of systems that are used for energy management and, secondly, in the context of systems comprising multiple integrated devices, such as cogeneration systems.

Device A device is some constructed, i. e., man-made, tool or machine. This thesis uses the term device for technical devices, such as home appliances or gas-fired boilers.

Home Appliance A home, household, or domestic appliance is a device that is used in buildings—in particular in residential buildings—to carry out tasks related to household functions. Self-evidently, some of these devices are used in commercial buildings, too. Examples of appliances include washing machines, tumble dryers, and toasters. This thesis uses the term appliance in the meaning of home appliances (see also Section 2.4.3). [131, p. 27]

2.4.1 Smart Building

The term *smart building* covers a wide range of different concepts and ideas of future buildings. Typical properties of buildings that make them smart include the following ones [327, 424, 475, 503]:

- Smart, intelligent, and interacting devices.
- Coordination of the building in a way that benefits the user or inhabitant.
- Additional sensors and actuators that help to monitor and control the building.
- Novel or enhanced functionality that assists, helps, protects, and supports the user by automating tasks, anticipating future states, analyzing data, and optimizing actions.

Table 2.1: Exemplary terms used for intelligent residential buildings in the literature

Term	Exemplary references	Term (cont.)	Exemplary references
Adaptive house	[119, 327, 503]	Home of the future	[227, 320]
Context-aware home	[421]	House of the future	[119, 327]
Intelligent home	[119, 227, 327, 651]	Smart home	[8, 32, 119, 227],
Internet home	[327]		[327, 387, 424, 475]
Interactive home	[227]	Smart house	[119, 225]

Smart Residential Buildings Residential buildings include single-family and multi-family buildings that are detached, semi-detached, or form big blocks and towers, such as apartment complexes. Often, they are distinguished into urban, sub-urban, rural, and farm buildings having typical properties. It is important to note that many residential buildings comprise multiple persons or households that have different objectives, goals, and contracts regarding their energy usage, which has to be reflected by the BEMS [133]. There are many terms for intelligent residential buildings, including the ones listed in Table 2.1. The term *smart residential building* is used throughout this thesis to describe intelligent residential buildings with enhanced functionality and equipment, comprising one or multiple households.

Smart Commercial Buildings Commercial buildings include all kinds of buildings that are used for commercial activities, such as office buildings, warehouses, and retail stores. Often, the term *smart building* is used to refer to smart commercial buildings, such as smart hotels or smart offices [370, 437, 554, 635]. Analogously to smart residential building, the term *smart commercial building* is used throughout this thesis for intelligent commercial buildings with enhanced functionality and equipment. When referring to both types of buildings—residential and commercial—this thesis uses the term *smart building*.

Smart Industrial Buildings Typically, industrial buildings, such as factories and breweries, are already using infrastructure that facilitates building automation and energy management and the concepts presented in this thesis may easily be transferred to them.

2.4.2 Energy Provision, Distribution, Storage, and Utilization in Buildings

Energy services in buildings utilize energy that is provisioned externally or locally. Within buildings, the energy is distributed using small local grids made of wires, cables, lines, pipes, and ventilation ducts. Nowadays, buildings are becoming energy providers to energy grids because DG is making them co-providers.

Prosumer and Co-provider More and more buildings are now generating energy, in particular electricity. When generating more electricity than being consumed locally, the buildings provide the surplus electricity back to the electricity grid: The consumers are sometimes becoming producers. Therefore, they are now often called *prosumers*, combining the terms producer and consumer. Sometimes, the term *co-provider* is used to describe local generation that does not always meet local needs. The prosumers contribute to the balancing of the grid in both ways, i. e., regarding their consumption as well as their generation, and may also trade electricity on markets. DG of other energy carriers than electricity that is fed back into grids or sold in some other way is uncommon. [19, 233, 602]

Distributed Generation in Buildings

There are several technologies that are widely used for DG in buildings or may become important in the future. These technologies are shortly described in the following paragraphs.

Fuel Cells Fuel cells convert fuels directly into electricity and heat without combustion processes as done by turbines and engines. The conversion process utilizes the oxidation of a fuel—typically hydrogen or methane—without moving parts in a so-called stack. [131, p. 240]

Microturbines Microturbines or turbo generators burn fuels, such as natural gas, propane, or gasoline in an internal combustion process that powers a turbine which is connected to an electrical generator. [131, p. 617]

Hydro Power Small-scale hydro power utilizes falling and flowing water to generate electricity using turbines and water wheels. The water pressure is first converted into mechanical energy which drives a generator to provide electricity. [131, pp. 296 ff.]

Photovoltaic and Solar Thermal Systems PV and solar thermal systems utilize sunlight, i. e., solar radiation, to generate electricity and hot water, respectively. PV systems comprise solar cells that are combined into PV modules and power inverters or DC converters that generate AC or DC power, respectively. Solar thermal systems comprise collectors that absorb solar radiation and convert it to thermal energy. [131, p. 119, 449, 548]

Reciprocating Engines Reciprocating engines are used by, e. g., engine-generators and CHPs, to generate pressure which is converted into rotating motion by burning some fuel, e. g., natural gas or diesel. [131, p. 489]

Wind Turbines Wind turbines utilize wind power to generate mechanical energy that is subsequently used for electricity generation or for pumping water. [131, p. 651]

Energy Consumption and Services in Buildings

Buildings, more precisely energy services in buildings, consume about 40 % of the global energy generation [576]. Self-evidently, the share of building energy consumption of primary energy generation differs throughout the world. Energy services in buildings include electricity for home appliances and lighting, space heating, DHW supply, and space cooling.

Better buildings designs, e. g., because of stricter building codes that enforce better insulation, and novel technologies, e. g., BESSs, promise to reduce the energy consumption. Nevertheless, humans tend to increase the consumption of energy services if it becomes cheaper, which is called *rebound effect* and often offsets improvements [260]. Additionally, the so-called Internet of Things (IoT) will lead to more devices consuming energy, to more energy consumption of devices because of communication modules, and to more devices relying on electricity for their function (see Section 2.6).

Technologies that are used to actively increase the energy efficiency of buildings or to make its energy consumption and generation more flexible include building automation, integrated technical building services, DSM, monitoring, DG, and energy storage. Visualization of energy service consumption and the inbound provision of energy is important to support these technologies by including the user and facilitate their participation. [554, 651]

Energy Distribution and Storage in Buildings

Energy for the utilization by energy services is distributed in buildings using small local grids comprising wires, cables, pipes, and ventilation ducts. Typically, electricity is distributed in a local one- or three-phase low-voltage AC grid made of cables and having a voltage of up to 400 V. Thermal energy is distributed using water that flows in closed heating circuits made of pipes, i. e., water has different temperatures in flow and return of the circuit, or air in ventilation shafts. DHW is sometimes distributed using a circuit enabling to keep nearly constant water temperatures in the supply system even if the water is tapped only from time to time. Nevertheless, the water is actually withdrawn from the system at the tapping point and only partly returned in a separate sewage system. Thus, the energy flow actually depends on the temperature of the fresh potable water when provisioned inbound to the building. All these different types of energy services have to be taken into account when optimizing the energy flows in buildings using some BEMS.

2.4.3 Devices and Systems in Buildings

There are many devices and systems, such as appliances and HVAC equipment, which are typically used in buildings. Although most buildings have a similar set of devices, the particular configuration of concrete models varies and is usually quite unique. There are many manufacturers and brands that produce different models of these devices and systems, resulting in a heterogeneous landscape.

Typical Appliances and Traditional Classification

Appliances are usually classified into the four classes given in Table 2.2. Sometimes, the classes of major and small appliances include small heating and cooling devices, such as electric boilers or air-conditioning units, or lighting is put into a separate class. Thus, this classification is not universally valid but more of a classification that originates in marketing. Anyhow, this thesis uses the terms appliance and device for all these devices and separates them according to their respective energy management functionality (see Section 4.4).

Table 2.2: Traditional classification of home appliances, partly based on [13, 171]

Term	Other term	Description	Examples
Major appliances	White goods	Washing and drying Refrigeration Cooking and baking Dish washing	Washing machine/washer, tumble dryer Refrigerator, deep freezer, wine cabinet Stove/range, oven, hob/cooktop Dishwasher
Small appliances	–	Clothes conditioning Refrigeration Cooking and baking Beverage preparation Lighting Other	Clothes iron Water cooler, icemaker Microwave, bread-maker, blender, toaster Kettle, coffeemaker, coffee machine Light fixture Vacuum cleaner, pool pump
Consumer electronics	Brown goods	Entertainment Information Communication, office	Television, audio system In-home display, weather station Telephone, router, computer, printer
HVAC equipment	Red goods (infrequent)	Heating Ventilation Air-conditioning	Boiler, heat pump Fan, ventilation system Air-conditioning system, humidifier

Hybrid Appliances The term hybrid is used in the context of appliances in two different meanings. Firstly, it refers to appliances that combine functionality that is usually provided by two separate appliances into a single one. Secondly, it is used to describe that appliances are able to use different energy carriers alternatively when providing the same function [412]. Hybrid appliances are analyzed in Sections 4.4.2 and 4.7.1. There, the usage of the terms hybrid, multi-modal, and multi-valent is analyzed and a consistent terminology is presented.

Heating, Ventilation, and Air-conditioning Systems and Devices

Although several devices that are used for HVAC purposes are regarded as appliances, HVAC is usually seen as a separate class of devices. These devices provide energy services in buildings that include space heating, DHW supply, ventilation, and space cooling. The interdependencies between energy carriers in the provision of energy services are detailed in Section 2.2 and depicted in Figure 2.6.

Water Heaters and Boilers Water heaters and boilers utilize some fuel, e. g., gas or oil, or electricity, and include electric storage water heaters, electric water boilers, electrical IHEs, instantaneous water heaters, oil boilers, and gas boilers. Often, boilers burning some fuel are available in two variants: conventional and condensing. Condensing boilers achieve a higher efficiency than conventional boilers by reusing waste heat from exhaust gases.

Air-conditioning Units and Systems Air-conditioning units and systems include all devices that use a refrigeration cycle or free cooling for cooling purposes, e. g., compression heat pumps or ab- and adsorption chillers (see below). Heat pumps work in both directions, i. e., providing heating or providing cooling. In case of air-conditioning in the sense of cooling, heat pumps provide heat outbound of the building into the environment.

Heat Pumps Heat pumps are devices that are able to transfer thermal energy from a heat source to a heat sink. Importantly, the heat source is on a lower temperature level than the heat sink. Hence, the heat is transferred against its spontaneous flow. In case of space heating, heat pumps provide environment heat inbound into buildings. [131, p. 280]

Ab-/Adsorption Chillers Absorption chillers use a refrigerant and an absorbent fluid to transfer thermal energy, whereas adsorption chillers use an adsorbent [131, p. 2]. The thermal energy is transferred from a heat source, i. e., the medium which chills the building, to a heat sink, i. e., some other medium that provides the heat outbound of the building.

Ventilation and Filtering Ventilation is the process of moving or exchanging, i. e., circulating, air. Ventilation systems include filtering, cooling, and moisture control. [131, p. 632]

Cogeneration: Combined Heat and Power Cogeneration incorporates the principle of *energy cascading*, i. e., the usage of residual heat from one system in another for improving overall system efficiency, into a single system. This system generates useful electricity and heat at the same time from a single fuel [131, p. 117, 197] and is mostly called CHP. Small CHPs having less than 15 kW electrical power are called microCHPs [143, 482]. Typical devices, systems, and technologies for cogeneration are combustion engines and fuel cells. For a deeper analysis of CHP plants, see Section 4.5.4.

Trigeneration: Combined Cooling, Heat, and Power Trigeneration in the sense of Combined Cooling, Heat, and Power Plant (CCHP)[3] combines cogeneration of heat and electricity from a single fuel with the generation of a third one: cooling [131, p. 613]. Typical devices include absorption and adsorption chillers, which use the heat to generate negative heat, i. e., realize cooling of an energy carrier such as chilled water or air (see also Figure 2.7 in Section 2.2.2). For an analysis of CHP plants, see Section 4.5.4.

2.4.4 Building Energy Management Systems

As already introduced in Section 2.3.4 and given in more detail in Appendix A.1.2, energy management is the forward-looking co-ordination of energy provision, conversion, distribution, storage, and utilization in an energy system. It has to take various objectives into account, which are usually conflicting, and trade them off against each other. For instance, operating costs and efficiency, investment costs, and security of energy provision are mostly conflicting criteria. This requires formalized, organized, and systematic decisions, which are usually supported by processes, hardware, and software in so-called EMSs. [610, p. 4]

Similar to DSM (see Section 2.3.4), energy management in buildings is often reduced to energy efficiency and conservation measures. Actually, there are several methods and objectives that are used by building energy management and optimization in BEMSs [13,234]:

- Energy efficiency and conservation
- Co-ordination of energy provision, conversion, distribution, storage, and utilization
  - Regarding the local energy system, i. e., only with respect to local objectives
  - Regarding the surrounding energy system, i. e., DSM and market activities
- Security of supply
- User comfort

BEMSs provide general, generic functions, which are given in detail in Appendix A.1.2. These functions are supported by hard- and software but not necessarily automated in autonomous systems. This thesis emphasizes the importance of automated energy management using EMSs that facilitate reactions on all measures of DSM while optimizing the whole local energy system, i. e., energy provision, conversion, distribution, storage, as well as utilization, with respect to local objectives. Such systems should work actively and automatically, i. e., mostly without human intervention.

Energy Management of Devices and Systems in Buildings

Energy management in buildings includes various devices and systems, many of them already having a device-internal energy management. Unfortunately, these internal energy management functions do not include external sensors and states, or other devices and thus are hardly able to reach a global optimum from the overall building's perspective.

[3]Sometimes, they are also called Combined Heat, Cooling, and Power (CHCP) systems [123].

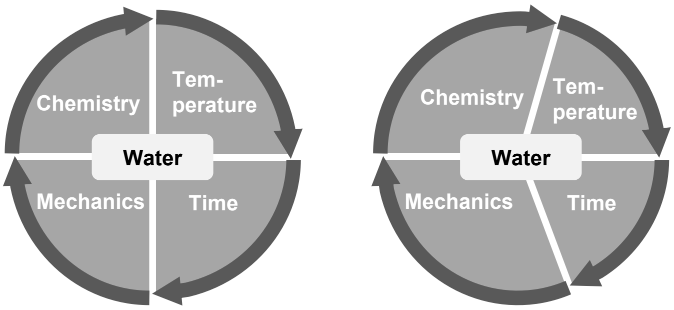


Figure 2.12: *The Sinner Circle*: two different combinations of the four factors chemistry, mechanics, temperature, and time in washing processes, based on [369]

Device-internal Energy Management Most devices have some internal energy management that controls and optimizes the energy consumption. Often, legal requirements enforce a particular standard that has to be reached and classify devices according to their energy consumption, e. g., the European energy label. Primarily, the device-internal management works in the manufacturers' interest, whose objectives include realization of certain technical specifications, safeguarding of corporate secrets, low production costs, adequate product quality and lifetime, and market positioning. Typically, it does not include external sensors and states, or other devices in its management. Thus, the device-internal energy management is often not able to reach a global optimum [412].

Example: The Sinner Circle The washing process in washing machines depends on four main factors that can partially be substituted with each other, i. e., an increase in one factor requires less of the other three factors for the same washing quality. The four factors have been defined by Sinner (1960) [551] and include chemical action, mechanical action, temperature or heat, and time, which are combined into the so-called *Sinner Circle* (see Figure 2.12). Actually, water is a fifth factor that influences all four factors. The internal energy management of washing machines aims at reducing the energy consumption as much as possible to obtain a positive energy labeling based on, e. g., the European energy label. Main driver of energy consumption is the temperature of the washing process. Thus, reducing the energy consumption increases the other three factors. Unfortunately, this has negative side-effects, such as worse hygiene or damaging of clothes. [6, 369, 551]

Cross-device Energy Management Energy management that works across devices has to utilize ICT to include information from external sensors and states from other devices in its management. Often, such an energy management is realized using some controller that is able to monitor and control multiple devices and hence optimize them in a combined way. For instance, HVAC controllers are able to manage all components of the building's physical plant. Self-evidently, cross-device energy management of heterogeneous devices that have been made by different manufacturers and provide a variety of interfaces is much more challenging than device-internal energy management.

Energy Management utilizing Appliances A BEMS using appliances can influence the devices' behavior in different ways. Examples of device control include direct remote control, manipulation of set points, limitations, temporary inhibition, and deferral of scheduled device operation, while respecting the users' preferences.

2.5 Simulation and Modeling of Energy Systems

Modeling and simulation of energy systems and their processes enable the analysis and prognosis of behavior under various conditions, e. g., the results and impacts of the introduction of intelligent appliances, variable tariffs, other measures of DSM, and BEMSs. This can be used to derive knowledge, i. e., useful information. [610, 659]

Initially, a model has to be built which imitates the original processes with a suitable accuracy. There are mathematical, physical, chemical, and knowledge-based models, each using different methods and concepts. The model has to be validated and verified before allowing for simulations of the real system. Afterward, the model allows for the repeated simulation of the real system without influencing or even destroying the latter. If different simulators, i. e., simulation tools, or simulations using different models are combined in an integrated simulation, it is called *co-simulation*. In some cases, components of the real systems are integrated into real-time simulations, which is called *hardware-in-the-loop* simulation. The results of simulations having different input values to the model are called experiments. These have to be set up and analyzed properly to derive knowledge about the original system and obtain conclusions. [72, 610, 659]

This thesis uses a bottom-up modeling and simulation approach to building energy consumption and generation. Individual devices and systems are modeled and simulated using an engineering method that works with usage statistics, time-of-use distributions, and load profiles of real devices. All major appliances and devices are simulated separately and then combined within buildings. Therefore, this thesis uses *discrete time system specification* to simulate the future behavior of buildings in simulations as well as in real-world application, which enables an optimization of the future behavior. In case of simulations of buildings with BEMS, another model is used to simulate the behavior of the building and its systems and devices, which is done with a higher precision.

Differential Equation, Discrete Event, and Discrete Time System Specification

There are three fundamental specification classes of simulated systems [72] [659, pp. 6 ff.]:

1. Differential equation system specification.
2. Discrete event dynamic system specification.
3. Discrete time system specification.

Differential equation system specification uses continuous states and time when formulating the system as differential equations. In contrast, discrete event and discrete time system specification use discrete steps, i. e., events or time intervals that define discrete points in time that are simulated and interpreted by an algorithm or an event processor. [72, 659]

In some cases, the discrete time system specification is seen as a specific case of *continuous time dynamic systems* having discrete and equidistant time "jumps" [72, p. 49]. In contrast, Zeigler et al. (2000) [659, p. 7] distinguish *differential equation system*, *discrete event system*, and *discrete time system specification*. The methods are defined to be all part of a common group that is separated whether the system is *quantized*, i. e., leading to discrete events, or *discretized*, i. e., leading to discrete time systems [659, pp. 8 f.]. Both groups lead to differential equation system specification if done in a sufficiently precise way.

2.5.1 Top-down and Bottom-up Simulation

There are two fundamentally different categories of modeling and simulation: top-down and bottom-up. Top-down approaches include econometric and technological approaches that attribute characteristics of the model based on general and universal values and variables, such as gross domestic product, climate conditions, and price indexes. In contrast, bottom-up approaches calculate the characteristics based on detailed statistical values or use an engineering method that models and simulates individual devices, systems, and buildings, which are then scaled up and combined into larger models. [578]

Top-down Simulation in Energy Systems Top-down approaches in building energy system modeling and simulation consider buildings as energy sinks that are modeled having typical load profiles. These profiles are subject to long-term changes, i. e., slow transitions but not unprecedented paradigm shifts, that affect the energy consumption of the aggregated buildings based on certain general variables. The calibration of top-down models requires historical data, such as climatic conditions, changes in the building stock, and development of device ownership. Major strengths of top-down-approaches are their reliance on aggregate data, which is more easily available, and their simplicity, whereas drawbacks of them are their reliance on historical data, their incapability to react on unprecedented paradigm shifts, and their lack of detail. [578]

Bottom-up Simulation in Energy Systems Bottom-up approaches in buildings energy system modeling and simulation use more detailed statistics, distributions, and samples. In the most detailed way, every single energy consuming device is modeled and simulated. Nevertheless, bottom-up approaches do not necessarily model all devices in an energy system encompassing a whole country but may scale small detailed models up and extrapolate them. If the model is based on statistical data, regression methods, analysis, and machine learning, it is called statistical bottom-up approach. If the model is based on engineering methods that model and simulate individual devices, systems, and buildings using distributions, archetypes, and samples, it is called engineering bottom-up approach. Major strengths of bottom-up approaches are their high levels of detail and possibility to model unprecedented paradigm shifts, whereas drawbacks of them are their reliance on detailed data and the complexity of modeling and simulation. [578]

Bottom-up Simulation in this Thesis This thesis uses a bottom-up modeling and simulation approach to building energy consumption and generation. Devices and systems are modeled and simulated using statistical values, time-of-use distributions, and recorded load profiles of concrete devices. The major appliances are simulated separately and then combined into buildings. In a further step, the buildings can be put together to form simulations of neighborhoods or even districts. This way, the results and impacts of intelligent appliances, variable tariffs, and BEMSs can be evaluated on a larger level.

2.5.2 Co-simulation, Wall-clock Time, and Hardware-in-the-loop Simulation

Co-simulation, wall-clock time simulation, and hardware-in-the-loop simulation denote different concepts of how the simulator performs simulations and whether it is integrated with other simulators or with real hardware.

Co-simulation Co-simulation, run-time coupling, or process model cooperation combine different simulators or simulations using different models in an integrated simulation by exchanging data between the simulations. Typically, the different models focus on different properties of the same system and thus complement each other. Advantages of co-simulation include the reuse of existing models and simulators in new contexts, the combination of heterogeneous and complementary tools, and the collaboration of different parties without disclosing all information. Energy systems are complex systems that consist of many entities having technical, physical, and chemical processes as well as energy markets and ICT, which are interrelated and interdependent [59, 592, 638]. This thesis facilitates co-simulation in a BEMS to allow for precise simulations of real buildings, systems, and devices as well as abstracted and simplified buildings, systems, and devices for optimization purposes.

Wall-clock Time Simulation and Hardware-in-the-loop Simulation In wall-clock time simulations, the simulated time is synchronized to the real time, i. e., one second in reality equals one second in the simulation. This allows for the coupling of real and simulated components, which is called Hardware-in-the-loop (HIL) simulation [638]. This thesis facilitates real-time simulation by enabling the simulations to run in real time, which can be given by an external clock. Nevertheless, actual HIL simulations are not part of this thesis.

2.5.3 Models, Modeling, Validation, and Verification

Simulation of a system requires a model that can be executed in a simulator. Firstly, the system at stake has to be analyzed and described. Then a conceptual model of the system has to be created. Afterward, this conceptual model has to be transformed into a model that can be executed by the simulator, which is usually called a mathematical model or a simulation program. Finally, the model has to be validated and verified (see below), before being executed in the simulator. The modeling and simulation of energy systems is more closely described in the following chapters of this thesis. [72, 659]

Models and Modeling in this Thesis Models of devices and systems are used in various ways in this thesis. Detailed models of the devices are combined to simulate a building in a bottom-up manner. In the actual BEMS, simplified models are used to simulate variants of possible future behavior of the devices and facilitate the optimization process. The optimizer varies the input of the models and aims at obtaining the best behavior possible. All models in this thesis are based on real, existing devices that are available in our laboratories.

Hierarchical System (De-)Composition Hierarchical composition and decomposition is the process of composing a system of multiple components or breaking a system down into components, respectively [659, pp. 4 f.]. In this thesis, buildings are constructed using modules that have standardized inputs and outputs and represent devices and systems. The other way around, buildings can be composed to grids.

Validation and Verification Validation and verification ensure that a right and at the same time correct model of the system is built. Thus, validation and verification refer to quality assurance that allow for realistic experiments and credible conclusions of the experiments. Although both terms are often used in different contexts and meanings, this thesis uses their notion as used in computer science. Thereby, validation refers to the assurance that it is the right model with respect to the original system, i. e., the features of model reflect features of the original system. In contrast, verification refers to the assurance that the model is right with respect to its implementation, required features, and formal correctness, i. e., the model can be executed and has really the desired features. [72, pp. 36 ff.]

2.5.4 Multi-agent Systems and Simulation

In the concept of multi-agent systems, multiple agents act autonomously in an environment while also forming a joint system. Although working and interacting in the same environment, the agents often have distinct capabilities. In order to achieve a higher goal, the agents have to cooperate or have to be coordinated by some entity, which may be another agent. The simulation of a multi-agent system is called *multi-agent simulation* [113]. A detailed definition of agents and multi-agent systems is given in [120].

2.6 Energy Informatics and Related Fields

This thesis touches many different topics and fields of research. It is part of the novel field of *Energy Informatics*, which combines informatics, economics, and electrical engineering. Energy Informatics handles energy systems as cyber-physical systems, which enables tackling challenges in energy systems with novel ICTs, control methods, and optimization approaches.

Energy Informatics

Energy Informatics aims at the realization of an energy system that is efficient and sustainable by addressing challenges in energy systems that are difficult to cope with when using conventional approaches of, e. g., control theory or power electronics. Goebel et al. (2014) [246] state that additional increases of energy efficiency are currently not yet achieved because of the following reasons:

- Lack of information.
- Lack of effective and cost efficient technical solutions and methods.
- Lack of adequate metrics for energy savings and efficiency.

Goebel et al. (2014) name two main developments in energy systems that will be supported by ICT and are dealt with by Energy Informatics:

- "[I]ncrease of energy efficiency beyond what engineering can do" [246]
- "[E]fficient integration of [...] [RES] by making power systems smarter" [246]

This includes particularly the reaction of loads to intermittent supply by RES, i. e., the flexibilization of the energy demand, where complex constraints and interdependencies have to be respected. Energy Informatics deals with systems and grids simultaneously, generating "significant synergies regarding the design of corresponding sensor/actuator infrastructures and software systems" [246]. Additionally, research in the field of Energy Informatics aims at "closing the information gap" and at the design of "control mechanisms that [control and] reduce energy consumption both effectively and efficiently" [246].

Goebel et al. (2014) emphasize the importance of *power proportionality*, which refers to an energy consumption of a cyber-physical system that is "proportional to the output actually required by its end users" [246]. They name three *integration levels* of ICT:

- Measurement and understanding of energy consumption,
- Automatic energy management with learning and prediction capabilities, and
- Control of energy usage and service provision.

Watson et al. (2010, 2012) and Kossahl et al. (2012) [362, 632, 633] use the term Energy Informatics in the *context of information systems*, which they define broader than information technology by including also social aspects. Watson et al. (2010) define information systems "as an integrated and cooperating set of people, processes, software, and information technologies to support individual, organizational, or societal goals" [632]. According to them, Energy Informatics is a new sub-field of information systems, "which applies information systems thinking and skills to increase energy efficiency" [632]. Kossahl et al. (2012) name three fundamental questions that typically arise in Energy Informatics:

- "[H]ow to focus its research to counteract climbing greenhouse gas emissions [...] [?]"
- "[How to] support sustainability [...] [?]"
- "[How to] to help the vision of a fully connected energy system [...] [?]"

Watson et al. (2010, 2012) [632, 633] see information as the fundamental enabler to "increase the efficiency of energy demand and supply systems" and "to support optimization of energy distribution and consumption networks" [632]. Watson et al. (2010) name three types of essential technologies that collect and exchange information: "flow networks, sensor networks, and sensitized objects" [632], which have "the capability to sense and report data" [632] about their use.

Although Watson et al. (2010) explicitly identify suppliers and consumers as the two parties of every energy transaction and distinguish two types of suppliers—the suppliers of energy and the suppliers of services, Watson et al. (2010, 2012) do not consider the changes due to the energy transition, emphasize efficiency and do address neither flexibility nor multiple energy carriers.

In contrast to the previous definitions, which classify Energy Informatics mainly to information systems and applied computer science, Uslar (2015) [598] emphasizes the importance of *practical computer science* and proposes a definition for Energy Informatics that focuses on aspects from software engineering and large-scale systems.

Energy Informatics will have to address exactly the question of how to increase energy efficiency and flexibility on the demand as well as the supply side beyond what electrical engineering can do by means of approaches, methods, and technologies not only from practical and technical computer science but also control engineering, having regard to different temporal and spatial scales when optimizing and controlling the energy system.

Related Fields and Visions

Energy management in buildings has to be seen in relation to many fields that tackle problems of energy systems, system complexity and heterogeneity, software engineering, and environmental challenges. Some of these fields comprise mainly general paradigms, visions, or concepts. Exemplary related fields and visions are described in the following paragraphs.

Cyber-physical Systems The field of cyber-physical systems addresses physical systems that are controlled by some computer or control system using ICT, i. e., the integration of computation, control, and physical process [371]. The term cyber-physical systems is quite often used in the context of energy systems [19, 204, 246, 338] and BEMSs [162].

Ambient Assisted Living Ambient assisted living utilizes ambient intelligence to facilitate individual support and assistance, tackling rising health and elderly care costs and improving the quality of services. Furthermore, it emphasizes the importance of personalized, high-quality, and secure services. [135, 648]

Ambient Intelligence The idea of ambient intelligence is to surround people with intuitive, interacting environments that provide so-called ambient intelligence, combining ubiquitous computing, communication, and user interaction. For instance, environments react on different persons, providing an individual context for human activities. Inevitably, ambient intelligence is strongly related to the domains of safety, security, and privacy. [8, 227, 228]

Context-aware Computing and Environments Context-aware environments comprise autonomous context-aware technology and computing that are self-aware, interconnected, and collaborating to support the user in their tasks by identifying their intentions and needs. The environments use pervasive, ubiquitous devices to facilitate ambient intelligence. Context-aware computing and environments emphasize the importance of contexts and context changes that have to be identified and recognized [421, 493, 513, 514]. The term context refers to the state of the reality, e. g., location, time, weather, and people. The term context-aware home is often used in the fields of ambient assisted living [421], smart homes [421], and ubiquitous computing [493].

Pervasive Computing and Ubiquitous Computing Pervasive computing is used similarly to ubiquitous computing and emphasizes the importance of interconnected devices that form dynamic networks using plug-and-play features [8, 81, 320]. Environments of ubiquitous computing comprise a great many embedded computing devices that are interconnected using ICT. The devices are coordinating their actions, interchanging information, and fulfilling tasks collaboratively that may not be completed by single devices. Therefore, information about objects and situations in the real physical world are sensed, reasoned, and mapped to a virtual world. The term ubiquitous computing is often used in the context of home automation, describing the incorporation of "smartness into dwellings for comfort, healthcare, safety, security, and energy conservation" [8], and smart homes [8, 67, 150, 493].

The concepts of *Autonomic Computing* and *Organic Computing* are closely related to pervasive and ubiquitous computing [442, p. vi] and described in Section 3.7 .

Smart City The main idea of smart cities is the realization of an intelligent urban system by cooperation and collaboration of many interacting distributed systems and devices. Smart cities use sensors and actuators to sense the state of the environment and infrastructure and react autonomously on conditions and disturbances. This touches many critical domains, such as energy and traffic systems [455] and benefits from standardized hardware and software components [445]. Thus, the concept of smart cities is actually an extension of context-aware computing and ambient intelligence to the public space of entire cities.

Smart Factory, Industry 4.0, and Digitization Smart factories are context-aware, interconnected, and collaborating environments that support and assist the workers and personnel in all their activities. Information in the real world, such as locations and alignments, is mirrored in the virtual world. Hence, the vision of a smart factory is closely connected to the field of context-aware environments [383]. This vision has been extended to the complete digitization of industry using ICT and recently coined *Industry 4.0*. The introduction of concepts and ideas from cyber-physical systems and the IoT leads to a new industrial revolution, which follows mechanization, mass production, and digitization [325].

Internet of Things and Internet of Everything The IoT—or sometimes even more visionary the *Internet of Everything*—comprises all kinds of things, devices, and systems that provide or receive data. It originates in technologies that provide identification technologies and addressing schemes to all kinds of things, such as radio frequency identification. It is the idea of a fully interconnected world, where all things share their information with other things, realizing machine to machine communication. The term IoT is often used in the context of building automation [373] or in combination with smart cities [445] but also other application domains, e. g., logistics and health care [30]. Interconnecting the heterogeneous variety of devices and enabling communication across data models, communication protocols, and media is a complex task that calls for gateways, i. e., translators between different groups of devices. Often, additional layers and middlewares are introduced to facilitate device abstraction, protocol translation, and data model conversion. [30, 373, 445, 577]

Internet of Energy The idea of the *Internet of Energy* is to increase the efficiency of energy provision, distribution, and utilization by providing new management systems, services, platforms, and markets. The Internet of Energy relies on ICT to exchange data, broker energy, and conclude contracts. Therefore, the field of *Energy Informatics* will actually provide the means, methods, and concepts that enable the Internet of Energy. [23, 102, 339]

Based on the basic terms and concepts as well as the background information that is provided in this chapter and complemented by the Appendix A.1, the Chapter 3 presents and analyzes work that is related to this thesis.

3 Related Work

There is various related work—both in the literature and in application—to this thesis. This includes work on general architectures for complex systems, specific architectures and concepts for smart grids and EMSs, approaches to optimization, and evaluations of smart buildings and DSM scenarios. This chapter summarizes related work and demonstrates that the latter does not sufficiently fulfill the requirements of EMSs: the latter shall be able to handle the multitude of entities in energy systems, their various capabilities and requirements, their interdependencies, and the systems' complexities.

Section 3.1 presents research related to the energy management of multiple energy carriers. Afterward, three sections outline EMSs for smart grids and buildings and provide an overview of research about appliances, devices, and communication protocols in the context of energy management. Section 3.5 covers the topic of simulating energy systems and appliances and Section 3.6 the optimization problems and approaches that arise in such systems. Finally, Section 3.7 presents approaches to complex systems, general design paradigms, and exemplary generic architectures that are used in the context of energy management.

3.1 Managing Multiple Energy Carriers

The energy management of multiple energy carriers at building level is often done using systems that are called hybrid energy systems [131, p. 294] or multi-energy systems [394][1]. It promises to flexibilize, optimize, and exploit the energy consumption, generation, and storage capabilities of buildings. Although there are several BEMSs that optimize buildings—mostly households—in simulations or in real-world applications and enable automated energy management, they focus mainly on electricity and carry out the optimization with respect to electricity prices and local electricity generation [556]. Even though some BEMSs consider multiple energy carriers [92, 276], the optimization usually does not allow to respect the interdependencies between multiple energy carriers, the alternative usage of two or more devices providing the same energy service, and hybrid devices with alternative operation modes, such as hybrid home appliances or trigeneration systems [412].

[1] See Section 4.7 for a proposed terminology of hybrid, multi-modal, multi-valent, and multi-energy.

Appliances and their operational optimization with respect to costs and load limitations have been subject to research for several decades [186, 239, 509]. Nevertheless, the topic of hybrid appliances and energy management has rarely been considered in scientific research. Although appliances have been integrated into energy systems utilizing multiple carriers, they have not been managed and optimized as hybrid devices themselves. For instance, Boscaino et al. (2014) [86] analyze a hybrid power supply for home appliances that uses fuel cells to co-provide electricity and Gudi et al. (2012) [265] integrate appliances into a hybrid renewable energy system. However, both focus on electricity for energy distribution within buildings and miss alternative operation modes of appliances using hot water or gas to provide their services. Although optimizing the operation of cogeneration and trigeneration systems at building level is relatively common [124, 394], these approaches do not provide an integrated optimization including other devices and systems generating or consuming the same energy carriers, e. g., electrical IHEs and heat pumps.

At district level, approaches and systems that use multiple energy carriers are much more common. Nevertheless, they focus mainly on investment planning and the optimization of the technical setup [394, 398] but not on the abstraction of many different devices in varying setups and their modular optimization with a high temporal resolution. Often, the approaches are too general and simplify the overall system drastically [238, 396].

3.1.1 Standards and Exemplary Research Projects

There are several standards and research projects that focus on energy systems comprising multiple energy carriers and their optimization.

Standards and Guidelines Standards and guidelines explicitly referring to the problem of optimizing multiple energy carriers concurrently are quite rare. One of the few examples is the VDI Guideline 4602 [610] about energy management, which stresses that EMSs have to asses and decide about the energy carriers that are used simultaneously. Another example is the standard EN 12309 [175, 176], which uses the terms *bivalent* and *hybrid* appliances in the context of heating appliances that provide their service by distinct components using different energy carriers. Meanwhile, some research projects and programs respond to the lack of standards and guidelines.

Research Projects and Programs Examples of research projects, initiatives, and programs about energy systems comprising multiple energy carriers include the *Hybrid Energy Grid Management* (HEGRID) project, which works on prototypes for EMSs that optimize multiple energy carriers [129]. Systems related to this project are *EF-Pi* [601] and *TRIANA* [43]. Other examples include the *Multi Grid Storage* project [214], the *Vision of Future Energy Networks* project [238], which introduced the *energy hub* concepts, and the *Energy Supply Cooperative* project, which used the *PowerMatcher* [601] system to optimize the operation of a heat pump with respect to the self-consumption rate of local PV generation.
Although these and numerous other projects emphasize the importance of integrating the management of multiple energy carriers, there are only few publications, such as [586], that disclose results related to these projects. The EF-Pi, PowerMatcher, and TRIANA systems as well as the energy hub concept are detailed later in this chapter.

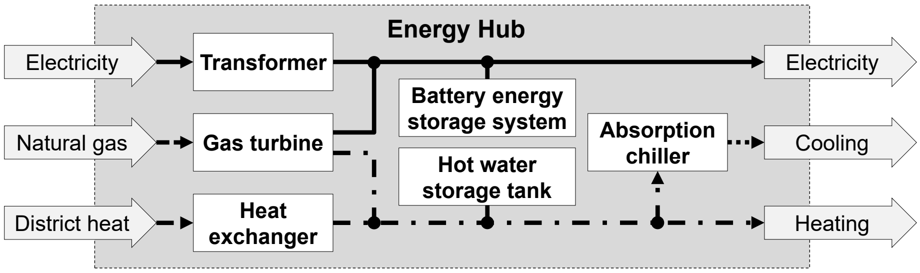


Figure 3.1: *Energy hub* concept by Geidl et al. (2007) [238]: Exemplary hybrid energy hub comprising an electrical transformer, a gas turbine, a heat exchanger, a battery energy storage system, a hot water storage tank, and an absorption chiller, based on [236, Fig. 2-1]

3.1.2 General Approaches and Concepts

There is a fundamental approach to the energy management of multiple energy carriers that aims at formalizing and modeling the transformation of energy carriers in different stages of the energy system: the *energy hub* concept [238]. This concept uses input-output matrix modeling [286] and has been utilized by Chicco and Mancarella (2009) [125] to optimize a trigeneration system and to develop the *multi-energy systems* concept [394].

Energy Hubs

Geidl et al. (2007) [236–238] and Hemmes et al. (2007) [286] introduce a formalized approach towards multi-source multi-product energy systems on multiple stages of the overall energy system, which they call *energy hub* modeling and analysis framework. The concept aims at the flexible integration of energy carriers by the introduction of so-called energy hubs that have multiple energy carrier inputs and outputs as well as storage capabilities (see Figure 3.1). It covers various optimization problems arising in such energy systems having uncertainties in terms of developments in energy markets and political changes: optimal dispatch and power flow, i. e., operational planning problems, as well as optimal investment and structural layout, i. e., strategic and design planning problems. Hence, the concept aims at optimizing and securing profitable and reliable energy systems under uncertainty.

In the formalized framework, the transformation of energy carriers in an energy system is done by the energy hubs. Every energy hub has input and output energy carriers, which are represented in so-called *input* and *output power vectors*. The vectors are linked by the *conversion* or *coupling matrix*, which determines the transformation of power from the input to the output vector of an energy hub. Efficiencies, conversion factors, and constraints of the energy chain are stated in these matrices and in additional constraints. Thus, every energy hub may also be handled as a *black-box* describing all input and output relations abstractly. [236–238]

In addition to the concept of energy hubs, Geidl et al. (2007) [238] propose the introduction of *energy interconnectors* that enable the combined transportation of multiple energy carriers—electrical, chemical, and thermal energy—in one integrated underground transmission device over long distances. Energy losses when transferring electricity, i. e., heat losses,

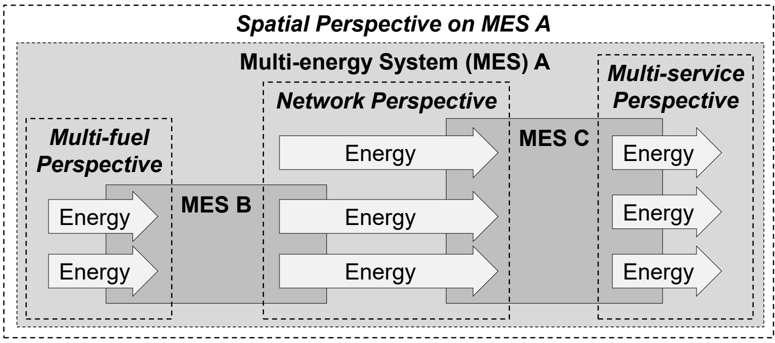


Figure 3.2: Four perspectives on *multi-energy systems* by Mancarella (2014) [394]: the *spatial perspective* defining system boundaries, the *multi-fuel perspective* on the inbound energy provision of multiple energy carriers, the *network perspective* on the interconnection of energy systems, and the *multi-service perspective* on the outbound provision of multiple energy carriers, partly based on [394, Fig. 1–5]

are captured by the natural gas that is transported in the same devices. Therefore, energy interconnectors provide the means to link multiple energy hubs in a way that supports the concurrent transmission of multiple energy carriers, enables maximum flexibility in energy transmissions, and reduces energy distribution losses.

The energy hub framework is a general concept that enables strategic optimization, but there are no implementations of productive EMSs that are based on this concept. This is mainly due to the fact that conversion rates and efficiencies in real systems are not constant but depend heavily on, e. g., storage temperatures, outside temperatures, or state of charge. Thus, the operational optimization of energy systems by EMSs—in particular in buildings and with a high temporal resolution—calls for an approach that incorporates a more detailed black-box approach of the devices.

Multi-energy Systems

Although the term *multi-energy system* has been used before, e. g., in Fabrizio et al. (2010) [201], it has been coined by Mancarella in 2014 [394]. The publication is based on earlier work of Chicco and Mancarella from 2007 [125] about the modeling and optimization of trigeneration systems and the energy hub concept. Subsequently, the approach has been used to model and assess an integrated district energy system comprising electricity, gas, and heat [376], the impact of heat pumps and cogeneration in residential buildings [252], and the expansion of a district heating system [402].

Multi-energy systems consider electricity, heating, cooling, and transportation in an integrated approach that respects their interactions and interdependencies. Inevitably, this applies at various levels of the energy system having different spatial perspectives, i. e., from small local systems via buildings and districts through to regions. The concept of multi-energy systems in [394] provides an integrated view on energy systems and aims at increasing energy efficiency, improving market interaction, and making the energy consumption and generation at the former demand side of energy grids more flexible. It consists of four perspectives or directions of categorization when regarding energy systems comprising multiple energy carriers, which are depicted in Figure 3.2: the *spatial*, the *multi-fuel*, the *multi-service*, and the *network perspective*. The spatial perspective provides different levels of spatial abstraction and aggregation of energy systems. The multi-fuel perspective regards the inbound provision of an energy portfolio, i. e., the input energy vectors into an energy system. The multi-service perspective considers the outbound provision of a certain energy portfolio, i. e., the output energy vectors of an energy system, which includes the utilization of energy carriers to provide energy services. Finally, the network perspective targets on the interconnection of an energy system to other systems and their interaction. Self-evidently, the network perspective depends heavily on the spatial perspective.

Similar to the energy hub framework, the concept of multi-energy systems is more of a methodology and framework that helps to structure approaches and provides a comprehensive view on energy systems. Nevertheless, the concept has been used in several approaches to the practical optimization and evaluation of integrated energy systems.

3.1.3 Multi-energy Management Systems and Optimization

Although there are many approaches to the optimization of energy systems comprising multiple energy carriers, they are mainly limited to the formulation of optimization problems. They are rarely applicable to real-world systems in the sense of being actual EMSs that support real devices and can be executed in real buildings or other energy systems.

Optimization of Multi-energy Systems

There are some publications that focus on the optimization of multiple energy carriers in energy systems. An overview of related work in the area of optimization in building energy management is given in Section 3.6.

For instance, Geidl et al. (2007) [236–238] and Hemmes et al. (2007) [286] use a matrix modeling approach towards the optimization of the so-called energy hubs. The matrices contain the efficiencies and conversion factors of the energy process and relate the input to the output power flows of a hub. Similarly, Chicco and Mancarella (2009) [124,125] optimize the operation of trigeneration systems with respect to overall costs. They use a matrix formulation of the optimization problem that results in a non-linear optimization problem and provide a small numerical example to demonstrate their approach. Fabrizio et al. (2009, 2010) [201, 202] use another similar matrix modeling approach for the optimization of multi-energy systems in buildings. Their model is non-linear and has an hourly resolution, focusing on optimization of the system at the design phase but not at the operation phase.

In [220], Franke et al. (2007) present the idea of *energy bundles* containing multiple energy carriers in a single product, e. g., electricity and heat. However, they present only a model and simulation results related to electricity. Similar bundles comprising heat and electricity are used by Block et al. (2008) [77] in a market mechanism that allows for the negotiation of energy demand and supply by arbitrage agents in microgrids having many microCHPs.

Söderman and Pettersson (2006) [523] optimize a district heating and electricity system structurally as well as operationally with respect to overall costs using a Mixed Integer Linear Programming (MILP) formulation. Similarly, Ren et al. (2010) [497, 498] use MILP to optimize a district energy system with respect to multiple objectives: total energy costs and annual CO_2 emissions. Using a resolution of one hour in their model, they investigate various scenarios consisting of different sets of devices. Mehleri et al. (2012) [415] present a MILP approach to the optimization of a district energy system with respect to investment and operation costs. Their model has a relatively low resolution and only six periods per exemplary day for each of the three seasons–winter, summer, and mid-season–of the year. Martínez Ceseña et al. (2015) [402] present the expansion planning and optimization of a district heating system with respect to net present operational costs using a MILP problem formulation. Their model uses a resolution of 30 min to simulate an entire year.

Having a focus on the building level, Anvari-Moghaddam et al. (2015) [20, 21] optimize a residential building comprising cogeneration, a gas boiler, and a heat pump using a Mixed Integer Non-linear Programming (MINLP) formulation with respect to total operation costs and user comfort. The temporal resolution of the model is one hour.

To sum up, all approaches have a relatively low temporal resolution, which is appropriate for economic analysis but not suitable for the operational optimization in a BEMS running in a real building, and do not provide functionality that is necessary in real environments, such as device abstraction and the character of an Operating System (OS) for buildings.

Energy Management Systems for Multi-energy Systems

EMSs that can be used in real-world application and which consider multiple energy carriers are—on the grid level—the PowerMatcher [601] and TRIANA [43], which are detailed in Section 3.2, and—on the building level—EF-Pi [601], OGEMA [454], and the Organic Smart Home [10], which are presented in Section 3.3. The various approaches to optimization in BEMSs are presented in detail in Section 3.6. However, although there are numerous other EMSs for grids and buildings, they focus mostly on electricity and consider other energy carriers only indirectly.

3.2 Smart Grids and Demand Side Management

This section provides an overview of related work on smart grids in general as well as about particular technologies, systems, and methods that are used in this context. The work presented hereafter does not explicitly focus on multiple energy carriers or BEMSs, but has a more general view on simulation, energy management, and communication in energy grids. Anyhow, BEMSs will be an integral component of smart grids, enabling the communication of buildings with other entities in the grid, providing information about local states, and participating in the operation and optimization of energy grids. Therefore, literature concerning the smart grid in general as well as particular technologies and systems is of utmost importance for the development of effective BEMSs.

3.2.1 Smart Grid Models and Frameworks

There are two basic models for the smart grid that are used in Europe and North America, which structure and abstract views on the smart grid: the *Smart Grid Conceptual Model* and the *Smart Grid Architecture Model*. Together, they form a structuring framework for smart grids. Another framework is the *Universal Smart Energy Framework*, which provides the concept of a market-based control mechanism and ICT architecture that interconnect energy markets, services, and products with each other.

Smart Grid Conceptual Model and Smart Grid Architecture Model

In [180, 261], a model for the smart grid has been defined: the *Smart Grid Conceptual Model* (SGCM). It consists of seven *domains*—customer, markets, service provider, operations, generation, transmission, and distribution—with roles and services, e. g., service operators [261, p. 126]. Every role is part of at least one domain. Roles within the same domain have similar objectives and often interact with each other. Additionally, most of the roles interact with roles from other domains as well. Often, these interactions require secure communication working independently of electrical flows [261, pp. 125 ff.].

The *Smart Grid Architecture Model* (SGAM) is a framework that is based on SGCM [114, 261]. The domains of SGCM are mapped to five domains in SGAM that represent the traditional energy chain of the electrical energy system: *generation*, *transmission*, *distribution*, *DER*, and *customer/premises*. This offers a slightly different view on the smart grid, because operation and market have been separated into the dimension of zones (see below). SGAM uses four levels to structure technical and business architectures: the *conceptual*, the *logical*, the *physical*, and the *implementation* level [261, p. 129]. These levels are mapped to five interoperability layers that abstract devices, communication technologies, and services: the *business*, the *function*, the *information*, the *communication*, and the *component layer* [114].

In addition to the two dimensions of layers and domains, there is a third dimension—the *zones*—that is used by SGAM to address the spatial and logical aggregation from process to market. These zones reflect different management parts of the energy system and are similar to the *automation pyramid* in process control and enterprise resource planning [455]: the *process*, the *field*, the *station*, the *operation*, the *enterprise*, and the *market* zone. Thus, the model considers two concepts of aggregation: data or informational aggregation and spatial aggregation [114, pp. 29 f.].

Thereby, SGCM and SGAM are capable of abstracting different stakeholders' views on a smart grid system while enabling the structuring and classification of technical and business architectures. They serve as a concept providing a generic model to structure the smart grid and its entities, which covers the system presented in this thesis. This BEMS is located in the domains of DER and customers, in the zones from operation down to process, and across all interoperability layers. Nevertheless, SGCM and SGAM neither specify the approaches to the optimization of the entities or the overall smart grid nor the concrete implementations and software architectures of EMSs. Unfortunately, they focus on electricity and do not include other energy carriers.

Universal Smart Energy Framework

The Universal Smart Energy Framework (USEF) [553] is a framework for energy markets and networks which is similar to the so-called *Traffic Light Concept* (or *Ampelmodell*) of the German *Bundesverband der Energie- und Wasserwirtschaft e. V.* (BDEW). It provides a market-based control mechanism and an ICT architecture that interconnect markets, services, and products. The framework allows for the standardized interconnection of customized products and services using a generic role model of actuators with defined interactions and transactions in usual and critical states of the grid. Additionally, it provides best-practices, specifications, and implementation guidelines and emphasizes the importance of privacy, security, and standardization.

In USEF, seven essential smart energy services are named [553, pp. 30 ff.]: *smart energy market*, *insight service*, *demand response smart appliances*, *demand response electric vehicles*, *manage local generation*, *manage local energy storage*, and *energy management*. The system presented in this thesis aims at facilitating these services in BEMSs. Although the framework claims to be universal for *smart energy*, it emphasizes the growing importance of electricity and lacks a holistic view on all energy carriers related to energy provision.

3.2.2 Standards and Alliances

Several standards cover the topic *smart grid* or are strongly related to it, while having different perspectives and coming from different industries and fields of research. For instance, some originate in electrical engineering, mechanical engineering, or telecommunication. This leads to numerous standards that have similar objectives and tackle similar problems. In particular, communication between different entities, i. e., devices, systems, or stakeholders, is covered by numerous standards that are not necessarily interoperable. Even in case of standards that originate from the same field, e. g., the International Electrotechnical Commission (IEC), they are overlapping in functionality and not fully compatible.

Standards by the International Electrotechnical Commission

There are several standards by the IEC that are of importance for the implementation of EMSs in the context of smart grids. These include in particular the following standards:

- IEC 60870 “Telecontrol equipment and systems” [312].
- IEC 61850 “Communication networks and systems in substations” [313].
- IEC 61968 “Application integration at electric utilities – System interfaces for distribution management” [315].
- IEC 61970 “Energy management system application program interface (EMS-API)” [314].
- IEC 62746-3 “Systems interface between customer energy management system and the power management system – Part 3: Architecture” (draft) [316].

These standards define communication interfaces, data models, and general system architectures that have to be respected by EMSs and implemented in BEMSs to enable buildings to become a part of a smart grid. IEC 60870 focuses on the communication of technical equipment in the grid with SCADA systems, i. e., grid automation, and provides communication profiles, formats, and protocols. One of the most important data models is the Common Information Model (CIM) defined in IEC 61968 and IEC 61970. It provides Unified Modeling Language (UML) models for application integration and information exchange in electrical networks. CIM is of greater importance for EMSs than the *Substation*

Configuration Language in IEC 61850, because the latter focuses only on substations, whereas CIM stresses the importance of communication between all systems in grids and thus covers more use cases. For instance, the interaction of EMSs using the CIM has been demonstrated by Uslar et al. (2005) [599]. The IEC 62746-3 standard defines communication between automated EMSs, services providers, aggregators, and trading systems on energy markets. Part 10 of the standard handles OpenADR (see also below).

Other Standards, Alliances, and Associations in the Context of Smart Grids

There are many alliances, associations, and initiatives that work on the standardization of data models, languages, and protocols in the context of smart grids and smart buildings. The following exemplary parties are working on these topics, while considering in particular energy management of multiple energy carriers, BEMSs, or device abstraction.

Agora Agora du Réseau Domiciliaire (Agora) is a French association that works on a data model for smart residential buildings that considers all potential services and domains, such as assistance, comfort, and security. The main idea of Agora is the development of a bridging data model and language and thus is pretty similar to that of EEBus (see below). Agora and EEBus are both now collaborating with Energy@home to work on common key functions regarding energy management in smart residential buildings that will be supported by all three data models and languages. Although Agora stresses the importance of energy management in buildings, it focuses solely on electricity. [4, 603]

AllSeen Alliance The AllSeen Alliance, which includes companies from various domains, such as Qualcomm, Microsoft, Electrolux, Haier, and Sony, works on the development of a software framework called *AllJoyn*. It has initially been developed by Qualcomm and enables connectivity in the IoT. It supports distributed systems by providing support for peer-to-peer communication in a network of devices. Preexisting networks using different protocols may be interconnected using so-called *Device System Bridges*. The efforts of the alliance focus on establishing a central software framework for device discovery and communication that is subsequently used to develop devices for smart buildings. AllJoyn includes important concepts of device abstraction and communication via a common bus using standardized data models, which enables the interconnection of different networks. [572, 603]

Association of Home Appliance Manufacturers The Association of Home Appliance Manufacturers is an American association of major companies in the home appliance industry. It published an extensive study on smart appliances and communication [27], which evaluates existing protocols and standards with respect to their applicability to the data exchange with appliances. The association defines a local gateway as central instance for interconnection and data communication but lacks the idea of direct communication between devices. Although the study acknowledges that there will various protocols in future buildings, it skims over topics such as concrete data models that define load profiles. [27, 603]

EEBus Initiative The EEBus Initiative originates in the German research program *E-Energy*, which was funded by the German *Federal Ministries of Economics and Technology* (BMWi) and *for the Environment, Nature Conservation and Nuclear Safety* (BMU). It aims at realizing interconnected devices, e. g., appliances, HVAC devices, and electric mobility, with an independent interoperability standard that can be used in different sectors and domains, including smart buildings and smart grids. The upcoming standard is meant to provide neutral, i. e., vendor-independent, messages and data models that provide a bridge between different sectors and domains.

The core of EEBus are messages, which are described by XML Schema Definitions (XSDs), and mappings, i. e., translation tables between EEBus messages and other proprietary messages of different other standards. In addition to the messages and mappings, EEBus provides also so-called *Smart Home IP* (SHIP) messages that enable communication directly in EEBus using TCP/IP. The actual architecture and messages have been designed around so-called *user stories* and *use cases* that reflect potential usage of intercommunicating devices in different domains and scenarios.

EEBus tackles the problem of interoperability and intercommunication between the various standards that are used for communication between devices. Applications that enable, e. g., energy management, may use EEBus as a potential intermediate communication standard to avoid implementing many other formats and technologies. Nevertheless, the EEBus Initiative does not provide the actual BEMS or best practices in energy management, although several use cases had been taken into account in the design phase. The EEBus Initiative is currently cooperating with the Agora association, the Energy@home Alliance, the KNX association, and the ZigBee Alliance. [16, 188, 189, 603]

Energy@home Alliance The Energy@home Alliance is an Italian organization that was founded by Electrolux, Enel Distribuzione, Indesit, and Telecom Italia. It is collaborating with the Agora association, the EEBus Initiative, and the ZigBee Alliance. Energy@home works on the standardization of a home energy management gateway, customer EMSs, and the intercommunication of appliances and other devices, such as meters and sensors, in a home area network. In case of communication with the utility, the connection is realized using the smart meter. The connection to other service providers is facilitated by some other home gateway. The proposed interfaces and data models (see also Section 3.4.3) are similar to those in the *Smart Energy Profile 2* of ZigBee and the EN 50523 standard. In addition to interfaces and data models, the alliance released the *Java Energy ManageMent Application Framework* (JEMMA). It is supposed to provide an open-source framework that implements the specifications proposed by Energy@home, enabling an integrated energy management in residential buildings. [193, 195, 196]

FIWARE Community The FIWARE Community (FIWARE) originates in the projects *FINSENY*, *FI-WARE*, and *FI-PPP* and develops a platform consisting of several standardized components that provide dedicated functionality. These components—so-called *generic enablers*—are software modules having standardized interfaces. Free and open-source reference implementations are provided by FIWARE. Thus, the main idea is the modularization of software components to facilitate their reuse when developing new applications. [445, 597, 622]

Home Gateway Initiative The Home Gateway Initiative (HGI) aims at the development of use cases, specifications, and test procedures that provide the basis for gateways combining telecommunication, entertainment, home automation, and energy management. HGI divides the path towards a higher energy efficiency in households into three basic phases [300]:

1. Home gateway: definition of a central gateway for residential buildings.

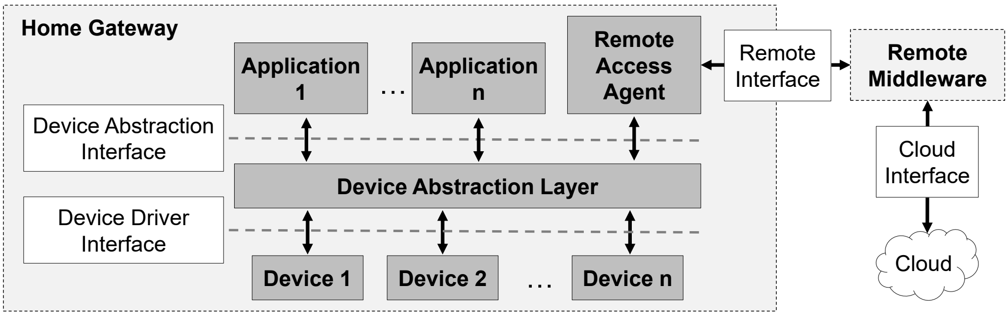


Figure 3.3: *Home Gateway Initiative*: Overview of the home gateway architecture comprising a *Device Abstraction Layer* and a *Remote Interface* having a *Remote Access Agent*, based on [363]

2. Home network: interconnection between the gateway and communication equipment.
3. Home energy management and control: connection to other devices and appliances.

The HGI proposes an architecture that includes device abstraction and modularization of device templates. The architecture comprises a *device driver interface* to the multiple heterogeneous devices, a *device abstraction layer* that provides a *device abstraction interface* to applications on the gateway, and a *remote interface* to external entities. Interestingly, the *cloud interface* is realized using a remote middleware but not directly on the local gateway (see Figure 3.3). The approach by the HGI is exemplary for the telecommunication industry: It focuses on communication technologies that are currently used in this industry and a gateway that may be combined with routers and modem devices that are widely used in residential buildings to provide an Internet connection. [300, 363]

OASIS Consortium The Organization for the Advancement of Structured Information Standards (OASIS) is a consortium that works on the development of open standards for information and communication. In the context of smart grids and smart buildings, OASIS intends to establish a series of standards that include *Energy Interoperation*, *Energy Market Information Exchange* (eMIX), *Web Services Calendar* (WS-Calendar), *Open Building Information Exchange* (oBIX), and *Message Queuing Telemetry Transport* (MQTT). These standards provide information models, messages, and protocols as well as methodologies and patterns that may be used in BEMSs. [372, 603]

OpenADR Alliance The activities by the OpenADR Alliance aim at the development of standards and concepts for automated DR. Measures of DR are seen by the OpenADR Alliance as being essential for electricity grid stabilization, in particular during the summer. The specification *OpenADR 2.0* is based on the Energy Interoperation specification by OASIS and provides signals that are exchanged between customers, wholesale producers, utilities, system operators, and aggregators. Different sites with DG, e. g., by RES, are connected to DR service providers, partially using aggregators that combine several sites. The service providers then offer their services to utilities and system operators. The OpenADR Alliance is responsible for certification and testing of automated DR functionality that is implemented according to the OpenADR 2.0 specification. Currently, the OpenADR alliance focuses solely on electricity, DR in the electricity grid, and the communication between customers—not single devices—and external entities. Energy management of other energy carriers than electricity is not part of closer consideration of OpenADR. [288, 299, 464, 603]

ZigBee 2030.5 / Smart Energy Profile 2.0 The ZigBee+HomePlug Joint Working Group, which is a cooperation of the *ZigBee Alliance* (see below) and the *HomePlug Alliance*, developed the *Smart Energy Profile 2.0* (SEP 2), which has been adopted by the Institute of Electrical and Electronics Engineers (IEEE) as a new standard called *IEEE 2030.5-2013*. This IP-based communication format supports secure communication using Transport Layer Security (TLS) via *ZigBee IP* as well as TCP/IP communication. It is meant for the communication of energy-related information and commands between devices at residential buildings and from these devices to utilities and other service providers. SEP 2 helps utilities and service providers to realize a secure home area network of devices that can be influenced or even controlled with respect to energy consumption, generation, and storage. Home and building automation are part of separate profiles by the ZigBee Alliance: the *Home Automation Profile* and the *Building automation Profile*. [317, 664]
SEP 2 regards different types of energy that have to be taken into account for a holistic energy management. It distinguishes different *commodities* that are combined with measurement *readings* and *usage points*, which are devices consuming or providing these commodities. The list of commodities contains, e. g., *Electricity*, *Air*, *NaturalGas*, *Propane*, and *PotableWater* [664]. Nevertheless, it focuses on electricity for DR and does currently not cover other relevant commodities, such as hydrogen, methane, methanol, graywater, blackwater, and rainwater. Additionally, hybrid devices are not considered by SEP 2, which calls for a revision and extension of the standard.

ZigBee Alliance The ZigBee Alliance (ZigBee) developed various communication protocols, e. g., the *ZigBee PRO* communication protocol, as well as specifications for various application profiles, such as SEP 2 (see above), the *Building Automation* profile, and the *Home Automation* profile. Currently, ZigBee is working on unifying the profiles *Building Automation*, *Home Automation*, *Light Link*, *Health Care*, *Retail Services*, and *Telecommunication* into one standard—*ZigBee 3.0*. Unfortunately, this communication protocol and specification does not include SEP 2, because ZigBee 3.0 does not yet support advanced security functionality that would be necessary to do so. [317, 603, 663]

Energy Management and Energy Management Standards

There are three major standards that provide guidance regarding the application of energy management and the realization of EMSs: the ISO 50001 [174], the IEC 61970 [314], and the VDI Guideline 4602 [610, 611].

ISO 50001 "Energy Management Systems" The international standard ISO 50001 replaced the European standard EN 16001 about EMSs in 2012. It applies to energy management in the entire commercial sector without providing concrete criteria that should be met. Instead, it emphasizes the continuous improvement with respect to energy usage. The standard is complementary to the ISO 9001 about *quality* management systems and the ISO 14001 about *environmental* management systems. It features the same general approach as the other two standards: continual improvement in the sense of *plan-do-check-act*. Nevertheless, all three standards are independent of each other and may be implemented separately [187, p. XXIII]. Although the cycle of *plan-do-check-act* is similar to control loops in measurement and control technology, it is not automated. Energy management in the sense of this thesis goes further than simply monitoring and deriving improvements: an automated BEMS optimizes the energy usage in buildings actively and automatically. [174]

IEC 61970 "Energy Management System API" The IEC 61970 provides scenarios, interfaces, and component-based reference models for applications in the domain of EMSs in smart grids. Most importantly, it defines CIM and the Component Interface Specification (CIS), including mappings to various technologies, and provides guidelines for the practical realization of EMSs. [314]

VDI Guideline 4602 "Energy Management" The VDI Guideline 4602 Part 1 [610] provides fundamentals, terminology, and requirements of energy management and Part 2 [611] provides examples of practical applications that are categorized into energy provision, distribution, trading, and utilization. For instance, the practical examples include the cost-optimized provision of cooling in the industrial sector and energy management in a gas distribution system. The guideline has been developed to provide "additional information and practical examples" [611] regarding the planning and implementation of energy management and the verification of its success. It is designed to be complementary to the international standard ISO 50001 on EMSs. The additional information as well as the fundamentals and the terminology of the VDI Guideline 4602 provide an essential part of the background of this thesis (see Appendix A and Section 2.1).

3.2.3 Smart Grid Energy Management Systems

There are several systems that can be used to simulate or operate smart grids with respect to energy management. Nevertheless, beyond the Organic Smart Home (OSH), there is only one application—the *PowerMatcher*—which is open-source, able to simulate smart buildings having a BEMS in a smart grid environment, and operate real buildings. In the PowerPatcher, the buildings are operated and simulated using *EF-Pi* (formerly known as *FPAI*). Recently, EF-Pi has also been combined with *TRIANA*, enabling similar simulations as in combination with the PowerMatcher. Commercial tools, such as *GridCommand* or *Network Manager*, focus on real-world application but are not able to simulate smart buildings using automated BEMSs. Some of the tools and applications that are used to realize energy management in smart grid scenarios are detailed in the following sections.

Smart Grid Energy Management Concepts and Systems

Currently, there is only one comprehensive EMS for smart grid applications available that is open-source: the *PowerMatcher* by the Flexible power Alliance Network. Other tools are TRIANA, which utilizes also EF-Pi for the device management and control, and EEPOS, which utilizes OGEMA. All tools are described in the following paragraphs in detail.

EEPOS Klebow et al. (2013) [352] present a concept for the integration of RES into *neighborhoods*, i. e., groups or associations, of smart residential, commercial, and industrial buildings, which they call *Energy management and decision support systems for Energy POSitive neighbourhoods* (EEPOS). In addition to buildings, other loads that are spatially close, such as street lighting, shall also be integrated into these groups. Thus, a neighborhood covers all consumers and producers in a single low-voltage grid. It aims at local electricity supply and demand matching, balancing on electricity market, and local congestion management in electricity grids. This functionality is to be reached in EEPOS mainly by shifting of electrical loads based on data analysis, end-user involvement, and supportive management information. [352]

EEPOS utilizes—among other tools—OGEMA (see Section 3.3.2) for the management and direct control of individual devices and systems, e. g., appliances, lighting, CHPs, and storage systems. It considers electricity and heating distribution grids as well as battery and thermal storage systems when optimizing loads. The thermal energy is merely a constraint for the optimization of electrical loads, although it is mentioned that heat consumption may be partially controlled [352]. The management systems are integrated into an *information and decision support system* platform that optimizes a neighborhood's energy consumption, taking additional information into account, e. g., weather forecasts and energy price profiles. Several applications by different stakeholders may be run on this platform, e. g., electricity supply and demand matching by the distribution system operator and electricity market level trading by a utility.

Klebow et al. (2013) emphasize the importance "to clearly distinguish between information required on the neighbourhood level (e.g., sum of current consumption and production rates and forecast values) and information which should not be transferred to the neighbourhood level (e.g., information on [...] individual household devices)" [352]. They mention four ancillary services for the electricity grid that may be realized by EEPOS: frequency control, voltage control, phase balance, and congestion management.

Although EEPOS is applied in field tests, there is little information about how the actual optimization is realized. Additionally, it is not clear, whether thermal energy will be an integral part of the optimization or just a constraint.

PowerMatcher There are two technologies by the Flexible power Alliance Network[2]: the *PowerMatcher* and EF-Pi (abbreviation for: *Energy Flexibility Platform and Interface*), which was formerly known as FPAI (abbreviation for: *Flexible Power Application Infrastructure*). Although they are independent, both are complementary and often combined (see also Section 3.3.2). The PowerMatcher serves as the smart grid coordination mechanism, whereas FPAI is the actual operating system that abstracts appliances and services to facilitate their usage by the PowerMatcher (see Figure 3.4). PowerMatcher is at the same time an architecture for distributed energy systems as well as a communication protocol. It targets on conventional and RES, households, and small business that are interlinked by ICT, aggregated by the PowerMatcher, and combined into virtual units. These virtual units optimize electricity generation and consumption and market their flexibilities. Basically, the PowerMatcher is based on an auction mechanism that matches demand and supply, where every participant, i. e., device, system, building, or virtual unit, is represented by an agent. This mechanism is used hierarchically: The bids by individual agents are aggregated by *concentrator agents* and cleared by an *auctioneer agent*. [84, 301, 358–360, 601]

[2] `http://www.flexiblepower.org` and `http://flexiblepower.github.io`

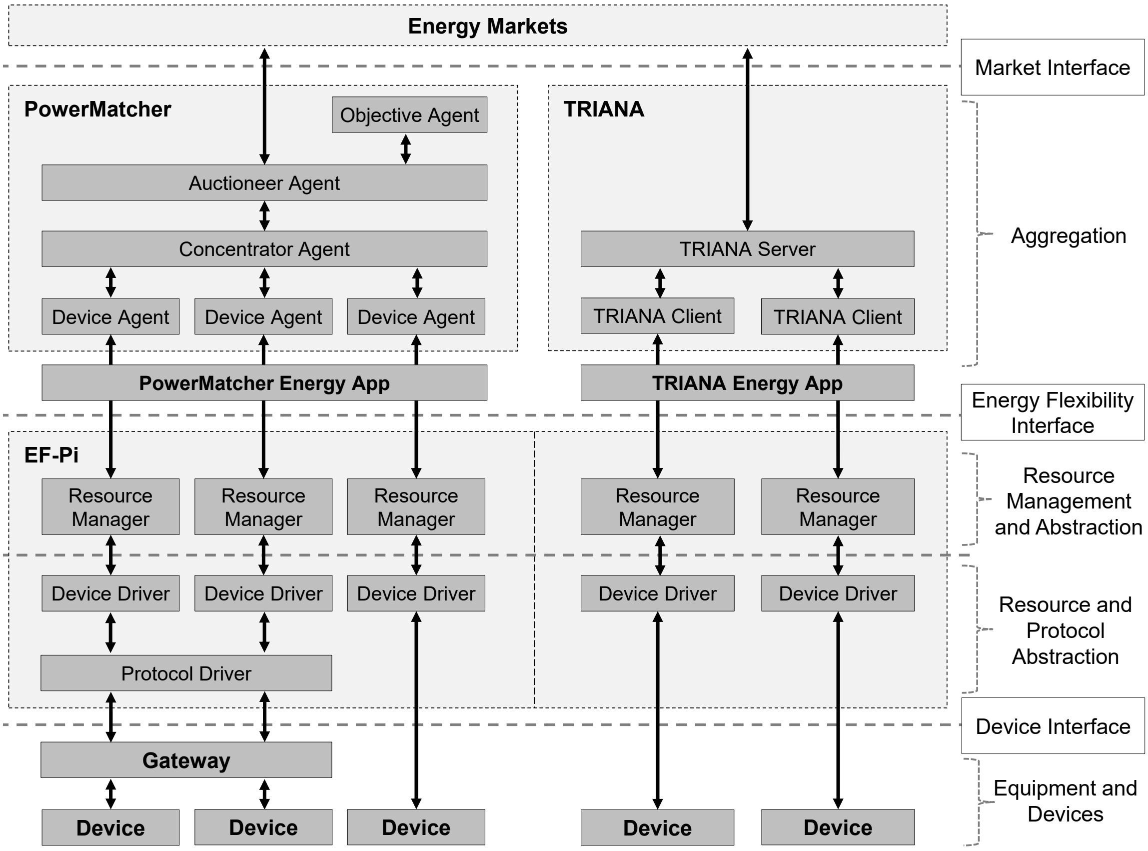


Figure 3.4: *EF-Pi*, *PowerMatcher*, and *TRIANA*: overview of the hierarchical architectures of PowerMatcher and of TRIANA, respectively, both using EF-Pi for the connection to and the abstraction of devices in buildings, based on [298, 586, 601]

A detailed assessment of the PowerMatcher with respect to several metrics, e. g., support of RES, reliability, and flexibility, is given in [579], showing that the supply-demand coordination mechanism of the PowerMatcher has been validated successfully according to most of these metrics in simulations and field tests. An evaluation of its network traffic and scalability is given in [298], showing that it scales well when having a rising number of participants. Recently, the PowerMatcher has been extended to support *Dynamic Programming* for optimization [485], becoming more similar to TRIANA (see below).

On a larger scale, the PowerMatcher serves a very similar purpose as the system presented in this thesis. The overall system is optimized by a mechanism that uses abstracted flexibilities of all resources, i. e., devices and systems. This mechanism receives all information about the flexibilities of the devices and systems and their interdependencies and optimizes them. Nevertheless, the PowerMatcher works with a comparatively low resolution of the optimization using 15 min for the next 24 hours [358, 359].

TRIANA TRIANA has been a major part of a series of PhD theses at the *University of Twente* [43, 89, 430]. It targets the optimization of energy efficiency, a better utilization of grid capacity, and the integration of renewable energies [432]. TRIANA is an alternative to the PowerMatcher and is used similarly in combination with instances of EF-Pi (see Figure 3.4 and also Section 3.3.2) [586]. Generally, it uses a three steps approach to the control strategy that is applied to the smart grid or parts thereof [432]:

1. Local prediction
2. Global planning
3. Local scheduling using iterative distributed dynamic programming

In TRIANA, using so-called *Control Space Controllers*, households and devices are combined into a VPP, which has to satisfy a global electricity generation plan. Artificial neural networks are used to predict heating demands of individual households based on historical data and weather forecasts. These predictions are then used to schedule microCHPs of the households globally using an iterative planning and optimization approach called *Iterative Distributed Dynamic Programming*. The result of the global planning is sent to the households as the *steering signal*. Each household is then scheduled individually based on this signal using local dynamic programming to solve an integer linear problem, respecting its dedicated constraints. This tree-like structure of a global controller—the *TRIANA Server*—and local controllers—the *TRIANA Controllers*—is used iteratively to adjust the steering signal based on the deviation of the intended and planned generation. Finally, a *real-time control algorithm* decides about which devices, e. g., appliances, should be switched on or off and when the microCHP should run [302, 432, 586].

Although TRIANA considers multiple energy carriers, e. g., electricity and hot water, it focuses on electricity and handles hot water in storage tanks only as a constraint for the operating times of the microCHPs.

Commercial Smart Grid Energy Management Systems

There are several commercial EMSs for smart grids, some of which are detailed in the following paragraphs. Such systems represent superior entities for the BEMS presented in this thesis and hence provide requirements for communication interfaces between single buildings and the grid.

DER-CAM The *Distributed Energy Resources Customer Adoption Model* (DER-CAM) is an optimization tool for the design support of microgrids that has been developed by the *Lawrence Berkeley National Laboratory* [566]. It is used for dynamic *model-in-the-loop* [243] optimizations and the assessment of measures of DSM. The optimization tool utilizes MILP and aims at the minimization of annual costs or CO_2 emissions. There are two major versions of the tool: one for investment and strategic planning, the other for the actual operation of a DER system [566].

Energy Management Operating System The *Energy Management Operating System* (EMOS) by *Princeton Power Systems* is able to monitor and control microgrids. The functionality is mainly dedicated to data logging, visualization, and relatively simple control algorithms. These algorithms enable programmed DR measures as well as ramp and voltage control of PV systems, BESSs, and generators. [484]

GridCommand The EMS *GridCommand* is an additional front-end for GridLAB-D that has been developed by the *Battelle Memorial Institute*, an American nonprofit research company. Although GridLAB-D is an open-source tool for scientific purposes, GridCommand is a commercial modeling, planning, forecasting, automation, demand management, and visualization platform [52, 53]. That way, it is demonstrated that GridLAB-D can be successfully integrated into other systems and turned into a commercial tool for application.

Network Manager The *Network Manager* by *ABB Asea Brown Boveri* is at the same time a SCADA system and an EMS. It targets on wide area monitoring, transmission and generation management, and visualization [26]. The system has been used in the research project *MeRegio – Aufbruch zu Minimum Emission Regions* that was part of the *E-Energy* funding program in the years 2008 to 2013 [341].

3.2.4 Demand Management Systems and Ancillary Services

Already in the early eighties of the 20th century, Gellings (1981, 1985) [239, 240] emphasized the importance of load management on the demand side, i. e., the shift from a "supply-side-only viewpoint to demand-side technologies" [239]. The usage of different tariffs at different times of the day, e. g., utilized by automatic storage heating, is actually much older and has already been used in the early 20th century [509]. Even the load management problem of electric vehicles has been foreseen in the past, although Gellings (1981) had been a little bit too optimistic regarding the time horizon of their introduction:

> "Electric vehicles, generally regarded as conservationally and environmentally benign, could be a load-management problem in the future. The consensus on battery-powered electric vehicles is clear: they are coming, probably in the last decade of this century." [239]

Nowadays, DSM[3] is widely used in practice, field tests, and research projects to help to balance the electricity grid [208, 218, 469]. Nevertheless, the focus of DSM has changed: In the past, load management aimed at equalizing the load variation during the day and the year [239] by doing peak clipping, valley filling, and load-shifting [240] to obtain a uniform electricity use. Today, load management aims at realizing a flexible load shape of the demand side that matches the variable and intermittent generation of RES that are utilized throughout the grid (see also Figure 2.10) [469].

Additionally, the methods for managing the demand side did change, too. In the past, DSM focused on switching customer devices on or off, i. e., doing direct physical DR. Nowadays, the focus of DSM is changing to indirect market DR (see also Figure 2.11), which uses prices and other signals to enable a lighter version of DSM with indirect control. For instance, already in the early nineties, Wacks (1991) [624] proposed a home automation and communications network to operate appliances at adapted load profiles and reduce energy services with minimum inconvenience to the customer [624]. The decision about which loads to change is now often made in a decentralized manner by systems on the demand side that react on dynamic prices [625].

[3]See Section 2.3.4 for a detailed definition and explanation of DSM and DR.

Capasso et al. (1993, 1994) [108, 109] model residential loads in a bottom-up manner to evaluate measures of DSM and enable their economic assessments. Palensky and Dietrich (2011) [469] provide a taxonomy of DSM and an overview of approaches, methods, and demonstration projects. Faruqui et al. (2005, 2010) [208, 209] examine the response of residential buildings to dynamic prices. The theoretical DR potential throughout Europe is quantified by Gils (2014) [244]. Von Appen et al. (2011) [619] evaluate the economic potential of decentralized reactive power supply in grids. Hagerman (2014) [181] stresses the importance of intelligent distribution management systems that enable bidirectional communication with the demand side and provide the means for DSM. These examples show that DSM and other technologies of smart grids are subject to intensive research. Some of this research is more closely described in the following paragraphs. Related work to the aspect of conducting the actual optimization process is described in Section 3.5.

Potential of Demand Side Management Determining the potential of load-shifting, peak-clipping, and profile-shaping is of utmost importance for assessing the potential of measures of DSM. Nevertheless, most literature focuses on reducing peak loads but neglects the importance of realizing profile shaping to support the utilization of RES.

Oldewurtel et al. (2010, 2011) [461, 462] assess the potential of real-time pricing and model predictive control in building control and storage management to reduce peak demand and shape load profiles. Their results show a mean demand reduction for the city of Zurich of 3.5 % in the case without batteries and of 17.5 % when using BESSs having a capacity of 5 kWh. In a similar evaluation, Miguel et al. (2014) [423] investigate the impact of DSM at the level of an entire city. They decompose the residential load profile of the city using statistical data, such as the typical distribution and market penetration of appliances, their usage times, and the acceptance of deferring their starting times. At a penetration rate of 20 % of EMSs in residential buildings, they estimate a load shifting potential of up to 3 %.

Labeeuw et al. (2015) [366] assess the DSM potential of wet appliances, i. e., washing machines, tumble dryers, and dishwashers, in Belgium, while assuming a participation of 29 %. Their results show a potential for demand reduction of about 4 %. The theoretical DR potential of all sectors, i. e., residential, commercial, and industrial consumers, covering the whole of Europe is quantified by Gils (2014) [244]. The results show significant regional distinctions—the peak load reduction ranges between 7 % and 26 %—and variations during the year, which are based on different climates and economic landscapes.

Gottwalt (2015) [254] analyzes DSM using a detailed model of residential buildings comprising appliances, battery storage, storage heaters, electric vehicles (EVs), PV systems, and wind power generation, and concludes that “batteries, EVs, and storage heaters are the most promising residential devices for balancing” [254] because of being large loads with substantial shifting potentials.

Field Tests of Demand Side Management Field tests show DSM potentials that strongly depend on the regions and differ heavily with the DSM mechanisms that are used. Often, the usage of automated DSM and EMSs is seen as a crucial factor to success.

By means of a Californian field test and a review of various other field tests, Faruqui et al. (2005, 2010) [208–210] examine the response of residential buildings to different dynamic pricing schemes. They show that a peak to off-peak ratio of ten to one results in up to 30 % load reduction in peak price periods when using automated DR and so-called enabling technologies, such as smart thermostats [208]. The review of 15 dynamic pricing trials concludes that "customers do respond to price" [209] but also that these responses have a high variation. In general, critical peak pricing shows reductions of up to 20 %, whereas time-of-use pricing typically leads only to up to 6 % reduction. Most importantly, Faruqui and Sergici (2010) conclude that automated DR and enabling technologies are crucial to obtain substantial impact [210].

In [290, 291], Hillemacher et al. (2013, 2014) analyze the results of the *MeRegio* field test [296] in the years 2009 to 2012 that used three price levels to influence the customer behavior. At times of low prices, the consumption increases on average by about 6 %, whereas at times of medium and high prices it decreases by about 1.5 % and 5 %, respectively. Hillemacher et al. (2013, 2014) conclude that incentive-based pricing is a promising way to influence the utilization of electricity, even if there is no automated control of the appliances.

The results of a trial of critical peak and real-time pricing including only air-conditioning equipment by Widergren et al. (2014) [643] in Ohio put load reduction at about 5 % in case of a 3.5-hour peak event and at about 8 % in case of a 2-hour event when having about 35 % of the households participating in the DSM scheme.

In a review of the DSM potential in cool temperature climates, Darby and McKenna (2012) [148] examine the results of several European field tests. They conclude that passive-user but automated-control EMSs will enable successful DSM. They stress that users must be able to manually override decisions of such automated systems and that "there is a significant difference between static and dynamic tariffs" [148] from the users' perspectives, which requires to gradually get them accustomed to dynamic tariffs.

Economic Assessment of Demand Side Management Some research analyzes DSM from an economic viewpoint. The results heavily depend on the pricing schemes, the spreads between lowest and highest prices, and the assumptions. For instance, Schroeder (2011) [535] models measures of DSM, electric vehicle charging, and BESSs in the electricity grid to assess grid reinforcement requirements and the economic potentials of DSM and battery storage. The results show that DSM is only beneficial if costing less than 200 EUR per consumer. In an assessment of thermostatically controlled loads, Mathieu et al. (2012) [404] demonstrate that devices, such as HVAC systems and refrigerators, are able to economically provide a substantial share of fast responsive loads.

Decentralized Provision of Ancillary Services *Ancillary services* [297], *dynamic system services* [579], or *smart grid services* [63] in electricity grids can be provided also in a distributed manner by smart buildings having EMSs or at least by intelligent devices. These services include frequency, voltage, and reactive control, phase balancing, and congestion management (see also Section 2.1.4 and Section 2.3.4). Although phase balancing is basically possible using the architecture and the system presented in this thesis, this is out of scope. Similarly, congestion management in grids is out of scope, too, and is not handled in this thesis but will be part of research using the BEMS. Measures of DSM can be used to realize the decentralized provision of frequency control and replace operating reserve (see also Figure 2.11 in Section 2.3.4). Therefore, the literature provided in the previous section is partly not limited to DSM but also referring to frequency control. Further examples of the decentralized provision of ancillary services include the utilization of flexible device pools in residential buildings [335], combined PV and BESSs [617], and domestic fridge-freezers [401] or other devices that have some kind of thermal storage [353]. Related work handles mostly the control of inverters of PV system to prevent overvoltage issues by using inductive reactive power or undervoltage issues by purposeful capacitive reactive power [161, 595]. In some cases, the PV systems are combined with BESSs [332, 620].

3.3 Smart Buildings and Building Energy Management Systems

Smart residential and commercial buildings have been subject to research for years, leading to a multitude of work on smart buildings, BEMSs, and Building Operating Systems (BOSs). Even when neglecting concepts and regarding only actual systems, there is a wide range of BEMSs for energy management in buildings. It is hardly possible to give a comprehensive account on all this related work. However, this section provides an overview of similar approaches, regardless whether they have academic, scientific, or commercial character.

Smart Buildings and Automated Building Energy Management

The term *smart building*, as introduced in Section 2.4.1, covers a wide range of different concepts and ideas. These range from the building design [320], control principles [150], building automation, and device interoperability [554] to energy management [3, 387] and DSM [469]. In general, the optimization of the local energy system, i. e., energy consumption and generation, offers the potential to save costs while achieving a higher comfort for the users. About 20 % of the world-wide energy consumption is related to residential and commercial buildings and, more precisely, most of it is related to HVAC [157].

A great part of the work that is related to this thesis covers residential buildings. One central idea related to energy is to facilitate energy conservation and changes in the consumption patterns through energy-use visualization and price information. Often, local displays are used to inform the user about energy consumption and variable tariffs [61, 651]. Another idea is the optimization of the operating times of appliances [12, 186, 255] to exploit variable tariffs and local DG. In case of commercial buildings, the literature focuses on building automation [554], energy conservation through optimized system design [5] and system operation [576], measures of DSM [469], and occupancy detection to control the buildings' infrastructure [3, 554].

Energy management is still often seen as a process that has to be maintained by the user (see also Appendix A.1.2). Nevertheless, more and more work arises in academics, science, and practical application that focuses on *automated* energy management using EMSs which are autonomous observing and—at the same time—controlling systems. To enable energy management by systems of ICT, artificial intelligence, machine learning, and optimization methods are of great importance [13, 32, 157, 227].

3.3.1 Basic Mechanisms and Concepts in Building Energy Management

There are several concepts that have been applied to active building energy management. Most importantly, there is the fundamental concept of a *building energy management controller* or more general a *building energy management system*. In addition, there are several concepts that have been applied to such systems. These include basic mechanisms and

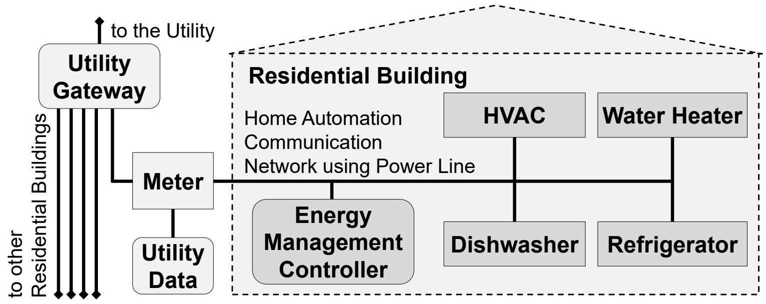


Figure 3.5: Wacks (1993): Concept of an energy management controller and a home automation network that facilitate distributed load management of various devices in residential buildings, based on [625, Fig. 6]

patterns, such as *two-way communication* and *publish-subscribe*, as well as more sophisticated concepts, such as *middleware*, *service-oriented architecture*, and *context-awareness*.

Energy Management Controller

In [624, 625], Wacks (1991, 1993) describes the impact of automated load management and depicts one of the first automated BEMSs (see Figure 3.5). It extends previous work by the same author that introduced three fundamental methods for DSM [624]: *Local control* utilizes electricity tariffs with different rates. The user knows about the different rates and adjust voluntarily their energy consumption to the tariffs by manually controlling the devices differently than usual. *Direct control* enables the utility to enforce an adjustment of energy consumption by allowing for direct remote control of devices. Usually, this requires a prior agreement of both parties and causes inconveniences for the user. *Distributed control* combines and extends local and direct control in a way that the control of the devices is given to a distributed, local system at the user's home, which optimizes the energy consumption with respect to costs, comfort, and convenience. This requires a home automation network which enables the communication between the system and the devices.

The most important component of the system presented by Wacks (1993) is the *energy management controller* (see Figure 3.5), which uses "software algorithms for managing the major electric loads" [625]. It optimizes the electricity costs with respect to changing energy rates, while preserving convenience for the user. The operation of devices is regulated by turning them off or on and switching to alternative operation modes having, e. g., a lower peak consumption. The user may override the controller at any time. In this case, the system informs the user about the consequences of their decisions, enabling them to make economic decisions without knowing the current energy rates or the technical background.

Two-way Communication

Two-way or *bidirectional communication* between the building that implements energy management and higher entities, such as the utility or transmission and distribution system operators, is inevitable to enable load management, automatic meter reading or smart metering, grid state supervision, and ancillary services that are provided by the buildings and their devices [454, 625]. For instance, it facilitates the negotiation of short-term energy contracts [405]. Thus, communication in both direction is of utmost importance for smart buildings in a smart grid (see also Section 3.2.2) [245, pp. 761 ff.] and is widely used in automated BEMSs [10, 405, 586].

Middleware and Middleware Service

The concept of a *middleware* that links low-level system software and applications originates in the 1960's [449, p. 14]. At large, middlewares and middleware services are of general purpose and located in between the OSs that provide low-level services and the applications, i. e., the software that provides concrete functionality, such as energy management [68].

Often, the abstraction of hardware, e. g., sensors or networks, is realized using a so-called *hardware abstraction layer* [421]. This allows for communication and interaction between heterogeneous devices, systems, and services [493]. Additionally, the heterogeneous landscape of devices, systems, and services can be utilized by multiple different applications and in different contexts [324].

Component-based and Service-oriented Architecture

In a *component-based architecture*, every component has clearly defined roles and responsibilities, which realizes "the principle of separation of concerns" [324]. It is a typical way of handling system complexity and enabling the collaboration of different teams when developing complex systems, such as BEMSs.

The concept of *service-oriented architectures* (SOAs) is closely related to that of component-based architectures. In a SOA, every component exposes its services to other components or applications. A component or application may utilize a set of services from one or multiple other components to realize its own services respective functionality [324]. The services require a proper description and have to support their discovery when executing applications on a system. This way, the system and its applications can be adapted to different situations and contexts at run-time [503].

A popular example of a component-based and service-oriented architecture is the *OSGi Service Platform* by the Open Services Gateway initiative (OSGi). It provides a component and service platform for *Java* and targets on embedded systems. The components (so-called *bundles*) are installed and run in an execution environment that provides life-cycle management and communication. They publish their services that can be utilized by other components [324]. These concepts ease the development and deployment of components and services and ultimately applications of different embedded systems [503].

Context-aware System

Making systems *context-aware* is the idea of utilizing information about the context in which a system is run to gain better semantic information [493, 503] and to achieve context-specific behavior [421, 493]. Often, this is realized using a so-called *context manager* that detects different contexts and then applies dedicated mechanisms and behavior [421].

Firstly, this facilitates better interactions between the system and its environment, in particular the building and the user, because it takes the user's "desires, whereabouts,

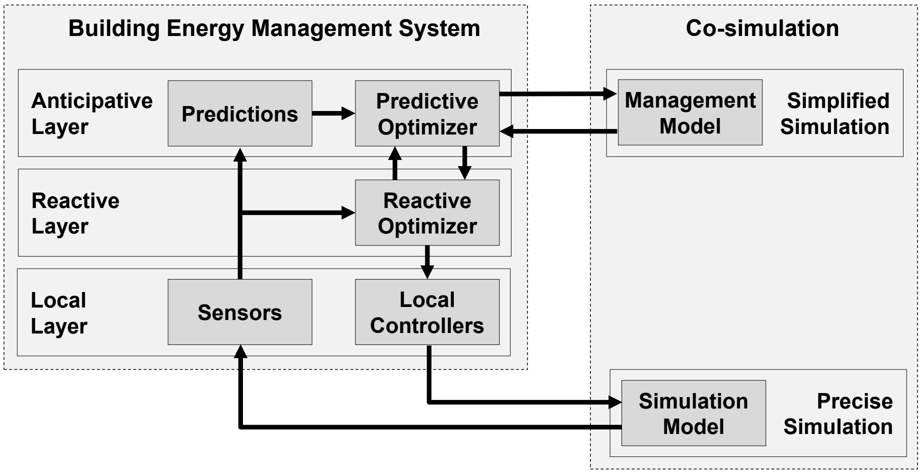


Figure 3.6: Abras et al. (2008) and others: the three-layer architecture of the *global Model Based Anticipative Building Energy Management System* and the general schema of the co-simulation approach, which uses a simplified simulation of the building in the optimizer and a precise simulation as a substitute for the real building in the evaluation of the BEMS, partially based on [36, 156, 424]

activities, needs, emotions and situations" [421] into account. This refers to context as being "the circumstances or situations in which a computing task takes place" [421], which includes different objectives by different users. Secondly, it facilitates better decisions of the system by enriching the information it receives from its sub-systems. This refers to high-level contexts that are deduced from low-level sensed contexts, e. g., spatial awareness [67] or interdependencies [289, 361], and requires reasoning and learning mechanisms [493].

3.3.2 Building Energy Management Concepts, Frameworks, and Systems

This section provides an overview on building energy management concepts, frameworks, systems, and demonstrators. Some of them are more like concepts than real EMSs that can be used for automated energy management, others are already commercially available. Nevertheless, they are all working on appropriate implementations of the concepts presented in the previous section. Table 3.1 on p. 87 provides a comparison of various frameworks and systems and their specific layers with respect to the general layers that are used in such systems, the challenges that are addressed by the layers, and the heterogeneities that occur in the layers. In Section 6.1, the frameworks and systems are compared in detail to the BEMS presented in this thesis.

Academic Approaches, Frameworks, and Systems

There is a large variety of BEMSs in academia. A great part of them is merely a concept or system that cannot be used in productive EMSs in real buildings, oversimplifies the problem of energy management, or does not use proper statistical data in simulations. Some of them are detailed in the following paragraphs.

Abras et al. (2008) and Others In a series of publications, Abras, Bacha, Ha, Jacomino, Joumaa, Ploix, and others [1, 36, 156, 267–272, 424, 425, 456, 530] present a BEMS that optimizes appliances in a building with respect to energy prices. It comprises three layers with dedicated functionality (see Figure 3.6 and Table 3.1): The *local layer* is responsible for the communication with sensors and local controllers that abstract the communication to the appliances. The *reactive layer* comprises a reactive optimizer that enables fast responses when constraints are violated, e. g., because of unpredicted events. The *anticipative layer* optimizes the future energy consumption and generation by taking predicted events into account and adjusting set points of the appliances using MILP [424, 425]. The system takes economic (e. g., total energy costs), comfort (e. g., user dissatisfaction), environmental (e. g., CO_2 emissions), and autonomy criteria (e. g., self-sufficiency) into account [268].
The authors use two different models to simulate the building and its components and to validate their system (see Figure 3.6): The actual optimization in the BEMS uses a simplified building simulation that contains the generalized *management model*. In contrast, the precise simulation uses a detailed *simulation model* that simulates the complex behavior of a building for validation purposes [424]. The precise simulator is based on MATLAB/Simulink and utilizes TRNSYS and HVACSIM+ (see also Section 3.5.3), whereas the simplified simulator uses some basic equations for the thermal simulation. Similarly, the load profiles of the appliances are simplified: the simulation model uses precise recorded profiles of real appliances, whereas the management model uses greatly simplified profiles that have a constant power during the operation cycle of the appliance.
In an early version, the system used *tabu search* for optimization. Meanwhile, it utilizes MILP and is called *Global Model Based Anticipative Building Energy Management System* (GMBA-BEMS) or *G-homeTech* [36, 268, 456]. A commercial variant is marketed by Vesta-System, whose energy management mechanism and methodology are detailed in [36].

Althaher et al. (2015) In [14], Althaher et al. (2015) present a BEMS that uses MINLP to optimize the operation of several appliances and devices in residential buildings with respect to costs while ensuring a certain comfort level. The actual problem is formulated in the mathematical programming language *Advanced Integrated Multidimensional Modeling Software* and solved using an outer approximation algorithm. The BEMS uses a rolling horizon and a resolution of 15 min to iteratively solve the optimization problem. If the total load exceeds a certain power limit, the price of electricity is set to a higher value, which results in a non-linear problem. The proposed BEMS has been applied to 30 different profiles of simulated residential buildings. The concept of this BEMS is limited to the scheduling of several classes of controllable appliances in an optimization engine, but may not be applied to real buildings.

Ameling et al. (2010) Ameling et al. (2010) [16] present a general architecture for EMSs which is inspired by enterprise resource planning and manufacturing execution systems that are used in manufacturing and industrial production. In that work, the actual EMS is limited to the presentation layer that is located on top of a logic layer, which does analysis, execution, and modeling, a persistence layer, which manages a database, and a connectivity layer, which abstracts devices and data sources using adapters and uses a so-called event bus to distribute information (see Figure 3.7 and Table 3.1 on p. 87).

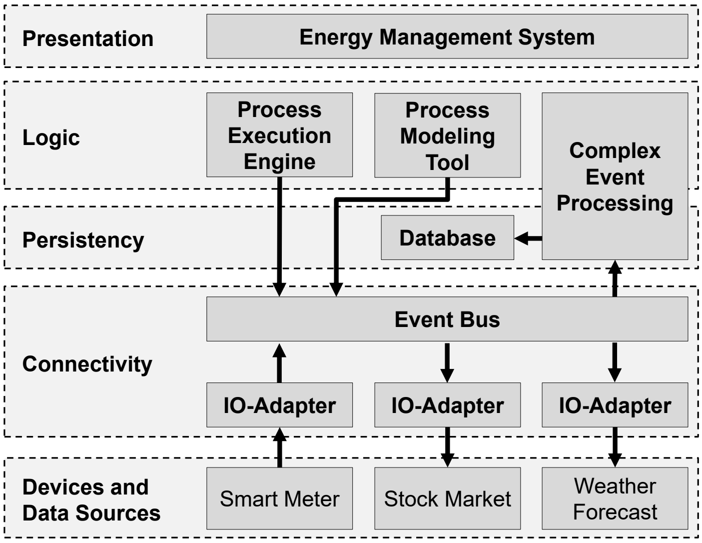


Figure 3.7: Ameling et al. (2010): Proposed architecture for *demand-side energy management* in manufacturing and production using a complex event processor for the analysis, processing, and combination of predefined rules, based on [16, Fig. 1]

Bozchalui et al. (2012) In [92], Bozchalui et al. (2012) use a MILP formulation of the optimization problem in BEMSs and a horizon of 24 hours at a resolution of 15 min. They use simple mathematical models of appliances, PV systems, and BESSs to evaluate several scenarios with different optimization objectives.

Chen et al. (2012) Chen et al. (2012) [121] use stochastic as well as robust optimization for the management of appliances and an electric vehicle, coping with uncertainties in the rolling optimization horizon in building energy management. The optimization problems are formulated as MILP problems at a resolution of 5 min. The stochastic optimization yields better results than the robust one but requires longer computational time.

Damm et al. (2011, 2012) In [145, 146], Damm et al. (2011, 2012) present a BEMS for decentralized energy management. They use a proportional-integral controller for thermal appliances and a cost optimization for deferrable appliances to demonstrate the load-balancing effect of a small setup comprising two refrigerators. Basically, they replace the on-off controller, i. e., hysteresis controller, of thermal devices with a proportional-integral controller, which calculates a load profile that is subsequently optimized by the BEMS using a price profile.

Di Giorgio and Pimpinella (2012) The conceptual BEMS of Di Giorgio and Pimpinella (2012) [170] is the formulation of a MILP problem that optimizes deferrable and controllable electrical loads in buildings. The optimization problem uses a resolution of 5 min to optimize the devices with respect to costs and strict power limits in a horizon of one day.

Hable et al. (2002–2004) In [274–276], Hable et al. (2002–2004) present an EMS comprising three modules: a prediction, an optimization, and a controlling module. They use

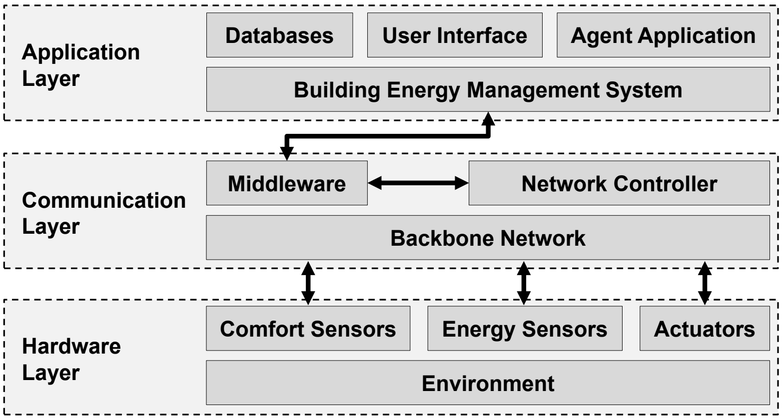


Figure 3.8: Hurtado et al. (2013): Proposed architecture comprising a hardware layer that contains the devices, a communication layer that enables device abstraction, and an application layer that contains the actual BEMS, based on [305]

an Evolutionary Algorithm (EA) to optimize the problem at a resolution of 15 min with respect to energy costs and emissions and "find reasonable results" [275]. The optimization is demonstrated in several exemplary energy systems that are composed of, e. g., wind power, PV, battery, and microCHP systems.

Hurtado et al. (2013) In [305], Hurtado et al. (2013) present a BEMS that aims at the optimization of comfort and energy-use and introduce the MATLAB/Simulink tool *Simscape* for the modeling and simulation of sub-systems of a building. Such sub-systems are named *zones* and represent, e. g., rooms or any part of the building that can be modeled physically. Simscape serves as a convenient tool for the simulation of rooms and energy systems through models with simplified convective and conductive heat transfer. The energy management and optimization is based on a multi-agent system and uses a distributed control strategy. The agents control dedicated zones or DER, ensuring comfort levels set by the user. Agents of different zones are aggregated to higher level agents that reflect, e. g., a floor of the building or the entire building. Objectives and flexibilities are also aggregated in a bottom-up approach. [305]

The overall system is structured in an architecture that comprises three layers (see Figure 3.8 and Table 3.1 on p. 87) [305]: the application layer, the communication layer, and the hardware layer. The hardware layer contains sensors, actuators, and the environment. It is connected to the communication layer using a network. At the communication layer, a network controller and a middleware on a communication gateway abstract the information for the application layer, which contains the actual BEMS as its main component. The BEMS is supported by databases, a user interface, and the multi-agent application. [305]

The approach oversimplifies the optimization problem of energy consumption and generation in buildings. It neglects the requirements of an actual cost optimization by simplifying the comfort objective and the cost objective to general and conceptualized functions. Energy consumption is distinguished based on devices but not with respect to energy carriers.

Lujano-Rojas et al. (2012) Lujano-Rojas et al. (2012) [384] use an optimization model of buildings with electric vehicles to optimize the idealized loads at a resolution of one hour. Although their optimization problem is simplified, they use a non-linear model of the battery, which results in a non-linear formulation that is solved using a Genetic Algorithm (GA) with respect to cost minimization in a time-of-use pricing scheme.

Soares et al. (2012–2016) In [557] and [558], Soares et al. (2012a, 2012b) introduce an integrated EMS for residential buildings. It uses information about the grid state, emergency signals, price signals, the local system status, and restrictions, i. e., the contracted maximum power, technical restrictions, and user preferences, to shift and interrupt loads or set new parameters to the devices. Hence, it decides when to consume, store, or sell electricity. Soares et al. (2012b, 2014) [558,559] propose a detailed categorization of the devices typically found in residential buildings, i. e., appliances and HVAC systems (see also Section 3.4.1). Based on this categorization, Soares et al. (2013) [561] use a GA to optimize the operating times and parameters of appliances and an HVAC system with respect to electricity costs, respecting the contracted maximum power and preferences of the user.

In [559], Soares et al. (2014) assess the impacts of DR and automated energy management on the average load profile of Portuguese households. The results show a decrease of electricity consumption in hours having high electricity prices, whereas consumption is increased in the other hours. This demonstrates the possibility of a decrease of the peak consumption of electricity when variable tariffs have been set properly. Soares et al. (2014) [556] and Soares (2016) [555] extend the approach to a multi-objective optimization that includes the minimization of electricity costs as well as the penalty caused by user dissatisfaction due to the deferral of devices and the risks of an interruption of the electricity supply.

However, Soares et al. (2012–2016) focus only on electricity and do not regard the capabilities of energy management that overcomes the borders of different energy carriers.

Open-Source Building Energy Management Systems

There are several BEMSs that are publicly available as open-source software. All follow their own principles and design paradigms in architecture and structure. Their functionality varies and some provide only hardware abstraction without energy management or optimization although claiming to be systems that are capable of building energy management. Often, the energy management functionality is separated from the system and provided by some abstract energy management application that is neither closer specified nor provided.

Building Energy Management Open Source Software (BEMOSS) The *Building Energy Management Open Source Software* (BEMOSS) by Khamphanchai et al. (2014) [348] is the concept of a general BEMS architecture. It consists of four layers: a *connectivity layer*, which includes all the devices and data sources, an *operating system and framework layer*, which manages and abstracts the devices, an *application and data management layer*, which enables the actual energy management functionality, and a *user interface layer*. BEMOSS utilizes the so-called VOLTTRON platform, which is a multi-agent system [273], as well as the *Simple Measuring and Actuation Profile* (see also Section 3.3.3) and is demonstrated in a small laboratory setup.

Energy Flexibility Platform and Interface (EF-Pi) / Flexible Power Application Infrastructure (FPAI) The Flexible power Alliance Network is responsible for two systems or technologies that are complementary to each other while remaining independent: the *PowerMatcher* and *FPAI*, which is now called EF-Pi. The combination of PowerMatcher and EF-Pi has been developed to exploit load flexibility in power grids by optimizing the operation of home appliances, HVAC systems, and DG (see also Figure 3.4 on p. 71). The PowerMatcher serves as the coordination mechanism, whereas EF-Pi is the system that abstracts devices and services, using the so-called *Energy Flexibility Interface* (EFI), *Resource Managers*, *Resource Drivers*, and *Protocol Drivers*. [601]

The Protocol Drivers connect devices via gateways with the BEMS and are similar to the *bus drivers* presented in this thesis (see Section 5.2). The Device Drivers communicate with the devices either directly or indirectly using the Protocol Drivers and abstract the communication and the properties of the devices. Thus, they share not only the name but also their main functionality with the *device drivers* of the present thesis. In combination with the *Resource Managers*, which abstract devices using the standardized *EFI*, the Device Drivers facilitate the optimization of the devices by an energy management application. Hence, the abstracted devices can be optimized by the PowerMatcher or some other external optimization service or application, e. g., *TRIANA* [586], that is connected to the EFI of EF-Pi. All services, applications, and drivers are bundled into *EF-Pi Apps* that can be installed from the *EF-Pi Store*. The modular system of EF-Pi is based on OSGi. [601]

The EFI of EF-Pi defines four types of resources, i. e., flexibility categories: uncontrolled, time shiftable, buffer, and unconstrained, which are detailed in Section 3.4.1. Devices, such as appliances or HVAC systems, have to be compatible to one of the four categories in order to be successfully abstracted by EF-Pi. After being installed into EF-Pi, the devices and services are visualized in the end-user interface that contains several *dashboards* and *widgets*, i. e., web-based applications. [601]

The combinations of EF-Pi and PowerMatcher or TRIANA offer the possibility to optimize a wide range of devices that may be abstracted using the EFI. Both combinations consider electricity as well as other energy carriers when optimizing the energy usage [600, 601]. Although the actual energy management functionality is not part of EF-Pi but of the energy management applications, it supports multiple energy carriers as abstract commodities. Nevertheless, a detailed simulation of devices, buildings, and user behavior is not part of EF-Pi [459] and the list of commodities is limited to the electricity, gas, and heat [600].

Hydra/LinkSmart In [324], Jahn et al. (2010) present an EMS that is based on the *Hydra/LinkSmart* framework[4]. Initially, the framework had been named Hydra but it is now called LinkSmart [307]. It is a middleware that "facilitates the intelligent communication of heterogeneous embedded devices through an overlay P2P network" [324]. The energy management and optimization is realized by the *Energy Manager*, a special component on top of the middleware; it is integrated into the actual smart home application running in the application layer. The *Energy Manager* serves as an interface between the utility and the user, taking variable electricity prices into account to adjust the energy consumption. It is claimed that the middleware is able "to optimize energy consumption on device level and to gain more energy efficiency in buildings" [307]. The framework has been used in

[4] `https://linksmart.eu`

the research project *ME ^{3}gas* (acronym for "Smart Gas Meters & Middleware for Energy Efficient Embedded Services") to improve the energy efficiency in residential buildings by integrating a smart gas metering system and appliances for visualization purposes [479].

Nevertheless, the framework Hydra/LinkSmart is just the middleware that facilitates communication between different devices and systems. The actual BEMS has to be implemented as an additional application on top of the middleware.

Open Energy Gateway Architecture and Open Gateway Energy Management (OGEMA) Nestle et al. (2010) [454] and Zillgith et al. (2013) [665] present the *Open Energy Gateway Architecture* for *Open Gateway Energy Management* (OGEMA) of the *Open Gateway Energy Management Alliance*[5], an architecture for building automation and BEMS that uses abstracted devices and services to provide energy management. OGEMA is based on the *bidirectional energy management interface* (BEMI), which is more closely described in [453, 508]. The devices, i. e., the appliances, electric vehicles, and HVAC systems, are abstracted and standardized using a tree structure of resources. In this hierarchical structure, more complex *top-level resources*, e. g., buildings or building pools, are composed of a set of *sub-resources*. The sub-resources at the lowest level—so-called *simple resources*—have a *schedule* that determines the future behavior of the abstracted devices [221]. [409, 410]

The actual optimization is done by multiple applications that provide dedicated functionality, i. e., the management of a single device. Therefore, OGEMA lacks an integrated approach to optimization as the scheduling of individual resources is provided by separate management applications. Nevertheless, the optimization with respect to variable prices is mentioned in [221], which is only possible when having closely collaborating applications.

Organic Smart Home (OSH) In [13], Allerding and Schmeck (2011) present the OSH[6]. Initially, it has been developed for residential buildings comprising intelligent appliances, electric vehicles, and DG, but it is now also applicable to commercial building scenarios [62, 410]. The major advantage of this BEMS is its capability of enabling simulations as well as real-world application in real buildings. Accordingly, it has been deployed to real residential and commercial buildings, allowing for evaluations and validation in real-world deployment [62, 468]. Additionally, it has been used in various simulation scenarios optimizing the operation of appliances [11, 406], heat pumps [378], and electric vehicles [443] to analyze their effects in smart buildings. [410]

See Table 3.1 on p. 87 and Section 4.9 for a detailed analysis of the OSH, its layers, and its functionality, which is substantially enhanced by the system presented in this thesis. A comparison to the original OSH is given in Table 6.5.

Commercial Building Energy Management Systems

Although there are quite many commercial systems for building energy management, most of them focus on visualization and home automation and do not allow for automated energy management, e. g., the *Fibaro Home Center*[7] or the *QIVICON Home Base*[8] by *Deutsche*

[5] http://www.ogema.org
[6] http://www.organicsmarthome.com
[7] http://www.fibaro.com
[8] https://www.qivicon.com

Telekom, or provide only a simple on-off logic instead of prediction and optimization, e. g., the *Energy Manager EM210* by *B-Control*[9]. The following three exemplary energy management systems enable automated management and optimization in the sense of this thesis. Nevertheless, their functionality is currently still limited and focuses on electricity.

Kiwigrid The *Kiwigrid*[10] system is a software platform for energy management applications by third parties. These applications provide, for instance, functionality for enabling the connection to a VPP, the charge management of electric vehicles and BESS, and the marketing of ancillary services. Hence, the system focuses on electricity and does not include other energy carriers. [367]

Innogy SmartHome and RWE easyOptimize The two products *innogy SmartHome*[11] by *innogy* (former name: *RWE SmartHome*) and *RWE easyOptimize* by *RWE Effizienz* enable home automation, device control, and the optimization of microCHPs and heat pumps. The *innogy SmartHome* is able to control smart plugs and appliances, whereas the *RWE easyOptimize* controller realizes the actual optimization with respect to self-consumption and variable tariffs of electricity. [521, 522]

SMA Smart Home The *Sunny Home Manager* by *SMA*[12] is a dedicated gateway enabling the prognosis of the electricity generation by PV systems. Additionally, it is capable of scheduling and controlling heat pumps and appliances with respect to an optimization of the self-consumption rate of locally generated electricity. [552]

3.3.3 Building Operating Systems

The idea of a BOS addresses another aspect of ICT in buildings: ICT may not only be used for energy management purposes but also for assistance, comfort, entertainment, health, information, safety, and security functionality. This offers a wider perspective of possible applications that utilize the devices and systems in buildings to make them smarter than conventional buildings. Additionally, it emphasizes the importance of several ancillary services that have to be provided by a system to enable energy management, such as logging, access control, or error handling.

The following paragraphs describe several operating systems that have been developed for the utilization in buildings to enable assistance, comfort, entertainment, information, safety, and security as well as energy management functionality.

Building Operating System Services (BOSS) In [152], Dawson-Haggerty et al. (2013) present a prototypical architecture for an OS that can be used in buildings. This system is motivated by "vertically integrated, closed subsystems [...] without uniform abstractions to write applications against" [152]. They propose a set of so-called *Building Operating System Services* (BOSS) and depict several architectural components and layers of a BOS to provide a uniform abstraction of heterogeneous commercial buildings and their sub-systems (see also Table 3.1). The architecture of the system is depicted in Figure 3.9. It utilizes the

[9] `http://www.b-control.com`
[10] `https://www.kiwigrid.com`
[11] `https://www.rwe-smarthome.de`
[12] `https://www.sma.de`

Table 3.1: Application of typical layers in building energy management and building operating systems, partly based on [179, 580]

<table>
<tr><th rowspan="2">General layer</th><th rowspan="2">Challenges</th><th rowspan="2">Heterogeneities</th><th colspan="6">Examples</th></tr>
<tr><th>Abras et al. (2008) [1]</th><th>Allerding (2013) [10]</th><th>Ameling et al. (2010) [16]</th><th>Hurtado et al. (2013) [305]</th><th>Taneja et al. (2013) [580]</th><th>Waaij et al. (2015) [601]</th></tr>
<tr><td>Application</td><td>Programmability, permissions</td><td>Programming languages, access</td><td rowspan="4">Anticipative Layer, Reactive Layer</td><td rowspan="2">Observer/ Controller Layer</td><td rowspan="2">Presentation, Logic, Persistency</td><td>Application Layer</td><td>Applications</td><td rowspan="2">Applications, Services</td></tr>
<tr><td>Management</td><td>Access control, conflict management, portability, fault-tolerance, security, data archiving</td><td>Access, coordination</td><td rowspan="3">Communication Layer</td><td rowspan="2">Building Application Stack, Building Operating System Services</td></tr>
<tr><td>Functionality</td><td>Resource and functionality abstraction</td><td>Device, functionality, function models</td><td rowspan="2">Hardware Abstraction Layer</td><td rowspan="2">Connectivity</td><td>Energy Flexibility Interface, Resource Managers</td></tr>
<tr><td>Connectivity, Communication</td><td>Device abstraction, data availability</td><td>Topology, protocols, data models</td><td>Drivers</td><td>Device Drivers, Protocol Drivers</td></tr>
<tr><td>Hardware</td><td>Physical data</td><td>Devices, systems</td><td>Local Layer</td><td>System under Observation and Control</td><td>Devices, Data Sources</td><td>Hardware Layer</td><td>Sensors, Actuators, Networks, Systems</td><td>Devices</td></tr>
</table>

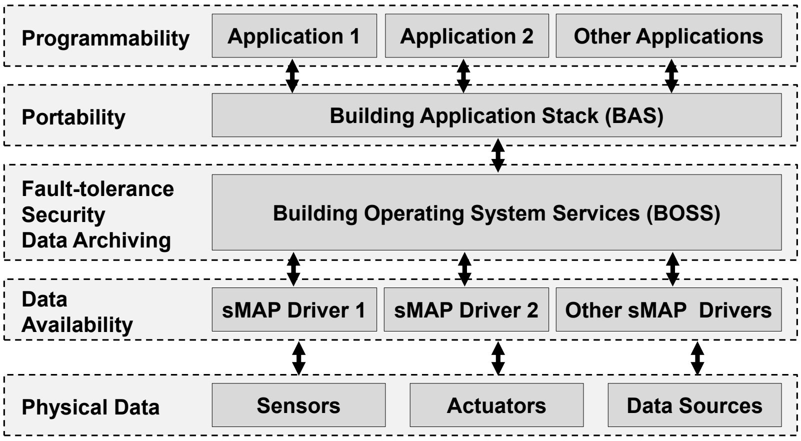


Figure 3.9: *Building Operating System Services* architecture using the *Building Application Stack* and *Simple Measuring and Actuation Profile* (sMAP), based on [580, Fig. 2]

Simple Measuring and Actuation Profile (sMAP) [151] and consists of six main sub-systems that provide the following dedicated services [152]:

1. Hardware discovery, naming, aggregation, and semantic modeling.
2. Hardware and access abstraction.
3. Time series processing and archiving.
4. Control transaction management.
5. Authorization.
6. Application runtime.

BOSS and sMAP are implemented in *Python* and *C* and have been evaluated in test buildings on the campus of the *University of California, Berkeley*, demonstrating their applicability, performance, and scalability. The system emphasizes the importance of robustness and safe fallback in case of (partial) failures. Then, the control transaction management simply reverts all changes made to a subordinate control process that is not affected by the failure. Ultimately, the system falls back to built-in control-loop strategies of the devices [152].

In [580], Taneja et al. (2013) expand the BOSS architecture by the so-called *Building Application Stack* (BAS). The BAS is located on top of the BOSS (see Figure 3.9), whereas sMAP is located below BOSS, and enables the portability of applications by providing a standardized interface and a runtime environment. In a field test, the system improves the air quality successfully and achieves energy savings of up to 80 % by optimizing the ventilation and filtration control. Taneja et al. (2013) call adaptable and evolving applications the "key to energy-efficient buildings in the future" [580]. They argue that "[e]xisting systems are ill-suited for this model of continuous change because reconfiguring them requires significant manual effort unique to each site", whereas the combination of BAS, BOSS, and sMAP on a programmable platform may be deployed to different existing buildings easily and is able to integrate additional data sources flexibly as soon as they are available.

An antecedent system of BOSS utilizing *model predictive control* (MPC) for the optimization of an HVAC system is used by Aswani et al. (2011) [29] to improve energy efficiency successfully while maintaining user comfort.

Gaia OS In [493, 513, 514], Roman et al. (2000, 2002) and Ranganathan & Campbell (2003) present *Gaia OS*, a meta-operating system using existing middleware. It enables so-called *active spaces* [513] or *smart spaces* [493] by making living spaces programmable through agents that represent users, spaces, applications, and services. Gaia OS provides five main services [514]: an event manager, a context service, a presence service, a space repository, and a context file system. It emphasizes the importance of context-awareness and utilizes a “predicate model” and “ontologies to describe different types of contexts”, e. g., rooms or buildings [493]. Nevertheless, it does not consider active energy management. Instead, Roman et al. (2002) provide examples that are close to building automation, such as a meeting room that runs specific applications when being triggered by different users.

HomeOS, HomeStore, HomeHub, and Lab of Things In 2010, *Microsoft Research* and *IBM Research* introduced the *HomeOS* as well as the *HomeStore* and the *HomeHub*. The HomeOS provides the abstraction of devices that are part of a building, which is similar to an OS that abstracts the components and peripherals of a computer. This targets on the simplification of the usage of physical devices by applications which are delivered by the HomeStore. These applications run independently of each other and are limited by access control rules on a central system, the so-called HomeHub. [178, 179]

Based on HomeOS, the *Lab of Things* (LoT) framework extends the building-centric perspective to multiple sites that may be located around the world. LoT provides remote monitoring, updating, logging, and storage services, whereas HomeOS is the core platform for device abstraction and interconnection [99]. The cloud-based approach and centrally collected data aim at easing the development of additional applications, such as the *LoT Analytics Engine*, which evaluates usage patterns and compares data sets, e. g., to find anomalies [528]. So far, LoT and HomeOS focus on computers that are connected to cloud-based services. Hence, systems based on them are highly centralized and lack decentralized, distributed approaches regarding the systems and applications that control the building.

3.4 Appliances and Devices

This section presents related work regarding the energy management of devices in buildings. For instance, it addresses device classifications with respect to capabilities and usability in energy management or analyzes the energy management potential of devices. Classification is an important prerequisite of energy management as well as approaches to hybrid appliances and their operation. The analysis of the energy management potential requires appropriate communication protocols, realistic load profiles, and a suitable simulation of the devices.

3.4.1 Classifications of Devices in Energy Management

There are several existing classifications and categorizations[13] that generalize devices, facilitate abstraction, and subsequently enable building energy management based on

[13]The terms classification and categorization are often used indiscriminately. Nevertheless, the term classification refers to a more systematic and rigorous separation, emphasizing exclusiveness and distinctness. In contrast, the term categorization allows for fuzzy boundaries and context-dependent, graded distinction [323]. This thesis uses the same terms as the original sources.

common properties. Some of the classifications and categorizations are described in the following paragraphs and given in the tables in Appendix B.1. Afterward, an analysis of them is presented, inferring the actual dimensions that are used.

Allerding and Schmeck (2011) In [13], Allerding and Schmeck (2011) propose the classification of home appliances that is listed in Table B.1. This classification is similar to the one proposed by Ha et al. (2006, 2012) and De Oliveira (2011) (see below and cf. Table B.7). The basic distinction is between observable and controllable appliances. The observable appliances are separated into predictable and unpredictable devices. Controllable appliances that have some kind of inherent storage capability are called permanent services, whereas the timed-services are switched on for a single run by the user.

Althaher et al. (2015) Althaher et al. (2015) [14] propose the five categories of appliances that are listed in Table B.2 and based on consumer preference and appliance functionality. Nonflexible deferrable appliances have a fixed load profile and may only be shifted in their operating time. Flexible deferrable appliances may change their load profile and have only a fixed required total energy consumption. Thermal appliances have certain temperature limits respecting the intertemporal dependencies. Finally, curtailable appliances may be switched off in emergency situations according to user-defined priorities, whereas the uncontrolled operation of critical appliances has to be preserved at all times.

Damm et al. (2011) In [146], Damm et al. (2011) propose the seven classes of appliances listed in Table B.3. They have been developed and used in the project *Smart Control of Demand for Consumption and Supply to enable balanced, energy-positive buildings and neighbourhoods* (SmartCoDe). The classification is based on different parameters—configuration, sensor input, and online input—that are used by the appliances as well as the possible energy management strategies that are derived from the properties of the devices.

Energy Flexibility Platform and Interface (EF-Pi) The EF-Pi system, which is described in Section 3.3.2 in detail, defines four types of resources or flexibility categories: uncontrolled, time shiftable, buffer, and unconstrained. The categories are briefly delineated in Table B.5 and more closely characterized in [600]. In energy management and optimization, each category is treated differently by EF-Pi. [600, 601]

Gottwalt et al. (2011) and Dethlefs et al. (2014) In [255], Gottwalt et al. (2011) propose the following three categories of devices in load control: automatic, semi-automatic, and not-controllable. They are introduced and briefly characterized in Table B.6. In [254, p. 42, Tab. 3.3], Gottwalt (2015) provides a more detailed description of the characteristics of appliances and a comparison to other categorizations. Dethlefs et al. (2014) [165] distinguish user-driven, program-driven, and fully-automated loads (see Table B.4) and thus the classification is very similar to the categories proposed by Gottwalt et al. (2011).

Ha et al. (2006, 2012), De Oliveira (2011), and Missaoui et al. (2014) In [156, 268, 272, 424], Ha et al. (2006, 2012), De Oliveira (2011), and Missaoui et al. (2014) propose a service-centric classification of devices and appliances that has two fundamental dimensions.

Firstly, services have a dimension related to time and availability: Some of them are *permanent services* that have to be scheduled for the whole time range of energy management, because their flexibility is based on the consumption and generation in the entire

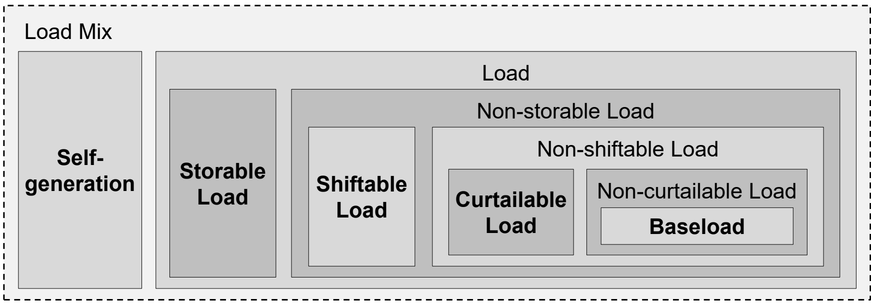


Figure 3.10: Load mix comprising five different categories of flexibility sources, based on He et al. (2011) [284, Fig. 2]

optimization horizon. Other services are *temporary/timed services* that may be scheduled several times or may not be available for longer time ranges during energy management [424]. Secondly, services have a dimension that describes their relation to the user: *End-user services* have a direct relation to the user and their comfort, *intermediate services* are responsible for the storage of energy, and *support services* provide the energy (see Figure B.7) [424].

Ha et al. (2012) add a third one to these two dimensions and distinguish whether services are *modifiable* by the EMS or not. Thereby, the character of the modifiability depends largely on the first dimension, i. e., whether it is a temporary or a timed service. Thus, this classification is actually similar to that by Allerding and Schmeck (2011) (see above).

He et al. (2011) In the *THINK project*, He et al. (2011, 2014) [284, pp. 11 ff.] [115, pp. 12 f.] propose the five categories depicted in Figure 3.10 and given in Table B.8. *Storable* or buffered loads have a service that is decoupled from energy consumption. The operation of *shiftable* loads can be shifted within certain temporal limits. In contrast, *curtailable* loads may only be interrupted, whereas the uncontrollable *baseload* can neither be shifted nor interrupted. The fifth category is the local generation that is partly freely controllable.

Kok et al. (2005) In [358], Kok et al. (2005) propose the six classes of devices that are listed and briefly described in Table B.9. In subsequent work, these classes have been reduced to the four classes that are currently used by *EF-Pi* and *PowerMatcher* to facilitate energy management (see above).

Soares et al. (2012) In [557, 558], Soares et al. (2012) propose the following categories, which are given and briefly described in Table B.10: uncontrollable, reparameterizable, interruptible, and shiftable loads. The four categories are used, e. g., in [556, 561], for the simulation of a BEMS utilizing home appliances.

Analysis of the Classifications and Categorizations

The classifications and categorizations that are described in the preceding paragraphs use different attributes and features to distinguish the classes and categories. These attributes and features form the so-called dimensions that are used by the different classifications and categorizations. Table 3.2 presents the dimensions and characteristic attributes that have been deduced from the previously presented classifications and categorizations.

Some characteristic attributes of the dimensions have strong cross-correlations. However, none of the classifications and categorizations uses all dimensions: each focuses on a certain aspect in the energy management of devices and none considers explicitly the aspect of devices utilizing or providing multiple energy carriers or having alternative energy portfolios. Therefore, this thesis presents a novel classification of devices in Section 4.4.3.

3.4.2 Energy Management using Appliances and Devices

There are many publications about the utilization of appliances and DG for energy management in buildings and smart grids. Some of them provide fundamental statistics, other focus on the optimization of particular devices, such as home appliances, thermal devices,

Table 3.2: Identified and generalized dimensions and characteristic attributes used by the classifications and categorizations of devices in the literature

Dimension	Description	Exemplary characteristic attributes
Controllability	Is the device controllable by the BEMS? And if so, is it automatically or does it require user interaction?	◦ Automatic/fully automated ◦ Semi-automatic (user interaction required) ◦ Uncontrollable/only manual control by user
Effect of control	What is the effect of control on the provision, distribution, conversion, storage, and utilization of energy?	◦ Temporal shift/deferral ◦ Interruption ◦ Reduction/increase/variable service ◦ Shift from one energy portfolio to another ◦ Re-parametrization/adapted profile ◦ Critical/non-curtailable/base
Reason for controllability	What enables the controllability of the provision, distribution, conversion, storage, and utilization of energy?	◦ Internal storage/buffer ◦ External storage/buffer ◦ Variable service, interruptibility ◦ Temporal shiftability/deferrability ◦ Unrestricted operation
Service	What kind of service does the device provide? Where in the energy chain is the device located?	◦ Support/generation (inbound provision) ◦ Intermediate (storage, conversion) ◦ End-user (energy service)
Energy carriers and portfolios	What are the input and output energy portfolios? Do they contain multiple energy carriers?	◦ Single energy carrier ◦ Multiple energy carriers/hybrid ◦ Concrete energy vectors
Time/availability/ occurrence	What is the availability of the device? When is it operated?	◦ Permanent ◦ Temporary/timed ◦ Stochastic ◦ User-/program-driven ◦ Cross-correlation to another device
Probability of occurrence	How often is the device operated?	◦ Frequency ◦ Permanentness
Predictability	Is the operating time predictable? Is the load profile predictable?	◦ Unpredictable ◦ Predictable

cogeneration or trigeneration systems, heat pumps, or BESSs. The following paragraphs describe exemplary work on energy management using devices and systems in buildings.

For instance, as early as in the first half of the 20th century, the load profiles of appliances and of an entire household were closely analyzed by Ritter (1927) [509]. In the late 20th century, Gellings (1985) [240] proposed to use appliances for DSM and Wacks (1991) [624] depicted this in an even more detailed way. In the early 21st century, the energy management potential [570] and the user acceptance [417] of smart appliances were closely analyzed. More recently, this is brought to a wider perspective including many buildings. In [296], Hirsch et al. (2010) propose bottom-up simulations of multiple households for the analysis of price elasticities as well as effects of DG and Gottwalt et al. (2011) [255] conduct simulations comprising 1,000 households to evaluate household behavior under variable prices.

Appliances The optimization of appliances in EMSs with algorithms that use energy price signals or power limit signals is demonstrated for instance in [186, 272, 427, 431]. More recent work, e. g., [13, 152, 454], focuses on the development of BEMSs that can be used in actual buildings. In particular, this includes a suitable and pragmatic abstraction of devices that allows for a modular optimization in heterogeneous scenarios [11, 586]. In addition, some—more theoretical—approaches consider not only deferrable but also interruptible appliances, such as Sou et al. (2011, 2013) [563, 564] and Kaczmarczyk et al. (2015) [333].

Thermal Devices Many experiments, e. g., by Daryanian et al. (1991) [149], and simulations, e. g., by Kok et al. (2005) [358], focus on thermal devices, i. e., devices that are related to heating and cooling energy services. Usually, the energy consumption of such devices is relatively high and there is inherent, e. g., buildings and freezers, or dedicated, e. g., storage tanks, energy storage. Therefore, such devices are often modeled and simulated to evaluate control [567] or pricing schemes [427] and included into the provision of ancillary services, e. g., by Kamper and Esser (2009) [336] or Martin Almenta et al. (2016) [401].

Cogeneration: Combined Heat and Power The optimization of cogeneration systems is analyzed in many publications. For instance, Caldon et al. (2004) [106] provide an optimization algorithm for VPP that considers CHP systems and Salgado and Pedrero (2008) [525] present a survey about short-term operation planning of cogeneration systems. A detailed modeling and simulation of a cogeneration system is done, e. g., by Onovwiona et al. (2007) [463] and Kelly et al. (2008) [344]. The scheduling problem of microCHPs is closely analyzed, for instance, by Bosman et al. (2009, 2010) [87, 88] and Wolfrum et al. (2014) [649]. A two-stage algorithm for the decentralized scheduling of microCHPs and charging of electric vehicles is presented in [329].

Trigeneration: Combined Cooling, Heat, and Power Chicco and Mancarella (2006, 2009) [123–125] analyze the extension of cogeneration to trigeneration, optimizing such systems and using a non-linear matrix modeling of the operational optimization problem of CCHP systems. Linear Programming (LP) problems of trigeneration systems are solved, e. g., by Rong and Lahdelma (2005) [515] or Lozano et al. (2009) [382]. Because of a non-linear modeling, Kavvadias and Maroulis (2010) [342] use a GA, other publications using EAs are, e. g., [5, 524, 629]. Many publications focus on the optimization of the technical setup of the system [5, 123, 342], do not respect interdependencies and non-linearity in the optimization [342,382,515,629], or use only a low resolution in the optimization [125,515,629].

3.4.3 Communication Protocols and Device Load Profiles

There are several communication protocols and data models for device load profiles that are commonly used to monitor, optimize, and control appliances and devices in buildings. Additionally, some standardization initiatives work on the harmonization of protocols and data models. Most of them are more described in the following paragraphs.

EN 50523 The European standard EN 50523 [117, 118] focuses on the communication between appliances as well as between appliances and BEMSs to enable monitoring and control of appliances in households. It provides common abbreviations, standardized device states, typical state diagrams of appliances, functional specifications, and data models that are utilized in this thesis. The standard defines messages that can be used to delay the operation of appliances, communicate tariffs, and enable load management. Although the standard considers not only electrical appliances but also gas appliances, the aspect of energy management of multiple energy carriers is not addressed.

EEBus The *EEBus Initiative* [188,189] (see also Section 3.2.2) works on the standardization of protocols, messages, and data models. The EEBus comprises a protocol for communication and data models for energy management, e. g., the *PowerSequence* defining load profiles. It provides mappings from and to other protocols and data models that allow for translation between different standards using the EEBus as intermediary. Together with *Energy@home*, the EEBus Initiative is working on a common data model for appliance profiles that will be standardized as a part of the standard EN 50631. The data model resulting from these efforts is similar to the data model for device load profiles presented in this thesis.

Energy@home In *Energy@home* [194, 196], the status of appliances is communicated in so-called *Appliance Control* objects, which contain information about the status, the current cycle and phase, the time to end, and the starting and finishing times of the corresponding appliances. The actual power profile of an appliance is split up into a sequence of phases. These phases are activated one after another in the operation cycle. Basic elements are the maximum activation delay and the expected duration, peak power, and energy consumption. For instance, Energy@home defines a power profile of a washing machine that is split into the following phases: *prewash*, *wash*, *rinse*, and *spin*. Each program phase i has one or multiple phases $D_{m,i}$ with a certain maximum power level $P_{m,i}$.

In general, the power profiles may contain multiple alternative modes m for the same program. Each phase has certain properties, such as the maximum power or the maximum delay. This information is communicated from the appliance to the BEMS, which uses the information to schedule the devices. [194, 196]

As a consequence of this extended power profile structure, the operation cycle of an appliance is not monolithic but flexible. Nevertheless, Energy@home focuses only on electricity currently. Additionally, the power profile contains only information about the peak consumption during a certain phase but not about the average and minimum consumption, which are also important values regarding energy management.

EF-Pi/FPAI The load profiles in EF-Pi use profile containers that are composed of profile elements having a certain duration and power value. The power value may be subject to a certain probability information that provides upper and lower boundaries that are respected with a certain probability. A profile container may have profiles for electricity, heat, and gas. In comparison to the efforts of EEBus and Energy@home, the load profile used by EF-Pi is rather simple and provides only the means for a limited functionality regarding energy management, because it does not support interruptions and additional information about power values, such as minimum or maximum values. [600, pp. 62 ff.]

3.5 Simulation of Energy Systems

Modeling and simulation (see also Section 2.5) of systems, e. g., energy systems, and their processes, e. g., load scheduling or market interaction, enable the analysis and prognosis of system behavior under various conditions. This way, the results and impacts of introducing, e. g., intelligent appliances, variable tariffs, other measures of DSM, and BEMSs, can be analyzed. Therefore, simulation of smart grids and its components is a common and appropriate approach [50, 610, 659].

Usually, simulations regard distinct parts of the simulated system, e. g., market simulation, but not the entire complex system. The simulation of buildings with EMSs in a smart grid context calls for the detailed simulation of devices and systems, such as appliances and heating systems, buildings comprising these devices, user behavior, and energy grids. Typically, simulators focus on certain aspects but are not capable of simulating all these aspects appropriately to study the impact of smart buildings and hybrid devices. In particular, the intelligent operation, i. e., the optimization using a BEMS, of a smart building is not supported by typical simulation tools. Therefore, co-simulation is becoming popular and is often used in simulations of energy systems. [50, 433, 512, 659]

This section provides an overview of common approaches to modeling, simulation, and co-simulation in the context of smart grids and smart buildings.

3.5.1 Multi-agent Simulation

The simulation of smart grids and other energy systems, such as microgrids, is often using the concept of *multi-agent systems*. Sometimes, e. g., in [241, 594], the concept of multi-agent systems is combined with the concept of holons and holarchies, which handles autonomy and cooperation of entities in a recursive structure and is more closely described in Section 3.7.4.

Exemplary Multi-agent Energy System Simulations There are several applications of multi-agent systems in the simulation of energy systems. Nevertheless, most of them address only very limited aspects of energy systems, e. g., condition monitoring of the electricity grid [113], transformer management [347], control of VPPs [173], simplified resource scheduling problems [331], or the simulation of energy markets [7, 634]. This is not sufficient to handle smart buildings in a smart grid context. For instance, the combination of EF-Pi [601] and PowerMatcher [359], which are detailed in Section 3.2.3, is able to optimize devices in smart buildings and coordinate the buildings in a smart grid. However, it is not capable of simulating typical user interaction and handling hybrid appliances, multiple energy carriers in the sense of commodities having additional properties, or energy grids.

3.5.2 Grid Simulation, Calculation, and Optimization

One of the problems that arises in energy management is the simulation of energy grids. Energy flows have to be simulated to calculate energy losses and determine overloads or other problems. Usually, the calculation of energy flows in a grid is an optimization problem that is tackled by tools that focus on certain aspects. For instance, there are three basic groups of tools for the simulation of electricity grids [426]:

1. *Transient state simulation tools* for detailed and precise evaluations of transient states.
2. *Real-time simulation tools* for HIL simulations and evaluations.
3. *Grid analysis and load flow calculation tools* for monitoring and planning purposes, such as overload detection and short-circuit current calculation.

Building energy management, as regarded by Energy Informatics and this thesis, targets problems that have a longer duration than transient problems in grids, such as turning a circuit breaker off or detecting a short-circuit. The latter are handled by control engineering using measurement and control technologies, which are not in the focus of this thesis. Real-time simulations are important for the evaluation of devices and systems in HIL simulations, which is not in focus, either. Therefore, only the calculation of load flows in so-called load flow studies is important for the integration into the EMS presented in this thesis. Nevertheless, real-time simulation might be included in future implementations when regarding the monitoring, optimization, and control of larger grids in real-world application.

Electricity Grid Calculation and Optimization

The calculation of DC and AC electricity grids uses linear and non-linear power-flow models, respectively. There are several algorithms that are used for the calculation of AC load flows in electricity grids. These include the load iteration method, the *Gauss-Seidel* method, the *Kersting* method, the *Newton-Raphson* method, the extended Newton-Raphson method, and the holomorphic embedding method [593]. Their usage depends on the structure of the grid and the requirements regarding calculation time and memory. Popular tools for the calculation of load flows include GridLAB-D, OpenDSS, and SimPowerSystems [426]. These tools are briefly explained in the following paragraphs.

GridLAB-D The basic idea of GridLAB-D[14] is the integrated modeling of electrical energy systems, energy markets, DG, and buildings using a multi-agent simulation. The approach to energy simulation and the solution method are similar to the energy simulation presented in this thesis, i. e., the *Energy Simulation Core*. In each time step of the simulation, the agents are subject to the following three-step calculation in a hierarchical manner [120]:

1. *First top-down pass*: agents prepare themselves for the update process, i. e., the information exchange with other agents
2. *Bottom-up pass*: agents provide information updates to other agents
3. *Second top-down pass*: agents update themselves based on the received updates

[14] `http://www.gridlabd.org`

GridLAB-D focuses on the simulation of electrical energy systems and lacks the support of multiple energy carriers in optimization as well as important concepts that are necessary in real-application, such as device abstraction.

OpenDSS and SimPowerSystems The Open Distribution System Simulator[15] (OpenDSS) is a standalone tool, whereas SimPowerSystems is an extension for MATLAB/Simulink. They enable the simulation and analysis of electrical energy grids and provide several models of RES and DG that facilitate the simulation of such energy systems and the analysis in the context of a grid. Both focus solely on electricity distribution grids and do not include other energy carriers. [50]

Multi-energy Grid Simulation Tools

There are only few simulations tools that are dedicated to the integrated simulation of multiple energy carriers. Many tools are actually co-simulation tools, e. g., the *Multienergy System Cosimulator* (see Section 3.5.5), which integrate different tools handling different energy carriers in a co-simulation.

Hybrid Optimization Model for Electric Renewables (HOMER) The *Hybrid Optimization Model for Electric Renewables*[16] is a tool that supports the design of microgrids by integrating various generation systems into one simulation and enabling economic evaluations. Although including various energy carriers in the simulation, HOMER focuses on electricity by DG and includes only simplified models of thermal generation and conversion. [202, 368]

Integrated District Energy Assessment by Simulation (IDEAS) Baetens et al. (2012) [38] present a simulation and evaluation tool for *Integrated District Energy Assessment by Simulation*[17] that is implemented in the modeling language Modelica (see also Section 3.5.3). It enables the integrated simulation of electrical and thermal energy flows in buildings up to a district level. The buildings and the energy consumption are modeled in a bottom-up manner using statistical data about occupancy and allow for the evaluation of DSM strategies and BEMSs.

Multiphysical Network Simulator (MYNTS) The *Multiphysical Network Simulator*[18] is a modeling and simulation tool for the analysis and optimization of electrical, gas, and water grids, i. e., grids comprising multiple energy carriers. MYNTS models the grids in differential-algebraic equations, i. e., a non-linear formulation of the system, which are similar for all energy carriers, no matter whether it is electricity, gas, or water. [645]

3.5.3 Building Simulation and Other Tools

The simulation of buildings is an important prerequisite for the optimization in BEMSs in real buildings as well as for simulation studies of smart buildings comprising such management systems. Actually, simulation is usually required twice: Firstly, for the detailed

[15] `http://electricdss.sourceforge.net`
[16] `http://www.homerenergy.com`
[17] `https://github.com/open-ideas/IDEAS`
[18] `http://www.mynts.de`

simulation of the real building which is to be optimized in a simulation study. In practical real-world application, this is not necessary. Secondly, for the simulation of possible future building behavior in optimization and prediction functionality.

Mostly, building simulation tools focus on certain aspects of the building and are not capable of simulating electrical loads, thermals loads, user behavior, and devices at the same time. For that reason, there are many different simulations tools that are specialized on certain aspects and which are sometimes combined in co-simulations to simulate several aspects of a complex system in one simulation.

Building Load Simulation

The combinations of EF-Pi and PowerMatcher as well as EF-Pi and TRIANA, respectively, offer a possibility to optimize a wide range of devices in buildings. They consider electricity as well as other energy carriers when optimizing the energy usage [601]. Although the actual energy management functionality is part of the energy management application and not of EF-Pi, the latter supports multiple energy carriers. Nevertheless, a detailed simulation of buildings and user behavior is not part of EF-Pi and PowerMatcher [459]. However, there are several other tools and concepts for the simulation of energy loads in buildings.

For instance, Capasso et al. (1993, 1994) [108, 109] model residential loads in a bottom-up manner to evaluate the potential and effects of DSM in residential areas. Von Appen et al. (2014) [618] model residential load profiles with a high resolution for different classes of households, such as single-person or family households. Similarly, Molitor et al. (2012) [434] use Standard Load Profiles (SLPs) as relative probability density for the generation of appliance usage. In [252], Good et al. (2015) model such profiles not only for electricity but also for other energy carriers. Based on an occupancy model for residential buildings [499] and time use surveys, Richardson et al. (2010) [500] present a model for residential buildings that simulates appliance use and provides load profiles at a resolution of 1 min. In [444], Muratori et al. (2013) model activity patterns of occupants of a residential building using Markov chains to simulate the electricity demand at a resolution of 10 min. In a similar way, Widé and Wäckelgård (2010) [641] achieve even a 1 min resolution, using a modeling approach based on time use data by Widé et al. (2009) [640].

Building Simulation Tools

Typically, the term *building simulation* refers to the thermal simulation of buildings and building simulation tools focus on the simulation of thermal loads and thermal energy generation. Nevertheless, many tools that have been developed for thermal simulation support a basic simulation of electricity generation and consumption, too. Unfortunately, most of the tools are made neither for the simulation of detailed, typical energy consumption patterns related to electricity usage in buildings, nor for the implementation of sophisticated operational optimization, i. e., sophisticated control mechanisms such as BEMSs [397].

Building Models Typically, building models are used to simulate the physical behavior of buildings by means of algebraic and differential relations with respect to the building's internal operation, devices, and systems as well as external influences, such as outdoor temperature and irradiance. Often, even detailed models of buildings result in a simulated behavior that is far from that of the modeled real buildings. This calls for a careful validation and calibration of building models. [132, 203, 397]

The following paragraphs provide a brief overview of some common building simulation tools. Detailed assessments of some them and of other similar tools and their capabilities are provided by Crawley et al. (2008) [137] and by Manfren et al. (2011) [398].

EnergyPlus *EnergyPlus*[19] is a popular open-source tool that is able to simulate buildings in variable time steps. Typically, the simulations use a time step of 15 min and focus on thermal demands and HVAC systems. Often, EnergyPlus is linked with TRNSYS, for instance in [592], enabling a co-simulation of both tools that benefits from the availability of a wider range of device models. [138, 139]

ESP-r The building simulation tool *ESP-r*[20] has been developed to enable the modeling of all processes and energy flows in buildings and is used for the evaluation of BEMSs [58, 389]. In [130], ESP-r is extended to support real-time simulation in a BEMS that derives control actions from the simulation results.

GridLAB-D In *GridLAB-D*, buildings are represented as agents comprising differential equations and using the equivalent thermal parameters method. These equations describe the relation of indoor and outdoor temperature, building internal heat gains, and the state of heating as well as cooling systems. [120]

Integrated Simulation Environment Language (INSEL) The *Integrated Simulation Environment Language*[21] (INSEL) is a graphical programming interface and simulation environment for energy systems. From 1989 to 1998, it has been developed at the *University of Oldenburg*, Germany. Today, it is maintained by the *Doppelintegral GbR* in Stuttgart, Germany. INSEL has been developed for the simulation of renewable, electrical energy supply systems [539] and thus is not able to handle productive real-world systems.

Toolkit for Optimization of Industrial Energy Systems (TOP-Energy) In [31], Augenstein et al. (2004) present the *Toolkit for Optimization of Industrial Energy Systems*[22], which aims at supporting the analysis and optimization of energy provision by energy consultants. The processes are based on the VDI Guideline 3922 [608]. TOP-Energy comprises several modules that target different aspects of energy consulting, such as the energetic simulation and the economic evaluation of energy generation systems. As it targets energy consulting, it is not suited for the optimization of productive system operation.

Transient System Simulation Tool (TRNSYS) The *Transient System Simulation Tool* (TRNSYS)[23] is a building simulation tool that enables transient simulations of systems at a building level. Several libraries enable the simulation of devices and systems comprising multiple energy carriers. It can be coupled with other simulation tools, e. g., EnergyPlus [592] or ESP-r [59], focuses on simulation, and is not suitable for the operation of real buildings. [398]

[19] `https://energyplus.net`
[20] `http://www.esru.strath.ac.uk/Programs/ESP-r.htm`
[21] `http://www.insel.eu`
[22] `http://www.top-energy.de`
[23] `http://www.trnsys.com`

General Purpose Simulation Tools

There is a multitude of tools facilitating the simulation of complex dynamic systems. Popular examples are MATLAB/Simulink, which focuses on generic dynamic systems that are computed numerically, and Modelica, which uses object-oriented equations to model the physical behavior of complex systems.

MATLAB/Simulink *Simulink*[24] extends the numerical computing environment *MATLAB* by the capability of modeling and simulating dynamic systems. The *SimPowerSystems* library contains models of electrical devices and systems, e. g., transformers, DG, and consumers, that enable the simulation of electrical energy systems [50]. For instance, Baumann and Boggasch (2010) [54] use a simplistic model of an energy system comprising several RES and a fuel cell that is installed in a laboratory environment in MATLAB/Simulink for the development of an energy management algorithm [54]. The *SIMulator for Buildings and Devices* (SIMBAD) is a specialized library enabling the modeling and simulation of buildings. Missaoui et al. (2014) [424] use a co-simulation of GMBA-BEMS (see also Section 3.3.2) and SIMBAD for the validation of the optimization algorithms in their BEMS. *Simscape* is a library facilitating the modeling and simulation of physical systems comprising mechanical, electrical, and hydraulic connections. In [305], Hurtado et al. (2013) use Simscape to model a room that is part of a building being managed by a BEMS.

Modelica Actually, *Modelica*[25] is not a simulation tool but a modeling language that utilizes equations to describe the physical behavior of complex systems. It uses different connectors for physical interactions, such as the transmission of mechanical or electrical energy, and basic model components containing equations that define the relation between the connectors, leading to more complex hierarchical models. The models are executed by so-called translators, e. g., *SimulationX*. In [596], SimulationX is used to simulate a building that is optimized by a BEMS. It comprises a detailed consumption model, DG, electric mobility, RES, and HVAC systems. Another example is the *Multienergy System Cosimulator* framework [433] (see Section 3.5.5), which aims at the integrated simulation and analysis of energy systems at a district scale (see section on co-simulation tools below).

3.5.4 Simulation and Modeling of Appliances

In general, appliances are mostly simulated in a simplified way using statistical usage data, such as time use surveys [500] or SLPs [434], and recorded load profiles of the appliances (see also Section 3.5.3). Nevertheless, there are some approaches to a more detailed modeling of appliances which are described in the following paragraphs.

State Diagrams, State Machines, and Automata

The EN 50523 [117, pp. 62 ff.] provides exemplary state diagrams for different types of appliances. The state machine models utilize the appliances states and transitions, which are the result of internal device status changes, user interactions, or commands, that are

[24] http://www.simulink.com
[25] https://www.modelica.org

defined in the standard. The appliances modeled in this thesis are based on these state machines. In [268], Ha et al. (2012) use finite-state machines to model temporary services that follow discrete events, such as washing machines, where every state is related to a certain power consumption.

Similarly, Costanzo et al. (2012) [136] propose the usage of finite-state machines to simulate appliances. They present a generic state machine that is similar to the state diagrams in the EN 50523. Nevertheless, the publication lacks examples of concrete appliances.

Allerding et al. (2014) [11] use an automaton to represent the microCHP system in the optimization of the BEMS. The operation of the CHP system switches between two states—on and off—that determine the generated power.

In [369], Lasic et al. (2015) present a generic model of a “virtual washing machine” that is based on empirical data of nine different models of washing machines. It comprises equations that use the machine’s capacity, the temperature setting, and several other parameters of washing machines to determine water, energy, and detergent consumption. Although returning the total energy consumption, the model does not provide detailed load profiles.

Other devices, such as HVAC equipment, are typically simulated in models that calculate the consumption based on temperature values, mass flows, and efficiency values. For instance, Fubara et al. (2014) [229] model several cogeneration systems—a conventional internal combustion engine, a Stirling engine, and solid oxide fuel cells (SOFC)—using non-linear efficiency rates. Simple devices, such as boilers, are mostly simulated having only two states that are mapped to certain fixed power values and efficiency rates [252].

3.5.5 Co-simulation in Energy Systems

The technique of co-simulation (see also Section 2.5.2) is frequently used in the simulation of energy systems. This is mainly due to the complexity of energy systems, which requires the usage of specialized tools, and the re-utilization of existing tools.

For instance, Missaoui et al. (2014) [424] use the co-simulation of GMBA-BEMS (see also Section 3.3.2) and SIMBAD for the validation of optimization algorithms in their BEMS. Bian et al. (2015) [71] use co-simulation of a grid simulator and an optimization and control system simulator in their analysis of electricity grids. In [592], Trčka et al. (2009) optimize an HVAC system using a co-simulation of EnergyPlus modeling the building, i. e., the air exchange and thermal flows, and TRNSYS modeling the mechanical and technical system, i. e., the fan and the controller. Similarly, Beausoleil-Morrison et al. (2012) [59] demonstrate the co-simulation of a solar thermal system modeled in ESP-r and TRNSYS.

Co-simulation Tools and Frameworks

There are many tools and frameworks that enable the generic integration of different simulators into a single simulator by co-simulation. The following paragraphs describe some of them briefly that focus on co-simulation in energy systems.

GridLAB-D Although GridLAB-D is often seen only as a tool for the calculation of load flows in electricity grids, it is actually a framework that facilitates co-simulations focusing on electricity. GridLAB-D is more closely described in Section 3.5.3.

Mosaik The *mosaik* framework[26] facilitates large-scale simulations of grids comprising multitudes of different consumers and producers, while considering the physical structure of the electricity grid. The simulations use abstraction concepts of the entities and utilize different simulation tools, models, and platforms in a co-simulation. The mosaik framework has a flexible architecture that addresses interoperability, validation, and modeling for the incorporation of the different sub-simulations and uses a domain specific language to describe the simulation scenarios. Similar to many other applications of multi-agent simulation in energy systems, mosaik uses different agents for the simulation of certain aspects of smart grids, e. g., the electricity market, and integrates many of these aspects into a single simulation framework. Nevertheless, mosaik focuses on simulations and lacks the ability to monitor, optimize, and control productive systems in real-world application. [410, 512, 540]

Multienergy System Cosimulator The *Multienergy System Cosimulator* (MESCOS) framework by Molitor et al. (2014) in [433] aims at the co-simulation and analysis of energy systems utilizing multiple energy carriers at a district scale by means of commercial off-the-shelf tools. It targets the evaluation of control mechanisms and energy management algorithms in long-term simulations of detailed building models comprising DG and appliances.

3.6 Optimization in Building Energy Management Systems

There are several approaches to optimization in energy systems and their various subsystems, such as BEMSs. The systems are optimized on different abstraction levels and with respect to diverse objectives and constraints. In general, the problems have to be formulated as optimization problems and either be solved exactly or heuristically.

As a consequence of the complexity of the overall energy system, publications focus on certain aspects, for instance the optimization of the technical setup of the system [5, 342], the building design [215], energy markets, and balancing groups [336, 634], the operational optimization by EMSs in buildings [10,186,561], or the provision of ancillary services [63,401]. Many approaches to the optimization of energy systems do not respect interdependencies, multiple energy carriers, or non-linearities of technical systems [125, 237]. Usually, the systems use temporal resolutions of 15 or 60 min [125, 515]. This leads to averaging effects that hide load peaks which would actually have to be handled by BEMSs [386, 561, 653]. Therefore, such low resolutions are not applicable in concrete productive systems that may, for instance, have to respect strict power limits.

Often, optimization problems in BEMSs are based on MILP [254, 268] or MINLP [12, 237]. Modeling such problems with a high temporal resolution results in thousands of variables and constraints. This holds true, even if the problem uses a resolution of only 5 or 15 min [92, 170, 268]. Solving such optimization problems may lead to computational and memory requirements that are neither practicable nor reasonable for BEMSs in practical application, which should run on low-power computers with limited system resources that do not waste energy [410]. Heuristic optimization has successfully been applied to a wide range of problems and has proved to optimize many of them efficiently [419]. Consequently, meta-heuristics have been used in the optimization of energy systems.

[26] `https://mosaik.offis.de`

The following sections provide an overview of approaches to the optimization in building energy management in general and of certain specific aspects, such as multiple energy carriers and optimization objectives. They show that there is a severe lack of a comprehensive approach to building energy management that is suitable for application in real buildings as well as simulations, and that supports multiple energy carriers, varying setups of devices and systems, and a high temporal resolution.

3.6.1 Optimization Problems and Objectives

This section provides a brief overview of scenarios that form building energy management problems and the approaches which enable an optimization with respect to typical objectives.

Building Energy Management Problems There are many different optimization problems in building energy management. Therefore, there is no such problem as *the* building energy management problem but a multitude of different building energy management *problems* that describe different scenarios. Typically, the scenarios in building energy management and optimization comprise appliances, HVAC systems, DG, and local energy storage. Basically, they include all devices and systems mentioned in Section 2.4.3. The smart buildings (see Section 2.4.1) become part of a smart grid (see Section 2.3.2) or a VPP (see Section 2.3.3) and react on measures and mechanisms of DSM (see also Section 2.3.4) or optimize their energy efficiency (see also Section 2.4.4). Devices and systems that are typically part of building energy management problems are listed in Table 3.3.

The parameters and the scheduling of these devices and systems are optimized with respect to different objectives using various approaches and optimization methods. Many of the differences in the approaches arise from the particular scenario, i. e., whether the buildings shall become part of a smart grid and react on measures and mechanisms of DSM or optimize their energy efficiency and reduce their local energy costs.

Objectives in Building Energy Management Systems Typically, building energy management and optimization is carried out with respect to costs, such as electricity costs and feed-in compensations [12, 186, 561]. In addition to costs, there are several other objectives that are frequently used. Some of them are listed in Table 3.4. This thesis uses total energy costs and load limitation as optimization objectives. Furthermore, the concept of

Table 3.3: Typical devices and systems in building energy management

Device or system	**Exemplary references**
Appliances, such as dishwashers, dryers, and washing machines	[12, 186, 255, 272, 556]
Hybrid appliances, such as bivalent dishwashers	[410, 412]
Devices related to HVAC, such as boilers, heat pumps, and chillers	[1, 272, 378]
Cogeneration systems, such as CHP systems	[11, 143, 329]
Trigeneration systems, such as CCHP systems	[125, 408]
DG of electricity, such as PV systems and small wind turbines	[11, 36]
Local energy storage, such as BESS and thermal storage tanks	[518, 658]
Electric vehicles	[254, 443]

ancillary commodities aims at including other objectives, e. g., the reduction of CO_2 and other pollutant emissions. Certain objectives, such as the user comfort and convenience, are included in form of constraints. Load shaping and grid stability are objectives that can be achieved by utilizing the presented system in a higher-level system, such as a regional EMS. Other objectives, such as a high self-consumption rate or self-sufficiency, can be achieved indirectly by using certain prices for the commodities.

Similar Optimization Problems

Basically, the optimization problem presented in this thesis is similar to any scheduling problem. In addition to the scheduling problem, it comprises parameters that can be modified, resulting in a modified behavior of the devices. Nevertheless, this behavior is subject to additional constraints and interdependencies, which have to be evaluated in a complex model of the overall system.

Constrained Scheduling Problems The scheduling problem presented in this thesis optimizes the energy consumption of buildings with respect to power limits that are soft constraints. This is similar to the *resource-constrained* and the *time-constrained project scheduling problems* [266], which optimize the schedules of projects with respect to resource limits, e. g., available workers, and within certain temporal limits, i. e., deadlines [10]. For instance, Merkle et al. (2002) [416] use the meta-heuristic Ant Colony Optimization and Baar et al. (1999) [35] use the meta-heuristic Tabu Search to optimize a resource-constrained project scheduling problem successfully.

Multi-energy Carrier Optimization Problems There are some publications that focus on the optimization of multiple energy carriers in the context of energy management in buildings. The so-called *multi-commodity flow problem* is an extension to the flow problem in networks using multiple commodities that have to be transferred from sources to sinks. It is presented as *multi-commodity network flow* in [2, 396]. Although using a

Table 3.4: Typical objectives in building energy management

Objective	**Exemplary references**
Emission of CO_2	[22, 92, 268, 274]
Emissions of pollutants	[22, 274]
Energy consumption	[92]
Exergy efficiency	[5]
Environmental impact	[498]
Grid stability	[432]
Inequity between participants in DSM	[111]
Load limitation, load shaping, and overloads	[12, 92, 249, 302, 436, 544]
Self-consumption rate	[11, 74]
Self-reliance and self-sufficiency rate	[11, 268]
Social welfare	[527]
User comfort or discomfort	[21, 268, 556]
User convenience and delay of appliances	[21, 268, 436, 662]

similar terminology, it is different to the optimization problem presented in this thesis, which focuses on scheduling problems in buildings. The optimization of *multi-commodity markets* [110] regards interdependencies of commodities on markets, which is different from the problem presented in this thesis, too.

The concepts of *multi-carrier energy systems* [236], which are also called *energy hubs*, *multi-source multi-product energy systems* [286], and *multi-energy systems* [394] (see also Section 3.1) handle problems that are similar to the problem of building energy management presented in this thesis. Nevertheless, they regard only simulations and not the practical operation of BEMSs and application in real buildings, which calls for an approach that enables the optimization of the operation at run-time.

The *multicommodity smart energy systems* presented in [74, 75] optimize appliances in buildings similarly to this thesis. However, they use only three commodities—electricity, gas, and heat—and do not respect energy costs in a realistic way: The optimization uses quadratic cost functions and does not distinguish different prices for the same energy carrier, e. g., due to different compensations for electricity generated by a CHP and a PV system.

3.6.2 Programming Problems and Other Approaches to Optimization

Typically, optimization problems in energy system and in building energy management are formulated as LP, MILP, and MINLP problems. Unfortunately, the formulation of such problems with a high temporal resolution results in thousands of variables and constraints that have to be handled by the solver. Solving such problems leads to extensive computational requirements that are neither practicable nor reasonable for BEMSs that are meant to run on low-power, energy-saving computers with limited system resources. Therefore, many approaches to device scheduling and building energy management use a temporal resolution of 5 [121, 170, 564] or 15 min [92, 268]. The following paragraphs provide exemplary publications about optimization problems in BEMSs using linear and non-linear formulations as well as dynamic and stochastic programming.

Linear and Mixed Integer Linear Programming

In [427], Mohsenian-Rad and Leon-Garcia (2010) present an LP approach to the scheduling of devices in residential buildings. The linear problem can be solved efficiently and they propose to deploy the algorithm to residential smart meters. Rong and Lahdelma (2005) [515] use an LP model for the optimization of a trigeneration system and propose a specialized simplex algorithm for solving such problems comprising three commodities.

MILP is used far more often than LP in scheduling problems in smart buildings. For instance, Bozchalui et al. (2012) [92] and Ha et al. (2012) [268] use a MILP formulation of the scheduling problem in residential buildings and optimize it with respect to multiple objectives, e. g., energy costs, emissions, and peak load, with a temporal resolution of 15 min and 1 h. In [121, 170, 563, 564], Chen et al. (2012), Di Giorgio and Pimpinella (2012) and Sou et al. (2011, 2013) use similar formulations with a temporal resolution of 5 min. Gottwalt (2015) [254] presents the concurrent optimization of 10,000 residential buildings comprising appliances, HVAC systems, and electric vehicles with a resolution of 15 min.

Mixed Integer Non-linear Programming

Anvari-Moghaddam et al. (2015) [20, 21] optimize a residential building comprising cogeneration, a gas boiler, and a heat pump using a MINLP formulation with respect to total operation costs and user comfort with a temporal resolution of 1 h. In [544, 545], Setlhaolo et al. (2014, 2015) present a BEMS scheduling appliances and a BESS at a resolution of 10 min and 1 h, respectively. The models of the appliances are greatly simplified and the simulation covers only a single day. Althaher et al. (2015) [14] introduce a BEMS using MINLP to optimize the operation of appliances and devices in residential buildings with respect to costs at a resolution of 15 min, ensuring a certain comfort level. In [12], Allerding et al. (2012) present a MINLP formulation of the problem using a resolution of 1 min.

Trigeneration systems are complex systems that are often modeled as non-linear problems. For instance, Chicco and Mancarella (2009) [125] use MINLP for the modeling of a complex trigeneration system comprising several CHPs, gas-fired boilers, absorption chillers, and compression chillers. Their approach extends the work of Geidl and Andersson (2007) [237], who present a similar non-linear optimization problem comprising multiple energy carriers.

Many non-linearities in building energy management arise from complex thermal models. In [546–548], Severini et al. (2013, 2014) propose to split the MINLP problem into a MILP and an NLP part that can be solved separately by a hybrid computational approach. Thereby, the MILP problem is solved deterministically and the NLP part is optimized using a GA. In an additional step, the two parts are subsequently combined using MILP.

In [399], Marco et al. (2014) compare MILP and MINLP modeling of a building energy management problem. They show that the scheduling benefits from a non-linear thermal model. Additionally, they point out that the chosen temporal resolution of one hour is low and may lead to unsatisfactory results.

Dynamic Programming

Tischer and Verbic (2011) [584] present a BEMS and Riffonneau et al. (2011) [504] a management system for combined PV and BESSs that utilize *Dynamic Programming*. Tischer and Verbic (2011) optimize a single day with a temporal resolution of 15 min and conclude that computational costs are the main drawback of Dynamic Programming in energy management problems. In [275], Hable et al. (2002) point out, too, that dynamic programming requires too many transitions in typical building energy management problems and is thus not suitable for solving such problems.

Although the TRIANA framework (see also Section 3.2.3) uses Dynamic Programming, the actual algorithm uses a distributed variant that is actually a heuristic. The method optimizes the devices separately and iteratively in dedicated Dynamic Programming problems for each of the devices [432, 586], which reduces the computational effort. Another solution to reduce the computational costs is *Adaptive* or *Approximate Dynamic Programming* [79, 303, 628].

In [377], Livengood and Larson (2009) present the *Energy Box*, a BEMS using *Stochastic Dynamic Programming* and a temporal resolution of one hour. The authors focus on uncertainty in the sequential decision processes in buildings and conclude that a rolling horizon of 24 hours is sufficient for energy management.

Other Approaches to the Optimization in Building Energy Management

In addition to exact solvers (see above) as well as heuristics and meta-heuristics (see below), there are other approaches to optimization in BEMSs. For instance, the *PowerMatcher* (see also Section 3.2.3) uses a market-based supply-demand coordination algorithm that works with abstracted models of the devices. Basically, a central agent—the auctioneer agent—handles all bids in an auction [360]. Samadi et al. (2011, 2012) [526, 527] use a *Vickrey-Clarke-Groves* mechanism to optimize the social welfare of multiple buildings using BEMSs that participate in DSM. The fundamental idea of this mechanism is to exploit the local information from rational users having incentives to declare this information truthfully.

In [7, 428, 429], Alam et al. (2013) and Mohsenian-Rad et al. (2010) propose a pricing scheme that facilitates the optimization of an appliance scheduling problem by means of a game-theoretic approach. They show that it is able to reduce total energy costs and enable DSM. In a similar approach, Blaauwbroek et al. (2015) [74] propose a decentralized supply and demand matching mechanism that solves local optimization problems iteratively, eventually leading to an optimal solution. Nevertheless, they note that the optimization of certain types of devices, such as deferrable appliances, can cause sub-optimal solutions.

3.6.3 Meta-heuristics in Building Energy Management Systems

Heuristic optimization has successfully been applied to a wide range of problems and proved to solve many of them efficiently [419]. In comparison to solvers, the most important advantages of heuristics are their low memory and flexible time requirements [276, 410].

Meta-heuristics, such as approaches from *evolutionary computation* and Particle Swarm Optimization (PSO), are generic heuristics that can be applied to various optimization problems. Consequently, meta-heuristics have been used in the optimization of energy systems. Frequently, they are used to optimize design parameters of devices in energy systems [5, 342, 629] and to solve scheduling problems. The following sections provide an overview of publications about meta-heuristics in the optimization of energy systems.

Evolutionary Algorithms

EAs, such as GAs, evolutionary programming, or differential evolution, are often used in the domain of energy systems. They do not only optimize scheduling problems in building energy management and smart grids but also technical setups and parameters. A comparison of several approaches to BEMSs using EAs is provided by Soares et al. (2013) [560, p. 332].

Allerding et al. (2012, 2014) In [12], Allerding et al. (2012) present a BEMS using an EA with binary encoding, several different evolution strategies, and an additional local search method in a smart residential building setup. The BEMS optimizes several appliances with respect to electricity costs using a MINLP formulation of the problem and a resolution of 1 min. They demonstrate that EAs are able to find good solutions in a short time, which are often superior to those found by a MINLP solver. Allerding et al. (2014) [11] present an extended approach, which includes a microCHP that uses natural gas, i. e., a second energy carrier. However, the microCHP is actually an integrated microCHP system using a simple gradient-based forecast of the hot water consumption and generation, and does not allow for setups comprising other additional devices providing hot water. In addition to simulation results, Allerding et al. (2014) present some qualitative results from trials in a real building.

Hable et al. (2003, 2004) Hable et al. (2003, 2004) [274, 276] present a BEMS that optimizes a scenario comprising some electricity consuming and generating devices, e. g., wind power, PV, battery, and CHP systems. They use a GA to optimize the problem at a resolution of 15 min [275]. The representation of the devices in the EA is done in a matrix using values in the interval $[-1, 1]$. This matrix is transformed into load profiles using models of the devices, which are evaluated with respect to costs and emissions.

Morganti et al. (2009) In [436], Morganti et al. (2009) optimize a simple smart residential building scenario without interdependencies between the devices. The scenario comprises a dishwasher, a washing machine, and an electric boiler that are optimized with respect to costs, relative delay, and number of overloads. The authors use the *Elitist Nondominated Sorting Genetic Algorithm II* (NSGA-II) and an integer representation in comparison to Tabu Search. In the simulated scenario, the former performs slightly better than the latter.

Soares et al. (2013, 2014) Soares et al. (2013) [561] use an EA, more precisely a GA with a random mask crossover, a special mutation operator that adds random deviation within a given range to the chromosomes, and a ternary tournament selection, to optimize the operating times and parameters of appliances and of an HVAC system with respect to electricity costs minimization. Additionally, the optimization respects power limits and user preferences. The starting times of the operation cycles of devices are encoded by a string of integers. The approach has a resolution of 1 min, is limited to electricity, and does not respect interdependencies of multiple devices and energy storages.
In [556], Soares et al. (2014) extend the approach to a multi-objective optimization that includes the minimization of electricity costs as well as the penalty caused by user dissatisfaction due to the deferral of devices and the risks of an interruption of the electricity supply. They use NSGA-II to identify non-dominated solutions that satisfy both objectives as good as possible. Again, Soares et al. (2014) focus on electricity and do not regard multiple energy carriers. The work of Soares et al. (2013, 2014) is closely related to research on direct load control by Gomes et al. (2004, 2007) presented in [248, 249] using also an EA.

Zhao et al. (2013) In [660], Zhao et al. (2013) present a scheduling method for BEMSs using a GA and different tariff schemes. They shift the operating times of appliances and HVAC equipment and perform an optimization with respect to electricity costs minimization. Although optimizing radiators and air-conditioning systems, the approach lacks a thermal model of the building and does not consider constraints that result from using such devices.

Particle Swarm Optimization, Simulated Annealing, and Tabu Search

In addition to EAs, PSO, Simulated Annealing, and Tabu Search are popular meta-heuristics to solve scheduling problems. The following paragraphs provide examples of these meta-heuristics being applied to optimization problems in energy systems.

The optimization of the operation of a microgrid comprising a micro-turbine, a fuel cell, and a BESS with respect to multiple objectives using PSO is presented by Anvari-Moghaddam et al. (2011) [22]. They use a resolution of one hour and demonstrate that PSO is superior to evolutionary optimization in their scenario. In [475], Pedrasa et al. (2010) use PSO to schedule the devices in a smart residential building. Their model uses a resolution of one hour and simplified models of an electric vehicle, space and DHW heating, a pool pump, and a PV system. Pedrasa et al. (2011) [474] extend this approach by including uncertainty and calculate robust schedules for the following day using stochastic programming and PSO. Zhu et al. (2015) [662] demonstrate the optimization of deferrable appliances, i. e., a dishwasher, a tumble dryer, and a washing machine, and of electrical space and water heaters with respect to electricity costs, user satisfaction, and power exchange to the electricity grid using PSO. Their approach uses a resolution of one hour and simulates the temperature of a residential building as well as water temperatures in the storage tanks.

Simulated Annealing is used by Sousa et al. (2012) [565] to optimize a distribution network comprising DG using RES and bidirectional electric vehicles. A comparison with MILP shows that Simulated Annealing is able to obtain comparable optimization results in a shorter execution time. The optimization of the energy consumption of residential buildings with respect to electricity costs and user satisfaction using Tabu Search is shown by Ha et al. (2006) [272]. Nevertheless, the authors conclude that the setup of proper optimization strategies in Tabu Search is difficult and use MILP in subsequent publications [156, 268].

3.7 Design Paradigms and Architectures of Complex Systems

Novel technologies and a rising number of interconnected devices and systems lead to increasingly complex systems. Not only the technical systems but also their intelligent control systems become complex. Hence, the complexity of energy systems leads to the complexity of control systems and challenges in their design and operation [491].

In complex systems, minor disturbances and emergent effects may lead to breakdowns and fatal errors because of interconnections and interdependencies [442]. Energy systems are such kinds of complex systems, where minor disturbances or actions sometimes lead to unforeseeable or unintended consequences, e. g., a single failure and an unfortunate series of events may cause a collapse of the whole grid. Control systems, such as EMSs, have the challenging task to monitor, optimize, and control energy systems, to increase their efficiency, and to exploit synergies of heterogeneous entities [610].

3.7.1 Design of Complex Systems

Smart grids (see Section 2.3) are exemplary complex systems having interconnections in many regards: They are interconnected in terms of the energy grid as well as the communication network, which leads to many interacting entities, e. g., devices, buildings, and grid operators [17, 207]. Fortunately, they are still in development and it is essential to design them keeping in mind their complexity and the associated challenges. Therefore, approaches to the design of future energy systems have to facilitate suitable methods and architectures for abstraction, optimization, and self-adaptivity of these systems [17, 410].

Decentralized Control and Self-organization Main goals of decentralized control and self-organization[27] are to reduce the complexity, to increase the reliability, and handle the

[27]The idea of self-organization is also called *synergetics* by Haken (1973) [278].

emergent effects of systems [501]. In general, a self-organizing system comprises elements, entities, sub-systems, or components that interact without centralized control to obtain emergent behavior and fulfill an intended global goal. To avoid unintended or unwanted emergent behavior, Richter et al. (2006) [501] stress the importance of controlled self-organization and propose the so-called *Observer/Controller Architecture*, which is described in more detail in the section on *Organic Computing* (see Section 3.7.3).

In [292], Hinrichs et al. (2011) motivate an approach to DSM using self-organizing mechanisms and agents. This work is closely related to the work by Troeschel (2010) [591], who proposes the introduction of holonic VPPs. The VPPs are build up in a self-organizing manner that facilitates distributed scheduling. This approach and the concept of holons are detailed below in the section on holons and holarchies.

System of Systems (SoS) The concept of *System of Systems* emphasizes the character of a complex system that is put together from independent systems. The sum of the parts, i. e., the systems, becomes greater than their actual sum. It uses several distinguishing characteristics to separate a simple system or a system of *sub-systems*, which do not work independently, from an actual SoS [78, 253]:

- Autonomy: SoS exercises autonomy and independence of its parts to fulfill a purpose.
- Belonging: Parts belong to it because of a greater purpose but remain decentralized.
- Connectivity: Parts are dynamically interconnected in a kind of network.
- Diversity: SoS comprises heterogeneous dedicated and specialized parts.
- Emergence: SoS facilitates unforeseen emergence to develop new properties.

This description fits well to the idea of a smart grid comprising smart microgrids and DG as well as the distributed provision of ancillary services.

Initiatives and Concepts The concept of SoS is only one concept that helps to characterize, structure, and build complex systems. There are several other concepts and initiatives that work on intelligent, distributed, and self-organizing systems. Examples include the *Autonomic Computing Initiative* and the *Organic Computing Initiative* as well as the concept of *holons*, which are explained in more detail hereafter.

3.7.2 Autonomic Computing

Autonomic Computing [345] focuses on autonomic, self-managing computer systems that do not require user interaction after the initial design phase. The theory of Autonomic Computing provides a central design paradigm: the introduction of so-called autonomic managers utilizing the *MAPE cycle* which consists of the four steps monitor, analyze, plan, and execute around a common knowledge base. This helps to structure the parts of complex systems and facilitates self-managing systems. Originally, Autonomic Computing focused mainly on servers and databases. Nowadays, there are some examples that apply the paradigms and methods to energy systems [224].

In Autonomic Computing, there are several basic concepts and patterns that are briefly described hereafter. Basically, they aim at addressing all typical problems in complex systems that arise due to conflicting objectives, system integration, and system complexity.

Self-management The central paradigm of Autonomic Computing is *self-management* by all elements to support users of the system and free them from many of their tasks, such as system operation and maintenance. Nevertheless, the system will always act according to the users' goals. Self-management comprises the following four aspects or concepts, helping to adjust to changing elements, environments, and goals as well as attacks and malicious actions [345]: self-configuration, self-optimization, self-healing, and self-protection.

Autonomic Element and Autonomic System The autonomic system is the combination of multiple autonomic elements. An autonomic element corresponds to a single agent and an autonomic system to a multi-agent system [345]. Often, autonomic elements and systems are separated into the *complex managed system*, *managed resource*, or *managed element* in the *application layer* and the *autonomic management resource* or *autonomic manager* in the *management layer* [223, 345].

MAPE Cycle The central design paradigm of Autonomic Computing is the *monitor-analyze-plan-execute* (MAPE) cycle, which forms a control loop around the managed element. The monitoring part of the autonomic manager uses sensors to obtain data about the managed element that is then analyzed. Based on the analyzed data, necessary activities and actions are planned and finally executed. The knowledge base is the central element of the autonomic manager and is used by all four functions. Therefore, the paradigm is sometimes also called MAPE-K, including the knowledge [304]. The goals are manifested in business goals that are provided by the user, e. g., the system administrator. [345, 502]

Architectural Integration Patterns In [223], Frey et al. (2012) propose several *architectural integration patterns* for the design of complex autonomic systems and their management. They address typical problems that arise in the integration of complex systems, in particular the problem of conflict resolution. Frey et al. (2012) propose to decouple the *conflict resolution* from the *management logic* and introduce several basic conflict resolution patterns. These basic patterns may be combined to form novel and more complex ones. Some variants of the Observer/Controller Architecture (see below) have corresponding architectural integration patterns and others are combinations of these basic patterns.

3.7.3 Organic Computing

Organic Computing (OC) addresses basic challenges of complex systems in dynamic environments. These challenges include in particular trustworthiness, flexibility, adaptivity, robustness, and effects of emergence [442]. OC has mainly been developed within the priority research program *1183 Organic Computing* of the German research foundation *Deutsche Forschungsgemeinschaft* (DFG). The concepts of OC are closely related to those of Autonomic Computing. Both initiatives have led to similar concepts, e. g., architectural design patterns that focus on the control of complex systems. Additionally, they are also similar to many generic control architectures and design patterns in areas like multi-agent systems, control theory, and software engineering of self-adaptive systems [122].

The fundamental idea of OC is to design technical systems in a way that they show organic, i. e., life-like, properties and behavior, such as self-awareness and the ability to adapt to changing environmental parameters [442]. Methods and concepts that are used in

OC may be—but not necessarily have to be—based on concepts that are found in nature, e. g., evolutionary computation or artificial neural networks. The resulting behavior of a system has to be in compliance with objectives and requirements of the user who supervises the overall system. Therefore, trustworthiness, dependability, and reliability play a key role. These requirements are also key requirements of energy systems. Any new energy system, e. g., smart grid, that evolves from the current state has to comply with these requirements.

A major outcome of OC is the so-called Observer/Controller Architecture (O/C Architecture), which is a generic architecture for complex systems that aim at decentralized control and self-organization. The architecture is actually a generic framework comprising various abstract components that are essential for the design of systems showing organic behavior, i. e., an adaptive, autonomic behavior similar to nature [502]. It has been successfully applied to various scenarios, e. g., robotics [442], traffic control [488, 589], production automation [542], and energy systems [13, 336].

The concepts of OC are a step towards systems having distributed intelligence and control. The system presented in this thesis is based on the generic O/C Architecture and follows the fundamental ideas and concepts of OC. Its main idea is the design of a BEMS that enables the automated control of smart buildings comprising different and changing sets of devices in a dynamic environment, respecting the user's preferences and goals.

Self-*-properties OC systems shall be designed in a way that they are aware of their "own capabilities, the requirements of the environment [...] and should be equipped with a number of so-called self-x-properties" [502, p. 186] or *self-*-properties* [441, 502, 587]:

- Self-awareness
- Self-adaptation and self-configuration
- Self-explanation
- Self-healing and self-repairing
- Self-learning
- Self-optimization and self-improving
- Self-organization
- Self-protection

Originally, some of these features and properties have been defined in Autonomic Computing (see above) [587]. OC extends the original four aspects of self-configuration, -optimization, -healing, and -protection to handle the multitude of different systems and scenarios.

Observer/Controller Architecture

The generic O/C Architecture serves as a framework for the design of systems showing organic behavior [502, 588]. It comprises various general components that are essential for such systems and utilizes a regulatory feedback mechanism, i. e., a closed control loop, as well as prediction and learning methods to achieve *controlled self-organization* and emerging global behavior of technical systems in dynamic environments. It supports the adaptation to changes and disturbances in the environment and helps the system to "acquire robustness and the ability to overcome breakdowns" [502, p. 181].

System under Observation and Control The general framework and its overall architecture is shown in Figure 3.11. It uses sensors and actuators to observe and control a so-called System under Observation and Control (SuOC). This SuOC may be a single device, such as

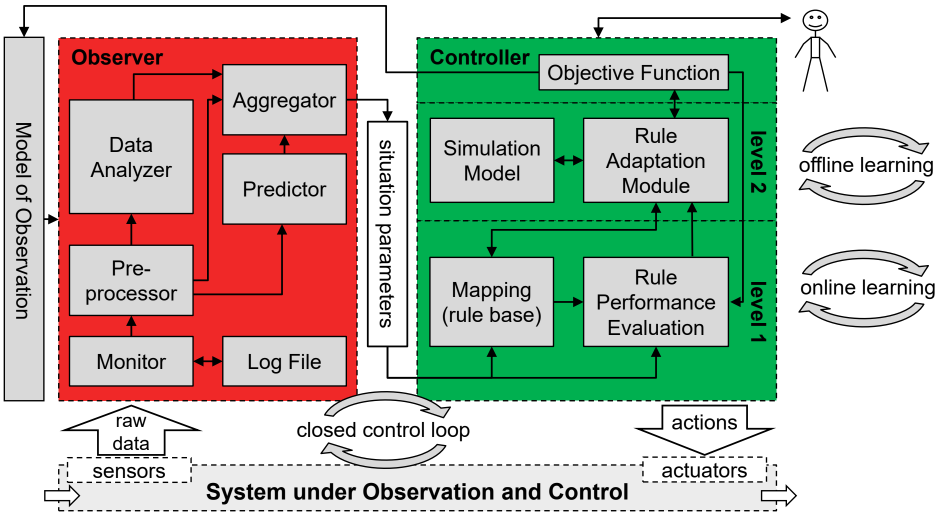


Figure 3.11: Overview of the *Observer/Controller Architecture*, based on [502, Fig. 4.1]

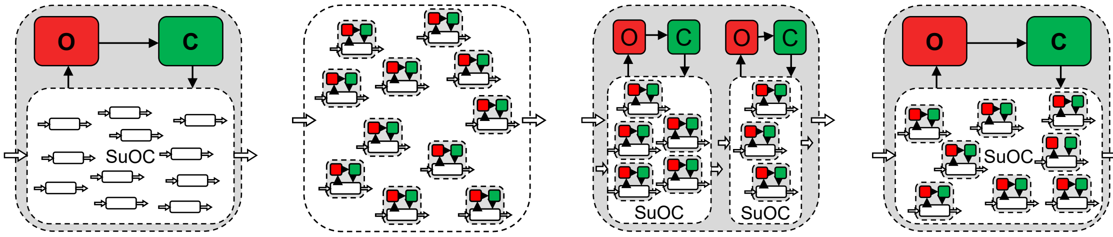
a single electricity consuming appliance, a system comprising several components, e. g., a trigeneration system, or even a system as large as a supranational electricity grid. In general, it has to respond adequately to internal and environmental changes of the SuOC. This leads to adaptation over time, which is also called controlled self-organization. [501, 502]

Observer/Controller-unit The sensors and actuators are supervised by the *Observer* and the *Controller*, which form the so-called Observer/Controller-unit (O/C-unit). The O/C-unit realizes a closed control loop around the SuOC, which is similar to the MAPE cycle of Autonomic Computing (see above) [345, 442]. In addition to this control loop, OC emphasizes the importance of regular user interaction and changing user objectives that have to be incorporated into the control loop [502].

Observer The Observer uses the *Monitor* component to collect raw data about the SuOC from the sensors. All data are logged into the *Log File*, which enables the retrieval of historic data. Afterward, the *Pre-processor* processes the data in a way that enables detailed analyses of the current and predictions of the future system behavior by the *Data Analyzer* and the *Predictor*. Finally, the data about the current situation are aggregated by the *Aggregator* and passed to the Controller. The operation mode of the Observer, e. g., the used prediction method, is determined by the Controller using the so-called *Model of Observation*.

Controller The Controller receives the aggregated observations and predictions and deduces actions that are passed to the actuators. It is structured in two major levels: The first level uses a *Mapping*, i. e., a rule base, to react on the current situation with suitable actions. Additionally, the *Rule Performance Evaluation*, which evaluates the performance of the relationship between situation parameters and control actions in the Mapping based on the *Objective Function*, enables *online learning*. This online learning loop evaluates the Mapping and adapts it according to their performance.

The learning capability is enhanced by a second level providing *offline learning*. In case of insufficient performance, the *Rule Adaptation Module* optimizes the rule base of the



(a) Centralized (b) Distributed (c) Multi-level (d) Hierarchical

Figure 3.12: Variants of the *Observer/Controller Architecture* comprising different structures of the Observer (O) and Controller (C), based on [502]

mapping using a *Simulation Model* of the SuOC. This allows for the development and evaluation of new rules in a simulated environment, without affecting the real environment in a potentially harmful way [502, p. 182]. Both online and offline learning are based on the objectives that are provided by the user and enable the adaptation to unforeseen situations and are also called *two-level learning* [502, p. 187]. The current performance of the overall system is provided to the user to allow for their supervision—if desired.

Design Variants This basic generic architecture is applied in various design variants, which are used to adapt it to specific systems, having different structure and complexity. In Figure 3.12, four exemplary general design variants are depicted: In the *centralized* variant (see Figure 3.12a), all components of the SuOC are handled by a single O/C-unit, whereas in the *distributed* variant (see Figure 3.12b) every SuOC has a dedicated O/C-unit. In the *multi-level* variant (see Figure 3.12c), there are multiple O/C-units on the highest level with different subordinate O/C-units, whereas in the *hierarchical* variant (see Figure 3.12d), there is only one global O/C-unit on the highest level managing all subordinate O/C-units [502]. In particular, the application of the hierarchical variant reduces the complexity by facilitating abstraction and reducing the variability [409].

The original work by Richter (2009) focuses on the controller and the learning capabilities based on *learning classifier systems* in a multi-agent predator/prey scenario [502, p. 182, 188]. Allerding (2013) [10] shifts this focus to the abstraction and optimization of the underlying SuOC and its components. Based on the enhancements of the *O/C Architecture* below, Section 5.1 presents the generalized *Extended Observer/Controller Architecture*.

Enhancements of the Observer/Controller Architecture

There are several publications that work on applications or enhancements of the generic O/C Architecture, for instance by Prothmann (2011) [488], Tomforde et al. (2011) [587], Allerding and Schmeck (2011) [13], Rigoll et al. (2014) [506], and Mauser et al. (2015) [409], some of which are detailed in the following two paragraphs.

Tomforde et al. (2011) and Sommer et al. (2015) In [587], Tomforde et al. (2011) separate the two levels of two-level learning, which are originally located in the Controller of a single O/C-unit, into two separate O/C-units. The first unit is responsible for the parameter selection in online learning, whereas the second unit has a simulator and performs the offline learning. This modified architecture is used by Sommer et al. (2015) [562] for traffic observation and control using different machine learning strategies.

Rigoll et al. (2014), Mauser et al. (2015), Hirsch (2015), and Rigoll (2017) In [506], Rigoll et al. (2014) propose the *Entity Abstraction Layer* and the so-called *Data Custodian Service*. The former is an additional layer between the O/C-units and the entities that form the SuOC and uses *entity drivers* to abstract the sub-systems by providing standardized interfaces to the O/C-units. It is more closely described by Hirsch (2015) [294]. The latter is a central service that "stores, handles, and distributes energy-data" [506], such as energy consumption data of smart meters. This dedicated service (see also Rigoll (2017) [505]) stores the data in databases and handles requests of external entities that ask for access to the local energy data. It decides about what data are provided and in which quality or whether they are provided at all. This helps to ensure data privacy and is thus also called privacy-aware O/C Architecture. The concept of abstracting and protecting an entity to superior entities is generalized by Mauser et al. (2015) [409]: In addition to the Entity Abstraction Layer abstracting subordinate entities, the *Communication Abstraction Layer* abstracts an entity to superior entities. This concept is described in Section 5.1 in detail.

3.7.4 Holon and Holarchy

In the context of philosophy and technical systems, the term *holon* has been introduced by Koestler (1968) [357]. It refers to an entity that is at the same time a whole and a part in a recursive manner. Although a holon is part of a higher entity, every holon has a defined boundary. Therefore, a holon is autonomous as well as cooperative, thus, having a dual role of controlling other holons and being controlled by a superior holon. The structure is recursive until some elementary sub-system is reached, i. e., every holon is basically the aggregation of self-similar sub-systems. The system of holons is called *holarchy*, which can be seen as a distributed system, because every holon can function autonomously. Nevertheless, their cooperation enables to accomplish mutual, higher and more complex goals. Changing environments and goals call for dynamic reorganization. Often, e. g., in [241, 594], the concept of holons is applied to multi-agent systems. [224, 452, 481]

Tröschel and Appelrath (2009), Tröschel (2010), and Hinrichs et al. (2011) In [591] and [292], Tröschel (2010) and Hinrichs et al. (2011) propose a holonic approach towards the scheduling of VPPs and the realization of DSM. Tröschel (2010) [591] uses holonic VPPs, which are composed in a self-organizing manner and tree-like structure, to facilitate distributed scheduling. Nevertheless, the communication overhead increases non-linearly in the number of VPPs. Therefore, Tröschel and Appelrath (2009) propose a dynamically adapting control hierarchy [594] that reduces communication while preserving a flexible and dynamic structure which adapts to changes in the energy system. This is reflected in the tree-like structure with adaptive reorganization in Tröschel (2010) [591]. In [292], Hinrichs et al. (2011) propose two distributed search algorithms, "which are based on the stigmergy mechanism in combination with a local search" [292], to facilitate supply and demand matching and DSM in the electricity grid.

Frey et al. (2012, 2013) Frey et al. (2012, 2013) [223, 224] propose a holonic architecture for smart microgrids that is based on the architectural integration patterns introduced earlier in this section. The basic idea of their approach is as follows: In smart grids, each entity, e. g., a smart building or DG, encounters a corresponding smart grid, which leads to contradictory objectives and conflicts that have to be resolved. Frey et al. (2012, 2013) use hierarchy, stigmergy, collaboration, and the integration patterns to build a control and optimization architecture for energy systems. They use rather simple models of energy systems, simplified smart devices, buildings, and microgrids, to demonstrate that the MAPE cycle and their proposed patterns are capable of handling such complex distributed systems [224]. However, their control architecture lacks important concepts of device abstraction that are essential for productive systems comprising different protocols and data models as well as more complex devices. [410]

Negeri et al. (2012, 2013) Negeri et al. (2012, 2013) [451, 452] propose a holonic architecture for smart grids, which is similar to the approach of Tröschel (2010) [591]. The generic service-oriented architecture comprises prosumers that may act autonomously but may also be controlled by a higher entity. Therefore, they are aggregated and organized recursively to avoid top-down organization and control.

Pitt and Diaconescu (2015) In [481], Pitt and Diaconescu (2015) regard the aspect of shared resources in energy systems, where conflicts arise due to the concurrent usage of the resources by multiple entities. They propose so-called *decentralized Community Energy Systems* to handle these conflicts and facilitate local energy provision. Here, the prosumers form communities, i. e., a holarchy, and enable “demand-side self-organisation” [481] to avoid centralized control structures.

Ferreira et al. (2015): Holonic Smart Grids Another similar holonic architecture for smart grids is proposed by Ferreira et al. (2015) [213]. They aim at decreasing the complexity in smart grids by limiting the number of different control algorithms. Each producer, consumer, storage, and other entity in the grid is modeled as a holon. Thus, a building holon comprises apartment holons which are composed of holons representing the physical devices, such as PV systems or loads. Holons negotiate with the higher level holons, the holons of the same holarchy, and subordinate holons.

4 Analysis and Approach

This thesis focuses on the integrated energy management of multiple energy carriers in simulated as well as real buildings comprising heterogeneous devices. Although there are many different approaches to management and optimization in energy systems—as shown and analyzed in Chapter 3—this chapter reveals by means of a more detailed analysis that literature and existing systems do not yet properly address the challenges of integrated and automated energy management of devices that consume and generate multiple energy carriers in an interdependent manner.

Therefore, this chapter analyzes the problems and requirements that arise when developing a BEMS as well as the data and statistics that are necessary in detailed bottom-up simulations of residential and commercial buildings. An existing system for building energy management—the OSH—is described in detail, depicting its architecture, analyzing its features, and showing that it covers a subset of the requirements, though not all of them. Finally, this chapter proposes a BEMS that is capable of optimizing interdependent devices utilizing multiple energy carriers in simulated as well as in real building environments.

Motivation, Analyses, Requirements, and Approach

There are two main purposes and thus reasons for the introduction and implementation of EMSs in buildings: Firstly, BEMSs may facilitate the optimization of local energy provision, conversion, and utilization across all energy carriers. Secondly, they enable buildings to become active and integral parts of smart grids by enabling measures of DSM that make the energy consumption and generation on the demand side of the energy system more flexible.

In smart grids, it is simply not feasible to optimize the operation of millions of individual devices and systems having different kinds of flexibilities, limitations, and constraints in a single optimization [80]. Therefore, some kind of aggregation or decentralized optimization is required to reduce this complexity. One solution is the introduction of BEMSs that abstract the flexibility of buildings and facilitate direct DR or which react on indirect measures of DSM, such as variable tariffs and specific pricing schemes (see also Section 2.3.4).

This thesis emphasizes the importance of regarding not only electricity in BEMSs but all energy carriers. It proposes to handle them as *commodities* having properties, such as a certain temperature or voltage. Every commodity is distinguished into multiple *ancillary commodities* having additional properties, such as being generated by a PV or a microCHP system. Thereby, BEMSs become able to optimize buildings comprising interdependent devices and systems that consume and generate multiple energy carriers and to achieve a better performance with respect to energy management.

The validation and verification of the proposed BEMSs call for detailed simulations of realistic smart residential and commercial buildings, because appropriate field tests are costly, time consuming, and mostly infeasible. These simulations have to demonstrate, whether the BEMS is able to realize improvements regarding the generation and consumption of energy and achieve a flexibilization of the demand side in general. Additionally, the simulations have to evaluate, whether the integrated energy management of energy carriers is capable of exploiting additional flexibilities and thus improving the local energy management.

Detailed simulations of residential and commercial buildings need appropriate statistical data, proper simulation models of the devices, systems, and energy services, and a suitable simulator using these data and models. Therefore, this chapter analyzes these kinds of buildings, the devices and systems that are found in them, and the requirements for the realization of a BEMS as well as of the actual optimization in the BEMS.

Types of Analyses

This chapter performs several types of analyses which answer the following questions:

- What are typical scenarios in building energy management?
- How to model and simulate smart residential and commercial buildings as well as the devices and systems in them, such as appliances and DG?
- What are the requirements of automated building energy management of multiple energy carriers in such buildings?
- How to realize an integrated energy simulation of multiple energy carriers?
- How does the optimization problem in the BEMS look like and how may it be solved?

These analyses are the basis for the generic architecture, the concrete BEMS, the energy simulation supporting multiple energy carriers and commodities, and the modular optimization of heterogeneous devices and systems that are proposed in the next chapter.

4.1 General Analysis: Buildings and Energy

The automated energy management in buildings is a challenging task because of the complexity and diversity of the heterogeneous energy systems that have to be handled by BEMSs. The energy systems include appliances, which have user-driven operation cycles, DG systems, which are as diverse as PV systems and microCHPs, HVAC systems, such as gas-fired boilers, electrical IHEs, and adsorption chillers powered by hot water, as well as energy storage, such as BESSs and thermal storage systems. Hence, the devices and systems are operated differently, have distinct constraints, which include temperature limits as well as temporal restrictions, interact with users, and may have interdependencies with other devices. Currently, the management of electrical and of thermal energy flows is often done separately. An integrated management of all energy carriers promises to achieve higher overall efficiencies and flexibilities.

Energy management has to respect controllable and non-controllable devices. There are different tariffs for the consumption and for the generation of electricity, depending on whether it is provisioned by the grid or generated locally. The same holds true for other energy carriers. These tariffs may be variable and have to be respected by the EMS. Additionally, the BEMS needs proper predictions of the future consumption and generation of energy carriers to consider them in optimizations. Therefore, the system has to be capable of learning—or at least forecasting—the electrical and thermal behavior of the building as a function of the past behavior, the current situation, and external predictions and forecasts, such as weather forecasts.

There are not only devices and systems but also—and actually most importantly—the users and their individual preferences and needs, which have to be given explicitly as an input to the BEMS or have to be learned by it. Additionally, these preferences and needs are usually not constant but change over time and thus every BEMS has to adapt to them from time to time. Learning and predicting user behavior and energy consumption under changing and uncertain conditions calls for mechanisms of online learning and frequent rescheduling to adapt the management of the building.

Apart from the energy management within the building, the building's energy system is also part of even more complex energy systems: the electricity, district heating, and natural gas grids. Smart buildings promise to increase the efficiency and stability of the grids, despite an increasing share of intermittent RES. Buildings may act as distributed systems that help to ease fluctuations and balancing energy generation and consumption [181]. Managing buildings depending on the grids' state and volatile generation utilizing RES makes the task of energy management even more challenging.

Buildings themselves are complex systems comprising heterogeneous devices and systems which are often not properly coordinated and integrated. Grids are even more complex systems comprising heterogeneous consumers and generators which are also often not properly coordinated and integrated. The introduction of automated building energy management and smart grids promises to facilitate an overall energy system that is more efficient, flexible, and resilient, despite an ever-increasing share of RES.

The following sections present typical scenarios and analyze the current state of the art in building energy management, the constraints and conditions, and challenges when developing an integrated BEMS that considers all energy carriers in buildings.

4.1.1 Buildings, Building Services, and Energy

This section presents the traditional domains in smart buildings, energy-related standards and guidelines, and typical building energy management scenarios, i. e., residential and commercial buildings, as well as an outlook on future changes and developments in buildings.

Service Domains in Smart Buildings In general, topics, services, and functions in smart buildings can be classified into the following domains or application areas [8,119,227,421,605]:

- Assistance, health, and wellness.

- Automation, comfort, and monitoring.
- Entertainment, communication, information, and socialization.
- Energy provision, conversion, storage, utilization, and management.
- Safety and security.

Self-evidently, these domains are not disjoint and thus topics, services, and functions can typically be used in more than one domain. Therefore, a central gateway that interconnects all devices and systems in buildings, considers requirements from all domains, and runs a BOS is a promising solution. However, this thesis focuses on the domain of energy, which is particularly connected to automation and monitoring.

Technical Building Services, Building Automation, and Energy Management Traditionally, energy management in buildings is a subset of technical *building services* and *building automation*[1]. The former emphasizes the provision of energy services in the building, e. g., the operation of HVAC systems, whereas the latter emphasizes the automation of tasks, such as controlling lighting or radiators by means of sensors and actuators. Nevertheless, both terms can mostly be used interchangeably.

The main tasks of building automation are the monitoring and the integrated control of installed devices and systems. Therefore, such systems typically use a hierarchical structure of controllers and multiple communication protocols and media that are integrated in a central workstation or control unit having some kind of user interface.
The control mechanisms originate mainly in control engineering and have usually only limited prediction, learning and adaptation, and scheduling capabilities. Thus, adapting such systems to novel environments requires manual interference from trained personnel and the optimization of the operation is only done in the installation phase of the system. [116,418]

Energy-related Standards and Guidelines in Buildings There is a multitude of standards and guidelines that provide not only definitions and fundamentals but also exemplary load profiles, reference values, and statistics regarding the energy provision, distribution, and utilization in buildings. Although energy management is one of the domains addressed by the *German Standardization Roadmap for Smart Home + Building* [605] and many standards are listed in that publication, it does not present standards that are related to energy management in buildings, except for standards related to smart metering and communication. Therefore, Table A.2 presents an overview of related standards and guidelines that are partially utilized in the following sections for the analysis of residential and commercial buildings. They provide important input for the modeling and simulation of demands, devices, systems, and entire buildings. A deeper analysis of some of these standards is presented in Section 3.2.

Residential Buildings Residential buildings include single-family and multi-family buildings that are (semi-)detached or form big blocks and towers, such as apartment complexes. Many residential buildings comprise multiple persons or households that have different objectives, goals, or contracts regarding their energy usage and tariffs, which a BEMS has

[1]The term building automation is mainly used in the context of commercial buildings. In residential buildings, the term *home automation* is more common and used for mostly less sophisticated systems.

to handle. Households are equipped with appliances, HVAC systems, and DG. This thesis focuses on single-family buildings with dedicated devices and systems. Some of them can be used for energy management purposes, e. g., smart appliances with start time delay functionality, HVAC systems having storage capabilities, and BESSs. Thus, a BEMS has to be able to handle different tariffs, appliances, HVAC systems, and DG systems.

Commercial Buildings Commercial buildings include all kinds of buildings that are used for commercial activities, such as office buildings, warehouses, and retail stores. Often, such buildings have more complex HVAC systems than residential buildings. For instance, many commercial buildings comprise air-conditioning, cogeneration systems, or even trigeneration systems. This thesis focuses on smart commercial buildings, such as smart hotels or smart offices, which are equipped with a trigeneration system that can be optimized with respect to energy efficiency and used for DSM. Thus, a BEMS has to be capable of managing such a complex system comprising a microCHP, a chiller, and the additional equipment.

Future Changes and Developments in Buildings The energy consumption of buildings correlates strongly with the outdoor temperature [281, 486]. Therefore, climate changes that lead to higher temperatures are likely to increase the energy consumption in the summer because of higher cooling energy service requirements and to decrease the energy consumption in the winter because of lower heating requirements. The balance of these contrary effects and the resulting costs or benefits depend largely on the geographic location [477] and show large and non-linear responses of the electricity consumption [25].

In addition to changes regarding the climate conditions, the comfort demands of occupants and the degree of equipment with air-conditioning systems increase due to economic prosperity [627]. Some of these changes will be countered by energy efficiency and conservation measures, such as stricter building codes and energy labeling requirements.

Regardless of being driven by climate change or increasing comfort demands and degree of equipment, air-conditioning is a main driver of increasing energy demand and additional load peaks in the residential sector in many countries [487, Ch. 9]. In general, a rising degree of equipment of all kinds of devices will lead to rising energy consumption, no matter whether it is air-conditioning or clothes drying. This is one of the main reasons why the overall residential buildings' energy consumption share of the total energy consumption in Germany has already risen sharply in the past decades [486]. It underlines the importance of including not only air-conditioning but all devices in a holistic approach to energy management.

4.1.2 Scenarios with Multiple Energy Carriers

Energy services in buildings inherently include multiple energy carriers. For instance, gas-fired boilers utilize mainly natural gas to generate hot water and only some electricity for controllers and pumps. Nevertheless, there are other devices and systems that utilize multiple energy carriers alternatively or provide multiple different energy carriers at the same or at a different time: so-called *hybrid* devices and systems. The following paragraphs depict these scenarios briefly, motivating the introduction of an integrated BEMS that manages all energy carriers in buildings. In general, the term *hybrid* refers to one of the following properties and there is no common definition of hybrid device, hybrid system, and hybrid operation in literature and practice:

1. Utilization of at least two different alternative energy carriers.
2. Usage of different technologies utilizing the same energy carrier in one device.
3. Provision of multiple energy services by one device instead of different ones.

Therefore, the following paragraphs describe various kinds of hybrid appliances, systems, and operation modes in the context of buildings.

Hybrid Home Appliances Traditionally, appliances utilize only a single energy carrier, e. g., electricity, hot water, or natural gas, in their energy-intensive processes, which are mostly heating processes. Naturally, electricity is nowadays used in nearly all appliances to power displays, controllers, sensors, or valves. Nevertheless, these functions require only little electrical energy. By contrast, *hybrid appliances* use multiple energy carriers alternatively or in parallel as main energy carriers in their processes. In particular, the electrical energy in the heating processes in dishwashers, washing machines, and even tumble dryers may be supported or substituted by hot water [412, 570]. In addition to these three appliances, hobs and ovens can be powered using electricity or natural gas, which is also possible within the same device [412]. A detailed technical analysis is presented in Section 4.4.

The decision about which operation mode to use, i. e., the main energy carrier, can be made by a BEMS and may depend on many situational parameters, such as local generation or current energy prices. Additionally, such energy load profiles consisting of different energy carriers lead to interdependencies with other devices. For instance, the temperature of the hot water storage tank is interdependent with other devices that are connected to the tank, because multiple devices work on the same storage tank, i. e., change, react, and depend on its temperature. [410]

Hybrid Heating and Cooling Systems More popular than hybrid appliances are hybrid heating systems that combine multiple systems in the provision of heating energy services. In general, there are many systems that can be used in parallel or alternatively (see also Figure 2.6 in Section 2.2.2) to provide thermal energy services, i. e., space heating, DHW, and space cooling. For instance, heat pumps are often combined with electrical heating elements to provide enough thermal power in case of peak demands or with gas or oil boilers to achieve a high overall efficiency at low temperatures [100, 365, 460]. A detailed study about such systems is presented by Näslund (2013) [447]. In addition to heat pumps, there are also fuel cells and CHPs, which are frequently combined with additional boilers to meet peak demands. The decision about which device and thus energy carrier to use has to be made by the BEMS and includes economic as well as ecologic assessments with respect to the minimization of total energy costs and emissions [610, p. 8].

Cogeneration Typically, a cogeneration system provides heat and electricity at the same time from a single fuel, increasing the overall system efficiency by using residual and waste heat from electricity generation for the provision of heat. Therefore, CHPs are becoming more popular to meet climate goals [143, 283]. Nowadays, CHPs with combustion engines are widely used in commercial and industrial buildings and become more popular in residential buildings. The basics of cogeneration are explained in Section 2.4.3 and a deeper analysis of CHP plants is provided below in Section 4.5.4. Often, CHPs are operated continuously to provide the baseloads of electricity or heat. Nevertheless, in many cases CHPs are connected to a thermal storage, e. g., hot water storage tank, and operated discontinuously. This enables short-term operation planning, i. e., the scheduling of the operation cycles by BEMSs [11, 88, 525].

Trigeneration In trigeneration systems, cogeneration of heat and electricity from a single fuel is extended by cooling as a third energy carrier. Therefore, these systems typically combine a CHP with an ab- or adsorption chiller and often even add another energy source, such as solar thermal energy. Usually, trigeneration systems are operated as cogeneration systems if there is no requirement for the third energy carrier. See Section 2.4.3 for the basics, Figure 2.7 on p. 34 for a schematic figure, and Section 4.5.5 for the analysis of trigeneration systems. The efficiency of ab- and adsorption chillers depends heavily on the hot water, chilled water, and outdoor temperatures. Therefore, the scheduling does not only affect the operating time of the sub-systems but also their efficiency. This leads to situations, where it is beneficial to generate chilled water in advance when there are low outdoor temperatures, e. g., in the night or in morning, and store it for later use, despite the standing losses. Nevertheless, this requires the knowledge or at least the prediction of future demands for chilled water and outdoor temperatures. A BEMS requires such predictions and has to schedule the CHP as well as the ab- or adsorption chiller accordingly.

In Section 4.7, the usage of the terms hybrid, multi-modal, and multi-valent is analyzed and a consistent naming of appliances and systems with respect to their utilization and provision of energy carriers and services is presented.

4.1.3 Pricing Schemes, Tariffs, and Power Limits

There are many pricing schemes that can be used as measures of DSM. A detailed overview of different pricing schemes is provided in Section 2.1.1. Some of them are already commonly used in several countries, such as block pricing, other are not yet common, such as real-time pricing. BEMSs have to be able to handle all prices and calculate energy costs based on these tariffs and the current consumption as well as the expected future consumption to allow for optimization. This is one of the main reasons for the introduction of the energy flow simulation—the *Energy Simulation Core*—presented in this thesis.

An increase of the overall energy tariff, i. e., a higher flat rate, decreases the consumption only slightly, because the total energy demand of buildings is relatively price-inelastic [34]. Nevertheless, many evaluations of DSM measures using special tariff schemes demonstrate that such schemes lead to the desired effects, particularly when being supported by automated EMSs (see also Section 3.2.4). For instance, in a review of several European field tests, Darby and McKenna (2012) [148] examine the DSM potential and conclude that automated-control by EMSs are crucial for its success. Similarly, Faruqui and Sergici (2010) conclude that automated DR and other enabling technologies are inevitable to obtain substantial impact [210]. Hagerman (2014) [181] stresses the importance of systems that enable bidirectional communication with the demand side.

The evaluation of the proposed BEMS requires suitable energy tariffs, i. e., flat rate as well as time-of-use tariffs. To obtain realistic results for a scenario that is similar to the current situation in Germany, the average German electricity and natural gas prices as well as the feed-in tariffs and compensation schemes for small PV and microCHP systems are given in the following paragraphs. The subsequent paragraphs present fictional electricity time-of-use tariffs, because currently there are nearly no time-of-use tariffs in Germany that are suitable for building energy management in the sense of this thesis. Furthermore, a (soft) power limit signal is introduced that aims at reducing consumption peaks (see also Section 4.8.2).

German Electricity and Natural Gas Tariffs In the year 2015, the German households paid an average gross electricity price of about 29.5 cent/kWh and a gross natural gas price of about 6.8 cent/kWh [163]. The feed-in tariffs in Germany for PV systems having a maximum feed-in power smaller than 10 kW and that are mounted on residential buildings are given in Table B.11 on p. 384. Despite regular reductions, the tariffs remained constant in the given period. The compensation schemes in Germany for CHP systems having an electrical power smaller than 50 kW are given in Table B.12 on p. 384. Although these values are subject to certain additional constraints, they are typically valid for microCHPs in residential and commercial buildings. In addition to these compensations, there is a payment for the electricity feed-in based on the price at the European Energy Exchange in Germany, which is currently about 3–4 cent/kWh, and a compensation for prevented electricity grid charges of about 0.5 cent/kWh [24].

Mauser (2012) and Allerding (2013): Fictional Electricity Time-of-use Tariff In [10, 405], Mauser (2012) and Allerding (2013) propose a dynamic time-of-use tariff that is based on the German SLP H0 for residential buildings. The fundamental idea is to introduce higher prices at times of high consumption and vice versa. Self-evidently, this does not take RES generation into account. This tariff has the following general characteristics [405]:

- There are fixed minimum and maximum electricity prices $c_{\mathrm{a}}^{\min}$ and $c_{\mathrm{a}}^{\max}$.
- There is a fixed average electricity price $c_{\mathrm{a}}^{\mathrm{avg}}$, which is achieved if the electrical power consumption is evenly distributed, i. e., constant throughout the day.
- The dynamics of the tariff follow the dynamics of the SLP H0.

The characteristic values, which have been used in [10, 405], are given in Table B.14 on p. 385. The buildings receive this tariff every 12 hours for the next 36 hours, i. e., there are always at least 24 hours available in advance, enabling a corresponding optimization horizon.

Liebe et al. (2015): Fictional Electricity Time-of-use Tariff In [374], Liebe et al. (2015) use the dynamic time-of-use tariff that is given in Table B.15 on p. 385 for the year 2015. It is a rather simple tariff comprising only six different prices periods that are based on day-ahead prices of the *European Power Exchange* showing slightly the typical *duck curve* which is caused by the feed-in from RES. In addition to the tariff of the year 2015, there are also tariffs for the years 2014, 2020, and 2025. All tariffs have the same structure and are only scaled to different average prices. For instance, the tariff of 2015 has an average price of 29.29 cent/kWh.

Fictional Tariffs and Compensations used in this Thesis

This thesis utilizes different tariffs in the simulations to demonstrate the capabilities of the BEMS, show the effects of energy management, and evaluate different scenarios. The prices are similar to the current energy tariffs in Germany in the year 2015. The variable time-of-use tariffs are based on similar evaluations in related work, e. g., in [374].

Flat Rate Electricity and Natural Gas Tariffs A flat electrical power tariff of 30 cent/kWh is used to obtain reference values and show effects of the energy management and optimization that are not related to a variable electricity tariff, such as changes of the self-consumption and self-sufficiency, because of an increasing usage of local generation.
Based on the assumption that natural gas will become slightly more expensive than today, this thesis uses a flat natural gas tariff of 8 cent/kWh (unless stated otherwise). The calculation of the natural gas costs assumes that the calorific value of the gas is constant.

Fictional Time-of-use Electrical Power Tariffs Although the tariff by Mauser (2012) and Allerding (2013) [10, 405] does not take the additional electricity generation by RES into account and thus determines the electricity prices only based on the average consumption profile of households, it is used also in this thesis. The characteristic values are adapted to new minimum, maximum, and average values and are given in Table B.14 on p. 385.
The electricity tariff proposed by Liebe et al. (2015) [374] is adapted to an average electricity price of 30 cent/kWh and used in this thesis. The resulting tariff is given in Table B.15.
Basically, the previous two fictional time-of-use electricity tariffs aim at shifting the consumption by multiple hours, e. g., from the noontime to the afternoon or from the evening into the night. To show the results of a tariff that aims at shifting the consumption by shorter periods, the tariffs given in Table B.16 are used in this thesis. The tariffs comprise periods of a duration of one or two hours, having alternating prices.

PV and MicroCHP Feed-in and Self-consumption Compensation The PV and microCHP compensation schemes are given in Table B.17 on p. 385. The feed-in of locally generated electricity is compensated with a rate that depends on the generating system. The self-consumption of electricity generated by the microCHP is compensated with 5 cent/kWh, whereas that generated by the PV system does not yield any compensation.

Fictional Power Limits used in this Thesis The power limit signals used in this thesis are given in Table B.13 on p. 384 (see also Section 4.8.2). It uses a consumption power limit of 3000 W for the active power that is provisioned by the electricity grid. Consumption above this limit has a penalty factor of $\tau_{\mathrm{a}}^{\mathrm{upper}} = 1$ and thus becomes twice as expensive as the regular tariff. The feed-in power limit is 3000 W and has a penalty factor of $\tau_{\mathrm{a}}^{\mathrm{lower}} = 1$. Hence, the compensation is capped above this limit. There is no limit for the capacitive and inductive reactive power exchanged with the electricity grid.

4.2 Residential Buildings

This section presents a detailed analysis of residential buildings and their energy consumption as well as of a real-life scenario that is used to develop the approach in this thesis. The resulting data and statistics form the basis for the bottom-up simulations by the BEMS.

The analysis focuses on German households and major appliances. It simplifies the relation between residential buildings and households. Although a residential building may be composed of multiple households, this structure is not further analyzed and the simulations assume that the BEMS monitors and controls both appliances and HVAC systems, i. e., every building comprises one household. Therefore, the following analysis of residential buildings is actually an analysis of households.

The simulated electricity consumption is based on an analysis of the major appliances and the German SLP of households. The consumption of other energy carriers requires an analysis of heating and cooling demands in residential buildings. This second analysis is given in this section, before finally presenting the real laboratory environment at the Karlsruhe Institute of Technology (KIT) called KIT Energy Smart Home Lab (ESHL).

Modeling of Households The bottom-up simulation of households requires several statistical values. First of all, the size of the household, i. e., the number of persons in a particular household, is important to determine the typical yearly total electrical energy consumption. On average, the overall electrical energy consumption follows a certain typical pattern that is reflected by the German SLP H0 of households. A more detailed simulation of households needs information about the appliances. This includes the appliance penetration, i. e., the availability and number per household, the usage or turn-on times, the usage duration or operating time, and load profiles or curves of the appliances [172].
In case of heating and cooling, the thermal demand for space heating, DHW, and space cooling is necessary. In particular, the demands for space heating and space cooling depend heavily on the location and insulation of the building, the weather and climate, and the preferences and behavior of the users. Actually, the heating and cooling demands depend mainly on the floor areas of the building being occupied by the household. Additionally, the floor area correlates with the number of persons and thus this thesis uses thermal demands that correspond to the number of persons in the household [655].

To sum up, statistical data is used to simulate the energy consumption of households. Although the approach is a bottom-up approach modeling particular devices, it is currently limited to five major appliances and the HVAC system. The remaining residual load is modeled using the German SLP H0 of households. The required statistical data is presented in the following sections. A more detailed bottom-up model is out of scope of this thesis, because the additional effort is out of proportion for the demonstration of the concepts and not necessary for the evaluations of the scenarios presented in Chapter 6.

4.2.1 Electricity Demand

Although a bottom-up simulation of residential buildings aims at simulating all devices and systems, this thesis is limited to a detailed and realistic modeling and simulation of the major appliances. Electricity consumption that is not modeled by the major appliances is modeled as so-called *residual load* using a SLP [10, 405]. Therefore, the average yearly electricity consumption and an average electrical load profile form the basis of the electricity consumption. Detailed models of the major appliances require detailed additional data, which is provided in the next section.

Average Yearly Electrical Energy Consumption Table B.18 on p. 386 presents an overview of the average yearly electricity consumption of households in the literature and statistics, depending on the size of the household and whether the DHW is generated using electricity. A detailed evaluation of the average yearly electricity consumption of households is presented by Bost et al. (2011) [90]. Their evaluation uses several more data sources and supports the findings of the Energieagentur.NRW (2015) [192]. Therefore, this thesis uses consumption values that are based on [192] and corrected according to the appliance penetration, i. e., the degree of equipment. The resulting average yearly electrical energy consumption is given in Table 4.1.

The average household has a certain degree of equipment, i. e., not every household has exactly one washing machine, one tumble dryer, and so on. The statistical values of the degree of equipment and the consumption share of the appliances, which are given in Table B.19 on p. 386, are used to correct the average yearly consumption in a way which is described in more detail in [405]. The resulting values are provided in the bottom row of Table B.18 on p. 386. The appliance usage, which is presented in the next section, is used to adapt the consumption shares of the appliances given, resulting in the values provided in Table B.19 on p. 386. Finally, these values are used to calculate the average yearly residual load, i. e., the load that is not explained by the simulated major appliances. The corrected average consumption and the remaining residual loads—depending on the size of the household—are listed in Table 4.1.

Actually, the electrical energy consumption of residential buildings is influenced by many parameters, such as the type of dwelling or the household income [414]. Nevertheless, this is out of scope of this thesis but may be incorporated by adapting the average yearly electrical energy consumption of a building in the simulations.

Average Electrical Load Profile The average German electrical SLP H0 of households [607] is normalized to a certain yearly electricity consumption and represents the average consumption of a large quantity of households in three different seasons: winter, summer, and transition time. In addition to the profile for households, there are also similar profiles for different types of commercial consumers and farms. To model and simulate the residual load, i. e., the combined load of all loads that are not modeled separately in a detailed way, the H0 profile is scaled to the average yearly electricity consumption of a particular household. This is a common approach that is used by many similar bottom-up simulation approaches [10, 294, 405, 618].

Electrical Baseload The load that is not caused by the simulated appliances, i. e., the residual load of yearly electricity consumption (see Table 4.1) is called baseload. In this

Table 4.1: Appliances: average yearly electrical energy consumption and resulting residual load in kWh/a, depending on the household size, without the electrical generation of domestic hot water and corrected according to the appliance penetration in this thesis

	Number of persons				
Average yearly consumption	1	2	3	4	5
Total consumption	2000	3100	4000	4700	5200
Major appliances	574	1003	1372	1707	1830
Remaining residual load	1426	2097	2628	2993	3370

thesis, the baseload is simulated according to the German SLP H0 and scaled to the expected residual load. In contrast to Allerding (2013) [10] and Mauser (2012) [405], this thesis uses the H0 profile at a resolution of 15 min instead of one hour.

Season and Weather Although the energy consumption of buildings is closely related to the season as well as to the weather [281, 472, 486], this thesis uses only seasonal effects that are part of the SLP H0. In the H0 profile, the daily load profiles are scaled using a correction factor reflecting the seasonal changes of the electricity consumption. This factor y_d for a particular day of the year $d \in \{1 \ldots 366\}$ is calculated using the following formula [607]:

$$y_d = -3.92 \cdot 10^{-10} \cdot d^4 + 0.00000032 \cdot d^3 - 0.0000702 \cdot d^2 + 0.0021 \cdot d + 1.24 \; . \tag{4.1}$$

This formula provides a maximum factor of 1.25722 and a minimum factor of 0.78466, which result—in combination with the three seasons of the profile—in seasonal changes that are similar to those given in detail by Prior (1997) [486].

Appliance Usage in Residential Buildings

The bottom-up simulation of residential buildings requires detailed statistical data about the appliance usage. This includes the average number of yearly appliance operation cycles per household, which depends on the household size, the time of use, i. e., the starting or operating times of the appliances, and the selected profiles. This section analyzes existing data and deduces the data sets that are used in this thesis. The approach is based on Mauser (2012) [405], but uses additional and updated statistical data.

Degree of Equipment The availability and penetration rates of appliances in households is the so-called degree of equipment. Statistical values for German households in the year 2015 are provided by [164] and given in Table B.19 on p. 386. These values are used to modify and thus correct the average yearly electricity consumption of households. In particular, small households comprising only one or two persons have a degree of equipment for dishwashers that is markedly lower than 100 %. Additionally, on average only about half of the households own a tumble dryer. Therefore, the average yearly consumption of simulated buildings has to be adapted to reflect a household having all five major appliances, i. e., one that is simulated in this thesis. It is assumed that all households own a hob and an oven. Similar approaches have been used by Mauser (2012) [405] and Molitor et al. (2012) [434].

Table 4.2: Appliances: average number of operation cycles per year in this thesis

	Number of persons				
Appliance	1	2	3	4	5
Dishwasher	90	160	240	310	340
Hob	170	300	350	400	420
Oven	85	150	175	200	210
Tumble dryer	80	140	210	270	280
Washing machine	120	200	280	360	420

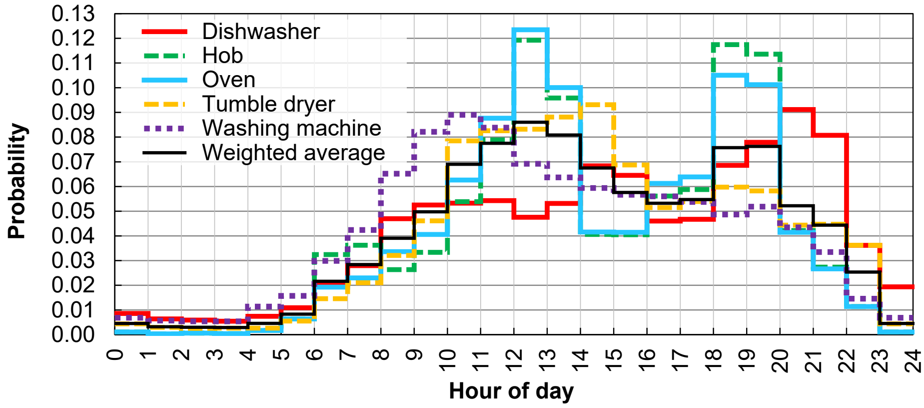


Figure 4.1: Probability distributions of the average appliance usage on all days for the five major appliances and the weighted average usage of all appliances

Average Number of Cycles The average numbers of appliance operation cycles per household and year largely depend on the number of persons per household [374, 486]. The values used in this thesis are given in Table 4.2 and based on statistical data given in [319, 374, 486, 533, 568–570] as well as data measured and recorded in the smart residential building ESHL at the KIT.

Program Selection Usually, the users of appliances do not always use the same program, e. g., the washing program "*Cotton 60° C*", but several ones. Table 4.3 and Table 4.4 provide the exemplary typical program selections for dishwasher and washing machine programs, respectively. Based on the data provided in [134, 319, 486, 533] and recorded data in our laboratories, typical programs and their share in all operation cycles are given in the Table C.1 on p. 399. Depending on the device, there are two, three, or four different programs that are selected with a certain probability. For all of these profiles, load profiles have been recorded in our laboratories (see Section 4.4.1).

Time of Use The time of use of appliances in residential buildings is depicted in Figure 4.1 as probability distributions of the average overall usage on all days of the week. They describe the probability that an appliance is started in the respective hour. The detailed data is based on the data given in [465, 486, 568, 570]. It is provided separately for weekdays in Table C.3, for Saturdays in Table C.4, and for Sundays in Table C.5. Season and weather influence the appliance usage [277, 486]. To take the seasonal differences in the average number of cycles and thus electricity consumption into account, the probability of operation cycles per day is revised using the Equation 4.1, which is originally used to dynamize the SLP profile H0. A seasonal influence on the program selection share is neglected.

Table 4.3: Appliances: dishwasher program selection, data from [319]

Dishwasher program	50/55 °C	Automatic	60/65 °C	Unknown	Sum
Program selection share	0.46	0.19	0.31	0.04	1.00

Acceptance of Energy Management Although users are not willing to accept forced load shedding that affects certain services, such as cooking or watching television [279], they get used to dynamic tariffs and automated energy management that optimizes the operating times of certain other services, such as the starting times of dishwashers and washing machines [417, 466, 568]. Detailed values of the typically accepted delays of these starting times are given in Section 4.4.

4.2.2 Heating and Cooling Demand

Cogeneration of CHP systems does not only generate electricity but also hot water. Therefore, an integrated optimization of all energy carriers has to include a realistic thermal simulation that generates thermal energy demands, i. e., heating hot water and DHW consumption. This thesis does not simulate air-conditioning systems in residential buildings. Therefore, the space cooling demand of households is not analyzed.

Space Heating Demand The thermal energy consumption of residential buildings depends on many factors, such as weather, insulation of the particular building, and user preferences as well as behavior [432]. A precise simulation of the thermal demand requires a detailed model of the building, which is out of scope of this thesis. Therefore, existing simulation data of the thermal demand is used to simulate the heating demand.

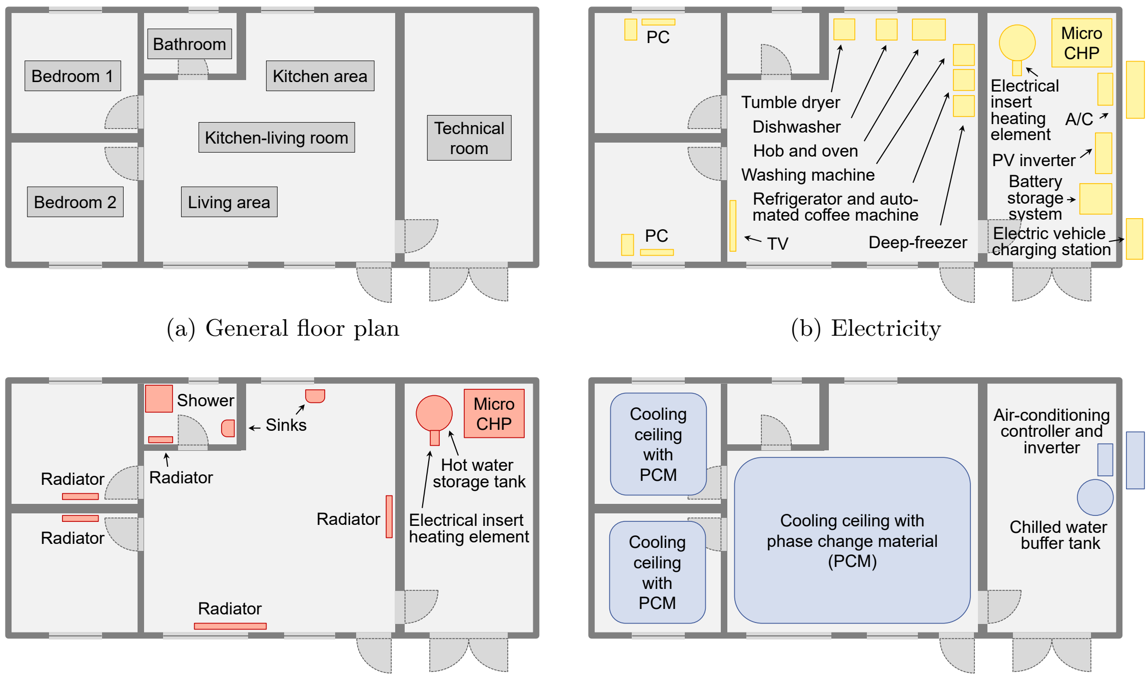
Similar to Allerding (2013) [10], this thesis uses static thermal load profiles for heating hot water based on Gräßle et al. (2011) [256]. The profiles have been obtained by means of a thermal simulation of the ESHL in TRNSYS (see also Section 3.5.3) and scaled to a yearly consumption of 2000 kWh per person in the household. The profile of a household comprising one person is depicted in Figure B.1 on p. 388. In contrast to Allerding (2013) [10], this thesis randomizes the given static profile and hence introduces uncertainty: The demand is randomly selected from the values for the current hour, the previous hour, and the following hour in the given profile. Additionally, it is scaled to a random value between 50 % and 150 % of the power P_h in the given profile using a uniform distribution.

Domestic Hot Water Demand In contrast to Gräßle (2011) [257] and Allerding (2013) [10], this thesis uses DHW consumption profiles that are randomly generated based on the VDI Guideline 6002 [613, Fig. D1 to D5]. Usually, consumption profiles of DHW are given in liters per unit of time. This thesis uses consumption profiles having a power consumption in W. The resulting profiles are given in Table D.19 and based on typical draw off profiles provided in the regulation of the energy labeling of space heaters by the European Commission [200].

The households have an average yearly consumption of 700 kWh per person and the consumption in the course of the year is made variable using the correction factors for the

Table 4.4: Appliances: washing machine program selection and their typical consumption in kWh/cycle, data from [319, 533]

Washing machine program	20 °C	30 °C	40 °C	50 °C	60 °C	90 °C	*Sum/Avg.*
Program selection share	0.02	0.26	0.40	0.03	0.23	0.06	1.00
Consumption in kWh/cycle	0.35	0.50	0.65	0.78	0.90	1.50	0.72



(a) General floor plan (b) Electricity

(c) Heating and DHW system (d) Cooling system

Figure 4.2: *KIT Energy Smart Home Lab*: overview of the energy carriers

months and the respective day of the week provided in Table D.20 and Table D.21. Usually, a large share of the thermal energy in DHW is lost in the circulation systems. These losses may account for up to 70 % of the consumption [40]. This thesis assumes that the thermal losses are already included in the power profile of 700 kWh per person.

Building Energy Balance and Thermal Capacity Buildings are energy systems not only utilizing different energy carriers but also having different losses and gains of energy. The basic energy balance of buildings can be summed up into the following simplified equation of energy gains and losses in a certain time period, i. e., the total energy balance E_{total}:

$$E_{\text{total}} = E_{\text{ventilation}} + E_{\text{sewage}} + E_{\text{envelope}} + E_{\text{solar}} + E_{\text{internal}} + E_{\text{heating}} + E_{\text{cooling}} + E_{\text{DHW}} \,. \quad (4.2)$$

The ventilation energy exchange $E_{\text{ventilation}}$ is caused by convection losses or gains, i. e., air exchange. The sewage losses E_{sewage} are losses that occur because of the sewage leaving the building. The losses and gains of the building envelope E_{envelope} are mainly conduction losses because of heat transfer. The solar gains E_{solar} are radiation gains through glass windows and doors. The internal gains E_{internal} include all types of gains that occur in the local utilization, distribution, and provision of energy, e. g., standing losses of storage systems, distribution losses of the heating system, and byproducts of energy services, as well as the body heat from the occupants.

4.2.3 Real-world Scenario: KIT Energy Smart Home Lab (ESHL)

The ESHL at the campus of the KIT is a smart residential building laboratory environment. It was built in the *MeRegioMobil* project and since then it has been used in various research, evaluation, and demonstration projects. For instance, the building was used to evaluate the user acceptance of energy management and dynamic tariffs [466, 467]. The laboratory comprises an apartment of $60\,\mathrm{m}^2$ and a technical room of $20\,\mathrm{m}^2$. The apartment consists of two bedrooms, a bathroom, and a combined kitchen-living room. The floor plan of the ESHL is depicted in Figure 4.2a. The ESHL is equipped with intelligent appliances, a microCHP, a hot water storage tank with electrical IHE, a PV system, an air-conditioning system with PCM in the ceiling, a BESS, an electric vehicle charging station, and metering systems. Table B.20 provides a detailed overview of the major devices and systems as well as their technical specifications.

The laboratory has been used to develop a prototypical BEMS—the OSH [10]—and a prototypical visualization, control, and configuration interface—the Energy Management Panel (EMP) [60]—as well as an approach to the optimization of the charging and discharging of a bidirectional electric vehicle [393]. Inhabitants use the EMP to provide their goals, objectives, and preferences to the BEMS, control devices and systems in the building, and obtain information about device states and energy flows. Thus, the EMP is the main interface between the OSH and the users. The OSH is analyzed and more closely described in Allerding (2013) [10] and in Section 4.9 of this thesis, the concept of the EMP is closely described by Becker (2014) [60] and in Section 4.6.4.

Many typical appliances and devices are available in the ESHL. This includes major appliances, e. g., dishwasher, hob, oven, tumble dryer, washing machine, refrigerator, deep-freezer, and automated coffee machine, and small appliances, e. g., water kettle and toaster. In addition to these appliances, there are other typical electrical devices available in the laboratory: a television (TV), a hi-fi system, and two personal computers (PCs). The ESHL comprises two systems for the DG of electricity: a PV system and a microCHP. Electricity is stored in a BESS. Additionally, there is an electric vehicle charging station that is capable of bidirectional charging, i. e., charging and discharging, of electric vehicles. Figure 4.2b provides an overview of the electrical devices and systems.

The heating and cooling systems are depicted in Figure 4.2c and Figure 4.2d, respectively. The former comprises a microCHP, which is supported by an electrical IHE, a hot water storage tank, and conventional radiators. The latter comprises an air-conditioning system, i. e., a compression chiller and an inverter, a chilled water buffer tank, and a cooling ceiling with PCM, i. e., an integrated cooling system that is able to store thermal energy in PCM.

The appliances, devices, and systems in the ESHL form the basis for the simulated smart residential building in this thesis. The load profiles have been recorded in this laboratory.

4.3 Commercial Buildings

Commercial buildings comprise multitudes of different devices and systems, leading to many scenarios. Often, most of these devices and systems are not interconnected but independent in their energy consumption, because they work separately from other devices and systems. Traditionally, energy management in commercial buildings has been part of technical *building services* and *building automation*, which are described in Section 4.1.1. Nowadays, the systems become more interconnected and interdependent, calling for an integrated and automated building energy management.

This thesis focuses on a particular interconnected and interdependent system that can be found in commercial buildings: a trigeneration system providing electricity, hot water, and chilled water, i. e., the combination of cogeneration by a CHP and an absorption or adsorption chiller. The optimization of the design as well as the operation of trigeneration systems are complex tasks [395]. This section presents and analyzes the trigeneration system in the FZI House of Living Labs (HoLL) at the FZI Research Center for Information Technology (FZI). A deeper and more general analysis of trigeneration systems is presented in Section 4.5.5.

4.3.1 Building Model, Parameters, and Thermal Demands

The main factors influencing thermal loads in buildings are the outside air temperature, the solar radiation, and the occupancy of the building [403]. Actually, the entire local climate has to be taken into account [91] and the building model has to be precise and detailed [139]. Nevertheless, even detailed models have to be calibrated properly, which is a time-consuming and complex task [132].

This thesis does not aim at detailed building simulation but at demonstrating a BEMS that is able to optimize all energy carriers and interdependent energy systems, such as trigeneration systems. This calls for a simplified simulation of the thermal demands of the commercial building, analogous to the thermal demands of the simulated smart residential buildings (see previous section). Hence, a simplified building model has to be built, enabling the simulation of cooling demands that have to be covered by the trigeneration system.

The HoLL is equipped with a trigeneration system as well as thermal heat meters. Therefore, the following paragraphs analyze the thermal demand of this building and present a simplified model of the space cooling demand.

4.3.2 Real-world Scenario: FZI House of Living Labs (HoLL)

The HoLL at the FZI is a research and demonstration building that facilitates interdisciplinary research, development, and evaluation in different laboratories addressing different research topics. The building is equipped with various building automation systems, several metering systems, DG, thermal and electrical ESSs, and a trigeneration system. These devices and systems aim at the flexibilization of energy generation and consumption as well as energy usage across different energy carriers: electricity for local consumption and heating, hot water for heating and generation of chilled water, and chilled water for air-conditioning. Although the HoLL is actually a commercial building, it includes several environments, e. g., a smart home, a smart office, and a smart production environment, which are called *Living Labs*. [11, 62]

The devices and systems include intelligent appliances with wireless communication, electric vehicles, a gas-fired condensing boiler, a microCHP, an adsorption chiller, hot water and chilled water storage tanks, a PV system, and a BESS (see Table B.21 on p. 389). The devices and systems are monitored and controlled by a BEMS—the OSH—that integrates

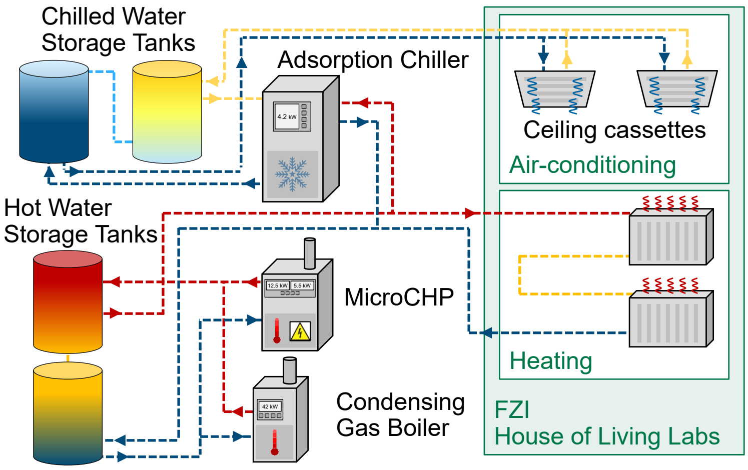


Figure 4.3: *FZI House of Living Labs*: trigeneration, heating, and cooling systems

various communication media and protocols and facilitates data recording and storage, data analysis and prediction, visualization, and the integrated optimization of all devices and systems. Becker et al. (2015) [62] describe the HoLL more closely and Figure B.2 provides a detailed overview of the building and its devices and systems. [62]

This thesis focuses on the operational optimization of the trigeneration system for cooling purposes in summer. Therefore, the analysis is limited to the space cooling demand and neither includes the heating demand nor the electricity consumption of other devices.

Trigeneration System

Figure 4.3 depicts the trigeneration system as well as the heating and cooling systems at the HoLL. The trigeneration system comprises a microCHP, an adsorption chiller, and hot water as well as chilled water storage tanks. An additional gas-fired condensing boiler is used in the winter to generate additional heat when the microCHP does not provide enough thermal power to heat the building.

The actual air-conditioning in the meeting room is done by two ceiling cassettes that utilize the chilled water to provide chilled air. Table B.21 on p. 389 provides an overview of the technical data of the trigeneration system. In this thesis, simulation models of these devices and systems are used to demonstrate the optimization of a trigeneration system.

Space Cooling Demand

As there is no detailed building model of the HoLL available, a simplified model of the thermal loads is used in simulations. Generally, the main factors of thermal loads in buildings are the outside air temperature, solar radiation, and the occupancy of the building [403]. The trigeneration system in the HoLL is used to air-condition a single meeting room. Therefore, the thermal building model is reduced to the space cooling demand of this single room as a function of the outdoor temperature and the presence of a reservation. This approach has been introduced by Feder (2014) [211] and subsequently used by Mauser et al. (2015) [408].

Outdoor Temperature At the HoLL, the HVAC controller—the *SolarNext chillii System Controller*—measures the outdoor temperature regularly using a temperature sensor that is located at the outer wall, close to the meeting room. The BEMS reads out this value at regular intervals and stores it in a database. The simulations use the recorded historical data to simulate the outdoor temperature profile.

Room Reservations There are two different sets of reservations that are used to determine the cooling demand: one of real reservations that is automatically extracted from the *Microsoft Exchange Calendar* (see Table B.23 on p. 392) and another of simulated reservations. The simulated reservations are generated randomly using the parameters given in Table 4.5, which are based on the typical values of real reservations in the meeting room [211, 408]. The temperature set point of the meeting room is 22 °C.

Cooling Demand In Feder (2014) [211], the cooling demand of the meeting room has been analyzed and an empirical formula has been determined that is based on measurements in the real building. In case of a reservation, the cooling demand P_{demand} in W as a function of the outdoor temperature θ_{outdoor} in K is calculated using the following equation [211, 408]:

$$P_{\text{demand}}(\theta_{\text{outdoor}}) = \max(0;\ 441.50\,\frac{\text{W}}{\text{K}} \cdot (\theta_{\text{outdoor}} - 295.03\,\text{K}))\,. \tag{4.3}$$

This simplified model of the meeting room leads to a cooling demand that is a linear function of the outdoor temperature, starting at an outdoor temperature of about 21.9 °C. This model has been recalibrated to match the temperatures given by the so-called *WESTE-XL* data (see Section 4.5.5) that is used in this thesis. The new simplified model of the meeting room leads to a cooling demand that starts at an outdoor temperature of about 18.7 °C:

$$\widetilde{P}_{\text{demand}}(\theta_{\text{outdoor}}) = \max(0;\ 274.84\,\frac{\text{W}}{\text{K}} \cdot (\theta_{\text{outdoor}} - 291.86\,\text{K}))\,. \tag{4.4}$$

The resulting space cooling demand in July 2014 is given in Figure B.5 on p. 392.

4.4 Appliances

The energy consumption of appliances does not only depend on the number of operation cycles and the program selection but also on the actual load profiles of the respective programs. There are many variables that influence the load profiles. For instance, the water

Table 4.5: Parameters of the simulated reservations, data from [410]

Parameter	Value
Number of reservations per day	$\{1, 2\}$
Duration of reservations in hours	$\{2, 3, 4\}$
Pause between reservations in hours	$\{2, 3\}$
Earliest time of first reservation	08:00 am
Pause before first reservation in hours	$\{0, 1, 2, 3\}$

inlet temperature in dishwashers and washing machines has a major influence on the energy consumption, because the water has to be heated up to a certain temperature by varying temperature differences. The energy consumption of tumble dryers heavily depends on the total amount of water in the clothes that have to be dried. To reduce the scope of this thesis, such kinds of influences are neglected.

This section analyzes the energy consumption of the major appliances and presents conventional load profiles that have been recorded in our laboratories as well as hybrid load profiles that have been deduced from them. Additionally, the general opportunities for energy management are analyzed and a novel classification of appliances with respect to their qualification for energy management is presented.

4.4.1 Energy Consumption and Load Profiles of Appliances

The optimization of appliances by a BEMS requires expected load profiles of the programs. These load profiles may be provided directly by the appliances, measured by metering devices, such as smart plugs, and learned by the BEMS, or be available in some sort of driver and its configuration file or a related simulation model. This thesis uses profiles of the major appliances that have been recorded in the ESHL. Since the BEMS presented in this thesis is able to simulate different load profiles per appliance, multiple load profiles of the active and reactive power of different programs have been recorded, using the appliances described in Table B.20 on p. 387. This section briefly presents these load profiles, which are depicted in the Figures C.1 to C.6. They have different peak to average ratios, which have implications for the energy management: for instance, a high peak to average ratio may lead to frequent violations of power limits, whereas a low ratio is more easily supplied by DG systems, such as microCHPs, without BESSs.

Dishwasher Dishwashers have different programs, such as low temperature rinsing, automatic mode, and high temperature rinsing (see also Table 4.3 on p. 129), that are used regularly in households. Therefore, this thesis uses four different programs, which are described in Table C.1 on p. 399 and depicted in Figure C.1 on p. 394. Typically, the load profiles of dishwashers have two heating phases with an electrical peak power of about 2 kW: Firstly, the heating phase of the actually washing and cleaning phase. Secondly, the heating phase of the rinsing phase, which provides the heat that is then utilized in the drying phase for the evaporation of water.

Hob In reality, the variety of load profiles is practically infinite, because they depend on the cooking process, which is mainly controlled by the user but the hob. Nevertheless, this thesis uses only three different load profiles to simulate the usage of the hob. These profiles are given in Table C.1 on p. 399 and depicted in Figure C.2 on p. 395. It is important to note that the given profiles have been recorded using an induction hob, which are thus different to those of radiant heating elements or hot plates. An induction hob has different power levels of the coils, whereas radiant heating elements or hot plates are mainly controlled by switching them on and off alternately in a certain duty cycle that has a similar average power. Thus, they result in a higher peak to average ratio than induction hobs.

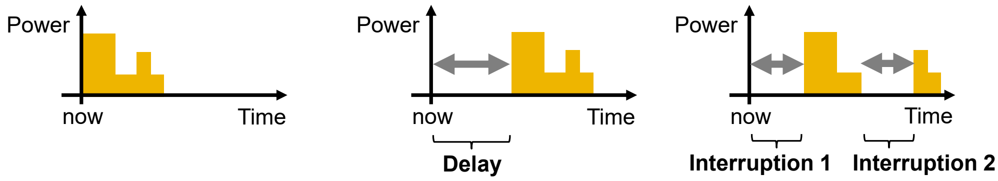
Oven Similar to hobs, ovens have a high variety of load profiles. However, based on our experiences in trial phases, the load profiles are more uniform because the users often use similar temperature settings and baking times. Additionally, there are less different levels of power values in the load profiles, because the electrical heating elements in electrical ovens are usually only switched on and off, i. e., the average power is determined by the duty cycle. This results in a load profile that has a high peak to average power ratio, too. This thesis uses three different load profiles of an electrical oven, which are described in Table C.1 on p. 399 and depicted in Figure C.3 on p. 396.

Tumble Dryer The load profiles of tumble dryers heavily depend on their type, i. e., whether they are conventional condenser dryers, conventional vented dryers, or modern heat pump dryers. Heat pump dryers have a higher energy efficiency with respect to their electricity consumption than conventional dryers because a great share of the heat is taken from the environmental air. Although they become more popular, this thesis uses two different load profiles of a conventional vented dryer that are described in Table C.1 on p. 399 and depicted in Figure C.4 on p. 397 because such a dryer is used in the ESHL.
Two load profiles showing the typical active power consumption profile of a vented dryer and a heat pump dryer are provided in Figure C.5 on p. 397 to visualize their typical distinctness. Conventional vented and condenser dryers have electrical heating elements that are switched on and off, which results in a load profile having a high peak to average ratio of the active power. In contrast, heat pump dryers have a relatively low peak to average profile, because the heat pump is run continuously, leading to a relatively constant power consumption having only a minor maximum in about the middle of the cycle.

Washing Machine The typical energy consumption of several washing programs is given in Table 4.4 in Section 4.2.1. This demonstrates the high variety of total energy consumption of washing machines, depending on the used washing program. A large share of the energy consumption of washing machines is used to heat the water in the washing phase. This thesis uses three different load profiles that are described in Table C.1 on p. 399 and depicted in Figure C.6 on p. 398. Typically, the load profiles of washing machines show a high power consumption at the beginning, i. e., when the water is heated in the washing process, and only a low energy consumption in the remaining phases of a cycle. This results in a high peak to average power ratio at the beginning of the profile.

Regulation and Policies

Typical regulatory instruments to improve the energy-efficiency of appliance usage are energy labeling requirements, i. e., information systems, and minimum energy performance standards, i. e., regulation [343,392]. Although cost and quality are the most important characteristics for users when purchasing new appliances, energy consumption ranks third [231]. Energy labeling and standards have to be supported by additional “policy instruments designed to shift the market toward greater energy efficiency” [644].
Although it may reduce the energy consumption by more than a fifth, the change to more energy-efficient appliances has only minor effects on the peak consumption of individual households and does not lead to load shifting effects [85]. Automated energy management of appliances enables load shifting, which may be used to reduce peak loads as well as to



(a) Non-deferrable appliance (b) Deferrable appliance (c) Interruptible appliance

Figure 4.4: Temporal energy management and load profiles of different appliances

adapt the load profile of the households to follow desirable consumption patterns. These patterns may reflect intermittent generation by RES. Therefore, intelligent appliances and BEMSs promise to increase the energy-efficiency and the environmental sustainability of the overall energy consumption by automated energy management.

4.4.2 Energy Management of Appliance Energy Consumption

The energy consumption of appliances can be optimized in different ways. This includes the deferral of the operating time, the interruption of an operation cycle, alternative modes of the same operation cycle, and the introduction of so-called hybrid or bivalent appliances (see also Section 4.7). This section provides a detailed analysis of these kinds of flexibilities in appliances and introduces the so-called Temporal Degree of Freedom (TDoF) and the Energy-related Degree of Freedom (EDoF) that are exploited by energy management in BEMSs. Based on the detailed analysis, the next section introduces a novel classification of appliances with respect to their qualification for energy management, covering the aspect of temporal as well as of energy-related optimization.

Deferrable Appliances

The operating time of so-called *deferrable appliances* may be shifted by a BEMS, i. e., the starting times of the appliances may be delayed (see Figure 4.4b). Therefore, deferrable appliances are sometimes also called delayable [406] or shiftable [158, 559, 586] appliances. In this thesis, the maximum delay is called degree of freedom and denoted by t^{tdof}. It is usually given by the user, who wants the service of the appliance to be done until a certain point of time, the deadline t^{d}. Thus, the t^{dof} is the time until the latest finishing time t^{d}, reduced by the expected operating time Δt^{o} (see also Figure 4.5):

$$t^{\text{dof,max}} = t^{\text{d}} - t^{\text{now}} - \Delta t^{\text{o}} \,. \tag{4.5}$$

See Section 5.5 and consult Allerding (2013) [10] and Mauser (2014) [406] for more detailed descriptions of the t^{dof}.

Technical Limitations, Statistics, and Data Delaying the appliance operation is possible for dishwashers, tumble dryers, and washing machines, because their service is usually not required immediately. Nowadays, many of these appliances have a time preselection function, which can be activated by the user. Automated BEMSs may optimize and select

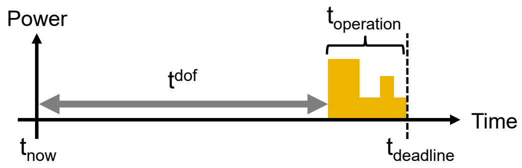


Figure 4.5: Visualization of the temporal degree of freedom, based on [406, Fig. 3]

the initial delay with respect to technical constraints, users' preferences, and optimization objectives. This does not hold true for hobs and ovens, because their service is usually required at once and may not be deferred [406].

In general, more than a third of all users accept any time of delay of dishwashers, tumble dryers, and washing machines if it is no longer than 24 hours. The remaining two-thirds of the users prefer a postponement of up to seven hours. In these cases, two to four hours are accepted most often [417, pp. 28 f.] [570, p. 213]. Other sources identify a maximum delay of up to nine hours for tumble dryers and washing machines and up to 19 hours for dishwashers [244, 465, 490] [570, p. 213]. In [568], about half of the interviewed users were willing to accept a delay of five or more hours.

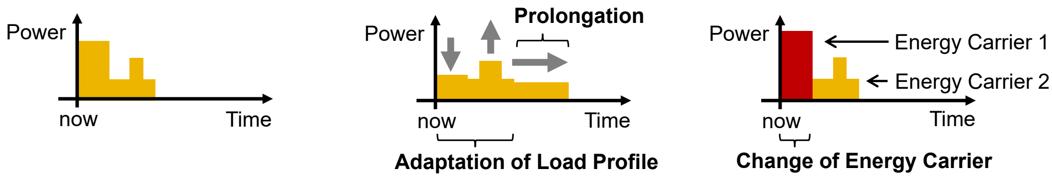
Derived Limitations and Probabilities Based on the values in the literature and the experience gained in trial phases in the ESHL, this thesis assumes a maximum TDoF of twelve hours for dishwashers, tumble dryers, and washing machines (see also Table 4.6). Self-evidently, the TDoF is not always the same but individual for every appliance cycle. Therefore, the actual value is chosen randomly using the following mechanism, which has also been used in [10, 405], leading to an average TDoF of half the maximum value:

- The appliances use the maximum TDoF values in seconds given in Table 4.6 to generate the actually used TDoF randomly.
- The maximum TDoF value $t_j^{\mathrm{dof,max}}$ in seconds is divided by two if the particular appliance j is used more than once at that day.
- The random variable t_j^{dof} is distributed according to the symmetric binomial distribution $B(n, p)$ having a maximum value of $n = t_j^{\mathrm{dof,max}} / 900$ and a symmetric distribution of $p = 0.5$, and using a quantization of 900 seconds:

$$t_j^{\mathrm{dof}} = 900 \cdot B\left(\frac{t_j^{\mathrm{dof,max}}}{900}, 0.5\right). \tag{4.6}$$

- If there is a remaining run from the previous day or more than one run on the current day, the generated runs are checked for potential conflicts. In case of a conflict, i. e., temporal overlap, the maximum TDoF value is halved and the run is randomly generated again.

As a result, the random values of TDoF t_j^{dof} in seconds are distributed according to the symmetric binomial distribution in steps of 15 min, i. e., 900 s, with the accumulation point at half the maximum TDoF, i. e., six hours.



(a) Conventional appliance (b) Alternative profiles (c) Hybrid appliance

Figure 4.6: Energy-related energy management and load profiles of different appliances

Interruptible Appliances and Alternative Load Profiles

The operation cycles of appliances may not only be shifted but also be interrupted (see Figure 4.4c). The maximum interruption is linked to the delay of the starting time, i. e., the TDoF, because a certain latest finishing time of the appliance operation cycle has to be respected. Additionally, there are technically and economically reasonable maximum delays that are based on additional energy losses as well as influences on the service quality caused by the interruptions. These negative effects have to be respected by BEMSs.

According to [422], tumble dryers have an unlimited interruptibility, whereas dishwashers and washing machines have one of about 30 minutes. In contrast, in [480], it is stated that dishwashers and washing machines do not have any interruptibility, whereas tumble dryers have one of about 30 minutes. Nevertheless, because of decreasing washing temperatures, interruptions cause less heat loss and may be even longer than the values stated in the literature. Additionally, dryer may use their convection fan to reduce the heat loss. Therefore, this thesis does not use any special limitations of the interruptions.

Simply put, the sum of all interruptions and the initial delay has to be shorter than the TDoF. If regarding the initial delay as well as the time after finishing the operation cycle as additional interruptions, this is simplified to the following equation for appliances having actually $n-2$ “actual” interruptions:

$$\sum_{i=1}^{n} t_{j,i} = t_j^{\mathrm{dof}}, \quad n > 2 \,. \tag{4.7}$$

Similar to deferrable appliances, automated BEMSs may optimize the duration of interruptions with respect to technical constraints, user preferences, and optimization objectives. Thereby, the TDoF has to be split among the initial delay and further interruptions, which is described in more detail by Mauser et al. (2014) [406].

The interruption of the appliance operation cycle leads to a different load profile. There are also other possibilities to modify the load profile. Appliances may offer alternative

Table 4.6: Maximum temporal degree of freedom of the appliances used in this thesis

Appliance j	**Dishwasher**	**Hob**	**Oven**	**Tumble dryer**	**Washing machine**
$t_j^{\mathrm{dof,max}}$	43 200 s	0 s	0 s	43 200 s	43 200 s

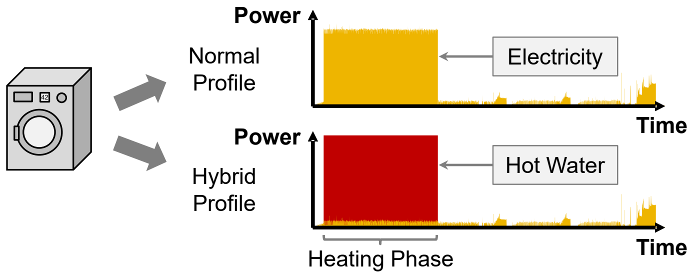


Figure 4.7: Hybrid washing machine using either electricity or hot water in its heating phase, based on [412, Fig. 4]

profiles for the same program (see Figure 4.6b): for instance, the water heating phase at the beginning of washing programs in washing machines may be reduced in its maximum power consumption while being prolonged in its duration and still having about the same energy consumption.

The internal energy management of the appliances may not only offer alternative profiles but also respect given values for the maximum program duration or maximum peak power consumption. Although these kinds of energy management would be possible for all five major appliances, it may not be applicable to certain appliance programs, e. g., the most energy intensive programs such as the grill function of an oven. BEMSs have to decide about which of the profile alternatives to use or which parameters to provide to the appliances. This needs an evaluation of all these alternatives. [406]

Hybrid Appliances

As introduced in Section 4.1.2, the term *hybrid* refers to different properties of devices, systems, and operation modes. This section focuses on single appliances utilizing at least two different alternative energy carriers when consuming energy (see Figure 4.6c). Usually, appliances use only a single energy carrier—mostly electricity—in their energy-intensive processes, which are typically heating phases (see Figure 4.7). In contrast, hybrid appliances use multiple energy carriers. A consistent naming scheme of hybrid appliances (and systems) is provided in Section 4.7.

The introduction of hybrid appliances, i. e., appliances using different energy carriers in their energy-intensive processes, which are typically heating processes, offers a fundamentally different way of modifying the energy consumption. Such appliances may shift energy consumption from one energy carrier to another. Thus, they provide a flexibility that is not only related to time but works across energy carriers. This kind of flexibility is called EDoF. For instance, a hybrid washing machine may heat cold water by means of electricity in an electrical heating element, of gas in a gas boiler, or of hot water in a heat exchanger. Alternatively, it may also directly utilize centrally provided DHW. This offers the possibility not only to use gas instead of electricity but also to utilize thermal energy storage of hot water or DHW in storage tanks.

At first glance, hybrid appliances may be seen as too futuristic. Furthermore, the additional investment costs that are caused by hybrid appliances are hard to estimate.

Nevertheless, many dishwashers and washing machines can already be connected to the building's DHW system and thus substitute electricity with DHW. Table 4.7 gives an overview of the different hybrid modes of appliances, i. e., the energy carrier that may be used in addition to electricity, and the following paragraphs provide more information about hybrid appliances.

Dishwasher Most dishwashers can already be connected to the DHW system. This reduces the amount of electricity that is required to heat the water. To avoid negative impacts by DHW which is too hot, an external mixing unit should be integrated into the dishwasher. Another option is the utilization of heating hot water via a heat exchanger. The usage of hot water may reduce the heating demand by 50 % in case of hot water with at least 50 °C and by up to 100 % in case of water with a temperature of at least 60 °C [570, pp. 77 ff.]. This thesis simulates a hybrid dishwasher utilizing hot water and a heat exchanger.

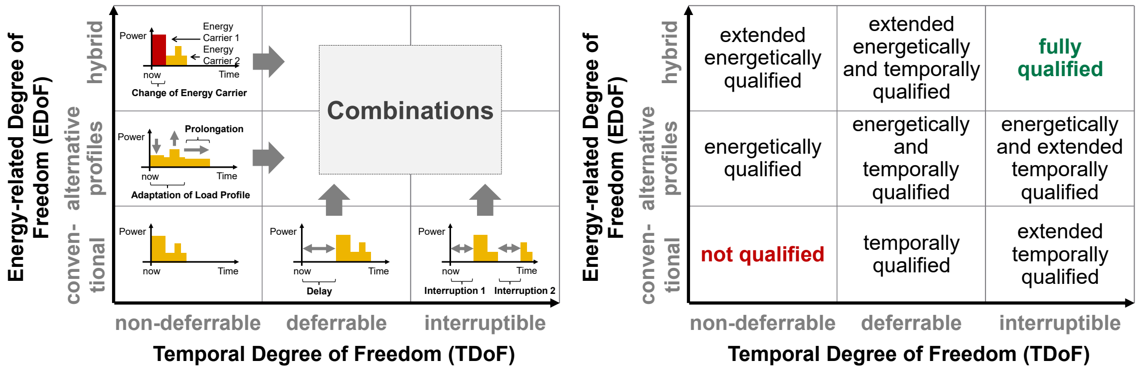
Hob and Oven The combination of electricity and gas heating in hobs and ovens is not widely available, yet. In hobs, hot plates utilizing electricity are combined with separate hot plates utilizing gas. Nevertheless, it would also be feasible to integrate both energy carriers in a single hot plate, which is much more convenient to the user. The same is true for ovens. The combination of electricity and gas in one oven is technically possible, though not widely available [412]. This thesis simulates a hybrid hob and a hybrid oven utilizing electricity and natural gas in a single device.

Tumble Dryer Tumble dryers may be connected to the heating hot water system using a heat exchanger. In so doing, the electricity demand can be reduced by up to 100 % when using hot water having at least 65 °C [570, p. 55]. Another alternative is the usage of natural gas in tumble dryers [570, p. 42]. More information about tumble dryers using natural gas is provided in [28]. However, there are currently no tumble dryers available that use electricity and gas within the same appliance. This thesis simulates a hybrid tumble dryer utilizing electricity or hot water and a heat exchanger.

Washing Machine Similar to dishwashers, washing machines can be connected to the DHW system [533]. According to [570, p. 40], heating by hot water may reduce the electricity demand by up to 50 % in case of hot water with at least 40 °C and by up to 100 % if using water that is as hot as the water required by the washing program, which is now mostly below 60 °C. If using DHW, an external mixing unit is beneficial: it ensures that the water temperature is limited as necessary by the washing program. Alternatively, a heat exchanger may be integrated into the washing machine that utilizes hot water from the heating system. In addition to the utilization of electricity and hot water, it is also possible to use gas.

Table 4.7: Hybrid appliance modes (this thesis: ✓, also possible: (✓), not possible: ✗)

	Dishwasher	Hob	Oven	Tumble dryer	Washing machine
Natural gas	(✓)	✓	✓	(✓)	(✓)
Hot water	✓	✗	✗	✓	✓
Domestic hot water	(✓)	✗	✗	✗	(✓)



(a) Load profiles (b) Qualification for optimization

Figure 4.8: Load profiles and qualification for optimization with respect to the temporal and the energy-related degree of freedom, partly based on [410]

Future hybrid washing machines may integrate multiple heating technologies in a single appliance and thus become hybrid washing machines. This thesis simulates a hybrid washing machine utilizing hot water by means of a heat exchanger.

Appliance Model of Hybrid Appliances Currently, there are no load profiles of real hybrid appliances available. Therefore, this thesis assumes that the energy consumption of the heating phase is about 1.3 times higher when using gas or hot water, respectively, instead of electricity (see Table C.1). This assumption is based on the fact that the utilization of hot water will lead to additional losses in the supply system and in the additional heat exchangers of the appliances. Similarly, tumble dryers utilizing gas have an energy consumption that is up to 40 % higher than conventional ones utilizing electricity [28]. The optimization of hybrid appliances has to decide not only about the operating times but also about the operating modes, e. g., whether to use only electricity or an additional energy carrier. This leads to interdependencies with other devices because of mutual storage tanks or supplier relationships.

4.4.3 Novel Classification of Appliances regarding Energy Management

As introduced in the previous section, appliances may have some kind of degree of freedom that can be exploited by an automated BEMS. This degree of freedom is either a TDoF, i. e., some kind of temporal deferrability or interruptibility (see Figure 4.4), or an EDoF, i. e., variability in the energy load profile for a particular program (see Figure 4.6). Both degrees of freedom cause a deviation of the typical load profile of an appliance.

Usually, energy management has only been done with respect to the TDoF, e. g., by Allerding (2013) [10], Gottwalt (2015) [254], Soares et al. (2013) [561], and Sou et al. (2011) [564] (see also Section 3.4.1). This thesis introduces the EDoF as a second dimension of the energy consumption of appliances, which may be optimized, too. This focuses on the dimension of energy carriers and energy portfolios as well as on device control in terms of the adaptation of the load profile (see Table 3.2 on p. 92).

Based on the load profiles presented in Figure 4.4 and Figure 4.6, this concept of two dimensions in energy management utilizing appliances is depicted in Figure 4.8. The figure visualizes the two dimensions, which may also be combined. They lead to a variety of load profiles that are realized by the same appliance in a single program. BEMSs exploiting both dimensions promise to increase the energy efficiency, diversify the energy utilization in buildings, and enable the flexibilization across the boundaries of energy carriers. Depending on what kind of EDoF or TDoF an appliance has, it is *energetically* or *temporally* qualified for energy management by a BEMS. None of the appliance classifications presented in Section 3.4.1 considers this kind of two-dimensional optimization by BEMSs. [406, 410, 412]

Although this section focuses on appliances, the concept of two dimensions in energy management applies also to HVAC systems. For instance, the operating times and operation mode, e. g., the power output, of microCHPs, chillers, and heat pumps can be optimized while respecting the technical constraints and temperature limits of thermal storage systems. In general, all devices and systems in a smart building have to be optimized with respect to the provision, conversion, storage, and utilization of the energy carriers used within a particular building. Therefore, energy management in buildings shall consider all devices, systems, and energy carriers. This is analyzed in Section 4.6 and a naming scheme for devices and systems utilizing multiple energy carriers is presented in Section 4.7. [406, 410]

4.5 Distributed Generation, HVAC, and Energy Storage

In residential buildings, appliances account only for a small share of the total energy consumption. In commercial buildings, the share is even smaller. In both cases, the major share of the total energy consumption is caused by space heating, space cooling, and the provision of DHW. The energy consumption of HVAC systems may also be shifted temporally and with respect to the utilization of different energy carriers. This is similar to the concept of TDoF and EDoF presented in the previous section. Nevertheless, appliances are utilized by the users in the way of operation cycles, whereas HVAC systems are running permanently and have to provide their services more or less continuously. They have to respect the users' preferences and requirements, e. g., for minimum and maximum temperatures. Not only electricity generation may be decarbonized by RES but also the provision of thermal energy services. Currently, many of them tend to be electrified, e. g., heat pumps and air-conditioning systems become more common, which will increase the interdependencies between the energy carriers [491]. A better usage and an integrated optimization of existing systems is a promising factor to achieve the successful transition of energy systems and make them sustainable.

In addition to HVAC systems, DG systems utilizing conventional energy sources or RES have to be optimized by automated BEMSs, too. They may optimize their operation with respect to, e. g., energy-efficiency, self-consumption, self-sufficiency, and total costs. The energy generation by DG depends largely on the availability of intermittent RES as well as the local requirements for electricity and hot water. Cogeneration systems may only be run efficiently if the electricity as well as the hot water is utilized. Therefore, BEMSs have to predict the future energy consumption of energy services, such as the expected heating or cooling demands, and the future potential of energy generation by RES as well as the limits determined by energy storage capabilities. The prediction capabilities of EMSs may be improved by functionality that learns thermal properties of buildings [491].

This section presents an analysis of systems for DG, HVAC, and energy storage in the context of automated energy management. Additionally, it provides exemplary data that has been collected in our research laboratories and is used for the simulations presented in Chapter 6.

4.5.1 Distributed Generation utilizing Renewable Energy Sources

Nowadays, the DG using RES in residential and commercial buildings does not only include the utilization of water and wind power by small power plants but also of solar radiation by PV systems. Hence, BEMSs have to be able to handle and optimize them all.

Photovoltaic Systems

In recent years, the DG of electricity using PV systems became popular. In Germany in the year 2015, the total generation capacity by PV systems was more than 30 GW [647]. Many of them are installed on buildings and connected to low-voltage grids. Therefore, PV systems shall be included in the energy management and optimization by BEMSs. For instance, BEMSs may exploit flexibilities of the buildings' energy consumption by shifting the electricity consumption of devices and systems to times with high PV generation. Thereby, the self-consumption and self-sufficiency rates may be optimized substantially and support the installation of additional and more powerful PV systems. An overview of the literature about the self-consumption of electricity generated by PV systems in buildings is given in [386]: when using measures of DSM, the self-consumption may be increased by about 2 to 15 percentage points. Additionally, the electricity generation may be optimized with respect to their active and reactive power control strategies [574] or provide ancillary services [63] in the low-voltage distribution grid. In general, the usage of BESS may help to increase the number of PV systems that may be installed in the grid [621].

Recorded PV Generation Profiles The technical data of the PV system at the HoLL is given in Table B.21 on p. 389. Actually, the PV system consists of three independent PV systems, each having a dedicated single-phase inverter and two arrays of PV cells. Although the nominal peak power of each of the three PV systems at the FZI is about 5 $\mathrm{kW_p}$, the maximum feed-in is limited to 4.6 kVA because of the VDE Application Rule VDE-AR-N 4105 by the *Verband der Elektrotechnik, Elektronik und Informationstechnik* (VDE) (English: German association for electrical, electronic, and information technologies). In 2013, this resulted in a total electrical energy generation of about 5300 kWh per phase and the load profile depicted in Figure D.3 on p. 417. Statistical data of the profile, which has been recorded at a resolution of one minute, is given in Table D.12 on p. 417. This thesis uses scaled versions of this profile to simulate the PV generation in residential buildings.
The generation profile of the PV system at the ESHL is atypical because the PV is subject to heavy shading by nearby trees and buildings. This causes a yearly generation that is not only lower than expected but also uncommonly distorted. Therefore, the recorded profiles of the ESHL are not used in this thesis.

Prediction of PV Generation The precise prediction of PV generation is a complex task because it requires a detailed irradiance or weather forecast which is then used to predict the PV profile [381]. Often, artificial neural networks [581, 656] or support vector machines [549] are used to realize predictions. In practical systems, the prediction is often simple. For instance, the prediction of Allerding (2013) [10] uses simply the profile of the previous day as the expected profile for the current day. In the system presented in this thesis, the prediction of the generation by the PV system uses the average generation profile of the previous 14 days. Self-evidently, this kind of prediction is basic and suboptimal, but the development of a detailed PV prediction is not part of this thesis.

The results of various simple PV prediction methods for the profiles recorded at KIT and FZI are given in Table 4.8. They show that using the average of the last 14 days leads to better results than the predictions using only the previous day, the average of the past seven days, or the SLP EV0. The usage of 21 days does not lead to further improvements.

Wind and Water Power

DG systems utilizing wind or water power are out of scope of this thesis. Nevertheless, their generation is also more—in case of wind power—or less—in case of water power—intermittent and has to be predicted and taken into account by BEMSs. The latter may provide the means for DSM reacting on forecast errors of wind power generation or for the load shifting of energy consumption that fits better to the mostly permanent and uniform DG using water power. For instance, the scheduling of BESSs for the mitigation of forecast errors of wind power generation is presented in [73]. This thesis assumes that DG by small wind and water turbines may be integrated similarly to the generation by PV systems.

Table 4.8: Evaluation of simple PV prediction methods showing the *root mean square percentage error* (RMSPE), the *standard error* (STDERR), and the *coefficient of determination* R^2 for profiles recorded at the *KIT Energy Smart Home Lab* and the *FZI House of Living Labs*

Evaluated PV profile	**Temporal resolution of profile**	**Measure**	**Prediction method**				
|	|	|	EV0	Last day	7 d avg.	14 d avg.	21 d avg.
ESHL 2011/12	1 s	RMSPE	.086	.092	.079	**.078**	**.078**
ESHL 2011/12	1 min	RMSPE	.092	.098	.084	**.083**	**.083**
HoLL 2013	1 min	RMSPE	.144	.170	**.140**	**.140**	**.140**
ESHL 2011/12	1 s	STDERR	390	421	362	**355**	359
ESHL 2011/12	1 min	STDERR	383	412	354	**348**	352
HoLL 2013	1 min	STDERR	696	829	683	669	**668**
ESHL 2011/12	1 s	R^2	.586	.570	.643	**.652**	.645
ESHL 2011/12	1 min	R^2	.594	.581	.652	**.661**	.654
HoLL 2013	1 min	R^2	.638	.538	.642	**.655**	**.655**

Bold: best value (row)

4.5.2 Heating Hot Water and Domestic Hot Water System

The heating system of a building has to provide heating as energy service. In general, the maximum heating power of the system should be at least as high as the maximum required heating power of the building. This may not always be the case and lead to a temperature in the building that is lower than the temperature set by the user. This section analyzes boilers and radiators briefly, which are used to generate hot heating water and convert hot water to heated air, respectively. Boilers are used to generate hot water by burning some kind of fuel. There are many types and models of boilers. Typical energy carriers that are utilized by boilers include natural gas, oil, and electricity. The analysis of cogeneration systems is presented in Section 4.5.4.

Fuel-based Boilers In case of boilers burning some kind of fuel, the efficiency, i. e., the heating power output in comparison to fuel input, depends heavily on the technology. So-called condensing boilers may generate more than 100 % energy output per energy input. This is based on a definition of energy input that uses the lower, i. e., net, heating value to determine the power input. Nowadays, condensing boilers are commonly used and non-condensing boilers are becoming rare. This thesis uses a simplified model of a gas-fired condensing boiler having an efficiency of 100 % calculated on the lower heating value (see also Table D.5 on p. 410).

Storage Water Heater and Instantaneous Water Heater Usually, storage water heaters, which are often called boilers, too, and instantaneous water heater are used to generate hot water close to the place of utilization, e. g., near the kitchen sink or the shower. Storage water heaters ensure that the water in a small tank remains within minimum and maximum temperature limits, whereas instantaneous water heaters provide hot water with a certain temperature when required. Most commonly, both types of heaters use electricity or gas as their main input energy carrier. Both types of heaters are not in scope of this thesis.

Electrical Insert Heating Element Typically, electrical IHEs, which are also called *resistance heaters*, *immersion heaters*, or *screw-in heaters*, are used in hot water storage tanks. Often, they are used to support heat pumps in case of low outdoor temperatures or at times of consumption peaks. Recently, they are also more commonly used in combination with PV systems to realize so-called *PV heating*. Some heating elements may only be switched on or off, other heating elements have several adjustable power steps [412]. Technical constraints of the heating elements lead to minimum and maximum on and off periods, e. g., to limit the number of cycles of the relays. This thesis uses an electrical IHE that has a power of up to 3.5 kW in steps of 0.5 kW, i. e., a total of eight discrete power steps, and an efficiency of 100 % (see also Table D.7 on p. 412).

Thermal Storage Heater Thermal storage heaters store sensible heat, e. g., in bricks made of clay. Typically, they use electricity as their input energy carrier. Often, they are also called night storage heaters, because their utilization of electricity has often been shifted to night-time to take advantage of low electricity rates. Nowadays, there are approaches to measures of DSM that use thermal storage heaters, e. g., Gottwalt (2015) [254]. However, they are not explicitly regarded in this thesis.

Heat Pump Heat pumps utilize electricity to transfer thermal energy from a heat source to a heat sink. Typically, heat pumps utilize air, brine, groundwater, or earth as sources. Thus, they use not only electricity but also another energy source to provide thermal energy. Therefore, their Coefficient of Performance (COP), i. e., the generated heat divided by the consumed electricity, is greater than one. Nevertheless, their efficiency heavily depends on the temperature of the heat source and the temperature of the heat sink. This relation is typically non-linear [378]. Nowadays, there are approaches to DSM measures using heat pumps, e. g., [251, 378, 450]. An integration of heat pumps into the OSH is shown in [378].

Solar Thermal System Solar thermal systems use solar heat collectors and utilize sunlight to provide hot water. They comprise collectors that absorb solar radiation and convert it to thermal energy. Nowadays, solar thermal systems are popular for the provision of DHW and the support of heating systems all over the world. Although solar thermal systems are also commonly used in combination with adsorption chillers and may easily be integrated into the BEMS, they are not part of this thesis.

Radiators and Under-floor Heating Systems There are different types of radiators that are used by heating systems to provide space heating. The detailed physical properties of radiators and under-floor heating are rather complicated. Therefore, this thesis simplifies their properties and regards the heating power required for space heating. The space heating demand of a residential building, which is used by the simulations of a smart residential building, is presented in Section 4.2.2.

4.5.3 Air-conditioning and Ventilation System

Air-conditioning includes different kinds of technologies that enable space cooling. Typical technologies include vapor-compression chillers, i. e., heat pumps working the reverse way of heating, and ab- and adsorption chillers. Nowadays, air-conditioning causes a large share of the increasing energy demand in residential buildings [487, Ch. 9]. This thesis demonstrates the integrated optimization of an adsorption chiller and a microCHP that are combined into a trigeneration system. The space cooling demand in a commercial building, which is used by the simulations of a trigeneration system, is presented in Section 4.3.2.

Compression Chillers (Vapor-) compression chillers are heat pumps. Actually, many heat pumps work in both directions, i. e., provide heating or cooling, depending on their operation mode. In case of air-conditioning in the sense of cooling, heat pumps provide heat outbound of the building into the environment. Typically, compression chillers use a vapor-compression refrigeration cycle of a refrigerant undergoing phase changes in an evaporator and a condenser part of the system, which show a non-linear behavior [202]. The COP of compression chillers depends on the temperatures of the refrigerant at the different stages of the refrigeration cycle. These temperatures depend on indoor and outdoor temperature as well as the required cooling power. Therefore, the integration into BEMSs calls for the prediction of all relevant temperatures, which is out of scope of this thesis.

Absorption and Adsorption Chillers Absorption and adsorption chillers utilize hot water to transfer thermal energy from a heat source, i. e., the medium chilling the building, which is usually chilled water, to a heat sink, which is usually cooling water that is subsequently cooled by air using a heat exchanger in a so-called cooler or re-cooler unit for heat rejection. The COP shows a non-linear behavior, which depends on the temperatures of the input hot water, the chilled water, and the cooling water as well as the required cooling power [410]. Hence, these devices show strong interdependencies with other devices and systems (see also Table D.3 on p. 408).

Ventilation Systems Ventilation systems utilize electricity to move, i. e., circulate, and to exchange air and realize filtering, cooling, and moisture control functionality. Therefore, their energy consumption depends on heating and cooling demands as well as all variables that influence the air quality in buildings, such as occupancy by users and device usage. Such a system is demonstrated in Grabowski et al. (2016) [259]. The energy management of ventilation systems is out of scope of this thesis.

4.5.4 Cogeneration: Combined Heat and Power

Cogeneration systems generate electricity and *useful* heat at the same time, i. e., two types of useful energy, from a single fuel. Typical cogeneration systems are based on combustion engines, Stirling engines, or gas turbines with an integrated generator and heat exchanger, i. e., CHPs, or fuel cells that generate electricity and heat from a fuel, such as hydrogen, methane, or methanol. Typically, their efficiencies show a non-linear behavior [229, 482].

Usually, small CHPs—so-called microCHPs—are connected to some kind of thermal storage system that facilitates the decoupling of thermal energy generation from its generation and thus a combined heat and electricity driven operation that enables energy management. The behavior of thermal storage tanks is more closely analyzed in Section 4.5.7.

In addition to cogeneration systems providing heat and electricity, there are other systems providing two energy carriers or energy services, too. For instance, many industrial processes generate secondary energy carriers, such as waste heat or electricity, or waste products, such as unneeded gases. They may be utilized by other processes or purposes [610, p. 34] and therefore included into BEMSs. However, this is out of scope of this thesis.

The following paragraphs present and analyze different technologies and operating strategies more closely that are used for the cogeneration of heat and power in buildings.

Operating Strategies and Control Logic

The operation of cogeneration systems providing electricity and heat may be controlled with respect to one of or both of the provided energy carriers. CHPs that are controlled based on heat requirements are called *heat driven* or *heat-led*, whereas the operation based on electricity requirements is called *electricity driven* or *electricity-led* operation.

The optimization of the operating strategy of a cogeneration system includes the optimization of the provision of electricity and heat as well as their ratio and the overall efficiency of the system while respecting the technical constraints. Often, the optimization is reduced to the decision about whether or when to switch the cogeneration system on or off when respecting minimum and maximum temperatures in a hot water storage tank [11, 88]. In practice, cogeneration systems are usually operated based on heating requirements, i. e., heat-led, or electricity requirements, i. e., electricity-led. Typical decision trees for electricity-led and heat-led operation of different cogeneration systems are provided by

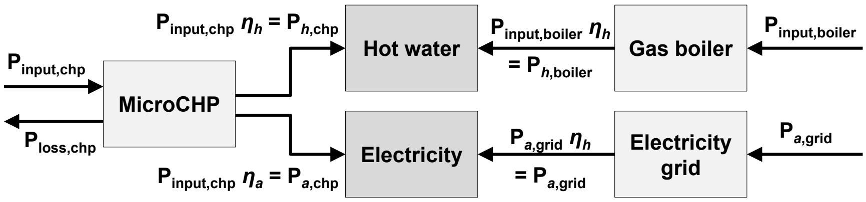


Figure 4.9: Cogeneration using a microCHP as well as the separate generation of electricity and hot water

Hawkes and Leach (2007) [283]. In a sensitivity analysis, they conclude that the operation of cogeneration systems has a high sensitivity to the electricity buyback rate.

In [525], Salgado and Pedrero (2008) present a detailed review of operating strategies of cogeneration systems. They distinguish three main research focuses: on the models of cogeneration systems, on the solution methods for the optimization problems, and on the evaluation of concrete operating strategies. The latter is mainly related to the concrete operation providing heat and electricity in a feasible amount and relation. They conclude that today "the proposition of multi-objective problems is not common in cogeneration systems" [525], which optimize the operation with respect to costs, heat generation, electricity generation, and emissions. Often, the optimization of the operating strategy of a cogeneration system is not properly integrated into the optimization of the overall energy system.

To sum up, BEMSs have to be able to decide about the operating times of cogeneration systems as well as about the operation parameters, such as the ratio of heat to electricity generation and the input of fuel. This leads to a—mostly non-linear—coupling of the energy carriers and thus interdependencies in the optimization.

Efficiency and Technical Constraints

There are several characteristic values of cogeneration systems, which are more closely defined hereafter. The so-called *primary energy ratio* (PER) is the ratio of useful energy, i. e., the sum of thermal and electrical energy $E_{\text{useful}} = \int (P_h + P_a)\,\mathrm{d}t$, to the primary energy input $E_{\text{input}} = \int P_{\text{input}}\,\mathrm{d}t$, i. e., the energy of the consumed fuel [143] (see Figure 4.9):

$$\mathrm{PER} = \frac{E_{\text{useful}}}{E_{\text{input}}} = \frac{\int (P_h + P_a)\,\mathrm{d}t}{\int P_{\text{input}}\,\mathrm{d}t}\,. \tag{4.8}$$

The PER at a certain point of time is also called *total energetic efficiency* η_{total}, *fuel utilization factor* [612, pp. 26 f.], or *energy utilization factor* (EUF) [123] and is equal to the sum of the thermal efficiency η_h and the electrical efficiency η_a:

$$\mathrm{EUF} = \frac{|P_h + P_a|}{P_{\text{input}}} = \frac{|P_h|}{P_{\text{input}}} + \frac{|P_a|}{P_{\text{input}}} = \eta_h + \eta_a = \eta_{\text{total}}\,. \tag{4.9}$$

Consequently, the loss η_w, i. e., the sum of waste heat and electrical loss, is defined as follows:

$$\eta_w = 1 - \eta_h - \eta_a = 1 - \eta_{\text{total}}\,. \tag{4.10}$$

The *CHP coefficient* or *electrical coefficient* σ_a is defined as the ratio of active power and thermal heat power [612, pp. 26 f.]. Analogously, the *thermal coefficient* σ_h [612, pp. 26 f.] is the reciprocal value of the *electrical coefficient*:

$$\sigma_a = \frac{P_a}{P_h} = \frac{\eta_a}{\eta_h} , \quad \sigma_h = \frac{1}{\sigma_a} = \frac{P_h}{P_a} = \frac{\eta_h}{\eta_a} . \tag{4.11}$$

In addition to these characteristic values, the temperatures of the flow and return of the heat transfer medium as well as the mass flow rate are of utmost importance [612, p. 27]. In general, the electrical and thermal efficiencies of real CHPs are not fixed values but depend on, e. g., the energy input, the CHP coefficient, and the flow and return temperatures of the heat transfer medium. Mostly, the efficiencies may be approximated by linear, quadratic, or cubic functions [229, 516]. Thereby, the ratio of thermal to electrical power is nearly linear, whereas the relation between PER and electrical or thermal power, respectively, is non-linear [516]. More information about CHP systems and additional definitions are provided in the VDI Guideline 4608 [609].

In addition to the parameters and the control whether they are switched on or off, CHPs are subject to technical constraints. For instance, engines shall not be switched on and off too often to avoid wear and additional thermal energy loss [96]. This leads to a necessary minimum operating time of the CHPs, which is a common technical constraint [10]. Often, there are also a maximum operating and a minimum off-time that has to be respected after being switched off as technical constraints to avoid overuse. When being switched on or off, CHPs show a typical behavior with respect to electricity and thermal generation. This typical behavior of CHPs during their start-up and shutdown phases is more closely described in [88] and is used in this thesis.

Exemplary MicroCHP: SenerTec Dachs G 5.5 standard

The technical data of the *SenerTec Dachs G 5.5 standard* microCHP is given in Table B.21 on p. 389 and an exemplary run is visualized in Figure D.1 on p. 405. The thermal load profile has been recorded at the HoLL and shows the characteristic behavior of the hot water generation. In case of a cold start, the nominal thermal power is reached only after about one hour. Similarly, after being switched off it takes about two hours until there is no more residual heat left in the engine and thus no more thermal generation by the microCHP. Nevertheless, only about the first ten minutes and last five minutes show a steep gradient of the thermal load profile. Therefore, this thesis simplifies the thermal generation load profile and assumes that there is a linear increase of the thermal power in the ten minutes after switching the microCHP on. Similarly, the thermal power decreases linearly in the five minutes after it has been switched off.

Similar to the thermal generation, the electricity generation is also not strictly rectangular, because the electricity generation does not immediately reach the nominal value. Actually, many microCHPs—depending on the type of the generator—consume electricity for a short period before starting to provide electricity. Afterward, the electricity generation increases slowly before reaching the nominal value. This thesis uses a model of the microCHP having a five-minute period of linear increase from 90 % to 100 % of the nominal electricity generation when being switched on. It neglects the short period of electricity consumption and assumes

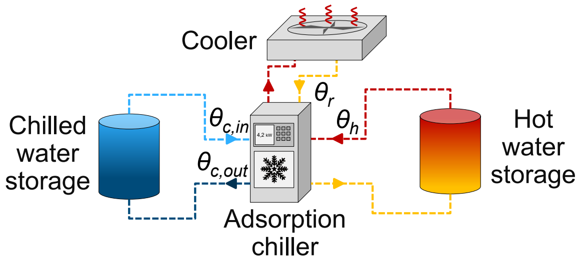


Figure 4.10: Adsorption chiller, cooler unit, and water storage tanks

that the electricity generation stops immediately when the microCHP is switched off. Nevertheless, the model is similar to the model used by Schütz et al. (2015) [532] and may easily be refined in the future. The model is given in Table D.1 on p. 406.

As a result, the model provides the incentive to prefer longer operating cycles because they lead to a higher PER (see Figure D.1 on p. 405): the impact of the lower EUF at the beginning of an operation cycle on the overall PER is reduced.

4.5.5 Trigeneration: Combined Cooling, Heat, and Power Plant

The trigeneration systems considered in this thesis are a combination of a cogeneration system and an ab- or adsorption chiller. In practical trigeneration systems, the CHPs are often supported by solar thermal systems utilizing solar radiation and enabling the generation of chilled water without the generation of electricity. For the analysis of CHP plants, see the previous section. The behavior of thermal storage tanks is more closely analyzed in Section 4.5.7. A typical trigeneration system is depicted schematically in Figure 2.7 on p. 34. Although they have an enormous potential, trigeneration systems are not yet widely used [19]. The smart commercial building scenario in this thesis is based on a trigeneration system (see Figure 4.3 in Section 4.3.2), which is optimized by scheduling the operation periods of the microCHP as well as of the adsorption chiller.

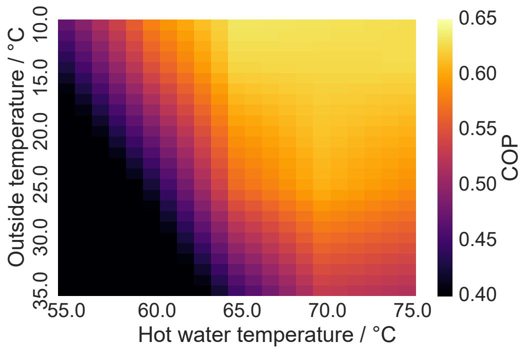
Efficiency and Technical Constraints

The coefficient of performance COP and the energetic cooling efficiency η_c are the ratio of the absolute[2] cooling power $|P_c|$ to the utilized heating power P_h:

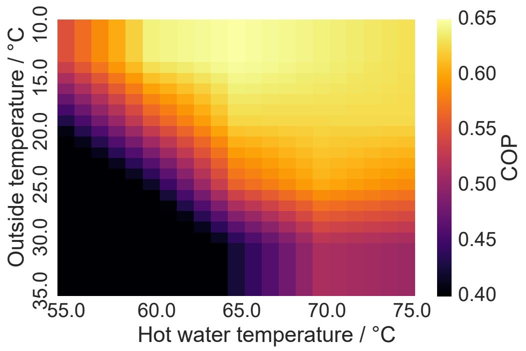
$$COP = \frac{|P_c|}{P_h} = \eta_c \,. \tag{4.12}$$

The COP depends mainly on the temperatures of the input hot water θ_h, the input chilled water $\theta_{c,in}$, the output chilled water $\theta_{c,out}$, the cooling water θ_r, i. e., the water temperature of the condenser circuit from the cooler to the condenser inside the adsorption chiller (see Figure 4.10), and the volumetric flow rates [408]. The interdependency of the efficiency and the temperatures is non-linear and depends on the concrete ab- or adsorption chiller model (see Figure 4.11a) [410]. The following paragraph provides an example of a concrete adsorption chiller.

[2] The cooling power P_c is negative, because an adsorption chiller provides chilled water.



(a) Using Equation 4.13



(b) Using Equation 4.14

Figure 4.11: Efficiency of the adsorption chiller (COP), based on technical data from [321] and measurements in the *FZI House of Living Labs*

Exemplary Adsorption Chiller: InvenSor LTC 09

The trigeneration system at the HoLL comprises an adsorption chiller of the type *InvenSor LTC 09*, custom-made and insulated water storage tanks for hot and chilled water, and a dry cooler of the type *InvenSor BE 24* (see Table B.21 on p. 389 for the technical data). The technical data sheet of the adsorption chiller [321] gives diagrams of the interdependencies between the cooling power and the hot water temperature, the water temperature of the condenser circuit return and the hot water temperature, the cooling power and the hot water temperature, as well as the COP and the hot water power. This data has been used by Feder (2014) [211] and Mauser (2015) [408] to derive a model of the adsorption chiller, interpolating the given values (see Figure 4.11a). This model is also used in this thesis to simulate the chiller (see also Table D.3 on p. 408).

However, this thesis uses an improved model of the dry cooler of the adsorption chiller, which calculates the water temperature of the return flow from the cooler to the actual condenser of the adsorption chiller, i. e., the input cooling temperature θ_{r} (see Figures 4.10 and 4.11), based on the outdoor temperature $\theta_{\mathrm{outdoor}}$. The model is derived from a data set including recordings from the HoLL as well as publicly available temperature data. More information about this data set is given in Table B.22 on p. 390. Non-relevant and invalid data has been removed from the data set using the *pandas* library for *Python* and the script provided in Listing F.12. The outdoor temperatures are based on the so-called *WESTE-XL* data [169] that is provided by the *German Meteorological Office*[3] (German: *Deutscher Wetterdienst*, DWD) for Karlsruhe, Germany. The values are interpolated (linear upsampling) to one minute, i. e., to the same temporal resolution as the data that has been recorded by the thermal meters in the HoLL.

The results for the first and second degree polynomial regression analysis using the least squares method are given in Table 4.9 and visualized in Figure B.3 on p. 391. The coefficient of determination R^2 has a value of 0.382 or 0.392, respectively. Hence, a second degree polynomial regression does not significantly improve the coefficient and thus the linear

[3] `https://www.dwd.de`

model is used in this thesis. The latter shows the following correlation between the outdoor temperature $\theta_{\mathrm{outdoor}}$ and the input cooling temperature θ_{r} in °C:

$$\theta_{\mathrm{r}} = 21.0182\,°\mathrm{C} + 0.4321 \cdot \theta_{\mathrm{outdoor}}\,. \tag{4.13}$$

Nevertheless, the second degree model is beneficial if the outdoor temperature is above 35 °C, because the linear model leads easily to values of the input cooling temperature that are lower than the outdoor temperature and thus not realistic. However, temperatures above 35 °C are very rare in Karlsruhe.

Unfortunately, an analysis of the data set revealed a misconfiguration of the HVAC system controller in the HoLL, which controls the circulating pumps of the cooler. Erroneously, the controller has been configured to a set temperature range of 31 °C to 34 °C of the cooling temperature θ_{r}. This results in a too high temperature of the return flow from the cooler and thus a low COP of the adsorption chiller. Therefore, a more realistic correlation of the outdoor temperature $\theta_{\mathrm{outdoor}}$ and the input cooling temperature θ_{r} in °C is the following:

$$\theta_{\mathrm{r}} = 10.5091\,°\mathrm{C} + 0.8642 \cdot \theta_{\mathrm{outdoor}}\,. \tag{4.14}$$

Depending on the equation, the adsorption chiller has the efficiencies that are depicted in Figure 4.11a for Equation 4.13 and in Figure 4.11b for Equation 4.14.

4.5.6 Electrical Energy Storage Systems

Nowadays, there are many examples of electrical ESSs that are already used or are likely to be widely used in buildings in the near future, e. g., BESSs and bidirectionally connected electric vehicles. In addition to electrical ESSs, there are also systems using electricity when charging but retrieving another form of energy, e. g., thermal energy storage using heat pumps or electrical IHEs. The latter are detailed in Section 4.5.7. The general requirements and modeling are given in Appendix D.11 on p. 416.

Battery Energy Storage Systems BESSs provide a convenient way of storing electrical energy. Although being expensive when compared to pumped-storage, they become more and more popular in energy systems and building energy management because they enable decentralized energy storage. Often, decentralized BESSs are used in combination with PV systems, enabling the storage of electrical energy for times without solar radiation. This calls for an economic sizing of the system [616]. Another option is the usage of BESSs to handle forecast errors of wind power generation [73]. A detailed review of the combination of PV systems, BESSs, and measures of DSM is provided in, e. g., [386]. The integration of a BESS into the BEMS presented in this thesis is demonstrated in Müller et al. (2016) [440].

Table 4.9: Overview of the polynomial regression fitting the relationship between the outdoor temperature $\theta_{\mathrm{outdoor}}$ and the input cooling temperature θ_{r} in °C: $\theta_{\mathrm{r}} = a_0\,°\mathrm{C} + a_1 \cdot \theta_{\mathrm{outdoor}} + a_2 \cdot \theta^2_{\mathrm{outdoor}}$ ($n = 44\,071$)

Regression	a_0	a_1	a_2	R^2	Adjusted R^2	F-statistic
First degree	21.0182	0.4321	–	0.382	0.382	2.719e+04
Second degree	27.2443	-0.1065	0.0110	0.392	0.392	1.423e+04

Electric Vehicles The integration of electric vehicles into BEMSs has been investigated, e. g., in Mültin (2012, 2014) [393, 443], and the intelligent charging of electric vehicles has been subject to many papers, articles, and theses, e. g., [254, 328, 538]. Nevertheless, most of them focus on abstracted scheduling problems of a multiplicity of electric vehicles, while neglecting the specifics of local optimization in buildings comprising DG and a single electric vehicle. In case of so-called bidirectional electric vehicles, the vehicles' batteries may be used in a similar way as local BESSs. Nevertheless, they are subject to additional constraints, which are explained in more detail in [443].

Operating Strategies, Control Logic, Efficiency, and Technical Constraints

Commercially available electric ESSs use mainly methods from control theory and control systems engineering, which define some kind of control logic in a control loop or model predictive control. For instance, the control of a BESS is typically based on local generation and consumption, i. e., the local energy balance, and neglects the prediction of future generation and consumption or variable tariffs. To enable an integrated optimization, ESS systems have to be included in the optimization performed by BEMSs that consider technical limitations of the storage systems as well as variable tariffs and other incentives. [440]

When being integrated into BEMSs, the operation of storage systems, i. e., the charging and discharging has to be optimized, while respecting technical limitations, e. g., the finite capacity of the storage system or power limits for the charging process. One approach is the optimization of the concrete schedule [443, 586], which determines certain charging and discharging cycles that are optimized, e. g., to market conditions. Another approach is the optimization of the parameters of the control logic and the logic itself [440, 658], which enables quick reactions in dynamic systems, i. e., at the run-time of the real system. Self-evidently, both approaches may also be combined, promising even better results that are based on an optimization being both exploitative and flexible.

Usually, BESSs include inverters generating AC power. These inverters that are not only able to provide active power but also reactive power. The reactive power can be used as an ancillary service and change the local voltage. This calls for adequate systems providing this service and combining it with local energy management [620], such as the BEMS presented in this thesis.

In general, electrical ESSs are not only subject to losses when being charged or discharged but also to standing losses, which lead to a certain overall system efficiency. Additionally, there are many technical limitations that have to be respected. For instance, the capacity of storage systems is limited, the charging and discharging processes have certain power limits and load patterns, and there are temperature limits of the systems, which limit their operation [440]. All these constraints have to be respected by BEMSs: the BEMS presented in this thesis paves the way for the integration of them in energy management.

4.5.7 Thermal Energy Storage Systems

The most important method of storing thermal energy is the usage of water storage tanks, which utilize sensible heat storage. They enable the decoupling of hot or chilled water generation, respectively, from the utilization of them by the corresponding energy services.

Another method of thermal energy storage—which is becoming more common in recent years—is the usage of PCMs, which are based on latent heat storage. An overview of the basics of thermal energy storage is given in Section 2.1.6.

Water Storage Tanks

Water storage tanks are common thermal storage devices for the storage of hot and chilled water. This includes water that is used for space heating and cooling as well as DHW. Often, hot water storage tanks for heating hot water and DHW are combined in a single storage tank. Important properties of storage tanks are their capacity, the thermal loss, and minimum and maximum temperatures of the water in the tank. The difference between the maximum and the minimum temperature, the volume V in m^3, the density of water ρ_{water} in $\frac{\mathrm{kg}}{\mathrm{m}^3}$, and the specific heat capacity h_{water} of water, which is about $4200\,\frac{\mathrm{J}}{\mathrm{kg\cdot K}}$ at room temperature, determine the maximum possible stored energy $E^{\max}$:

$$E^{\max} = V \cdot \rho_{\mathrm{water}} \cdot h_{\mathrm{water}} \cdot (\theta^{\max} - \theta^{\min})\,. \tag{4.15}$$

Actually, the specific heat capacity is also temperature-dependent and shows a non-linear behavior, which is neglected in this thesis. Additionally, the input water temperature limits the minimum possible temperature in the storage tank and thus has to be taken into account.

Thermal Loss Practically all storage systems are subject to losses. Some of them occur only when the storage system is charged or discharged, other occur all the time and depend on the state of charge. For instance, the standing loss of water storage tanks depends on the insulation of the tank, i. e., the thermal transmittance, and the temperature difference between the water in the tank and the surroundings and the exposed surface area. Therefore, the heat transfer P_{transfer} in W from the storage tank to the outside depends on the thermal transmittance U in $\frac{\mathrm{W}}{\mathrm{K\cdot m^2}}$, the surface area A in m^2, and the temperature difference $\Delta\theta$ between the outside temperature $\theta_{\mathrm{outside}}$ and the inside temperature θ_{inside} of the tank in °C as follows:

$$P_{\mathrm{transfer}} = A \cdot U \cdot \Delta\theta = A \cdot U \cdot (\theta_{\mathrm{outside}} - \theta_{\mathrm{inside}})\,. \tag{4.16}$$

Actually, the total thermal loss is based on three different kinds of losses: the thermal radiation, the thermal convection, and the thermal conduction. All three kinds of losses are combined in the value of the thermal transmittance U. Self-evidently, the temperature in storage tanks is not homogeneous. Nevertheless, the heat transfer is practically linear in the temperature difference. Therefore, an inhomogeneous distribution of the temperature in the tank having a higher temperature at the top part and lower temperature at the bottom may be simplified using the average temperature in the storage tank or a fixed temperature difference between top and bottom of the tank.

A more detailed model of storage tanks is presented, for instance, in [65, p. 35] and may easily be integrated into the OSH, as demonstrated by Xing (2013) [654]. In [532], Schütz et al. (2015) show that the simple capacity model using a homogeneous temperature may overestimate the efficiency of a heating system and underestimate the operating costs if the temperature determines the working of the heating system. However, this is not relevant when using a given heating hot water demand profile and thus the OSH uses currently the following simplified model. Furthermore, a more detailed model leads to significantly longer computing times [532], which are not longer practicable in the BEMS.

Exemplary Water Storage Tank This thesis simplifies the simulation of storage tanks and assumes a homogeneous temperature of the water. In [200, Annex II], the EU regulation of the labeling of hot water storage tanks provides energy efficiency classes and an approximation of the standing loss P_{transfer} depending solely on the volume V in m^3 and a factor a. For instance, in case of $a = 1$, the equation provides the boundary value between the energy efficiency classes *"B"* and *"C"*. This thesis assumes that the equation is based on a temperature difference of 40 K, resulting in the following equation that is used in this thesis:

$$P_{\text{transfer}} = a \cdot \left(12\,\mathrm{W} + 5.93\,\mathrm{W} \cdot (\frac{1000}{\mathrm{m}^3} \cdot V)^{0.4} \cdot \frac{(\theta_{\text{outside}} - \theta_{\text{inside}})}{40\,\mathrm{K}} \right) . \tag{4.17}$$

In practice, this leads to a standing loss that is comparable to the losses calculated by long-term measurements at the HoLL ($a = 8$) and the ESHL ($a = 1$). In case of the hot water storage tank at the HoLL, Equation 4.17 leads to a standing loss of 31 kWh per day[4] and in the ESHL to 2.3 kWh per day when assuming that there is a constant average tank temperature of 60 °C and an ambient temperature of 20 °C. This is in line [543, pp. 47 & 89] with typical standing losses of thermal water storage tanks and measurements in the laboratories [654]. It results in the modeling given in Appendix D.9 on p. 414.

Phase Change Material

Thermal energy storage in PCMs utilizes mainly latent thermal energy storage, i. e., the phase change of materials at a constant temperature and pressure. For instance, PCM packs in the ceiling may support the air-conditioning that is based on a chilled water circulation system. Basically, the PCM packs stabilize the temperature of the rooms at their nominal temperature and enable energy management by providing additional cooling power at temperatures above this temperature. For instance, in the ESHL, the PCM packs in the ceiling have a nominal temperature of about 24 °C.

The chilled water of an air-conditioning system may "charge" the PCM packs by making them solid. When fully charged, the packs may chill the air in the room without the circulation of additional chilled water, i. e., additional cooling power, if the temperature rises above the nominal melting point. When not fully charged, the packs consume cooling power until they are fully charged. Therefore, PCMs change the thermal capacity of a building and have to be included in the thermal simulation of the building. As they are heavily interdependent with the indoor temperature and the thermal energy flows within the building, the detailed simulation of PCM packs is out of scope of this thesis. Nevertheless, they are implicitly simulated and part of the simulated heating demand of the ESHL. A separate simulation of PCM in the BEMS of this thesis is presented in Tibelius (2014) [583].

[4] The value is comparatively high. It has been validated by measurements and is caused by insufficient insulation of the tanks and the pipes that are used to circulate the water. A value of $a = 2$ is more realistic for correctly insulated and configured systems, leading to a standing loss of 7.8 kWh per day.

4.5.8 Other Relevant Devices in Buildings

In addition to appliances, DG, and HVAC systems, there are several auxiliary devices that are used to enable and to support building energy management. These devices include all kinds of sensors and actuators, such as energy meters, heat flow meters, smart plugs, thermostats, and contact sensors. The following paragraphs briefly explain these devices, their relevance for energy management, and their integration into BEMSs.

Metering and Measurement of Energy Usually, the energy consumption of buildings as well as of individual devices, such as PV systems and microCHPs, has to be measured periodically, i. e., metered, to allow for a billing of the electricity consumption. For instance, the electrical energy consumption is metered by electricity meters and hot water by heat flow meters. In case of energy management, an even more detailed electrical metering of devices by appliance energy meters or smart plugs is often used to obtain detailed load profiles of individual devices. In case of HVAC systems, the information of heat flow meters is used to realize the billing or to improve the controllability of the system. BEMSs have to be capable of combining several meters as well as of enriching the measured data of a metering system with additional information by the metered device. In addition to energy management, such information can also be analyzed to detect patterns and realize preventive maintenance [458] or other safety and security functionality.

Access Control, Detectors, Sensors, Notification, and Warning There are several other devices in buildings that are utilized by building automation, technical building services, and energy management. These devices include the devices listed in Table 4.10. Many of them, such as contact, motion, and volatile organic compounds sensors, are included in BEMSs for simple automation functionality. For instance, the detection of user presence or absence enables the control of HVAC systems deliberately and to reduce energy consumption [44,258]. In commercial buildings, interior lighting is responsible for a large share of the electricity consumption and causes additional heat input. Therefore, the lighting may not only be included in evaluations within the building design phase [439] but also in the optimization of a BEMS, as presented by Braun et al. (2016) [96].

Table 4.10: Devices used for access control, acting, sensing, notification, and warning

Devices	**Examples**
Detectors, sensors	Thermostats, contact sensors, smoke detectors, gas detectors, volatile organic compounds sensors, fire detectors, frost detectors, motion detectors, humidity sensors
Body sensors	Wearables, heart-rate sensors
Actuators	Shutters, light actuators, automatic irrigation systems
Notification, warning, emergency	Displays, horns, warning lights, emergency switches
Access control, surveillance	Locks, cameras, safety light curtains

4.6 Building Energy Management and Operating System

The energy management in buildings has to consider all devices, systems, and energy carriers and provide a holistic and integrated energy management of them. This leads to a complex technical system with a rising number of interconnected entities, such as sensors, actuators, devices, and systems. Typically, complex systems are prone to fatal breakdowns and errors caused by minor disturbances, malfunctions, or emergent effects [442].

Actually, the overall smart grid is an example of a complex system that is still in development [17, 207]. BEMSs will be part of this complex distributed system and thus it is essential to design them with keeping the superior system in mind and facilitate—or even enforce—suitable methods for their abstraction, optimization, and self-adaptivity. Nevertheless, there is no universal approach to the design of complex systems in general [502, pp. 186 f.] or BEMSs in particular. Therefore, this section presents an analysis of the requirements and criteria as well as of the functionality that is required by automated building energy management.

4.6.1 General Requirements of Building Energy Management Systems

Advanced building energy management—such as the management presented in this thesis—has some general requirements and fundamental principles:

- Automated and integrated energy management of multiple devices and systems
- Consideration of all relevant energy carriers in buildings
- Abstraction of subordinate devices and systems
- Abstraction of superior systems and external information
- Abstraction of the BEMS towards superior systems
- Conflict Resolution in distributed systems
- Real-world application and simulation

These requirements and principles are detailed in the following paragraphs.

Automated and Integrated Energy Management of Multiple Devices and Systems The introduction of BEMSs enables the automated management and optimization of the entire local energy system with respect to local objectives. Automated energy management opens a chance not only to monitor the local situation but also to consider changing external signals, such as variable prices, and react accordingly using automated optimization and control. In so doing, BEMSs should work actively and automatically, i. e., mostly without human intervention. The local energy system, i. e., the building, consists of multiple different devices and systems, which have to be optimized in an integrated manner that respects their interdependencies. Therefore, the real devices and their interrelations have to be abstracted and represented by a virtual counterpart in the optimization, using a suitable modeling of the technical and physical properties.

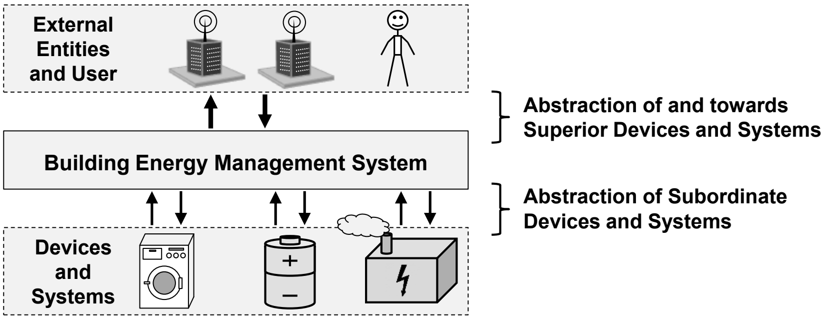


Figure 4.12: The two types of abstraction in a BEMS

Consideration of all Relevant Energy Carriers in Buildings Most energy systems utilize multiple energy carriers. Nevertheless, BEMSs are often limited to electricity or do not consider all carriers on an equal footing. To manage the devices and systems in an integrated manner, a BEMS has to consider all energy carriers that introduce interdependencies, for instance, hot water that is stored in a shared storage tank.

Abstraction of Subordinate Devices and Systems Devices and systems that are managed by a BEMS have to be abstracted in a suitable manner (see Figure 4.12). This includes the abstraction of protocols and communication media as well as the observed information, the data received by the BEMS from the devices, and the control actions that are sent to the devices. Device abstraction reduces the differences of devices and facilitates the optimization of different devices by similar mechanisms and approaches.

Abstraction of Superior Systems and External Information A BEMS has to be capable of abstracting and handling not only subordinate entities but also superior systems and external interfaces and signals. This includes user goals and objectives as well as price signals and other signals, e. g., by the utility or some kind of demand side manager.

Abstraction of the System Towards Superior Systems In particular, if the BEMS becomes part of a larger system and is controlled by a superior entity, the building and its subordinate devices and systems have to be abstracted in a suitable way that allows for their optimization with respect to global goals and—at the same time—local goals, such as the preservation of data privacy. The global goals may easily conflict with the goals of the user, calling for some kind of conflict resolution mechanism.

Conflict Resolution in Distributed Systems In case of hierarchical or multi-level systems, conflicts between different entities are likely to arise, in particular if they have different users providing goals and objectives. Additionally, there may be even conflicts in case of a common goal if multiple entities intend to use the same resources to fulfill it. Therefore, complex autonomic and interacting systems, such as distributed EMSs, call for a conflict resolution mechanism or a certain structure that avoids and handles conflicts. The latter may not only arise within a building and its devices and systems but also between the building and external entities. Therefore, it is beneficial to translate global goals into local goals or incentives that lead to emergent behavior and cooperation.

Real-world Application and Simulation Although the theory of complex systems has made a lot of progress in past years, the techniques and mechanisms for building and managing complex systems call for an extensive evaluation before applying them to critical infrastructure, such as energy grids. To be as close as possible to the behavior of the real BEMS, it shall not only be run in productive buildings but also in high-resolution simulations. Therefore, a dynamic simulation of the BEMS and its optimization mechanisms as well as its integration into the energy grids is necessary. This offers also the possibility to test and evaluate the BEMS before applying it to the real world.

4.6.2 Functionality of Building Energy Management Systems

As briefly introduced in Appendix A.1.2, BEMSs have to provide the following general categories of functions, which are supported by hard- and software but not necessarily automated in systems that work autonomously:

- Observation and monitoring
- Forecasting and prediction
- Simulation and calculation
- Optimization and scheduling
- Operation and control
- Security and privacy management

This thesis emphasizes the importance of automating energy management using BEMSs that provide these functions. They are detailed hereafter.

Observation, Monitoring, Analysis, and State Estimation BEMSs have to provide observation functionality. The observation of a building requires the integration of different data sources. Device abstraction reduces the differences of observed devices and is essential for productive systems in real-world application that comprise different protocols, communication media, and data models. Although different devices may offer the same functionality, they may use different protocols or may be connected using intermediary devices, such as gateways. To enable energy management and optimization, the data provided by the devices has to be monitored and analyzed. This may also include state estimation functionality to estimate the internal states of devices that may not be observed directly.

Forecasting and Prediction Building energy management requires not only the analysis of the current but also forecasts of the future energy consumption and generation. This includes short-term load forecasts to enable operational energy management and measures of DR as well as forecasts for longer terms, such as an entire day, several days or even longer periods, to enable tactical and strategic energy management, e. g., the adaptation of energy contracts. Often, energy data, in particular energy data time series, include regular patterns of change, i. e., seasonality or dependency on other values, such as weather and climate.

Simulation and Calculation Simulation is used to obtain knowledge, i. e., useful information, about the building. It requires the modeling of systems and devices as well as their internal processes and interaction. Additionally, it may require calculations that include optimization routines for certain problems, such as power flow studies. Simulation can be used to obtain forecasts of future behavior under various conditions, e. g., variable tariffs, measures of DSM, and—of course—building energy management. Therefore, it is crucial for the working of optimization and scheduling.

Optimization and Scheduling Buildings have to be optimized with respect to diverse objectives, such as total costs or comfort, and are subject to constraints, such as technical constraints of the devices. In general, the problems have to be formulated as optimization problems and either be solved using an exact solver or be optimized heuristically. The optimization in BEMSs includes scheduling problems as well as the optimization of parameter settings and control sequences. In combination with forecast and prediction, optimization and scheduling enable preventive actions that eliminate potential undesired states.

Operating and Control Similar to observation and monitoring, BEMSs have to enable the operating and control of devices and systems in buildings, i. e., provide the means for controlling devices and systems in a systematic way. The control of subordinate entities by a BEMS benefits from device abstraction, too, because many control sequences may be abstracted to similar actions, such as switching something on or off. In contrast to optimization and scheduling, the operating and control focuses on the usage of static rule sets and control loops, i. e., corrective actions instead of preventive actions. However, it may also include preventive actions focusing on the short-term.

Security, Privacy, and Contract Management BEMSs have to consider and handle security issues and threats, such as vulnerabilities and malicious attacks, and provide the means for contract management. The latter is necessary to enable tactical and strategic energy management, e. g., the adaptation of energy contracts, and to handle energy tariffs that are negotiated at the run-time of the system, such as the voluntary price signals presented by Mauser (2014) [411].

4.6.3 Criteria for the Evaluation of Building Energy Management Systems

The evaluation of automated building energy management requires a set of suitable criteria and metrics. In [579], Syed et al. (2014) name several criteria and metrics for supply and demand coordination mechanisms. This list has been adapted to building energy management, allowing them to be used for the evaluation of automated BEMSs:

- Local building energy management
- Integration of RES, DG, and ESSs
- Support of ancillary services
- Adaptability, flexibility, modularity
- Performance and scalability
- Reliability and robustness
- Privacy and security
- Usability and user-orientedness

These criteria are detailed in the following paragraphs.

Local Building Energy Management A BEMS shall provide some kind of benefit to its user. This may be an economical or some other kind of benefit. Economic benefits include the optimization of the efficiency, an increase in productivity, or financial incentives provided by an external entity, which are exploited by the BEMS. Other benefits include increases in self-consumption, self-reliance, and self-sufficiency. Generally, the BEMS has to be capable of pursuing all goals that are set by the user or some external entity.

Integration and Exploitation of RES, DG, and ESSs A BEMS shall facilitate the integration of DG into buildings and the exploitation of RES. Additionally, BEMSs have to optimize the operation of energy storage in buildings, such as stationary BESSs and electric vehicles. These criteria are closely linked to the local energy management and the support of ancillary services.

Support of Ancillary Services and Global Energy Management Goals A BEMS shall support global energy management goals in energy grids. For instance, it shall enable measures of DSM that support the balancing of the grid and reduce investments in the physical grid infrastructure, providing a benefit to external entities. This includes direct load control but also other approaches to DSM, such as variable energy tariffs (see Section 2.3.4). In addition, a BEMS shall be able to provide ancillary services. These services include frequency, voltage, and reactive control, phase balancing, and congestion management in grids (see Section 2.1.4). Therefore, the BEMS has to be interoperable with other entities in the smart grid.

Applicability, Adaptability, Flexibility, and Modularity A BEMS shall be capable of supporting all kinds of different scenarios. This includes not only different devices and systems but also different regulatory regimes and pricing schemes. Additionally, the scenario of a certain BEMS may change dynamically over time, e. g., because new and previously unknown devices are included into the management or the user changes the goals of the system. This has effects on the optimization: its problem has to be composed at the run-time of the system, because the scenario is not completely known at the design-time of the system and may change over time. A modular approach towards the integration and optimization of devices enables a customizable BEMS that is adaptable and flexible.

Performance and Scalability A BEMS shall have a suitable computational performance because a frequent rescheduling is likely and quick responses are desired by the user. Actions of the BEMS do not have to be optimal, because productive systems have to handle a dynamic environment that requires a rolling horizon and continuous re-optimization. The performance has to be able to handle different and potentially increasing numbers of devices and systems. In addition, indirect measures of DSM that are enabled by BEMSs, such as variable tariffs, are one way to achieve scalability in smart grids.

Reliability and Robustness A BEMS shall be reliable and provide robust optimization results. For instance, due to some kind of failure, a BEMS may be disconnected from the Internet. This may lead to undesired effects, in particular if the optimization, prediction, or control logic are run outside of the building or use external information, such as weather forecasts. In addition, there is uncertainty with respect to all kinds of predictions and forecasts, e. g., the future electricity demand in the building or the outdoor temperature. A BEMS has to cope with the uncertainty and provide a robust behavior.

Privacy and Security A BEMS shall protect the privacy of the user and ensure security of the user and the BEMS. For instance, communication with external entities may lead to privacy and security issues. The risks may be reduced by following the principles of data reduction and data economy, avoiding the collection of unnecessary data, and limiting the communication with external entities as far as possible.

Usability and User-oriented Operation A BEMS shall be user-friendly in its configuration, parametrization, and operation. This may be realized by capabilities that are similar to “plug-and-play”. The user has to be able to specify their personal goals and adapt the system to the buildings and its devices and systems. In addition, the BEMS has to provide a convenient user interface that supports the users in understanding the actions of the BEMS.

4.6.4 Automated Building Energy Management and the User

In addition to measures of DR, there are also measures of energy efficiency and energy conservation (see also Section 2.3.4 and Figure 2.11 on p. 41). Typically, the latter are DSM measures that apply to the properties of the devices and systems, the building structures, and the users’ behavior. Such measures include energy taxes, standards, building codes, regulation, user information and feedback, energy labeling of devices, and energy audits. In addition to these measures, there are other factors that support energy efficiency and conservation, e. g., policies, economic strategies, and the promotion of research and development [380]. Although these measures work without automated energy management, BEMSs should be capable of supporting these measures. Therefore, some of them are described in the following paragraphs, while also analyzing the requirements for BEMSs.

Regulation and Standards In order to reduce the consumption of buildings and devices, governments frequently use building codes and energy efficiency regulations that set minimum standards for them. These kinds of regulations are energy efficiency and conservation measures that lead to permanent effects. Nevertheless, they enable only an increase of energy efficiency and a reduction of the energy consumption but do not facilitate the flexibilization of energy consumption that helps reacting on intermittent generation by RES.

Feedback and Behavioral Change The behavior of users is crucial for reductions of energy consumption and improvements related to energy efficiency. Therefore, behavioral change is an import measure of realizing them [379, 380]. Feedback about energy consumption and costs facilitates such changes in residential as well as in commercial buildings [147, 210]. To enable feedback to the user, energy metering and monitoring systems, intelligent appliances, and ICT are necessary prerequisites. The forms of direct feedback include not only displays showing the current values as well as reports and visualizations of historic values but also elements of gamification (see paragraph about gamification below). In addition to direct feedback, i. e., consequence information, there is also general information [650]. For instance, Darby (2006) [147] analyzes the savings of direct feedback, e. g., immediate visualization on displays, and indirect feedback, e. g., frequent billing, concluding that direct feedback of the consumption, tariff, and CO_2 emissions are important for a lasting behavioral change.

Visualization The permanent visualization of energy consumption and energy service usage on local display is a method that is frequently used to facilitate energy saving and improvements of energy efficiency. Wood and Newborough (2003, 2007) [650, 651] evaluate different methods of presenting energy consumption and appliance usage on local displays. In [651], they provide an extensive summary of options to structure and present relevant information as well as motivational factors when building a display that provides information related to energy consumption and device usage.

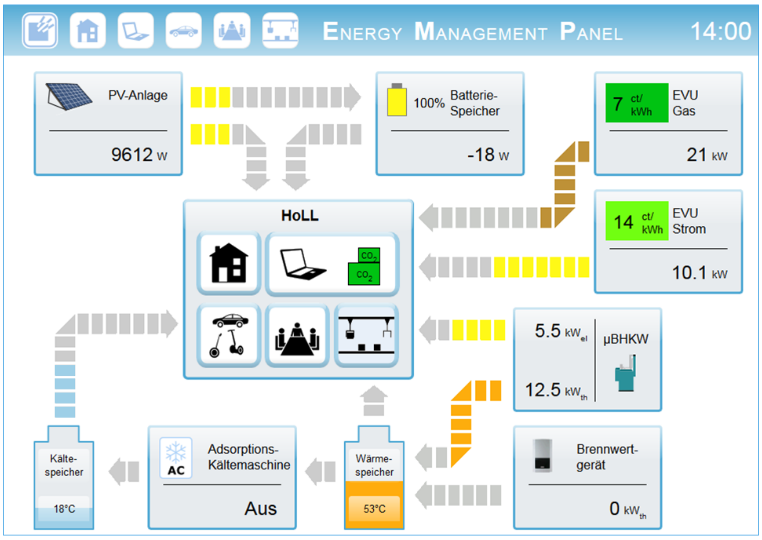


Figure 4.13: *Energy Management Panel*: Visualization of the energy flows of different energy carriers in the *FZI House of Living Labs* (electricity: yellow, natural gas: brown, hot water: orange, chilled water: blue), based on Becker (2014) [60, Fig. 4.5]

Faruqui et al. (2010) [210] review the effects of local displays in a dozen pilot programs and conclude that direct feedback by local displays enables energy savings of about 7 %, which is consistent with previous findings of similar works. A detailed evaluation of the interaction of users with local displays is presented by Hargreaves et al. (2010, 2013) [279, 280].
Karjalainen (2011) [337] evaluates several prototypes of local displays and concludes that providing a curve of the consumed energy in kWh per period of time is more useful than giving only the current power. Additionally, the costs per period as well as a detailed breakdown of the costs and consumption per appliances are shown to be useful.
In [82], Bonino et al. (2012) present the results of an online survey including about 1000 participants and evaluating a local display which shows a detailed floor plan of a residential building that has the rooms colored depending on the respective energy consumption. Their results show that the users prefer goal setting, which is described in more detail in the paragraph about gamification below, to mere direct feedback, such as curves and bars.
Palensky and Dietrich (2011) [469] name several important requirements and calculations, such as a suitable data acquisition and application infrastructure, interfaces for the visualization and configuration, and the calculation of statistical values.
In [60], Becker (2014) presents a concept for the visualization, configuration, and parametrization of BEMSs utilizing a local display being called EMP. The main view of the display used in the HoLL is shown in Figure 4.13 and visualizes the energy flows of multiple energy carriers. The data acquisition is realized by means of the system presented in this thesis.

Gamification Based on visualization and interaction with the user, the concept of *gamification* creates motivational factors by means of competition and comparison with the users themselves, i. e., historical values and changes, and with other users based on goal setting and financial as well as non-financial rewards. All these methods have proven to lead to intended changes of the user's energy consumption [651]. Thus, BEMSs have to be able to provide the necessary data to displays and support the user in reaching the (self-)set goals.

BEMSs may provide the means, i. e., the back end, to operate and manage the monitoring infrastructure, the databases, and user interfaces. Since many of the typical calculations that are presented to the users are also necessary for prediction and machine learning methods in energy management, it is rational to calculate the data in the BEMS and provide it to the corresponding visualization.

User Acceptance

Social science provides advice for systems that are likely to gain user acceptance. Mostly, the literature focuses on residential buildings because the user acceptance and the acceptability of data collection are seen more critically in private life [228]. In [150], Davidoff et al. (2006) present several principles for design of control systems in buildings:

- Organic evolution of routines and plans.
- Construction of new and modification of existing behaviors.
- Understanding of periodic changes, exceptions, and improvisation.
- Design for breakdowns.
- Consideration of multiple and potentially conflicting goals.
- Participation in the construction of identity; a building is more than a location.

Friedewald et al. (2005) [227] have a slightly different focus and name the following general principles to be of utmost importance in smart residential buildings:

- Support of a happy, healthy, and safe life.
- Integration of home, work, learning, and leisure activities.
- Automatic execution of tasks and managing of the house.
- Hide the technical details and complexity.

In [421], Meyer and Rakotonirainy (2003) emphasize the importance of the following general requirements in residential building environments:

- Usability, usefulness, and no administration.
- Social acceptance and privacy protection.
- Low costs.

These principles and requirements above have to be respected when designing a BEMS, which has to interact successfully with and be accepted by the users [466] when working in different environments and with different devices and sub-systems.

User-centric and User-respecting Energy Management Systems

Although building energy management may be realized using an *automated* BEMS, the system has to be user-centric and user-respecting. Users have to be able to provide their objectives and goals to the BEMS. Most buildings have multiple occupants or users and usually these users have “multiple, overlapping and occasionally conflicting goals” [150], which have to be taken in account and resolved by the BEMS. The BEMS has to follow the goals and take also changes and exceptions into account [150]. Finally, the BEMS has to support the users in understanding the reasons for and “the consequences of the automated actions” [491] as well as to allow for manual interventions and active participation by the users [49]. For instance, users have to get accustomed to dynamic tariffs, understand the reasons for automated actions, and learn to accept them, which is supported if they remain capable of overriding decisions of automated systems manually [148].

4.6.5 Building Operating System

ICT systems in buildings may not only be used for energy management but also for services from other domains that realize, e. g., assistance, comfort, entertainment, information, safety, and security functionality. Therefore, a BEMS may be based on a BOS, enabling a wide range of applications that utilize the devices and systems in a building to make it smarter than the usual building. Basically, the idea of a BOS emphasizes the importance of several elementary and supporting services that have to be provided by a system to enable energy management, such as logging, access control, or error handling.

Requirements of Operating Systems Silberschatz et al. (1998) [550] define five elementary services of OS:

- Program execution: load and run programs.
- I/O operation: perform input and output operations.
- File-system manipulation: create, read, write, and delete files.
- Communication: information exchange with other systems.
- Error detection: detect errors in hard- and software.

In addition to these elementary services, three supporting services ensure efficiency when operating a system [550]:

- Resource allocation: allow for multiple users or parallel jobs.
- Accounting: record usage statistics.
- Protection: access control to system resources.

Typically, a BOS runs on top of a normal OS and thus may also be called *meta-operating system* [514]. Buildings are dynamic environments that require management systems that support adaptation [361]. This adaptivity may be facilitated by the BOS: the BEMS utilizes the BOS for auxiliary services, such as device abstraction or data storage.

4.7 Multi-modal Energy Management of Hybrid Devices and Systems

The optimization of multiple energy carriers at a building level promises to optimize and exploit the energy provision, conversion, storage, distribution, and utilization in buildings by considering all energy carriers in an automated BEMS: this is named *multi-modal energy management* in this thesis (see Section 4.7.3) and is done in systems that are called, e. g., hybrid energy systems [131, p. 294] or multi-energy systems [394]. Table 4.11 shows an overview of the multitude of terms that are used in this context.

Multi-energy and hybrid energy systems allow for a flexible provisioning, distribution, conversion, storage, and utilization of energy carriers and services. Although their selection and optimization has to respect interdependencies as well as individual constraints, the integration enables to overcome individual availabilities, intermittencies, limitations, uncertainties, and risks of the energy carriers. At the same time, it increases the overall performance economically and environmentally [201, 394]. In summary, it helps to make "the most out of different energy carriers" [129, pp. 23 ff.] and enable measures of DSM that allow shifting energy utilization across the traditional boundaries of energy carriers [395].

The concept of a smart grid (see Section 2.3.2) is not limited to the electricity grid: a truly smart grid includes all energy carriers and thus is sometimes called *smart energy grid* [19, p. 124]. The integration of the different grids into a combined *multi-energy smart grid* will provide additional opportunities. For instance, it provides a holistic view on all energy carriers and enables additional flexibilities by shifting energy consumption and generation, respectively, from one energy carrier to another. This thesis emphasizes the importance of including all energy carriers in a single smart grid and optimizing them in a suitable integrated manner, which is named *multi-commodity optimization* (see Section 4.7.4).

This chapter first analyzes the different terms that are already used in the energy management of multiple energy carriers and the operation of devices and systems utilizing or providing multiple carriers, before presenting a consistent naming scheme for the utilization, distribution, conversion, storage, and provision of multiple energy carriers, sources, and services in energy systems. Afterward, this thesis introduces and defines the terms *multi-modal energy management* and *multi-commodity optimization*. Finally, the similarities of different energy carriers and energy flows are highlighted.

4.7.1 Bivalent operation, Hybrid Devices, and Multi-energy Systems

There is no consistent terminology, neither in the context of energy management of multiple energy carriers in energy systems nor in the context of devices and systems utilizing or providing multiple energy carriers or services. An overview of the terms that are typically used in the context of multi-energy utilization, distribution, and provision is given in Table 4.11. In addition, there is no common definition of *multi-valent* or *hybrid* devices and device operation in the literature and in practice. For instance, the terms may refer to properties, such as the utilization of different energy carriers, the usage of different energy sources, the combination of different conversion technologies in one system, and the provision of different energy services by the same device.

Monovalent, Bivalent, Multi-valent, and Hybrid Devices

Kulcar et al. (2008) [365] and Ochsner (2012) [460] name three different operation modes of heat pumps: *monovalent*, *bivalent alternative*, and *bivalent parallel operation*. These operation modes are detailed in the following paragraphs:

Monovalent Operation The main heating component, i. e., the heat pump, operates without any auxiliary heating component, e. g., electrical IHE. Actually, it uses two energy carriers: electricity and environmental heat from air, groundwater, or ground. Nevertheless, the latter is usually not handled as a separate energy carrier.

Bivalent Alternative Operation There are two main heating components that work alternatively: above a certain temperature limit only the heat pump is operated and below the temperature only the other heating component is used, e. g., a gas or oil boiler or an electrical heating element. In some cases, the operation of two heating components using the same energy carrier is called *mono-energetic* [614] and separated from bivalent operation modes using two different energy carriers.

Bivalent Parallel Operation The main heating component, i. e., the heat pump, is used in parallel with another heating component when the heating power of the main component does not provide sufficient supply. Often, an IHE element is used to generate the supplementary heat and thus the operation is in this case actually mono-energetic, i. e., limited to a single energy carrier, because electricity is the only energy carrier except from environmental heat.

In addition to these operation modes, the terms *bivalent storage*, *hybrid device*, and *hybrid appliance* are used in literature, patents, and practice. In the context of heating appliances, the terms *monovalent*, *bivalent*, *bi-thermal*, and *hybrid* appliances are used in the standard EN 12309 [175, 176]: Monovalent appliances have a single heating component. Bivalent or bi-thermal appliances comprise a main and an auxiliary heating component or alternatively two main heating components that are assembled into a single appliance. The auxiliary heating component is used when the required heating power is higher than the maximum power provided by the main component. The appliance is called hybrid if there is some

Table 4.11: Terms used for energy management of multiple energy carriers

Term	**Exemplary references**	**Term (cont.)**	**Exemplary references**
Dual-fuel	[447]	Multi-generation	[124, 394, 395]
Integrated energy systems	[520, 657]	Multi-modal	[129, 420, 582]
Hybrid	[56, 129, 175–177]	Multi-service	[394, 435]
	[201, 351, 447]	Multi-source	[286]
Multi-carrier	[236, 250, 492]	multi-product	
Multi-commodity	[2, 74, 75, 358, 396]	Multi-valent / bi-valent	[175–177, 390]
Multi-energy	[201, 394, 402, 433]	Multi-vector	[252, 376, 394]
Multi-fuel	[18, 308, 394]	Polygeneration	[398]

kind of device management that optimizes energy costs and emissions when operating the two main heating components [175, 176, 447]. Several additional examples are given in the following paragraphs.

Bivalent Storage In the VDI Guideline 6002 [613], the term *bivalent storage tank* refers to storage using different devices connected to the same tank and is defined as follows:

> "[A] [b]ivalent storage tank [...] [is] divided into two sections which are charged from different energy systems. Example: Solar energy is supplied to the lower section, conventional energy to the upper section." [613]

Such a bivalent storage is often a stratified storage tank. For instance, the stratified hot water storage tanks in the HoLL are completely charged by the microCHP, whereas the condensing boiler charges only the upper part of one of the tanks. Similarly, the hot water storage tank in the ESHL may be completely charged by the microCHP, while the electrical IHE charges only the upper part of the tank.

Hybrid Device and Hybrid Appliance A heating device with a bivalent alternative operation that uses two different energy carriers—in addition to environmental heat—is also called *hybrid device* [56, 177]. Usually, such devices combine a heat pump with a gas or an oil boiler. The former is used when the outdoor temperature is above a certain temperature limit, i. e., whenever the heat pump has a high efficiency, and the latter is run when it is below this limit. Sometimes, the temperature limit is calculated based on the current electricity and gas prices or the total emissions (see also above). Additionally, bivalent heating installations using heat pumps are sometimes realized using a heat pump and solar thermal collectors that switch at a certain temperature from bivalent parallel to bivalent alternative operation [390].
In addition to this definition of hybrid devices, the term *hybrid heat pump* is also used for heat pumps that use multiple sources of environmental heat, e. g., brine-to-water and air-to-water as well as air-conditioning systems that combine compression and ab- or adsorption cooling processes [351]. In [74], the term *hybrid energy appliance* is used for heat pumps and CHPs because they utilize or provide electrical as well as thermal energy.
The patent EP2025802A2 [100] describes a *hybrid dryer* combining an electrical heating element with a heat pump. Actually, the term dryer refers in this patent to any kind of tumble dryer, washer-dryer, i. e., the combination of washing machine and tumble dryer, or dishwasher.

Hybrid Summary

To sum up, in the literature, the term hybrid refers to one of the following properties:

- Utilization of at least two energy carriers (in addition to environmental heat)
- Utilization of different (environmental) heat sources
- Usage of different conversion technologies for the same carrier in one device
- Distribution and storage of multiple energy carriers in a combined energy grid
- Provision of multiple energy services by a single device instead of different ones

Hence, there is no common definition of multi-valent or hybrid devices and device operation in literature and practice. Therefore, a consistent terminology of appliances with respect to their usage of energy carriers and their provision of energy services is provided hereafter.

4.7.2 Terminology in the Context of Multi-energy Systems and Energy Management

The terms that are commonly used in the context of energy management of multiple energy carriers are listed in Table 4.11. The publications do not use these terms consistently: Sometimes, different terms are used for the same thing, or the same term is used for different things. Therefore, Table 4.12 presents an analysis and categorization according to the usage of the terms in different publications. The table shows the usage of the terms in different parts of the energy chain, i. e., the utilization, distribution, conversion, storage, and provision of different forms of energy by devices and systems.

It is important to note that the meaning of energy utilization and energy provision depends on the perspective (see also Figure 3.2 on p. 60): In case of the conventional external view on an energy system, there are an inbound energy utilization going into the system and an outbound energy provision going out of the system. From an internal perspective, the energy entering the system is called provision, whereas the energy leaving the system is called utilization. This is summed up in Table 4.13 and depicted in Figure 4.14.

Table 4.12: Multi-energy carrier utilization, distribution, and provision vocabulary and naming in the literature

Reference	**Utilization**	**Distribution, conversion, storage**	**Provision**
Adhikari and ↪ Manfren (2012) [2]	–	Multi-commodity	–
Blaauwbroek ↪ et al. (2015) [74, 75]	Multi-commodity	Multi-commodity	Multi-commodity
Chicco and ↪ Mancarella (2009) [124]	–	–	Multi-generation
Fabrizio et al. (2010) [201]	Multi-energy, hybrid	Multi-energy, hybrid	Multi-energy, hybrid
Geidl (2007) [236]	Multi-carrier	Multi-carrier	Multi-carrier
Good et al. (2015) [252]	Input energy vector		Output energy vector
Hemmes et al. (2007) [286]	Multi-source	–	Multi-product
Kok et al. (2005) [358]	Multi-commodity	–	Multi-commodity
Mancarella (2014) [394]	Multi-fuel, multi-energy	Network perspective, multi-energy	Multi-service, multi-energy
Molitor et al. (2014) [433]	Multienergy	Multienergy	Multienergy
Näslund (2013) [447]	Hybrid	Hybrid	–
Thiem et al. (2015) [582]	Multi modal	Multi modal	Multi modal

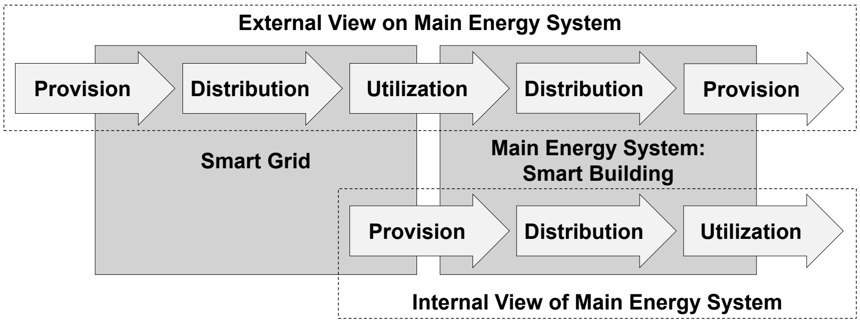


Figure 4.14: Internal and external view on an energy system and its energy flows

Proposed Terms for Multi-energy Systems and Hybrid Devices

This thesis presents a consistent naming and terminology of devices, systems, and their functionality with respect to the utilization, distribution, conversion, storage, and provision of energy carriers as well as the provision of energy services. In general, this is summarized by the following stages of the energy chain that are separated to be able to achieve a consistent terminology:

1. Utilization of at least two alternative energy carriers or energy sources.
2. Distribution of multiple energy carriers or by means of multiple links.
3. Conversion using different technologies utilizing the same energy carrier in one device.
4. Storage of different energy carriers or by means of multiple energy storage technologies.
5. Provision of multiple energy carriers or services by one device instead of multiple ones.

Based on a review of literature, a deep analysis of energy systems, and experience in the realization of a BEMS, this thesis proposes the terminology given in Table 4.14. The proposed terms use a naming scheme based on the utilization, distribution, conversion, storage, and provision of multiple energy carriers, sources, links, storage systems, and services from the external view onto energy systems.

In case of the utilization of energy carriers, one has to distinguish whether there are multiple sources of possibly the same energy carrier or whether there are multiple different energy carriers that are utilized by a single energy system. The distribution of energy within the energy system may be using multiple different energy carriers or offer the possibility of using alternative links, i. e., routes within the energy chains. The conversion of energy carriers in the energy chain may include multiple different energy carriers, stages of the

Table 4.13: Terms and perspectives in multi-energy provision and utilization

Description	Into the system	Out of the system
Energy portfolio (see also Figure A.5 on p. 359)	Inbound provision	Outbound provision
External view on energy system (conventional)	Utilization	Provision
Internal view of energy system	Provision	Utilization

conversion process, or conversion technologies. When regarding the storage of energy in the system, there may be the possibility to store different energy carriers or to use different ESSs, e. g., technologies, when storing a single energy carrier. Finally, the energy system may provide multiple energy carriers or different energy services. Self-evidently, the multi-energy devices may also combine several of these aspects. Although basically all devices and systems consume also electricity for, e. g., controllers, valves, or pumps, this utilization of electricity is not relevant for the classification with respect to the given terminology, because it is related to auxiliary functions only.

For instance, a CHP system utilizing gas to provide hot water and electricity is a multi-carrier provision system. When including a hot water storage tank with an electrical IHE into this kind of energy system, the system becomes also a multi-carrier utilization system. A trigeneration system comprising a CHP, storage tanks, and an adsorption chiller includes additionally multi-stage conversion and multi-carrier storage. If defining the heating and cooling system of a building to be the energy system, this energy system is actually a multi-service provision system because the focus is then on the provision of space heating and space cooling, which are energy services rather than energy carriers. Exemplary building energy systems and their classification with respect to this terminology are given below.

Hybrid Devices and Systems The meaning of hybrid devices and systems may now be clarified using this terminology: A hybrid washing machine utilizing electricity or hot water

Table 4.14: Proposed terminology for the utilization, distribution, conversion, storage, and provision of or by multiple energy carriers, sources, links, storage systems, and services from the external view onto an energy system

Description	**Proposed term**
Utilization (general)	Multi-utilization
Utilization of multiple energy carriers	Multi-carrier utilization
Utilization of multiple energy sources	Multi-source utilization
Distribution (general)	Multi-distribution
Distribution using multiple energy carriers	Multi-carrier distribution
Distribution using multiple links	Multi-link distribution
Distribution using multiple technologies	Multi-technology distribution
Conversion (general)	Multi-conversion
Conversion of multiple energy carriers	Multi-carrier conversion
Conversion using multiple stages	Multi-stage conversion
Conversion using multiple technologies	Multi-technology conversion
Storage (general)	Multi-storage
Storage of multiple energy carriers	Multi-carrier storage
Storage in multiple energy storage systems	Multi-system storage
Storage using multiple technologies	Multi-technology storage
Provision (general)	Multi-provision
Provision of multiple energy carriers	Multi-carrier provision
Provision of multiple energy services	Multi-service provision

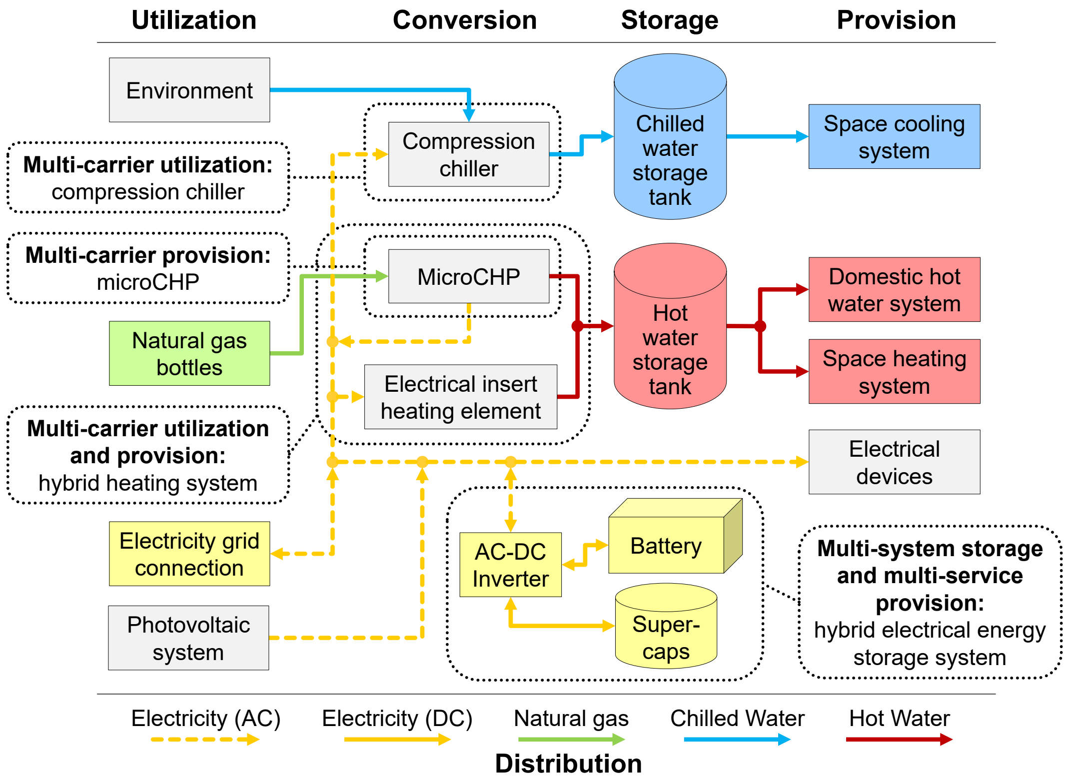


Figure 4.15: *KIT Energy Smart Home Lab*: utilization, distribution, conversion, storage, and provision in the local multi-energy system

is a hybrid with respect to multi-carrier utilization; a hybrid microwave oven providing not only microwave cooking functionality by means of a magnetron but also convection cooking by heated air is a hybrid appliance with respect to multi-service provision.
However, this terminology is not sufficient for all kinds of systems. Hybrid systems may comprise sub-systems that are independent, i. e., sub-systems that work independently and may actually be separated, or are deeply integrated and practically indivisible. An example of the latter is a heat pump utilizing the waste heat in the exhaust gases of a gas boiler [447], whereas a heat pump with an electrical IHE is an independent hybrid system, because both sub-systems, i. e., the actual heat pump and the electrical IHE may also work independently. Therefore, hybrid systems may also be distinguished whether they consist of *independent* or *integrated*, i. e., indivisible, sub-systems.

Exemplary Multi-energy Systems

To exemplify the definitions and the proposed terminology that are provided in Table 4.14, the energy systems of the ESHL and the HoLL are illustrated in the Figures 4.15 and 4.16.

KIT Energy Smart Home Lab The local energy system of the ESHL is depicted in Figure 4.15. The microCHP enables *multi-carrier provision* of electricity and hot water. In combination with the electrical IHE, it is actually a hybrid heating system facilitating

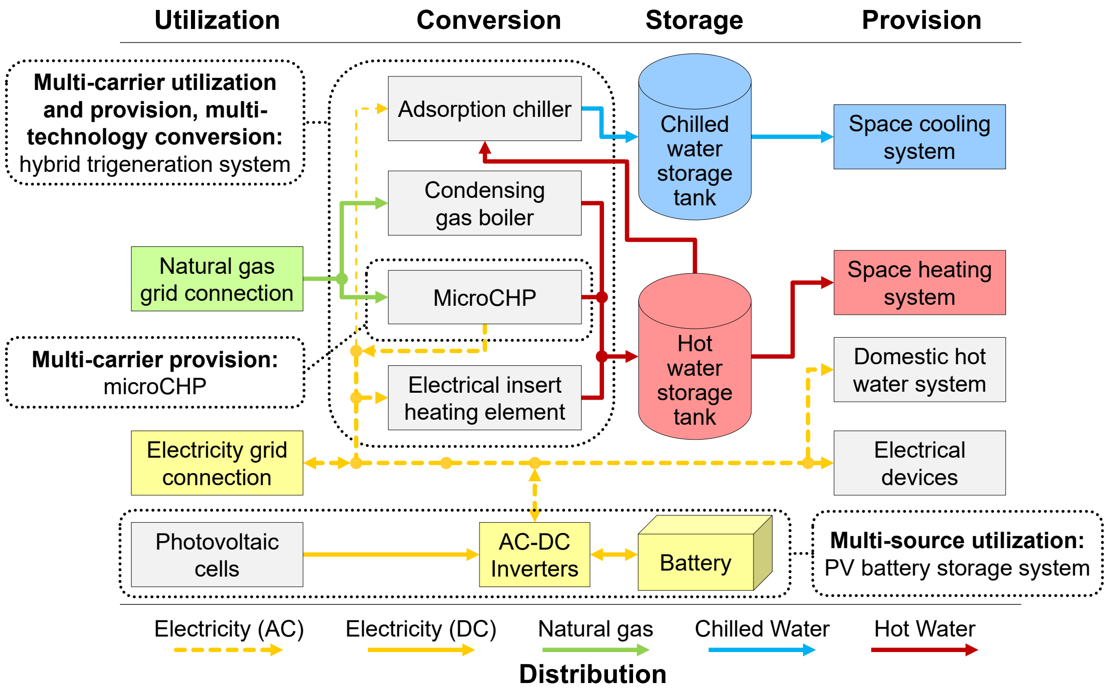


Figure 4.16: *FZI House of Living Labs*: utilization, distribution, conversion, storage, and provision in the local multi-energy system

also *multi-carrier utilization* of natural gas and electricity. The compression chiller for AC may be defined to do *multi-carrier utilization* of environmental heat and electricity. The hybrid electrical ESS consists of batteries and supercapacitors (supercaps) and thus enables *multi-system storage*. More information about the hybrid electrical ESS is provided in [355].

FZI House of Living Labs Similar to the ESHL, the HoLL (see Figure 4.16) consists of a microCHP and an electrical IHE. In addition, an adsorption chiller provides chilled water and a condensing gas boiler may also convert the natural gas to hot water without providing electricity. Hence, it is actually a hybrid trigeneration system that facilitates not only *multi-energy utilization* of electricity and natural gas as well as *multi-carrier provision* of hot water, chilled water, and electricity but also *multi-technology conversion* of natural gas into hot water. Although the adsorption chiller utilizes quite a lot of electricity, this energy carrier is only used by the controllers, valves, and pumps and thus not relevant for the classification with respect to the terminology.

4.7.3 Multi-modal Energy Management

This thesis introduces the term *multi-modal energy management*. It denotes an integrated management of all energy carriers in an energy system to optimize the overall energy chain from the provision to the utilization of energy. The term is analogous to *multi-modal* *transportation*[5], which refers to the transportation of goods by means of different carriers in a chain of transportation modes.

It is important to note that *multi-modal* denotes a different meaning in the context of multi-objective optimization. *Multi-modal optimization* refers to an optimization that pursues to find multiple optima. More information about multi-modal optimization is given, for instance, in [160, 483]. To avoid confusion, this thesis denotes the optimization of the utilization, distribution, conversion, storage, and provision of multiple energy carriers as *multi-modal energy management.* The actual optimization process is realized using the concept of *multi-commodity optimization* (see next section). Therefore, this thesis defines multi-modal energy management as follows:

> **Definition:** Multi-modal energy management is the integrated management and optimization of the provision, distribution, conversion, storage, and utilization of multiple energy carriers in an energy system, i. e., the optimization of the overall energy chain from input provision to output provision of energy carriers and energy services. This includes the management and optimization of the utilization of multiple energy carriers and sources, of the distribution using multiple energy carriers, links, and technologies, of the conversion using multiple energy carriers, stages, and technologies, of the storage using multiple energy carriers, storage systems, and technologies, and of the provision of multiple energy carriers and services.

This definition is in line with the definition of *multi-modal energy systems* provided by Thiem et al. (2015) [582]:

> "Multi modal energy systems combine some of the commonly mentioned measures, such as sector coupling, energy storages, or flexible demand." [582]

Additionally, the definition is similar to the definition of *multi-carrier optimal power flow* by Geidl (2007) [236]:

> "Multi-carrier optimal power flow is the determination of an optimal operating policy of an energy system and its complete state, including transmission and conversion of multiple energy carriers within security constraints." [236, p. 47]

Although multi-modal energy management may utilize multi-modal optimization with respect to multiple objectives, providing multiple solutions, this thesis focuses on the optimization with respect to total costs only. Multi-modal optimization approaches towards energy management in buildings are presented, for instance, by Braun et al. (2016) [96] and Soares et al. (2014) [556].

4.7.4 Multi-commodity Optimization

This thesis introduces the concept of *multi-commodity optimization* to facilitate the energy management of interdependent devices consuming and generating multiple energy carriers

[5] Often, the term *inter-modal* transportation is used interchangeably to multi-modal transportation. Occasionally, inter-modal refers also to multi-modal transportation using a single container [571].

in buildings. To evaluate and optimize the energy chain in buildings, the total input and the total output of energy carriers and energy services of the energy system, i. e., the building, have to be assessed, e. g., the net electrical load.

In a building, every device has certain input and certain output profiles of different energy carriers. This thesis proposes to denote and handle them as so-called *commodities* (see also Appendix A.1.1 and Figure A.11 on p. 370). In general, commodities are standardized and thus interchangeable and tradeable goods. Each load profile provides the *rate*, i. e., the amount of energy per unit of time, of a commodity, e. g., the electrical active power, which is exchanged with other devices or grids via interconnections.

In addition to its type, every energy carrier has an *origin*, i. e., the energy carrier is linked to a device, e. g., the PV system. This provides additional information for the optimization, which is important because the evaluation of the overall energy portfolio of a building depends on the devices in use. For instance, the active power generated by a PV system and that of a CHP system have different compensation schemes and thus have to be distinguished in the evaluation. Therefore, the commodities are further separated into so-called *ancillary commodities* (see Section 5.2.3 and Figure A.12 on p. 376). This way, the BEMS is not only able to optimize interdependent devices with respect to total costs and to consider different compensation tariffs but also to optimize them with respect to other objectives, such as emissions of GHG, if the relevant information is included as separate commodity profiles or can be deduced from existing profiles.

> **Definition:** Multi-commodity optimization is the optimization of multiple energy carriers in energy systems, e. g., devices, buildings, properties, regions, or even entire politico-economic unions, by distinguishing energy carriers into commodities and further into ancillary commodities that provide additional information about the energy carriers and allow not only for their economic evaluation and assessment but also for evaluations with respect to other objectives, such as the emission of pollutants.

The concept of multi-commodity optimization is implemented by the BEMS presented in this thesis and described in a more technical way in Chapter 5. There, the separation of commodities and ancillary commodities is described in more detail.

Handling of Different Energy Carriers and Flows

In order to facilitate the optimization of the multiple commodities in buildings, their utilization and provision and thus their flows have to be simulated, calculated, and analyzed. Although the energy carriers that form the basis for the commodities are diverse, there are certain analogies between them. For instance, the voltage in an electricity grid is similar to the pressure in natural gas and district heating grids, while the electrical current is similar to the mass flows.

This thesis simulates the flows between the devices and systems in the building in a simplified way, using the so-called *Energy Simulation Core* (cf. Section 5.3). The connections between the devices and systems are represented by relations that facilitate the simulation of energy flows, i. e., the exchange of power, and flows of non-energetic commodities, such as emissions. Thus, the flows of the different commodities are actually handled as *rates*, such as the electrical power, i. e., rate of doing work, and generated emissions, i. e., the emission rates, enabling the integration of commodities that are not based on energy carriers. In addition to the power flow, the relations define ancillary state variables that are necessary to perform simulations: voltages, temperatures, mass flows, and pressures have to be exchanged to consider the different physical laws and calculate the power flows properly. Additional properties of the physical connections, such as the resistance, reactance, diameter, or length, may also be included into these relations. Therefore, the multi-commodity optimization presented in this thesis uses a simplified calculation of the rates determining the exchange of energy and causing of emissions.

In large scale energy distribution systems, such as electricity distribution grids, natural gas grids, and district heating, there are more complex load flow equations for all of the energy carriers. Examples for these equations are given, for instance, in Geidl (2007) [236, pp. 31 ff.] and Prousch et al. (2012) [489, Tab. 2]. Although such flow equations are not used in the system presented in this thesis, the interfaces of the *Energy Simulation Core*, which is introduced in this thesis for the calculations of energy flows, have been designed to allow for the integration of solvers using such kinds of equations. This has been presented for power flows in Kochanneck et al. (2015) [354, 356], using a solver implemented in MATLAB. Similarly, it is also possible to integrate a solver for flow equations in natural gas and district heating grids, which consider, for instance, linepack effects, i. e., inherent storage capabilities of the gas grid, grid losses, compressor-dependent pressures, and varying calorific values, e. g., because of hydrogen or methane feed-in caused by power-to-gas technologies, or specific heat capacities, respectively.

4.8 Optimization Problem and Heuristic Algorithms

This section provides details about the optimization problem that occurs in building energy management. Although, for instance, Nguyen (2011) notes that "the ultimate goal of any optimization algorithm is to be applicable to real-world situations" [457], the selection of a particular algorithm is a challenging task.

In general, most optimization problems in buildings can be solved using exact solvers. However, computational requirements of exact solvers, i. e., memory usage and computation time, easily become too high for low-power computers that are likely to run BEMSs. In addition, exact solvers are not designed and might not be flexible enough to be used in modular and customizable productive systems. Therefore, this thesis proposes the usage of a heuristic that runs well on computers in practical systems. In doing so, it avoids high additional electrical power consumption due to the automated energy management.

4.8.1 Optimization Problem and its Complexity

In general, the optimization problems in BEMSs change over time: additional devices and systems are included into the optimization problem, e. g., by adding them to the building or simply switching them on. Furthermore, energy tariffs may be variable and depend not only on the time of energy utilization but also on the current power consumption. The DG from RES is intermittent and users provide different goals and objectives.

The simulation and optimization in BEMSs usually *discretizes the time horizon* that is optimized. This results in states of the devices having interdependencies at every time step. Additionally, the optimization has to be done periodically to consider various conditions in buildings, take imperfect predictions into account, and to adjust to flaws from imperfect models of the devices and systems. Therefore, the optimization is done with an optimization horizon of a specified duration, e. g., several hours, and repeated periodically or in case of deviations that exceed certain limits. This results in a so-called *rolling horizon optimization*, which is also called *rolling window* or *receding horizon optimization* [329].

Typical characteristics of devices and systems as well as thermal building models in optimization problems in BEMSs cause non-linear and non-convex relationships of objectives, constraints, and decision variables [93, 399, 531, 563]. They lead to many variables and constraints as well as numerous integer variables, making the problems harder and more computationally expensive to solve [12, 93, 294, 430, 555].

Time Discretization and Optimization Horizon

Dynamic systems are typically modeled using differential equations and continuous states, recursive algorithms and discrete time steps, or event processors and discrete events [72, 659] (see Section 2.5). Building energy management by means of a BEMS does not aim at competing with methods of control systems engineering. Therefore, the analysis of transient states and the facilitation of optimization using a temporal resolution higher than one second is out of scope of the system presented in this thesis.

Although many relations in buildings are usually described by differential equations, e. g., the heat equation in thermodynamics, this thesis simplifies the modeling and simulation of buildings and does not aim at competing with building simulation tools. Therefore, this thesis uses *discrete time system specification* and the *Euler method* [72, p. 294], i. e., *difference equations*, to simulate the buildings' and devices' behavior in the optimization and in the detailed simulation of the building in the simulation mode of the BEMS. However, due to the definition of suitable interfaces, the simplified calculation of difference equations may easily be replaced by more sophisticated methods (see also Section 5.3).

The simulations require the discretization of time at a certain resolution: the optimization horizon is discretized into consecutive time intervals of a certain step size. In general, a discretization using a high resolution, i. e., small time steps, leads to many variables and constraints that have to be handled [156, 564]. This makes the problem impracticable to be solved by means of exact solvers in BEMSs [12, 93, 555]. However, the discretized time has to be sufficiently precise to be able to reflect the dynamics of the system, because the variability within a time step is neglected. For instance, power limit signals and technical limitations of loads have to be considered when simulating and optimizing the system. Otherwise, the optimization will simply not consider the behavior of the real system, rendering the optimization inaccurate and thus useless. Within a time step, all values, e. g., loads, temperatures, and efficiencies, have a constant value, which is typically an average value for the entire step. This leads to so-called *averaging effects*.

Averaging Effects Comparisons of different resolutions, i. e., temporal precisions, show the averaging effects that reduce load peaks and make it hard to take load limitations or load-variable tariffs into account. Additionally, the averaging effects lead to an overestimation of the self-consumption and self-sufficiency rates, because fluctuations of the consumption as well as of the generation are equalized and thus have a higher simultaneity [282, 386].

In the literature, many different resolutions of time discretization are used in building energy management and in the monitoring of energy consumption. Typical values include a temporal resolution of 1 s [10], 30 s [39], 1 min [561], 5 min [450], 6 min [432], 10 min [283], 15 min [254], 30 min [282], or 60 min [252]. This shows that there is no consensus in the literature about a reasonable resolution in the simulation of automated building energy management using BEMSs that optimize with respect to the total energy cost.

A detailed analysis of recorded electrical and DHW load profiles by Bagge and Johansson (2011) [39] demonstrates the effects of different resolutions and shows that there is already a discrepancy of minimum and maximum loads when comparing a resolution of 30 s and 1 min, which gets drastically larger when comparing it to 6 or 30 minutes. In [282], Hawkes and Leach (2005) analyze the effects of different resolutions in a residential building scenario comprising a microCHP and a separate boiler that are optimized over one year. They conclude that a resolution of at least 10 minutes for thermal load profiles is required to obtain a good estimation of the required boiler peak load and realistic lifetime costs in economic assessments.

Wright and Firth (2007) [653] conclude that a resolution of 1 or 2 min is required to catch the details of electrical load profiles. This is in line with Soares et al. (2013) [561] using a resolution of 1 min to be able to take power peaks into account. Even when aggregating 2200 artificial electrical load profiles of residential buildings, which have been modeled for DR studies, Good et al. (2015) [252] show that there is a difference of up to 0.5 kW (about 10-20 %) between the 1 min-resolution and the 60 min-resolution profiles. They conclude that a temporal resolution of at least 1 min is required when studying the impacts of energy management and measures of DR.

To be able to simulate the detailed effects of RES and load peaks of devices and systems, e. g., appliances, this thesis uses a temporal resolution of 1 s in the simulation of the actual building and its devices. In the optimization, the temporal resolution is decreased to reduce the computational effort and to allow for practical usability in real systems. Therefore, this thesis uses a temporal resolution of 1 min in the optimization process and of 1 s in the simulation of the real building. In comparison, a BEMS that is similar to the one presented in this thesis—the combination of TRIANA and EF-Pi—uses a resolution of 15 min [586] in the optimization as well as the simulation of buildings, leading to large averaging effects.

Temporal Interdependencies and Coupling of Time Periods When regarding the behavior of an energy system over time, the intertemporal dependencies have to be respected and state variables are used to couple time periods. For instance, the state of charge of an ESS depends on its state in the previous time step and the amount of energy that has been stored in or retrieved from the storage since. Other examples include temporal limitations of power changes, e. g., when charging a battery, and minimum and maximum operating times of microCHPs that may be shorter than or may not be a multiple of 15 minutes[6]. This emphasizes the importance of using a higher temporal resolution.

[6] This resolution is common because many energy markets trade in increments of 15 min.

Optimization Horizon In general, the optimization horizon has to be chosen in a way that allows for the suitable reflection of all interdependencies and relevant future states. Hence, the horizon shall be as short as possible and only as long as necessary. In BEMSs, the optimization horizon depends on the devices and systems that are optimized. For instance, operation cycles of deferrable appliances have to be finished until certain deadlines are reached that are usually defined by the user. Therefore, the optimization horizon has to be at least as long as the latest deadline of all the jobs.

Often, uncertainties in future thermal demands and conditions limit the possible horizon. Nevertheless, the example of trigeneration systems, which have an efficiency depending heavily on the outdoor temperature, reveal that BEMSs should be able to schedule the generation of chilled water based on predicted consumption and environmental conditions to exploit better system efficiencies and the capabilities of storage systems. This leads to an optimization horizon covering at least half a day, enabling to move the device usage to periods of lower outdoor temperatures, e. g., in case of adsorption chillers, or vice versa, as it might be reasonable in the case of heat pumps. Similarly, the DG by PV systems is only possible during day-time and has to be taken into account, in particular if the optimization of BESSs is included in the energy management. Hence, this leads to a suitable optimization horizon of 24 hours that includes charging as well as discharging of the storage systems.

Thus, the optimization horizon used by the BEMS proposed in this thesis is of variable length and depends on the devices that are part of the optimization process. Each device proposes a minimum optimization horizon that has to be optimized and the BEMS uses the maximum value of all proposed horizons, which typically results in up to 24 hours.

Rolling Horizon In case of novel information, varying conditions, different sets of devices and systems, or unforeseen deviations, BEMSs have to reschedule the operation of the devices and systems. This results in a permanent re-optimization of the rolling horizon using updated information. Thereby, the BEMSs try to preserve (technical) constraints and optimize the operation with respect to given objectives in a sliding window. For instance, if the user programs an appliance with a degree of freedom, the BEMS has to perform not only an optimization of this appliance but also of the other devices and systems that have already been optimized before and which still offer some degree of freedom.

Actually, a rolling horizon is not only practical to handle uncertainty and deviations because of imperfect predictions, changing objective functions, and imprecise models but also to reduce the computational costs. Hence, the computational costs and complexities when modeling and calculating precise models have to be balanced against the uncertainty that is inevitable because of the user's interaction with devices and systems [410, 504].

Non-linearities, Non-convexities, and Complexity

Multi-modal energy management leads to non-linear and often non-convex problems, which are usually simplified or reformulated when being solved. For instance, systems comprising multiple energy carriers and conversion stages, where one device provisions an energy carrier that is utilized by multiple other devices, have so-called *dispatch factors* that determine the shares that are transferred to each device or system. These dispatch factors introduce non-linearity in the programming problems, because of products of operational variables [125].

In general, many efficiencies depend on the optimization and the states of other devices: for instance, the efficiency of the adsorption chiller depends on the water temperatures of its three circuits (see Figure 4.10 on p. 152) [321]. Thus, the character of energy systems is easily non-linear, e. g., the efficiency of devices or the models of storage systems and buildings [548], or non-convex, e. g., because of prohibited operating zones of devices and discrete modes of cogeneration or trigeneration systems [18,105,375,525]. In particular, the thermal behavior of devices, systems, and buildings leads to highly non-linear problems [547]. Other examples of non-linear systems include also cost functions [396, 563], in particular in case of load-variable tariffs [12].

Additional binary variables can be used to model or to approximate many non-linear [15, 125, 563] and non-convex problems [93, 105] as MILP problems. However, this is not always feasible or practicable because it may require many segments to approximate functions, leading to actually infeasible solutions, or adding many binary variables to the problem that make it computationally expensive to solve. For instance, the optimization of multiple appliances, a microCHP system, and a load limitation provided by a (soft) power limit signal leads to MINLP problems [12,14,563]. These problems are *NP-hard* if formulated as *resource-constrained project scheduling problems* [272, 416] or in form of other *NP-complete* problems, e. g., the *3-partition problem* [89, 432]. This is demonstrated in detail in [89, pp. 54 ff.] for the microCHP planning problem and given for the smart residential building scenario in [563].

In general, the computational effort of evaluating potential solutions when solving these problems depends mainly on the number of time slots, i. e., the temporal resolution and the length of the optimization horizon, on the number of the regarded devices and systems as well as the elaborateness of their models, and the temporal resolution of the load profiles.

In addition, the structure of the objective functions, the constraints, the (price) signals, and the functions describing the working of devices and systems may lead to systems that are non-linear and thus not necessarily scalable with respect to the temporal resolution when being solved exactly.

4.8.2 Variables, Constraints, Models, and Optimization Objectives

The energy management of buildings calls for the optimization with respect to a set of objectives. The variables are subject to constraints that are mainly determined by technical and physical limitations that are included in models of the building as well as of the devices and systems.

Although the optimization problem in building energy management can be formulated mathematically and the objective function is presented below in this section, the approach chosen in this thesis uses neither MILP nor MINLP but an algorithmic formulation of the optimization problem. The constraints are incorporated into the entity models that are provided to the optimization module in the optimization process (see Section 5.2 and Appendixes B and C). In addition, these models include simple controllers, e. g., on-off control (also called bang-bang control), that use values provided by other devices to ensure the validity of the solutions based on the control sequences. For instance, a water boiler is operated using a hysteresis. Furthermore, the boiler tries to keep the temperature in the hot water storage tank always between a minimum and a maximum temperature limit.

Variables in Energy Management The behavior of the devices and systems in a building may be described by a set of parameters and decision variables, which define the states as well as the control actions that are optimized. Typically, in optimization problems, which are optimized by BEMSs, there are binary decision variables, e. g., whether a device is switched on or off, integer decision variables, e. g., giving the number of devices to use, and real-valued variables, e. g., the degree of utilization of a device. Additionally, these variables may change over time, i. e., the number of decision variables depends on the duration of the optimization horizon and its temporal resolution. Furthermore, there are constraints that set boundaries for the variables or define relations between variables.

The typical input variables of devices and systems, i. e., their parameters and control actions that are used in this thesis, are provided in Chapter 5 and in the more detailed tables given in Appendix B and C.

Constraints and Models The technical constraints of devices and systems, e. g., minimum and maximum operating times of microCHPs and temperature limits of storage systems, and hard constraints provided by the user, e. g., maximum delay or interruption times of appliances, have to be met by the optimization at all times. A detailed mathematical modeling of deferrable or interruptible appliances is provided, for instance, in [96, 333, 406, 555, 563, 564]. Models of microCHPs are given in [88, 432, 532] and of trigeneration systems in [125, 410, 515].

The typical constraints of devices and systems that are used in this thesis, e. g., the maximum delay of the operation, technical limitations, and temperature limits, are similar to these models but used in an algorithmic formulation and provided in Chapter 5 and in the tables given in Appendix B and C.

Optimization Objective The single optimization objective in this thesis is the total cost of the energy consumption, i. e., the sum of all expenses for the consumption of electricity and natural gas from the grids, reduced by the compensation for feed-in to the electricity grid and auto-consumption. Here, the compensation is handled as negative costs. In the optimization, the total costs C_{total} are the sum of the costs of all commodities within the optimization horizon, i. e., between the current time t^{now} and the last time step that is relevant for the optimization t^{end}. Each time step has a length of Δt.

The set of all commodities is denoted by E and contains exemplarily the two commodities electricity in the sense of active power denoted by 'a' and natural gas denoted by 'n'. For instance, although reactive power is also calculated by the system, it is not used in the cost calculation in this thesis. In general, additional commodities can easily added by extending the set E and including additional cost functions $C_\varepsilon(t)$ for each $\varepsilon \in E$. Hence, the total costs of the energy consumption in the optimization horizon $C_{\text{total}}(t^{\text{now}}, t^{\text{end}})$ are calculated as follows:

$$\begin{aligned} C_{\text{total}}(t^{\text{now}}, t^{\text{end}}) &= \sum_{t=t^{\text{now}}}^{t^{\text{end}}} \textstyle\sum_{\varepsilon \in E} C_\varepsilon(t)\,, \\ & E = \{\text{a}, \text{n}\}\,. \end{aligned}$$

To distinguish the feed-in of electrical power by the PV and the microCHP system, the commodities of E are further separated into sets of ancillary commodities[7] related to electrical active power $\tilde{E}_{\mathrm{a}}$ and to natural gas power $\tilde{E}_{\mathrm{n}}$.

The former contains the costs related to the electrical power at the grid connection point $C_{\mathrm{a,grid}}$, to the violation of the load limitation at the grid connection point $C_{\mathrm{a,grid,limit}}$, and to the generation by the microCHP system $C_{\mathrm{a,chp,grid}}$ and $C_{\mathrm{a,chp,building}}$ as well as to the generation by the PV system $C_{\mathrm{a,pv,grid}}$ and $C_{\mathrm{a,pv,building}}$ that are caused by feed-in to the grid or self-consumption in the building, respectively. The latter contains only the natural gas consumption costs at the grid connection point $C_{\mathrm{n,grid}}$:

$$
\begin{aligned}
C_{\varepsilon}(t) \quad &= \quad \textstyle\sum_{\tilde{\varepsilon}\in\tilde{E}_{\varepsilon}} C_{\tilde{\varepsilon}}(t)\,, \\
&\tilde{E}_{\mathrm{a}} = \{(\mathrm{a,grid}), (\mathrm{a,grid,limit}), (\mathrm{a,chp,grid}), (\mathrm{a,pv,grid}), \\
&\qquad (\mathrm{a,chp,building}), (\mathrm{a,pv,building})\}\,, \\
&\tilde{E}_{\mathrm{n}} = \{(\mathrm{n,grid})\}\,.
\end{aligned}
$$

The costs $C_{\mathrm{a}}(t)$ at time step t consist of the costs of the electrical power at the grid connection point $C_{\mathrm{a,grid}}(t)$, the costs caused by a violation of the load limitation at the grid connection point $C_{\mathrm{a,grid,limit}}(t)$, the compensation[8] of the generation by the microCHP system that is fed into the grid $C_{\mathrm{a,chp,grid}}(t)$ or self-consumed in the building $C_{\mathrm{a,chp,building}}(t)$, and the generation by the PV system that is fed into the grid $C_{\mathrm{a,pv,grid}}(t)$ or self-consumed in the building $C_{\mathrm{a,pv,building}}(t)$:

$$
\begin{aligned}
C_{\mathrm{a}}(t) \quad &= \quad C_{\mathrm{a,grid}}(t) + C_{\mathrm{a,grid,limit}}(t) + C_{\mathrm{a,chp,grid}}(t) + C_{\mathrm{a,pv,grid}}(t) \\
&\quad + C_{\mathrm{a,chp,building}}(t) + C_{\mathrm{a,pv,building}}(t)\,.
\end{aligned}
$$

If the active power at the grid connection point is positive, i. e., if there is a net consumption by the building, the *Iverson bracket* $[P_{\mathrm{a,grid}}(t) > 0]$ denotes 1 and the consumption is priced with the time-variable price signal $c_{\mathrm{a,grid}}(t)$:

$$
C_{\mathrm{a,grid}}(t) \quad = \quad P_{\mathrm{a,grid}}(t) \cdot c_{\mathrm{a,grid}}(t) \cdot \Delta t \cdot [P_{\mathrm{a,grid}}(t) > 0]\ .
$$

If the active power at the grid connection point exceeds a certain upper limit $L^{\mathrm{upper}}_{\mathrm{a,grid}}(t)$ or lower limit $L^{\mathrm{lower}}_{\mathrm{a,grid}}(t)$, it is priced with the time-variable price signal multiplied by a positive

[7]In Chapter 5, the separation of commodities and ancillary commodities and the necessary calculation of the respective power flows that is done by the Energy Simulation Core are described in detail.

[8]The terms cost and compensation are interchangeable: compensations are negative costs. The tariffs may be variable and change from positive to negative values, i. e., from costs to compensations, within the optimization horizon and vice versa.

penalty factor τ^{upper} or the feed-in compensation multiplied with τ^{lower}, respectively:

$$\begin{aligned} C_{\text{a,grid,limit}}(t) &= \tau^{\text{upper}} \cdot \left(P_{\text{a,grid}}(t) - L^{\text{upper}}_{\text{a,grid}}(t)\right) \cdot c_{\text{a,grid}}(t) \cdot \Delta t \cdot \left[P_{\text{a,grid}}(t) > L^{\text{upper}}_{\text{a,grid}}(t)\right] \\ &+ \tau^{\text{lower}} \cdot \frac{L^{\text{lower}}_{\text{a,grid}}(t) - P_{\text{a,grid}}(t)}{P_{\text{a,grid}}(t)} \cdot \left(C_{\text{a,chp,grid}}(t) + C_{\text{a,pv,grid}}(t)\right) \\ &\cdot \left[P_{\text{a,grid}}(t) < L^{\text{lower}}_{\text{a,grid}}(t)\right] . \end{aligned}$$

This penalizes power consumption from and feed-in to the grid that violate the limits set by the power limit signals. Thus, a factor of $\tau^{\text{upper}} = 1$ means that the power consumption above the limit is in total twice as expensive as below the limit. A factor of $\tau^{\text{lower}} = 1$ means that the compensation is capped, because the feed-in is penalized by the same amount as it is compensated.

The feed-in to the grid is compensated with the microCHP feed-in tariff $c_{\text{a,chp,grid}}(t)$ and the PV feed-in tariff $c_{\text{a,pv,grid}}(t)$, depending on the share of each device in the total power generation:

$$\begin{aligned} C_{\text{a,chp,grid}}(t) &= \frac{P_{\text{a,chp}}(t)}{P_{\text{a,chp}}(t) + P_{\text{a,pv}}(t)} \cdot P_{\text{a,grid}}(t) \cdot c_{\text{a,chp,grid}}(t) \cdot \Delta t \cdot \left[P_{\text{a,grid}}(t) < 0\right] , \\ C_{\text{a,pv,grid}}(t) &= \frac{P_{\text{a,pv}}(t)}{P_{\text{a,chp}}(t) + P_{\text{a,pv}}(t)} \cdot P_{\text{a,grid}}(t) \cdot c_{\text{a,pv,grid}}(t) \cdot \Delta t \cdot \left[P_{\text{a,grid}}(t) < 0\right] . \end{aligned}$$

Self-consumption of locally generated electricity is compensated (or penalized) using the self-consumption compensation tariffs $c_{\text{a,chp,building}}(t)$ and $c_{\text{a,pv,building}}(t)$ for the microCHP and the PV, respectively, depending on the share of each device in the total power generation:

$$\begin{aligned} C_{\text{a,chp,building}}(t) &= \frac{P_{\text{a,chp}}(t)}{P_{\text{a,chp}}(t) + P_{\text{a,pv}}(t)} \cdot \left(P_{\text{a,grid}}(t) - P_{\text{a,chp}}(t) - P_{\text{a,pv}}(t)\right) \cdot c_{\text{a,chp,building}}(t) \cdot \Delta t \\ &\cdot \left[P_{\text{a,grid}}(t) > P_{\text{a,chp}}(t) + P_{\text{a,pv}}(t)\right] , \\ C_{\text{a,pv,building}}(t) &= \frac{P_{\text{a,pv}}(t)}{P_{\text{a,chp}}(t) + P_{\text{a,pv}}(t)} \cdot \left(P_{\text{a,grid}}(t) - P_{\text{a,chp}}(t) - P_{\text{a,pv}}(t)\right) \cdot c_{\text{a,pv,building}}(t) \cdot \Delta t \\ &\cdot \left[P_{\text{a,grid}}(t) > P_{\text{a,chp}}(t) + P_{\text{a,pv}}(t)\right] . \end{aligned}$$

The costs of the natural gas consumption at the grid connection point $C_{\text{n,grid}}(t)$ are calculated as follows:

$$C_{\text{n,grid}}(t) = P_{\text{a,grid}}(t) \cdot c_{\text{n,grid}}(t) \cdot \Delta t .$$

Finally, the objective function C_{total}, which is minimized by the optimization module of the BEMS presented in this thesis, can also be formulated as follows:

$$C_{\text{total}} = C_{\text{a}} + C_{\text{n}} = \sum_{t=t^{\text{now}}}^{t^{\text{end}}} \left(C_{\text{a}}(t) + C_{\text{n}}(t)\right) . \tag{4.18}$$

Following this structure, the objective functions may easily be extended to include additional objectives, such as the costs of reactive power consumption, auto-consumption compensations, i. e., additional compensation for the self-consumption of locally generated electricity, load-variable tariffs, and additional DG having other compensation schemes.

Other Objectives This thesis focuses on variable energy tariffs, i. e., cost-related objectives that result in an optimization of the total costs. Nevertheless, there are many other objectives that may be included in building energy management, e. g., comfort or emissions (see also Section 3.6.1). Some objectives are closely interrelated, e. g., comfort is not only related to temperature and illumination but also to emissions of particles, noise, and vibrations by devices and systems when operating. An optimization with respect to multiple objectives is given by Braun et al. (2016) [96]. The introduction of ancillary commodities, which reflect, e. g., emissions, simplifies the integration of additional objectives in the future.

Objective Function and Fitness Function

The optimization problem is subject to uncertainties as well as to some shortcomings in its formulation and the evaluation of the objective function, because the objective function does not include all externalities. Therefore, these are tackled by the introduction of a so-called *additional penalties*, i. e., *virtual costs*, into the optimization.

For instance, the optimization tends to reduce the state of charge of the ESSs and thermal storage as much as possible towards the end of the optimization horizon because there is no inherent benefit of a fully charged storage at the end of the horizon. Similarly, in case of actually identical costs, it is reasonable to delay the operation of appliances as long as possible to wait for possible runs of other appliances that may trigger a run of the microCHP, which is hard to include directly into the optimization problem. Other shortcomings are, for instance, the wear of devices and additional energy loss because of frequent starts and short operating times. Some of them may be directly internalized, such as energy losses, other have to be included in form of penalties, i. e., indirect virtual costs that reflect expected, predicted, or assumed (future) costs or benefits.

Therefore, Equation 4.18 is extended by the additional penalty $\mathcal{P}$ to the following fitness function F_{total} that is to be minimized by the optimization:

$$F_{\text{total}} = C_{\text{total}} + \mathcal{P} \, . \tag{4.19}$$

The additional penalty $\mathcal{P}$ is the sum of all penalties related to the devices or systems J within the optimization horizon. These virtual costs are used to steer the optimization towards better solutions:

$$\mathcal{P} = \sum_{t=t^{\text{now}}}^{t^{\text{end}}} \left(\sum\nolimits_{j \in J} \mathcal{P}_j(t) \right) \, . \tag{4.20}$$

Table E.1 on p. 430 provides a list of the inherently considered effects, i. e., those that are internalized in the objective function, as well as of the additional penalties that are used in this thesis to improve the optimization.

4.8.3 Heuristic and Meta-heuristic Optimization

In contrast to heuristics, which are problem-specific and may only be used to a narrow class of optimization problems, meta-heuristics are abstract and can be employed on a wide range of problems. Therefore, meta-heuristics promise to be suitable for the optimization of heterogeneous buildings, which provide different combinatorial optimization problems, e. g., assignment and scheduling problems, because of their discrete nature.

This thesis uses an EA—more precisely a GA using a string of numbers in the representation of individuals—in the optimization process. EAs emulate the general principles of evolution which are found in nature:

- There is at least one population of individuals.
- The individuals compete for survival.
- The competition is based on survival of the fittest.
- There is some kind of fitness function that allows for the evaluation of individuals.
- The individuals are subject to variation.

This is reflected in Algorithm 1 on p. 435, which provides the general functioning of generic EAs as pseudo-code: The main advantages of using a GA in the context of this thesis are:

- Independence from the structure of the problem, e. g., non-linearity
- Parallel evaluation of solution candidates
- Possibility to perform multi-objective optimization

These advantages allow for a modular and customizable optimization with respect to multiple criteria in the BEMS, which benefits from multiple processors. The approach used in this thesis is similar to approaches in *blackbox optimization* [330], which is used when unknown and expensive functions have to be evaluated.

The development of new problem-specific heuristics, the combination of existing methods, and the adaptation of meta-heuristics to a specific problem are typical approaches to the optimization of complex problems. Additionally, the calibration, tuning, and control of the parameters that are used in a (meta-)heuristic is a promising way of improving the results. According to De Jong (2006) [154, pp. 26 ff.], the main advantage of GAs is their independence from specific applications because of the universality when tackling novel problems. Therefore, the BEMS presented in this thesis uses a GA and does not use a combination of heuristics. However, combining several heuristics may be an interesting approach in future work.

Parameter Calibration, Tuning, and Control

In the context of meta-heuristics, parameter calibration refers to two different approaches to the adaptation of parameters of a heuristic to a concrete optimization problem: *parameter tuning* and *parameter control* [155].

Parameter Tuning Parameter tuning is parameter calibration that is done before running the heuristic optimization process. Typically, this requires running and evaluating the heuristic with different settings and is done for every application of a heuristic. [155]

Parameter Control Parameter control is parameter calibration that is done when running the heuristic optimization process. Parameter control is distinguished into the following three categories [155]: *Deterministic parameter control* alters the parameters deterministically without a feedback loop. In contrast, *adaptive parameter control* alters the parameters according to explicit rules that utilize feedback in form of the quality of the resulting parameters. *Self-adaptive parameter control* alters the parameters according to rules that are altered based on the feedback, i. e., the quality of resulting parameters. This may be done using another heuristic, e. g., another EA that is therefore also called *meta-EA*.

Approaches to Parameter Calibration In order to realize parameter calibration, de Landgraaf et al. (2007) [155] propose the introduction of an additional layer—a design layer—in the heuristic optimization, which is added onto the problem layer comprising the optimization problem and the algorithm layer, i. e., the actual (meta-)heuristic. They note that parameter calibration "can be handled very well by a GA" [155]. Other approaches include *Iterated Local Search* [306], which utilizes local search and acceptance criteria in an iterative manner, and *Sequential Parameter Optimization* [48], which utilizes computational statistics, data analysis, and stochastic process models of the search space.

Effects of Parameter Calibration In [406], Mauser et al. (2014a) show exemplary results of parameter calibration in a BEMS optimizing several appliances and a microCHP. These qualitative results are depicted in Figure G.1 on p. 445: the default parameters achieve only a partial synchronization of the operation of appliances and the microCHP (see Figure G.1a), whereas the calibrated parameters lead to a better coordination of the devices (see Figure G.1b). The effects of parameter calibration for a BEMS using a GA are presented by Mauser et al. (2014b) [407], motivating the introduction of parameter calibration in BEMSs, which is described in Section 5.9 in detail.

4.9 Organic Smart Home and Observer/Controller Architecture

This section analyzes the capabilities of the OSH and its system architecture that is based on the O/C Architecture, before briefly presenting the new approach of this thesis.

4.9.1 Observer/Controller Architecture

As already introduced and described in Section 3.7.3, the generic O/C Architecture serves as a framework for the design of systems that aim at showing an organic behavior. Although it comprises various important general components and concepts, such as prediction and learning methods and a regulatory feedback mechanism, i. e., a closed control loop, it originates in a certain setup and lacks some concepts that help to realize complex BEMSs.

Close Relation to Learning Classifier Systems Although it has also been presented in a more generic way [501], the original architecture in [502] is closely related to learning classifier systems, which use human readable rules to control the SuOC. This results in certain generic components having names based on the working of learning classifier systems: for instance, the *rules* are applied according to the *rule base* and adapted by the *Rule Performance Evaluation* (see Figure 3.11 on p. 113) [502].

Therefore, Allerding (2013) [10] introduced an adapted architecture and naming (see [10, Fig. 4.4]), which uses a generic optimization mechanism comprising a *longterm* and a *realtime optimization*. However, this results in a naming that is less generic and limits the mapping of situations to actions to some kind of optimization.

Missing Model of Control Although there is a *Model of Observation* that adapts the operation mode of the *Observer*, i. e., the observation functionality, to specific use cases or conditions, there is no such model for the *Controller* that makes the optimization and control functionality adaptive, for instance, to the current SuOC and its particular sensors, actuators, devices, and systems as well as to the intended optimization functionality.

Missing Abstraction of Actuators, Sensors, Devices, and Systems In real systems, the SuOC, actuators, and sensors have to be abstracted, because the same O/C-unit shall be used for different systems, actuators, sensors, and devices having a similar functionality.

Allerding (2013) [10] presents the *Hardware Abstraction Layer* as a solution to abstract the concrete hardware from different manufacturers using different protocols and communication media into generic exchange objects (see also Section 4.9.2). In addition to that, Allerding (2013) [10] describes the *Household Abstraction Layer*, abstracting different households to a common *demand side manager*. This concept of an additional layer abstracting the subordinate systems is generalized by Mauser et al. (2015) [409] and named *Entity Abstraction Layer*. The additional layer between the O/C-units and the entities that form the SuOC uses *entity drivers* to abstract the sub-systems by providing standardized interfaces to the O/C-units and is more closely described by Hirsch (2015) [294].

Missing Abstraction Towards Superior Entities Although introducing hierarchical and multi-level structures (see Figure 3.12 on p. 114), the original O/C Architecture does not handle the abstraction of O/C-units towards superior entities. Similar to the sensors, actuators, and devices forming the SuOC, the O/C-units have to be abstracted towards O/C-units observing and controlling them in a hierarchical or multi-level manner. This flaw is closely related to the missing goal and objective management as well as the missing conflict resolution mechanism described in the next paragraph.

In [506], Rigoll et al. (2014) propose the introduction of a so-called *Data Custodian Service* managing the energy-data, such as energy consumption data of smart meters. This dedicated service, which is described in more detail by Rigoll (2017) [505], stores the data in databases and handles requests of external entities that ask for access to the local energy data. The Data Custodian Service decides about what data and in which quality is provided or whether it is provided at all. This helps ensuring data privacy and thus the concept is also called *Privacy-aware O/C Architecture*. In a more generalized way, Frey et al. (2013) [225] describe the *Provided Monitor Interface* and the *Provided Action Interface* of the *goal management layer* that allow for interaction with superior entities and control elements, i. e., being observed and controlled by them in a defined way.

The concept of abstracting and protecting an entity to superior entities is generalized by Mauser et al. (2015) [409]: in addition to the Entity Abstraction Layer (see previous paragraph) abstracting subordinate entities, the *Communication Abstraction Layer* abstracts an entity and its O/C-unit to superior entities. This concept is more closely described as part of this thesis in Section 5.1.

Missing Objective Management and Conflict Resolution Mechanism Goals and objectives of the user (or superior O/C-units) have to be interpreted and integrated in the control loop. Additionally, the goals and objectives may change of time, for instance, because of a change regarding the user who is in charge. The original O/C Architecture lacks a component that is responsible for handling and managing this.
In case of hierarchical or multi-level systems, conflicts between the goals and objectives of the O/C-units may arise. This is true for O/C-units having different users providing their goals and objectives. In general, the local goals and objectives of a particular O/C-unit may conflict with the goals of another O/C-unit or with the global goals of a superior O/C-unit.

In [562, 587], the user interaction with and the supervision of the O/C-unit are passed through dedicated *Monitoring* and *Goal Management* components. Similarly, [225] uses a *goal manager* in an additional *goal management layer* to adjust the goals for the *base control layer* comprising the actual manager of the resource, i. e., the SuOC.
Frey et al. (2012) [223] analyze several integration issues in complex systems and present general integration patterns for conflict resolution. In Allerding (2013) [10], the *global O/C-unit* performs an integrated, global optimization of all devices, avoiding the conflicts at all. Additionally, external goals and objectives, e. g., of a superior *demand side manager*, are incorporated into the building energy management through price signals, which imposes the goals of the superior entity upon the subordinate entities in an indirect way. Another possibility is the introduction of auctions [358], negotiations, or voluntary price signals [405].

Although having some minor flaws, the O/C Architecture serves well as a generic framework for the design of complex systems. This includes the design and realization of BEMSs managing many different sensors, actuators, devices, and systems. Therefore, this thesis uses the O/C Architecture and proposes certain adaptations to cope better with certain requirements that arise in automated energy management.

4.9.2 Organic Smart Home

The architecture of the OSH has initially been presented in Allerding and Schmeck (2011) [13] and is more closely described by Allerding (2013) [10]. It is based on the O/C Architecture and has been developed for residential buildings comprising intelligent appliances, electric vehicles, and DG. It has been deployed to real buildings—the ESHL at the KIT and the HoLL at the FZI—and evaluated in multiple trial phases. [410]

Real-world Application and Simulation The OSH is able to perform automated energy management in real as well as in simulated buildings, allowing for the analysis of intelligent residential buildings in different scenarios and the testing and validation of its functionality before deploying it to productive systems in real buildings. In contrast to building simulation tools, which focus on thermal energy flows and use time steps at a resolution of multiple minutes [138], the OSH uses a temporal resolution of one second, which is a reasonable approach when considering electricity, power limits, and measures of DR.

Modeled Devices Originally, the OSH supports the simulation and integrated optimization of five major appliances, the electrical baseload, and a PV system by dedicated drivers. The microCHP and the hot water storage system providing space heating are realized in a

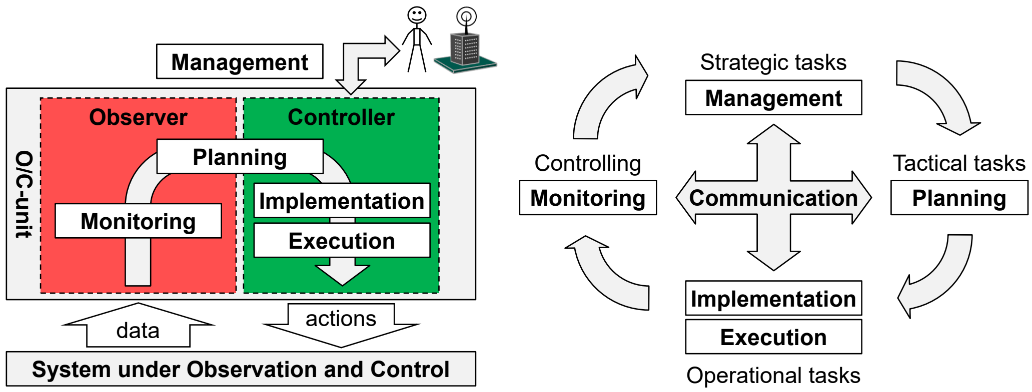


Figure 4.17: The *Generic O/C Architecture* (left) and the *circle of actions* in the VDI Guideline 4602 [610] (right), partly based on [610, Fig. 2]

single integrated driver, which is not modular [10]. Modified versions of the OSH enable the optimization of electric vehicles [393, 443] or heat pumps that are modeled in a separate simulation tool [378]. Hence, the original OSH supports only a limited number of devices and, for instance, does not support the modular combination of devices and sub-systems of the heating system.

Energy Carriers The OSH supports the calculation of active and reactive power. Hot water for heating purposes and DHW are only used in the integrated microCHP and hot water storage system [10]. Therefore, there is only a very limited support of multiple energy carriers, which has to be extended significantly to support multi-modal energy management and fully modular multi-commodity optimization.

Architecture

The OSH uses the hierarchical design variant of the O/C Architecture (see Section 3.7.3), separating the O/C-units into *local* O/C-units and a *global* O/C-unit. This aims at tackling the complexity of EMSs and realizing a flexible, modular approach, which is closely described in [10, 12, 13]. The original system architecture is outlined in [10, Fig. 4.4]. The O/C-units filter, aggregate, and enrich the data provided by the devices and systems and enable energy management based on predictions and optimized control actions. The latter result in a schedule of planned actions, which is applied to the controlled devices and systems.

The O/C Architecture shows a structuring that is similar to the so-called *circle of actions of energy management systems* provided by the VDI Guideline 4602 [610]. This similarity is depicted in Figure 4.17, mapping the actions of the circle, i. e., monitoring, planning, implementation, execution, and management, to the Observer and the Controller of the O/C Architecture.

Hardware Abstraction Layer, Device, and Communication Drivers The OSH introduces the so-called Hardware Abstraction Layer (HAL), which abstracts distinct devices, protocols, and communication media of the components and connects them to generic O/C-units in the first Observer/Controller Layer (O/C-layer) by using device-specific *device drivers*. In simulations, the device drivers are replaced by *device simulation drivers*, which work as virtual devices, i. e., agents of a multi-agent simulation, and emulate the device usage. The simulation drivers are coordinated by the *simulation engine* [10]. In addition to device drivers, the OSH utilizes so-called *communication drivers* to receive signals and other data from external entities, such as energy tariffs and weather forecasts, as well as goals and objectives of the user. The user interface is the EMP [60, 61]. Although having the Household Abstraction Layer and communication drivers, the OSH does not include the directed abstraction of buildings to higher entities in a uniform manner that is consistent with its architecture. Additionally, it does not provide suitable drivers for the communication with gateways handling multiple devices that are controlled by dedicated O/C-units.

Observer/Controller-layers The OSH comprises two hierarchical O/C-layers: the local O/C-units in the first and the global O/C-unit in the second layer. The O/C-units utilize sensors and actuators to observe and control the smart residential building and its devices and systems. On the first O/C-layer, the devices form the SuOCs, whereas the SuOC of the second layer is the entirety of O/C-units of the first layer. The local O/C-units provide so-called *Problem Parts*, which are used by the global O/C-unit to optimize the devices and systems (see [11, Fig. 2] and also below). Thus, the first O/C-layer provides the device-specific management and enables quick reactions, whereas the second O/C-layer performs the integrated optimization of all devices and systems using the Problem Parts. [410]

Registry The OSH uses the so-called *Registry* to enable the communication between the O/C-units as well as between the drivers. This component is similar to event bus or message queue concepts. It supports command messages from a sender to a dedicated receiver, broadcast messages from a sender to all entities that are subscribed for them, and state messages that are lodged at the Registry and can be fetched by other entities. This covers all types of communication that are typically used by components in such systems. Nevertheless, all communication is handled by a single communication bus—the *Registry*—and thus does not enforce the strict separation that is actually induced by the O/C Architecture.

Optimization

The OSH uses a GA in a specialized modular optimization approach to optimize energy utilization, conversion, storage, and provision in buildings.

Degree of Freedom The basic idea of the optimization in the OSH is the exploitation of so-called *degrees of freedom*. For instance, appliances have a degree of freedom if the starting time of an operation cycle can be shifted. This includes dishwashers, tumble dryers, and washing machines with delay functionality. Additionally, the operating time of CHP systems with thermal storage can be scheduled in a way respecting the minimum and maximum temperature limits of the hot water storage. [10]

Sub-problem-based Optimization and Problem Parts Residential buildings have differing setups comprising specific sets of devices and systems. Therefore, the OSH uses a “plug-and-play” approach for their integration into the BEMS. Additionally, the status of devices and systems and availability changes from time to time, i. e., sometimes they have to be included in the optimization, sometimes they are excluded. For this reason, the OSH does not state the energy management and optimization problem *a priori* but composes it at run-time from so-called *sub-problems* that are given in *Problem Parts*. Each Problem Part represents a device or system in the optimization process and thus includes all relevant information, such as the current status and the expected load profile. [11]

Although this enables a modular approach towards energy management, the Problem Parts do not respect interdependencies between the devices and systems, i. e., the resulting load profile of one Problem Part is independent of the load profile of another Problem Part. Therefore, they do not allow for the integrated optimization of interdependent and interrelated devices and systems in a modular manner. In the original OSH, corresponding devices and systems have to be handled by a single (simulation) device driver.

Bit String Possible control sequences or settings for a particular device are represented by an abstract bit string, i. e., concatenated bits that are interpreted by the corresponding Problem Part and which encode the actual behavior of the device. For instance, a bit string for a deferrable appliance encodes the time until it is started, whereas a bit string for a microCHP encodes the periods when it is running. The concrete interpretation is defined in the Problem Part and may be encoded directly, e. g., a gray encoded number, or indirectly, e. g., as input for an automaton. Thus, every Problem Part provides a device-specific encoding of its controllability using a bit string of a specific length. For instance, uncontrollable devices have a bit string of the size zero and microCHPs have a bit string varying in length with the duration of the optimization horizon. This results in an identical structure of all devices in the optimization process, which is a consistent and practical approach, because practically all variables may be encoded in a bit string. [11]

Evolutionary Algorithm To optimize energy usage in buildings, the OSH uses an EA or more precisely a GA, i. e., a meta-heuristic. Every time there is significant change in the state of the building or a device that has to be optimized, it formulates the problem instance that has to be solved dynamically at the run-time of the system using a rolling horizon. Thus, there is usually a frequent rescheduling, i. e., re-optimization process generating approximate solutions using a heuristic, which promises to be practicable for productive BEMSs. Although the optimizer in the global O/C-unit calculates an optimized schedule for all devices, the scheduled actions may be overridden by their particular O/C-units. For instance, the microCHP is forced to run if the temperature of a hot water storage tank is falling below a defined threshold temperature, triggering a rescheduling of all devices. There are various inputs for the optimization: energy tariffs, power limit signals, user preferences, goals, and objectives, and the current and predicted states of devices and systems. [11, 410]

Optimization Process The optimization process in the OSH is depicted in [11, Fig. 2], showing a simplified scenario of the optimization of a washing machine cycle that has to be finished until 6:00 pm, a dishwasher cycle that has to be finished until 5:00 pm, and microCHP requiring 2 hours of operation in the optimization horizon. The Problem Parts are constructed in the local O/C-units. The GA determines bit strings that are evaluated by the Problem Parts and result in load profiles. These load profiles are aggregated and assessed using a fitness function, which considers external signals and user preferences. The fitness function is used by the GA to rate the evaluated bit strings. Finally, the best solution is selected by the optimizer and transformed to control commands and parameters for the real or simulated devices. The main advantage of this approach is that it can be executed on small computers having limited system resources, because the global O/C-unit has to perform only simple calculations and does not have to solve a set of thousands of equations and variables. Additionally, the execution time of the algorithm can easily be restricted and provide good but not optimal solutions, which is beneficial when frequent rescheduling is likely anyway and quick responses are desirable. [410]

4.9.3 Own Approach

In Chapter 3, an extensive overview of related work has been presented. Some of these approaches, architectures, and EMSs use concepts of device abstraction, modular optimization, and the integrated handling of multiple commodities. Nevertheless, none of them combines all necessary concepts and mechanisms that facilitate the integrated energy management of multiple energy carriers in real as well as simulated buildings. In particular, real buildings require an architecture that provides abstraction, flexibility, and modularity to optimize varying sets of devices and systems from different manufacturers in heterogeneous scenarios with respect to individual objectives and goals of the users.

Although the OSH by Allerding (2013) [10] is a BEMS that can be used in simulations as well as in real buildings, provides the support for a number of devices and systems found in buildings, and introduces a modular approach to the decentralized optimization of them, it does not support the optimization of devices and systems utilizing multiple energy carriers or having interdependencies in a fully modular and flexible approach. Therefore, this thesis introduces the important concept of *multi-commodity optimization* in *multi-modal energy management* and presents the so-called *Energy Simulation Core*, which is able to handle the different energy carriers, to distinguish their origin and quality by the introduction of so-called commodities and ancillary commodities, and finally to facilitate a modular optimization that considers variable tariffs and power limit signals.

The OSH uses the O/C Architecture, which provides a generic framework for the structuring of the components. Although this architecture is well-suited for the realization of complex systems, there are some shortcomings that arise in its application to the smart grid, for instance, in the realization of BEMSs in smart buildings.

Therefore, this thesis presents an extended version of the O/C Architecture and a proper way of structuring the OSH according to this general framework as well as in the sense of a BOS. The next chapter describes the *Extended O/C Architecture* in detail and presents the important novel concepts and implementations, such as the *Energy Simulation Core* and the *Interdependent Problem Parts*, which have been integrated into the OSH, making it fully flexible by being able to optimize interdependent devices and systems as well as—and most importantly—capable of handling all energy carriers in an integrated way.

5 Concepts, Architecture, and Implementation

The basic idea of this thesis is to rethink energy efficiency and energy management. Energy efficiency is definitely important. However, energy systems utilizing RES have sometimes an abundant and sometimes an insufficient supply of energy. Therefore, BEMSs shall support the paradigm change towards a flexible and adaptive demand of electricity and exploit the opportunities of adapting the energy utilization and provision across all kinds of energy carriers. This will help to avoid unnecessarily costly and complex measures and technologies increasing energy efficiency and flexibility.

For instance, heating systems may adapt their input provision and washing machines their washing programs—based on the Sinner Circle (see Section 2.4.4)—depending on the availability of generation from RES. This would also help to reduce the usage of detergents and avoid long and thus inconvenient operating times of modern energy-saving appliances, i. e., dishwashers and washing machines. The complexity of managing and optimizing the provision, conversion, storage, distribution, and utilization of energy in an integrated way can only be handled by suitable and powerful BEMSs.

Although the original OSH enables energy management in simulations as well as in real buildings, it lacks appropriate concepts towards the handling of multiple energy carriers and the fully modular optimization of devices and systems. Therefore, this thesis introduces a BEMS based on the OSH that is capable of optimizing multiple interdependent devices and energy carriers in a unitized approach.

This chapter presents the fundamental concepts, the developed architecture, and the implementation that facilitate such a kind of energy management by a BEMS. The architecture and concepts are based on the analysis presented in the previous chapter. Although they are independent of a specific implementation, this section presents an exemplary BEMS and refers to concrete implementations and configurations, i. e., *Java* classes and Extensible Markup Language (XML) files, which are provided separately[1]. In the next chapter, the implemented BEMS is evaluated and used to perform exemplary simulations and evaluations of scenarios comprising multiple energy carriers and interdependent devices.

[1]The source code is available at `https://github.com/organicsmarthome`.

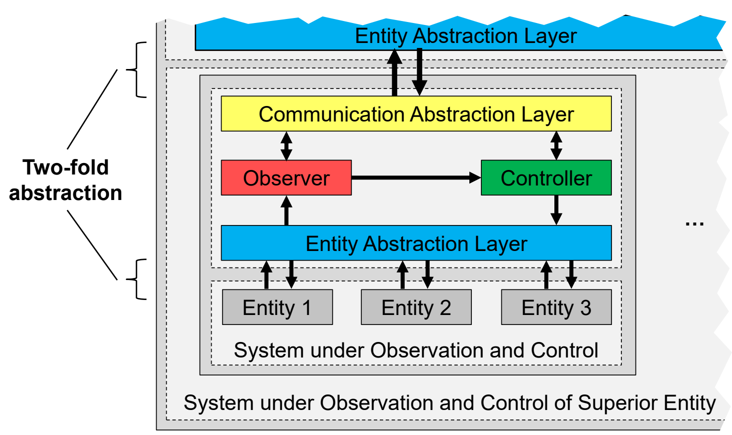


Figure 5.1: Concept of the two-fold abstraction using the *Entity Abstraction Layer* and the *Communication Abstraction Layer*, based on [409]

5.1 Extended Generic Observer/Controller Architecture

The analysis of the O/C Architecture in the context of energy management, which is presented in Section 4.9, reveals certain shortcomings. Some of them, e. g., the close relation to learning classifier systems and the abstraction of actuators, sensors, devices, and systems, have already been addressed by Allerding (2013) [10]. However, these changes and adaptations are not sufficient to enable a flexible hierarchical approach or to provide a generalized approach towards different kinds of entities in energy systems [409].

Concept of Entities A first step towards a flexible and generalized approach has been the introduction of the *concept of entities*, which generalizes subordinate entities and introduces a dedicated abstraction layer for them [506]. The term *entity* refers to all kinds of devices and systems that form the SuOC. The additional layer between the O/C-units and the entities that form the SuOC is called *Entity Abstraction Layer*.

Hierarchical Architecture of Entities on Different Levels The concept of entities allows for a hierarchical architecture comprising a multiplicity of entities in a hierarchy of control loops (see Figure 3.12d on p. 114). Such an architecture is intuitive and distributes the control among the hierarchical layers. This enables specialization to different spatio-temporal requirements, such as different temporal resolutions, response times, and control areas. In [506], we introduced a naming that calls low-level entities that do not have a dedicated O/C-unit *basic entities* and those having an O/C-unit and thus forming an OC system *aggregate entities*.

In the BEMS presented in this thesis, the managed devices and systems are integrated using dedicated O/C-units on the first layer, transforming them from basic to aggregate entities. Actually, most devices and systems have their own internal control systems—although usually not using the O/C Architecture—that make them aggregate entities and which have to be respected and abstracted by the BEMS.

5.1.1 Extended Architecture: Concept of Two-fold Abstraction

The introduction of entities and a dedicated layer is not sufficient to achieve a clean structuring of the functionality because abstraction may work in two directions (see Figure 5.1): On the one hand, it may abstract subordinate entities and the way a superior entity observes and controls them, e. g., by introducing common data models and commands, such as the *Observer Exchange* and *Controller Exchange* objects presented by Allerding (2011, 2013) [10, pp. 71 ff.] [13]. On the other hand, an entity may abstract the way itself is being observed and controlled by one or multiple superior entities, i. e., its observability and controllability. The *Entity Abstraction Layer* tackles the first direction, whereas the new *Communication Abstraction Layer* abstracts an entity and its O/C-unit towards superior entities. This concept is called *two-fold abstraction*.

Entity Abstraction Layer In [506], we propose the introduction of the Entity Abstraction Layer (EAL). It is an additional layer that is located in between the O/C-units and the entities that form the SuOC. Hence, it generalizes the concepts of a HAL in BEMSs and of a *Household Abstraction Layer* [10] in regional EMSs. The EAL uses so-called *entity drivers* to abstract the sub-systems by providing standardized interfaces to the O/C-units and is more closely described by Hirsch (2015) [294, pp. 57 ff.]. Thus, the abstraction is actually done in the drivers, decoupling the management layer, i. e., the O/C-units, from specific entities. Typically, this includes the abstraction from entity-specific data models, protocols, and communication media.

Communication Abstraction Layer The Communication Abstraction Layer (CAL) abstracts the way an entity can be observed and controlled by one or many superior entities, i. e., the entity's observability and controllability. It manages and abstracts the properties of the entity by means of so-called *communication drivers* and enables services that ensure data privacy [506]. In addition to the observability and controllability, the CAL manages also the *perception* of external signals provided by superior entities, such as control signals, commands, and above all, the user's goals, objectives, and preferences [409]. This facilitates measures of DSM, such as the *two-way handshake* for voluntary energy tariffs, which has been presented and evaluated by Mauser (2012, 2014) [405, 411].

Extended Generic Architecture The introduction of the EAL and the CAL leads to the so-called *Extended Generic Observer/Controller Architecture* (see Figure 5.2): The observation and control of the SuOC is handled by the EAL. In contrast, the CAL handles the observability and controllability of the OC-system, i. e., of the O/C-unit and the SuOC, as well as the perception of external signals and objectives. This architecture does not only extend but also generalize the original O/C Architecture of Richter (2009) [502] (see Figure 3.11 on p. 111) and make it more independent of learning classifier systems by removing references to the term "rule". In general, the Extended O/C Architecture targets complex systems, such as EMSs in buildings and smart grids, which integrate heterogeneous systems and thus require various kinds of abstraction. Furthermore, due to the multiplicity and diversity of situations in such systems, it is unlikely that similar situations occur multiple times. Therefore, in the following chapters, this thesis does refer to the *Mapping Module* as *optimization module* of the BEMS.

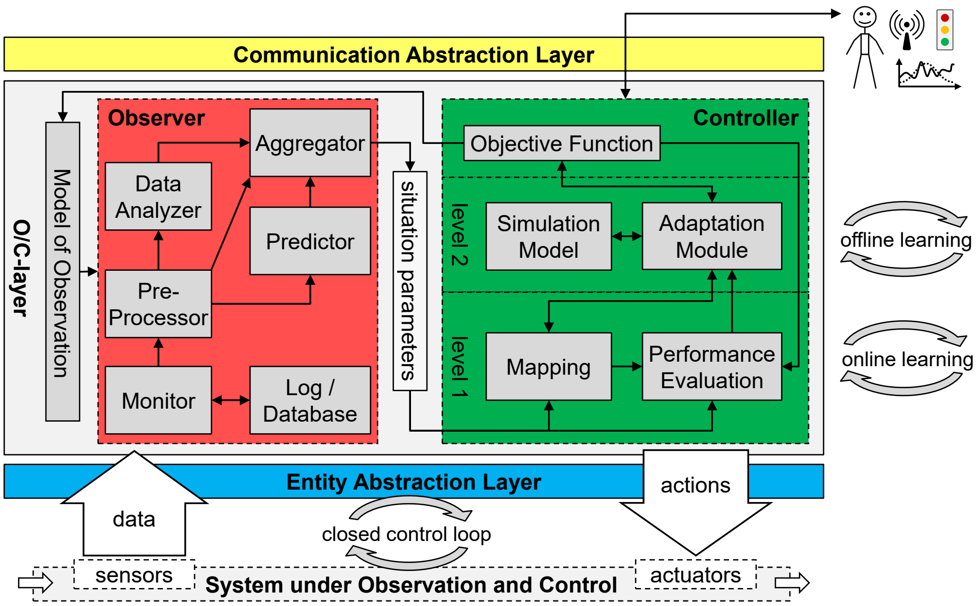


Figure 5.2: *Extended Observer/Controller Architecture*, partly based on [409, 502]

5.1.2 Application: Management Systems for Entities in Smart Grids

In general, there are numerous ways of applying the O/C Architecture to control systems in energy systems. Some general variants are depicted in Figure 3.12 on p. 111. Smart grids are complex systems comprising many different entities. Therefore, the introduction of a centralized structure (see Figure 3.12a), i. e., a single O/C-unit managing all entities, is only of limited use: For one thing, it does not reduce the complexity and requires a powerful centralized system. For another, it poses a major single point of failure. The introduction of a distributed structure (see Figure 3.12b) does not provide such a single point of failure, but may lead to a high communication and coordination overhead. [409]

In contrast, the introduction of a mostly hierarchical structure of multiple hierarchical layers is suitable for smart grids (see Figure 3.12d). This approach is supported by the concepts of self-similarity and recursion, which are also typical of so-called holons (see Section 3.7.4). These concepts enable not only the usage of the same architecture but also of similar algorithms and implementations of an O/C-unit for different entities and include the usage of the same layers in simulations as well as in productive applications of EMSs in smart grids [11]. When designing control systems for smart grids that use the O/C Architecture, the overall system is composed of entities following the same design principles and supporting an organic behavior [442]: in case of a breakdown of a higher-level entity, the subordinate entities may run autonomously. Nevertheless, the introduction of the CAL and the EAL allows for the integration with systems using other approaches. [409]

Management systems in smart grids may be grouped in different ways that lead to a mostly hierarchical structure. From the perspective of electricity grids, the grouping may follow the physical structure of the electricity grids: Each entity is managed by a dedicated O/C-unit and grouped by a superior O/C-unit for the respective distribution grid (see

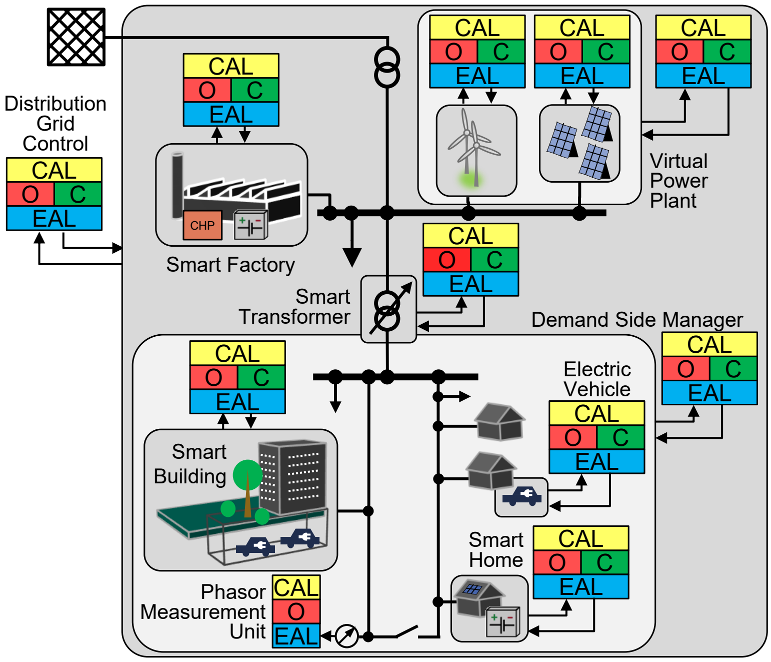


Figure 5.3: Smart distribution grid with an exemplary hierarchical *O/C Architecture* containing *Observers* (O), *Controllers* (C), *Entity Abstraction Layers* (EAL), and *Communication Abstraction Layers* (CAL), based on [409]

Figure 5.3). However, O/C-units may also provide the management for virtual entities, such as VPPs that span multiple distribution grids. Additionally, this grouping according to the physical electricity grid may also conflict with groupings that follow grids of other energy carriers, e. g., district heating or cooling. Nevertheless, the spatial grouping is often similar and conflicts may be mediated by an additional O/C-unit. For these reasons, the structure does not necessarily follow that of the physical electricity grids. Furthermore, a strictly hierarchical structure is unlikely because of regulatory, market, and technical requirements.

To reduce the complexity of each O/C-unit, most entities have to be managed by several layers of O/C-units that split up necessary tasks. Each O/C-unit is responsible for abstracting the properties of its SuOC, such as its provided information and flexibilities for the optimization. For instance, DG comprising PV systems and CHPs can be aggregated to VPPs that provide abstracted flexibilities. These are then used by another entity to provide, for instance, ancillary services to the grid. Beyond VPPs, there may be also entities having no direct equivalent in the physical electricity grid or others spanning across multiple voltage levels: for instance, so-called *demand side managers* may enable measures of DSM and facilitate *regional energy management*.

In addition to the spatial dimension, there is also the temporal dimension: the entities may work on different temporal scales when fulfilling their tasks, such as the provision of different types of operating reserves or of operational and strategical energy management. This has to be taken into account by the O/C-units and has implications for the methods that are used, e. g., scheduling and control engineering. [409]

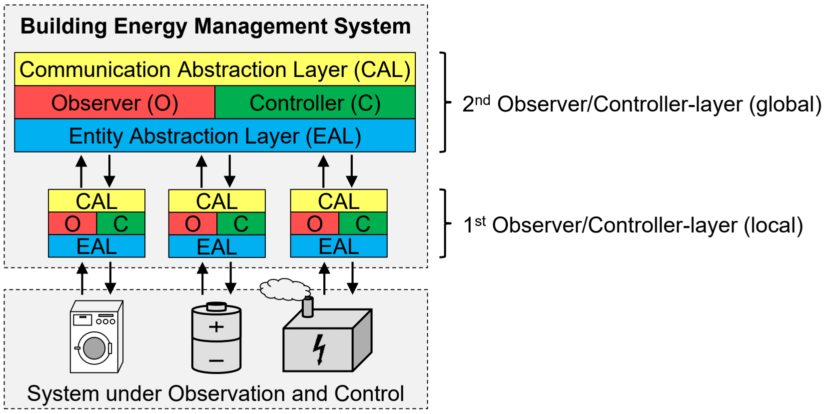


Figure 5.4: Hierarchical *Extended Generic O/C Architecture* utilized by a BEMS

Building Energy Management Systems Allerding (2013) [10] proposes the usage of a hierarchical O/C Architecture using two layers for building energy management. Observable and controllable devices and systems in buildings, such as appliances, PV systems, BESSs, microCHPs, form the SuOC (see Figure 5.4). More precisely, the devices and systems are observed and controlled by dedicated local O/C-units in the *local* O/C-layer which in turn are managed by a global O/C-unit of the *global* O/C-layer (see also Figure 5.5). Actually, each device or system may also include a device-internal control unit that is based on the O/C Architecture and forms another O/C-layer. In Section 4.9.2, the usage of the O/C Architecture in the OSH is described in more detail.

Not only BEMSs may benefit from the Extended O/C Architecture but also management systems of many other entities, such as generators, transformers, and sensor equipment (see Figure 5.3). Based on [409], some of them are briefly explained in the following paragraphs.

Demand Side Managers, Demand Management Systems, and Regional Energy Management Systems In general, *demand side managers* [409], *demand response managers* [136], *demand management systems* [181], and *regional energy management systems* [356] are entities that help to balance the supply and the demand in energy systems. This complex task requires information about the grids' states and the available flexibilities. Based on this information, the measures, such as changing or rescheduling the operation of heat pumps or the (dis-)charging of electric vehicles, have to be optimized. Actually, an automated BEMS provides local demand management and works as a local demand side manager, enforcing load limitations and optimizing energy costs within a single building.

Smart Producers, Electric Vehicles, and Energy Storage Systems A smart control of DG and BESSs may help to avoid congestion in the grid and voltage problems [63, 161, 620]. In the future electricity grid, controlling the charging of electric vehicles is essential for the grid's stability because otherwise it could lead to high peak loads at some times of the day [216, 328]. Quite the opposite, smart charging may provide additional flexibility to the grid [254]. Furthermore, bidirectionally connected electric vehicles may provide additional energy storage capacity, increasing the flexibility even more [443, 537].

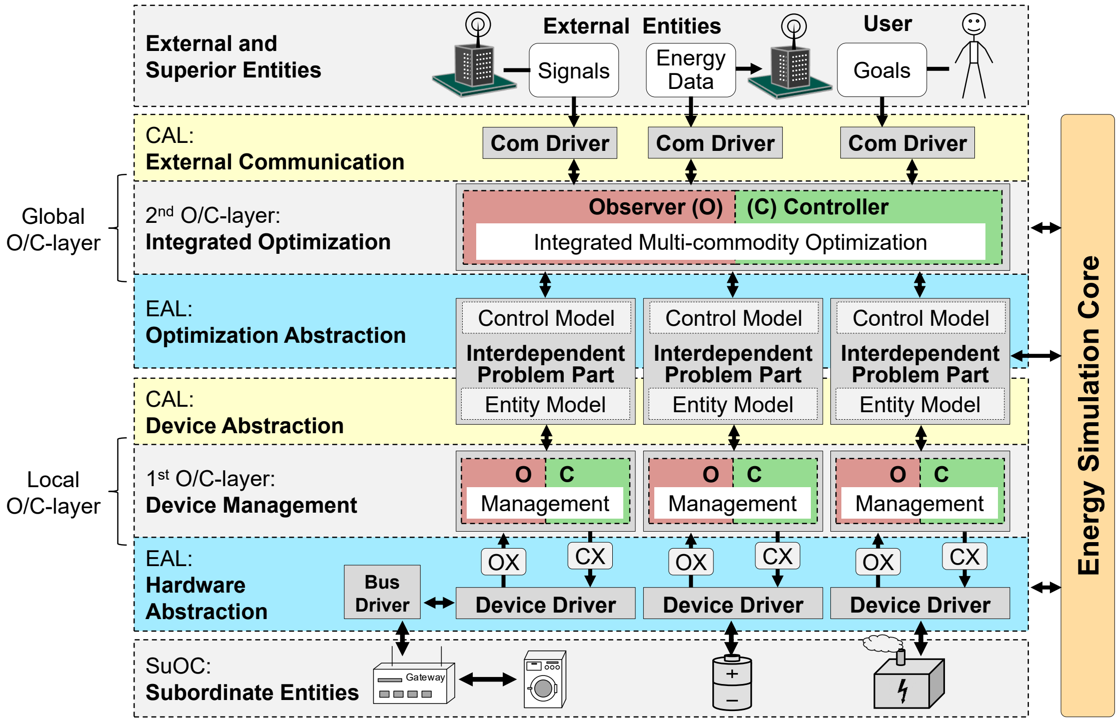


Figure 5.5: Architecture of the *Organic Smart Home*, partially based on [409]

Grid Operation Equipment and Infrastructure In addition to the information that is provided by smart buildings, producers, and storage systems, an O/C-unit managing a grid may need additional information about its state and equipment to control it. This includes additional grid infrastructure, such as phasor measurement units, remotely controllable disconnecting switches, smart transformers, and flexible AC transmission systems, that is included in the SuOC by means of corresponding O/C-units.

5.2 Novel Concepts, Functionality, and Implementations

This section provides an overview of the implemented concepts and extensions in the BEMS (see Figures 5.5 and 5.6). Firstly, there are *bus drivers*, which allow for the integration of gateways that provide connections to multiple devices, and the separation of the internal communication into multiple so-called *Registries*. Secondly, there is the introduction of multiple energy carriers and multi-modal energy management by means of the so-called *Energy Simulation Core*, which distinguishes commodities and ancillary commodities, and the so-called *Interdependent Problem Parts*.

5.2.1 Bus Drivers

Many devices and systems in buildings are not directly connected to BEMSs but have some kind of intermediary gateway that provides an abstraction of protocols and communication media, i. e., hardware interfaces, and extends the spatial coverage of a BEMS. Typically,

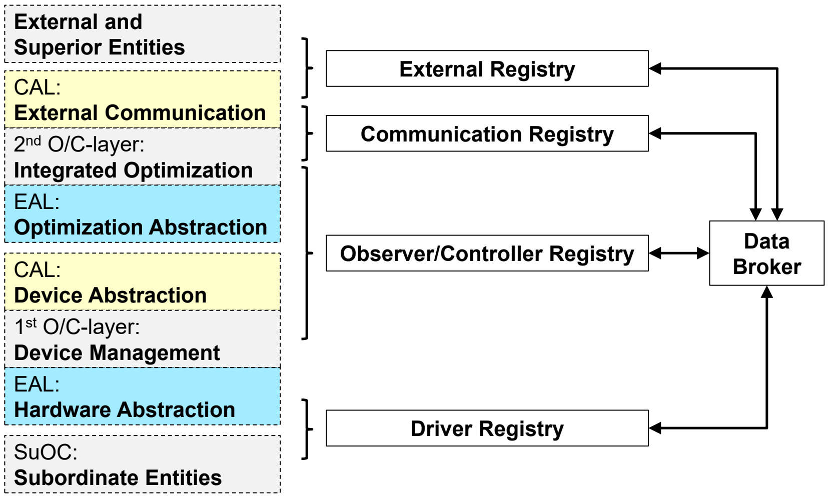


Figure 5.6: Architecture of the *Organic Smart Home*: separation of *Registries*, enforcing the strict separation of the layers that is originally induced by the *O/C Architecture*

such a gateway connects multiple devices to a BEMS. Although it is principally possible to open one communication channel to the gateway for each *device driver* of a device that is connected to the gateway, this may cause problems, such as keeping too many active connections, and requires all device drivers to monitor the connection to the gateway, e. g., to detect a connection loss. Additionally, there would be no component in BEMSs that can react on new devices which are connected to the gateway and call for dynamic integration into the management at the run-time of the system.

Therefore, this thesis introduces *bus drivers* (see Figure 5.5, bottom left). Each bus driver maintains a connection to one gateway and distributes the data from connected devices to their corresponding device drivers. Additionally, bus drivers can trigger the loading of device drivers for devices that are newly connected to or discovered by the gateway. Hence, bus drivers are an important component to enable *plug-and-play* functionality.

5.2.2 Multiple Registries, Simulation Engines, and Random Seeds

To improve the structure of the framework and facilitate simulations of multiple buildings, this thesis improves fundamental components of the OSH.

Multiple Registries The separation of the communication of the various layers and the introduction of clear communication lines, which were intended by the O/C Architecture, are enforced by the introduction of multiple *Registries* (see Figure 5.6). The communication between the device drivers and the bus drivers is handled by the *Driver Registry*. Observers and Controllers use the *Observer/Controller Registry* as well as the *Communication Registry* for the communication with *communication drivers*. The communication with external entities, such as demand side managers or regional energy management systems is handled by the *External Registry*. In addition, there is the so-called *Data Broker* that manages the information exchange with external entities via the External Registry as well as across the internally used registries.

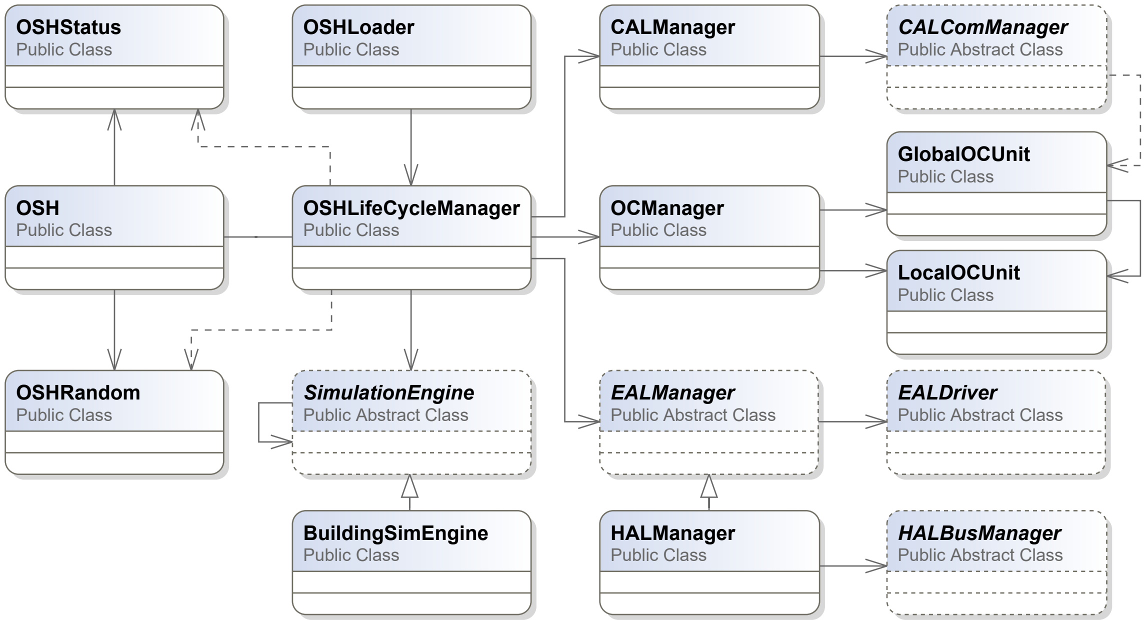


Figure 5.7: Simplified UML class diagram of basic classes of the *Organic Smart Home*

The registries are instances of an adapted version of the generic registry introduced by Allerding (2013) [10], which is similar to event bus or message queue concepts [46]. The registries support direct messages from a sender to a dedicated receiver, i. e., commands, broadcast messages from a sender to subscribed entities, state messages that are stored in the registry and fetched by other entities, and notifications about state changes. The separation into multiple registries facilitates the partial replacement of the registries by other implementations. This is demonstrated by Bao et al. (2016) [46, 47] in detail.

Multiple Simulation Engines Originally, the OSH used a single *simulation engine* to handle all tasks related to the simulation of devices and systems in the simulation mode. To support simulations of buildings comprising multiple flats as well as scenarios comprising multiple buildings, the simulation functionality has been extended to support multiple simulation engines of the `class SimulationEngine` (see Figure 5.7). The most superior engine triggers periodically, i. e., in every time step, each subordinate simulation engine instance in a recursive manner. These in turn trigger their related subordinate simulation engines. In the smart building scenarios that are evaluated in this thesis, there is just one simulation engine triggering the simulated devices and systems. However, the evaluation of multi-building scenarios in [354, 356] use multiple, hierarchical simulation engines.

Multiple Independent Random Seeds The random seeds providing pseudo random numbers that are used in simulations are generated centrally by the `class OSHRandom` (see Figure 5.7). Each simulation driver of the OSH receives its own random seed via the `OSHLifeCycleManager` and thus determines its randomized behavior and values independently of the other drivers. In so doing, it is easy to ensure the repeatability as well as the comparability of experiments in the simulation mode.

Separation of Configuration Files Each manager of the OSH (see Figure 5.7) uses a separate XML file that contains the configuration: The `CALConfiguration.xml` provides the configuration of the CAL, i. e., the communication drivers, whereas the `OCConfiguration.xml` provides the configuration of the O/C-units. Finally, the `EALConfiguration.xml` provides the configuration of the EAL, i. e., the bus drivers and device (simulation) drivers. The Interdependent Problem Parts (IPPs) (see later in this chapter) are configured via the corresponding O/C-units.

See Section 4.9, Allerding (2011) [13], and Allerding (2013) [10, pp. 93 ff.] for detailed descriptions of the remaining components depicted in Figure 5.7, which are related to the Extended O/C Architecture presented in Section 5.1.

5.2.3 Energy Carriers, Commodities, and Ancillary Commodities

To be able to apply BEMSs to many different scenarios and enable an efficient and effective integration of RES and DG into energy systems, all energy carriers in buildings have to be managed and optimized in an integrated yet modular way. Consequently, the presented BEMS considers not only electricity in terms of active power but also electricity in terms of reactive power, fuels, such as natural gas, and hot as well as chilled water.

Multi-modal Energy Management The integrated optimization is facilitated by multi-modal energy management, which is introduced, defined, and described in Section 4.7.3 in detail. Briefly worded, it is the integrated optimization of the provision, distribution, conversion, storage, and utilization of multiple energy carriers in an energy system, i. e., of the overall energy chain from input provision to output provision of energy carriers and energy services. This includes the optimization of the utilization of multiple energy sources and carriers, the distribution using multiple energy carriers and links, the conversion using multiple devices and systems, the storage using multiple energy carriers and ESS, and the provision of multiple energy carriers and services. To manage the different energy carriers by the BEMS, they are distinguished into different *commodities*.

Multi-commodity Optimization The concept of commodities is depicted in Figure A.11 on p. 362 and—in combination with multi-commodity optimization—more closely described and defined in Section 4.7.4. Nevertheless, the lone introduction of commodities is not sufficient for the kind of energy management and optimization that is required in buildings. For instance, active power that is generated by a PV system is different from active power that is generated by a microCHP system in various ways. Firstly, the compensation schemes for them are different and have to be respected by BEMSs that optimize with respect to total costs. Secondly, the related CO_2 emissions are different and have to be respected by BEMSs that optimize with respect to these emissions. This leads to the introduction of multiple *ancillary commodities* for each commodity.

Ancillary Commodities In multi-modal energy management and multi-commodity optimization (see Section 4.7), energy carriers are standardized and thus interchangeable by defining corresponding commodities for the carriers (see Figure A.11 on p. 370). Actually, electricity or other energy carriers, such as natural gas or fuels, are not commodities *per se*. They are available in many different qualities and provisioned by different devices and

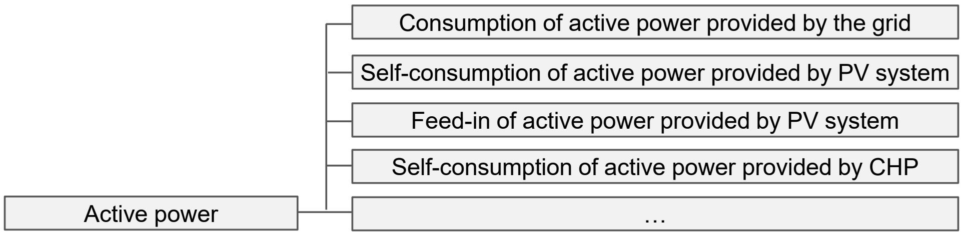


Figure 5.8: Commodity *active power* and exemplary related ancillary commodities

systems (see Figure A.12 on p. 376). To facilitate the integrated optimization, their specific properties and characteristics, such as voltage or calorific value, as well as their origin have to be determined and included into the optimization. This is done by separating every commodity into multiple ancillary commodities and providing information in addition to the mere power. The overall relation between energy sources, carriers, commodities, and ancillary commodities is presented in Figure A.13.

For instance, electricity in AC systems may be separated into two basic commodities: active power and reactive power. Subsequently, the commodity active power is further distinguished into different ancillary commodities having different origins and final uses, i. e., different ways of being provisioned and utilized (see Figure 5.8). There are many different pricing regimes that determine the costs for consumption or the compensation for feed-in of active power. The active power that is managed by the BEMS may have been provided, e. g., by the grid, generated by the PV system or a microCHP, fed back into the grid, or self-consumed by the local energy system, i. e., the building. Depending on the pricing regime, this leads to different costs that have to be determined correctly.

5.2.4 Energy Simulation for Multi-modal Energy Management

The determination of the properties and characteristics of ancillary commodities requires a detailed simulation of all energy flows in a building. This thesis introduces the *Energy Simulation Core*, which uses a stepwise simulation to enable the simulation of energy flows in the BEMS. Furthermore, it utilizes so-called *Interdependent Problem Parts*, which resemble real entities in suitable models, and *Interdependency and Interconnection Information* to facilitate the energy simulation.

Modeling of Building and Physical Entity Models

This thesis uses models of the devices and systems, which are composed to models of buildings. Basically, models are required for two different purposes in the BEMS: firstly, the simulation of the devices and systems in the simulation mode, i. e., replacing the real entities, and secondly, in the optimization module of the optimization layer. Therefore, there are actually two different models, which use, for instance, different temporal resolutions.

In the simulation of a building with BEMS, detailed models of the devices and systems are combined and coordinated by the *simulation engine* to simulate a building in a bottom-up manner (see Figure 5.9) using a relatively high resolution of one second. Thus, the *building*

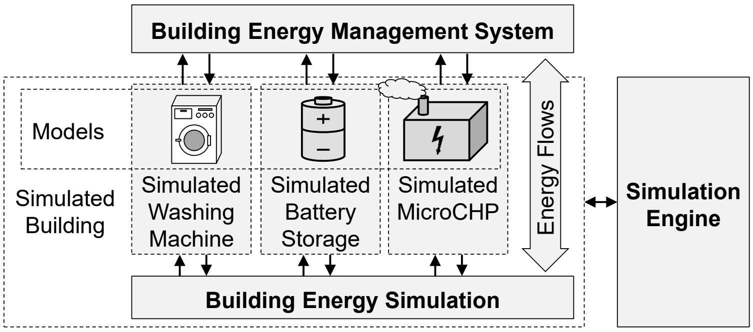


Figure 5.9: *Building Energy Simulation*: simulated devices and systems are part of the simulated building

energy simulation of energy flows in the simulated building and the interaction of entities, i. e., the devices in the simulation, work with a one-second resolution, which has been determined to be sufficiently precise to capture the dynamics of energy flows in buildings and simulate the building regarding the peak loads [10, 252, 638].

In both simulation and real-world application, simplified models are used in the optimization layer, i. e., the actual energy management and optimization, to simulate variants of possible future behavior of the entities, determine future load behavior and profiles, evaluate them, and ultimately facilitate the optimization process. The optimizer varies the input of the models and aims at obtaining the best behavior possible. This model of the building is run at a lower temporal resolution—usually at a resolution of one minute—because in real productive systems, it is difficult to build detailed and precise models of the entities that benefit from a higher resolution [138]. Therefore, the model has to be suitable for building energy management. This may also include the abstraction of the building's electricity grid to a single "copperplate", as it is done in this thesis.

Usually, thermal models require a lower resolution than electrical models to be suitable because electrical load profiles may have relevant spikes and short-term deviations (see also Section 3.5.3). This dynamic has to be respected by the optimization, e. g., to respect load limitation. Therefore, the system presented in this thesis allows for different resolutions of the resulting load profiles.

Energy Simulation Core

The Energy Simulation Core (ESC) simulates the local energy flows in the building, i. e., in the local electrical and thermal grids, in a multi-energy simulation. It handles not only the simulated energy flows between the devices but also the information exchange of additional information about the devices' states, such as tank temperatures or voltages. In so doing, devices are able to observe other devices and react on their statuses. To enable energy management across all energy carriers, i. e., multi-modal energy management, and respect interdependencies between the devices and systems, it distinguishes energy carriers into many ancillary commodities when simulating the energy flows (see Section 4.7 and Section 5.2.3). The optimizer performs a multi-commodity optimization, using the load profiles of all ancillary commodities (see Figure 5.10).

The ESC utilizes the IPPs, which act as proxies of the real devices in the simulation of the building. This facilitates a modular approach to building energy management and optimization because a concrete building scenario is dynamically composed of the IPPs. The interdependencies and physical connections between the devices are provided by the Interdependency and Interconnection Information (I^3). This enables the integrated optimization of so-called *interdependent entities*, which have to be optimized concurrently, because the behavior and the energy consumption of one entity are directly related to at least one other entity.

For instance, *trigeneration* systems are typical examples for systems that are composed of devices having interdependencies: In a CCHP system, the adsorption chiller as well as the CHP work on the same hot water storage tank and thus influence each other, because the required thermal energy in terms of hot water consumption of the chillers depends on the temperature of the hot water as well as of the chilled water. Other examples are hybrid appliances and BESSs. Typically, the charging and discharging power of BESSs depends on the combined electrical power of all other devices in the building [440]. In Section 5.3, the ESC is explained in detail. Section 5.4 describes the general concept of IPPs in detail. Concrete examples of the IPPs are presented in the Sections 5.5, 5.6, and 5.7.

Interdependent Problem Parts

The adaptivity and modularity of the integrated multi-commodity optimization is facilitated by the concept of IPPs. Although the IPPs are based on the *Problem Parts* presented in [10,11], their functioning is fundamentally different and enables a fully modular optimization of interdependent entities. This has not been possible when using the Problem Parts of the original OSH. The IPPs are provided by the local O/C-units in the *Device Management Layer* and used by the *Integrated Optimization Layer* (see Figure 5.5 on p. 201).

In Section 5.4, the concept, working, and usage of IPPs are described in detail. The concrete IPPs of the devices and systems are presented in the subsequent sections. Put simply, each IPP contains information about the entity's behavior and the feasible control sequences and interactions. Thus, each IPP represents a single device, e. g., a microCHP, or system, e. g., a space heating system consisting of multiple radiators. The models contain, for instance, built-in operating and control strategies, e. g., on-off control or hysteresis functions, which ensure that control sequences of the optimization lead only to valid states of the entities. Thus, the control strategies provide a basic level of control, which works also as a kind of fallback control in the optimization. The IPPs are used by the ESC to interpret solution candidates of the optimizer and to create ancillary commodity load profiles of the devices in a simulation using discrete time steps and respecting their interdependencies which are given in the I^3 of the local grids (see Figure 5.10).

Heuristic Multi-commodity Optimization

The BEMS presented in this thesis uses an EA—more precisely a GA—in the multi-commodity optimization process. The GA is based on a refined version of the *generic Genetic Algorithm* from the *jMetal* framework [184, 185]. The meta-heuristic operates on a bit string and has proven to cope with the complexity of the optimization problem

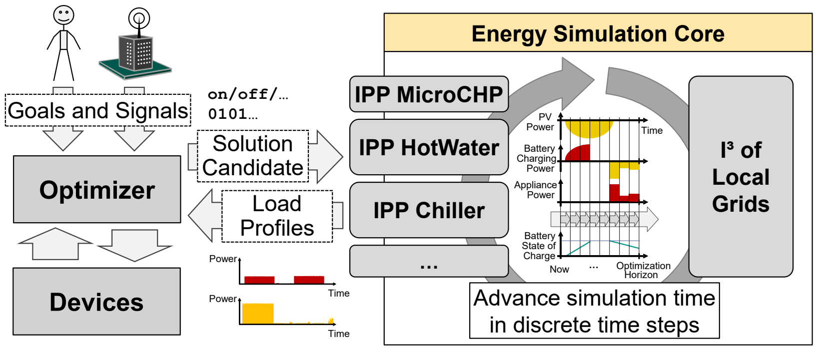


Figure 5.10: Usage of the *Energy Simulation Core* in the optimization process

that arises in certain scenarios. The optimization problem uses a dynamic formulation of the modular problem instances—represented in the IPPs—at the operation of the system, because solving the optimization problem *ex ante* is only possible when having complete information about future energy flows, which is not the case in real BEMSs. [410]

Although BEMSs should run on low-power computers utilizing only little electrical energy and thus having limited system resources, the execution time of the optimization algorithm is crucial because frequent rescheduling is likely and a quick reaction on user interaction is desirable. Hence, generating approximate solutions by a heuristic that allows for frequent rescheduling in varying setups promises to be of better use for productive energy management than solving exactly. This is in accordance with the results of the analysis presented in Section 4.8.

Rolling Optimization Horizon The optimization uses a rolling optimization horizon. The length of this horizon is determined using the IPPs: Every IPP includes the desired length of the optimization horizon of the corresponding device. Thus, the actual horizon is based on the maximum desired length of all IPPs that are currently part of the optimization. Each time there is significant change in the state of one of the devices, a new optimization process is triggered and a new problem instance is formulated. [410, 412]

Optimization Process A simplified overview of the optimization process is depicted in Figure 5.10. The optimizer uses information and IPPs from the devices, goals of the user, and signals from external entities to generate solution candidates, which are evaluated in the ESC by means of the IPPs and the I^3. Then, the resulting load profiles are assessed with respect to the objectives of the optimization. Based on this assessment, the best candidate is applied to the devices and systems. The evaluation in the ESC is described in detail in Section 5.3 and the actual optimization process is closely described in Section 5.8.

Encoding used by the Genetic Algorithm In principle, the solution candidates may consist of real numbers, bit strings, or any other representation of the future behavior or parameters of the devices. However, this thesis uses a binary encoding in form of a combined bit string. The sub-problems of the optimization, i. e., the IPPs, are included into the optimization process by using bit strings that encode the future behavior of the devices. For instance, a bit string may encode the delay until a deferrable device is started (see Section 5.5), the periods

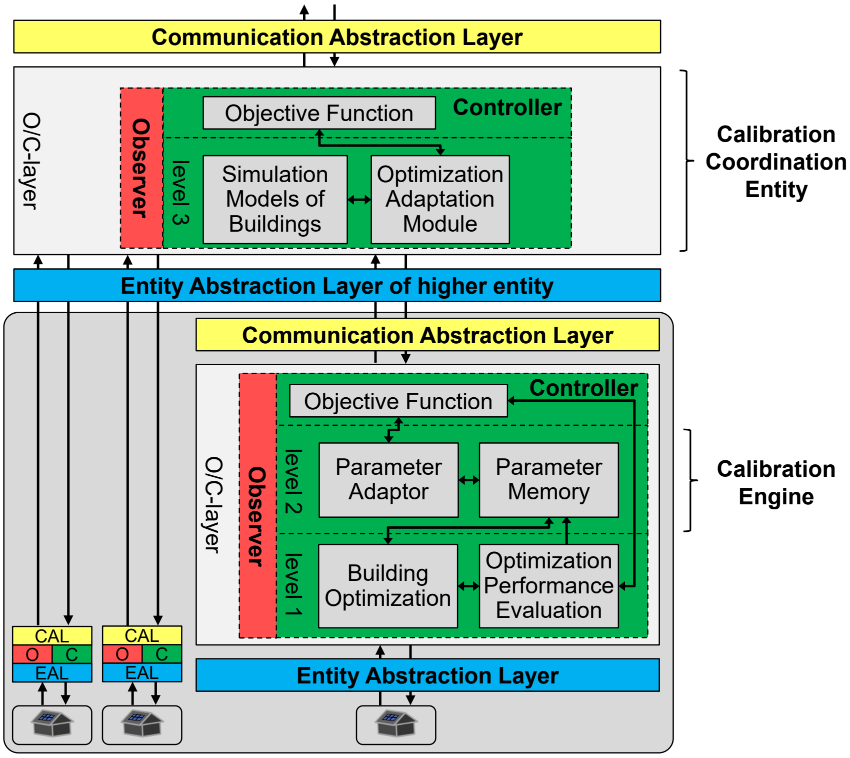


Figure 5.11: Parameter calibration and tuning process for multiple buildings by higher entity using the *Extended O/C Architecture*, based on [409, Fig. 8]

when a microCHP will be running (see Section 5.6), or the parameters of a BESS [440]. Binary encodings are flexible, simple, and easy to modify by a GA [12, 247, 274, 410]: the optimizer simply operates on the concatenated bit string of all substrings.

Automated Parameter Calibration and Tuning The heuristic optimization using a GA requires suitable parameters for the crossover and the mutation rates. To obtain them, a parameter calibration has to be carried out before the execution. In real environments, there are many different scenarios. Therefore, this thesis proposes the introduction of a so-called *Calibration Engine* and a so-called *Calibration Coordination Entity* (see Figure 5.11). The former realizes the adaptation of the optimization in a second level of the controller of the BEMS and the latter coordinates the parameter calibration process of multiple buildings, promotes the collaboration of similar buildings, and avoids the overfitting of parameters to specific past behavior. This process of automated parameter calibration and tuning is more closely described in Section 5.9.

5.2.5 Novel Devices supported by the BEMS

The BEMS presented in this thesis does not only support the simulation and optimization of smart buildings scenarios comprising deferrable appliances, PV systems, and microCHPs as presented by Allerding (2013) [10] but also the following devices and systems:

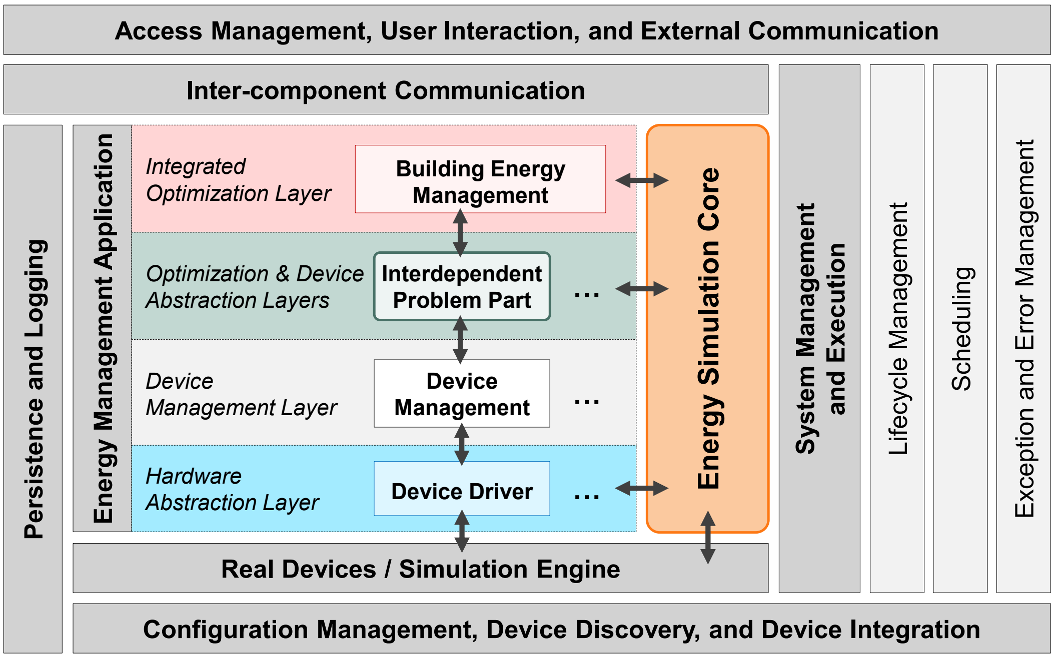


Figure 5.12: Architecture of the building operating system

- Future, i. e., interruptible and hybrid, home appliances (see Section 5.5)
- Adsorption chillers and trigeneration systems (see Section 5.6.2)
- Gas boilers (see Section 5.6.3)
- Electrical IHEs (see Section 5.6.4)

In addition to these novel devices and systems, the BEMS does also enable the optimization of BESSs. However, this is not part of this thesis. More information about the optimization of a BESS is provided by Müller et al. (2016) [440]. Furthermore, existing models of conventional appliances, the microCHP, and the PV system as well as the simulated hot water consumption have been enhanced by more realistic load profiles and usage statistics. Additionally, the thermal demands and storage systems are now optimized in a modular way. See Tables 6.3 and 6.4 on pp. 263 ff. for a comparison to other BEMSs and Table 6.5 on p. 268 for a detailed comparison to the original OSH by Allerding (2013) [10].

5.2.6 Building Operating System

The BEMS presented in this thesis comprises dedicated components that provide elementary services and device abstraction functionality. These services and functionality facilitate adaptivity in dynamic environments and may not only be used for energy management but also for services from other domains, such as assistance, comfort, entertainment, information, safety, and security (see Section 4.1.1). Therefore, the building energy management is part of a BOS, which enables a wide range of applications that utilize the devices and systems in a smart building. Actually, the BEMS is executed on top of a normal OS and is thus a *meta*-OS for buildings.

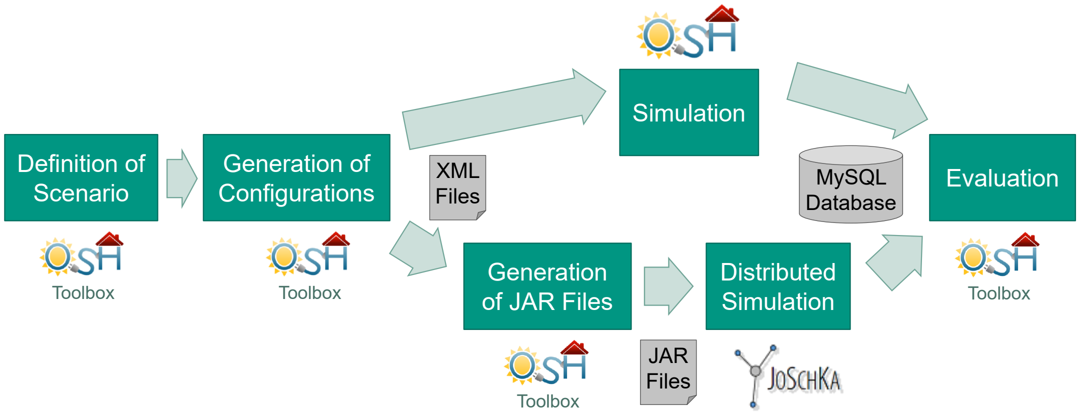


Figure 5.13: Standard procedures when running the *Organic Smart Home* (OSH): local simulation and distributed simulation using the *Job Scheduling Karlsruhe* (JoSchKa) system

Figure 5.12 depicts the architecture of the BOS and the actual *energy management application*, which realizes building energy management and optimization. The *system management and execution* module is responsible for the initialization and execution of the system as well as for error management and exception handling. The *persistence and logging* module performs input and output operations and manipulates data sources. The *access management, user interaction, and external communication* module provides access control and exchanges information with the user and other systems. The *configuration management, device discovery, and device integration* module enables the adaptivity of the BEMS.

The *energy management application* is handled by the *lifecycle management* and supported by the *simulation engine* (see Figure 5.7 on p. 203) as well as the ESC (see Section 5.3), which are part of the OSH framework. The functionality of the modules is consistent with the elementary and supporting services of OS, which have been proposed by Silberschatz et al. (1998) [550] (see Section 4.6.5). The Figures E.3 and E.4 on pp. 434 f. provide simplified UML class diagrams of the OSH, which has been implemented using *Java 8*.

5.2.7 Job Scheduling Karlsruhe and Database-support

The toolbox of the OSH has been extended to support the creation of *JAR* files that include smart building scenarios and can be executed using the Job Scheduling Karlsruhe (JoSchKa) IT infrastructure at the KIT. More information about JoSchKa is given in [83].

Hence, there are now two standard procedures when executing simulations using the OSH (see Figure 5.13). After defining the scenarios that are to be simulated, corresponding configuration XML files are generated by the OSH toolbox. Afterward, these files can either be used directly in the simulation mode of the OSH or be used by generated executable JAR files. The JAR files may be loaded into the JoSchKa system and automatically distributed to several dozens of computers for distributed execution and thus simulation of the scenarios. Results of the simulations are always logged redundantly into multiple SQL databases. The OSH provides tools to evaluate these results and generate spreadsheets.

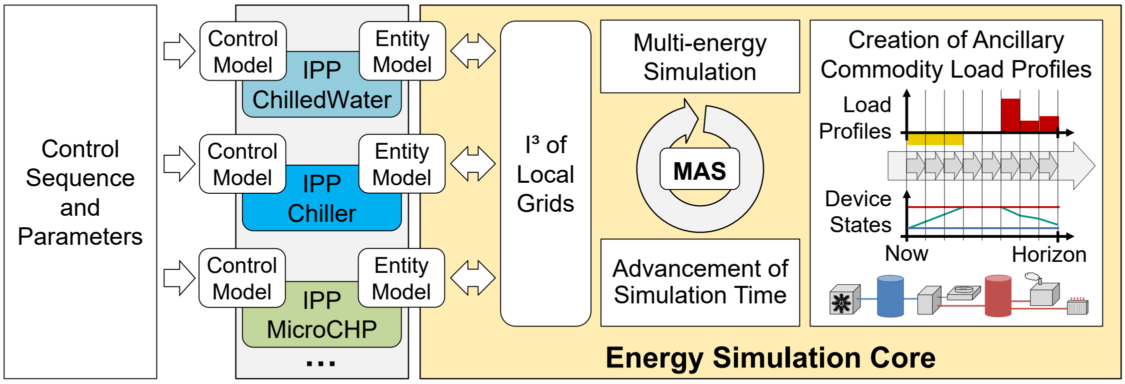


Figure 5.14: Parametrization and interpretation of *Interdependent Problem Parts* using a solution candidate and creation of ancillary commodity load profiles

5.3 Energy Simulation Core

The ESC performs a multi-energy simulation of the energy flows in a building, i. e., between the devices and systems that are related to the building. These entities are interconnected in the local energy grids, i. e., electricity, gas, and thermal grids. For this purpose, the ESC uses IPPs, which provide so-called *entity models* and *control models* of the real entities. Thus, they act as proxies of the real devices in the building for the simulation by emulating the behavior of the entities based on control actions and parameters that are passed to the control models (see Figure 5.14).

The interdependencies and physical connections between the entities are provided by the I^3, enabling the simulation of energy flows, the exchange of additional information about the devices' states, and hence the creation of ancillary commodity load profiles, which provide the basis for the concurrent optimization of all entities.

In general, the ESC facilitates the dynamic simulation of buildings, of the energy systems and supply infrastructure within the buildings, and of the control as well as scheduling algorithms, tackling the fundamental requirements of energy system simulation platforms [433].

5.3.1 General Concepts and Integration into Energy Management

The general idea of this thesis is the introduction of a fully *modular approach* to the simulation of energy systems that allows for the consideration of interdependencies between the entities. The latter are resembled by so-called IPPs and interconnected using the so-called I^3, which defines links and interconnections between them. The actual simulation is then executed in the ESC.

Essentially, this concept is a *multi-agent system* that uses the ESC as executor of the simulation, the IPPs as agents, and the I^3 as environment, thus defining the possible interaction between the agents, i. e., information and virtual power exchange between devices of the energy system. Hence, the multi-agent system is actually a *discrete time system specification* based on *first-order difference equations* that define the *recurrence relations* not only with respect to time but also across the agents.

The prototypical implementation of the ESC is exemplarily integrated into the BEMS that is presented in this thesis. However, it may easily be transferred to other use cases (see Section 5.10). This section provides the details from the perspectives of discrete time system specification and multi-agent systems.

Discrete Time System Specification and Difference Equations

Building energy management by means of optimization does not aim at competing with methods of control systems engineering, therefore the analysis of transient states and the facilitation of sub-second optimization is out of scope of the system presented in this thesis. Although many interdependencies in buildings are described by differential equations, e. g., the heat equation in thermodynamics, this thesis simplifies the modeling and simulation of buildings and their devices and systems and does not aim at competing with building simulation tools (see also Section 2.5 and cf. [72, 659] and Section 4.8.1). Therefore, this thesis uses *discrete time system specification* to simulate the future behavior of buildings in simulations as well as in real-world application of the BEMS. In case of simulations of buildings with BEMSs, another model is used to simulate them precisely.

The discretized time has to be able to reflect the dynamics of the system, because the variability within a time step is neglected. For instance, power limit signals and technical limitations of loads have to be considered when simulating and optimizing the system. Otherwise, the optimization will simply not reflect the behavior of the real system, rendering it inaccurate and probably even useless. Typically, all values, e. g., loads, temperatures, and efficiencies, have a constant value within a time step. However, the ESC supports also load-profiles that are not constant within the time steps.

The discrete time state dynamics are determined using the *Euler method* with a sample time of $\Delta t = 1\,\mathrm{s}$ in the detailed simulation of the building and with a sample time of $\Delta t = 1\,\mathrm{min}$ in the optimization. The Euler method is a numerically stable method for the calculation of difference equations [659, p. 55]. Similar systems use also other *Runge-Kutta* methods, such as the *Crank-Nicolson method* [252]. However, it is only necessary to use these more complex methods if the temporal resolution is significantly lower than the one that is used in the OSH, because of the relatively low dynamics of the energy systems regarded in this thesis [39, 252, 500, 532].

The new state $x_j(t_{n+1})$ of an entity j at time step $n+1$ is calculated using the old state $x_j(t_n)$ from the previous time step n as well as the reaction $f(x_j(t_n), Y_j(t_n))$ of the entity on this previous state and the input $Y_j(t_n)$ from other entities. Essentially, this may be expressed by the following formula, defining a first-order difference equation:

$$x_j(t_{n+1}) = x_j(t_n) + f\left(x_j(t_n), Y_j(t_n)\right) \, . \tag{5.1}$$

In general, this leads to a *state trajectory* $\mathcal{S}$ of the vectors $X(t_n), X(t_{n+1})...X(t_{\max})$ for all m entities in the optimization horizon having the duration $t_{\max}$:

$$X(t_n) = \left(x_1(t_n), x_2(t_n) \, ... \, x_m(t_n)\right)^\top , \tag{5.2}$$

$$\mathcal{S} = \left(X(t_1), X(t_2) \, ... \, X(t_{\max})\right) \, . \tag{5.3}$$

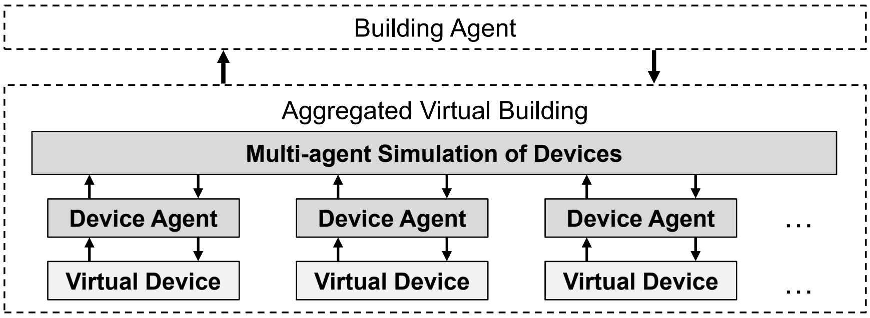


Figure 5.15: Multi-agent simulation of device agents utilizing virtual devices, leading to the aggregated virtual building that is represented by the building agent

Basically, the input $Y(t_n)$ from other entities is based on the interaction of the agent $\mathcal{A}_j$ having the state $x_j(t_n)$ with the other agents, i. e., their states $X(t_n)$, within the environment $\mathcal{E}$. Finally, this results in a certain state trajectory $\mathcal{S}$ that is evaluated. This is more closely described in the following section from the perspective of multi-agent systems.

Multi-agent Simulation

The energy simulation of multiple energy carriers in the ESC is a *multi-agent simulation* (see Figure 5.15). Devices are represented by *device agents*, i. e., the device internal control systems, their controllability, and *virtual devices*, i. e., the models of the real devices. The combined simulation of all devices leads to the *aggregated virtual building*, which is managed by the *building agent*, i. e., the integrated building energy management. This approach introduces modularity to building energy management and optimization, because a concrete building scenario is composed dynamically using the IPPs and new devices are simply appended by adding new agents and extending the information about their environment and possible interaction. This is necessary, because the concrete operational scenarios, i. e., the different setups of devices and characteristics of devices as well as the optimization objectives and goals of the users, are unknown *a priori* to the installation of the BEMS. Furthermore, the properties of the scenarios may change over time, for instance, when additional devices are added.

The multi-agent simulation uses the I^3 when simulating the interaction of the device agents, i. e., the IPPs in the evaluation. Thus, the I^3 determines the interaction of the agents $\mathcal{A}$ in their environment $\mathcal{E}$ by transforming the states $X(t_n)$ of the agents to inputs for other agents $Y(t_{n+1})$:

$$X(t_n) \xrightarrow{\mathcal{E}(\mathrm{I}^3)} Y(t_{n+1})\,. \tag{5.4}$$

The states of all agents over the optimization horizon $\mathcal{H}$ form the so-called state trajectory $\mathcal{S}$. The state trajectory of a single agent is $S_{j\bullet}$, i. e., the row j of the matrix S. The states of all agents at a single time step are expressed by $X(t_n)$ (see also above). More information about other multi-agent simulations in energy systems is provided, for instance, in [120, 413, 540].

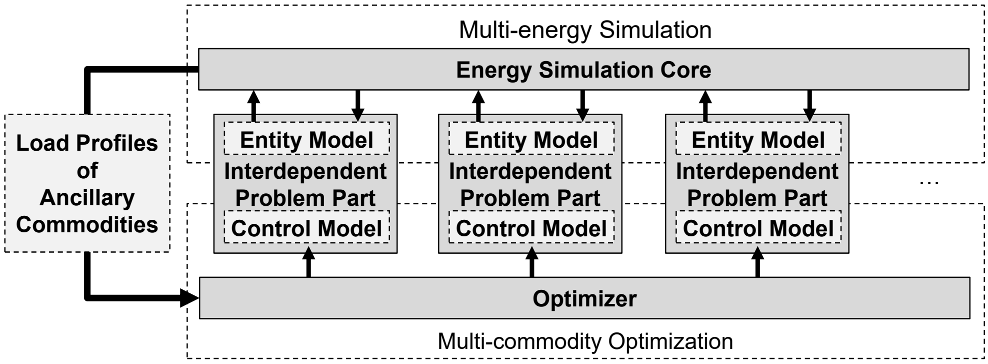


Figure 5.16: Interaction of the multi-energy simulation and the multi-commodity optimization to create the ancillary commodity load profiles: the *Interdependent Problem Parts* receive input from the optimizer via their *control models* and interact with the *Energy Simulation Core* via their *entity models*

Steps of the Multi-agent Simulation The actual multi-agent simulation separates the abstract construction of the state trajectory into the following steps, which are executed by the ESC using the IPPs:

1. ***Initialization Step***:
   The environment $\mathcal{E}$ and the agents are initialized using the I^3, the models, and their initial values and states.
2. ***Execution of Multi-agent Simulation***
   The optimization horizon $\mathcal{H}$ is simulated.
   a) ***Energy and Information Exchange Step***:
      Agents receive information updates $Y(t_n)$ about the previous states, i. e., the state vector $X(t_{n-1})$, from other agents.
   b) ***Behavior and State Update Step***:
      The agents are updated using the received information.
   c) ***Energy Flow Simulation and Ancillary Commodity Calculation Step***:
      Based on the environment $\mathcal{E}$ and information from agents $\mathcal{A}$, the energy flows are simulated, i. e., the commodities, and the ancillary commodities are calculated (see also Section 5.3.4), resulting in the state vector $X(t_n) = (x_1(t_n), x_2(t_n) \dots x_m(t_n))^\top$ for the m agents.
3. ***Finalization Step***:
   Resulting state trajectory $\mathcal{S} = (X(t_1), X(t_2) \dots X(t_{\max}))$ is prepared for evaluation.

Integration and Usage in Building Energy Management Systems

The simulation of buildings and their devices and systems is an important prerequisite for the optimization in BEMSs in simulated as well as in real buildings. This thesis uses models of the devices and systems, which are then combined into the models of buildings.

Basically, models are required twice in the BEMS: firstly, in the optimization module of the optimization layer and, secondly, in the simulation mode for the simulation of the devices

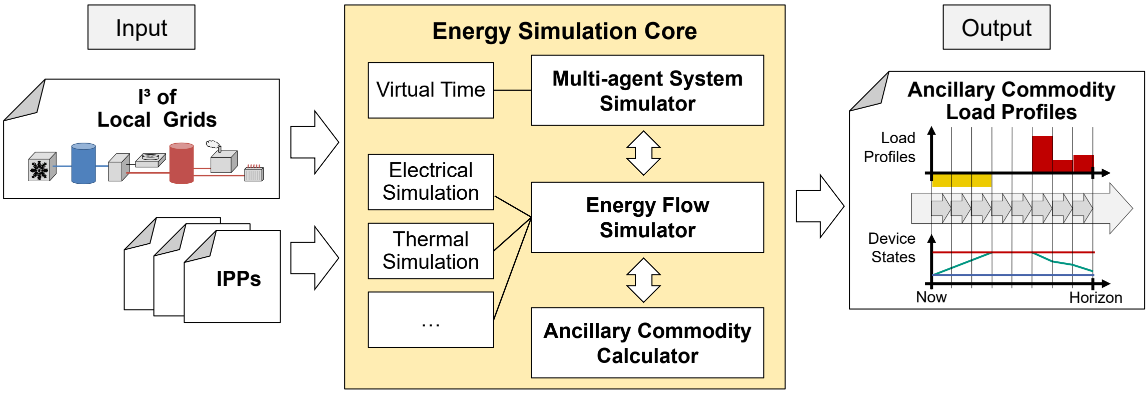


Figure 5.17: *Energy Simulation Core*: general operating principle in the optimization module

and systems. In real buildings, energy simulation is only required in the optimization process for the evaluation of possible future building behavior, whereas in simulated buildings, it is also required for the detailed simulation of the real building which is to be optimized in a simulation study.

Figure 5.16 depicts the integration of the ESC into the BEMS: The optimizer selects eligible inputs for the *control models* of the IPPs, which define the possible control actions, parameters, and interactions with other entities and the user. The ESC exchanges information with the IPPs using their *entity models*, which reflect the physical and technical behavior of the devices, generating load profiles of the ancillary commodities. These load profiles are evaluated by the optimizer (see Section 5.4).

5.3.2 Architecture and Components

The general architecture of the ESC is depicted in Figure 5.17. The ESC handles the information exchange between all simulated devices, orchestrates the steps of the multi-agent simulation (see above), and comprises three main components: the *Multi-Agent Simulator*, which performs the multi-agent simulation, the *Energy Flow Simulator*, which uses an *Electrical Simulation* and a *Thermal Simulation* to determine the actual energy flows, and the *Ancillary Commodity Calculator*, which calculates ancillary commodity load profiles in so-called virtual meters. Figure 5.18 as well as Figures E.3 and E.4 on pp. 433 f. provide class diagrams of the exemplary Java implementation of the ESC and their components in both kinds of simulations. A UML sequence diagram showing the interactions between the solver of the optimization module, the energy management problem that is solved, the IPPs, and the ESC of the global O/C-unit is given in Figure E.2 on p. 432.

The local electricity grid consists of the electrical connections, i. e., the wiring, between all devices consuming or producing electricity in a building. In contrast, the local thermal grid consists of thermal connections between the devices, e. g., pipes, convection, and thermal bridging. Therefore, each simulator handles a specific set of energy carriers and simulates their respective local grids. [408, 410]

The general interaction of the ESC with the IPPs is depicted in the Figures 5.14 and 5.16. The ESC uses the I^3, which contains the information about physical and informational

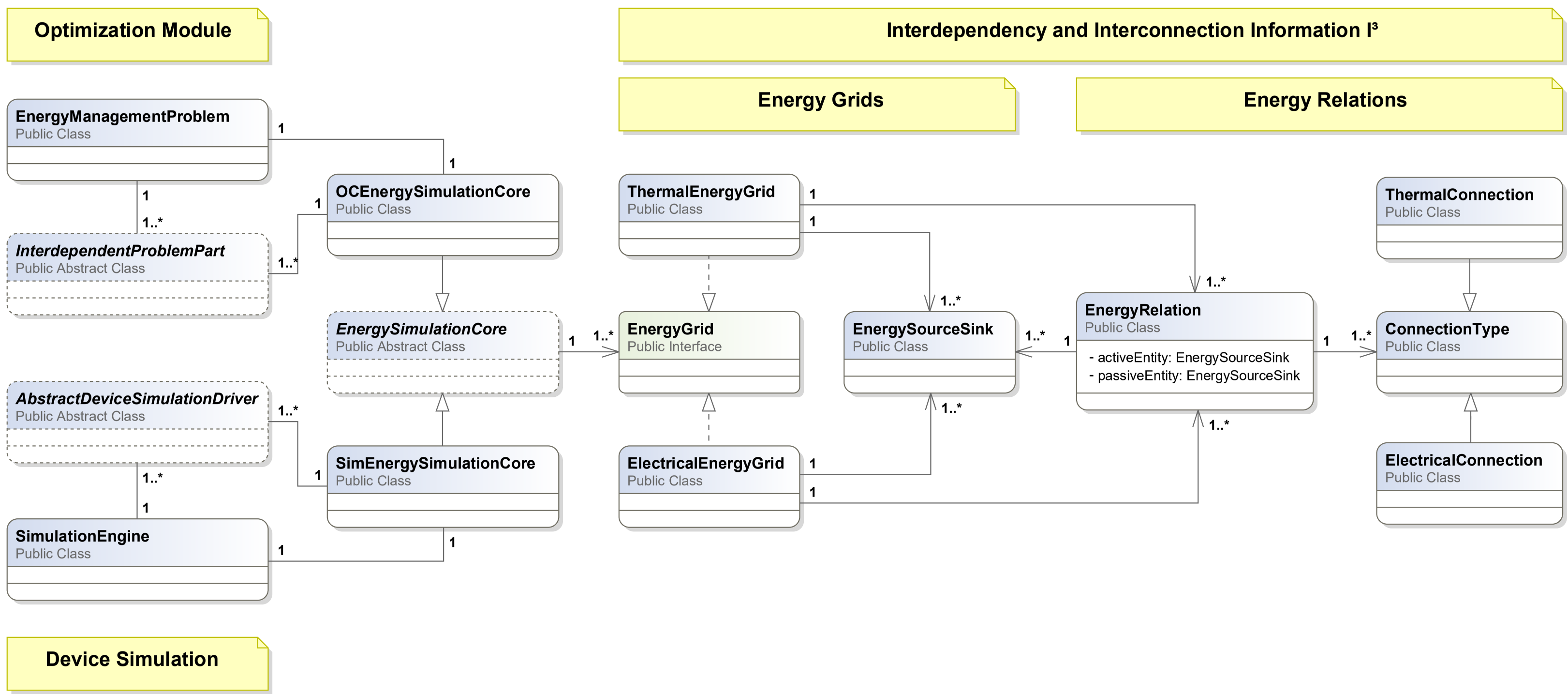


Figure 5.18: *Energy Simulation Core*: UML class diagram of the core components of the energy simulation in the *simulation mode* (simplified diagram)

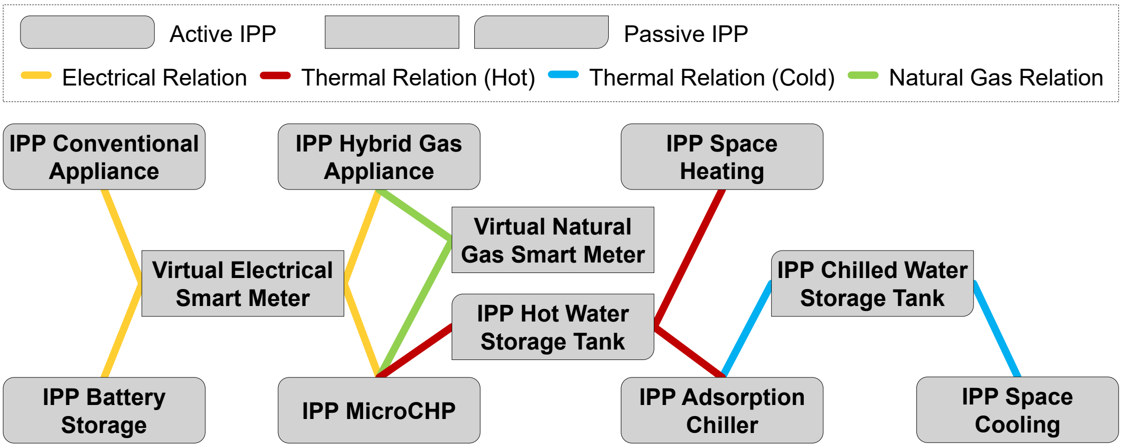


Figure 5.19: Exemplary electrical, thermal, and natural gas relations of *active* and *passive Interdependent Problem Parts* (IPPs)

interconnections, to perform a multi-energy simulation that creates ancillary commodity load profiles (see also next section). In the optimization process, these load profiles are evaluated by the optimizer. In the detailed simulation in a virtual building, the load profiles are provided by virtual meters.

In addition to the power flows between the devices, the ESC handles the exchange of additional information between the devices, such as voltage, temperature, and mass flow values. Hence, the devices are able to observe other devices and react on their states, facilitating control loops that have not been possible in the original OSH. For instance, the microCHP starts producing hot water when the temperature limit of the hot water storage tank is violated. Moreover, devices may determine their efficiency, power consumption, and generation based on the states of other devices, energy carriers, or the environment. For example, the efficiency of adsorption chillers depends on the hot water and the chilled water temperatures in the storage tanks as well as the temperature of the recooling water. [408,410]

5.3.3 Interdependency and Interconnection Information

In contrast to the IPPs, which define the behavior and inner working of the devices as well as their controllability, the I^3 defines the actual interconnections and interdependencies between the IPPs and thus the simulated entities. The XSD file that is used to validate the XML files defining local energy grids is given in Listing F.1 on p. 436.

The I^3 uses different kinds of energy relations to define the interconnections between IPPs, based on the types of local energy grids (see Figure 5.19). These relations determine not only the (virtual) commodities that are exchanged between the devices but also the additional information has to be exchanged. Table 5.1 provides examples of the energy grids and the corresponding nodes, arcs, flows, and commodities as well as the additional information that is exchanged to enable integrated energy management.

Energy Relations and Other Relations

The main two energy relations are *electrical relations* and *thermal relations*, which correspond to the *Electrical Simulation* and the *Thermal Simulation* (see Figure 5.17) that handle, i. e., simulate and calculate, a different set of energy carriers. An exemplary local energy system using electrical, thermal, and gas relations is depicted in Figure 5.19. It visualizes the I^3 and gives all relations between the IPPs in a fictional smart building. The grid connection points of electricity and natural gas are connected to so-called *virtual meters*, which work as slack buses for the calculation of flows, calculating the balance with external grids.

The actual simulation of energy flows is based on power values, i. e., the rate of transferred energy, for the energy carriers and thus commodities. It requires the calculation of power flows based on energy densities, flow and return temperatures of transfer media, electric charge and voltage, mass, and volumetric flows as well as temperatures. This additional information is part of the energy relations. The commodities are distinguished into *ancillary commodities*, determining their origin to take for instance different feed-in compensations into account and facilitate the calculation of interdependent efficiencies and power settings.

The local multi-energy grid is defined by a list of relations between entities (see below). Each relation comprises an *active* and a *passive entity* in the simulation, which is described in more detail in the next section. Additionally, the relations define two connections, one from the active to the passive part and one vice versa (see also Listing F.4 on p. 439), enabling uni- and bidirectional connections and thus information exchange.

Electrical Relation The local electricity grid consists of the wiring, i. e., the electrical connections between all devices consuming or producing electricity in a building. This includes AC as well as DC connections of different voltage levels. In the current implementation, the electrical properties of the arcs within a building are neglected.

Thermal Relation The local thermal grid comprises all physical interconnections that are used for the transfer of thermal energy, e. g., pipes between the devices that circulate water or some other medium. The flow may be unidirectional, e. g., in case of DHW, or bidirectional, e. g., in case of heating hot water or chilled water for air-conditioning.

Table 5.1: Examples of energy grids and the corresponding nodes, arcs, flows, commodities, and additional information

Energy carrier	Nodes	Arcs	Flow	Commodities	Additional information
Electricity	Connections	Cables, wires	Electrical current	Active power, reactive power	Voltage, impedance, frequency
Water	Valves, fittings	Pipes	Hot/chilled water flow	Thermal power: heating power, cooling power	Flow/return temperatures, mass flow
Fuel	Valves, fittings	Pipes	Fuel flow	Fuel power	Temperature, calorific value, volumetric flow, pressure

Fuel Relation The local fuel grid facilitates the provision of fuels, such as natural gas, to devices and systems from a grid connection point, in particular in the case of natural gas, or from some local storage of the fuel, e. g., in case of liquid gas, such as propane.

Other Relations Although the ESC focuses on the simulation of energy relations, it is also capable of handling other relations, such as the transfer of other fuels and the emission of CO_2, noise, vibrations, or any other kind of information which is relevant for the optimization.

Local Energy Grids

The relations are provided as XML files (`GridLayout.xsd`, see Listing F.1 on p. 436) and combined into the *local energy grids*, i. e., the networks of local devices, comprising relations related to energy but also to information exchange. The relations are used by the energy grid classes to calculate the energy flows. The general interface of energy grid classes is given in Listing F.8 on p. 440. It defines suitable *initialize* and *finalize* methods as well as methods that provide the active IPPs, the passive IPPs, and the virtual meters (see also the next section and Section 5.4.1). In addition, it defines the methods that are used by the *energy flow simulator* of the ESC to calculate the energy flows in the local energy grids. The actual calculation is implemented in the particular energy grid classes.

Listing F.9 on p. 440 provides an excerpt of the implementation of the `class ElectricalEnergyGrid`, which is used in both simulation and practical application. The simulation of energy flows in the optimization layer is different from the one of the detailed bottom-up simulation of the devices and systems using simulation device drivers. The former uses the method `doCalculation()`, whereas the latter uses the two separate methods `doActiveToPassiveCalculation()` and `doPassiveToActiveCalculation()`. This separation of calculation is the crucial point of the implementation and is described and explained in detail in the next section. The thermal energy grid has been implemented similarly and considers both thermal and fuel relations.

5.3.4 Modeling and Simulation of Energy Flows

The energy flow simulation and the ancillary commodity calculation (see also Figure 5.17 on p. 216) are based on two fundamental concepts:

1. Activeness: separation of active and passive IPPs in the optimization module
2. Virtual meters: calculation of the values of ancillary commodities by means of virtual meters

The general steps of the energy simulation are given on p. 214 as steps of the multi-agent simulation and depicted in Figure 5.20 in a simplified and in Figure E.1 on p. 431 in a more detailed version.

Activeness The activeness of an IPP refers to the property whether the represented entity does determine the power flow to interconnected IPPs (*active* IPP) or whether it does not (*passive* IPP). Active and passive IPPs are always connected in an alternating manner. This structure is depicted in Figure 5.19 for an exemplary building. Typically, passive parts include storage systems and grid connections, whereas active ones include all other devices (see Table 5.2).

The crucial point of the implementation is the separation of the calculation in the optimization layer and in the detailed simulation of devices and systems into specialized methods in the ESC (see Figures E.3 and E.4 on pp. 434 f.). The calculation in the optimization benefits from the alternating calculation of active and passive IPPs, based on the states of the respective others. Within a simulated time step, first, the active parts are calculated, based on the states of the passive parts resulting from the previous time step. Afterward, the passive parts are calculated using the current states of the active parts. Hence, passive parts, such as storage systems or grid connections points, are directly updated using the new state of the passive parts. This facilitates the mutually interdependent reaction of the entities with a minimal delay, because passive parts are updated using the current state of the active parts of the same time step.

In the simulation of the devices and systems in the simulation mode of the BEMS, i. e., by means of the simulation device drivers, this separation is not necessary because all states may be calculated in a single step. By means of UML diagrams, this is more closely described below in this section.

Virtual Meters The calculation of ancillary commodities is realized by *virtual meters* (see Figure 5.19 on p. 218). These meters use the additional information that is provided by the IPPs and the device drivers to determine not only the energy flows but also to facilitate the correct pricing of the energy. Thus, the virtual meters resemble the—often extensive and complex—installation of multiple meters in real systems that enable, for instance, the calculation and thus compensation of electricity generated by PV systems or microCHPs.

Energy Flow Simulator and Ancillary Commodity Calculator

Although the energy flow simulation is similar to *network flow programming* [126, Ch. 10] and *multi-commodity network flow* [2, 396] problems (see Section 3.6), it relaxes the strict characteristics of these problems and uses a simplified energy balance model [131, p. 196] that defines entities, i. e., nodes, and relations, i. e., arcs between the entities.

Capacity Constraints and Flow Conservation Conventional network flow algorithms emphasize capacity constraints and flow conservation at the nodes. The ESC does not enforce these constraints: Capacity constraints are considered inherently by the adaptation of the ancillary commodities to new values, e. g., temperatures and mass flows, by the active entities. Flow conservation is not strictly given, because entities may generate or consume energy utilizing external sources, such as environmental heat or solar irradiance.

Table 5.2: Examples of active and passive entities and *Interdependent Problem Parts*

Entity type	Examples
Active	Appliances, microCHPs, PV systems, electrical IHEs, BESSs
Passive	Water storage tanks, batteries, grid connection points

Energy Entities and Relations Each IPP and device driver is a node, i. e., an *entity*, in the respective energy flow simulation. The arcs between the nodes are represented in so-called *energy relations*. Thereby, each entity is either active or passive and each relation defines an arc between an active and a passive entity (see Listing F.4). In total, the relations lead to the set of relations $\mathcal{R}$, which consists of a—usually symmetric—binary matrix $\mathcal{R}_\varepsilon \in \mathbb{B}^{m \times m}$ per commodity ε, defining the given relations between the m entities in the set of all entities J of the energy simulation.

Calculation of Energy Flows The actual exemplary calculation of energy flows is implemented in a way that simply adds up all power values per commodity and entity, which is sufficiently precise for energy management in single buildings. However, this way of calculating the flows may easily be adapted to more complex calculations, e. g., in case of detailed electricity grid calculations using the *Newton-Raphson* method, when the ESC is used in a low-voltage grid scenario that requires an exact calculation of the complex power flow (see Section 5.10 and [354, 356]).

In general, the inbound and outbound energy flows of an entity j are summed up to a total value that is then communicated to the entity. A positive inbound energy flow is power flowing into the entity and vice versa. Other information about the commodities is handled in similar yet suitable ways, such as the voltage $U_{\varepsilon,j}$, the current $I_{\varepsilon,j}$, the temperature $\theta_{\varepsilon,j}$, and the mass flow $\dot{m}_{\varepsilon,j}$, leading to the total inbound state $s_{\varepsilon,j}$ per commodity ε into a device j:

$$s_{\varepsilon,j} = \left(P_{\varepsilon,j}, U_{\varepsilon,j}, I_{\varepsilon,j}, \theta_{\varepsilon,j}, \dot{m}_{\varepsilon,j}\right)^\top , \tag{5.5}$$

$$P_{\varepsilon,j} = \sum_{i \in J} P_{\varepsilon,i,out} \cdot \mathcal{R}_{\varepsilon,i,j} \,. \tag{5.6}$$

The available information depends on the type of relation, i. e., whether it is an electrical, a thermal, a fuel, or some other kind of relation (see also Section 5.3.3). The power is only communicated from active to passive entities. Additional information, such as the voltage, is communicated into both directions. The passive entity, e. g., the storage tank or system, updates its, for instance, temperature or state of charge based on the previous power flow.

Visualization of the Approach

By means of exemplary values and an artificial situation, the overall approach in the simulation is depicted in Figure 5.20. More details are given in Figure E.1 on p. 431.

In the given example, the chilled water storage tank has an initial temperature of 14 °C. The adsorption chiller is operating and generating 7 kW chilled water power. At the same time, it is consuming 11 kW hot water from the hot water storage tank, which has an initial temperature of 65 °C. The latter is charged by the microCHP, which is generating 12.5 kW hot water and 5.5 kW electricity, while consuming 20.5 kW natural gas. All IPPs receive their respective part of the solution candidate, i. e., a bit string of a certain length, determining their future behavior. Some IPPs are not controllable and thus receive 0 bits. Other IPPs are controllable and receive a certain number of bits[2].

[2]The Figures 5.20 and E.1 use arbitrary values in terms of the numbers of bits. More details about the determination of the exact numbers are given in Sections 5.5 and 5.6.

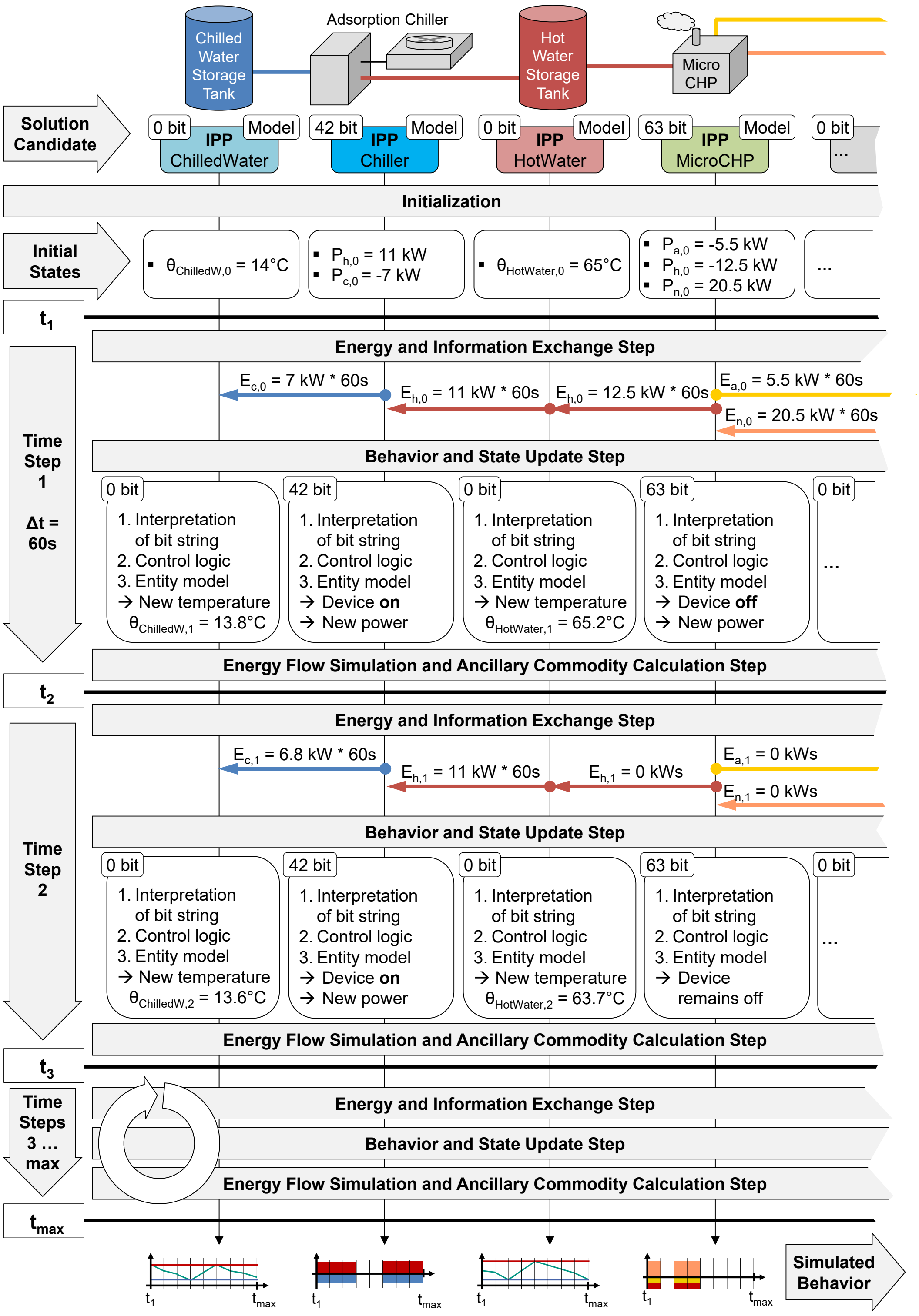


Figure 5.20: *Energy Simulation Core*: simplified interpretation of an exemplary solution candidate by means of the *Interdependent Problem Parts* in an artificial situation (see Figure E.1 on p. 431 for the detailed version)

At time step t_1, firstly, the energy flows are exchanged between the IPPs. Based on this exchange within the *energy and information exchange step*, the state of the chilled water tank is updated to 13.8 °C and the hot water tank to 65.2 °C in the *behavior and update step*. The adsorption chiller remains in the operating state, because the minimum temperature limit of 10 °C of the chilled water storage tank is not violated. However, on grounds of the temperature of 65.2 °C, the microCHP is switched off, because the lower temperature limit of 60 °C plus a hysteresis, which is in this case 5 K, is no longer violated and the bit string does not call for operation. The violation of the minimum temperature has been in place when the optimization was started and led to the operation of the microCHP.

The next time step t_2 is performed similarly: Firstly, the energy and information are exchanged, secondly, the behaviors and states of the IPPs are updated. Due to the lower temperature of the chilled water and thus lower efficiency of the adsorption chiller, the chilled water is generated with a power of 6.8 kW. Based on the model of the hot water storage tank, the high consumption of the adsorption chiller leads to a decrease of the hot water tank temperature to 63.7 °C.

Afterward, the simulation steps are repeated until the final time step $t_{\max}$ is reached. The virtual meters permanently calculate and record the energy flows of the commodities by means of additional information about the origin of flows. This leads to a simulated behavior of the building's energy system and the resulting ancillary commodity load profiles that may be evaluated.

In the simulation mode of the OSH, the same approach is used in the HAL: There, the IPPs are replaced with the *device simulation drivers*, which simulate the devices' behavior in a similar yet more detailed way (cf. Figures E.3 and E.4 on pp. 433 f.).

5.4 Interdependent Problem Parts

The adaptivity and modularity of the integrated multi-commodity optimization is facilitated by the IPPs. Despite originally being based on the *Problem Parts* presented in [10, 11] and partially sharing their name, the functioning of the IPPs is fundamentally different and enables now a *fully modular optimization of interdependent entities.* In case of interdependent devices, this has not been possible when using the Problem Parts of the original OSH.

Each IPP represents a single entity, i. e., a device or a system, such as the space heating system consisting of multiple radiators. The IPPs are used by the optimization to formulate the actual optimization problem and to determine the load profiles of solution candidates (see Figure 5.10 on p. 208). The IPPs are provided by the local O/C-units in the *Device Management Layer*, i. e., the first O/C-layer, and used by the global O/C-unit in the *Integrated Optimization Layer*, i. e., the second O/C-layer (see Figure 5.5 on p. 201).

Hence, the IPPs have to facilitate the *device* as well as the *optimization abstraction* of the entities in the optimization. Each IPP contains information that is necessary to optimize the corresponding device, respecting its technical specifications, possible control, and interdependencies to other devices. Therefore, each IPP contains information about the entity's behavior and specifications, i. e., the *entity model* using the `interface IOCEnergySubject`, and the possible control sequences and interactions, i. e., the *control model* using the `interface IOptimizationSubject` in the implementation (see Figure 5.21).

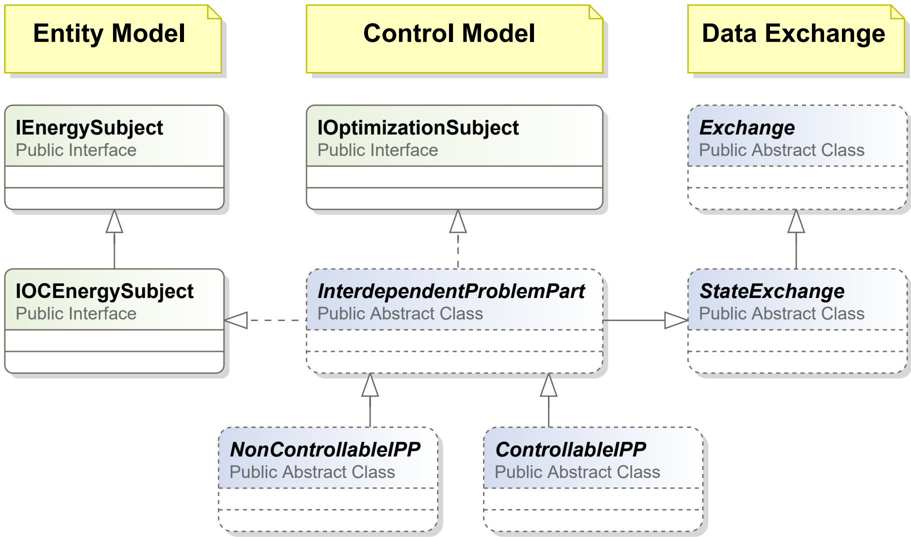


Figure 5.21: Simplified UML class diagram of the `class InterdependentProblemPart`

The models have to reflect the physical and technical behavior, limitations, observability, controllability, and possible interaction of the real devices. Therefore, model validation and verification have to ensure the quality of models and enable realistic experiments that allow for credible conclusions of the experiments. In addition to deviations between the model and the real building, there is also uncertainty of the input, e. g., of future outdoor temperature or user interaction. This uncertainty in the input leads to uncertainty in the model output, which may be analyzed by uncertainty propagation. However, this is out of scope of this thesis. The `class InterdependentProblemPart` extends the `class StateExchange`, because the IPPs are communicated using the registries (see Section 5.2.2).

The following sections describe the general properties of the IPPs as well as the concrete device and control models of the used devices and systems in detail.

5.4.1 General Properties of Interdependent Problem Parts

There are three fundamental properties of IPPs: *controllability*, *activeness*, and *interdependency*, defining their interaction in the BEMS.

Controllability The controllability of an IPP refers to the property whether the represented entity offers some way of being controlled, i. e., the control model offers some kind of interaction with the optimization. If the device is *non-controllable*, the respective IPP does not provide any bits to the optimizer, i. e., it has zero bits. If the device is *controllable*, the IPP provides at least one bit to the optimization. [408]

Activeness The activeness of an IPP refers to the property of the entity whether it does determine the power flow to interconnected IPPs (*active*) or whether it does not (*passive*). This approach eases the calculation of power flows and is more closely described in Section 5.3.4. Examples of active and passive entities are given in Table 5.2 on p. 221.

Interdependency The interdependency refers to the property that the IPP depends on the state or behavior of at least one other IPP. This dependency may also be the other way around or bidirectional. IPPs that are not interdependent work similarly to the Problem Parts of Allerding (2013) [10]: their load profiles may be calculated without considering other IPPs or reacting on input from them. For instance, the heating system of Allerding (2013) is a fully integrated system and thus the non-modular Problem Part represents the combined system of the microCHP, the storage tank, and the heating demand. Although non-interdependent IPPs may be seen similar to the Problem Parts, they are implemented differently, because they have to be able to provide also partial profiles if there is at least one truly interdependent IPP that calls for a stepwise simulation of the optimization horizon.

Based on the optimization target and the current state, the same entity may be handled by different IPPs having varying properties. For instance, one IPP may be non-controllable and active, e. g., a conventional appliance, whereas another may be controllable and active, e. g., a deferrable appliance. In the first case, the entity controls itself, e. g., by using on-off control. In the second case, the entity receives an optimized control sequence by the global optimization. In both cases, it determines actively its inbound and outbound power flows, making it active. On the contrary to the active entities, passive ones do not determine their inbound and outbound power flows (see also Section 5.3.4). Basically, most IPPs have some kind of *interdependency* to another IPP and thus depend on the behavior of another entity or the other way around. However, this is not necessarily the case: an integrated and self-contained trigeneration system may have no interdependencies at all.

5.4.2 Simulation Interface: Entity Model

The entity models of the entities and thus the IPPs reflect the physical, technical, and operational behavior, limitations, and observability. They are used to generate the load profiles of the energy carriers, which are then transformed by the virtual meters into load profiles of the ancillary commodities. Basically, the models interact with the ESC (see Figure 5.14 on p. 212) and are the agents of the multi-agent energy simulation (see Section 5.3.1). This interaction is based on additional information about the interconnections and interdependencies, i. e., the I^3 (see Section 5.3.3 and Figure 5.17 on p. 216).

Physical Entity Model and Interfaces In the multi-agent simulation, each IPP utilizes, converts, stores, or provides one or multiple energy carriers. In the actual implementation used in the OSH, this is done using the interfaces `IEnergySubject` and `IOCEnergySubject` (see Figure 5.21 on p. 225, Listing F.10 on p. 442, and Figures E.3 and E.4 on pp. 433 f.). The interfaces define methods for the exchange of power values as well as of additional information, such as voltages, temperatures, and mass flows. This is more flexible than the input-output matrix formulations of efficiencies used by [125, 236], which use fixed relations of the inputs and outputs without additional information influencing these relations.

Decision and Control The entity models comprise built-in operating strategies and control logic of the original entities, e. g., on-off control or hysteresis functions, ensuring that control sequences of the optimization lead only to valid states of the entities. Thus, the operating strategies provide a basic level of control, which works also as a kind of fallback control in case of invalid control sequences that are provided by the optimizer. Hence, the built-in operating and control strategies are the essential feature that helps to ensure that all solution candidates are valid: Simple approaches that are typically used in such systems, such as on-off control, counteract a behavior of the entities that violates limits. Additionally, there are no invalid solution candidates[3] that have to be eliminated or repaired (see Section 5.8).

The actual operating and control strategies may be subject to parameters that are set by the optimization. This has been demonstrated for electrical IHEs by Mauser et al. (2015) [412] and for BESSs by Müller et al. (2016) [440] and proved to be a suitable approach to the optimization of entities that have a control-loop-like behavior. For instance, the (dis-)charging of a BESS or an electric vehicle can be determined by a simple set of rules instead of a detailed curve, which is hard to optimize because of the multiplicity of possible curves. The rule set reacts instantly, e. g., on variations of the generation by a PV system, and adapts the (dis-)charging power, whereas an optimization would have to manage to obtain curves that change their power significantly at every time step, e. g., when following the load changes of a PV system. Thus, in comparison to the approaches of Mültin (2014) [393] and Schuberth (2014) [536], the introduction of IPPs and the ESC facilitates a simpler and more suitable optimization of such entities.

5.4.3 Optimization Interface: Control Model

The control models of the IPPs enable the abstraction of the entities for the integrated optimization in the upper O/C-layer and thus the internal EAL. This is depicted in the Extended O/C Architecture in Figure 5.5 on p. 201. In so doing, the IPPs are communicated from the local O/C-units to the global O/C-unit via the Observer/Controller Registry (see Figure 5.5 on p. 201). The control models define the possible control actions, parameters, and interactions with other entities and are the interface to the optimizer, which selects eligible inputs that are to be evaluated (see Figure 5.14 on p. 212). Hence, the control models are the interface of the IPPs in the multi-agent energy simulation to "external" inputs, i. e., the inputs provided by the optimizer in form of bit strings (see Figure 5.16 on p. 215). The control models are responsible for the interpretation of these bit strings, which encode some degree of freedom in the optimization.

Interfaces There are two important methods that represent the interface of the control model to the optimizer. Firstly, the method `int getBitCount()` of the `class InterdependentProblemPart` provides the number of bits that are required by the respective IPP to the optimizer. Secondly, the method `void initializeInterdependentCalculation(..., BitSet solution, ...)` of the `interface IOptimizationSubject` that is implemented by the `class InterdependentProblemPart` (cf. Figure 5.21 on p. 225 and Figures E.2 to E.4 on pp. 432 ff.) receives the actual bit string that has to be interpreted by the IPP for the optimizer. Furthermore, the interface provides the duration of the optimization horizon that is desired by the respective IPP. Hence, the actual horizon is based on the IPPs that are currently part of the optimization and the maximum duration being requested.

[3]Self-evidently, if there is always a higher consumption of hot water than generation, the temperature of the storage tank would fall below the defined minimum. However, this kind of invalid behavior will arise not only in the optimization but also in the real system.

Bit String The IPPs use encoding schemes that lead to a homogeneous structure: all result in bit strings of a certain length. However, the bit strings may be interpreted completely differently. One bit string may encode a time delay of the operation cycle of an entity, another the schedule when an entity is switched on or off, and yet another the selected variation of its operation mode. In so doing, certain parts of the overall bit string represent control sequences, others parameter settings, and still others the times and durations of deferrals or interruptions. Thus, the encoding reflects in particular the classification of the device with respect to the different degrees of freedom and thus to energy management (see Section 4.4.3). The following sections present appropriate bit string encodings for the different active entities.

Although referring only to bit strings above, the interface may easily be substituted by another interface that uses instead, for instance, real values or mixed data types. This is demonstrated by Schuberth (2014) [536].

5.5 Integration of Future Appliances

This thesis introduces the notion of *future appliances* into multi-modal energy management and multi-commodity optimization. In contrast to the intelligent appliances by Allerding (2013) [10], they offer additional energy management functionality, e. g., by providing multiple different programs or hybrid modes. In addition, their operation may also be interrupted, making them a combination of interruptible and hybrid appliances. This is more closely described in Section 4.4. The approach to their integration into energy management may also be applied to any other load showing similar functionality and properties.

The load profiles of the appliances are based on recorded profiles of the appliances by *Miele* that are located in the ESHL. See Table B.20 on p. 387 for more details and their models, the Figures C.1 to C.6 on pp. 394 ff. for the load profiles, and the Table C.1 on p. 399 for details about the energy consumption of the appliances.

Overview and Features To realize the integration of interruptible and hybrid appliances, the recorded profiles are cut into phases and extended by alternative load profiles that enable hybrid modes. An overview of the profiles is given in Table C.1 on p. 399. Self-evidently, ovens and hobs do not provide interruptible modes that would render them useless for their energy service, i. e., proper cooking and baking. However, hybrid modes are available, introducing energy flexibility to these appliances that has not been available before.

The load profiles of the appliances are directly related to *appliance program configurations*, which are defined by the selected program, such as "*Cotton 60° C*", as well as the selected options and extras, such as "*Delicate*". The mapping of appliance program configurations to load profiles is stored in dedicated configuration files (see Listing F.2 for the XSD file). Each load profile of an operation cycle, i. e., a single usage of the appliance, consists of *phases* that have a certain minimum and maximum duration as well as a load profile of the expected energy consumption of the energy carriers. Interruptions are handled as separate phases of the operation cycles. Hence, a non-deferrable and non-interruptible appliance has a single phase per program configuration, a deferrable and non-interruptible appliance has three phases, and a deferrable and interruptible appliance has at least five phases (see Table C.1 on p. 399 for an overview of the programs and their number of phases).

5.5.1 Drivers and Configuration

In order to simulate future appliances, a generic *device simulation driver* for appliances has been developed. The driver is capable of simulating different kinds of appliances, such as the five major appliances demonstrated in this thesis. In addition, *device drivers* and *bus drivers* for an exemplary tumble dryer and a dishwasher have been developed and run successfully in trial periods at one of our laboratories. These real appliances were optimized using the same local O/C-unit as the simulation driver that is presented in this thesis.

Device Simulation Driver The device simulation driver for future appliances has been implemented as `class GenericFutureApplianceSimulationDriver`. Currently, there are appliance program configurations (see also below) for the five major appliance. Additional appliances can easily be realized by adding corresponding configuration files.

Device Drivers and Bus Drivers The device drivers for the two experimental appliances that have been evaluated at one of our laboratories used corresponding bus drivers that handled the connections to the appliances by means of two different wireless technologies. The detour via specific bus drivers has been chosen, because it enables the integration and evaluation of potential additional appliances in the future. However, the application mode is not in focus of this thesis and thus detailed descriptions of the device and bus drivers of the real appliances are out of scope.

Appliance Program Configurations

The programs, extras, and options of an appliance are configured by the *appliance program configurations* XML file that provides an extensive list of the feasible combinations that may be programmed by the user and lead to a specific operation cycle. This file is validated against the `ApplianceProgramConfigurations` XSD file given in Listing F.2 on p. 436. This approach is partly based on the approach presented by Rothenbacher (2013) [519], which introduced also detailed simulation of appliances using state charts and finite automata.

List of Configurations Usually, an appliance has several different programs as well as extras and options to choose from. Every unique combination of a program and the selected options and extras is called a *configuration*. These configurations are saved in a *list of possible configurations*. A certain configuration, such as "*Cotton 60 °C & delicate*", contains one or multiple possible alternative load profiles.

Load Profile There is at least one load profile per configuration. For instance, hybrid appliances have one load profile—using only electricity—for the conventional operation mode and another profile—using an alternative energy carrier—for the hybrid mode. In addition, there may be alternative profiles for the same operation mode. Each load profile contains a sequence of phases. This approach to load profiles is compatible to the data model described in [55].

Phases and Ticks Each phase of a load profile contains information about its minimum and the maximum duration and the concrete load profile. Thus, the phases are lists of *ticks* comprising average as well as minimum and maximum power values for all commodities per time period of a certain duration. The minimum duration of an entire phase may be as short as one second: for instance, the initial delay before starting the operation cycle. In case of deferrable appliances, the maximum duration of the initial "delay" phase is the TDoF. In case of possible additional interruptions, the TDoF is split between all these phases. Usual phases of an appliance have an equal minimum and maximum phase length, because their duration may not be optimized and has a fixed expected length. Thus, all phases of the operation cycle of the appliances—no matter whether they are delay, interruptions, or actual program executions—are handled similarly (see Section 5.2.4). This is different to the strict separation of "pauses" and "phases" presented by Mauser et al. (2014) [406], making energy management more flexible and consistent to implement.

5.5.2 Local O/C-unit

The local O/C-units of future appliances comprise local Observers of the `class FutureApplianceLocalObserver` and local Controllers of the `class FutureApplianceLocalController`. The information is communicated between them using the *Model of Observation Exchange* of `class GenericApplianceMOX` (see also [10, pp. 62 ff.]). Each O/C-unit is responsible for creating a suitable IPP that represents the appliance in the optimization and facilitates its optimization by using a specific encoding that is compatible to the capabilities of the appliance. These IPPs are detailed in the next section.

Appliance Program Configuration Status The current status of each future appliance is communicated to the particular local O/C-unit using a special *appliance program configuration status* object. It contains the selected appliance configuration, the corresponding load profiles of the (remaining) phases, and the durations of the phases. Among other information, such as the current power of the appliance, this status is communicated using an object of the `class FutureApplianceObserverExchange`. Based on the status, the local O/C-unit decides about updating its IPP and triggering a new run of the optimizer.

5.5.3 Interdependent Problem Parts and Encodings

Energy management requires suitable IPPs that represent the appliances in the optimization and allow for their optimization by providing an appliance-specific encoding, which is compatible to its capabilities, to the optimizer and a model of the appliance to the ESC. The latter is realized by the load profiles of the appliances. This section presents several encodings that are suitable for appliances having different degrees of freedom, i. e., different kinds of flexibilities. In the implementation, they are used by the `class FutureApplianceIPP`, which optimizes all kinds of appliances, such as deferrable, interruptible, and hybrid ones but also non-optimizable appliances.

Interdependent Problem Part: Appliances having Temporal Flexibility

The conventional appliances, such as the original device drivers for the appliances by *Miele*, have a temporal flexibility, i. e., a TDoF (see also Section 4.4.2) and an indivisible load profile that may be deferred up to a certain deadline that is usually defined by the user. The encoding has been presented by Allerding (2013) [10] and in more detail by Mauser

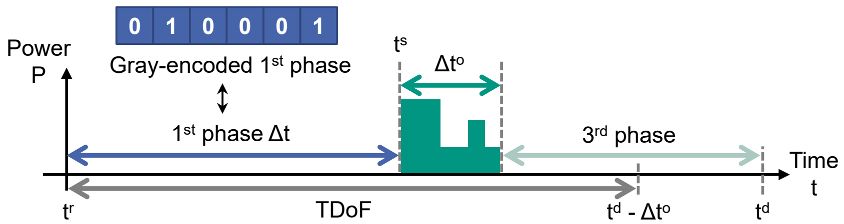


Figure 5.22: Encoding scheme of a deferrable load, based on [406, Fig. 3]

et al. (2014) [406]. It is suitable for deferrable appliances, such as dishwashers, washing machines, and tumble dryers.

Encoding of Deferrable Appliances The maximum deferral of an appliance's operation cycle is usually defined by the user, who sets a certain deadline t_j^{d} when the appliance j has to have finished its cycle. The period between the release time t_j^{r} of the appliance, i. e., the time of programming by the user or the earliest starting time, and its deadline, reduced by the operating time Δt_j^{o}, i. e., the time required for running the program cycle, is the TDoF $t_j^{\mathrm{dof,max}}$ [406]:

$$t_j^{\mathrm{dof,max}} = t_j^{\mathrm{d}} - t_j^{\mathrm{r}} - \Delta t_j^{\mathrm{o}} \,. \tag{5.7}$$

The value of Δt_j is encoded in a bit string and has a maximum value of $t_j^{\mathrm{dof,max}}$. The optimizer selects a suitable deferral Δt_j by shifting the starting time t_j^{s} within this predefined period, beginning at the release time t_j^{r}. Thus, the constraint for shifting the start time of appliance j is [406]:

$$t_j^{\mathrm{s}} = t_j^{\mathrm{r}} + \Delta t_j \ \text{ s.t. } 0 \le \Delta t_j \le t_j^{\mathrm{dof,max}} \,. \tag{5.8}$$

To facilitate a shifting of the appliances that is as precise as the highest resolution of the BEMS, the deferral is defined in seconds (see Figure 5.22). It is represented by a *Gray*-encoded bit string, enabling a planning accuracy based on seconds and overcoming the so-called *Hamming cliff* [112]. The latter denotes the effect that small changes to the bit string may cause large changes of value of the bit string. Therefore, the bit string is not encoded in the usual binary representation but using a function gray(), returning a gray-encoded bit string of a given integer value, and a function $\mathrm{gray}^{-1}()$ doing it vice versa. The bit string B_j has a variable length of $b_j^{\mathrm{deferrable}}$ bits, depending on the $t_j^{\mathrm{dof,max}}$ in seconds:

$$b_j^{\mathrm{deferrable}} = b_j^{\mathrm{tdof,max}} = \lceil \log_2 \left(t_j^{\mathrm{dof,max}} \right) \rceil \,. \tag{5.9}$$

Finally, the actual bit string $B_j \in \{0,1\}^{b_j^{\mathrm{deferrable}}}$ and the realized duration of the delay Δt_j are defined as follows:

$$B_j(\Delta t_j) = \mathrm{gray}(\lceil \frac{2^{b_j^{\mathrm{deferrable}}}}{t_j^{\mathrm{dof,max}}} \cdot \Delta t_j \rceil) \,, \tag{5.10}$$

$$\Delta t_j(B_j) = \lceil \mathrm{gray}^{-1}(B_j) \cdot \frac{t_j^{\mathrm{dof,max}}}{2^{b_j^{\mathrm{deferrable}}}} \rceil \,. \tag{5.11}$$

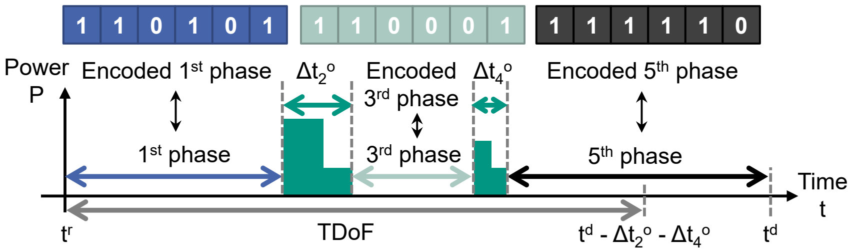


Figure 5.23: Encoding scheme of an interruptible load, based on [406, Fig. 4]

Generalized Encoding of Deferrable and Interruptible Appliances Some appliances may also be interrupted by the BEMS at certain predefined points in their operation cycle. Thus, the corresponding IPPs have to contain the expected load profiles of the device with possible interruptions and an adapted encoding that splits the TDoF up between the initial deferral and the interruptions (see Figure 5.23). Such an encoding using dedicated "pauses" and "phases" parts of the load profile has been presented by Mauser et al. (2014) [406].

Mauser et al. (2016) [410] introduce a slightly different approach, which is refined in this thesis. Instead of defining alternating parts of "pauses" and "phases", there is no differentiation between those different parts of the load profile. Hence, instead of partitioning the TDoF only to the "pauses", every *phase* has a certain minimum as well as maximum duration, making the "pauses" to phases, too. The optimizer may adapt the length of each phase within the limits. In case of phases having a fixed length[4], such as the "phases" in [406], the minimum is equal to the maximum duration (see also Section 5.5.1). In case of phases having a variable length, such as the "pauses" presented in [406], the maximum duration reflects technical restrictions as well as the user-defined TDoF.

To name an example, a deferrable appliance with a single operational phase will have three phases: the first phase is the initial delay, the second phase is the actual operation cycle, and the final phase is the time until the predefined deadline of the user, i. e., the time when the appliance has to have finished its cycle and the user intends to unload the appliance and to switch it off. This final phase may still cause additional energy consumption, e. g., for periodic rotations by the anti-crease program of the washing machine or of the tumble dryer. Hence, for p_j^{fixed} regular phases of the operation cycle of appliance j, there are $p_j^{\text{flexible}} = p_j^{\text{fixed}} + 1$ phases having a flexible length. This results in $p_j = 2 \cdot p_j^{\text{fixed}} + 1$ phases (see also Table C.2 on p. 400).

To simplify the encoding, the maximum duration of each phase is neglected and each of the p_j phases gets $b_j^{\text{tdof,max}}$ bits, which are calculated using $t_j^{\text{dof,max}}$ (see Equation 5.9). This results in a bit string of the length $b_j^{\text{interruptible}}$:

$$b_j^{\text{interruptible}} = b_j^{\text{tdof,max}} \cdot p_j = \left\lceil \log_2 \left(t_j^{\text{dof,max}} \right) \right\rceil \cdot p_j \,. \tag{5.12}$$

Using Equation 5.11 and the minimum duration $t_{j,i}^{\min}$ as well as the maximum duration $t_{j,i}^{\max}$

[4]Self-evidently, the length may be adapted by the appliance itself, e. g., because of automatic adjustments by the device-internal control. For instance, a dishwasher may still shorten the length of the "*rinsing*" phase depending on the soiling of the dishes. However, this will cause a new run of the optimization, because it causes the appliance to send an updated appliance configuration of the current run.

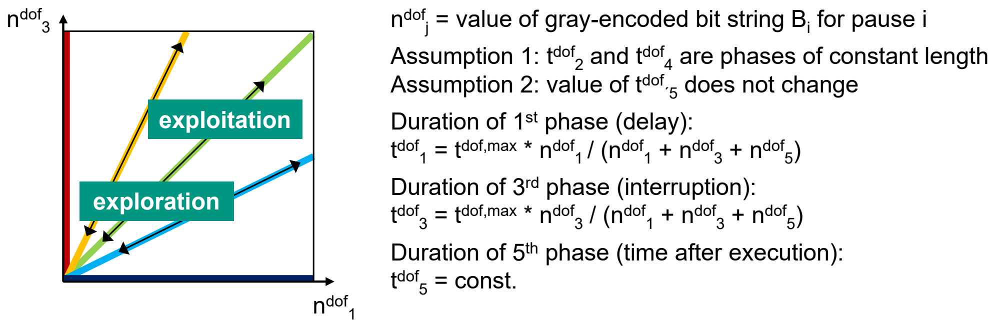


Figure 5.24: Exemplary and simplified interpretation of the encoding scheme of an interruptible load having two phases of constant length and three variable phases, showing the areas of exploration and exploitation, the colored bars indicate values leading to the same resulting values of the $t^{dof}_{j,i}$, based on [406, Fig. 5]

of the phase, the selected duration $\Delta t_{j,i}$ of each partial bit string $B_{j,i}$ per phase i of the device j is interpreted as follows:

$$\Delta t_{j,i}(B_{j,i}) = \max\left(t^{\min}_{j,i},\ \min\left(t^{\max}_{j,i},\ \lceil \frac{\text{gray}^{-1}(B_{j,i})}{\sum_{i=1}^{p_j}\text{gray}^{-1}(B_{j,i})} \cdot t^{\text{dof,max}}_j \rceil\right)\right). \tag{5.13}$$

In so doing, the differentiation of special phases, i. e., the “pauses” and “phases”, as introduced by Mauser et al. (2014) [406] is annihilated (see Figure 5.23). This enables a simplified and more flexible implementation of the IPPs: each load profile comprises simply p_j phases having a minimum and maximum duration (see Figure 5.26). This includes phases of program execution as well as delays and interruptions at predefined points in the operation cycle.

Exemplary Interpretation of the Bit String The interpretation of the bit string of a deferrable appliance that can be interrupted once in its operation cycle is depicted in Figure 5.24: The ratio of the value of each part $B_{j,i}$ of the bit string B_j to the sum of all values determines the allocation of the TDoF $t^{\text{dof,max}}_j$ to the phases $i \in \{1, 2...5\}$. In this example, the durations of the phases $i \in \{2, 4\}$ are fixed and thus neglected. To simplify the visualization, the phase $i = 5$, i. e., the last phase, is assumed to have a constant value. This way, the encoding leads to two different general search behaviors of the GA: If the gray-encoded integer values of $B_{j,1}$ and $B_{j,3}$ are small (and $B_{j,5}$ remains constant), minor changes to $B_{j,1}$ or $B_{j,3}$, i. e., the search space, cause tremendous changes to their respective share of the TDoF, i. e., an *exploration* of the solution space. Correspondingly, in case of high values of $B_{j,1}$ and $B_{j,3}$, small changes of them lead to *exploitation*, because changes of the values cause only small deviations to their respective share of the TDoF.
This is beneficial because encodings used in GA should allow for both exploitative and explorative search behavior [604]. Two exemplary optimization processes with the same parameter settings in the GA are visualized in Figure 5.25, showing both behaviors for the best individuals of the runs. [406]

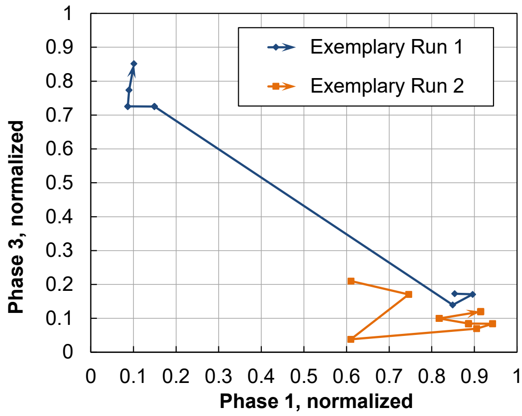


Figure 5.25: Exemplary trajectories of the best individual in two exemplary runs, optimizing an appliance's deferral: the selected values for the first phase ("Phase 1") and the final phase ("Phase 3") have been normalized to $[0, 1]$, based on [406, Fig. 9]

Interdependent Problem Part: Appliances having Energy-related Flexibility

As introduced in Section 4.4, appliances may have not only temporal but also energy-related flexibility. For instance, appliances may have alternative load profiles for the same operation cycle or even hybrid profiles that allow for a shift of energy-consumption from one energy-carrier to another. An example of alternative load profiles is the reduction of peak loads in the profile or even the overall power consumption (cf. Figure 2.12 on p. 49) in exchange for extending the duration of the load profile. Examples for hybrid modes are the phases utilizing hot water of natural gas by the hybrid appliances presented on pp. 141 ff., which are able to utilize different energy-carriers for their energy services.

Encoding of Appliances having Alternative Profiles and Modes Mauser et al. (2014) [406] present an encoding for appliances having alternative profiles or hybrid modes, e. g., hybrid or bivalent appliances. The alternative profiles using different energy carriers or operation cycles are enumerated, encoded, and then added as additional substring to the previously presented encoding (see Figure 5.26). In case of a_j alternative profiles for device j, the bit string B_j for the selection of the alternative has to be of length b_j^{edof}:

$$b_j^{\text{edof}} = \lceil \log_2 (a_j) \rceil . \tag{5.14}$$

Finally, the selected profile k_j is then calculated based on the usual interpretation of the binary bit string B_j as integer value $|B_j|$:

$$k_j = \lfloor |B_j| \cdot \frac{a_j}{2^{b_j^{\text{edof}}}} \rfloor . \tag{5.15}$$

This encoding scheme enables the inclusion of the profile selection into the optimization process. It can be applied to both deferrable and interruptible appliances having alternative profiles for the same program. The encoding does not use Gray-encoding, because the enumeration does not imply relations and thus would not benefit of doing so.

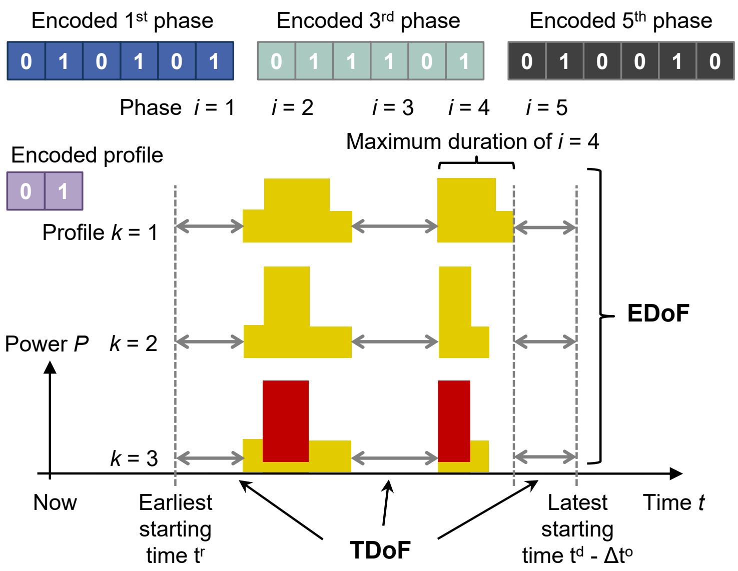


Figure 5.26: Encoding for interruptible hybrid devices with minimum and maximum durations of the interruptions and the phases of the operation cycle (yellow: active power consumption, red: hot water power consumption), based on [410, Fig. 9]

Interdependent Problem Part: Interruptible Hybrid Appliances

The previous two encodings are combined into an integrated encoding, supporting the optimization of all appliances visualized in Figure 4.8, i. e., using the TDoF as well as the EDoF (see Figure 5.26). Thus, the length b_j of the overall bit string B_j of device j having a_j alternative profiles with p_j phases[5] and a TDoF of $t_j^{\text{dof,max}}$ is defined as follows:

$$b_j = b_j^{\text{tdof}} + b_j^{\text{edof}} = \left\lceil \log_2 \left(t_j^{\text{dof,max}} \right) \right\rceil \cdot p_j + \left\lceil \log_2 (a_j) \right\rceil . \tag{5.16}$$

Finally, the control sequence $\mathcal{C}_j$ for the appliances j is a tuple of a list of the prolongations T_j^{dof}[6] of the phases and an indicator k_j of the selected alternative:

$$\mathcal{C}_j = \left(T_j^{\text{dof}}, k_j \right) = \left((t_{j,1}^{\text{dof}} \dots t_{j,p_j}^{\text{dof}}), k_j \right) . \tag{5.17}$$

Here, the encoding has been presented in the context of appliances. Nevertheless, the encoding may also be used for all kinds of devices and systems that have *program-driven* operating cycles that are usually executed only once and programmed by the user.

Additional Penalty

There are two possible shortcomings of the future appliances'IPPs in the optimization. Firstly, a deferred start of an appliance may benefit from potential future usage of other devices, because this may lead to an accumulation of electricity consumption that triggers

[5] This description is simplified because each profile may actually have a different amount of phases.
[6] This is equivalent to a list of "starting times" for the phases.

for instance the microCHP. Hence, in case of similar costs it may be beneficial to prefer a later start of the appliance over an earlier one, which is not reflected in the IPP. Secondly, hybrid appliances may utilize hot water from the storage tank. This thermal energy is free of a direct charge because it leads only to indirect costs later on when the tank has to be recharged. Thus, this provides an incentive to prefer hot water over electricity.

The other way around, if utilizing electricity avoids recharging the hot water storage tank within the optimization horizon, it will be preferred over hot water; Although the tank would probably have to be recharged anyway after the optimization horizon.

To tackle the first issue, a small additional penalty for each device start is introduced that is gradually decreasing over time horizon of the TDoF. In doing so, a later start is incentivized. A longer duration of the optimization horizon reduces the second shortcoming. However, there is also an additional penalty for the hot water storage tank based on the temperature difference between the temperature at the beginning and the end of the optimization horizon (see also Table C.7 on p. 403 and Table E.1 on p. 430).

5.5.4 Electrical Baseload

The load that is simulated neither by the future appliances nor by any other device or system is called baseload. In the simulation mode, this load is simulated by the *device simulation driver* `class BaseloadSimulationDriver` using the German SLP H0 at a resolution of 15 minutes, which is scaled to the required residual load (see also Section 4.2.1). In the ESHL, the baseload is calculated by the *device driver* `class WAMPBaseloadDriver`. It uses the values provided by the local metering system to calculate the electrical load that is not caused by the other currently observed devices and systems.

The baseload is observed by the `class BaseloadLocalObserver`, which provides a prediction of the future load to the `class BaseloadNonControllableIPP`. The prediction calculates the average load of the past 14 days, using a weight of 5 for the same days of the week of the two previous two weeks and a weight of 1 for all other days. In doing so, not only the typical periodic behavior depending on time of the day but also on the day of the week is reproduced in the prediction [294, pp. 69 ff.]. Using comparable days, e. g., the same day of the week of the previous two weeks, is in households of up to four persons only slightly worse than using more complex *seasonal auto-regressive integrated moving average* (SARIMA) models or *artificial neural networks* (ANN) [294, p. 77].

5.6 Integration of Distributed Generation and Thermal Storage

In addition to the appliances, other devices and systems for DG and for local provision of energy carriers are modeled. These call for IPPs having adequate entity models as well as suitable encodings because they are usually not all program-driven.

5.6.1 Combined Heat and Power Plant

There are two types of microCHPs that are regarded in this thesis: non-controllable ones having only on-off control and controllable ones that may be switched on by the BEMS. Therefore, there are actually two different IPPs provided by different O/C-units and thus the effects of the optimization can be analyzed. Nevertheless, both IPPs use the same basic physical entity model, which is based on a real microCHP that is analyzed in Section 4.5.4. The results of the analysis and the details of the entity model are given in Tables D.1 and D.2 on pp. 406 f.

Drivers and Local O/C-unit

To simulate the microCHP, a *device simulation driver* has been developed. Furthermore, there are suitable *device drivers* for the real microCHPs in our laboratories. Although the drivers are based on the one presented by Allerding (2013) [10], they have been deeply revised: The original implementation was not fully modular but integrated with the heating system and the hot water storage tank used very simplified model.

Device Drivers The device simulation driver of a microCHP has been implemented as `class DachsChpSimulationDriver`. Although the device mode is based on the *SenerTec Dachs G 5.5 standard* (see Table B.21 on p. 389 for the technical data), it may easily be adapted to other microCHPs by modifying the configuration files using, for instance, other nominal power values or efficiency curves. The device driver for the real microCHPs is implemented in the `abstract class DachsChpDriver`. It is extended by the driver `class GLTDachsChpDriver` using the proprietary *GLT-interface* of the microCHP, which is based on HTTP.

Local O/C-unit The local O/C-unit of the microCHP comprises a local Observer of the `class DachsChpLocalObserver` and a local Controller of the `class DachsChpLocalController`. It uses the standardized observer exchange object of the `class ChpObserverExchange`, which is based on the `interfaces IHALChpDetails, IHALElectricalPowerDetails, IHALHotWater-PowerDetails, and IHALGasPowerDetails`. The information is communicated between the Observer and the Controller using the *Model of Observation Exchange*[7] object of the `class DachsChpMOX`. The `class ChpControllerExchange` provides control actions obtained in the optimization to the drivers.

Interdependent Problem Parts

The IPPs of the microCHPs implement on-off control, ensuring that the storage tank temperatures remain within given limits. The encoding of the controllable IPP uses a bit string that is interpreted and results in an entire control sequence of future actions switching the microCHP on and off.

Entity Model Both IPPs—the controllable and the non-controllable one—implement on-off control based on the storage tank temperature as operating strategy. It aims at keeping the storage tank temperatures within limits. This thermal management, which is independent of the actual bit string in the optimization, helps to ensure that each solution candidate is valid with respect to the constraints. The device is turned on or off, respectively, even if the control sequence that is encoded in the bit string would actually not start or stop it, respectively, and thus lead to a violation of a temperature limit.

[7] The concept of the Model of Observation Exchange is described by Allerding (2013) [10, pp. 62 ff.] in detail.

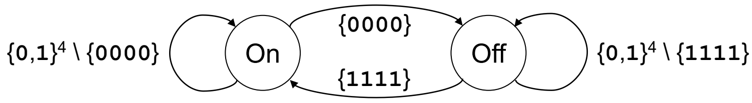


Figure 5.27: Finite-state machine $\mathcal{F}_c$ used by the encoding scheme of the microCHP in the OSH, having the two states "On" and "Off" that may both be the initial state, based on Mauser et al. (2014) [406]

In both cases, the respective IPP is actively participating in the energy simulation of the ESC, because the state of the microCHP, i. e., being on or off, and thus its generation of hot water and electricity depends on another device: the hot water storage tank. More about the model of the microCHP, which is also used in the device simulation driver, is given in Section 4.5.4 and in Table D.2 on p. 407. The entity model includes also minimum on and off times that have to be respected by the optimization. [408, 410]

Control Model and Encoding The microCHP is controlled and thus optimized by signals that switch it on or off. The encoding utilized by the IPP uses a sequence of bits that is interpreted by an automaton, i. e., translated into scheduled operating times.
In residential buildings, microCHPs are usually controlled with respect to thermal demand, i. e., heat-led. This is reflected by the non-controllable IPP implemented in the `class DachsChpNonControllableIPP`, which does not coordinate its generation with the electrical demand in the building. It uses solely on-off control based on the limits of the hot water storage. Hence, it is switched on when the minimum temperature is violated and is then operated continuously until a defined temperature is reached, e. g., using a hysteresis.

In contrast, the controllable IPP that is implemented in the `class DachsChpIPP` is able to split up its operation into sequences which may be coordinated with the electricity demand. Therefore, it uses an encoding that has been presented by Allerding (2013) [10] and Mauser et al. (2014) [406]. However, the encoding is changed and uses now four instead of three bits per time slot in the smart residential building scenarios and five bits in the smart commercial building scenarios, providing slightly better results (see Sections 6.2.3 and 6.4). The following paragraphs describe the usage of four bits in encoding. In case of five bits, the encoding is done analogously.

In the encoding, the duration of the intended optimization horizon $\mathcal{H}$ is set to 24 hours and segmented into p_c time slots of five minutes. Each period is encoded with a sequence of four bits, leading to a bit string B_c of the microCHP c having a length $b_c = 4 \cdot p_c$:

$$B_c \in \{0,1\}^{b_c} = \{\{0,1\}^4\}^{p_c} . \tag{5.18}$$

Table 5.3: Interpretation of an exemplary bit string B_c by the control model of the microCHP, assuming that the microCHP is initially switched off, partly based on Mauser et al. (2014) [406, Fig. 8]

Time slot i	1	2	3	4	5	6	7	8	9	10
Substring $B_{c,i}$	1001	0010	1111	1001	1111	0001	1000	0000	0010	1010
Control sequence $\mathcal{C}_{c,i}$	off	off	on	on	on	on	on	off	off	off

The p_c substrings $B_{c,i}$ of the overall bit string B_c are the input of a finite-state machine $\mathcal{F}_c$, i. e., they are then interpreted by an automaton (see Figure 5.27 and Table 5.3): The microCHP is switched on if the substring is equal to '`1111`'. It is switched off if the substring is equal to '`0000`'. In case of all other substrings, the microCHP remains in its previous state [406, 410]. This results in a control sequence $\mathcal{C}_c$ for the microCHP of a variable length $i, \max$, which toggles its state at time step t_i^{toggle}, i. e., switches it on and off, respectively:

$$B_c \xrightarrow{\mathcal{F}_c} \mathcal{C}_c = \left(t_1^{\text{toggle}} \ldots\, t_{i,\max}^{\text{toggle}}\right) . \tag{5.19}$$

Actually, the original bit string is corrected by an automaton $\mathcal{F}'_c$, which enforces the minimum and maximum operating and off times as well as the on-off control, resulting in the final control sequence $\mathcal{C}'_c$:

$$B_c \xrightarrow{\mathcal{F}'_c} \mathcal{C}'_c = \left(t_1^{\text{toggle'}} \ldots\, t_{i,\max'}^{\text{toggle'}}\right) . \tag{5.20}$$

Nevertheless, this final step may also be omitted, because it is done internally by the (simulated) microCHP anyway.

As a result, the encoding and thus the optimization automatically favor longer and continuous operating cycles and off-times, which lead to less wear of the microCHP. This effect depends heavily on the number of bits per time slot, i. e., for every input of the automaton, and the defined transitions of the automaton. Another approach is presented by Braun et al. (2016) [96]: in addition to total costs, there is wear, leading to multi-objective optimization. Alternatively, it is also possible to introduce an additional term $\mathcal{P}_c$ that adds a certain penalty to the total costs for every device start and stop. However, this is not used in the current modeling in the OSH because the lower hot water generation at the beginning of an operation cycle is a kind of inherent penalty for starting the microCHP. Nevertheless, there is another kind of penalty: in case of a forced turn on or off by the on-off control, a small penalty is added to the total costs, penalizing an actually invalid original control sequence $\mathcal{C}_c$ (see also Table D.2 on p. 407 and Table E.1 on p. 430).

Alternative Encodings In [96], Braun et al. (2016) present an alternative encoding for microCHPs. Instead of encoding fixed time slots, it uses a variable number of operating times having a flexible duration. Hence, the number of cycles as well as their respective starting time and duration is optimized. However, an evaluation prior to this thesis favors the encoding presented above.

5.6.2 Adsorption Chiller

The OSH is now capable of simulating an adsorption chiller, which is based on a real device (see also Section 4.5.5). It utilizes hot water to provide chilled water, showing a non-linear behavior regarding the water and the outdoor temperatures. Hence, it is interdependent with the hot as well as the chilled water storage and the current weather. The details of the analysis are given in Table D.3 on p. 408.

Drivers and Local O/C-unit

To simulate the trigeneration system in the HoLL, a *device simulation driver* as well as suitable IPPs have been developed. Originally, they are partly based on the microCHP and have been presented by Mauser et al. (2015) [408].

Device Simulation Driver The device simulation driver of the adsorption chiller has been implemented as `class AdsorptionChillerSimulationDriver`. Although it is based on the *InvenSor LTC 09*, it may easily be adapted to other adsorption chillers by modifying the configurations files, i. e., the parameters, or the model itself, i. e., the non-linear behavior of the efficiency. The technical data is provided in Table B.21 on p. 389.

Local O/C-unit The local O/C-unit of the adsorption chiller comprises a local Observer of the `class AdsorptionChillerLocalObserver` and a local Controller of the `class Adsorption-ChillerLocalController`. The information is communicated between the Observer and the Controller using the Model of Observation Exchange of the `class AdsorptionChillerMOX`.

Interdependent Problem Parts

The adsorption chiller uses IPPs that are similar to those of the microCHP, i. e., there is a non-controllable and a controllable IPP. Other than that, it utilizes hot water from the hot water storage tank and provides chilled water that is stored in the chilled water storage tank, leading to interdependencies with both storage tanks.

Entity Model The IPPs implement an on-off control that keeps the temperature of the chilled water tank within its temperature limits. In addition to the on-off control with respect to the chilled water tank, there are temperature limits of the hot water storage that are respected. Furthermore, the entity model considers the hot water as well as the outdoor temperature. The latter determines the performance of the heat exchanger for the recooling process and thus the efficiency.

More about the entity model, which is used in the IPPs as well as in the simulation driver, is given in Section 4.5.5 and in Table D.4 on p. 409.

Control Model and Encoding The adsorption chiller is controlled and thus optimized by scheduling its operating times. It uses an encoding that is equal to that of the microCHP. The sequence of bits is interpreted by an automaton and translated to operating times. A conventional adsorption chiller, which uses on-off control with a hysteresis on the chilled water tank temperature is reflected by the non-controllable IPP, which is implemented in the `class AdsorptionChillerNonControllableIPP`. It does not coordinate its provision of chilled water based on the possibility to achieve a high efficiency or in relation to the generation of hot water by the microCHP but according to the on-off control. In contrast, the controllable IPP, which is implemented in the `class AdsorptionChillerControllableIPP`, may freely be controlled within the boundaries of the operating strategy and thus optimized.

The modeling of the adsorption chiller is prone to similar shortcomings as the microCHP. Therefore, the IPPs use the same inherent considerations, except for the additional losses when starting the device, and also an analog additional penalty (see Table D.4 on p. 409 and Table E.1 on p. 430).

5.6.3 Gas-fired Condensing Boiler

As an alternative to the microCHP, the OSH is now able to simulate a gas boiler that is based on a simplified model of a gas-fired *condensing* boiler (see Section 4.5.2). Originally, the gas boiler has been introduced by Mauser et al. (2015) [412]. It utilizes natural gas to provide hot water. The details of the analysis are given in Table D.5 on p. 410.

Device Simulation Driver and Local O/C-unit The device simulation driver of the gas-fired condensing boiler has been implemented as `class GasBoilerSimulationDriver`. It has a single power level of 15 kW and an efficiency of 100 %. However, this may be adapted by modifying the configuration files or enhancing the entity model. More about the thermal model is given in Table D.6 on p. 411.

The local O/C-unit of the gas boiler comprises a local Observer of the `class GasBoiler-LocalObserver`, using the `class GasBoilerObserverExchange`, and does not require a local Controller, because the boiler is only observed but not controlled by the BEMS.

Interdependent Problem Part The gas boiler uses a non-controllable IPP of the `class GasBoilerNonControllableIPP`. It implements on-off control, using minimum and maximum temperature limits of the hot water storage tank. The entity model utilizes the same model of a gas-fired condensing boiler as the device simulation driver.

5.6.4 Electrical Insert Heating Element

The OSH is able to simulate an advanced electrical IHE, which is screwed directly into the hot water storage tank and has multiple power steps. It is based on a real device, the *E.G.O. EGO Smart Heater* (see also Section 4.5.2). The IHE utilizes electricity to provide hot water, having a practically constant efficiency. The details of the analysis of electrical IHEs are given in Table D.7 on p. 412.

Device Simulation Driver and Local O/C-unit The device simulation driver has been implemented as `class SmartHeaterSimulationDriver`. Usually, electrical IHEs have only a single power level. In contrast, the regarded advanced IHE has an electrical power of up to 3.5 kW in steps of 0.5 kW, i. e., a total of eight discrete power steps, and for sake of simplicity an efficiency of 100 %. Technical constraints of the heating elements lead to minimum and maximum on and off periods, e. g., to limit the number of cycles of the relays. More about the model is given below and in Table D.8 on p. 413. However, the number of levels, their respective power and efficiency, and the technical constraints may be freely configured.

The local O/C-unit of the IHE comprises a local Observer of the `class SmartHeater-LocalObserver`, using the `class SmartHeaterObserverExchange`. It does not require a local Controller, because the IHE is only observed but not controlled by the BEMS.

Interdependent Problem Part The IHE uses a non-controllable IPP of the `class Smart-HeaterNonControllableIPP`. It does not implement on-off control based on temperature limits. Instead, it aims at reducing the electricity feed-in to the electricity grid. Therefore, it uses the information of the virtual electrical meter of the ESC to set the power level of the IHE to the highest possible power step that does not lead to a net consumption of the building. In so doing, several constraints about the minimum and maximum on as well as off times of the power levels have to be respected. Actually, the power levels are provided by means of three heating elements having a nominal power of 0.5 kW, 1 kW, and 2 kW, respectively. The minimum on and off times are related to these three heating elements and thus the on and off times depend on the combinations of these three heating elements that realize the eight power levels. This model of the IHE is not only used by the IPP but also by the device simulation driver.

5.6.5 Thermal Energy Storage System: Water Storage Tank

Thermal ESSs[8], such as hot water and chilled water storage tanks, may be simulated using the OSH. The thermal model of such a tank is based on a simple artificial model having a single temperature (see Section 4.5.7). Originally, this kind of simulated thermal storage is introduced by Mauser et al. (2015) [412]. It is similar to the simulated tank that is used by Allerding (2013) [10]. The details of the analysis are given in Table D.9 on p. 414.

Device Simulation Driver and Local O/C-unit The device simulation driver of the water storage tanks has been implemented as `class WaterTankSimulationDriver`. The thermal loss of the storage tank is calculated based on the volume of the storage, the tank temperature, and the ambient temperature. More information about the thermal model is given in Table D.10 on p. 415. Improved models of water tanks may easily be integrated into the OSH by a configuration of the parameters or by changing the thermal modal of the tank, to use, for instance, a more detailed model of a stratified storage tank or a combined domestic and heating hot water storage tank (cf. [65, 654]).

The local O/C-units of the water tanks comprise only a local Observer of the `class WaterTankLocalObserver`, using the `class WaterTankObserverExchange`, and no local Controller, because the storage tanks are only observed but not controlled by the BEMS.

Interdependent Problem Part The water storage tanks use non-controllable IPPs of the `class WaterTankNonControllableIPP`. The IPPs provide their temperature to related IPPs of interdependent entities, enabling the on-off control of devices that charge the thermal storage. The entity model uses the same model of a water storage tank as the device simulation driver.

5.6.6 Photovoltaic System

The OSH is cable of simulating various PV systems, i. e., integrated systems[9] comprising PV cells and inverters, based on (scaled) recorded profiles as well as on a randomized profile based on the SLP EV0. The profiles of real systems have been recorded at KIT and FZI (see Section 4.5.1). The details of the analysis of PV systems are given in Table D.13 on p. 418. The integration into the OSH is summed up in Table D.14 on p. 419.

[8] Although the OSH is also capable of simulating a BESS, i. e., electrical energy storage, the corresponding drivers, O/C-units, and IPPs are not presented as part of this thesis. See Müller et al. (2016) [440] for more details. The analysis of electrical storage systems is given in Table D.11 on p. 416.

[9] Actually, PV systems may be split up into their components and simulated separately in the OSH using DC electricity connections. However, this is out of scope of this thesis, because it offers only limited benefit to the presented simulations. In case of combined PV-BESS or a local DC grid that is fed, e. g., by DC/DC converters, it makes sense to simulate them separately.

Device Simulation Driver and Local O/C-unit The device simulation driver of PV systems has been implemented as `class PvSimulationDriver`. It uses recorded profiles, which may also be subject to randomization, in the simulation. More information about the recorded profiles and the corresponding PV systems is given in Section 4.5.1, in Table B.20 on p. 387, in Table B.21 on p. 389, and in Table D.12 on p. 417.

Although a controllable PV system adapting its reactive power based on the total reactive power of the building is presented by Mauser (2012) [405], this kind of control is currently no longer implemented, because it offers only very limited benefit for building energy management neglecting reactive power. Therefore, the local O/C-unit comprises just a local Observer of the `class PvLocalObserver`. Nevertheless, a Controller that may alter the reactive power of PV systems and provide it as a part of an ancillary service is still available as `class PvLocalController`.

Interdependent Problem Part The PV system's O/C-unit uses non-controllable IPPs of the `class PvNonControllableIPP`, which simulates the expected future generation of the PV system based on a PV generation forecast. The forecasting method is described in Section 4.5.1 in detail.

5.7 Integration of Heating and Cooling Demands

In addition to the previously presented devices and systems there are demands for space heating and cooling as well as for DHW. Therefore, suitable drivers and IPPs for these demands have been implemented and are presented in the following sections.

5.7.1 Space Heating Demand

The space heating demand of buildings depends largely on the outdoor temperature, the intended inside temperature, and the thermal transmittance of the building, i. e., the result of the building's energy balance (see Section 4.2.2). The actual heating system of the building may use various types of technologies, such as radiators or underfloor heating, which are rather different and complex in their functioning and thus out of scope of this thesis. Therefore, the demand is abstracted to a power demand over time. The details of the analysis of space heating demands are given in Table D.15 on p. 420. The integration into the OSH is summed up in Table D.16 on p. 421.

Device Simulation Driver and Device Driver The space heating demand of buildings is simulated by means of the `class SpaceHeatingSimulationDriver`. It uses a thermal demand load profile, which has been obtained in a building simulation of the ESHL (see Section 4.2.2). To fit to residential buildings of varying household sizes, it is scaled to a corresponding yearly consumption. This approach is similar to Allerding (2013) [10]. However, there is an additional randomization of this profile.

The device driver for real buildings, such as the ESHL, is implemented in the `class SpaceHeatingDriver`, which uses thermal building models (see Table D.16 on p. 421). In case of the ESHL, the model uses the predicted outdoor temperature curve that is provided by an external weather forecast to calculate the expected space heating demand.

Local O/C-unit In contrast to Braun et al. (2016) [96], where the heating demand is influenced using the indoor temperature set point, the space heating is currently not controlled by the OSH. Therefore, the local O/C-unit comprises only a local Observer of the `class ThermalDemandLocalObserver`. Nevertheless, a controllable heating demand may easily be integrated into the BEMS by adapting the `class ThermalDemandLocalController`.

In the simulation, the Observer provides a demand forecast that is similar to the one used by the PV system: the prediction is calculated based on the load profiles of the previous seven days (see Section 4.5.1). In contrast to this prediction in the simulation, the Observer in the real application, e. g., in the ESHL, uses a thermal demand forecast based on an external weather forecast (see Bao et al. (2016) [46]).

Interdependent Problem Part The O/C-unit uses non-controllable IPPs of the `class HotWaterDemandNonControllableIPP`, which simulate the expected future space heating demand. This simulated demand is the space heating demand forecast that is provided by the Observer of the local O/C-unit.

5.7.2 Space Cooling Demand

Similar to the space heating, the space cooling is also abstracted to a power demand over time. The details of the analysis of space heating demands are given in Table D.17 on p. 422. The integration into the OSH is summed up in Table D.18 on p. 423.

Device Simulation Driver and Local O/C-unit The space cooling demand is simulated using the `class SpaceCoolingSimulationDriver`. It is capable of simulating recorded as well as randomly generated meeting room reservations in the HoLL (see also Section 4.3.2). Similar to the space heating demand, the space cooling demand is also not controllable. Hence, the local O/C-unit comprises a local Observer of the `class SpaceCoolingLocalObserver`. It provides a temperature forecast to the IPPs, which is then used to simulate the future cooling demand.

Interdependent Problem Part The O/C-unit uses the non-controllable IPPs of the `class ChilledWaterDemandNonControllableIPP`, simulating the expected future space cooling demand. The simulated demand is based on the space cooling demand forecast that is provided by the Observer. The chilled water is drawn from the chilled water storage tank.

5.7.3 Domestic Hot Water Demand

The DHW demand is abstracted to a power demand over time, too. Other than the heating demand, it is potable water that has been heated up utilizing hot water from the hot water storage tank. The details of the analysis of DHW demands are given in Table D.23 on p. 426. The integration into the OSH is summed up in Table D.24 on p. 427.

Device Simulation Driver, Device Driver, and Local O/C-unit The DHW demand is simulated using the `class VDI6002DomesticHotWaterSimulationDriver`. It simulates the DHW demand in residential buildings by means of the average values given in the VDI Guideline 6002 [613] (see Section 4.2.2). These values are reached by simulating several typical draw-off profiles, which are provided in Table D.19 on p. 424. The device driver for

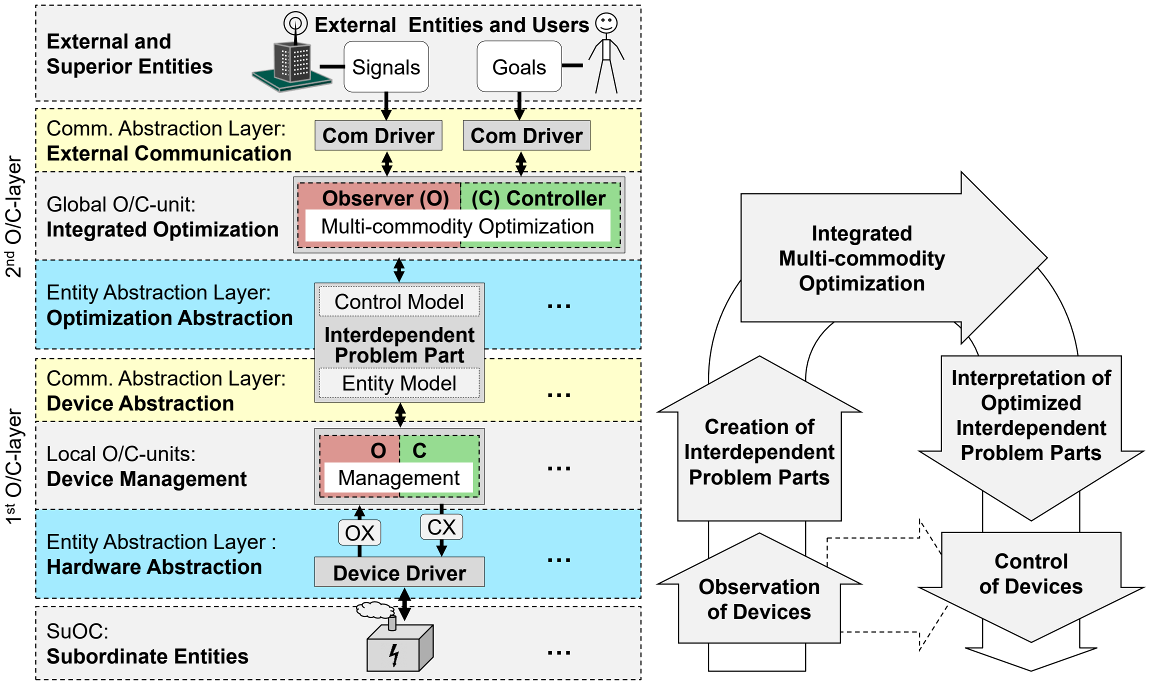


Figure 5.28: Overview of the observation, abstraction, optimization, and control process steps in the context of the *Extended O/C Architecture* used by a BEMS

real buildings is implemented in the `class VDI6002DomesticHotWaterDriver`, which may be used to observe and predict demands in real buildings. Other than the space heating and cooling demands, the DHW demand is practically never controllable[10]. Hence, the local O/C-unit comprises a local Observer of the `class VDI6002DomesticHotWaterLocalObserver`. It provides a demand forecast to the IPP, which is used by the optimization.

Interdependent Problem Part The O/C-unit uses non-controllable IPPs of the `class DomesticHotWaterNonControllableIPP` that simulates the expected future DHW demand. This simulated demand is based on the DHW demand forecast that is provided by the Observer and thus giving averaged values of the expected demand.

5.8 Optimization Process and Module

To optimize the building's energy system, there is a loop from the actual devices and systems to the optimizer and back to the entities. This loop is structured into several steps that include different kinds of abstractions. In so doing, the energy management problem depends on the availability and configuration of the entities, the preferences and goals of the users, and the external signals.

[10] Possibilities to control the heating demand of DHW provision include the temperature reduction of the provisioned DHW, the scheduling of the legionella protection function, and the control of the circulation pump that ensures a constant flow in the DHW system and thus comfortable temperature.

A general overview of the steps of the observation, abstraction, optimization, and control process in the context of the Extended O/C Architecture of the system is given in Figure 5.28. The EAL performs the hardware abstraction of the subordinate entities, i. e., the devices and systems, in the SuOC, using the drivers and the *Observation Exchange* (OX) and *Controller Exchange* (CX) objects. The local O/C-units perform the device management and create the IPPs, which abstract the entities into an entity model and a control model, for the optimization. The global O/C-unit performs an integrated multi-commodity optimization using the ESC to determine the load profiles of all entities in a detailed manner, i. e., by means of ancillary commodities. The solution of the optimization is then interpreted by the IPPs, which define the resulting control sequences that are then communicated from the local Controllers to the entities.

A detailed overview of the observation, abstraction, optimization, and control process is given in Figure 5.29, focusing on the actual optimization process, i. e., the integrated multi-commodity optimization, which is done by the optimizer using a GA and the ESC. These steps are described in more detail in the following sections.

5.8.1 Observation of Entities and Creation of Interdependent Problem Parts

In advance to the actual multi-commodity optimization, the heterogeneous devices and systems have to be observed and abstracted in a suitable manner, getting their current status and making them homogeneous regarding their handling by the modular optimization.

Observation and Abstraction of Devices and Systems The drivers of the *Entity Abstraction Layer* perform *hardware abstraction* of the subordinate entities in the SuOC, i. e., the devices and systems in the building. The states of the entities are abstracted using the *Observation Exchange* (OX) objects (cf. Allerding and Schmeck (2011) [13] and Allerding (2013) [10, pp. 71 ff.]), containing standardized information of otherwise heterogeneous entities that are managed by instances of the same local O/C-unit.

For instance, all deferrable appliances may be managed by instances of the same O/C-unit, no matter what concrete type of appliance they are or which communication protocol or medium is used by the respective appliance. However, this requires different (bus) drivers that provide abstraction and combine information from different devices, such as separate metering systems. The local O/C-units are located in the *first O/C-layer* (see Figure 5.28) and perform the *device management*, i. e., the direct control in a closed-loop manner[11].

Creation of Interdependent Problem Parts In addition to managing the devices, the local O/C-units create the IPPs (see Figure 5.29, top), resulting in the device abstraction of the entities into entity models and the optimization abstraction into control models. The integrated optimization is then done by the global O/C-unit. The IPPs are created periodically by the corresponding O/C-units whenever there are changes in the state of the observed entity. A new IPP does not necessarily trigger a new run of the optimization. Only in case of relevant changes, such as the selection of another program or larger deviations between the expected and the observed tank temperatures, a new optimization run is

[11] However, strictly speaking, this is closed-loop control not in the sense of control theory and process control but of Energy Informatics (see also Section 2.6), i. e., at the transition of classical control theory and scheduling.

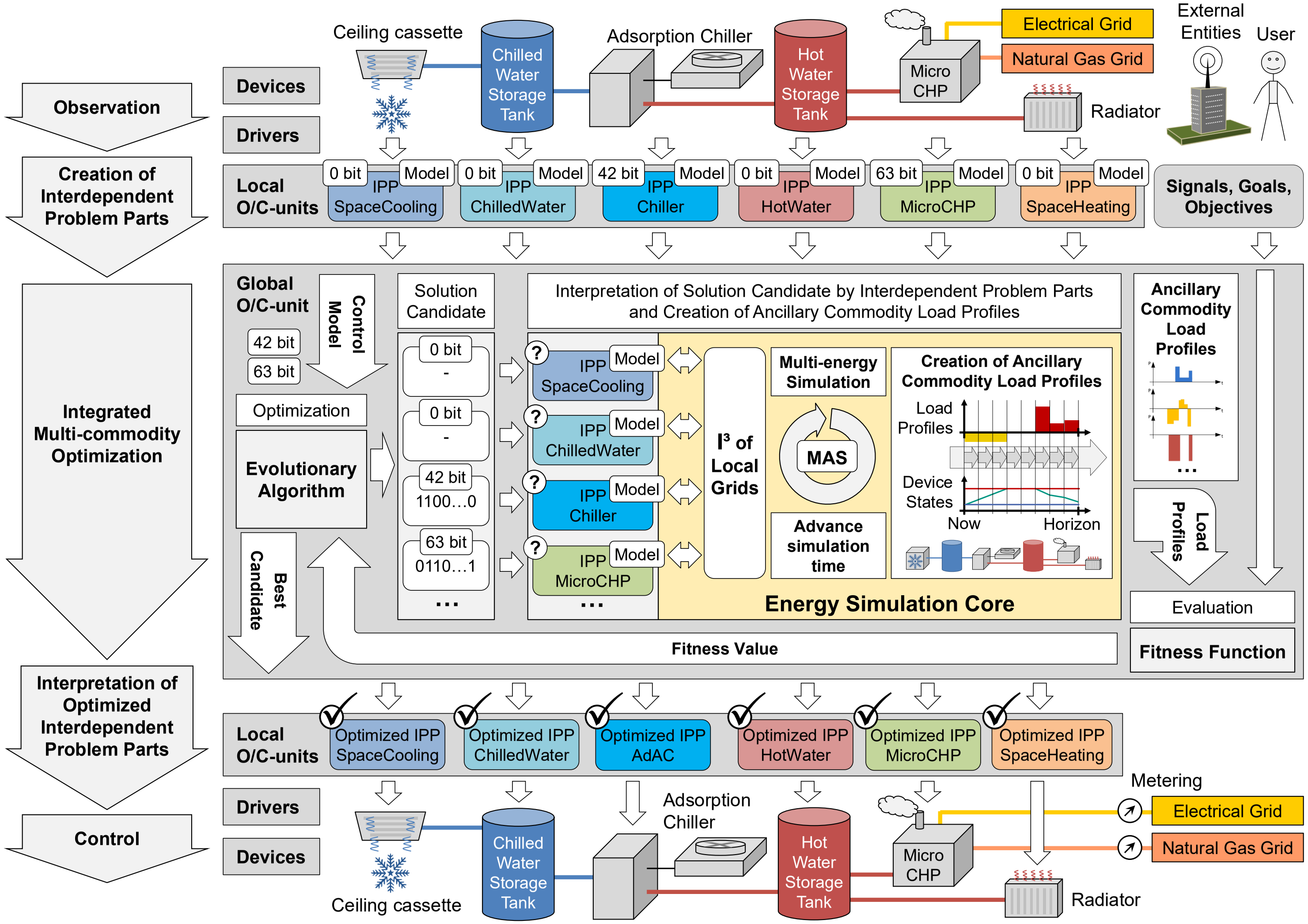


Figure 5.29: Overview of the steps in the optimization module, focusing on the actual optimization using the *Evolutionary Algorithm*, the *Energy Simulation Core*, and the *Interdependent Problem Parts*, partly based on [410, Fig. 6 & 7]

triggered by the corresponding IPP. Nevertheless, each IPP is updated frequently to contain the latest states, because the optimization may be triggered by another IPP.

Each IPP possesses all necessary information to optimize the corresponding entity (see also Section 5.4). Therefore, the entity model provides an appropriate physical model regarding the technical specifications and capabilities and the control model defines a certain number of bits which are required from the optimizer. These bits form a bit string and encode the overall *degree of freedom* to be exploited by the optimization, such as the TDoF, the EDoF, and other parameters. Hence, an IPP is capable of translating the bit string into a control sequence and thus behavior of its entity by means of a suitable encoding. In so doing, controllable entities require one or more bits, whereas non-controllable entities require none. For instance, the states of the storage tanks and the predictions of heating and cooling demands are handled as non-controllable IPPs. The interdependencies to other entities are stored in the I^3 of the local energy grids (see Section 5.3.3).

Thus, the IPPs represent sub-problems of the optimization problem that is solved by the integrated multi-commodity optimization. Therefore, all IPPs are communicated to the global O/C-unit and combined to represent the global optimization problem in the building for the current optimization horizon.

5.8.2 Integrated Multi-commodity Optimization

The global optimization problem that is solved by the integrated multi-commodity optimization is composed of the entirety of all IPPs. The aggregated optimization problem is not stated in a closed and static form, but dynamically compiled at run-time of the OSH from the IPPs. Hence, the OSH is able to manage and optimize fundamentally differing buildings with different sets of devices and systems by using just another set of drivers and O/C-units providing suitable IPPs.

In case of relevant changes, such as the selection of another program or larger deviations between the expected and the observed tank temperatures, a new optimization run is triggered by the corresponding IPP. Nevertheless, there is usually a frequent rescheduling, i. e., the optimization process is often rerun. Therefore, the approach of generating approximate solutions using a heuristic is practicable for productive BEMSs, such as the OSH.

Integrated Optimization The global O/C-unit performs an integrated multi-commodity optimization, using the ESC to determine the load profiles of all entities in a detailed manner, i. e., as ancillary commodities (see Figure 5.29, middle part). The optimization aims at finding a combination of control sequences and parameters, i. e., a signal trajectory, that optimizes a global goal, such as the minimization of the total energy costs. These sequences and parameters have to be encoded in a way that can be provided by the optimizer.

To support practically all possible inputs and have a homogeneous representation, the encoding into a bit string is chosen. This way, parts of the overall bit string are interpreted as control sequences, others as parameter settings, and still others as time periods the devices can be deferred or interrupted in their operation. The OSH uses a GA to generate the bit strings, i. e., the candidate solutions, that are evaluated by the ESC in a multi-agent simulation using the IPPs (see also Figure 5.16 on p. 215). The solution candidates are passed to the ESC and result in expected future load profiles of ancillary commodities that are assessed by the *fitness function* with respect to user objectives and by means of signals, tariffs, and user preferences. Based on the fitness values, new candidate solutions are generated until a certain stopping criterion is reached. Finally, the best solution of the optimization is interpreted by the IPPs and passed back to the local Controllers, which apply the control sequences and parameters to the entities.

Although the optimizer in the global O/C-unit calculates a schedule for all devices, the scheduled actions may be overridden by their particular O/C-units, e. g., the microCHP is forced to run if the temperature of the storage tank is below a defined temperature limit. However, such an intervention causes a new IPP that retriggers the optimization.

Genetic Algorithm This thesis uses an adapted and improved version of the *generic Genetic Algorithm* (gGA) from the *jMetal* framework [184, 185]. Unless stated otherwise, the algorithm in the OSH uses the parameters given in Table 5.4. These parameters have been selected based on standard values that are recommended in the literature, such as a mutation rate $p_m^{\text{default}} = \frac{1}{b}$ per bit of the bit string B having the length b [154, p. 149], the experience gained in numerous publications, such as [11, 406–408, 410, 412, 440], and evaluations given in Section 6.2 that led to the adaption of these usual settings.

Adapted Genetic Algorithm The original GA has been adapted in various ways. For instance, the mutation rate is no longer fixed but variable, depending on the length b of the bit string B. In addition, it is significantly higher than proposed in the literature: the mutation rate has been set to $p_m = \frac{9}{b}$ or $p_m = \frac{21}{b}$, respectively, based on the results provided in Section 6.2. This is mainly caused by the structure of the encoding of the devices and systems, which show a stable behavior due to the usage of an automaton, the inherent control logic, and a high temporal precision (see Sections 5.4 to 5.6).

To reduce the number of evaluations, an additional stopping criterion has been introduced: the optimization process is terminated prematurely, i. e., before reaching the maximum number of generations, if there is a relative change Δ_{fitness} of the fitness in the past $k^{\max} = 20$

Table 5.4: Configuration of the *generic Genetic Algorithm* in this thesis

	Residential building	**Commercial building**
Strategy of μ parents and λ children	Elitist (μ,λ)-strategy	
Selection mechanism	Binary tournament selection	
Population size $\lvert P\rvert$	$\lvert P\rvert = 100$	
Maximum number of generations $\lvert G\rvert$	$\lvert G\rvert = 200$	$\lvert G\rvert = 600$
Additional stopping criterion	$k = 20$, $\Delta_{\min} = 5 \cdot 10^{-15}$	–
Crossover	Two-point binary crossover	
Crossover probability p_c	$p_c = 0.99$	
Mutation	Bit-flip-mutation (relative probability)	
Mutation factor m	$m = 9$	$m = 21$
Mutation probability p_m per ↪ bit of bit string B	$p_m = \frac{m}{b} = \frac{9}{b}$	$p_m = \frac{21}{b}$

generations $\{G_{i-20} \dots G_i\}$ that is smaller than a defined threshold $\Delta_{\min}$:

$$\Delta_{\text{fitness}}(G_{i-k}, G_i) = \frac{G_{i-k} - G_i}{G_{i-k}} < 5 \cdot 10^{-15} = \Delta_{\min} \quad \forall k \in \{1 \dots k^{\max}\}.$$

Thus, the GA is stopped when there is no further convergence above the threshold, saving time on most probably minor improvements. This is a common approach in real-world application that reduces the number of evaluations significantly in exchange for slightly less good solutions [391].

Further improvements include the parallelization of the candidate solution evaluations in the GA and many small changes in representations and data structures that help speeding up the optimization process.

Determination of Load Profiles by the Energy Simulation Core The joint evaluation of the solution candidates is done by the ESC (see Figure 5.29, middle). It uses the IPPs, which represent the devices and systems, and the I^3, which contains the information about the actual interdependencies, in a multi-agent and multi-energy simulation (see Section 5.3.1). The solution candidates are passed to the IPPs, which simulate the behavior and thus energy flows according to the control sequences that are represented by the solution candidates (see also Figure E.2 on p. 432).

The energy flows that can actually be measured by metering devices and sensors in productive systems are calculated by virtual meters and the entities update their behaviors and states at every simulated time step based on these values (see Section 5.3.1). In the optimization process, the iterative calculation is necessary to determine the energy flows of interconnected and interdependent devices reacting on each other [408,410]. The information about the energy carriers in the energy-flow simulation is enriched by the origin of the energy flows, facilitating the creation of ancillary commodity load profiles. Hence, the ESC handles not only the simulated energy flows between the devices but also the information exchange of additional information about the devices' states, such as tank temperatures or voltages. In so doing, devices are able to observe other devices and systems and react on their statuses. Afterward, these expected future load profiles of ancillary commodities are passed to the *fitness function* (see Figure 5.29, middle).

Assessment of Load Profiles using the Fitness Function The ancillary commodity load profiles are assessed using the *fitness function* (see Figure 5.29, middle), which is given and explained in Section 4.8.2. The fitness function calculates a fitness for every candidate solution, i. e., set of ancillary commodity load profiles, based on the external signals, e. g., price signals and load limitations, and the user preferences, goals, and objectives. Thus, the fitness value may reflect not only the total costs but also other results. The fitness value of each candidate solution is then passed back to the optimization algorithm.

5.8.3 Interpretation of Solution and Device Control

The final step of the optimization process is depicted in the bottom part of Figure 5.29. In this step, the best candidate solution of the optimization is passed back to the IPPs. The IPPs convert their corresponding part of the solution into specific control sequences and parameters, which are passed to the particular device drivers by means of standardized

Controller Exchange objects. Finally, the device drivers translate these control sequences and parameters into device- and thus also manufacturer-specific commands and actions. The resulting commands and actions are communicated either immediately to the devices or delayed until some later time, because not all devices support storing commands for later execution or commands determining future behavior. The communication to the entities may also include a detour using bus drivers (see Section 5.2.1).

5.9 Automated Parameter Calibration and Tuning

The calibration of parameters with respect to the given problem is essential for the performance of heuristics, as shown in Section 4.8. In BEMSs, there are several reasons why different sets of parameters are necessary: Firstly, BEMSs are applied to various environments, e. g., residential buildings and commercial buildings. Secondly, these buildings are equipped with different devices and systems. Additionally, the available devices and systems in a particular building may change over time and are used in various ways at different times of the year, i. e., more often or not at all.

To obtain suitable parameter sets for all operation scenarios, a parameter calibration has to be carried out and redone periodically to calibrate the parameters to the current situation. The task of finding good ones for the optimization calls for an additional module that is able to adapt the parameters of the GA, which requires suitable crossover and the mutation rates. Therefore, this thesis proposes—based on the work by Dorscheid (2013) [183] and Mauser et al. (2014) [407]—to introduce an extra level into the BEMS for automated parameter calibration and tuning.

There are several approaches to parameter calibration for meta-heuristic algorithms (see Section 4.8.3). However, they are often performed only manually or in a semi-automatic way, and have a high complexity of modeling and evaluation [407]. In contrast, this thesis addresses the practical and fully automated realization in a BEMS. Therefore, we propose the introduction of the *Calibration Engine*, which realizes the adaptation of the optimization in an additional level of the controller of the BEMS by evaluating past optimization problems, and of the *Calibration Coordination Entity*, which coordinates the parameter calibration process of multiple buildings, promotes collaboration of similar buildings, and avoids the overfitting of parameters to one-time-only past behavior (see also Figure 5.11 on page 209). A detailed evaluation of the proposed mechanisms is out of scope of this thesis. However, an evaluation demonstrating its capabilities is given by Mauser et al. (2014) [407].

Calibration Engine

The Calibration Engine realizes the adaptation of the parameters in the second level of the controller of the BEMS, which is the practical realization of the *two-level learning approach* by Rochner et al. (2006) [511]. The calibration is done by means of replaying and optimizing past optimization problems based on *Screenplays*, which are recordings of past energy consumption, user interaction, and device utilization. In so doing, the parameters are adapted to the local scenario based on its past situations. Hence, the Calibration Engine enables automatic self-adaptation to different scenarios in BEMSs.

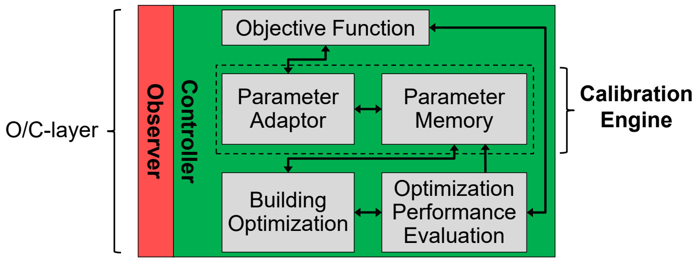


Figure 5.30: *Calibration Engine*: overview of the architecture

Architecture The general architecture of the Calibration Engine is depicted in Figure 5.30. It consists of two main modules: The first main module is the *Parameter Memory*, which stores suitable sets of parameters for the optimization algorithm using a storage schema that reflects already known energy management scenarios. This schema refers to the setup in the building, user objectives, and external signals and allows for the selection of suitable parameters sets. The second main module is the *Parameter Adaptor*, which improves the parameters for concrete problem instances that occur in the buildings.

General Operation and Parameter Calibration Process At run-time of the BEMS, the optimization algorithm in the *Building Optimization* module receives suitable sets of parameters from the Parameter Memory. Therefore, the latter selects parameters that have proven to be applicable to scenarios which are similar to the current one in the building. In case of changes of the local scenario, e. g., because of novel devices and user objectives, or poor performance of the optimization, the Parameter Adaptor is triggered and calibrates the parameters systematically. The Parameter Adaptor uses a *simulation model* of the real building and the BEMS to evaluate possible parameter sets (see Figure 5.31). As a result, the parameter calibration process does not affect the productive real building because it is done offline. Finally, the Parameter Adaptor updates the Parameter Memory by storing the novel parameter set for the evaluated scenario using the storage schema, i. e., characteristic parameters of the setup. The actual calibration process, i. e., the tuning of parameters before executing the heuristic optimization process in the building, selects and evaluates different sets of parameters in a systematic way. The search space, i. e., the different combinations of parameters, is explored and information about solutions that have proven to be suitable is exploited by local search. [407]

Parameter tuning for a certain building and situation requires extensive information about the productive system, i. e., the concrete scenario in the real world, such as the present and the past states of the devices and systems, external signals, and user objectives. The scenario is defined by the *Building Configuration*, i. e., the available devices, the *Screenplay*, which contains records of past user behavior and interaction, device usage, other limitations, such as physical constraints, *User Input*, i. e., preferences, goals, and objectives of the users, and *External Input*, i. e., price signals and power limits.

In the prototypical implementation presented by Mauser et al. (2014) [407], the Parameter Adaptor uses a GA to optimize the parameter settings and hence the approach is actually a meta-GA in the BEMS. In the meta-GA, the parameter settings are represented as real-valued genes of the individuals. In the evolutionary process, the individuals are evaluated

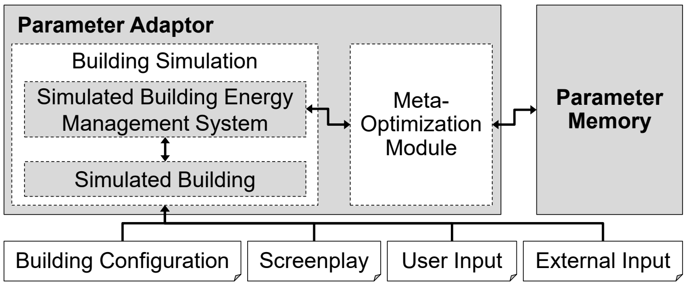


Figure 5.31: *Calibration Engine*: overview of the parameter adaption process and the used data, partly based on [407, Fig. 3]

by means of the *Building Simulation*, which is a detailed replica of the productive real world BEMS and the building during a certain period in the past.

The mechanism for the generation of new parameters extends a meta-evolutionary parameter tuning approach presented in [222]. Its main advantage is the ability to evaluate possible parameter settings in a distributed and parallel way. Additionally, the implementation of the GA for energy management and load optimization may be reused for the parameter tuning, simplifying the design and implementation as well as reducing the complexity of the BEMS by avoiding different implementations. Typically, BEMSs in real-world scenarios are run on low-power computers with limited resources and thus the parameter calibration process may only be performed at times when the actual optimization is idle. Therefore, it is advantageous to utilize information from similar buildings, e. g., parameter sets that have proven to be appropriate somewhere else, or to perform a distributed evaluation of the parameter settings as described in the following section.

Calibration Coordination Entity

A BEMS may be used in a multiplicity of different buildings. Additionally, if a BEMS is installed in a new building and has to be initialized, there is no history about past behavior, i. e., recorded Screenplay, available that can be used to find suitable parameters. Instead of using the same default parameter set for all buildings, a BEMS may use parameters that have proven to be applicable to *similar* buildings. Thus, it is beneficial to have an entity that facilitates sharing parameters by providing some kind of database of suitable parameters. Additionally, the calibration process may be outsourced from the BEMS to an external entity that performs the parameter calibration process on a more powerful system. This saves computational time on the distributed low-power computers and may also be energy-saving because of a higher efficiency of specialized hardware.

Not only performance issues but also risks of overfitting call for a collaborative approach. When using only the Screenplays from a single building, the parameters are calibrated according to its particular past behavior. Thus, the parameters become specialized on this past behavior but may perform badly at future behavior in the building. Therefore, it is beneficial to exploit information from similar buildings and utilize multiple Screenplays. This way, the parameters are calibrated in a way that performs better and more robust, increasing the overall effectiveness and efficiency [407].

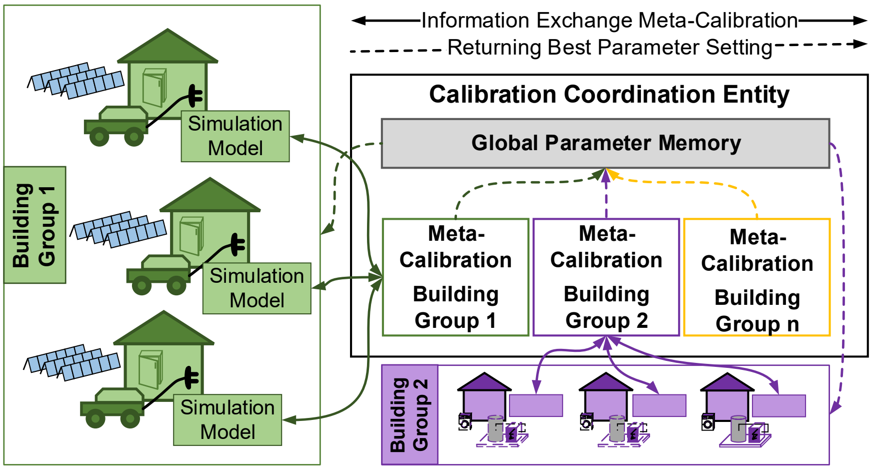


Figure 5.32: Calibration Coordination Entity with different groups of buildings, partly based on [407, Fig. 4]

Therefore, the parameter calibration is enhanced to an approach using multiple buildings, which are grouped according to their similarity, i. e., their devices, systems, objectives, energy consumption, and typical behavior of their users. These grouping criteria are called *characteristic parameters* and a proposed list of them is given in Table 5.5. However, these parameters are only preliminary and require further research to develop an adequate metric that can be used to classify similar buildings. Currently, there is simply not enough extensive data about real buildings having BEMSs available. The simulations presented by Mauser et al. (2014) [407] have been generated using the same characteristic parameters, i. e., the same usage statistics and number of occupants, and are thus assumed to be similar with respect to such a metric.

Each group optimizes the set of parameters collaboratively, utilizing the Calibration Coordination Entity, which is depicted in Figure 5.32. This extends the *two-level learning approach* in [502, 511] by a third level and is thus also called *three-level learning approach*. Such an entity that helps to find new parameter sets for multiple buildings and which stores suitable parameters in a *Global Parameter Memory* to facilitate collaboration may either be realized in a centralized or a decentralized way.

Centralized Calibration Service The concept of a Calibration Coordination Entity may be realized in a centralized way: The parameterized simulation models of the buildings and the input data are all passed to the Calibration Coordination Entity and the parameter

Table 5.5: Proposed characteristic parameters for grouping of buildings

Building type	Single-family, multi-family, apartment, office, ...
Energy carriers	Electricity, natural gas, district heating/cooling, ...
Devices & systems	Appliances, microCHP, PV system, BESS, electric vehicles, ...
Statistics	Yearly energy consumption, number of persons, load profiles, ...

calibration process is executed centrally. The Calibration Coordination Entity executes a separate process for each group of similar buildings. In the calibration process, each candidate, i. e., set of parameters, is evaluated using all simulation models and the overall fitness of a candidate is determined by averaging the fitness that is achieved by every single simulation model. Thus, the entire calibration process is actually run on the Calibration Coordination Entity and does not burden the distributed BEMS.

At the end of a calibration process, the resulting parameters are stored in the Global Parameter Memory and passed to all buildings of the respective group. The resulting parameters have thus proven to be most qualified for all buildings of a group, avoiding overfitting to a specific Screenplay, i. e., they are suitable for all buildings of a group and their typical but not their temporary or one-time-only behavior, which is represented by one simulation model and a single Screenplay.

An appropriate entity for running the Central Calibration Service is an entity providing measures of DSM, such as a regional EMS. There, the calibration process could easily also be run with alternative constraints and signals, e. g., other price signals, in order to develop, test, and tweak possible future DSM signals.

Distributed and Privacy-aware Calibration Service As partially presented by Mauser et al. (2014) [407], the concept of the Calibration Coordination Entity may also be realized in a distributed way: Instead of evaluating the candidates centrally, the parameter sets are passed to the buildings and evaluated by them in a distributed manner, using only their own simulation model and Screenplay. Only the resulting fitness values are communicated back to the Calibration Coordination Entity, where they are then averaged over all buildings of a group, leading to similar overall fitness results as the central approach presented above. In so doing, the distributed approach is respecting data privacy in a better way, since the simulation models and Screenplays, which reflect detailed building models as well as user behavior and thus very intimate data of the users, do not have to be passed to an entity outside of the building.

Both approaches may also be extended in a way similar to the concept of *Island Models* [94]: from time to time, the parameter sets that have been optimized for are particular building group are distributed to another building group. This will probably lead to better results by exploiting suitable settings from other building groups and help overcoming possible local minima of a single group. This idea can also be applied in a peer-to-peer manner, where single buildings exchange their parameters mutually in a direct way.

5.10 Generalization and Transferability of the Concepts

Although the EMS presented in this thesis focuses on residential and commercial buildings, the concepts may also be used in larger settings, e. g., factories or other industrial buildings, and control not only devices and systems but also production processes. Additionally, it may also be used by complex single systems providing multiple energy carriers, e. g., a trigeneration system providing district heating and cooling. Thus, not only the Extended O/C Architecture may be used for other entities (see Section 5.1.2) but the entire concept of multi-energy simulation and multi-commodity optimization in energy systems. Another

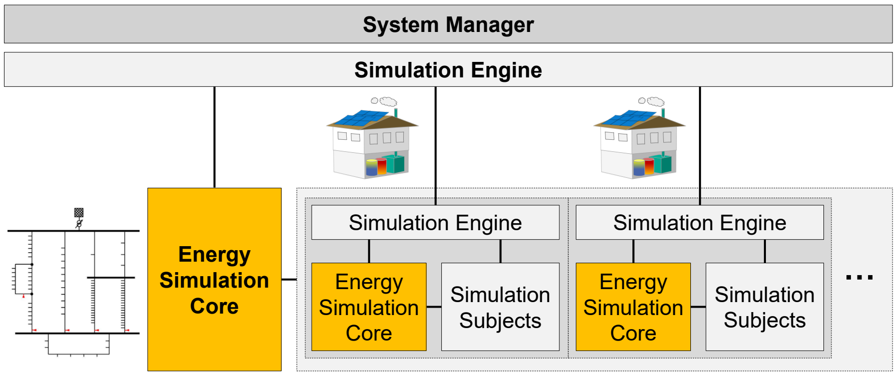


Figure 5.33: Hierarchical structure of simulation engines in a scenario comprising multiple smart buildings that are interconnected in a distribution grid

possibility is to use the hierarchical structure for adding another layer and thus realizing the simulation and optimization of multiple buildings, e. g., in a DSM scenario. This is depicted in Figure 5.33.

Generalization: Multiple Buildings The architecture of the BEMS may be used to realize bottom-up simulations of smart distribution grids comprising multiple buildings that are optimized by separate instances of BEMSs, resulting in multi-building simulations. Bottom-up simulations of distribution grids enable a detailed analysis of the effects of DSM and energy management. Other entities in the grid, such as entities providing measures of DSM or facilitating VPPs, may be simulated by similar management systems that are also utilizing the Extended O/C Architecture.

Initial simulations of multiple buildings using the BEMS and of measures of DSM are presented by Mauser (2012) and Mauser and Schmeck (2014) [405, 411], the concept of abstracting households in such simulations is described by Allerding (2013) [10, pp. 91 f.] and generalized by Mauser et al. (2015) [409] and Hirsch (2015) [294, pp. 57 ff.]. Detailed bottom-up simulations of distribution grids based on the BEMS presented in this thesis are demonstrated and analyzed by Kochanneck et al. (2015) [354, 356].

It is reasonable to test the large-scale effects of measures of DSM in simulations and virtual scenarios before applying them to the real world [296]. Only measures that perform well in simulations and do not show unintended secondary effects, such as herding behavior or negative emergence, are finally tested in field tests, reducing costs and the time to market. Therefore, it is beneficial to have a system that may be used in both productive real-world application and simulation, including in HIL simulations [355].

Generalization: Energy Simulation Core and Grid Simulation The ESC may not only simulate the local energy grids in buildings but also large energy grids. This has been used by Kochanneck et al. (2015) [354, 356] to simulate suburban distribution grids comprising one hundred households: instead of simply adding up the electrical power values as done in the simulation of a single building, the power values of the buildings are passed to a Newton-Raphson algorithm (see also Section 3.5.2), which has been implemented in MATLAB and performs a grid calculation, using the same defined interface.

Enhancement: Provision of Ancillary Services The system presented in this thesis can be used to facilitate ancillary services, such as voltage and reactive power control [63, 355, 356, 411]. It enables communication and provides the means to react on signals from an entity handling the particular grid, e. g., a utility, an independent system operator, a regional energy manager, or a demand side manager, and control the local devices accordingly. Additionally, it can control the devices based on local measurements to enable voltage and reactive power support to the grid.

Enhancement: HIL Simulation The BEMS may be used to perform HIL simulations by coupling real and simulated components in a simulation environment that runs according to the wall-clock time, which is given by an external clock. This is explained in detail by Kochanneck et al. (2015) [355].

Enhancement: Multi-objective Optimization The optimization in the BEMS may easily be extended to multi-objective optimization and there are several multi-objective EAs that may substitute the single-objective GA that has been used in this thesis. For instance, Soares et al. (2014) [556] optimize devices in a smart residential building scenario with respect to total costs and user dissatisfaction. Braun et al. (2016) [96] present a comparison of four different multi-objective EAs in smart building scenarios, showing that the *Electrostatic Potential Energy Evolutionary Algorithm* (ESPEA) [97] and the *Non-dominated Sorting Genetic Algorithm-II* (NSGA-II) [159] perform best in their scenarios when minimizing total costs, CO_2 emissions, user discomfort, and technical wear of the devices.

Enhancement: Scalable Optimization Similar to the calibration process that is executed by the Centralized Calibration Service, the actual optimization process may also be executed by an optimization service. This approach is sometimes called *Optimization as a Service* (OaaS) [217, 478] and may provide the computing power that is required to perform an optimization run quickly without running the BEMS on powerful hardware. For instance, a cloud-based optimization approach for meta-heuristics is presented in [478].

Another approach towards a scalable optimization is a locally distributed optimization using various computers that are available anyway. This may include desktop computers, laptops, and many other devices that are (temporarily) available at the building, such as mobile phones and tablet computers. For instance, a service-oriented architecture for EAs is described in [230] and the concept of a platform-independent EA using *JavaScript* to perform the distributed evaluation of solution candidates is presented in [510].

6 Evaluation

This chapter evaluates the presented BEMS and its architecture as well as the simulations that use the system to answer the research questions of this thesis (see Section 1.2). Therefore, the BEMS is assessed in Section 6.2 with respect to its applicability and functionality and compared to similar approaches and systems. This assessment includes several criteria for the evaluation of BEMSs and multi-energy systems that are presented in the literature.

To demonstrate and evaluate the BEMS as well as to answer the research questions, two general scenarios—a *smart residential building* (see Section 6.3) and a *smart commercial building* (see Section 6.4)—are simulated in various configurations. In both scenarios, the utilization, conversion, and provision of multiple energy carriers has to be optimized by minimizing the costs. The scenarios use the tariffs, statistical data, and simulation values that are presented in Chapter 4. Unless otherwise stated, the evaluations for one year include 364 days, i. e., exactly 52 weeks.

Overall, more than 100,000 configurations of smart buildings have been simulated using the JoSchKa system (see Section 5.2.7) and evaluated to assess the effects of multi-modal energy management. The results of the evaluations are discussed in Section 6.5. Finally, the deployment of the BEMS to a real smart residential building is demonstrated in Section 6.6.

6.1 Assessment and Comparison

First of all, the BEMS is assessed using relevant criteria in the domain of building energy management, showing its applicability and functionality.

6.1.1 Evaluation of Applicability and Architecture

In [201], Fabrizio et al. (2010) name three kinds of analyses of multi-energy systems, which relate to their applicability in productive systems as well as in simulations:

1. Operational optimization of productive systems
2. Simulation of such systems
3. Design optimization of the system setup and configuration

The OSH enables all three kinds of analyses: it may be used in the operational optimization of productive systems as well as in simulations. The latter may be used to perform a design optimization, to assess, e. g., novel technologies, solutions, methods, or tariffs, and to create detailed artificial load profiles of future smart buildings.

Molitor et al. (2014) [433] name four requirements that have to be met by multi-energy simulations and simulators:

1. Dynamic simulation of building energy systems
2. Simulation of the energy supply infrastructure
3. Simulation of control and energy management
4. Computational performance

The OSH meets all of these requirements. It is able to simulate the building's energy system, the energy supply infrastructure, and the control and energy management of a building. Because of its computational performance, it can easily be used to simulate thousands of configurations for an entire year at the resolution of one second (see also below). Table G.1 on p. 446 provides an overview of the typical computation time required for simulations.

Furthermore, the OSH provides a consistent BEMS concept and an architecture that is based on the Extended O/C Architecture (see Section 5.1). It reduces the close relation of the original O/C Architecture to learning classifier systems and introduces additional layers that abstract entities, such as actuators and sensors, as well as the communication towards superior entities, respectively (see Section 4.9.1). Moreover, the OSH provides elementary and supporting services of a BOS (see also Section 4.6.5). As the OSH is implemented in *Java 8*, it is not limited to a single OS but platform-independent. Although there is currently only a single program—the energy management application—loaded and executed by the OSH, it may easily be extended to use an OSGi framework. This would strengthen its character as a BOS, similar to that of EF-Pi, *Eclipse SmartHome*, and QIVICON, which are able to run separate applications in addition to energy management. However, this is out of scope of this thesis.

6.1.2 Evaluation of the Features and Services

In Section 4.6, general requirements, generic functionality, and evaluation criteria for BEMSs are identified. The requirements of BEMSs are given in Section 4.6.1 and the typically required generic functionality is provided in Section 4.6.2. A set of evaluation criteria for automated BEMS is presented in Section 4.6.3. The criteria are partly based on the requirements presented in [579] and have been adapted to the domain of building energy management. Table 6.1 provides an evaluation of the BEMS presented in this thesis with respect to these requirements, generic functionality, and criteria. The details column gives more information about the compliance of the OSH and references the corresponding sections of this thesis as well as related work.

BEMSs may have to provide the means, i. e., the back end, to operate and manage the monitoring infrastructure, the databases, and user interfaces that provide visualization and facilitate behavioral change, e. g., by means of feedback and gamification (see Section 4.6.4). Therefore, it is rational to calculate the data in the BEMS and provide it to the related

Table 6.1: Evaluation of the *Organic Smart Home* with respect to the requirements and criteria presented in Section 4.6

	Detailed requirement/functionality/criterion	**OSH**	**Details about the compliance**
General requirements (Section 4.6.1)	Automated and integrated energy management	✓	*This thesis*
	Consideration of all relevant energy carriers in buildings	✓	Concept of *commodities* and *ancillary commodities* (see Sections 2.1, 2.2, 4.7, and 5.2)
	Abstraction of subordinate devices and systems	✓	EAL (see Section 5.1), *device (simulation) drivers*, IPPs (see Sections 5.2 to 5.7)
	Abstraction of superior systems and external information	✓	CAL (see Section 5.1 and also [45, 47, 409, 506]), *energy price* and *load limitation signals* (see Sections 2.1, 4.1, and 4.8)
	Abstraction of the BEMS towards superior systems	(✓)	Concept of *two-fold abstraction*, CAL (see Section 5.1 and also [45, 47, 409, 506])
	Conflict resolution in distributed systems	✓	Hierarchical Extended O/C Architecture (see Section 5.1 and also [47, 294, 409]); *energy price* and *load limitation signals* (market demand response) avoid direct conflicts of the building with other buildings (see [294, 356, 411])
	Real-world application and simulation	✓	Simulation mode and productive application in real buildings (see Chapter 6 and also [62, 355])
Generic functionality (Section 4.6.2)	Observation and monitoring	✓	*Local* and *Global Observers* of the O/C Architecture (see Sections 3.7.3 and 5.1 and also [46, 47])
	Forecasting and prediction	✓	*Prediction module* in the *Observers*, e. g., prediction of PV generation (see Section 4.5.1)
	Simulation and calculation	✓	ESC and *simulation drivers* (see Sections 5.3 to 5.7)
	Optimization and scheduling	✓	Multi-commodity optimization (see Sections 4.7 and 5.8)
	Operation and control	✓	ESC and IPPs (see Sections 5.3 and 5.4)
	Security and privacy management	(✓)	CAL (see Section 5.1 and also [45, 47, 409, 506])
Evaluation criteria (Section 4.6.3)	Local building energy management	✓	Multi-commodity optimization (see Sections 4.7 and 5.8)
	Integration of RES, DG, and ESSs	✓	MicroCHP, PV system, thermal energy storage (see Section 5.6), electrical energy storage (see [410, 440])
	Support of ancillary services	(✓)	Not in focus of this thesis, see [63, 355, 356]
	Adaptability, flexibility, modularity	✓	*Device (simulation) drivers*, *bus drivers*, IPPs (see Sections 5.2 to 5.7)
	Performance and scalability	✓	Adaptable energy simulation in the ESC (see Section 5.3), heuristic optimization using a GA (see Section 5.8)
	Reliability and robustness	(✓)	Permanent and stable execution at the ESHL and the HoLL (see Section 6.6)
	Privacy and security	(✓)	CAL (see Section 5.1 and also [45, 47, 409, 506])
	Usability and user-orientedness	✓	Configuration files (see Sections 5.3 and 5.4), user interface (see Section 4.6.4 and also [60, 466])

✓: compliant/available and demonstrated/shown, (✓): compliant, but not explicitly demonstrated/shown, ✗: not compliant / not available applications. However, the actual process of data acquisition and storage may be separated from the actual management and optimization part of the BEMS. This is presented in detail in [47], showing the separation of the energy management and optimization from services that handle the connections to devices and systems.

The Universal Smart Energy Framework (see Section 3.2.1) names seven essential smart energy services [553, pp. 30 ff.]. An evaluation of the OSH with respect to these seven services is given in Table 6.2. In summary, it can be stated that the OSH supports all of them. However, not all of them are explicitly demonstrated in this thesis.

6.1.3 Comparison to other Approaches to Building Energy Management

Similar approaches and BEMSs that can be used in simulations are presented in Table 6.3 and those that may be used in productive systems in Table 6.4. The properties in the tables are described in detail in Table A.3 on p. 379. The tables show that the application in productive systems and the usage in simulations are usually not done using the same approach or BEMS. Hence, the OSH is a special approach combining both functionalities in a single system. The only similar approaches are the combinations of EF-Pi and PowerMatcher or TRIANA, respectively.

Applicability and Functionality Table 6.3 reveals that most approaches to the simulation of BEMSs do mostly not cover functionality related connectivity, building automation, energy monitoring, or the participation in a VPP and lack consistent concepts related to building energy management as well as to BOS. Most of them are just abstract and simplified approaches to the optimization of the operation of devices and systems in buildings, which is only of limited use in real productive systems.

In contrast to the approaches that focus on simulation and optimization, the productive systems in Table 6.4 focus on connectivity and device abstraction, including functionality related to building automation. This is hardly surprising, as many of these systems focus more on automation than on real automated energy management. Only a few of them promote measures of DSM or the active participation in a VPP.

Table 6.2: Evaluation of the *Organic Smart Home* with respect to the seven essential smart energy services given in [553, pp. 30 ff.]

Service	**OSH**	**Details about the compliance**
Smart energy market	✓	Support of various measures of market demand response, communication of expected load profiles
Insight service	✓	Abstraction of devices and systems
DR smart appliances	✓	Integration and optimization of appliances
DR electric vehicles	(✓)	Integration and optimization of electric vehicles [393]
Manage local generation	✓	MicroCHPs, PV systems, adsorption chiller
Manage local energy storage	✓	Thermal storage, BESS [410]
Energy management	✓	Multi-modal building energy management

✓: compliant/available and demonstrated/shown, (✓): not explicitly demonstrated/shown,
✗: not compliant/not available

Table 6.3: Comparison to other building energy management systems and approaches that focus on simulation

Aspect	Property	**Allerding (2012)** [12]	**Althaher et al. (2015)** [14]	**Bozchalui et al. (2012)** [92]	**Di Giorgio & Pimpinella (2012)** [170]	**Good et al. (2015)** [252]	**Gottwalt (2015)** [254]	**Hable et al. (2002-2004)** [274–276]	**Hurtado et al. (2013)** [305]	**Lujano-Rojas et al. (2012)** [384]	**Soares (2016)** [555]	**Sou et al. (2011, 2013)** [563, 564]	**This thesis**
Category and applicability	Productive system												✓
	Simulation	✓	✓	✓	✓	✓	✓	✓	(✓)	✓	✓	✓	✓
	BEMS concept/architecture			✓					✓				✓
	BOS												✓
Functionality	Connectivity		✓										✓
	Building automation												✓
	Energy monitoring												(✓) [47]
	Automated EMS	✓	✓	✓	✓		✓	✓	✓	✓	✓	✓	✓
	DR	✓	✓	✓	✓		✓	✓		✓	✓	✓	✓
	VPP participation												✓
Devices and systems	Deferrable appliances	✓	✓	✓	✓		✓			✓	✓	✓	✓
	Interruptible appl.											✓	✓
	Hybrid appl.												✓
	Refrigerator/freezer	✓		✓			✓				✓		(✓) [64]
	MicroCHP					✓		✓					✓
	CCHP												✓
	PV system			✓			✓	✓		✓	✓		✓
	Electrical IHE			✓		✓	✓				✓		✓
	Storage heater		✓			✓	✓		✓				(✓)
	Heat pump					✓							(✓) [378]
	Hot water storage			✓		✓		✓			✓		✓
	Chilled water storage												✓
	BESS			✓			✓	✓			✓		(✓) [440]
	Electric vehicle		✓	✓			✓			✓	✓		(✓)
	Compression chiller			✓					(✓)	✓	✓		(✓) [583]
	Ab-/Adsorption chiller												✓

✓: yes/possible/available, (✓): yes/possible/available but not explicitly demonstrated/shown, ?: unclear/unknown, ' ': not available/applicable

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Aspect	Property	**Allerding (2012)** [12]	**Althaher et al. (2015)** [14]	**Bozchalui et al. (2012)** [92]	**Di Giorgio & Pimpinella (2012)** [170]	**Good et al. (2015)** [252]	**Gottwalt (2015)** [254]	**Hable et al. (2002-2004)** [274–276]	**Hurtado et al. (2013)** [305]	**Lujano-Rojas et al. (2012)** [384]	**Soares (2016)** [555]	**Sou et al. (2011, 2013)** [563, 564]	**This thesis**
Appliance load profiles	Real appl. profiles	✓	✓		✓	✓	✓				✓	(✓)	✓
	Temporal resolution	1 min	15 min	15 min	5 min	1 min	15 min	10 min	1 s	60 min	1 min	1 min	1 s
	Multiple per appl.		✓										✓
Simulation	User behavior			✓		✓	✓				✓		✓
	Thermal load profile		✓				✓	✓					✓
	Thermal model		✓	✓		✓			✓		✓		(✓)
	Horizon	24 h	24 h	24 h	24 h	24 h	12 w	24 h	24 h	24 h	36 h	24 h	1 y
	Temporal resolution	1 min	15 min	15 min	5 min	1 min	15 min	10 min	1 s	60 min	1 min	1 min	1 s
Control	Closed-loop		(✓)			✓			✓				✓
Optimization	Horizon	24 h	24 h	24 h	24 h		7 d	24 h		24 h	36 h	24 h	24 h
	Temporal resolution	1 min	15 min	15 min	5 min		15 min	10 min		60 min	1 min	1 min	1 min
	Algorithm	EA/MINLP	MINLP	MILP	MILP		MILP	EA		EA	EA	MILP	EA
	Rolling horizon		(✓)				✓						✓
	Multi-objective (MO)										✓	✓	(✓)
	Scalarized MO			✓							(✓)		✓
Objective	Energy costs	✓	✓	✓	✓		✓	✓		✓	✓	✓	✓
	CO_2 emissions			✓				(✓)				✓	(✓)
	(Dis-)Comfort		✓								✓		
	Peak load			✓									(✓)
	Energy consumption			✓				(✓)	(✓)				(✓)
	Self-consumption												(✓)
Tariff/pricing	Time-variable prices	✓	✓	✓	✓		✓	✓		✓	✓	✓	✓
	Power-variable prices	✓	✓		✓		✓				✓		✓
	Power limit (hard)			✓							(✓)	✓	(✓)
Energy carriers	Electricity	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
	Natural gas			✓		✓			✓				✓
	Hot water			✓		✓							✓
	Chilled water												✓

✓: yes/possible/available, (✓): yes/possible/available but not explicitly demonstrated/shown, ?: unclear/unknown, ' ': not available/applicable

Table 6.4: Comparison to other building energy management systems and approaches that focus on practical application

Aspect	Property	**Abras et al. (2008-14)** [1, 36, 156, 268, 424, 456]	**Allerding (2013)** [10]	**Beegy beegyHUB** [66]	**BEMOSS + VOLTTRON** [273, 348]	**BOSS** [152, 580]	**EF-Pi + PowerMatcher** [459, 600]	**EF-Pi + TRIANA** [302, 586]	**Hydra/LinkSmart** [307, 324, 479]	**Kiwigrid** [367]	**OGEMA** [221, 454, 665]	**QIVICON** [166]	**RWE easyOptimize** [521, 522]	**RWE/innogy Smart Home**	**SMA Smart Home** [552]	**This thesis**
Category and applicability	Productive system	(✓)	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
	Simulation	✓	✓				✓	✓			(✓)					✓
	BEMS concept/architecture	✓	✓	(✓)	✓	✓	✓	✓	✓	(✓)	✓	(✓)	(✓)	(✓)	(✓)	✓
	BOS		(✓)	(✓)	✓	✓	✓	✓	✓	(✓)	✓	✓		(✓)		✓
Functionality	Connectivity	(✓)	✓	✓	(✓)	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
	Building automation		✓	✓	✓	✓			✓		✓	✓		✓		✓
	Energy monitoring		✓	✓	(✓)	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	(✓) [47]
	Automated EMS	✓	✓	✓	(✓)	✓	✓	✓	(✓)	✓	(✓)	(✓)	(✓)	(✓)	✓	✓
	DR	✓	✓	?	(✓)	(✓)	✓	✓		✓	(✓)		✓		✓	✓
	VPP participation		(✓)	?			✓	✓		✓	(✓)		✓			✓
Devices and systems	Deferrable appliances	✓	✓				✓	✓			(✓)	(✓)			✓	✓
	Interruptible appl.															✓
	Hybrid appl.															✓
	Refrigerator/freezer	✓					✓	✓			✓					(✓) [64]
	MicroCHP		✓				✓	✓			✓		✓			✓
	CCHP															✓
	PV system	✓	✓	✓			✓	✓		✓	✓	✓	✓		✓	✓
	Electrical IHE			✓			(✓)	(✓)					✓		(✓)	✓
	Storage heater	✓														(✓)
	Heat pump			✓			✓	✓		✓	✓					(✓) [378]
	Hot water storage		✓				(✓)	(✓)		✓	✓		✓		✓	✓
	Chilled water storage		(✓)													✓
	BESS			✓			✓	✓		✓	(✓)				✓	(✓) [440]
	Electric vehicle		(✓)	?			(✓)	✓		✓	✓				(✓)	(✓)
	Compression chiller				(✓)	✓										(✓) [583]
	Ab-/Adsorption chiller															✓

✓: yes/possible/available, (✓): yes/possible/available but not explicitly demonstrated/shown, ?: unclear/unknown, ' ': not available/applicable

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Aspect	Property	Abras et al. (2008-14) [1, 36, 156, 268, 424, 456]	Allerding (2013) [10]	Beegy beegyHUB [66]	BEMOSS + VOLTTRON [273, 348]	BOSS [152, 580]	EF-Pi + PowerMatcher [459, 600]	EF-Pi + TRIANA [302, 586]	Hydra/LinkSmart [307, 324, 479]	Kiwigrid [367]	OGEMA [221, 454, 665]	QIVICON [166]	RWE easyOptimize [521, 522]	RWE/innogy Smart Home	SMA Smart Home [552]	This thesis
Appliance load profiles	Real appl. profiles	✓	✓	?						?		?	?		?	✓
	Temporal resolution	1 s	1 s				15 min	15 min								1 s
	Multiple per appl.															✓
Simulation	User behavior		✓													✓
	Thermal load profile	✓	✓				✓	✓								✓
	Thermal model	✓														(✓)
	Horizon	24 h	1 y				24 h	1 y								1 y
	Temporal resolution	60 min	1 s				1 s	1 s								1 s
Control	Closed-loop	(✓)	(✓)	?	(✓)	✓	(✓)	(✓)		?	✓	✓	✓	✓	✓	✓
Optimization	Horizon	24 h	24 h	?			24 h	?		?	?		?		?	24 h
	Temporal resolution	60 min	1 s	?			15 min	?		?	?		?		?	1 min
	Algorithm	MI(N)LP	EA	?			Auction	HDP		?	?		?		?	EA
	Rolling horizon		✓	✓			✓	✓		✓	?		✓		✓	✓
	Multi-objective (MO)			?						?	?				?	(✓)
	Scalarized MO	✓	(✓)	?			✓			?	?		?		?	✓
Objective	Energy costs	✓	✓	✓			✓	✓		✓	✓		?		?	✓
	CO_2 emissions						✓			?	?				?	(✓)
	(Dis-)Comfort	✓				✓				?	?	✓		✓	?	
	Peak load			?			✓	✓		✓	?				?	(✓)
	Energy consumption			?			✓			?	?				?	(✓)
	Self-consumption			✓						✓	✓		✓		✓	(✓)
Tariff/pricing	Time-variable prices	✓	✓	?	(✓)	(✓)	✓	✓		?	✓	?	?	?	?	✓
	Power-variable prices		✓	?	(✓)	?	(✓)	(✓)		?	?	?	?	?	?	✓
	Power limit (hard)	✓		?	(✓)	?	✓			?		?	?	?	?	(✓)
Energy carriers	Electricity	✓	✓	✓			✓	✓		✓	✓	✓	✓	✓	✓	✓
	Natural gas		(✓)	?			✓	✓								✓
	Hot water		(✓)	?			✓	✓								✓
	Chilled water			?												✓

✓: yes/possible/available, (✓): yes/possible/available but not explicitly demonstrated/shown, ?: unclear/unknown, ' ': not available/applicable

Devices, Systems, and Appliance Load Profiles Regarding the support of devices and systems, even the simulation systems do not necessarily demonstrate the support of many different devices and systems. Some of them focus only on home appliances, other on the HVAC system. Not all the approaches support devices related to DG. This thesis is the only approach explicitly considering hybrid home appliances. In general, the used appliance load profiles have a rather low resolution and are often not based on real appliances but greatly simplified. In productive systems, the support of devices and systems does not necessarily mean that they are included into some kind of energy management and optimization.

Simulation Most of the systems simulate just a single day. Unfortunately, this leads to less meaningful results, because it does not consider storage systems appropriately: Storing energy beyond a single day is not possible. In addition, the simulation results depend heavily on the state of charge of the storage systems at the beginning of the optimization horizon as well as on its end. More often than not, the simulations are done just once and for a single day, often including perfect information. This is not realistic and leads to unrepresentative simulation results. Furthermore, the resolution of the simulation is often limited to 15 minutes and thus is prone to averaging effects (cf. Section 4.8.1).

Control, Optimization, and Objectives Most approaches that focus on simulation do not support closed-loop control and focus only on the optimization using fixed load profiles that do not respect interdependencies between the devices and by means of MILP and MINLP or EAs. Typically, the optimization is only done once and not in a rolling manner as it is required in real systems, which are always subject to deviations and imperfect information. The productive systems are mostly not able to perform building energy management based on optimization methods but use simple control rules to automate actions that are performed in the building. Typically, the building is optimized with respect to energy costs. However, many approaches include also other objectives, such as CO_2 emissions, user comfort, peak load shaving, total energy consumption, and self-consumption.

Tariffs and Pricing Most of the approaches demonstrate some kind of time-variable or load-variable tariff. Nevertheless, there are large differences in the concrete tariffs that are used. For instance, power-variable tariffs include load limitation signals that lead to a certain penalty if they are violated as well as signals having prices that are linearly increasing depending on the power.

Energy Carriers In terms of supported energy carriers, the evaluations in the Tables 6.3 and 6.4 show that nearly all approaches are limited to electricity and do not aim at an integrated optimization of all energy carriers. None of the other approaches does even consider chilled water as an equivalent energy carrier in buildings that may be provided by multiple sources and included in the optimization.

6.1.4 Comparison to the Original Organic Smart Home

Table 6.5 provides a detailed comparison of the capabilities of the extended and enhanced OSH to the original version by Allerding (2013) [10]. It shows whether a certain property is available and has been demonstrated (marker: "✓"), is available but has not been demonstrated (marker: "(✓)"), is theoretically possible but not available (marker: "–"), or

Table 6.5: Detailed comparison of the original *Organic Smart Home* and the extended and enhanced version that has been developed as part of this thesis

Property	**Allerding (2013)**	**This thesis**
Resolution of the SLP H0	60 min	15 min
Dishwasher, hob, oven, dryer, washing machine	✓	✓
Appliance programs	One	Multiple
Multiple load profiles per appliance program	–	✓
Starting times of home appliances based on	SLP H0	Statistics
Deferrable home appliances	✓	✓
Interruptible home appliances	–	✓
Hybrid home appliances	✗	✓
Refrigerator, deep-freezer	–	(✓) [64]
MicroCHP system with integrated storage tank	✓	(✓) [11]
MicroCHP (modular, i. e., separated from storage tank)	✗	✓
PV system	✓	✓
PV feed-in profiles	SLP EV0	HoLL, (ESHL) [412], (SLP EV0)
Resolution of PV feed-in profile	15 min	1 min, (1 s) [412], (15 min)
Prediction of PV generation	Last day	14 d average
Electrical IHE (modular)	✗	✓
Gas-fired condensing boiler (modular)	✗	✓
Heat pump (modular)	✗	(✓) [378]
Adsorption chiller (modular)	✗	✓
Hot water storage tank	✓	✓
Chilled water storage tank	–	✓
Phase-change material	–	(✓) [583]
Controlled BESS	✗	(✓) [440]
Optimized BESS	–	(✓) [440]
Optimized bidirectional electric vehicle	(✓) [393]	(✓)
Heating hot water demand based on given profile	✓	(✓) [412]
Randomized heating demand based on given profile	–	✓
Resolution of heating hot water consumption profile	60 min	60 min
Simulated space heating demand using building model	–	(✓) [46]
Static DHW consumption	✓	(✓) [405]
Randomized static DHW consumption	–	(✓) [407]
DHW consumption based on VDI Guideline 6002	–	✓
Resolution of DHW consumption	60 min	1 s
Simulated space cooling demand using building model	–	✓
Device drivers, communication drivers	✓	✓
Bus drivers	–	✓
Multiple simulation engines and random seeds	–	(✓) [354, 356]
Multi-building simulation	–	(✓) [354, 356]
Wall-clock time simulation	–	(✓) [355]
JoSchKa support	–	✓

✓: demonstrated, (✓): available but not demonstrated in the particular thesis,
–: theoretically possible but not available, ✗: not possible

not possible at all (marker: "✗") in the particular version of the OSH. The term modular refers to devices that are not inherently combined with a storage tank.

Most importantly, the OSH does now support multiple energy carriers, i. e., not only electricity but also for instance hot and chilled water. In addition, it supports closed-loop control in the optimization of the building's energy systems, facilitating the integration of electrical IHEs, BESSs, and electric vehicle that are handled as separate devices in a close-loop control manner in the optimization. Moreover, the detailed comparison reveals that important properties of the system, such as the resolutions of utilized profiles, e. g., the SLP H0 and the PV profile, the support of future appliances, and the closeness to reality, e. g., in terms of hot water consumption, have been improved significantly.

Based on the initial approaches towards multi-building simulation by Mauser (2012, 2014) [405,411], the OSH may now also be used in detailed simulations of multiple interacting buildings in a distribution grid. Additionally, there is now a workflow that facilitates the distributed execution of multiple simulations using JoSchKa (see Section 5.2.7), reducing the manual effort as well as the required time to conduct simulations and to evaluate them.

6.2 Calibration, Validation, and Verification

To calibrate and validate the simulation of smart buildings as well as the optimization, several tests are performed. First of all, the compression of appliance load profiles is evaluated. This is done to reduce the computational costs of evaluating solution candidates in the optimization and still obtain good optimization results. Furthermore, the parameters of the GA are calibrated to obtain better results of the heuristic optimization. Similarly, different encodings of the microCHP and an additional stopping criterion that helps to speed up the optimization are evaluated.

Finally, the average load of the simulated residential as well as commercial buildings is validated and compared to similar systems, including results with and without optimization. An overview of the used tariffs and their abbreviations that are used in the following sections is provided in Table 6.6 (see Section 4.1.3 for more details).

Table 6.6: Overview of the electricity tariffs that are used in the evaluations

Abbrev.	**Detailed name**	**Reference**
FLAT-30	Flat electricity price of 30 cent/kWh	–
FLAT-30-09-15	See FLAT-30, 09:00 to 10:00 price of 15 cent/kWh	–
FLAT-30-12-15	See FLAT-30, 12:00 to 13:00 price of 15 cent/kWh	–
H0-30	Time-of-use (TOU) tariff based on German SLP H0	Table B.14 on p. 385
WIK-30	TOU tariff based on [374]	Table B.15 on p. 385
ALT-20-40	TOU tariff: alternating prices of 20 and 40 cent/kWh	Table B.16 on p. 385
ALT-10-50	TOU tariff: alternating prices of 10 and 50 cent/kWh	Table B.16 on p. 385

Note: All tariffs are combined with the power limit signal given in Table B.13 on p. 384.

6.2.1 Compression of Load Profiles

The computational effort to calculate the objective function in the optimization depends heavily on the resolution of the appliance load profiles, because it requires many calculations of sums and products to combine and evaluate them. To reduce the number of data points of the profiles, there are two compression methods implemented in the OSH: firstly, the averaging of the profiles in a certain lower temporal resolution, i. e., sample rate conversion, and, secondly, the reduction to profiles containing only discontinuities of a higher value.

Downsampling using Averaging The averaging of load profiles to lower temporal resolutions reduces the number of data points significantly. For instance, a load profile having a duration of two hours requires 7200 data points when using one sample per second. However, the reduction of data points reduces also precision of the time series and leads to averaging effects (see Section 4.8.1).

Discontinuities To reduce the negative effect of downsampling, another method is implemented in the OSH, which uses a variable sample frequency. Although reducing the number of data points by means of a lossy compression, it aims at keeping significant changes of the load profiles. Therefore, it adds only a new data point to the compressed profile if the power value of the next data point exceeds a certain threshold, i. e., has a significant discontinuity. This way, short peaks of the load profile are retained in the compressed load profile. The implementation of the algorithm is given in Listing F.11.

Table 6.7: Characteristic values of exemplary compressed load profiles of dishwasher (DW), hob (IH), oven (OV), tumble dryer (TD), and washing machine (WM) using the two different compression methods

	Number of Data Points					Peak Power in Watt				
	DW	**IH**	**OV**	**TD**	**WM**	**DW**	**IH**	**OV**	**TD**	**WM**
Downsampling										
1 s	5400	2645	5939	6910	4920	1958	4208	3616	2870	2244
15 s	361	178	397	462	329	1937	4191	3578	2709	2101
60 s	91	46	100	117	83	1933	3744	3419	2701	2082
120 s	46	24	51	59	42	1932	3453	3426	2688	2077
300 s	19	10	21	25	18	1923	3242	1550	2685	2069
900 s	7	4	8	9	7	1908	2972	993	1999	2012
Discontinuities										
1 W	498	243	906	1476	1760	1958	4208	3616	2870	2244
10 W	107	243	735	528	1375	1958	4208	3616	2870	2244
50 W	10	66	694	203	482	1923	4184	3583	2870	2244
100 W	6	58	692	184	323	1923	4184	3583	2870	2244
250 W	6	45	516	70	26	1923	4184	3447	2711	2065
500 W	6	29	512	57	10	1923	4174	3447	2711	2065
1000 W	6	21	273	40	4	1923	4184	3447	2711	2065

Evaluation Characteristic values of the two compression methods being applied to exemplary load profiles of the appliances are given in Table 6.7. The results show that downsampling does not only reduce the number of data points but may also reduce the peak power of the load profiles significantly. For instance, the peak power of the electrical oven is reduced from about 3600 W to less than 1000 W when using a downsampling to 15 min. The reduction of the peak power is far less when using the variable sample frequency based on discontinuities, which remains true until a value of 100 W. Here, the number of data points may be reduced even more (see profile of dishwasher) or far less (see profile of oven). This is based on the structure of the load profile. The profile of the dishwasher has only two major load peaks (see Figure C.1 on p. 394), whereas the oven shows many load peaks (see Figure C.3 on p. 396).

Based on characteristic values given in Table 6.7, the optimizer of the OSH has been configured to use the compression by means of a variable sampling frequency based on discontinuities with a threshold value of 100 W. This is a reasonable compromise between the number of data points that cause higher computational costs and the precision of the profile that leads to better results in the optimization. Moreover, the load peaks are relevant in simulations comprising hard load limitations or BESSs that have technical restrictions of their maximal power (cf. [410, 440]).

6.2.2 Calibration of Parameters

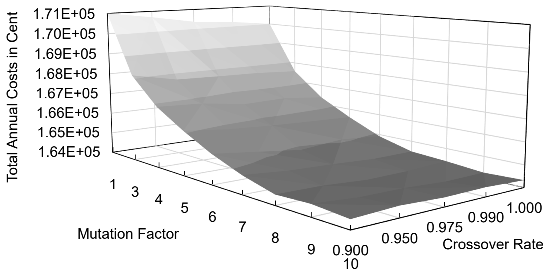
In order to obtain good results in the optimization, the parameters of the GA are analyzed and calibrated to the given scenarios. For instance, in [407], we show that the parameters have to be selected based on the particular building scenario. The parameters that are to be analyzed include the crossover and mutation probabilities and the number of generations.

Prior to this thesis and based on a detailed evaluation by Kramer (2015) [364], the original *single-point-crossover* operator in the GA has been changed to a *two-point-crossover* operator, leading to better results and a faster convergence. In addition, the encoding of the microCHP has been modified (see also Section 5.6.1 for more details). The evaluation of various microCHP encodings is given in the next section.

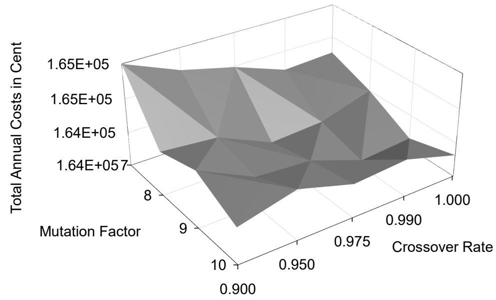
Because of these changes, the *crossover* as well as the *mutation* probabilities are recalibrated. The calibration scenario is a four-person residential building comprising deferrable appliances and an intelligent, i. e., optimizable, microCHP that is simulated for one year. Each parameter combination has been tested using $n = 30$ different random seeds. The results are given in Figure 6.1, showing the average annual total energy costs for different mutation factors and crossover rates. The actual mutation probability of each bit is calculated based on the length of the bit string that is to be optimized (see Section 5.8.2).

Figure 6.1a reveals that increasing both the mutation and the crossover rates tends to improve the results. However, a more detailed depiction in Figure 6.1b shows that the combination of a mutation factor of $m = 9$ and a crossover rate of $p_c = 0.99$ leads to the best results. Furthermore, Figure 6.1c shows that smaller mutation factors require a lower average number of generations, i. e., lead to an earlier termination of the optimization because of the additional stopping criterion (see Section 6.2.4 for more details). This indicates that low mutation rates lead to a premature convergence of the algorithm.

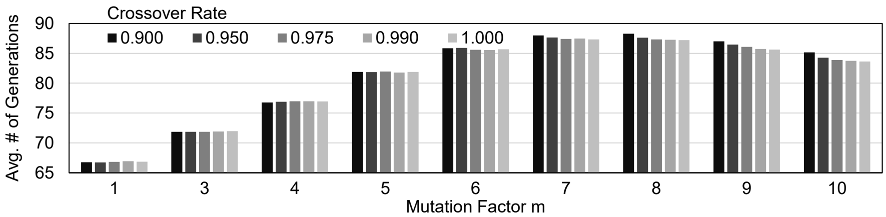
In Figure 6.2, the convergence of the average yearly total costs, the self-consumption



(a) Avg. total costs of all mutation factors



(b) Avg. total costs of mutation factors $m \in \{7, 8, 9, 10\}$



(c) Avg. number of generations of all mutation factors

Figure 6.1: Average total energy costs (Figure 6.1a and Figure 6.1b) and average number of generations (Figure 6.1c) for different values of the mutation factor m that determines the mutation rate $P_m = \frac{m}{b}$ based on the length b of the bit string (see also Section 5.8.2) and for different crossover rates p_c (Tariff: H0-30, $n = 30$)

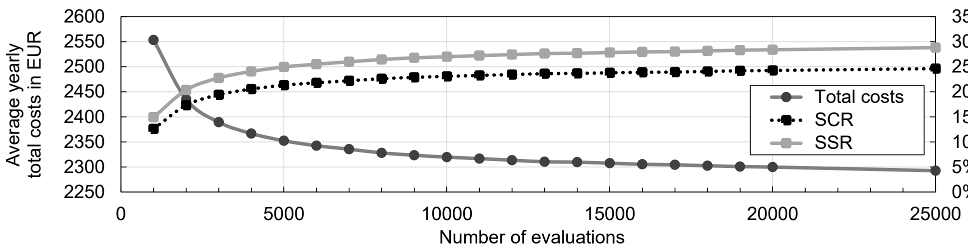
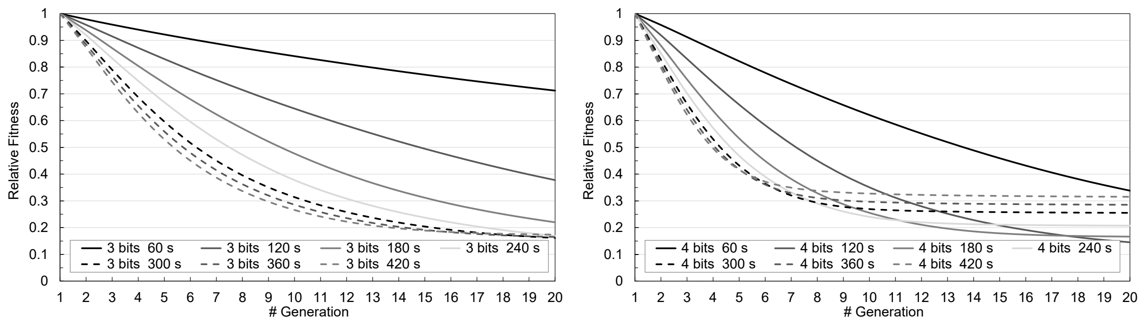


Figure 6.2: Average yearly total costs, self-consumption rate (SCR), and self-sufficiency rate (SSR) of a four-person household with deferrable appliances and an optimized microCHP; without the additional stopping criterion (Tariff: H0-30, $n = 30$)

rate, and the self-sufficiency rate of a four-person household with deferrable appliances and an optimized microCHP based on the number of evaluations is depicted. The number of evaluations is the product of the population size having a fixed value of 100 and a variable number of generations. The results show a clear convergence of all three values starting at about 15,000 evaluations, i. e., 150 generations. Therefore, this thesis uses a maximum of 200 generations and introduces an additional stopping criterion (see Section 6.2.4).

More details about the calibration of the parameters in the smart commercial building scenario are given in Section 6.4.



(a) 3 bits per time slot

(b) 4 bits per time slot

Figure 6.3: Relative convergence of the normalized fitness of the 3 bit and the 4 bit microCHP encodings using a generation size of 100 in a four-person household without PV system (Tariff: H0-30, $n = 10$), see Figure G.2 on p. 448 for all results

6.2.3 Evaluation of MicroCHP Encodings

Originally, the microCHP used 3 bits per time slot (see Section 5.6.1). Due to the adaptions that are applied to the optimization algorithm, an evaluation with respect to the number of bits as well as of the duration of each time slot in the encoding is performed.

The results of the evaluation are given in Table 6.8 and show that an encoding using 4 bits is better than the original encoding of Mauser (2012) [405] and Allerding (2013) [10] using 3 bits. When regarding the duration of the time slots, shorter periods perform worse than time slots having a duration of 300 s. Therefore, the encoding of the microCHP is changed from 3 bits to 4 bits and the duration of the time slots is kept at 300 .

The convergence of the tested microCHP encodings is depicted in Figure 6.3 and in Figure G.2 on p. 448. The figures show the relative convergence of the normalized fitness of the four different encodings using 2 to 5 bits: The best individual of the initial generation ('0')

Table 6.8: Average annual total energy costs in EUR when using different numbers of bits per time slot and durations of the time slots by the microCHP encoding in a four-person household without PV system (Tariff: H0-30, $n = 10$)

		# of bits per time slot			
	Duration	2	3	4	5
Deferrable appliances, optimized microCHP	60 s	3724	2809	2387	2371
	120 s	2960	2414	2337	2362
	180 s	2681	2367	2331	2365
	240 s	2594	2359	2331	2369
	300 s	2545	2350	**2330**	2369
	360 s	2525	2350	2335	2374
	420 s	2509	2347	2340	2384

bold: best value

of each configuration has been normalized to a fitness of 1 and thus all subsequent generations have a better relative fitness of the best individual than the first generation. The resulting curve shows the annual average of all optimization runs of each configuration, such as the configuration comprising 3 bits and 60 s per time slot that is given as solid black curve in Figure 6.3a.

The results show that a higher number of bits leads to a faster convergence, i. e., the relative changes per generation become smaller at an earlier generation. The same holds true for the duration of each time slot. Nevertheless, the best solution of the initial generation of every configuration is different. Therefore, the figures as well as the curves within each figure may not be compared to each other regarding their (real) fitness and thus total costs. In combination with the results given in Table 6.8, it can be concluded that in particular the encodings using 3, 4 and 5 bits are able to find good initial solutions. However, the encoding using 4 bits (see Figure 6.3b) is better in improving the initial best solution and achieving low average annual energy costs.

6.2.4 Evaluation of the Additional Stopping Criterion

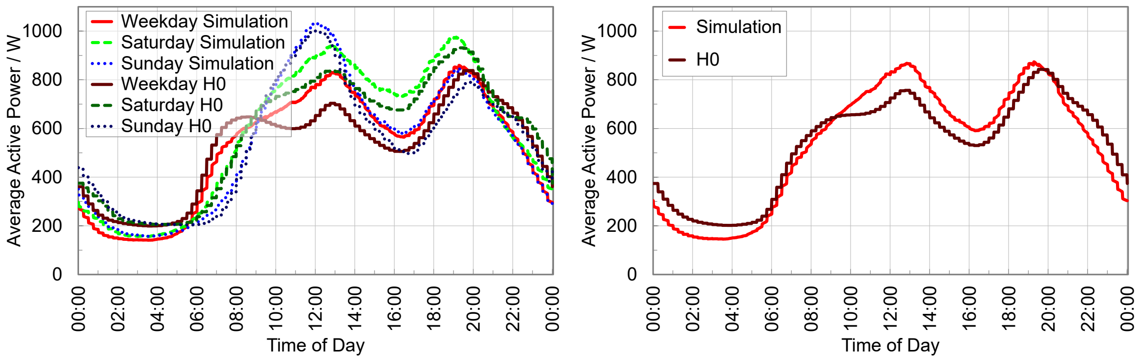
To reduce the number of evaluations automatically and thus the run-time of the optimization, an additional stopping criterion is included: The optimization process is terminated prematurely, i. e., before reaching the maximum number of generations, if the change Δ_{fitness} of the fitness in the past generations is smaller than a defined threshold (see also Section 5.8.2). Hence, the GA is stopped when there is no further significant convergence, saving time that is otherwise wasted on most probably minor further improvements.

The results (see Table G.4 on p. 449) show that the introduction of the threshold does not significantly worsen the results of the optimization if the microCHP is not optimized. In some cases, the additional stopping criterion reduces the number of evaluations by up to 90 %. In general, the number is reduced by more than 50 % on average and thus also the time that is required to perform the optimization, because most of the computational time of the optimization is spent on the evaluation of solution candidates.

Nevertheless, when optimizing the operating times of the microCHP, the additional stopping criterion using a limit of 20 generations worsens the results of the scenarios comprising hybrid (deferrable) appliances. The average total costs in case of the non-optimized microCHP are better than in case of the optimized one (compare a_1 and a_2 as well as b_1 and b_2 in Table G.4 on p. 449). Therefore, a limit of 35 generations (compare a_1 and a_3) for the hybrid and of 50 generations (compare b_1 and b_4) for hybrid deferrable appliances would be better than the proposed 20 generations. However, the higher limits increase also the average number of generations by about 60 % and 70 %, respectively. Due to the high number of evaluations that have been executed as part of this thesis, the number of generations has been set to a consistent value of 20 generations.

In addition, the simulation results provide a first indication for the effects of interruptible and hybrid appliances: Interruptible appliances show only a slight cost reduction in case of a non-optimized microCHP. In all other cases, the additional energy loss due to the interruptions[1] annihilates any benefit. In particular, in the scenario without microCHP, the

[1] The interruption of an appliance causes additional electricity consumption.



(a) Average profile per day of week

(b) Average profile of all days

Figure 6.4: Average load profiles of a four-person household in the simulation and of the standard load profile SLP H0 scaled to a yearly consumption of 4700 kWh

hybrid appliances may reduce the energy costs significantly. Hybrid interruptible appliances do not show any benefit at all.

6.2.5 Residential Building Load Profiles and Results

To validate the load of residential buildings that are simulated by the OSH, it is compared to the German SLP H0 and to exemplary results that are obtained in similar simulations.

H0 Profile

In contrast to the approach introduced by Mauser (2012) [405, pp. 94 ff.] and subsequently used by Allerding (2013) [10], the usage probability distribution of an appliance is no longer based on the SLP H0 but on its statistical usage that has been deducted from several data sources (see Section 4.2.1). Additionally, the simulation of the electrical load in residential buildings that is not covered by the simulated appliances is directly based on the scaled SLP H0, without being subject to the distortion introduced by Mauser (2012) [405, p. 92][2].

The deviation between the weighted average of the appliance usage probabilities (see Figure 4.1 on p. 129) and the SLP H0 leads inevitably to a deviation between the average simulated residential building load profiles and the SLP H0. The average load profiles in the simulation of a four-person building show a lower load in the evening and at night-time, whereas the load is higher during the day (see Figure 6.4b). Although the device usage probabilities differ for weekday, Saturday, Sunday, these deviations to the SLP H0 are similar for all days of the week (see Figure 6.4a).

In principle, these deviations between the average simulated load profiles and the SLP H0 reduce the validity of the evaluations presented in the following section. However, even large sets of smart meter data show a significant deviation from the SLP H0 [295, 575]. In some cases, the SLP H0 leads to an underestimation [293, 575] and in some other cases to

[2] In [10, 405], the SLP H0 is not simply scaled to the residual load. Instead, only the load above the daily minimum is reduced by the load that is simulated by the major appliances.

an overestimation [476, pp. 153 ff.] [585] of the power consumption during the low power period at night. Due to the shortcoming of the SLP H0, it will be replaced in Germany partly by additionally automated meter reading of smart meters in the future [104].

In addition, devices and systems that run all day or are typically used at night-time, such as refrigerators, freezers, circulation pumps, and lighting, are likely to become more energy efficient and thus cause a lower baseload. Therefore, the evaluations of smart residential buildings presented in the following section are likely to remain valid and provide an appropriate evaluation of the effects of energy management in residential buildings in Germany. However, the observed deviation from the SLP H0 is likely to lead to a slight overestimation of the self-consumption and self-sufficiency rates in households having PV systems because a larger share of the electricity consumption is at daytime, i. e., when there is PV generation.

Comparison of Exemplary Results to Results of Similar Simulations

In order to validate the simulations of this thesis, exemplary results are compared to results of similar simulations in the literature by means of several indicators. These indicators include not only cost reductions, which are hard to compare, but also particularly the self-consumption and self-sufficiency rates. Some related work allows also for a comparison of the changes induced by energy management, i. e., the measures of DR leading to the optimization of the operating times of appliances and microCHPs.

Allerding et al. (2014) In [11], Allerding et al. (2014) use a scenario that is similar to the one that is used in this thesis. When optimizing the microCHP and the appliances, the yearly electricity costs are reduced by up to 18 % without increasing the expenses for the natural gas used by the microCHP. The self-consumption rate without optimization is 9 % and 13 % for households with three and five persons and is increased by the optimization to 17 % and 20 %, respectively.

Table 6.9 provides a comparison of the results for a five-person household given in [11] and results for a four-person household obtained in the context of this thesis. Although the time-variable tariffs are slightly different, the comparison shows similar results regarding the total yearly electricity costs and the self-consumption rates. Some differences are caused

Table 6.9: Comparison of the effects of conventional (C) and deferrable (D) appliances and a non-optimized (NO) and optimized (O) microCHPs in smart residential building scenarios (Tariff: H0-30, $n = 20$) that are similar to Allerding et al. (2014) [11]

Appliances		**MicroCHP**		**Electricity costs in EUR/a (change)**		**Self-consumption rate**	
C	D	NO	O	in [11]	in this thesis	in [11]	in this thesis
✓	✗	✓	✗	1273	1439	13 %	10 %
✗	✓	✓	✗	1139 (-11 %)	1267 (-12 %)	12 %	16 %
✓	✗	✗	✓	1179 (-7 %)	1202 (-16 %)	19 %	21 %
✗	✓	✗	✓	1035 (-19 %)	1100 (-24 %)	20 %	24 %

by the different sizes of households. However, there are two differences: In this thesis, the optimization of the microCHP has a larger influence on the electricity costs, whereas the deferrable appliances have a larger one on the self-consumption rate. This is partly caused by better parameters of the GA and the changed encoding of the microCHP, i. e., an optimization that is better calibrated to scenarios including microCHPs. Moreover, the feed-in compensation for electrical generation by the microCHP is different.

Liebe et al. (2015) Another configuration of the scenario of this thesis is similar to the one by Liebe et al. (2015) [374] that uses a time-variable tariff for the year 2015 (see Section 4.1.3 for more details about the tariff) and households consuming about 4000-6000 kWh per year. Their evaluations of smart residential buildings with intelligent appliances show a gross benefit, i. e., a benefit without considering the costs for smart metering and intelligent devices, of about 24 EUR to 54 EUR per year. In comparison, the simulation of a four-person household without PV system or microCHP using the OSH shows a reduction of the electricity costs of about 40 EUR per year when optimizing the appliances' operating times. This simulation does not include the optimization of the refrigerator and the freezer and thus the benefit is likely to be slightly larger and comparable to the results by Liebe et al. (2015). The time-variable tariff that is proposed by Liebe et al. (2015) is used in the evaluation presented the next section.

Femia et al. (2013) Femia et al. (2013) [212] calculate the effects of measures of DR using deferrable appliances on the self-consumption and self-sufficiency rates in residential buildings. According to their results (see Table 6.10), the energy management increases the self-consumption rate by about 9 or 15 percentage points and the self-sufficiency rate by about 5 or 24 percentage points in a four- or a two-person household, respectively. However, these results contrast with those obtained by the OSH as well as in other studies.

Luthander et al. (2015) In [386], Luthander et al. (2015) compare several studies about DSM and PV systems in residential buildings. Their comparison shows that measures of DSM are likely to increase the self-consumption rate by 2 to 15 percentage points.

Table 6.10: Comparison of the effects of conventional (C) and deferrable (D) appliances on the self-consumption and self-sufficiency rates in various configurations of the residential building scenario without microCHP as given by Femia et al. (2013) [212] and calculated in this thesis (Tariff: FLAT-30, $n = 10$)

			Self-consump- ↪ tion rate		Self-sufficiency ↪ rate	
Source	**Consump.**	**PV system**	C	D	C	D
This thesis	2000 kWh/a	3.0 kW$_p$, 3000 kWh/a	23.4 %	23.8 %	34.8 %	35.4 %
[212]	2336 kWh/a	2.9 kW$_p$, 3456 kWh/a	16 %	31 %	24 %	48 %
This thesis	2000 kWh/a	3.5 kW$_p$, 3500 kWh/a	20.8 %	21.2 %	36.2 %	36.9 %
This thesis	4700 kWh/a	3.0 kW$_p$, 3000 kWh/a	43.8 %	44.8 %	27.6 %	28.3 %
[212]	4992 kWh/a	2.9 kW$_p$, 3456 kWh/a	44 %	53 %	32 %	38 %
This thesis	4700 kWh/a	3.5 kW$_p$, 3500 kWh/a	39.9 %	41.0 %	29.4 %	30.1 %

Nevertheless, in particular the studies by Widén and Munkhammar (2013, 2014) [639, 642] calculate an increase of only about 2 to 4 percentage points. In contrast to these results, this thesis determines an increase of only about 1 to 2 percentage points if the appliances are scheduled intelligently (see Table 6.10).

Weniger et al. (2013, 2014) Being based on the methods presented by Weniger et al. (2013, 2014) [636,637], the *Unabhängigkeitsrechner*[3] (Engl. "independence calculator") of the *HTW Berlin University of Applied Sciences* is a tool that provides arbitrary self-consumption and self-sufficiency rates of residential buildings. Weniger et al. (2013, 2014) use a real PV system load profile and the reference load profiles for residential buildings that are given in the VDI Guideline 4655. Table 6.11 compares the values provided by the tool to those calculated using the OSH. The comparison shows that the simulation in the OSH leads to a slightly higher self-sufficiency and a considerably higher self-consumption rate.

An even more detailed comparison of the self-consumption and self-sufficiency rates in residential building scenarios that are given in the literature and those calculated in this thesis is provided in Table G.5 on p. 450. It reveals that the given rates are mostly similar to those calculated by the OSH in most of the cases.

6.2.6 Commercial Building Results

The smart commercial building scenario focuses on the optimization of a trigeneration system comprising an adsorption chiller and a microCHP that provides air-conditioning to a meeting room in a simulated office building that is based on the HoLL.

Trigeneration System

The model of the adsorption chiller is presented in Section 4.5.5. Although it is mainly based on the technical data sheet [321] and the return water temperature from the cooler has been obtained by means of a regression of the measured values in the HoLL, the efficiency of the real adsorption chiller is significantly lower than the values given in the technical data sheet (compare Figure 4.11 on p. 153, Figure B.4 on p. 391, and Table 6.12).

More precisely, the real adsorption chiller has an average COP of about 36 %, whereas the simulated chiller has one of about 46 %. This is mainly caused by the configuration

[3] `http://pvspeicher.htw-berlin.de/unabhaengigkeitsrechner/`

Table 6.11: Comparison of the self-consumption and self-sufficiency rates in residential buildings given in [636, 637] and in this thesis using a four-person household having a yearly consumption of 4700 kWh (Tariff: FLAT-30, $n = 10$)

	Self-consumption rate		**Self-sufficiency rate**	
PV system	in [636, 637]	in this thesis	in [636, 637]	in this thesis
$2\,kW_p$, 2000 kWh/a	50 %	54.7 %	22 %	23.0 %
$4\,kW_p$, 4000 kWh/a	33 %	36.5 %	29 %	30.7 %

of the real adsorption chiller: The cooling power of the ceiling cassettes in the meeting room (see [496, p. 26]) depends largely on the chilled water temperature. To achieve a sufficiently high cooling power, the temperature of the chilled water has to be relatively low. It is automatically set—depending on the outdoor temperature—to 9 °C to 14 °C by the climate controller, which is well below the 15 °C that are used by most of the graphs in the data sheet of the adsorption chiller. The graphs in the technical data sheet [321] indicates that this temperature difference is likely to decrease the efficiency by up to 25 %. Furthermore, the return flow temperature is often well above the recooling temperature of 27 °C that is given in the data sheet (see Figure B.3 on p. 391) and thus decreases the efficiency, too. To sum up, due to technical reasons in the HoLL, the real trigeneration system at the FZI is operated at an operating point that has a relatively low COP.

The lower temperature of the chilled water in the real storage tank leads to a significantly higher thermal standing loss. This is one reason why the adsorption chiller generates less chilled water in the simulation (see $E_{\text{AC,out}}$ in Table 6.12). In addition, the thermal building model is relatively simple and based on the one given in [211], which deduced the required cooling power from the temperature difference between the flow and return temperatures of the cooling water that is pumped to the meeting room as well as the technical data and the settings of the circulating pump. Unfortunately, there is no heat meter available at the outlet of the chilled water storage tank and thus a more detailed calibration of the thermal model of the building has not been possible. Furthermore, the space cooling demand has been calculated for the closed meeting room. In reality, the windows as well as the door are frequently opened. This increases the cooling demand in real building. Still, the values given in Table 6.12 show that a similar and relatively large share of the hot water generated by the microCHP gets lost due to standing losses in the storage tanks.

Therefore, the comparability of the real and the simulated trigeneration system is limited. Nevertheless, the simulated system is closer to a correctly dimensioned and configured system and is thus used in the evaluations given in Section 6.4.

Table 6.12: *FZI House of Living Labs*: total cumulative energy of the hot water generation by the microCHP ($E_{\text{CHP,out}}$) and of the consumption ($E_{\text{AC,in}}$) as well as the chilled water generation ($E_{\text{AC,out}}$) by the adsorption chiller, resulting in the calculated efficiencies of the adsorption chiller (η_{AC}) and of the overall trigeneration system (η_{CCHP}), and the average hot water tank temperature $\theta^{\text{avg}}_{\text{hot}}$ as well as chilled water tank temperature $\theta^{\text{avg}}_{\text{chilled}}$ in July 2014 in the real building as well as in the simulation using the cooler model B (see Equation 4.13 on p. 154)

	Heat loss factor a	$E_{\text{CHP,out}}$ in kWh	$E_{\text{AC,in}}$ in kWh	$E_{\text{AC,out}}$ in kWh	$\frac{E_{\text{AC,out}}}{E_{\text{AC,in}}} = \eta_{\text{AC}}$	$\frac{E_{\text{AC,out}}}{E_{\text{CHP,out}}} = \eta_{\text{CCHP}}$	$\theta^{\text{avg}}_{\text{hot}}$ in °C	$\theta^{\text{avg}}_{\text{chilled}}$ in °C
HoLL	$a \approx 8$	2253	1350	482	36 %	21 %	64.9	13.9
Simulation	$a = 8$	1672	718	343	48 %	21 %	65.8	15.6
Simulation	$a = 2$	750	457	215	47 %	29 %	66.3	15.6

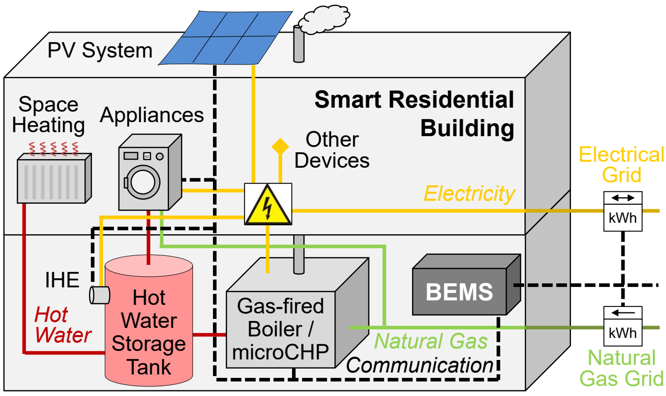


Figure 6.5: Smart residential building: overview of the general scenario (IHE: electrical insert heating element), based on [412, Fig. 1]

6.3 Scenarios and Experiments: Smart Residential Building

To answer the main research question of this thesis (see Section 1.2) and evaluate the hypotheses related to residential buildings, many different configurations of smart residential buildings have been simulated. These configurations, i. e., the detailed properties of the devices and systems as well as the tariffs and load profiles of the general smart residential building scenario, are based on the analysis that is given in Chapter 4. Only a very small subset of all simulations is provided in this section and analyzed in more detail.

Section 6.3.1 provides an overview of the general residential building scenario and of its various configurations. The effects of the automated BEMS in case of deferrable and interruptible appliances and PV systems of different sizes on the self-consumption and sufficiency are presented in Section 6.3.2. This includes also the evaluation of scenarios with a microCHP and exemplary measures of market DR. In Section 6.3.3, the impact of hybrid and hybrid deferrable appliances is demonstrated in exemplary configurations. The effects of an electrical IHE are presented in Section 6.3.4. The detailed evaluation of the hypotheses of this thesis is given in Section 6.5.

6.3.1 Smart Residential Building Scenarios

The energy consumption of appliances can be optimized in different ways (see Section 4.4.2). This includes the deferral of the operating time, the interruption of an active operation cycle, the selection of alternative modes of an operation cycle, and the introduction of hybrid appliances (see Section 4.7).

The effects of these optimizations on a building's energy system and thus on the achieved total costs, the self-consumption rate, and the self-sufficiency rate depend on the given scenario, i. e., the availability of DG, such as a PV system and a microCHP. Therefore, several scenarios that are based on the general smart residential building scenario are simulated to demonstrate and evaluate these effects. The general scenario is depicted in Figure 6.5 and resembles a German residential building with a single household (see also Section 4.2) that is equipped with a (sub-)set of the following devices: conventional, deferrable, interruptible, and hybrid appliances (see also Sections 4.4 and 5.5), a gas-fired condensing boiler or a microCHP with a hot water storage tank, a PV system, and an electrical IHE that has controllable power levels (see also Sections 4.5 and 5.6). Hence, there are three main energy carriers involved in the building energy management: electricity, natural gas, and hot water. The demands for space heating and DHW are simulated based on typical load profiles and statistics (see Sections 4.2 and 5.7). Unless otherwise stated, the residential buildings are four-person households. Additional results for other household sizes are given in Appendix G.

The optimization module of the BEMS uses the parameters that are given in Section 5.8. An overview of the used tariffs, which are closely described in Section 4.1.3, is given in Table 6.6 on p. 269. To account for the randomized behavior of the households and the GA, each household configuration has been simulated several times. This is indicated in the following tables and figures by the number n of used random seeds. Simulations of a single month comprise 28 consecutive days, i. e., 4 weeks, and those of an entire year 364 days. Due to the high number of experiments, the simulations have been conducted using the JoSchKa system and the results stored to an SQL database (see Section 5.2.7).

6.3.2 Deferrable and Interruptible Appliances

This section evaluates the effects of deferrable and interruptible appliances in smart residential buildings on the average self-consumption and self-sufficiency rates as well as on the average load profile of the households.

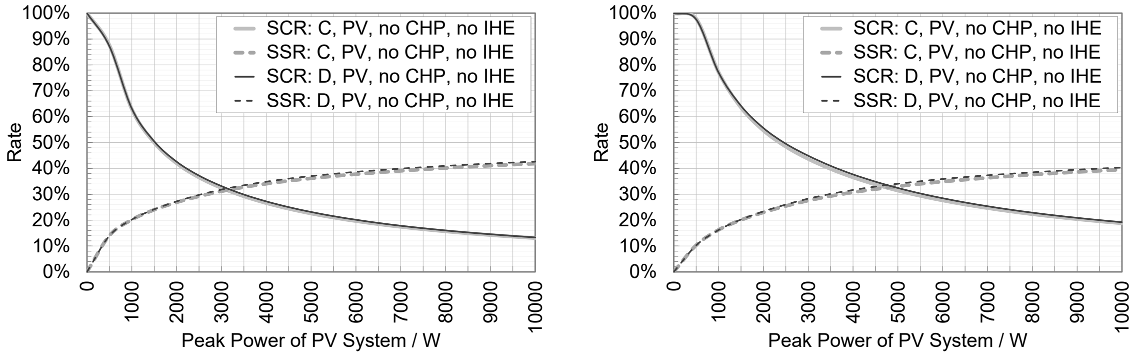
Scenario: Residential Building with PV System

Exemplary results of the yearly average self-consumption and self-sufficiency rates of two- and four-person households with deferrable appliances are given in Figure 6.6. The households comprise a PV system of a varying size and conventional or deferrable appliances. The Figures G.3 to G.26 on pp. 451 f. provide also the results of one-, three-, and five-person households. Each configuration has been simulated using ten different random seeds.

In general, the self-consumption rate increases with the size of the household, whereas the self-sufficiency rate decreases (compare Figure 6.6a to Figure 6.6b). Even large PV systems do not lead to a self-sufficiency rate that is significantly higher than 40 % (see dashed lines in Figure 6.6).

As already foreshadowed in Section 6.2.5 (see Table 6.10 on p. 277), the simulation results show that the effects of deferrable appliances on the self-consumption and self-sufficiency rates are rather low. In case of the flat electricity tariff FLAT-30 and households having only a PV system but neither a microCHP nor an electrical IHE, the self-consumption and self-sufficiency rates increase only minimally, no matter what peak power the PV system has (see Figure 6.6 and compare gray and black curves). Hence, the benefit of the additional flexibility that is provided by deferrable appliances is limited in this scenario.

Figure 6.7 shows the annual average load profile of a four-person household with PV system and conventional or deferrable appliances with or without, respectively, an additional penalty (see also Section 5.5.3 and Table E.1 on p. 430). The figure reveals that appliances that are programmed in the morning (06:00 to 10:30) are deferred to the time around



(a) Two-person household

(b) Four-person household

Figure 6.6: Average yearly self-consumption (SCR) and self-sufficiency rates (SSR) of two- and four-person households with conventional (C) / deferrable (D) appliances and PV system (Tariff: FLAT-30, $n = 10$)

midday, i. e., to the time showing the highest average generation by the PV system. In addition, the appliances that are started in the evening hours (16:00 to 23:00) are delayed to the time after 23:00 and thus exploit the available TDoF.

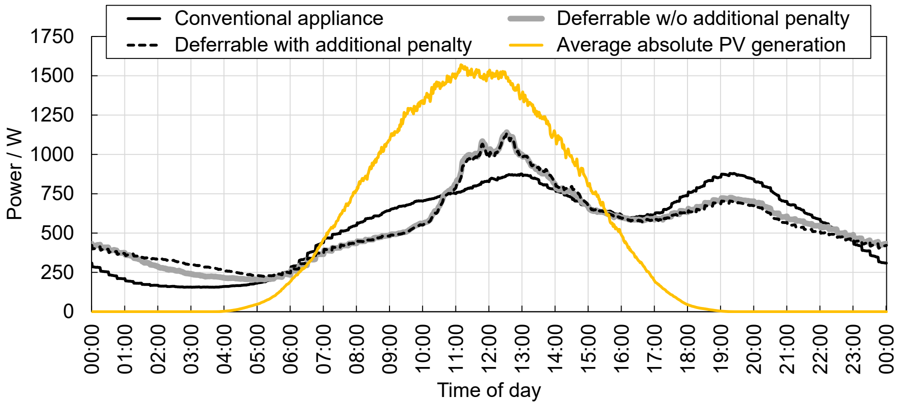
Nevertheless, there are differences regarding the load curve in the evening and night-time hours: Without the additional penalty, the appliances are slightly more often run in the evening and less often during the night. Hence, the typical delay of the appliances' operating times is reduced. This effect was to be expected because the additional penalty rewards a later operation of the appliances. The penalty has been introduced to incentivize longer delays that could benefit from future actions of other devices and systems, such as the operation of another appliance. Jointly, they are more likely to trigger an additional run of the microCHP. Even though there is no microCHP available in this scenario, there is clearly a benefit induced by the additional penalty: it helps to increase the nightly baseload.

Overall, the deferrability of the appliances leads to a higher consumption peak at about noon and a lower consumption peak in the evening. Moreover, the minimal load at night-time is increased. The average maximal residual load, i. e., the net consumption, is decreased and the minimal residual load, i. e., the net feed-in, remains at about the same value (see Figure 6.7b). However, the time of the highest feed-in happens about one hour earlier.

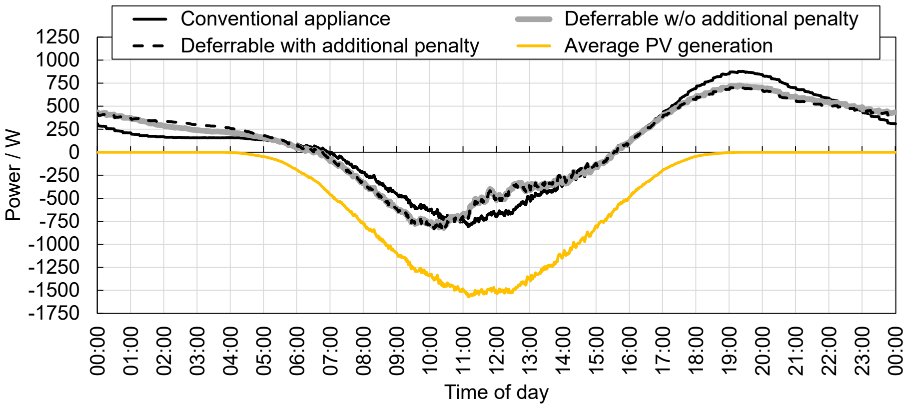
Scenario: Residential Building with MicroCHP and PV System

In contrast to the scenarios with PV systems, the simulations of buildings with CHP show a significant increase of the self-consumption as well as the self-sufficiency rate (see Figure 6.8, Tables G.8 and G.9 on pp. 479 f., and Figures G.3 to G.27 on pp. 451 ff.) when using deferrable appliances.

The optimization of the operating times of deferrable appliances increases the self-consumption as well as the self-sufficiency rate significantly, no matter whether the microCHP is optimized (see Figure 6.8b) or not (see Figure 6.8a). However, the difference between conventional and deferrable appliances is larger in case of a non-optimized microCHP.



(a) Average yearly consumption and generation load profiles



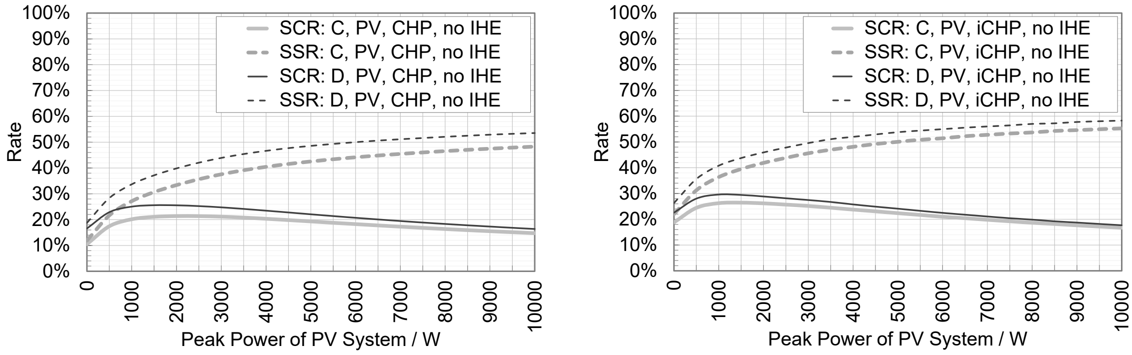
(b) Average yearly residual and generation load profiles

Figure 6.7: Average yearly electricity load profiles of a four-person household with PV system (solid yellow curve) and conventional (solid black curve), deferrable (thick gray curve), or deferrable appliances using the additional penalty (dashed black curve; see also Figure E.1 on p. 430), respectively (Tariff: FLAT-30, $n = 100$)

Furthermore, in both cases, the relative effect decreases when increasing the size of the PV system (see Figure 6.8 and compare the solid black and gray lines).

Scenario: Residential Building with Interruptible Appliances

To evaluate the effects of interruptible appliances, various scenarios of residential buildings without as well as with a (non-)optimized microCHP, a PV system having 4 kW_p, and conventional, deferrable, or interruptible appliances are simulated. Five different electricity tariffs are used in the evaluations. Theoretically, the interruptible appliances may benefit from a higher temporal flexibility that allows for a better synchronization with the local generation as well as nesting of the load profiles among each other. Particularly in the tariffs ALT-20-40 and ALT-10-50, the appliances may be started in a low-price period, interrupted for the subsequent high-price period, and finished in the next one having low prices.



(a) Non-optimized microCHP (CHP)

(b) Optimized microCHP (iCHP)

Figure 6.8: Comparison of the combined self-consumption (SCR) and self-sufficiency rates (SSR): four-person household with conventional (C) / deferrable (D) appliances, PV system, and microCHP (Tariff: FLAT-30, $n = 10$)

The results of the average yearly total costs and self-consumption rates are given in Table 6.13. They show that the interruptible appliances lead only to a very small effect and benefit when compared to the deferrable appliances. This follows the results given in Section 6.2.4, indicating that interruptible appliances achieve only a slight cost reduction in case of a non-optimized microCHP (see also Table G.4 on p. 449).

Table 6.13: Comparison of the average yearly total costs and self-consumption rate in residential buildings comprising a PV system having $4\,\mathrm{kW_p}$, a (non-)optimized microCHP, and conventional, deferrable, or interruptible appliances, see Table G.3 on p. 447 for the abbreviations ($n = 20$)

			Avg. total costs in EUR					**Avg. self-consumption rate in %**				
	Appliances	**MicroCHP**	**FLAT-30**	**H0-30**	**WIK-30**	**ALT-20-40**	**ALT-10-50**	**FLAT-30**	**H0-30**	**WIK-30**	**ALT-20-40**	**ALT-10-50**
Yearly	C	–	1694	1844	1713	1708	1698	36.5	36.7	36.5	36.5	36.5
	D	–	1680	1732	1671	1604	1577	37.6	37.0	37.2	36.5	36.5
	I	–	1680	1731	1671	1603	1493	37.5	37.0	37.2	36.6	34.6
	C	NO	1716	1841	1730	1726	1719	20.2	20.3	20.2	20.3	20.3
	D	NO	1634	1701	1631	1604	1584	23.4	23.2	23.4	23.0	22.9
	I	NO	1629	1693	1625	1595	1531	23.6	23.3	23.5	23.2	22.4
	C	O	1628	1700	1633	1591	1524	24.7	25.0	24.7	24.9	24.5
	D	O	1573	1619	1570	1534	1466	26.7	26.4	26.7	26.4	25.7
	I	O	1574	1615	1572	1536	1454	26.9	26.6	26.7	26.2	24.8

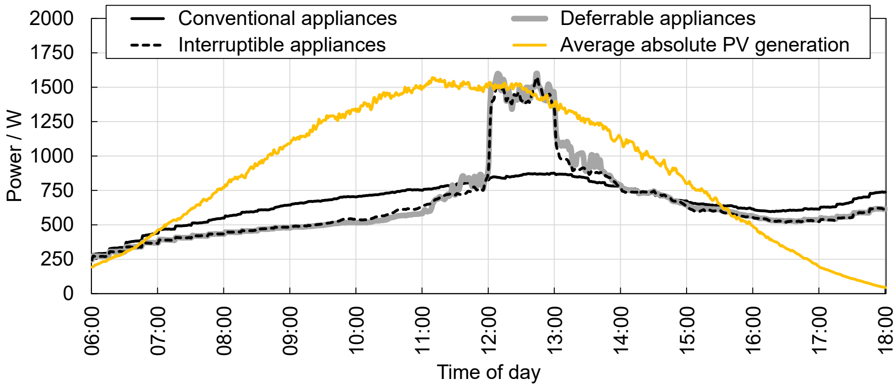


Figure 6.9: Average yearly electricity load profiles of a four-person household with a PV system (solid yellow curve) and conventional or interruptible appliances, respectively; using different exemplary tariffs (Tariff: FLAT-30-12-15, $n = 100$), see also Figure G.28 on p. 481

The low benefit is caused by two facts: Firstly, the microCHP is always operated continuously for a certain period and the interruptions between operating periods are usually pretty long. Secondly, the intermittent generation by the PV system is currently not reflected in the prediction of the future generation which is used in the optimization. Hence, adding some kind of prediction mechanism that provides a better PV generation forecast for the near future, e. g., the next hour, may help to provide a benefit by means of interruptible appliances. Furthermore, an additional control logic in the appliances' local controllers may help, too. The control logic would interrupt the operation of a device if there is unexpected low PV generation that is, however, likely to rise in the soon future.

Nevertheless, interruptible appliances provide a benefit in case of measures of DR that use temporary price changes: The interruptibility helps to achieve sharper load changes when using variable tariffs (see Figure 6.9 and compare the solid thick gray lines and dashed black lines). In the given example, the electricity rate is changed from 30 to 15 cent/kWh for one hour at 12:00. Additional examples are given in Figure G.28 on p. 481. However, the provision of measures of DSM is out of scope of this thesis.

To sum up, in the given scenarios and using the current implementation of the BEMS, the interruptible appliances provide no substantial benefit, except for the tariff ALT-10-50. However, they increase the required computational time by nearly 100 % (see Table G.1 on p. 446). Because of the negligible effects of interruptible appliances in most of the given scenarios, they are disregarded in the following evaluations.

6.3.3 Hybrid and Hybrid Deferrable Appliances

So far, home appliances utilize a single main energy carrier, e. g., electricity or natural gas, to perform their functionality. By contrast, hybrid appliances are able to utilize two energy carriers alternatively. The BEMS has to decide for each operation cycle of the appliance which main energy carrier to utilize. This influence on the energy consumption of the building is analyzed in the following sections.

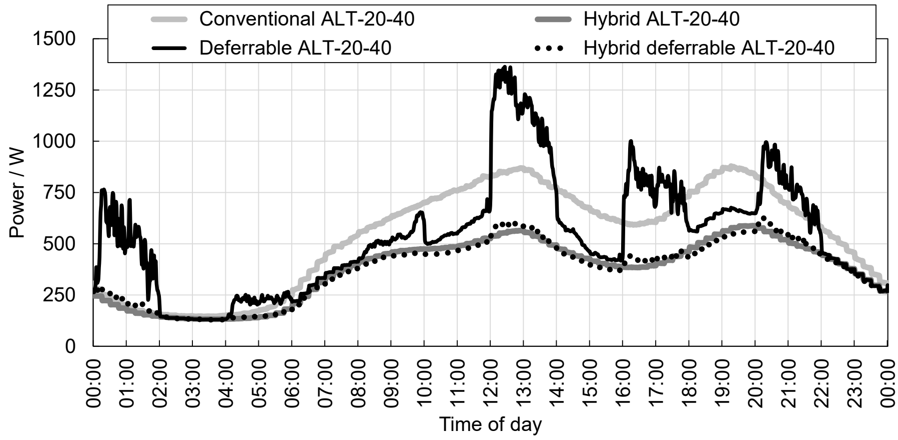


Figure 6.10: Average yearly electricity load profiles of a four-person household with a PV system having 4 kW_p and conventional (bold solid light gray curve), deferrable (solid black curve), hybrid (bold solid dark gray curve), and hybrid deferrable appliances (dotted black curve), respectively (Tariff: ALT-20-40, $n = 100$)

Flat Electricity Tariff

The results of simulations using the electricity tariff FLAT-30 and comparing four-person households with conventional, deferrable, hybrid, and hybrid deferrable appliances are given in the Tables G.7 to G.10 on pp. 477 f.: Table G.7 provides the total costs, Table G.8 the self-consumption, and Table G.9 the self-sufficiency rates for the months of January and July as well as for the entire year. The resulting yearly consumption of electricity and natural gas is given in Table G.10.

In general, the usage of hybrid appliances leads to a cost reduction of about 10 % (see Table G.7), no matter whether there is a microCHP, a PV system, or an electrical IHE. Only a small share of these savings is realized by reducing the additional costs that are caused by the power limit signal (see Section 4.8.2). Even in the residential building comprising conventional appliances and neither a PV system nor a microCHP, the additional costs for power above the given power limit of 3000 kW are below 25 EUR per year.

At the same time, the hybrid appliances decrease also the self-consumption rate (see Table G.8). Most of the time, the utilization of electricity is substituted by that of another energy carrier in the hybrid operation mode. Therefore, the overall electricity consumption is reduced by about 30 % (see Table G.10). Making the hybrid appliances deferrable limits the decrease of the self-consumption rate and in some cases even compensates it.

In most of the configurations, the hybrid appliances increase the self-sufficiency. Interestingly, the usage of hybrid appliances in buildings comprising an optimized microCHP leads to a decrease of the self-sufficiency rate (see Table G.9). This effect is caused by the fact that the hybrid appliances use mostly the hybrid operation mode, even though they could also use the electricity that is generated by the microCHP. Therefore, the DG is no longer synchronized to the consumption of the appliances and thus a larger share is fed into the grid; The consumption by other devices, i. e., the baseload, is simply not high enough to consume a significant share of the generation by the microCHP.

Other Electricity Tariffs

The simulation results of four-person households comprising various types of appliances and partly an electrical IHE as well as a PV system are given in Table G.6 on p. 476. There, the average yearly total costs, the self-consumption rates, and the self-sufficiency rates are given for four different types of electricity tariffs (see Table 6.6 on p. 269 for more details).

The results show that making the appliances hybrid has large effects on all three measurements, no matter which electricity tariff is used. Depending on the tariff, making conventional appliances deferrable may lead to significant cost reductions. In contrast, the effects of making hybrid appliances deferrable are negligible.

Exemplary differences between conventional, deferrable, and hybrid appliances are depicted in Figure 6.10. In case of the (conventional) deferrable appliances, the average load profile of the given residential building scenario changes considerably (compare the bold solid light gray curve and the solid black curve). As opposed to this, the hybrid deferrable appliances show only slight differences of the electricity load profile to the non-deferrable ones (compare the bold solid dark gray curve and the dotted black curve). This is caused by the fact that most of the runs of the hybrid appliances use the hybrid mode and thus utilize hot water or natural gas instead of electricity (compare the bold solid light gray curve and the bold solid dark gray curve). Hence, the hybrid appliances are less sensitive to the given price deviations of the tariff ALT-20-40. This has implications for measures of market DR, because small temporary price changes may have nearly no effect at all.

6.3.4 Electrical IHE, PV System, and MicroCHP

Instead of storing electrical energy in a BESS, the surplus generation of the microCHP or the PV systems may be converted to hot water using the electrical IHE and stored in the hot water storage tank. In so doing, the hot water provision by the gas boiler or the microCHP and thus utilization of natural gas may be reduced and the provision of hot water becomes more flexible, as it may utilize natural gas or electricity.

The results of simulations comparing four-person households with and without electrical IHEs are given in the Tables G.7 to G.10 on pp. 477 ff.: Table G.7 provides the total costs, Table G.8 the self-consumption, and Table G.9 the self-sufficiency rates of January and July as well as of the entire year. The information about the resulting yearly consumption of electricity and natural gas is given in Table G.9. It is a matter of course that the simulations by the new version of the OSH provide much information that may be used in evaluations of smart residential building scenarios, such as the average tank temperatures and a detailed breakdown of the energy costs (and earnings).

The best results are obtained in residential buildings with hybrid deferrable appliances, a non-optimized microCHP, and an IHE. The simulations with an optimized microCHP lead to slightly worse results. This is likely to be caused by the additional stopping criterion, stopping the optimization prematurely and hindering slightly better results of the hybrid deferrable appliances in combination with a controllable microCHP, as explained in Section 6.2.4. Additional effects of IHEs, PV systems, and microCHPs on the self-consumption and self-sufficiency rates in one- to five-person households are given in the Figures G.3 to G.27 on pp. 451 ff. The following sections focus on four-person households.

Effects of the Electrical Insert Heating Element

With respect to the total costs (see Table G.7), the electrical IHE is only able to realize a cost reduction in conjunction with the microCHP. Furthermore, in the given scenario, it ensures that the usage of the microCHP has a positive effect, no matter what type of appliance is used. Without the microCHP, the IHE leads to a cost increase of up to about 2 %, particularly in the summer (see the results of July), by reducing the compensation that is gained by the feed-in of PV generation. Hence, from an economic point of view, the usage of electrical IHEs will make only sense if the feed-in compensation for electricity that is generated by a PV system is reduced below the costs of generating hot water by means of natural gas or any other available energy sources, such as district heating.

Although there is only a slight cost reduction in case of the combination of a microCHP and an IHE, the self-consumption rate increases. Generally, the usage of the IHE leads to a strong increase of the self-consumption rate by about 20 to 50 percentage points. The annual average self-consumption rate—even with a PV system having 4 kW_p—amounts to at least 69 %. However, in case of an optimized microCHP and a PV system having 4 kW_p, the results of July show only an increase to about 45 %. For one thing, this is caused by the limited storage capability of the hot water storage tank. The tank temperature shows an average value that is only 2 K below the upper temperature limit. For another thing, the microCHP is scheduled to be run at times when there is the first significant electricity consumption, i. e., in the morning. This heats the storage and thus limits the usage of the IHE to utilize the electricity that is generated by the PV system. Therefore, the self-consumption rate is typically higher in January than in July, except for buildings without PV system.

In general, the electrical IHE helps to increase the self-sufficiency rate significantly (see Table G.9). In residential buildings with PV system but without microCHP, the increase is about 6 to 21 percentage points. If there is also a microCHP, the increase is even about 16 to 36 percentage points. Hence, although there is only a small cost reduction, there is a large increase of the self-sufficiency rate. At the same time, the yearly electricity consumption is increased and the utilization of natural gas is decreased (see Table G.10).

However, when having a microCHP, the reduction of the gas consumption implies that its total operating time is reduced. Considering the fact that microCHPs are currently only operated economically when run nearly continuously, their usage in residential buildings makes little sense. Therefore, smaller microCHPs may be of better use. Furthermore, the introduction of cogeneration by means of fuel cells that may be operated more flexibly and have less maintenance requirements may be interesting in the future. This is supported by the fact that the combination of the microCHP and the electrical IHE is beneficial. Actually, this combination is practically equivalent to a microCHP that is able to reduce its electrical coefficient in favor of a higher thermal coefficient (see also Section 4.5.4).

Further simulation results of four-person households comprising an IHE and PV system are depicted in Appendix G.7 on pp. 455 ff. The graphs show the self-consumption and self-sufficiency rates as a function of the peak power of the installed PV system and the type of appliance.

Effects of the PV System

The usage of a PV system leads to a significant reduction of the total costs (see Table G.7). In case of the PV system having 2 kW_p and without the microCHP, the self-consumption amounts to more than 50 %. In case of the larger PV system, the self-consumption is about a third of the generation. Without the electrical IHE, the introduction of a PV system increases the self-consumption rate because a larger share of its generated electricity is utilized in the building. In combination with the IHE, the PV system slightly decreases the self-consumption of the electricity that is generated by both devices, because the overall generation gets too high to be utilized by the local consumption or the IHE. The capacity of the tank is simply not big enough to store the hot water that may actually be generated.

In general, the PV system increases the self-sufficiency rate because of the additional local generation (see Table G.9). In buildings with a microCHP but without a PV system, the self-sufficiency is higher in January than in July, because there is less electricity generation by the microCHP in the summer than in the winter. With a PV system, it is the other way around: the self-sufficiency is higher in July than in January, because there is much more generation by PV systems in the summer. This shows the complementary character of microCHPs and PV systems.

The size of the PV system has a significant influence on the reduction of the natural gas consumption (see Table G.10). In case of the PV system having 2 kW_p, the reduction is significantly lower than in combination with the one having 4 kW. Hence, the former is actually undersized to allow for a relevant usage of the electrical IHE.

In contrast to the relatively small effects of measures of DSM on the self-consumption and self-sufficiency in the given scenarios comprising deferrable appliances and PV systems, the integration of BESSs has significant effects on these rates: The self-consumption as well as the self-sufficiency curves that are visualized, e. g., in Figure 6.6 on p. 282, are both shifted clearly towards 100 %, as, for instance, demonstrated in [626, 636] and depicted in [646, Fig. 4]. However, the evaluation of BESSs is not part of this thesis.

Effects of the MicroCHP

The microCHP reduces the total costs if there is an electrical IHE or if the appliances are deferrable (see Table G.7). However, in case of hybrid and hybrid deferrable appliances, the introduction of a microCHP increases the costs and thus has a negative effect. This is caused by a sharp increase of the gas costs: The hybrid appliances use mainly the hybrid operating modes utilizing natural gas or hot water. The hot water is generated by the microCHP, which utilizes natural gas, too. However, the microCHP has a lower thermal coefficient than the condensing boiler and thus utilizes more natural gas. Furthermore, the benefit of the local electricity generation is unable to compensate the additional costs of the additional natural gas consumption, because the electricity may simply not be used locally and receives a relatively low feed-in compensation (see Table G.8).

The integration of the microCHP—in addition to a PV system—decreases the overall self-consumption rate (see Table G.8). The integration of an IHE reduces this effect. In general, the optimization of the microCHP leads to a significant increase of the self-consumption rate, in particular in July. However, in conjunction with an IHE and a PV system having

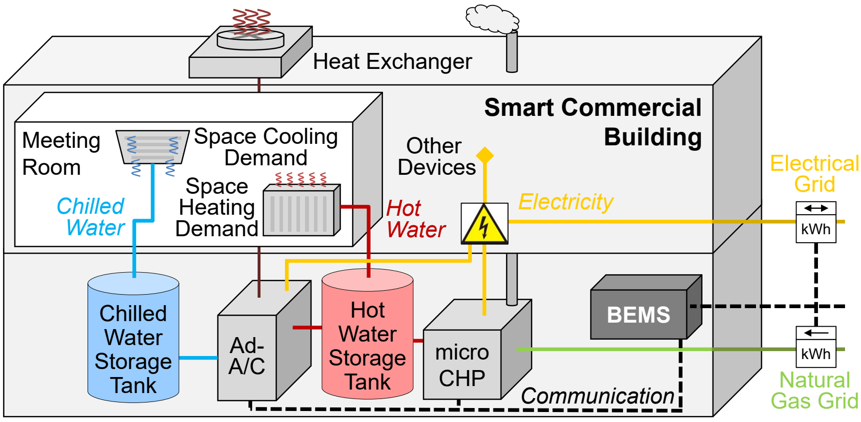


Figure 6.11: Smart commercial building: overview of the scenario (Ad-A/C: adsorption chiller), based on [410, Fig. 4]

4 $\mathrm{kW_p}$, there is significant decrease of the self-consumption. This is caused by the limiting storage capacity of the hot water tank. There is a large increase of the self-sufficiency rate when using a microCHP (see Table G.9). Optimizing the operating times of the microCHP increases the self-sufficiency rate by up to 12 percentage points. However, the optimization has larger effects if there is no IHE available.

Without the IHE, the usage of a microCHP has no influence on the yearly electricity consumption (see Table G.10). In combination with the IHE, there is a significant increase of the electricity consumption, which is further decreased if the microCHP is optimized. In general, using a microCHP increases the consumption of natural gas, because the efficiency in terms of the generation of hot water is lower and thus more natural gas has to be consumed to provide enough thermal energy. Furthermore, optimizing the operation of the microCHP increases the average yearly gas consumption. This is caused by a higher average tank temperature that implies higher thermal losses.

6.4 Scenarios and Experiments: Smart Commercial Building

The smart commercial building scenario comprises a microCHP, an adsorption chiller, and hot as well as chilled water storage tanks (see Figure 6.11, Table G.11 on p. 482, and cf. Section 4.3.2). This trigeneration system is used to air-condition a meeting room that has a certain space cooling demand. The demand is simulated using a building model of the HoLL (see Table D.18 on p. 423) and two types of reservations, i. e., usage of the meeting room. The first type are the *real* reservations that have been extracted from the meeting room's calendar (see Table B.23 on p. 392). The second type of reservations are the *simulated* reservations that are generated randomly based on real reservations of several months (see Table 4.5 on p. 135 and [410]).

Both reservation types are simulated using one of the four combinations of a (non-)controllable and thus (non-)optimized adsorption chiller or microCHP, respectively. Each experiment (see Table 6.14) is simulated 30 times by means of different random seeds. In case of the real reservations, the random seeds have only an influence on the heuristic optimization, whereas in case of the simulated ones, they lead to different random sets of reservations, i. e., varying numbers of reservations at different times of the day.

All experiments simulate the first four weeks, i. e., 28 days, of July 2014 using recorded outdoor temperatures from Rheinstetten, Germany. More details about the real building that is modeled in the smart commercial building scenario are given in Section 4.3.2. As outlined in Section 4.5.7, the real storage tanks in the HoLL show a comparably high thermal standing loss. Therefore, every experiment is simulated using two different *variations of the storage tanks* (see also Table 6.14): firstly, the high standing loss using a heat loss factor of $a = 8$ and, secondly, a more realistic one of $a = 2$. As explained in Section 4.5.5, there is a misconfiguration of the HVAC system controller at the HoLL, leading to a too high water temperature of the return flow from the cooler. For that reason, the experiments are also simulated using the *original cooler model A* and the *improved model B*.

The GA in the optimization module uses the settings given in Table 5.4 on p. 249, which are based on the results provided in Figure G.29 on p. 483. The encodings of the microCHP and of the adsorption chiller use 5 bits per time slot, providing better results than the 4 bits per time slot that are used in the smart residential building scenarios for the microCHP. The mutation factor is set to $m = 21$ and the GA uses 600 generations of a population of 100 individuals, i. e., 60 000 evaluations, because higher numbers of evaluations show only slight improvements of the total costs.

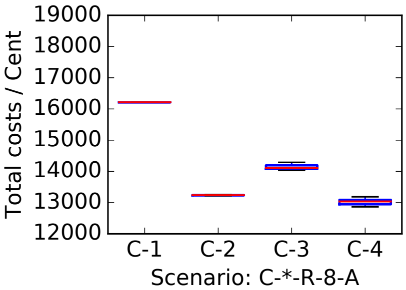
The results of the simulations are provided in Table 6.15 and visualized in Figure 6.12. All experiments are named according to the naming schema given in Table 6.14 and extended by a suffix that refers to the variations of the storage tank and cooler models.

Results of the Smart Commercial Building Scenarios

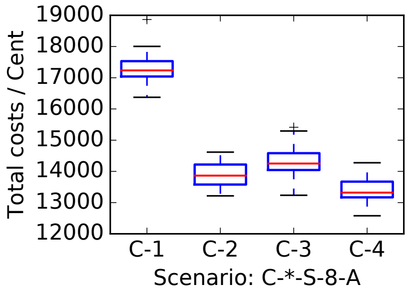
The results of the simulations are given in Table 6.15 on p. 293 and depicted in the box plots in Figure 6.12 on p. 292. The simulations show similar results for the real and the simulated reservations. However, the results of the simulations using real reservations show a lower standard deviation of the total costs and relative improvements than those using simulated reservations. This is caused by the fact that in case of real reservations the different random seeds influence only the heuristic of the optimization module, whereas in case of the simulated ones lead to a varying number of room reservations and thus to a different space cooling demand.

Table 6.14: Smart commercial building scenario: the eight experiments that comprise two different types of room reservations and four combinations of the devices

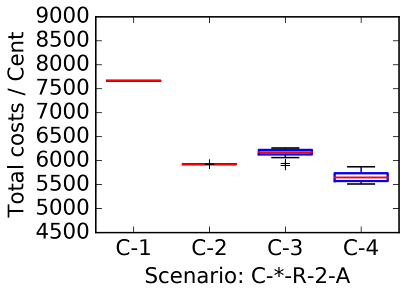
Experiment	Adsorption chiller	MicroCHP	Room reservations	Heat loss factor a	Cooler model
C-1-R/S-2/8-A/B	NO	NO	Real/Simulated	2/8	A/B
C-2-R/S-2/8-A/B	NO	O	Real/Simulated	2/8	A/B
C-3-R/S-2/8-A/B	O	NO	Real/Simulated	2/8	A/B
C-4-R/S-2/8-A/B	O	O	Real/Simulated	2/8	A/B



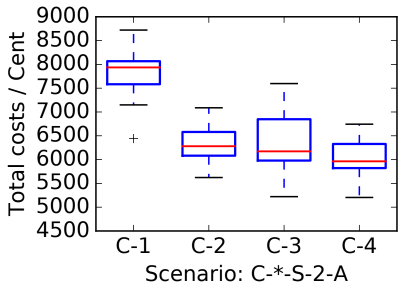
(a) Real reservations, $a = 8$, cooler model A



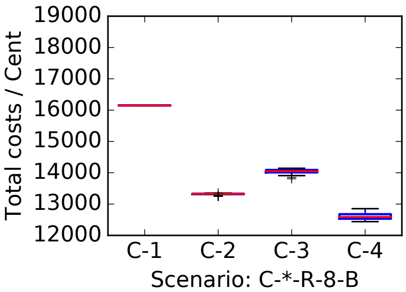
(b) Simulated reservations, $a = 8$, cooler model A



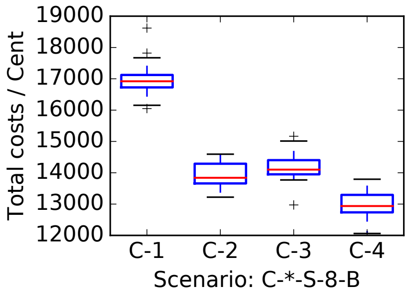
(c) Real reservations, $a = 2$, cooler model A



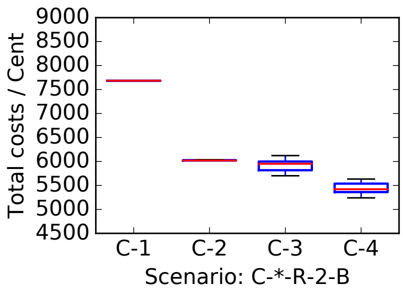
(d) Simulated reservations, $a = 2$, cooler model A



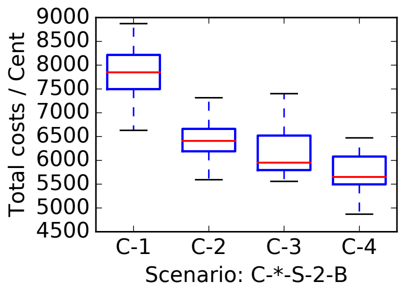
(e) Real reservations, $a = 8$, cooler model B



(f) Simulated reservations, $a = 8$, cooler model B



(g) Real reservations, $a = 2$, cooler model B



(h) Simulated reservations, $a = 2$, cooler model B

Figure 6.12: Smart commercial building scenario: box plots of the simulation results showing the total costs (Tariff: FLAT-30, $n = 30$)

Table 6.15: Smart commercial building scenario: total costs and the improvement over the non-optimized experiments (Tariff: FLAT-30, $n = 30$)

	Total costs in cent				**Improvement to C-1-*-*-***				***t*-test**
Exp.	Min.	Avg.	Max.	SD_S	Min.	Avg.	Max.	SD_S	p-val.
Heat loss factor $a = 8$, cooler model A									
C-1-R-8-A	16213	16213	16213	0	–	–	–	–	–
C-2-R-8-A	13221	13237	13254	8	18.2 %	18.4 %	18.5 %	0.1 %	0.000
C-3-R-8-A	14030	14136	14290	81	11.9 %	12.8 %	13.5 %	0.5 %	0.000
C-4-R-8-A	12865	13023	13186	83	18.7 %	19.7 %	20.7 %	0.5 %	0.000
C-1-S-8-A	16374	17317	18865	502	–	–	–	–	–
C-2-S-8-A	13216	13882	14617	382	16.9 %	19.8 %	22.5 %	1.5 %	0.000
C-3-S-8-A	13235	14357	15414	531	14.2 %	17.1 %	20.9 %	1.7 %	0.000
C-4-S-8-A	12578	13417	14277	413	20.4 %	22.5 %	24.8 %	1.2 %	0.000
Heat loss factor $a = 2$, cooler model A									
C-1-R-2-A	7666	7666	7666	0	–	–	–	–	–
C-2-R-2-A	5923	5926	5933	2	22.6 %	22.7 %	22.7 %	0.0 %	0.000
C-3-R-2-A	5895	6146	6265	115	18.3 %	19.8 %	23.1 %	1.5 %	0.000
C-4-R-2-A	5514	5660	5873	107	23.4 %	26.2 %	28.1 %	1.4 %	0.000
C-1-S-2-A	6441	7852	8721	463	–	–	–	–	–
C-2-S-2-A	5623	6342	7088	415	12.3 %	19.2 %	25.6 %	3.6 %	0.000
C-3-S-2-A	5221	6386	7597	576	3.7 %	18.7 %	27.5 %	5.6 %	0.000
C-4-S-2-A	5204	6020	6744	364	13.8 %	23.3 %	28.5 %	3.5 %	0.000
Heat loss factor $a = 8$, cooler model B									
C-1-R-8-B	16147	16147	16147	0	–	–	–	–	–
C-2-R-8-B	13243	13313	13355	35	17.3 %	17.6 %	18.0 %	0.2 %	0.000
C-3-R-8-B	13806	14036	14143	81	12.4 %	13.1 %	14.5 %	0.5 %	0.000
C-4-R-8-B	12440	12608	12853	104	20.4 %	21.9 %	23.0 %	0.6 %	0.000
C-1-S-8-B	16050	16982	18619	520	–	–	–	–	–
C-2-S-8-B	13221	13929	14593	387	14.7 %	17.9 %	21.6 %	1.9 %	0.000
C-3-S-8-B	12972	14190	15166	437	12.7 %	16.4 %	19.4 %	1.8 %	0.000
C-4-S-8-B	12061	13009	13794	450	19.0 %	23.4 %	27.4 %	1.8 %	0.000
Heat loss factor $a = 2$, cooler model B									
C-1-R-2-B	7684	7684	7684	0	–	–	–	–	–
C-2-R-2-B	6017	6022	6036	5	21.4 %	21.6 %	21.7 %	0.1 %	0.000
C-3-R-2-B	5702	5920	6122	114	20.3 %	23.0 %	25.8 %	1.5 %	0.000
C-4-R-2-B	5241	5439	5633	108	26.7 %	29.2 %	31.8 %	1.4 %	0.000
C-1-S-2-B	6630	7854	8873	536	–	–	–	–	–
C-2-S-2-B	5593	6454	7315	442	10.7 %	17.7 %	23.9 %	3.6 %	0.000
C-3-S-2-B	5558	6126	7402	469	9.8 %	21.9 %	29.3 %	4.7 %	0.000
C-4-S-2-B	4870	5732	6472	374	18.5 %	26.9 %	32.7 %	3.4 %	0.000

In most of the simulations, the optimization of the microCHP leads to a higher improvement than that of the adsorption chiller. Furthermore, in case of the simulated reservations, the results of the experiments including the optimized adsorption chiller (see C-3-S-*-* and C-4-S-*-*) show a larger standard deviation of the total costs. This indicates that the parameters of the GA and the selected encoding of both devices are probably not perfectly suitable for the adsorption chiller.

In case of the simulations that are closest to the real system in the HoLL (see C-*-R-8-A), the optimization of both devices (C-4-R-8-G) leads to a cost reduction of up to 20.7 % and an average cost reduction of 19.7 %. When optimizing only one of the two devices, the improvement is lower and optimizing the microCHP (C-2-R-8-G) leads to better results than optimizing the adsorption chiller (C-3-R-8-G). In fact, the optimization of both devices is only about one percentage point better than the optimization of the microCHP.

When using the lower heat loss factor, i. e., reducing the standing losses of the storage tanks, the results show that the optimization is able to achieve larger improvements (compare C-*-*-8-* and C-*-*-2-*). However, there are two experiments showing a lower minimal improvement: when using the simulated reservations and the lower heat loss and optimizing only the operation of the adsorption chiller, the optimization is not always able to achieve an improvement of more than 10 % (see C-3-S-2-*).

In general, the simulations using the cooler model B lead to higher improvements, except for the experiment optimizing only the operating times of the microCHP. Hence, the adsorption chiller is able to benefit from the greater variation of return flow temperature from the cooler and thus exploit lower outdoor temperatures. In case of the more realistic model B and heat loss factor $a = 2$, the optimization using both devices leads to a cost reduction of up to 32.7 % and an average reduction of 26.9 % (C-4-S-2-B).

Table 6.16 provides the average COP of the adsorption chiller in the experiments. The results show that the optimization is able to increase the COP by up to 13.7 percentage points. The optimization of the adsorption chiller leads to the best values of the COP, whereas the optimization of both devices shows a lower efficiency. This is caused by the multi-commodity optimization of the overall total costs of all energy carriers. Although the adsorption chiller utilizes mostly hot water, it consumes also more than 400 W electricity when operating. In the given scenario, this leads to the synchronization of the operation of both devices, increasing the self-consumption of electricity by the trigeneration system.

Table 6.16: Smart commercial building scenario: average coefficient of performance (COP) of the adsorption chiller (Tariff: FLAT-30, $n = 30$)

	Heat	**Average COP in %**							
Cooler	**loss**	C-1-R	C-2-R	C-3-R	C-4-R	C-1-S	C-2-S	C-3-S	C-4-S
Model A	$a = 8$	47.8	57.6	58.8	56.2	45.3	57.1	58.9	56.4
Model A	$a = 2$	47.0	58.8	57.7	56.9	47.2	58.1	58.0	56.4
Model B	$a = 8$	48.1	56.1	60.2	59.2	46.9	55.8	60.4	59.3
Model B	$a = 2$	47.1	57.5	60.6	60.4	47.3	56.5	61.0	59.7

6.5 Assessment and Discussion of the Results

This section discusses the results of the smart residential and commercial building scenarios given in the previous sections and provides an assessment of the hypotheses that are related to *Research Question RQ 1*: "What is the contribution of an automated building energy management of all energy carriers to the flexibilization of energy demand and supply as well as to the energy efficiency?" (see Section 1.2).

Discussion of the Smart Residential Building Scenarios

The simulation results of the smart residential building scenarios demonstrate the effects of automated energy management by means of multi-commodity optimization, deferrable, interruptible, and hybrid appliances, PV systems, microCHPs, and electrical IHEs. Although the results corroborate the hypotheses of this thesis, some of the positive effects of multi-modal energy management are rather low in residential buildings. Some results show that the effects are most probably even lower than those given in the literature.

Automated Energy Management in Residential Buildings The introduction of hybrid home appliances that may use electricity as well as another energy carrier diversifies the energy utilization in residential buildings. In the given scenarios, the hybrid appliances use mainly hot water or natural gas, respectively, instead of electricity. Nevertheless, in case of high local generation or temporally low electricity prices, they are automatically switched to the conventional operation mode utilizing electricity by the automated BEMS. Hence, these appliances remain available for measures of DSM, such as measures of market DR. This helps flexibilizing the local energy system and supports the *Hypothesis H 1 A* that automated energy management has positive effects on the provision, conversion, and utilization of energy in buildings.

However, automated energy management of (conventional) deferrable appliances has only limited effects on the self-consumption and self-sufficiency, particularly in scenarios comprising only DG by means of PV systems. Furthermore, the observed effects in the simulations are mostly lower than the values given in the literature (see Section 6.2.5). In scenarios comprising DG by a microCHP, the optimization of the operation of deferrable appliances leads to a significant decrease of the total energy costs and an increase of the self-consumption rate by 4 to 6 percentage points in a four-person household (see Table 6.9 on p. 276). In most of the residential building scenarios, the microCHP is only beneficial if it is also optimized or, alternatively, if the appliances are optimized.

Multi-modal Energy Management and Multi-commodity Optimization The effects of optimizing the operation of deferrable appliances on the total costs depend mainly on the tariff that is used (see Table 6.13 on p. 284). In case of the given tariffs, deferrable appliances may reduce the total costs of a four-person household by up to 12 %. In contrast, the optimization has only limited effects on the self-consumption and self-sufficiency rates. This holds true even if there is local generation by a PV system. However, deferrable and interruptible appliances may be used to realize measures of market DR.

Hybrid appliances provide a link between the utilization of electricity and of hot water or natural gas, respectively. In case of the given electricity tariffs, they reduce the total costs as well as the electricity consumption of households because the usage of the hybrid mode is most of the time beneficial. In combination with an electrical IHE, the hybrid appliances help to utilize a larger share of the local electricity generation if there is a microCHP or a large PV system (see Table G.10 on p. 480).

The introduction of a microCHP leads to a reduction of the total costs in the residential building scenarios. This cost reduction becomes larger if it is also optimized, showing the benefit of multi-commodity optimization in the given scenarios. Furthermore, the optimization of the microCHP has a considerably larger effect on the self-consumption and self-sufficiency rates than the optimization of deferrable appliances.

The IHE that is used in this thesis is only controllable in the sense of an internal operating strategy, which adapts its power to the current feed-in into the electricity grid. This strategy helps to make the microCHP more beneficial in the given smart residential building scenarios and demonstrates the potential of including the IHE into the optimization. Similar to the approach to BESSs by Müller et al. (2016) [440], future approaches may increase the benefit of multi-modal energy management of IHEs by optimizing the operating strategy.

The results support the *Hypothesis H 1 B* that the integrated energy management of all energy carriers has positive effects on the provision, conversion, and utilization of energy in buildings. Although these effects are rather low in the given scenarios, the presented BEMS provides the means to optimize all kinds of devices and systems, including those that have interdependencies. For instance, when including the air-conditioning into the energy management, the positive effects are likely to become larger (see also the commercial building scenario below). However, air-conditioning in residential buildings is out of scope of this thesis because it is still of minor importance in Germany.

Interruptible and Hybrid Appliances Interruptible appliances lead only to a very small effect and benefit when compared to the deferrable appliances. This is caused by two facts: Firstly, the microCHP is mostly operated for relatively long periods, reducing the benefit of making appliances interruptible. Secondly, the intermittent generation by the PV system is not reflected in the prediction of the generation. Hence, adding some kind of prediction mechanism that provides a better PV generation forecast for the near future, e. g., the next hour, may help to provide a larger benefit of the introduction of interruptible appliances. Furthermore, this calls for an operating strategy in the appliances' local controllers that interrupts their operation temporally if the generation is unexpectedly low but will most probably rise again after a short period. Nevertheless, the presented interruptible appliances provide a benefit regarding their usage in measures of market DR: The interruptibility helps to achieve sharper load changes when using variable tariffs (see Figure G.28 on p. 481).

In general, hybrid appliances lead to a significant cost reduction, no matter whether there is also a microCHP, a PV system, or an electrical IHE available. In a four-person household, the cost reduction is—depending on the availability of the previously mentioned other devices—about 150 to 300 EUR per year. Most of these savings are achieved by using less electricity and more natural gas, which has lower costs. In case of local generation, hybrid appliances reduce the self-consumption rate of the electricity, because most of the time it is substituted by another energy carrier that is used in the hybrid operation mode. Therefore, the overall electricity consumption in a four-person household is typically reduced by about 30 %. Making the hybrid appliances deferrable or interruptible limits the decrease of the self-consumption rate and in some cases even compensates the reduction.

Interestingly, the usage of hybrid appliances in households having an optimized microCHP decreases the self-sufficiency rate and thus the self-reliance. This effect is caused by the fact that the hybrid appliances use mostly the hybrid operation mode, even at times when there is electricity generation by the microCHP. Hence, the generation by the microCHP is no longer synchronized to the electricity consumption of the major appliances and thus a larger share of the local generation is fed into the grid. This decreases not only the self-consumption but also the self-sufficiency rate because the remaining electricity by other devices is simply not high enough to consume a significant share of the generation by the microCHP. Nevertheless, in buildings without an optimized microCHP, the hybrid appliances increase the self-sufficiency.

At large, the introduction of a microCHP reduces the cost decrease that is caused by the hybrid home appliances or even increases the total costs (see Table G.7 on p. 477). Hence, hybrid appliances and microCHPs are easily mutually exclusive. However, in conjunction with an electrical IHE, there is a benefit of combining hybrid appliances and a microCHP in a household. This shows that cogeneration systems having a more flexible CHP coefficient may provide a larger benefit.

These results support the *Hypothesis H 1 C* that the introduction of interruptible as well as of hybrid home appliances has positive effects on the provision, conversion, and utilization of energy in buildings. Although the benefit of interruptible appliances is relatively low in the given scenarios, they help to provide measures of DR. Furthermore, adding an operating strategy to the local controller of the interruptible appliances, which reacts on the intermittent generation by the PV system, may help to increase their effects. The introduction of hybrid appliances reduces the consumption of electricity because they use mainly their hybrid operation mode. This is caused by relatively high prices for electricity and low prices for natural gas. In addition, the feed-in tariffs for locally generated electricity that are used in this thesis are comparatively high. In case of electricity tariffs that have periods of very low prices, the hybrid appliances switch to the conventional operation mode, helping to make the energy demand of buildings more flexible.

Electrical Insert Heating Element The electrical IHE makes the provision of electricity and hot water by the microCHP more flexible and reduces the total costs in scenarios comprising a microCHP. Furthermore, it ensures that using a microCHP has a positive effect on the total costs, no matter what type of appliances is used: Although there is only a slight cost reduction in case of the combination of a microCHP and an IHE, there is a high increase of the self-consumption rate.

Without a microCHP, the IHE leads to a slight cost increase, because the compensation that is gained by the feed-in of PV generation is more reduced than the costs of the natural gas. Hence, from an economic point of view, the usage of IHEs makes more sense if the feed-in compensation of electricity that is generated by a PV system becomes lower than the costs of generating hot water by means of, e. g., natural gas or district heating. In contrast, the electricity prices regarded in most of the scenarios provide actually an incentive to utilize natural gas instead of electricity, because the generation by means of a gas-fired condensing boiler is cheaper than using the IHE to convert electricity from the PV system to hot water. However, in case of future variable electricity tariffs, the control-loop of the IHE will have to take these variations into account and may then contribute to the flexibilization of energy utilization and provision in residential buildings.

Generally, the IHE increases the self-consumption rate by about 20 to 50 percentage points and the self-sufficiency by up to about 35 percentage points in the given four-person household scenarios (see Table G.8 and Table G.9 on pp. 478 f.). In particular, in the summer, the increase is limited by storage capacity of the hot water tank. Hence, although there is only a small cost reduction or even a slight cost increase, the IHE has significant effects on the self-consumption and self-sufficiency rates and thus may help to reduce negative effects of DG on distribution grids.

Nevertheless, when having a microCHP, the reduction of the gas consumption implies that the total operating time of the microCHP is reduced. Considering that microCHPs are currently typically only operated economically when run nearly continuously, the usage of them in residential buildings makes little sense. This is why the usage of smaller microCHPs may be of better use. However, a more continuous operation of the microCHP is likely to reduce the effects of the energy management because the degree of freedom is reduced. Furthermore, the introduction of cogeneration by means of fuel cells that may be operated more flexibly and have less maintenance requirements may be interesting in the future. This is supported by the fact that the combination of the microCHP with the IHE is beneficial. Actually, this combination is practically equivalent to a microCHP that is able to reduce its electrical coefficient in favor of a higher thermal coefficient (see also Section 4.5.4).

To sum up, the results of the simulations support the *Hypothesis H 1 D* that electrical IHEs help to make the energy demand in buildings more flexible. Although the benefits with respect to the total costs are mainly realized in the scenarios comprising a microCHP, the IHE helps to reduce the consumption of natural gas. In this thesis, the IHE uses always the same internal operating strategy, which adapts its power to the current feed-in into the electricity grid. In case of future variable electricity feed-in tariffs, it makes sense to adapt this strategy dynamically to increase the benefit of multi-modal energy management using the electrical IHEs.

Discussion of the Smart Commercial Building Scenarios

The evaluation of the simulation results of the smart commercial building scenario shows that the optimization is able to decrease the total costs of the trigeneration system by about 20 % to 29 %. The cost reduction is realized by increasing the efficiency of the entire system, i. e., by reducing the natural gas consumption that is needed to heat up the water and subsequently also the chilled water that is required to provide the necessary cooling. Hence, the increase of efficiency is achieved by the optimized operation of both the adsorption chiller, which is run at times having a lower outdoor temperature and thus a higher efficiency, and the microCHP, which is operated in suitable manner to increase the efficiency of the adsorption chiller. The latter refers to an operation of the microCHP that leads to a sufficiently high hot water tank temperature when the adsorption chiller is operated and thus a higher efficiency of the chilled water generation. Furthermore, hot water is only generated when it is utilized soon, reducing the standing loss of the hot water storage tank. The same holds true for the chilled water storage tank. When optimizing the operation of only one of the two devices, the improvement with respect to the energy costs

Figure 6.13: *Raspberry Pi 3 Model B* running the OSH in the ESHL at the KIT and the corresponding circuit breaker as well as the power supply (from left to right)

is lower and the microCHP is able to achieve higher improvement, except for the scenario using the low heat loss factor and the cooler model B.

To sum up, the BEMS is able to increase the efficiency of the trigeneration system and the results support the *Hypotheses H 1 A* and *H 1 E*. Optimizing the operation of trigeneration systems has not been possible using the original OSH, because it has not been able to optimize the adsorption chiller and the microCHP when considering their interdependencies via the storage tanks. The simulations show that there is a potential to optimize the efficiency of trigeneration systems and reduce the energy costs by more than 20 %. This calculation does not include the potential additional benefit that is provided by the local generation of the microCHP, because the given simulations do not include other devices that lead to self-consumption. Therefore, future simulations may have to cover more extensive smart commercial building scenarios comprising other devices and systems, such as space heating, lighting, computers, or also electric vehicle charging stations.

6.6 Demonstration of the Deployment to a Real Building

To demonstrate the OSH in practical application, it has been deployed to the ESHL and the HoLL. However, the OSH is permanently operating in both buildings and there is neither data of comparable days without building energy management by the OSH nor data of similar buildings available. Furthermore, both laboratories are used in various research projects that prevent extensive trial phases, such as the ones that have been performed in the past. Hence, there are no comparable data sets of periods with and without building energy management by the new OSH available that may be used for an evaluation or at least for a small demonstration of the effects of automated energy management.

To obtain such data and to demonstrate the applicability of the system to real buildings, a two-day evaluation phase in the ESHL has been conducted in December 2016. The appliances in the ESHL have been used on these two consecutive days in a very similar manner. The first day, the energy management was active and optimized the operation of the appliances as well as of the microCHP. The second day, the OSH had been deactivated: the appliances were started right away after programming them and the microCHP was operating using the built-in on-off control. More details about the ESHL are given in Section 4.2.3 and in Table B.20 on p. 387. The *Raspberry Pi 3 Model B* that is mounted into one of the electrical enclosures and running the OSH in the ESHL is depicted in Figure 6.13. The floor plan of the ESHL is given in Figure 4.2 on p. 131. Images of the ESHL are given in [10, Fig. 8.2] and [60, Fig. 6.1].

This section provides an evaluation of these two days, revealing some typical effects of energy management in buildings. Unfortunately, due to different outdoor temperatures, the hot water consumption has been different and thus the total time of operation of the microCHP. Therefore, the data of the second day is also recalculated using the microCHP generation of the first day and given as a more comparable artificial data set.

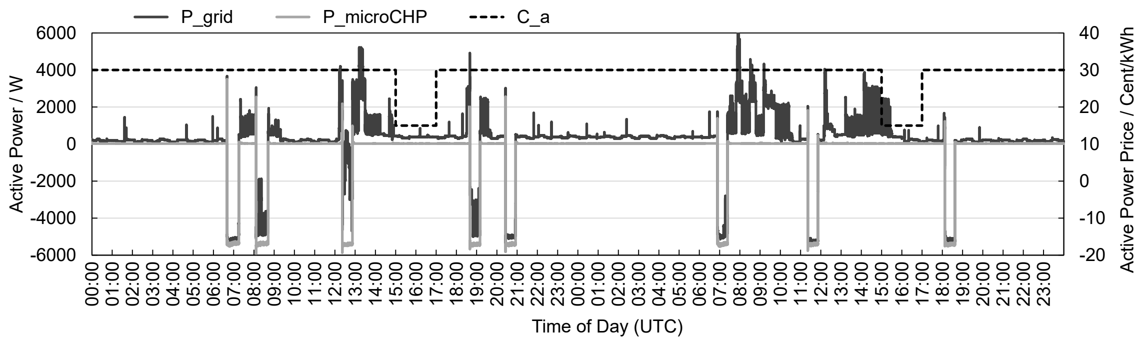
Scenario and Qualitative Description

To obtain a comparable energy consumption on both days, the devices were used in a very similar way, i. e., at about the same times of the day and using the same appliance programs. More details about the usage of the devices and the interaction with the BEMS are given in Table G.12 on p. 484. To avoid disturbances by a different PV generation as well as prediction, the generation by the real PV system has been switched off.

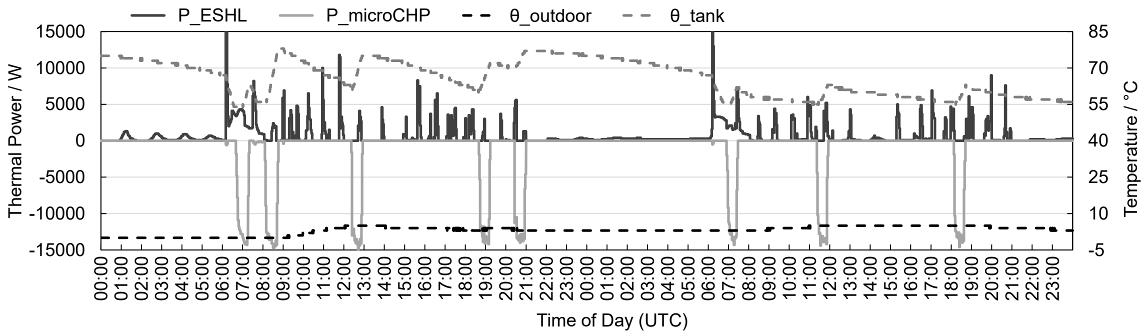
The compensation for microCHP generation has been set to 9 cent/kWh for active power feed-in and to 5 cent/kWh for self-consumed active power. The natural gas price has been set to 9 cent/kWh and the active power price to a constant value of 30 cent/kWh, except for the time from 15:00 to 17:00 (UTC) when the active power price has been set to a constant value of 15 cent/kWh (see also Figure 6.14). The power limit signal has been deactivated.

Day 1: Optimized Operation On *Day 1*, the energy management was active and scheduled the operation of the appliances as well as of the microCHP by minimizing the total costs. The user interaction (see also Table G.12 on p. 484) led to the following behavior:

- The microCHP is started at about 06:40 (UTC) because the minimum temperature limit of the hot water tank is reached.
- The operation of the dishwasher that is programmed at 07:40 (UTC) is scheduled to the early afternoon and synchronized with a 40 min long operation of the microCHP.
- After being programmed at 07:50 (UTC), the washing machine is scheduled to be run in the low-price period from 15:00 to 17:00 (UTC). The dishwasher is rescheduled by the OSH to operate a little earlier.
- At about 08:05 (UTC), the microCHP is started for a scheduled run of 1 h to prevent a violation of the tank temperature limit. The start of the microCHP causes a rescheduling by the OSH that changes the starting time of the dishwasher also to the low-price period.
- Afterward, at about 08:10 (UTC), the TDoF of the washing machine is changed to 4 h, causing it to be started immediately by another rescheduling of the OSH.
- The run of the microCHP is prematurely interrupted at about 08:40 (UTC) because the maximum temperature limit of the hot water tank is already violated.
- The tumble dryer is programmed at about 09:15 (UTC) and scheduled to the afternoon.



(a) Net active power to the electricity grid (P_grid), active power generation of the microCHP (P_microCHP), and active power tariff (C_a)



(b) Thermal power of the heating and DHW system (P_ESHL) and of the microCHP (P_microCHP), outdoor temperature (θ_outdoor), and temperature of the hot water storage tank (θ_tank)

Figure 6.14: Recorded data of the two-day evaluation phase in the ESHL

- Starting the induction hob and the oven at about 12:15 (UTC) triggers a rescheduling, setting the starting times of the dishwasher and the tumble dryer to about 12:20 (UTC) and starting the microCHP at about the same time for 35 min.
- When programming the tumble dryer with a TDoF of 2 h at about 14:10 (UTC), it is scheduled to the low-price period.
- Changing the TDoF of the tumble dryer to 10 h at about 14:40 (UTC) causes a rescheduling that synchronizes the run of the tumble dryer with another run of the microCHP in the evening.

The resulting load profiles are depicted in Figure 6.14. They reveal that three out of the five runs of the microCHP on the first day are in some way synchronized to the operation of the appliances. Nevertheless, none of the appliances is scheduled to the low-price period.

Day 2: Non-optimized Operation On *Day 2*, the OSH has been deactivated and thus the appliances have been started right away after programming them. The microCHP was operating using only the build-in on-off control based on the temperature of the hot water storage tank. The detailed user interaction is given in Table G.12 on p. 484 and the resulting load profiles are visualized in Figure 6.14. In contrast to the runs of the microCHP on the first day, all three runs on the second day are not synchronized to the operation of the appliances. Only the first run is coincidentally partly synchronized with the initial heating phase of the coffee machine.

Day 2*: Artificial Non-optimized Operation The *Day 2** is a combination of the microCHP generation data of the first day and the consumption data of the second day. Although this makes the results of the second day better comparable to the first one, the results are likely to overstate the self-consumption and self-sufficiency rates, because the operation of the microCHP on the first day is not only synchronized to the deferrable appliances but also to the non-deferrable ones.

Evaluation of the Two-day Evaluation Phase

An overview of the results is given in Table 6.17. The first day, the self-consumption and self-sufficiency rates are about 27 % and 31 %, respectively. The second day, these rates are only about 6 % and 4 %. Even when using the microCHP generation data of the first day, which include an optimization of the microCHP but not the appliances, and the consumption data of the second day, the rates are only about 11 % and 12 %. In comparison to *Day 2**, the optimized *Day 1* results in about 28 % lower total electricity costs C_{a}, i. e., without taking the natural gas costs C_{n} into account.

To sum up, the optimization of the microCHP and the appliances increases the self-consumption as well as the self-sufficiency rate significantly and reduces the total costs. However, the microCHP is obviously too large for the smart residential building scenario,

Table 6.17: Results of the two consecutive evaluation days in December 2015 and of the second day using the microCHP generation data of the first day (Day 2*)

Property	Day 1	Day 2	Day 2*
$P_{\mathrm{a,total}}^{\mathrm{min}}$	-5370 W	-5483 W	-5700 W
$P_{\mathrm{a,total}}^{\mathrm{max}}$	5218 W	6047 W	6047 W
Standard deviation of $P_{\mathrm{a,total}}$	1557 W	1523 W	1821 W
$E_{\mathrm{a,total}}$	-1.26 kWh	5.14 kWh	-1.24 kWh
$E_{\mathrm{a,CHP,total}}$	-13.85 kWh	-7.48 kWh	-13.85 kWh
$E_{\mathrm{a,CHP,generation}}$	-14.43 kWh	-8.08 kWh	-14.43 kWh
$E_{\mathrm{a,total}} - E_{\mathrm{CHP,total}}$	12.59 kWh	12.62 kWh	12.62 kWh
$E_{\mathrm{a,grid}}$	9.27 kWh	12.71 kWh	11.63 kWh
$E_{\mathrm{a,CHP,feedin}}$	-10.54 kWh	-7.57 kWh	-12.86 kWh
$E_{\mathrm{n,CHP}}$	≈ 54 kWh	≈ 30 kWh	≈ 54 kWh
Self-consumption rate	27.0 %	6.2 %	10.8 %
Self-sufficiency rate	30.9 %	4.0 %	12.4 %
$C_{\mathrm{a}} = C_{\mathrm{a,grid}} + C_{\mathrm{a,CHP,feedin}} + C_{\mathrm{a,CHP,building}}$	152 cent	297 cent	212 cent
Costs in comparison to Day 1	–	+ 95 %	+ 39 %
$C_{\mathrm{total}} = C_{\mathrm{a}} + C_{\mathrm{n}}$	636 cent	568 cent	696 cent
Costs in comparison to Day 1 (incl. natural gas)	–	- 11 %	+ 9 %

because it is run for less than three hours. Although the presented evaluation phase is rather short, this demonstration shows the applicability of the presented BEMS in real buildings (cf. *Research Question 2*).

The evaluation of the recorded data reveals two typical effects of building energy management as well as of behavior that may appear inexplicable at first sight. However, a closer look helps to explain this behavior.

Firstly, none of the appliances of the first day is scheduled to the low-price period in the evening. This is explained by the fact that the compensation for electricity generated by the microCHP is lower than the costs of electricity of 15 cent/kWh during the low-price period. Therefore, it is more beneficial to synchronize the operation of the appliances and the microCHP than to exploit the low prices. The same holds true for the electricity generated by the PV system. Thus, measures of market DR (see Section 2.3.4) may have no effects at all or show non-linear reactions. For instance, temporarily lower prices below a certain tipping point may lead to the effect that all smart residential buildings synchronize the operation of their appliances to the lower prices instead to their microCHPs or PV systems. This effect is likely to be the more extreme, the more buildings have also the same feed-in tariffs. Therefore, a detailed evaluation of the effects of measures of market DR is of utmost importance to avoid unintended behavior, such as herding effects. The OSH provides the means to simulate smart buildings that are subject to measures of market DR and thus helps to assess these measures.

Secondly, the absolute values of the minimum as well as of the maximum power at the grid connection point are not significantly lower. In part, this may be explained by the absence of a power limit signal that penalizes the net consumption above as well as probably also the net feed-in below certain threshold values (see also Section 4.8.2). However, short consumption and feed-in peaks are still likely to occur even when using such thresholds, such as power limit signals, because they may cause only relatively low additional costs. Furthermore, there is no device in the present scenario that may help to reduce them. This calls for the introduction of BESSs—or when regarding only the feed-in—of electrical IHEs that react on the residual power of all other devices and systems.

7 Conclusion and Outlook

This thesis contributes to the field of *Energy Informatics* by providing, firstly, the foundations of multi-energy systems, multi-modal energy management, and multi-commodity optimization, secondly, the architectural design and exemplary implementation of an automated BEMS performing multi-modal energy management by means of multi-commodity optimization, and, finally, the evaluation of exemplary smart buildings using this automated BEMS, quantifying the expected effects of building energy management and measures of DSM. It is based on an extensive survey of related work and a detailed analysis of smart residential and commercial buildings.

7.1 Conclusions and Contribution

This thesis analyzes future smart buildings comprising exemplary devices and systems: For the first time, the effects of hybrid home appliances are analyzed by means of a detailed evaluation. This includes the optimization of the operation of deferrable as well as of interruptible conventional and hybrid appliances. Furthermore, this thesis presents an evaluation of the effects of introducing microCHPs and electrical IHEs into smart residential buildings comprising intelligent appliances and PV systems of various sizes. Finally, it demonstrates the optimization of the operation of an exemplary trigeneration system comprising a microCHP and an adsorption chiller.

The results show that most of the effects of measures of market DR which are limited to electricity and of the optimization with respect to the utilization of local generation are most probably smaller than given in the literature. However, the usage of hybrid appliances and multi-modal energy management is able to increase the effects as well as the energy efficiency and to reduce the electricity consumption of buildings.

The proposed BEMS realizes a modular energy management and optimization of the operation of devices and systems in real as well as in simulated buildings. It allows for the integration of all kinds of devices and systems that are typically found in residential and commercial buildings. This includes also devices and systems that have interdependencies in their provision, conversion, and utilization of energy. The modular multi-energy simulation and the heuristic multi-commodity optimization are able to optimize the provision, conversion, distribution, storage, and utilization of all relevant energy carriers in buildings.

The BEMS facilitates bottom-up simulations of smart buildings that may be used to evaluate the behavior of smart buildings, calculate typical load profiles of them, and assess measures of market DR. Hence, it helps to plan, assess, optimize, and ultimately operate future energy systems. Moreover, it has the character of a BOS that can be used in real buildings, as it is demonstrated by its operation in our smart buildings. A comparison to similar systems and approaches to building energy management shows that none of them is capable of providing a comparably extensive set of functionality in simulation as well as in practical application.

In so doing, the given BEMS supports the paradigm change from "supply follows demand" towards "demand follows supply" and thus the energy transition from fossil energy carriers and centralized power plants towards intermittent RES and DG. It provides the means to adapt the energy demand of buildings to the availability of renewable and thus sustainable energy and increases the efficiency of energy systems.

7.1.1 Evaluation of the Hypotheses

This section assesses the hypotheses that are related to the research questions (see Section 1.2), provides references to the corresponding parts of this thesis, and draws conclusions.

Research Question RQ 1 "What is the contribution of an automated building energy management of all energy carriers to the flexibilization of energy demand and supply as well as to the energy efficiency?"

As demonstrated in the Sections 6.3 and 6.4, automated building energy management helps to increase the energy efficiency and to make the provision, distribution, and utilization of energy more flexible, leading to an increase of the self-consumption and self-sufficiency rates of locally generated energy (cf. *Hypothesis H 1 A*).

The introduction of *hybrid appliances* diversifies the energy utilization in residential buildings and makes additional appliances—hobs and ovens—available for measures of DSM, such as measures of market DR, by introducing the *energy-related degree of freedom* in addition to the commonly regarded temporal one, i. e., deferrability of appliances. Automated energy management of deferrable appliances has only limited effects on the self-consumption and self-sufficiency, particularly in scenarios comprising only DG by means of PV systems. Furthermore, these effects are mostly lower than the values given in the literature that are based on less detailed simulations (see Section 6.2.5).

In scenarios comprising DG by a microCHP in a four-person household, the optimization of deferrable appliances leads to savings of about 65 to 93 EUR per year, i. e., about 3 to 4 % of the total energy costs or about 13 to 16 % of the electricity costs, and an increase of the average self-consumption rate by 4 to 6 percentage points when using energy tariffs that are similar to those in Germany. In most of the residential building scenarios, the microCHP is only beneficial if it is optimized or, alternatively, if at least the appliances are optimized. This is partly caused by the fact that the used microCHP is overdesigned for the space heating demand in small households of the given scenarios and thus the usage of a smaller microCHP would actually be better (see Section 6.3.4).

In addition to residential buildings, this thesis analyzes a commercial building scenario, in which a *trigeneration system* comprising a microCHP and an adsorption chiller is used to air-condition a meeting room (see Section 6.4 and also Sections 4.5.5 and 5.6.2). The results demonstrate the ability of the automated BEMS to increase the energy efficiency of such a system (cf. *Hypothesis H 1 E*) and reduce the total energy costs by up to about 30 %. The operation of the adsorption chiller is scheduled to times of lower outdoor temperatures and thus higher efficiency of the chiller. Furthermore, the operation of the microCHP is coordinated to the adsorption chiller, resulting in an adequate hot water temperature that further increases the overall efficiency.

An integrated energy management of all energy carriers has positive effects on the provision, conversion, and utilization of energy in buildings (cf. *Hypothesis H 1 B*). For instance, the operation of hybrid appliances using their conventional modes is synchronized to the local generation or to low electricity prices, whereas the hybrid operation modes using hot water influence the operation of the microCHP. Although some effects are rather low in the given scenarios, the presented BEMS provides the means to optimize all kinds of devices and systems, including those that have interdependencies. In case of the analyzed trigeneration system, the integrated optimization of the operation of both the microCHP and the adsorption chiller leads to better results than that of only one of them.

Interruptible and hybrid appliances have positive effects on the provision, conversion, and utilization of energy in buildings (cf. *Hypothesis H 1 C*). Although the benefit of interruptible appliances is relatively low in most of the given scenarios, they help to provide measures of DR by allowing for sharp short-term changes of the building load profiles. The introduction of hybrid appliances (see Section 6.3.3 and also Section 5.5) reduces not only the total energy costs by about 150 to 300 EUR per year in a four-person household, i. e., by about 7 to 13 % of the total costs, but also the consumption of electricity by about 30 %, because they use mainly their hybrid operation mode. This is caused by relatively high prices for electricity, low prices for natural gas, and comparatively high feed-in tariffs for locally generated electricity that are typical for Germany. In case of electricity tariffs that have periods of very low prices, the hybrid appliances switch to the conventional operation mode utilizing electricity, helping to flexibilize the energy demand of buildings. Unfortunately, the additional investment costs that are caused by hybrid appliances are hard to estimate.

The introduction of electrical IHEs helps to make the energy demand in buildings more flexible (cf. *Hypothesis H 1 D*), too. Although the benefits with respect to the total costs are mainly realized in the scenarios comprising also a microCHP, an IHE helps to reduce the consumption of natural gas (see Section 6.3.4). In this thesis, the IHE uses always an internal operating strategy that adapts its power to the current net power at the electricity grid connection point (see also Section 5.6.4). In case of future variable electricity feed-in tariffs, it makes sense to adapt this strategy dynamically to increase the benefit of multi-modal energy management using IHEs.

Research Question RQ 2 “How to realize the modular energy management and optimization of devices and systems in real and simulated buildings when taking multiple energy carriers into account?”

The architectural approach of the given BEMS is based on a detailed analysis of building energy management in Section 4, presented in Chapter 5, and evaluated in Chapter 6.1. It is based on the *Extended O/C Architecture* of *Organic Computing* (see Section 5.1) and novel concepts, functionality, and implementations that enhance and extend the original OSH (see Section 5.2). These improvements help to adapt the BEMS to different setups and to realize energy management and optimization in simulated as well as in real buildings (cf. *Hypothesis H 2 A*).

Based on the background of this thesis (see Chapter 2 and Appendix A), the extensive survey of related work (see Chapter 3), and the analysis of the requirements of automated energy management (see Section 4.6), this thesis concludes that the energy management of multiple energy carriers requires a holistic and integrated approach to optimization that considers interdependencies in the energy generation and consumption of different devices (cf. *Hypothesis H 2 B*).

To realize an integrated approach to energy management and optimization in simulation as well as in real-world application, a suitable energy simulation of the building and its components is inevitable (cf. *Hypothesis H 2 C*). It requires a sufficiently high temporal resolution to capture load peaks and avoid averaging effects (see Section 4.8.1). Therefore, this thesis presents the *Energy Simulation Core* (ESC), which is used in the building simulation in the optimization module as well as in the detailed simulation of a building that is required in the simulation mode of the BEMS (see Sections 5.3 and 6.6).

The evaluation of the original OSH (see Section 4.9) and the comparison to similar approaches and systems (see Section 6.1) show that there is neither an EMS nor an architectural framework available that covers the requirements (see Section 4.6) of an integrated, holistic energy management, taking all relevant energy carriers in buildings into account and reflecting as well as respecting their interdependencies (cf. *Hypothesis H 2 D*).

Research Question RQ 2.1 "Which interdependencies in the provision, conversion, storage, and utilization of different energy carriers have to be considered in buildings to allow for the best response to intermittent availability of energy?"

The analysis of existing work on devices and systems utilizing or providing multiple energy carriers (see Section 4.7) shows that there has been no *consistent terminology* (cf. *Hypothesis H 2.1 A*). This is why this thesis proposes a terminology for *hybrid devices* (see Section 4.7.1) and for the general utilization, distribution, conversion, storage, and provision of or by multiple energy carriers, sources, links, storage systems, and services (see Section 4.7.2). Furthermore, it coins the terms of *multi-modal energy management* (see Section 4.7.3) and of *multi-commodity optimization* (see Section 4.7.4).

This thesis introduces *hybrid appliances* as well as an additional degree of freedom, the *energy-related degree of freedom*, making the optimization of appliances in buildings more flexible and increase their qualification for optimization (see Section 4.4 and in particular Figure 4.8 on p. 143). However, these appliances as well as cogeneration and trigeneration systems (see Section 4.5) cause many interdependencies (see also Section 2.2) of the energy carriers in future buildings (cf. *Hypothesis H 2.1 B*).

Research Question RQ 2.2 "How to consider the utilization and provision of the same energy carriers by different devices in different qualities and prices?"

The multitude of energy carriers (see Appendix A.1.1 and Figure A.10 on p. 367) is categorized into different standardized commodities, e. g., active and reactive power or natural gas, that are used in buildings and relevant for energy management (see Figure A.11 on p. 370). This allows for their consideration in multi-modal BEMSs (see Section 5.3 and cf. *Hypothesis H 2.2 A*).

To account for different origins, prices, and qualities of the commodities, e. g., related emissions and feed-in tariffs, they are distinguished into *ancillary commodities*, such as the active power that is generated by a photovoltaic system (see Sections 4.7.4 and 5.2.3). This provides a suitable way of facilitating a modular optimization (see Sections 4.8 and 5.8, cf. *Hypothesis H 2.2 B*).

Research Question RQ 2.3 "How to design the architecture of the automated energy management system, the energy simulation, and the integrated optimization in a way making them adaptable and flexible with respect to different scenarios, multiple energy carriers, and interdependencies?"

This thesis proposes an architectural design of a BEMS allowing for the simulation of building energy systems and an integrated optimization that is adaptable and flexible with respect to different scenarios, multiple energy carriers, and interdependencies. The actual energy simulation is implemented as a separate system which is interlinked with the parts of the BEMS providing BOS functionality and with the multi-commodity optimization module by means of standardized interfaces, allowing for an easy replacement (see Section 4.7 and Sections 5.2 to 5.8, cf. *Hypothesis H 2.3 A*).

The devices and systems as well as the demands of energy services in buildings are represented in the energy simulation using physical-technical and optimization models abstracting their behavior and controllability (see Sections 5.4 to 5.7, cf. *Hypothesis H 2.3 B*). Hence, the energy simulation and optimization is actually similar to a multi-agent system (see Section 5.3).

Research Question RQ 2.4 "What kind of approach to optimization is suitable for this kind of optimization in integrated energy management in heterogeneous setups and scenarios?"

The utilization of a heuristic optimization is a practicable way in energy systems, which are characterized by dynamic changes and uncertainties (cf. *Hypothesis H 2.4 A*). This is caused by the fact that unforeseen user interaction as well as deviations from forecasts and predictions lead to a frequent rescheduling by the automated BEMS. Moreover, the exact solution of a certain optimization horizon may even be suboptimal when being regarded *ex post* (see Sections 4.8 and 5.8).

Using an EA—in this thesis a GA—offers the required adaptability to different setups and scenarios, because the control of all kinds of devices and systems is abstracted by means of *optimization models* to generic representations using bit strings. The interdependencies of devices and systems are given in their *entity models* and in the information about their energy relations (see Sections 5.3 and 5.4). This allows for a fully modular approach towards multi-commodity optimization, which does not need changes to some kind of programming problem and allows for the integration of arbitrary devices and systems.

Furthermore, EAs are able to cope with the complexity that arises in some of the potential setups and scenarios of smart buildings (see Sections 4.8 and 5.8, cf. *Hypothesis H 2.4 B*). Therefore, they are a suitable approach to the optimization by BEMSs in heterogeneous setups and scenarios. The calibration and tuning of parameters that are used by the EA offers the possibility of a collaborative approach, helping to avoid the overfitting of the parameters to the particular past behavior of a single building (see Section 5.9).

This thesis considers only a subset of the possible scenarios in smart residential buildings and focuses particularly on the situation in Germany. Furthermore, the commercial building scenario is limited to a trigeneration system and thus is a rather specific scenario. Therefore, future work has to provide additional insight into the contribution and the effects of multi-modal energy management and multi-energy systems in buildings, such as hybrid appliances and trigeneration systems, as well as into the question of how to realize an automated BEMS. Before providing a detailed outlook and suggestions for further work in Section 7.2, the following section sums up the implications and recommendations that result from the evaluations and gives possibilities of commercial application and utilization.

7.1.2 Implications, Recommendations, and Commercial Application

This section provides an overview of the implications and recommendations resulting from this thesis. Moreover, it gives potential business models, commercial applications, and approaches to the utilization of this work.

Deferrable and Interruptible Appliances The automated energy management of deferrable appliances has only limited effects on the self-consumption and self-sufficiency when having tariffs that are similar to those in Germany and optimizing the total energy costs. The observed effects are mostly lower than the values given in the literature and show an increase of the self-consumption rate by about 1 to 2 percentage points, whereas the literature provides values from about 2 to more than 10 percentage points. When having not only a PV system but also a microCHP, the effects of deferrable appliances are larger and show an increase of the self-consumption rate by about 2 to 6 percentage points.

The deferrability of appliances increases the average consumption at noon-time as well as night-time and decreases the load in evening. This may help to cope with an ever-larger share of electricity generation by means of wind and solar power in energy systems. In addition, deferrable as well as interruptible appliances may be used to enable DSM, as it is demonstrated using several exemplary tariffs. Therefore, this thesis recommends to verify the effects of deferrable and interruptible appliances by means of field trials and to analyze additional operating strategies—in particular of interruptible appliances—which react on the intermittent generation by local PV systems or short-time price deviations.

Hybrid Appliances Hybrid appliances provide a possibility to reduce not only the utilization of electricity in residential buildings but also the energy costs. Additionally, they help to make the energy consumption of buildings more flexible with respect to the energy carriers. This enables a management of energy that does not delay or interrupt energy services but switches the utilization to another energy carrier. By utilizing hot water from a hot water storage system, which is cheap, reliable, and requires little maintenance, they also help to make the utilization of electricity more flexible with respect to the time of use and avoiding expensive BESSs that are prone to wear and aging processes. Therefore, they promise to be a transition technology that helps to use of existing fossil fuels, renewable fuels, power-to-heat technologies, and thermal storage systems.

Electrical Insert Heating Element IHEs help to make the energy demand in buildings more flexible. Although the benefits with respect to the total costs are mainly realized in the scenarios comprising a microCHP, the IHE helps to reduce the consumption of natural gas. In this thesis, the IHE uses always the same internal operating strategy, which adapts its power to the current feed-in into the electricity grid. In case of future variable electricity feed-in tariffs, it makes sense to adapt this strategy dynamically to increase the benefit of multi-modal energy management using the electrical IHEs. This is a promising approach and may be part of future work. Furthermore, their usage in hybrid heating systems (see below) could be beneficial. However, the COP of IHEs with respect to the utilization of electricity is virtually always lower than that of heat pumps. Therefore, the usage of heat pumps in hybrid heating systems may be more beneficial and this thesis recommends to do further research on the evaluation of such systems.

Distributed Generation: MicroCHP and PV System The microCHP that has been used in the simulated scenarios is comparatively large. Although showing a certain benefit, this reduction of the total costs is low when compared to its price. Since microCHPs are currently only operated economically when run nearly continuously, their usage in residential buildings makes little sense. Therefore, the introduction of smaller microCHPs may be of better use. Furthermore, the simulation results show that the combination of the microCHP and the electrical IHE is beneficial. This combination is practically equivalent to a microCHP that is able to reduce its electrical coefficient in favor of a higher thermal coefficient. That is why the combination of gas boiler and smaller microCHP in a hybrid heating system (see also below) makes sense, too. Furthermore, the introduction of cogeneration by means of fuel cells that may be operated more flexibly and have less maintenance requirements may be interesting in the future.

Trigeneration: MicroCHP and Adsorption Chiller There is a huge potential to optimize the efficiency of trigeneration systems comprising a microCHP and an adsorption chiller. The presented BEMS schedules the operation of the adsorption chiller to times when the outdoor temperature is lower and thus the efficiency of the chiller is higher. Furthermore, the operation of the microCHP is coordinated to the adsorption chiller, resulting in an adequate hot water temperature that further increases the overall efficiency. Considering that the efficiency of the overall system is comparably low and that there is still an electricity consumption of more than 400 W, which is caused by the adsorption chiller and the circulating pumps, it is a debatable point whether the operation of adsorption chillers does actually make sense in the given scenario. However, in most cases, the operation of such trigeneration systems may benefit heavily from an automated building energy management and be made more reasonable. In particular, the technical design and the configuration of CCHPs are challenging tasks, which have to be supported by suitable tools that do not only consider usual operating strategies but also the scheduling by means of BEMSs.

Hybrid Heating and Cooling Systems Potential hybrid energy systems in buildings include many more heating and cooling systems that utilize and provide multiple energy carriers and energy services. For instance, heat pumps are frequently combined with electrical IHE or with gas boilers that may help to provide peak power, particularly at times having a low outdoor temperature. Nevertheless, they may also be used to provide the space heating more flexibly, when being integrated into the BEMS presented in this thesis. Another example of a hybrid system is the combination of adsorption chillers and conventional air-conditioning units utilizing electricity.

Commercial Application and Utilization Regarding potential business models that may benefit from this thesis, there are several possible applications. Firstly, the BEMS may be commercialized for practical application in real buildings. Secondly, it may be used by consultants, manufacturers, and vendors to facilitate investment decisions and support the decision process of buyers, e. g., when equipping smart buildings with devices and systems. Moreover, it may be used by energy utilities and providers to assess new tariffs and incentive schemes. This includes not only measures of market DR, such as time-variable tariffs for electricity, that may have spillover effects on the energy provision and utilization of other energy carriers but also new incentive schemes that focus on multiple energy carriers, such as combined tariffs of gas and electricity, which may be introduced in the future. Another use case is the calculation of potential SLPs of smart buildings that will occur in different future scenarios and may have strong implications for the expansion of energy grids.

7.2 Outlook and Further Work

Multi-modal energy management by BEMSs using multi-commodity optimization in simulations as well as real buildings encompasses many devices and systems. However, this thesis is limited to single smart residential and commercial buildings having a certain set of devices and to an optimization of the total operational energy costs. Therefore, future work may cover additional devices and systems, other types of buildings, such as factories or other industrial buildings, and larger settings, such as properties or even city districts.

Building Energy Management System

Automated building energy management has to be able to handle and ultimately optimize the operation of many heterogeneous devices and systems. This thesis covers not only ones using electricity but also particularly such using other energy carriers and allows for the modular optimization of practically all of them. Still, the scope of the evaluations presented in this thesis is limited to the scenarios that are evaluated and thus there is potential future work regarding energy management in smart buildings.

Devices and Systems Although the BEMS presented in this thesis includes many different devices and systems, there are additional devices and systems that may be considered in the future. This includes appliances, such as refrigerators and freezers, storage heaters, heat pumps, compression chillers, BESSs, electric vehicles, modulating gas boilers, electrical IHEs that are not only controlled but optimized, and heat pumps. Although many of them are already supported, detailed simulations of evaluations of them are out of scope of this thesis and may be subject of future work. Furthermore, future detailed simulations of devices and systems may be based on state charts and finite automata, which may be exchanged using standardized interchange formats.

Electrical and Thermal Simulation The BEMS presented in this thesis deliberately uses simplified electrical and thermal simulations in the *Energy Simulation Core*. Nevertheless, its interfaces and general architecture have been designed a way that allows for easily integrating more detailed simulations, including also external tools. Future work may integrate and evaluate more detailed simulations and in particular external tools, such as common electricity grid calculation and thermal simulation tools.

Forecasting, Prediction, and Uncertainty To exploit the potentials of energy management, the optimization requires precise and reliable forecasting and prediction methods. The methods used in this thesis are rather basic and future work may help to improve them. This is closely related to self-adaption and -learning capabilities as outlined in the next paragraph. In addition, forecasting and prediction will always be prone to uncertainties and unpredictable behavior of the users. Therefore, coping with these uncertainties may be subject of future work and some kind of more robust optimization.

Self-adapting Device, System, and Building Models In this thesis, the usage of the appliances is simulated based on the average usage. However, real households have their very own typical usage. In addition, the models of the devices and systems in the optimization module of the BEMS are very similar to the ones used when simulating the real devices in the simulation drivers. Future work may investigate self-adapting device and system models that learn the properties of their corresponding real devices. Furthermore, the thermal energy demands of the building may be learned to use historical weather data and local measurements. The latter may also be used to adapt externally provided weather forecasts to the microclimate, such as urban heat islands.

Optimization Algorithm The heuristic in the optimization module of the BEMS may be substituted with an exact solver to compare the current results to optimal solutions. This would require a different kind of abstraction of the devices and systems that is capable of providing a similar modular and thus flexible approach. Although modular approaches towards exact solving have been subject of research, there is additional need for research in the field of systems that are applied to real environments.

Following the approach of this thesis, future work may perform a detailed comparison of the selected GA and its operators to other heuristics. This may include also combinations of heuristics, such as the two-step approaches combining EAs and iterated local search in so-called *Memetic Algorithms*.

Due to the usage of a standardized optimization framework, the optimization in the BEMS may easily be altered to multi-objective optimization, considering for instance CO_2 emissions, wear of the devices, and user discomfort, which may be included as separate (virtual) commodities and thus profiles similar to those that are currently regarded.

The optimization may also be adapted towards robustness: Deviations from predictions are inevitable. Therefore, solutions of the optimization and thus the future behavior of the building energy system have to be robust with respect to them. Such a robust optimization is a promising approach particularly in applied systems in real buildings.

Automated Parameter Calibration and Optimization Service This thesis presents the concept of automated parameter calibration by a centralized service, avoiding the overfitting of the parameters of the heuristic to locally observed past behavior. The practical application of this concept needs appropriate metrics and characteristic parameters of smart buildings that help to classify them into sufficiently similar groups. Similar to the calibration process, the actual optimization by the BEMS may also be executed by an optimization service, making use of powerful computing hardware that is shared among many smart buildings. Alternatively, approaches of distributed optimization on local systems may be another promising approach that helps to cope with the peak workload of the hardware running the BEMS when executing the optimization process.

Provision of Ancillary Services The provision of ancillary services for electricity grids, such as voltage and reactive power control, requires adequate signals from a dedicated superior entity, e. g., a regional EMS. This may also include becoming part of a VPP providing operating reserve. Alternatively, the BEMS may control the devices and systems based on local measurements, e. g., the voltage at the grid connection point, to provide for instance inductive or capacitive reactive power and thus influence the voltage. Although such functionality has been included in prior work, it is not part of this thesis and a detailed evaluation may be part of future work.

Abstraction of Energy Flexibility towards Superior Entities The provision of ancillary services, e. g., when becoming part of a VPP, calls for a suitable abstraction of the local energy flexibility and the supported measures of DSM (cf. Figure 2.10 on p. 40). This may include the formalization of an abstracted flexibility and the communication of the expected future load profile of the building as well as intended and alternative schedules of the local energy provision and utilization to superior entities. This may be part of future work related to regional energy management, VPPs, and the distributed provision of ancillary services.

Building Operating System and Extended O/C Architecture

Establishing a proper BOS facilitating not only energy management but also services from other domains in smart buildings, such as ambient assistance, comfort, safety, and security, requires further research. For instance, it may be implemented based on OSGi.

There are many elementary and supporting services that are required by multiple of these domains and which shall be provided by standardized services of BOSs. Additionally, there are some important aspects that have to be investigated in detail to simplify the deployment in different environments and support customer acceptance.

Self-configuration Truly self-configuring systems in the sense of plug-and-play have to be supported by the BEMS and include functionality of, e. g., automatic configuration and self-adapting entity models (see above). However, this is only possible if it is supported by the devices and systems, too, e. g., by standardized self-description and protocols.

Privacy and Security BOSs and the applications running on them are pervasive systems that collect vast amounts of data and intrude the privacy of the users. Hence, data avoidance and minimization as well as local storage of the data may avoid negative effects. However, business models related to cloud computing, big data, and IoT point into the opposite direction. One of the key questions is thus how to exchange data and benefit from them without harming the privacy and probably even the safety and security of the users. This calls for suitable approaches towards anonymization and data protection.

Application of Extended O/C Architecture The *Extended O/C Architecture* that is presented in this thesis may be applied to entities in the smart grid other than smart buildings. This will extend the two layers of O/C-units by additional layers and help to reduce the complexity of the system by using the same design principles over and over again and support an organic behavior of the overall energy system. Future research may work on using and evaluating the generic Extended O/C Architecture in additional entities.

Evaluations of Multi-Modal Building Energy Systems

In addition to the devices and systems given above that may be included in the BEMS and thus evaluated in the future, in particular the following evaluations are of utmost interest and may be part of future work.

Hybrid Heating and Cooling Systems More popular than hybrid appliances are hybrid heating systems that combine multiple devices that work in parallel or alternatively in the provision of heating energy services. For instance, heat pumps are often combined with electrical IHEs to provide enough thermal power in case of peak demands or with gas or oil boilers to achieve a high overall efficiency at low temperatures. Another example is the combination of a microCHP, a boiler, and an IHE. Furthermore, CCHPs may be combined with conventional compression chillers to realize hybrid cooling systems. In all these cases, the decision about which device and thus energy carrier to use has to be made by the BEMS and includes economic as well as ecologic assessments with respect to, e. g., the minimization of total energy costs and emissions. The BEMS that is presented in this thesis may be used in future research to simulate as well as to operate such systems.

Energy Storage Systems The effects of electrical ESSs, such as BESSs, on building energy management and its results are high. Therefore, further work has to evaluate their impact in multi-modal building energy systems. Additionally, hybrid electrical ESSs that are capable of providing more functionality than solely storing electrical energy, e. g., phase balancing and the provision of reactive as well as short-circuit power, i. e., ancillary services (see also below), may be evaluated in future work. Furthermore, the capacity as well as the costs of all kinds of ESSs in buildings may be optimized.

Trial Phases in Real Buildings Although the BEMS presented in this thesis may be used in simulations as well as in practical application, its evaluation focuses on simulations. Therefore, future research may work on further validations as well as evaluations in real buildings by means of trial phases in exemplary buildings as well as widespread field tests.

Hardware-in-the-loop Simulations and Evaluations Although the BEMS supports now wall-clock time as well as HIL simulation coupling real and simulated components in a novel operation mode that combines the simulation and the application mode, the demonstration and evaluation of this functionality is not part of this thesis and may be part of future work.

Other Scenarios and Countries Two general scenarios are regarded in this thesis: residential buildings comprising a single household and commercial buildings comprising a trigeneration system. Future work may research residential buildings comprising multiple households and additional commercial building scenarios.

Return on Investment This thesis focuses on the optimization of the operation of energy systems, i. e., the minimization of operational costs, and neglects not only other objectives but also investment costs. Nevertheless, the proposed energy management system may be used in future evaluations to facilitate investment decisions and support the decision process of buyers when equipping a building.

Multi-Modal Energy Systems

Although the BEMS presented in this thesis focuses on residential and commercial buildings, the concepts may also be used in larger settings, e. g., factories or other industrial buildings, and control not only devices and systems but also production processes.

Smart Factory and Industrial Processes The concepts of multi-modal energy management may also be used in larger settings, e. g., smart factories and other industrial buildings. In addition, EMSs may control not only devices and systems but also production processes comprising many steps and thus devices, systems, and buffers in an interlinked way.

Mobility and Electric Vehicles In the past years, there has been a lot of research related to electric vehicles and their integration into the energy system, e. g., by means of pricing schemes influencing their charging, as well as into building energy management. However, the effects of (bidirectional) electric vehicles in multi-modal energy systems have not been studied, yet. Furthermore, future mobility is most likely to not be limited to electricity but includes biofuels, such as biogas or biogasoline, and corresponding power-to-* technologies too. Therefore, a deeper understanding of incorporating these generation processes into multi-modal energy systems is necessary.

Power-to-* Technologies In addition to the mobility sector, other sectors, such as the electricity, heating, and cooling sectors as well as the chemical industry, may benefit from power-to-* technologies. Hence, the electricity sector will be increasingly interdependent with other sectors. Future research may investigate these technologies on a more global level, i. e., large scale, as well as on a more local, i. e., building-scale, level. It may not only include the comparison of different technologies but also their spatial implementation, i. e., whether it makes sense to realize them in a distributed way in buildings or use them more centralized.

Multi-building Simulation The simulation-mode of the BEMS may easily be extended by an additional layer facilitating the concurrent simulation of multiple buildings. In so doing, the bottom-up simulation of households may be extended to the simulation of an entire low-voltage distribution grid, a small spatial region encompassing also district heating, or a group of spatially scattered buildings working as a VPP. This will enable future work to perform detailed analyses of the effects of measures of DSM as well as regional energy management (see below), before applying novel approaches and methods to real energy systems using expensive field tests. Furthermore, in case of the commercial building scenarios, this may be used to simulate and evaluate commercial properties comprising multiple buildings.

Regional Multi-modal Energy Management The simulation of many buildings in a spatially confined region calls for a regional multi-modal energy management. This includes multi-modal microgrids, distribution grids, and urban quarters, which work in a self-sustaining way making them independent from surrounding energy grids, e. g., by providing all necessary ancillary services (see above). When regarding not only electricity but all energy carriers, this concept outreaches that of electrical microgrids and works on the realization of fully self-sustaining energy regions.

Multi-modal Virtual Power Plants Currently, VPPs focus on the provision of electricity. Nevertheless, future work may research on the concept of *multi-modal virtual power plants* or *multi-modal virtual energy provision*. This may include not only the provision of operating reserve in the electricity grid by VPPs but also the provision of, e. g., virtual gas or fuel.

Multi-modal Smart Grid Finally, multi-modal energy management may be applied in the entire smart grid, resulting in the *multi-modal smart grid*. It addresses not only RES, DER, DG, and DSM but supports also sector coupling by using conversion technologies, such as power-to-* technologies, and realizing novel supervision, control, and management technologies and concepts that use multi-modal energy management and multi-commodity optimization.

In conclusion, although this thesis is limited to multi-modal building energy management, it provides the foundations for an integrated energy management of all energy carriers. The insights, results, and findings motivate more detailed and comprehensive research on the topic of multi-modal energy management from a wider perspective that includes entire distribution grids, city districts, and energy systems beyond. Therefore, this thesis strongly encourages further scientific research on the topic of *multi-modal energy management*.

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A Definition and Explanation of Basic Terms and Concepts

There are some important general terms, fundamentals, principles, and concepts as well as specific ones in the domain of energy systems that are defined and described hereafter to help to understand this thesis.

A.1 Basic Terms and Concepts in Energy Systems

Most of the terms defined hereafter are often used in different ways and contradictory meanings. In order to have a uniform and definitive definition throughout this thesis and in the context of energy management of multiple energy carriers, different aspects and definitions of the terms are provided and their meaning is clarified.

Energy and Power

Energy is the most fundamental term in this thesis. It is used in a multitude of different ways and fields: e. g., in natural sciences, social sciences, and religious or spiritual contexts. Sometimes, the concept of energy is separated from the concept of *exergy*, which is described in more detail in the next section. Thus, it is important to narrow the meaning of energy and provide a consistent definition and usage of the term in this thesis.

The definition of the *term* energy is simple and common knowledge. For instance, the *Dictionary of Energy* [131] names it “a fundamental physical concept, defined classically as the capacity to do work [...] [and] the use of this capacity to perform useful functions for humans, such as heating or cooling buildings [...]” [131, p. 196]. In the context of energy management, this definition falls short of the important aspect that there are different forms of energy. For this reason, Eccleston et al. (2012) [187] define *energy* in the context of energy management and based on the ISO 50001 [174, Ch. 3] as follows:

> “Energy [...] refers to the various forms of primary or secondary energy that can be purchased, treated, stored, or used in equipment, a process, or recovered for future use. With respect to an [...] [energy management system], it includes [...] fuels, electricity, heat, steam, compressed air, as well as renewables and other similar media.” [187, p. 243]

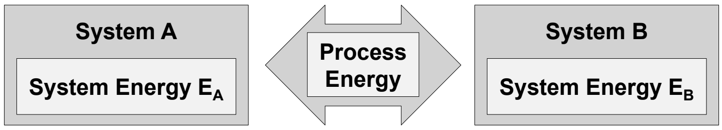


Figure A.1: Interplay of *system* and *process energy* in two systems A and B

Obviously, this second definition confounds the terms energy, energy sources, and energy carriers (see next section), which eases the readability drastically, because the term energy is usually used in this simplified and generalized way. However, this applies only to the general usage of the term energy in this thesis but not to the usage in combination with the energy simulation and optimization system presented later. There, energy, energy sources, and energy carriers have to be clearly differentiated from each other. For this purpose, kinds of energy have to be defined more precisely and linked to specific contexts. This is done, e. g., in the VDI Guideline 4661 of the association of German engineers *Verein Deutscher Ingenieure* (VDI), which defines the following two basic *classes of energy* [612] (see also Figure A.1):

- *System energy*: energy that is stored or bound into a system.
- *Process energy*: energy that is transferred between systems, i. e., across boundaries.

BEMSs have to distinguish between these two basic classes of energy, because every energy system consists of a variety of different sub-systems that contain or store system energy and work together by exchanging process energy. Additionally, the energy in or between a system is of different kind of energy, i. e., way in which energy is transferred or bound into that systems. Therefore, VDI Guideline 4661 defines the following *forms of energy* [612]:

- External energy: mechanical energy
  - Potential energy
  - Kinetic energy
- Internal energy: bounded energy content
  - Thermal system energy, i. e., sensible and latent thermal energy
  - Chemically bounded system energy
  - Nuclear bounded system energy, i. e., binding energy
  - Electric field energy (sometimes also called electrical energy)
  - Magnetic field energy (sometimes also called electrical energy, too)
- Work: mechanically transferred process energy
- Heat (quantity): physically transferred process energy (due to contact); sometimes also called thermal work
- Electromagnetic radiation: electromagnetically transferred process energy

These are the most fundamental forms of energy we know from physics and chemistry. Some other are derived from these forms of energy, i. e., combinations of them. For instance, *enthalpy* is the sum of internal energy and work of displacement, i. e., work due to pressure and change of volume.

All the devices and systems regarded in this thesis use one way or another to store system energy, transform one form of energy to another, or transfer process energy to other entities. When transferring or converting energy, this is done within a certain period of time or per unit of time, i. e., with a certain *power*. Thus, whenever regarding a system and its behavior with respect to energy and time, power will be of utmost importance. Self-evidently, the terms energy and power are closely related. The two most basic forms of power are called [612]:

- *Power P*: work performed in a period of time, e. g., electrical or mechanical power
- *Thermal power* or *heat flow rate $\dot{Q}$*: heat quantity Q transferred in a period of time

To ease the readability of this thesis, P is used for all forms of power. The energy consumption ΔW over a period Δt may be averaged and denoted as *average power*:

$$P_{\text{average}} = \Delta W / \Delta t\,. \tag{A.1}$$

In contrast, *instantaneous power* denotes the power for an infinitesimal small value of Δt:

$$P_{\text{instantaneous}} = \mathrm{d}W / \mathrm{d}t\,. \tag{A.2}$$

Although giving an explanation and providing a common definition of exergy and anergy in the following section, this thesis will not further distinguish between energy, exergy, and anergy but *use the term energy* throughout this thesis.

Energy System and Energy Infrastructure

The term *energy system* denotes a system with defined boundaries, e. g., a building, that is responsible for the provision, distribution, and utilization of energy. The boundaries are in particular of material, spatial, and temporal nature. The *energy infrastructure* comprises all devices and systems, e. g., technical facilities, that provide the functionality of the overall energy system. [608, 612]

Energy Service, Demand, Consumption, and Generation

Eccleston et al. (2012) [187] provide a simple and straightforward definition of *energy consumption* in the context of energy management:

> "Energy Consumption refers to the quantity of energy that is consumed." [187, p. 243]

The standard DIN EN ISO 50001 provides an only slightly different and similarly short definition of energy consumption [174]:

> "The quantity of the energy applied is expressed as energy consumption." [174, Ch. 3]

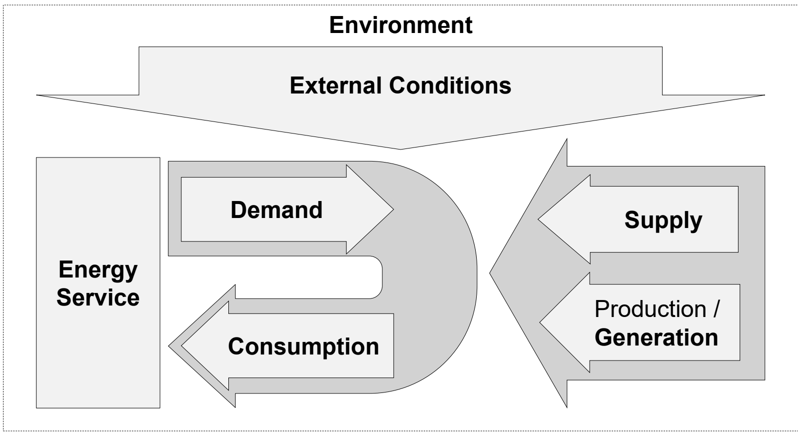


Figure A.2: Relation of energy *demand*, *supply*, *generation*, and *consumption* under external conditions and in the context of an *energy service*

The VDI Guideline 4661 [612] defines energy consumption in connection to the term *energy demand*:

> "Energy consumption is the quantity of particular forms of energy consumed in order to cover energy demands under real conditions." [612, p. 15]

These definitions definitely oversimplify the term energy consumption[1]. For instance, the DIN EN ISO 50001 states the important aspect of *quantification*, which requires some kind of measurement. Quantification is the key to valuation of energy flows in systems and enables their optimization based on objectives, e. g., cost minimization. The VDI Standard 4661 adds the aspect of *energy demand*, which is the "energy to be used in order to perform a defined energy service" [612, p. 15]. The demand consists of different forms of energy for which there is a usage incentive. It is "the maximum amount of [...] energy that may be required at a given time", whereas the consumption "is the amount of [...] energy that is actually used" [131, p. 153]. The actual consumption of energy carriers depends on the demand as well as the current external conditions determining the supply and subsequently the generation (see also Figure A.2).

An *energy service* has requirements for energy that have to be satisfied, i. e., the energy service determines the usage of useful energy [264]. The requirements of an energy service for different forms of energy that are provided by various energy carriers depend on the environmental conditions [612, p. 13]. The term energy carrier is thoroughly defined in Appendix A.1.1 below.

It is important to note that the distribution of energy can be very different in its nature. In case of electricity, the transmission of electrical energy is usually done by solid landlines that are made of metal. By contrast, hot heating water that is used for space heating is flowing in a closed circuit and energy is transferred by having a temperature difference of flow and return. Again, this is different to hot potable water, which is unidirectional flowing out of the system and replaced with cold potable water that has to be heated.

[1] As a matter of fact, there are actually no such thing as energy consumption. This is clarified below.

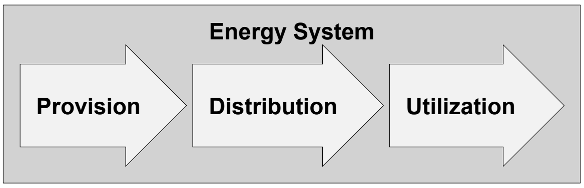


Figure A.3: Relation of *provision*, *distribution*, and *utilization* in an energy system

Additionally, heating up water using electricity that is generated by a large nuclear power plant has a different set of consequences for the energy system than using natural gas locally in a water boiler. This depicts why the whole chain of converting one form of energy into another has to be taken into account when assessing energy consumption.

Energy for energy consumption—in the sense of a quantified amount of energy that is applied in an *energy use* to cover *energy demand* of an energy service, e. g., energy used for heating a building—has to be produced or generated to be available in the first place. For ease of readability, the terms *energy production* and *energy generation* are used interchangeably in this thesis and refer to the process of generating one form of energy from an energy source, which is usually another energy carrier. Nevertheless, the term energy generation is favored over energy production because the latter is typically used in the fields of engineering and economics, where actual goods are produced.

As a matter of fact, there are actually no such things as energy consumption, production, or generation. The law of conservation of energy states that the energy of a closed system is constant [37, p. 54] [153, pp. 11 ff.]. Still, these terms are commonly used and actually all these terms refer to some kind of conversion process.

Energy Provision, Distribution, and Utilization

The VDI Guideline 4602 [610] uses three different terms to characterize parts of energy systems (see also Figure A.3): energy provision, energy distribution, and energy utilization[2]. This characterization helps to structure any energy system into different parts that have distinct capabilities and functionality.

Energy provision or *energy provisioning* refers to the task of importing (*energy procurement*) or generating (*energy generation*) some form of energy or energy carrier or transforming one into another (*energy conversion*) using process energy.

Energy distribution refers to the process of distributing or transporting energy. Often, distribution is used to describe systems that distribute energy among many systems that utilize it, whereas transportation describes systems that transport energy from a single point to another single point or system.

Energy utilization or *energy use* is the “manner or kind of application of energy” [174, Ch. 3] “for the particular purpose of an energy service” [612, p. 15]. This is usually an energy service as lighting or movement but may also lead to the provision of another type of energy.

[2] Actually, the VDI Guideline 4602 defines another category—energy trading—which is closely related to energy provision and handles methods, markets, and products to optimize the procurement of energy. Therefore, this thesis includes energy trading into energy provision.

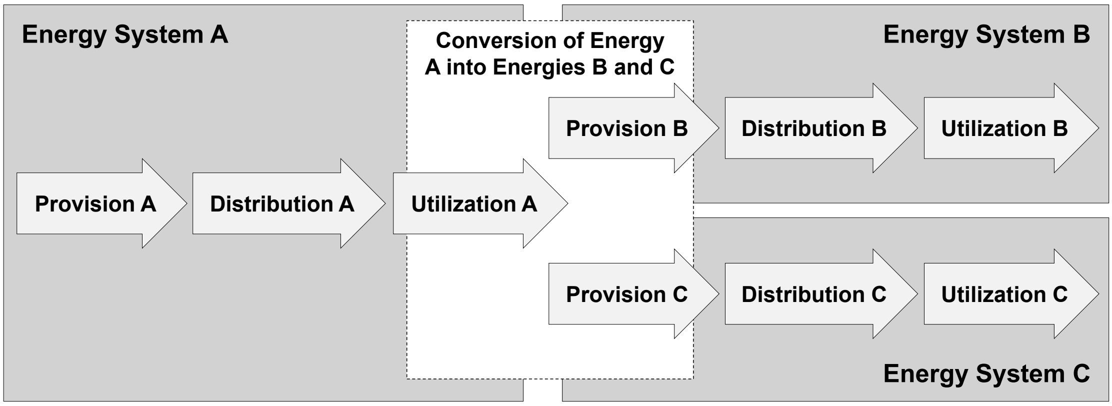


Figure A.4: Relation of energy *provision*, *distribution*, and *utilization* of three kinds of energy A, B, and C, where A is converted or transformed within an energy *conversion* into B and C

Several types of energy and multiple systems may be involved when provisioning, distributing, and utilizing energy or converting one energy into another. In Figure A.4, energy A is first provided by some part of the system, then distributed, and finally utilized. Then, energy A is converted or transformed into the energies B and C, i. e., their provisioning, before they are distributed and finally utilized in some other part of the energy system.

Energy losses, which is the "portion of energy input [...] that is not converted into useful work" [131, p. 200], may occur when provisioning, distributing, or utilizing energy. Accordingly, these are called, e. g., generation losses, distribution losses, or conversion losses (see also Appendix A.1.1).

Energy Portfolio and Energy Balance

The VDI Guideline 4602 [610] defines the term *energy portfolio* in the context of energy management as follows:

> "An energy portfolio means a collection of the energy carriers which an organisation purchases, sells, provides and uses for its own purposes (for example, production). As a rule companies will endeavour to keep a well-balanced and diversified range of options in their portfolios." [610, p. 16]

This definition is based on a view onto energy management that it is done by some function or unit in an organization. With respect to automated building energy management as presented in this thesis, this may partly be done by the management system itself. In general, one has to distinguish whether it is the decision about the technical capabilities of the energy system, i. e., which energy carriers it should be able to procure, distribute, and use, or whether it is the decision about the currently utilized energy portfolio, which is optimized when operating the system respecting the technical constrains (see Figure A.5). The former is a strategic investment decision that has to be done by the user of the BEMS. The latter is the operational management that is done by the BEMS based on the objectives that are provided by the user. The capability leads to a strategic decision, because it is

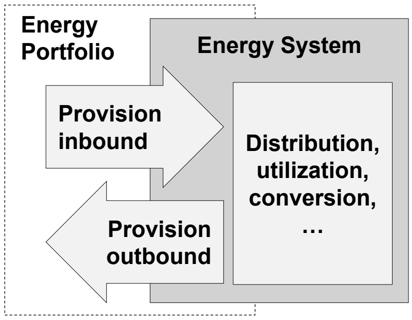


Figure A.5: *Energy portfolio* of an energy system

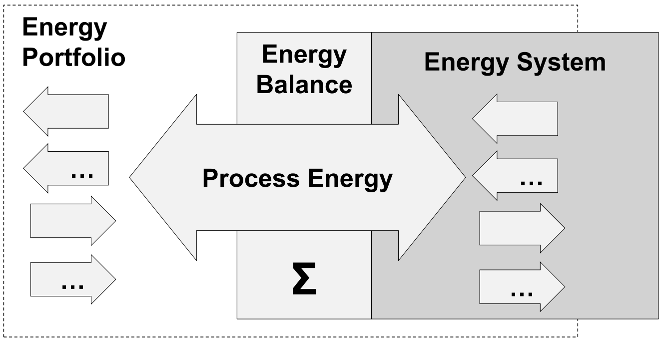


Figure A.6: Relation of *process energy*, *energy portfolio*, and *energy balance* of an energy system

directly connected to the equipment, i. e., systems and devices such as the heating system, that is available in the building.

The portfolio used in the past has to be evaluated and the portfolio that is presently used has to be optimized to manage the future portfolio better [610, p. 17]. The objectives may focus on long-term goals, e. g., adaptation to changing market conditions and technologies, or on objectives that reflect the short-term perspective, e. g., load management and current provision portfolio of energy.

The *energy balance* of a system is "the quantities of energy of the energy flows entering or leaving a system in a defined period of time" [612, p. 28]. This requires a defined material but also spatial and temporal boundaries of a system. For instance, energy balances are used to describe the energy sector in an economy with respect to the consumption of energy carriers and their interdependencies when converting and using them. Thus, it is actually a holistic energy balancing that considers each of the three steps—energy provision, distribution, and utilization—for the integrated energy sector. [612, pp. 29 f.]

To sum up, the process energy is all the energy entering or leaving a system, the energy portfolio is the variety of different energies entering and leaving a system, while the energy balance denotes the quantities of process energies entering or leaving a system. This is depicted in Figure A.6. The inbound provision portfolio is sometimes also named *energy signature* [131, p. 201].

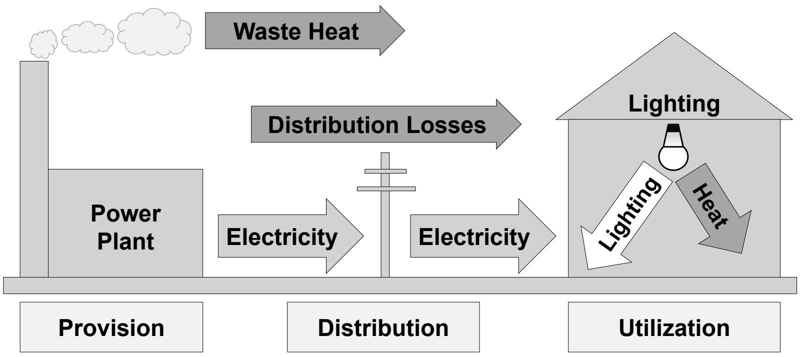


Figure A.7: *Energy efficiency* when lighting a building with a conventional incandescent light bulb, inspired by [19, p. 119]

Energy Storage and Energy Storage Systems

Saving spare energy for a later usage is done by doing energy storage in energy stores, energy storage devices, or ESSs. In [131], the term *energy storage* is defined as follows:

> "[Energy storage is] any process or state of maintaining energy in a form that permits the energy to be made available in a useful form at a later point in time; five basic methods of storage are chemical, electrochemical, magnetic, mechanical, and thermal." [131, p. 201]

Thus, energy storage is a process that may be realized using different forms of energy and different energy stores. The characteristics of a particular technology determine the provision, distribution, and utilization flexibility that is used by energy management. All ways of storing energy have their advantages and disadvantages, which have to be taken into account when realizing building energy management that utilizes ESSs.

For ease of understanding, the term *energy storage system* is used throughout this thesis for every device or system that facilitates *energy storage*.

Energy Efficiency and Energy Intensity

Large and complex systems, such as the energy systems, are often prone to inefficiencies, due to avoidable losses in provision, distribution, utilization, storage, and conversion of energy. Some processes have maximum efficiencies, e. g., the maximum efficiency of heat engines is defined by Carnot's theorem and the second law of thermodynamics. Much potential of reducing inefficiencies can be exploited using intelligent "sensing, communications, and control technologies" [19, p. 119], which is demonstrated in this thesis. Eccleston et al. (2012) [187] define the term *energy efficiency* in the context of energy management based on the ISO 50001 [174, Ch. 3] as follows:

> "Energy Efficiency is the ratio or other quantitative relationship between an input of energy and output of performance, service, goods, or energy. Examples include the conversion efficiency, energy required/energy used, or output/input." [187, p. 243]

A popular example of low efficiency in providing an energy service[3] is depicted in Figure A.7, where less than two percent of the energy input are actually used for providing lighting by a conventional incandescent light bulb. Fortunately, many of the losses are waste heat that may be captured and used for other purposes. Thus, efficiency has to be measured by regarding all forms of energy and their respective usage or loss.

Better energy efficiency has always also socio-economic and "sustainability implications as it lengthens the lives of existing resource reserves" while entailing "greater use of materials, labor and more complex devices" [517]. The inverse of energy efficiency is named *energy intensity* [174, Ch. 3] and is, e. g., the amount of energy input per economic output [131, p. 199].

Energy Conservation

As a result of economic, political, strategic, and environmental reasons, *energy conservation* is always in the center of detailed consideration about improving energy systems. Energy conservation is stimulated by technological progress and change, shortage and conflict, volatile and increasing price, codes and standards, as well as information. In the *Dictionary of Energy* [131], the term *energy conservation* is simply defined as follows:

> "[Energy conservation is] a collective term for activities that reduce end-use demand for energy by reducing the service demanded [...]." [131, p. 197]

The collective term of energy conservation is used particularly in the following three meanings [131, p. 197]:

1. Energy efficiency increase in means of more output per energy input.
2. Curtailment of energy provisioning.
3. Usage of alternative energy sources that are more abundant.

Often, political reasons or conflicts and results thereof, such as wars and embargoes, lead to forced or voluntary measures of energy conservation in form of curtailment or the usage of alternative energy sources.

Energy Performance

Eccleston et al. (2012) [187] define the term *energy performance* in the context of energy management as follows:

> "Energy Performance refers to the measurable results related to energy use and energy consumption. With respect to the [energy management system], results can be measured against the organization's energy policy, objectives, targets, and other energy performance requirements." [187, p. 243]

Thus, the goal of any EMS is performance, which is measured by indicators, e. g., by higher efficiency rates, lower energy costs[4], and reduced CO_2 emissions.

[3] More about *energy services* is given in Appendix A.1.1.

[4] The term *energy costs* may refer to monetary costs for energy as well as the amount of energy used [131, pp. 198 f.]. In this thesis, energy costs are used in the sense of monetary costs, whereas to used energy it is referred to as energy input, inbound provision, energy signature, or energy portfolio.

Energy Policy, Energy Objective, and Energy Target

According to DIN EN ISO 50001 [174], the *energy policy* states "the organization's commitment for achieving improved energy performance" [174, Ch. 4] and the "overall intentions and direction of an organization related to its energy performance as formally expressed by top management that provides a framework for action" [174, Ch. 3].

Eccleston et al. (2012) [187] define *energy objective* and *energy target* in the context of energy management as follows:

> "Energy Objective is the specified outcome or achievement established to meet the organization's energy policy in terms of improved energy performance." [187, p. 243]

> "Energy Target is the detailed and quantifiable energy performance requirement, applicable to all or part of an organization, that arises from the energy objective and that needs to be met in order to achieve this objective." [187, p. 243]

Variables that are part of energy targets include [610]:

- Energy costs.
- Energy-related infrastructure and equipment costs and investments.
- Energy efficiency.
- Energy-related emissions.
- Monitoring and visualization requirements.
- Reliability, resilience, and security of the energy system.
- Quality of processes, products, and services.

Self-evidently, energy objectives and energy targets have to be defined in accordance with the energy policy [174, Chapter 4]. Alternatively, the set of energy objectives, which consists of measurable energy targets, may actually define the overall energy policy, ensuring their consistency, inherently.

Often, energy objectives or energy targets, respectively, are in conflict to each other and have to be balanced properly by an energy management respecting all of them simultaneously while defining trade-offs between them [610].

A.1.1 Energy Sources, Carriers, and Commodities

In addition to the important basic terms of energy, energy system, the structuring of energy systems, and the interrelations of energy systems, there are important terms about the sources and carriers of energy, their origin, state, and quality within the energy chain and whether they are distributed, renewable, or marketable resources.

Energy Sources and Energy Carriers

The terms energy sources and carriers are often used interchangeably. Nevertheless, both terms actually emphasize slightly different functions of forms of energy. In [131], the term *energy source* is defined as follows, emphasizing that it is the origin of energy:

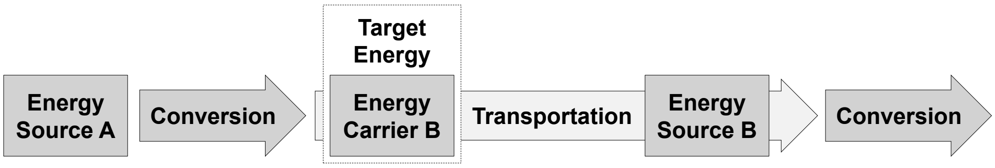


Figure A.8: From *energy source* to *energy carriers*

> "[An energy source is] a collective term for all resources providing useful energy such as human and animal power, wind, water power, coal, petroleum, natural gas, and nuclear power, as well as alternatives such as geothermal and solar energy." [131, p. 201]

In comparison to energy source, the term *energy carrier* emphasizes the form of energy and is defined in [131] as follows:

> "[An energy carrier is] a form of matter that can transport energy from one point to another; e.g., electricity, hydrogen, or adenosine triphosphate (ATP) in living systems." [131, p. 197]

The ISO 13600 standard[5] provides a slightly different definition:

> "[An energy carrier is a] substance or phenomenon that can be used to produce mechanical work or heat, or to operate chemical or physical processes." [322]

In summary, the term energy source emphasizes the character of an energy as being the source, i. e., the origin, of energy. In contrast, the term energy carrier refers to the transportation and storage of a specific form of energy. After their transportation and storage, energy carriers are energy sources for the generation of other energy carriers or for the utilization by an energy service that serves a useful purpose for the user. This is depicted in Figure A.8.

Primary Energy, Secondary Energy, and Final Energy

The very beginning of every energy consumption chain is some kind of *primary energy* [131] or *prime energy* [264], which is found in nature or taken from the environment that surrounds us. The *Dictionary of Energy* [131] defines primary energy simply as follows:

> "[Primary energy is] the energy directly embodied in natural resources, prior to its being converted or transformed for use." [131, p. 466]

Sometimes, primary energy is separated into sources and carriers that are renewable, i. e., nearly inexhaustible or replenishing, and such that are not, i. e., exhaustible and non-replenishing[6]. In the VDI Guideline 4661, this seized in the definition of *primary energy*:

[5] Although the ISO 13600 series of standards targets on a comprehensive approach to energy statistics and forecasting [264], the status of the standards is nontransparent, because some of them are withdrawn and other are yet to be published.

[6] This distinction into renewable and non-renewable sources is more closely described in the paragraph about RES at the end of this section.

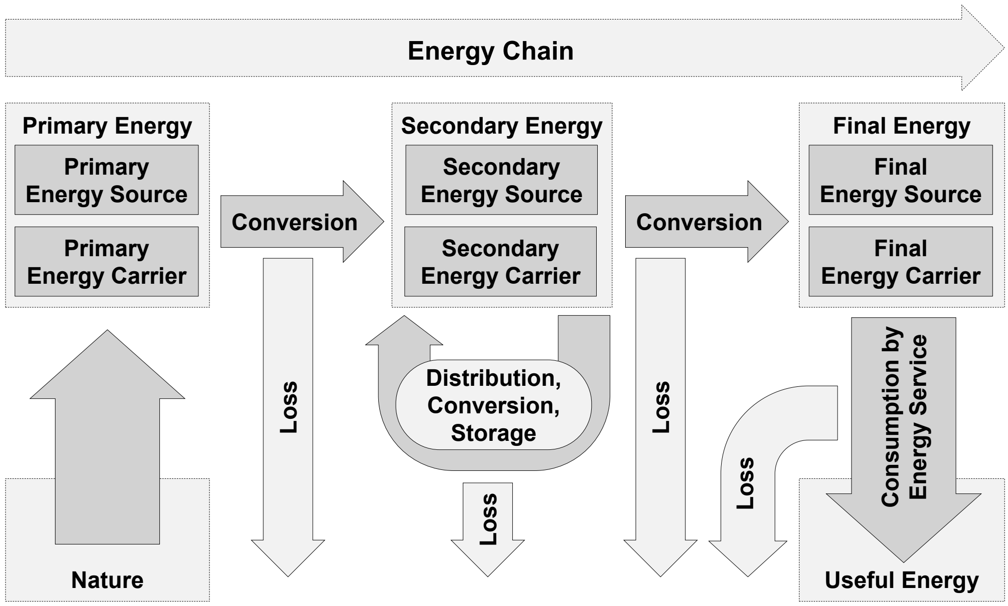


Figure A.9: From *primary energy* over *secondary energies* and *final energy* to *useful energy* that is consumed by *energy services*

> "Primary energy is the energy of energy sources or carriers which are found in nature and which have not yet been converted by technical processes. A distinction is drawn between inexhaustible – measured by human standards – or regenerative fuels, between fossil and nuclear energy sources." [612, p. 11]

In addition to the introduction of exhaustible and regenerative energy, this definition also names energy *sources* and *carriers* as being the origin of primary energy. The primary energy sources or resources are the forms of energy that originate directly in nature:

> "Examples of primary energy resources include coal, crude oil, sunlight, wind, running rivers, vegetation, and uranium." [131, p. 467]

In contrast to energy source, the term *energy carrier* focuses on forms of matter that allow for transport, as already introduced in the paragraph about energy sources and carriers above. In [334], this is clarified as follows:

> "Primary energy carriers are substances which have not yet undergone any technical conversion, whereby the term primary energy refers to the energy content of the primary energy carriers and the "primary" energy flows." [334, p. 2] [7]

It is important to note that the term *primary energy consumption* refers to something different than the direct consumption of primary energy: Primary energy consumption is the *total* consumption of *all* primary energy. In the *Dictionary of Energy* [131], it is defined as follows:

[7] Kaltschmitt et al. (2007) [334] use the term *energy flow* in the sense of energy source and not as defined in the paragraph about energy flows and energy chain below.

> "[Primary energy consumption is] the total amount of energy consumed by end users, plus any losses that occur in the generation, transmission, and distribution of energy." [131, pp. 466 f.]

Analogously to primary energy, primary energy source, and primary energy carrier, the terms secondary energy, secondary energy source, and secondary energy carrier refer to those energies that are not directly found in nature. Accordingly, the term *secondary energy* is defined in the *Dictionary of Energy* [131] in relation to primary energy, while adding the aspect of being more easily usable:

> "[Secondary energy is] energy converted from primary natural sources, such as coal, crude oil, or sunlight, into a form that is more easily usable for consumption, such as electricity or refined petroleum products." [131, p. 522]

In the VDI Guideline 4661 [612], it is clarified that secondary energy is obtained from primary energy by at least one conversion or transformation:

> "Secondary energy is the energy of energy carriers which have been obtained from primary energy by means of one or more conversion operations." [612, p. 11]

The following definition of *secondary energy carrier* by Kaltschmitt et al. (2007) [334] stresses the fact that every distribution and conversion is subject to losses before the energy becomes a final energy that is consumed by the user:

> "Secondary energy carriers are energy carriers that are produced from primary or other secondary energy carriers, either directly or by one or several technical conversion processes (e.g. gasoline, heating oil, rape oil, electrical energy), whereby the term secondary energy refers to the energy content of the secondary energy carrier and the corresponding energy flow. This processing of primary energy is subject to conversion and distribution losses. Secondary energy carriers and secondary energies are available to be converted into other secondary or final energy carriers or energies by the consumers." [334, p. 2]

The *final energy* is simply all energy that is utilized by the user and thus defined in the *Dictionary of Energy* [131] as follows:

> "[Final energy is] a collective term for forms of energy sold to or used by the ultimate consumers (e. g., households, industrial facilities)." [131, p. 223]

Ultimately, final energy is used for the provision of *useful energy* (see below), which is all energy that is used by energy services. Thus, final energy is no longer available for distribution, conversion, or storage, which is reflected in the definition in [612]:

> "Final energy includes only the traded energy carriers which are used for generating or converting useful energy and are thereby finally taken off the market as energy sources. This means that long-term storages are not a part of final energy." [612, p. 12]

The relations of primary energy, secondary energy, final energy, and useful energy as well as the relation to energy sources, carriers, losses, and services is depicted in Figure A.9. The conversion of primary energy sources to energy carriers and important criteria that are used when deciding which source or carrier to use for the provision of energy is shown in Figure A.10. There are several criteria that support the decision on which primary energy source to use [652]:

- Accessibility: convenience, costs, and efficiency of the provisioning.
- Availability: quality and reliability of the energy source.
- Acceptability: dangers, emissions, and hazards that accompany the exploitation of the energy source.

Energy Flows and Energy Chain

The movement of energy through a system is usually characterized as an *energy flow.* This system may be the energy system as a whole or every sub-system thereof. Thus, the term *energy flow* is defined in the *Dictionary of Energy* [131] simply as follows:

> "[Energy flow is] the movement of energy through a society [...] [or] [...] through a biological system [...]." [131, p. 199]

In contrast to energy flow, the term *energy chain* emphasizes the importance to distinguish different stages in the energy flow, i. e., the character of an overall energy flow to comprise sub-flows in sub-systems that lead to substantial changes in the involved forms of energy. In the *Dictionary of Energy* [131], the term energy chain is defined as follows:

> "[The energy chain is made of] all the successive stages involved with the supply of an energy source to the end user, such as given fuel product's characterization, exploration, extraction, conversion, processing, and delivery, and the treatment and disposal of its wastes." [131, p. 197]

Figure A.9 depicts the generalized energy chain, beginning at the primary energy which is converted into secondary energy before being consumed as final energy, where useful energy provides energy services, such as lighting or heating. Every movement of energy in this chain is an energy flow and typically subject to losses.

Target Energy, Useful Energy, and Energy Service

In each stage of the energy chain, there is some kind of *target energy*[8] that is the output of a conversion. The very final target energy is the *useful energy* that is consumed by an *energy service* that provides a specific and intended purpose for the user (see Figure A.9). When we utilize energy, we use it because it is consumed by an energy service. For instance, we may not buy light to illuminate our buildings but electricity that is then consumed by lighting devices that emit it[9].

[8]The term target energy is not to be confused with the term energy target (see Appendix A.1).
[9]Unintentionally, we get a heating service as well (see also Figure A.7).

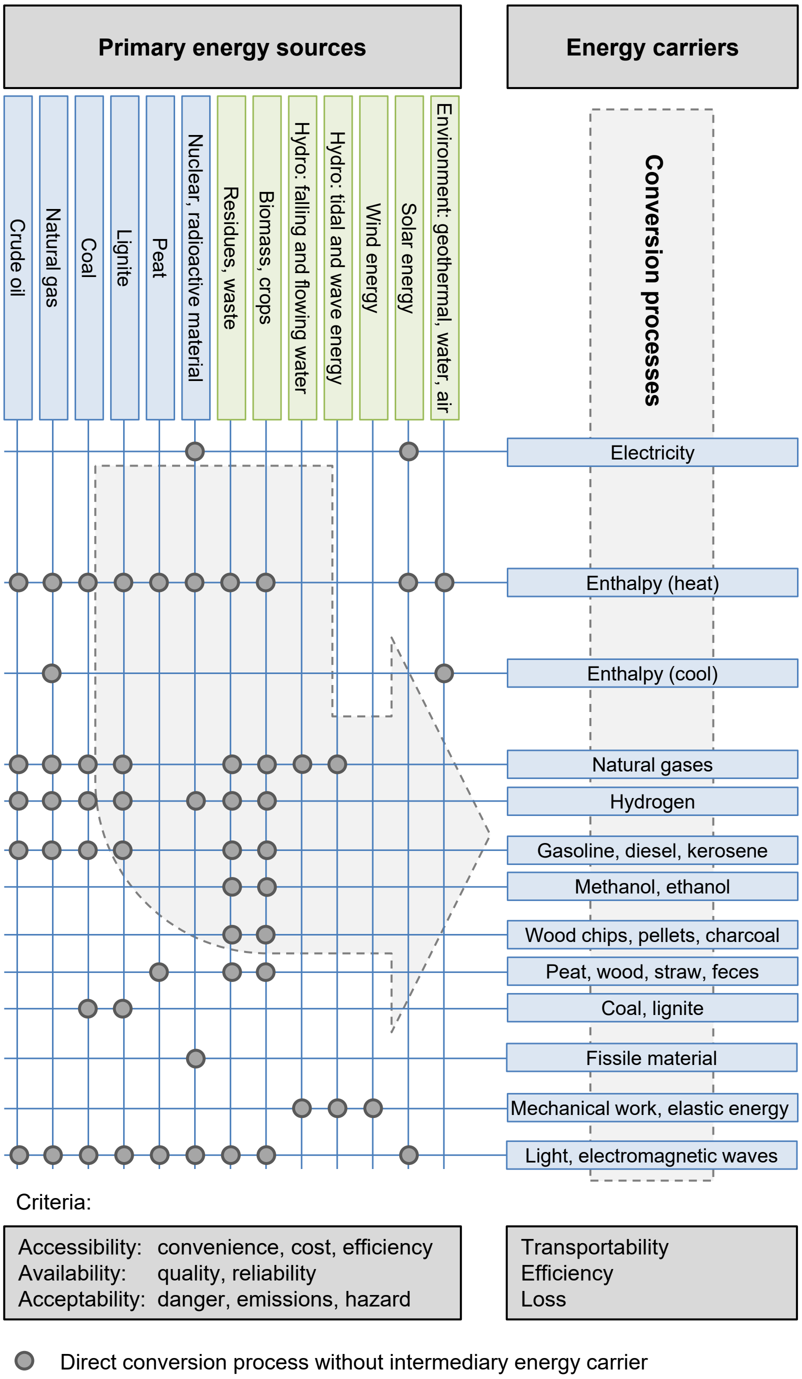


Figure A.10: Conversion of primary energy sources to energy carriers and important criteria that are used in the decision which source or carrier to use, partially based on [334, 652]

Target Energy In the VDI Guideline 4661 [612], the term *target energy* is defined as follows:

> "Target energy is the form of energy aimed at in an energy-conversion process or a technical energy transformation, respectively. Target energy may consist of one or – e.g. in the case of combined generation or conversion of power and heat in a district heating power station, for example – even more different forms of energy." [612, p. 12]

Useful Energy The previous definition already introduces the importance of considering multiple energy carriers when regarding an energy system. Thus, the energy chain is actually not a linear series of links but an interwoven system of energy systems that enables the provision, distribution, and utilization of most diverse forms of energy (see also Figure A.4). Finally, at the end of the energy chain, the energy is a *useful energy*, as defined by [131, 334, 612]:

> "[Useful energy is] the actual energy used by a consumer to perform a desired function (heat, lighting, mechanical power, and so on) [...] [and,] [...] in general, any form of energy that serves a valid purpose for humans." [131, p. 627][10]

> "Useful energy covers all technological forms of energy which the consumer ultimately requires – in other words, heat, mechanical energy, light, electrical and magnetic field energy [...] and electromagnetic radiation – in order to be able to perform energy services. In general, the various types of useful energy must be generated from final energy by energy converters at the time and place they are required." [612, p. 12]

> "Useful energy refers to the energy available to the consumer after the last conversion step to satisfy the respective requirements or energy demands (e.g. space heating [...]). It is produced from final energy carrier or final energy, reduced by losses of this last conversion (e.g. losses due to heat dissipation by a light bulb to generate light [...])." [334, pp. 2 f.]

Energy Service These three definitions in the paragraph above already provide a link to the term *energy service*, which is defined by [612] as follows:

> "[Energy] services are the requirements satisfied by or the goods produced from the use of useful energy and other production factors; examples include lighting areas and spaces, movement and transportation, heating and cooling materials and goods, [...] etc." [612, p. 13]

This final step of the energy chain, i. e., the consumption of useful energy by an energy service, is depicted in Figure A.9.

[10] In this definition, the term function is used synonymously to the term energy service.

Commodities

The term *commodity* originates in the field of economics. The definition by [76] describe it as a standardized and thus interchangeable good that is sold in large quantities:

> "[A commodity is a] standardized good, which is traded in bulk and whose units are interchangeable. Commodities are mostly the output of the primary sector, that is, agriculture and mining, or semi-processed products. Because these goods are standardized, commodity markets can trade spot goods by sample, and can trade in futures and forward contracts in commodities." [76, p. 67]

The definition of the term commodity by [131] stresses the character of being an object or substance, including energy carriers:

> "[A commodity is] 1. any physical object produced in an economic process. 2. specifically, a standard agricultural or industrial substance that is marketed in its raw, unprocessed state; e. g., wheat, rice, sugar, cotton, gold, silver, crude oil, natural gas." [131, p. 121]

In the context of this thesis, the term commodity is not only used for physical objects but all products that are standardized outputs of intended processes. In particular, this includes electricity, which is in line with literature, e. g., [359, 396, 553]. Self-evidently, electricity is usually a standardized (see also Section 2.1.4) and interchangeable good that is sold in large quantities. Additionally, it is traded in energy exchanges.

Electricity or other energy carriers, such as natural gas or fuels, are actually not a commodity *per se*. They are available in many different *qualities*. To make them tradable, their specific properties and characteristics, such as voltage or calorific value, have to be measured and included into the trade as well. This results in Figure A.11, which shows exemplary and still generalized commodities that result from energy carriers. The decision about which energy carrier to use depends on criteria related to transportability, efficiency, and loss, whereas the decision about the commodity is based on accessibility, availability, and acceptability [652].

Table A.1: Exemplary technologies for centralized generation and distributed generation of heat and electricity with different centralized and decentralized (non-)renewable energy sources

Energy source		**Centralized generation**	**Distributed generation**
Centralized	Non-renewable	Coal, nuclear, gas power plant	MicroCHP, diesel generator, coal oven
Centralized	Renewable	Biogas CHP	Biogas microCHP
Distributed	Non-renewable	–	Shale gas power plant
Distributed	Renewable	PV farm, wind farm, hydro power, solar thermal power plants	PV system, wind turbine, biogas microCHP, small hydro power

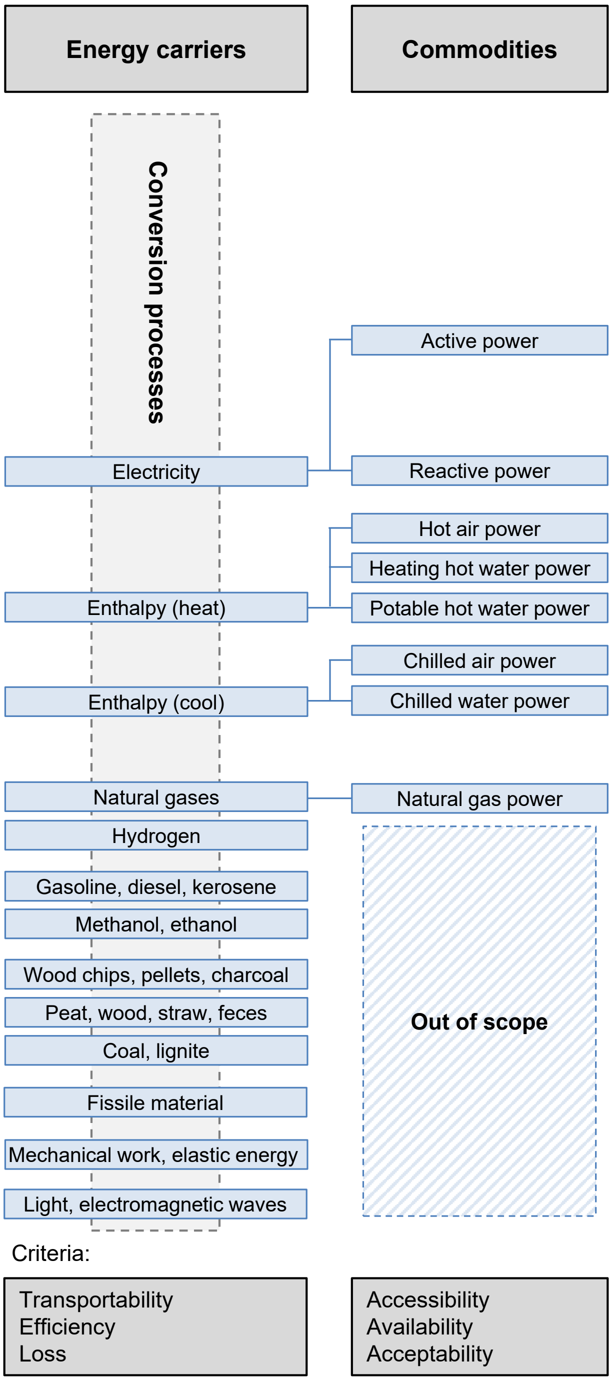


Figure A.11: From energy carriers to commodities, partly based on [334, 652]

Distributed and Renewable Energy

It is important to distinguish the terms *distributed energy source* as well as *renewable energy source* and the DG using these sources. Renewable energy sources are often distributed and thus used in DG but not necessarily, as the example of large concentrating solar thermal power plants demonstrates. Therefore, not every renewable energy is exploited in a distributed manner and not every utilized distributed energy source is necessarily renewable. Some exemplary technologies are provided in Table A.1.

Distributed Energy Sources and Distributed Generation

DG uses distributed energy sources or resources that have been distributed for the purpose of generating other forms of energy. Distributed energy sources are often RES, though not necessarily. They include the distributed usage of small distributed fossil energy sources, such as natural gas and coal, as well as RES, such as solar radiation and wind power. Thus, the generation technologies may be fundamentally different, such as internal combustion engines and PV cells. Nevertheless, many technologies may be fueled by an energy sources that are fossil or renewable, e. g., generation from natural gas or biogas [131, p. 166] [398]. The system may be grid-connected, i. e., part of a subordinate energy system, or an off-grid energy system [19, p. xvi].

In the *Dictionary of Energy* [131], the term *distributed energy* is used synonymously to the term *distributed generation* and defined as follows:

> "[Distributed energy is] the generation of electricity (and heat) at or close to the point of demand." [131, p. 166]

However, the focus of the two terms—DER and DG—is different. DER emphasizes the origin of energy, whereas DG stresses the act of conversion of the energy source into another form that is done in a distributed manner.

Renewable Energy Sources

One of the most important motivations for energy management is the increasing usage of RES. The *Dictionary of Energy* [131] defines the term *renewable energy* as follows:

> "[Renewable energy is] any energy resource that is naturally regenerated over a short time scale and either derived directly from solar energy (solar thermal, photochemical, and photoelectric), indirectly from the sun (wind, hydropower, and photosynthetic energy stored in biomass), or from other natural energy flows (geothermal, tidal, wave, and current energy). [...]" [131, p. 498]

Some energy carriers, e. g., peat, take several thousand years to replenish and thus are sometimes called *slowly renewable* [131, p. 439]. Although some other energy carriers are replenishing when regarding a period of millions of years, e. g., crude oil, coal, and natural gas, they are usually not called RES but *non-renewable energy* or *finite sources* [131, p. 498]. Annaswamy et al. (2013) [19] add another aspect to this definition by emphasizing that RES are *flow-limited sources*:

> "[Renewable energy sources are] [...] resources that are naturally replenishing but flow-limited. They are virtually inexhaustible in duration but limited in the amount of energy that is available per unit of time." [19, p. xix]

The flow of RES, i. e., the renewable energy that is available per unit of time, is usually erratic, fluctuating, and intermittent and thus the energy generation by renewable energy is variable and volatile, too. For instance, to store energy for times without or with less renewable energy than required, plants store photosynthetic energy and apply energy management, e. g., by reducing their consumption in winter time.

From a seasonal perspective in Europe, i. e., when monthly average wind and solar power generation are aggregated, wind and solar are complementary, because wind power generation is stronger in winter than summer and solar power is vice versa. Nevertheless, there would be still enormous requirements for temporal equalization using seasonal storages, which may not be met using the currently available storage capacities, and spatial balancing in power grids, which would require a strong expansion of the grid [285]. Short-term imbalances would already heavily benefit from an efficient storage system that enables up to six hours of electricity storage, which actually motivates measures of DSM, which is working in a similar timescale [494] (see also Section 2.3.4).

A.1.2 Energy Management and Load Optimization

Energy management is the organized and prudent coordination and optimization of energy provision, distribution, and utilization and is formalized in EMSs.

Energy Management

The term *energy management* is often used but seldom defined. One exception is the VDI Guideline 4602 [610] , which defines *energy management* as follows:

> "Energy management is the forward-looking, organised and systematic co-ordination of the procurement, conversion, distribution and utilisation of energy [...] to cover requirements and which takes ecological and economic objectives into consideration." [610, p. 3]

Although this definition misses the aspect of energy storage, it is comprehensive and emphasizes the importance of different objectives. In general, energy management has to take various objectives into account, which are usually conflicting. Examples of objectives include operating costs, investment costs, efficiency, and security of energy provision. Thus, energy management has to trade them off against each other to enable concrete decisions [610, p. 4]. Energy management is formalized to systematic decisions that are supported by processes, hard-, and software in EMSs, enabling systematic decisions.

Energy Management System

There is a multitude of definitions of the term *energy management system*. Often, the term is used in the context of energy management in an organizational entity, such as a company.

Whereas in this thesis, the term EMS is mainly used in the context of a software system that enables energy management in single devices, more complex systems, and entire buildings, i. e., in each entity that may benefit from energy management.

In the ISO 50001 [174], an EMS is defined in a rather generic and abstract way as a set of elements that are used in an organization to establish and achieve energy policy and energy objectives:

> "Set of interrelated or interacting elements of an organization to establish energy policy and objectives and to achieve those objectives." [174]

This definition is static and unidirectional and does not include reoccurring adjustment to feedback that is given back from the organization when the set is applied in practice. In contrast, the definition in the VDI Guideline 4602 [610] explicitly describes the EMS as a control loop consisting of applied energy tasks that are evaluated against initial targets with the objective to review and adapt them:

> "The energy management system is a control loop in which, starting with set targets, an energy task is performed and the results checked and evaluated. Only on the basis of this evaluation does it become possible to review and adapt the set target or to identify optimisation criteria." [610, p. 8]

The definition in the VDI Guideline 4602 [610] extends the definition in the ISO 50001 [174] to include not only organizations and information but also technical resources:

> "The term "energy management system" covers not only the organisational and information structures required for implementing the energy management system but also the technical resources needed for this (software and hardware, for example)." [610, p. 8]

This inclusion of hardware and software coincides with the definition by Annaswamy et al. (2013) [19], which emphasizes the character of a regional system:

> "The suite of software and hardware that supports a regional control center in managing the production, purchasing, transmission, distribution, and sale of electrical energy in the power system at a minimal cost with respect to safety and reliability." [19, p. xvii]

Nevertheless, this definition lacks the understanding that the system has closed boundaries that do not necessarily have to be of spatial character but may also be virtually (see Section 2.3.3). Interestingly, the *Dictionary of Energy* [131] defines EMS only in the context of HVAC systems, showing that this term lacks a common and comprehensive definition:

> "[An energy management system (EMS) is] a control system capable of monitoring environmental and system loads and adjusting HVAC operations accordingly, in order to conserve energy while maintaining comfort." [131, p. 200]

In the context of grid operation, Annaswamy et al. (2013) [19] define the term *energy management system* as follows, emphasizing the complexity and the interaction of many different parties, devices, and systems:

> "An energy management system (EMS) is a general term used to describe a wide ranging suite of software and hardware that supports a regional control center in managing the production, purchasing, transmission, distribution, and sale of electrical energy in the power system at a minimal cost with respect to safety and reliability. Management of the real-time operation of an electric power system [...] is a complex task that requires interaction of human operators, computer systems, communications networks, and realtime data-gathering devices in power plants and substations." [19, p. 18]

In general, EMSs have to provide the following categories of functions, which are closely described in Section 4.6 when analyzing the requirements of EMSs [19, 131, 610]:

- Observation and monitoring
- Forecasting and prediction
- Simulation and calculation
- Optimization and scheduling
- Operation and control
- Security and privacy management

The functions are supported by hard- and software but not necessarily automated in systems that work autonomously. This thesis emphasizes the importance of automating energy management using EMSs.

Automated Energy Management and Load Optimization

Manual energy management in buildings is a sophisticated task if to be done properly. Additionally, it is often being annoying, because it includes many tasks that have to be done periodically and which are rather simple, such as checking if the windows are closed, the hot water temperature has been set correctly, or switching off unnecessary energy services. In addition, users often lack the interest, available time, or knowledge to do a proper energy management. [1, 13, 170, 468, 556]

Automated energy management paves the way for flexible and dynamic adaptations of the energy consumption, generation, and storage in buildings. This enables the optimization of energy provision, distribution, and utilization in a single energy system as well as across the energy system's boundaries by taking external signals and incentives into account.
Examples for automated energy management include automated DR, which facilitates mostly load reductions in case of critical electricity grid states, and automated EMSs, which realize a more sophisticated energy management on behalf of the users (see also Section 2.3.4). This thesis focuses on such automated EMSs that collect all necessary information and states, take changing signals and incentives by external entities into account, respect the user's objectives, and automatically control devices and systems in an energy system to optimize the load, i. e., consumption, generation, and storage, of all relevant energy carriers in a building. This way, not only energy costs but also, e. g., GHG emissions can be reduced, while still providing energy services to the user within their preferences.

The VDI Guideline 4602 [610] defines *load optimization* as follows:

> "[Load optimization is the calculation of a production output] [...] which is optimum under the applicable production constraints, energy-related aspects and the market situation (energy market and product market):
>
> - comparative moderation of load by optimisation within an energy carrier

- comparative moderation of load by coordinating different installations with the same energy carrier
- balancing load by coordinating different energy carriers in the same or different installations" [610, p. 20]

This definition focuses only on the production but has actually to be seen in the context of energy services that consume final energy in an optimized manner, i. e., with an optimized load. Interestingly, the balancing and coordination of multiple energy carriers already introduces the idea of multi-modal energy management, which is described in more detail hereafter and in Section 4.7.1.

A.1.3 Energy Management of Multiple Energy Carriers

Self-evidently, all energy systems utilize multiple energy carriers. For instance, burning fuel to generate electricity includes the energy carriers fuel, heat, mechanical work, and electricity. Nevertheless, energy systems are typically analyzed with a focus on one of the energy carriers that are used.

Although there is no consistent term or naming scheme for the energy management of multiple energy carriers in energy systems (see also Section 4.7.1), the basic idea is in all cases the same or at least very similar. Firstly, energy management of multiple energy carriers has to be considered from energy provision over its distribution to its utilization [610, p. 3]. Secondly, there are usually multiple different routes that may be implemented and executed to provide an energy service. Additionally, energy carriers are often utilized simultaneously and thus have to be assessed jointly:

> "Since different energy carriers can be used simultaneously in energy processes (for example, heating with natural gas and/or with electricity), an energy management system will also have the task of assessing (ecologically, economically) the different energy carriers and of making the decision as to their use." [610, p. 8]

Inevitably, this leads to the inclusion of ESSs and the flexibility of energy demand of a particular energy carrier. From a more global perspective on energy systems than single devices or buildings, there is the consideration of energy sectors: "Multi modal energy systems combine some of the commonly mentioned measures, such as sector coupling, energy storages, or flexible demand" [582]. Thus, the energy management of multiple energy carrier has to take particularly the coupling of the different grids and networks into account, as emphasized by Metzger (2013) [420]:

> "A modular approach gets even more important if one likes to realize a smart multi-modal energy system, that optimally uses the coupling between power grid, district heating/cooling, water and gas networks." [420, p. 66]

General interdependencies in energy systems are detailed in Section 2.2. Different approaches to the energy management of multiple energy carriers are outlined in Section 3.1. A review and analysis of the usage of the terms hybrid, multi-modal, and multi-valent in the context of appliances, a consistent terminology, and the challenges of energy management of multiple energy carriers are given in Section 4.7.

A.2 Energy Carriers, Commodities, and Ancillary Commodities

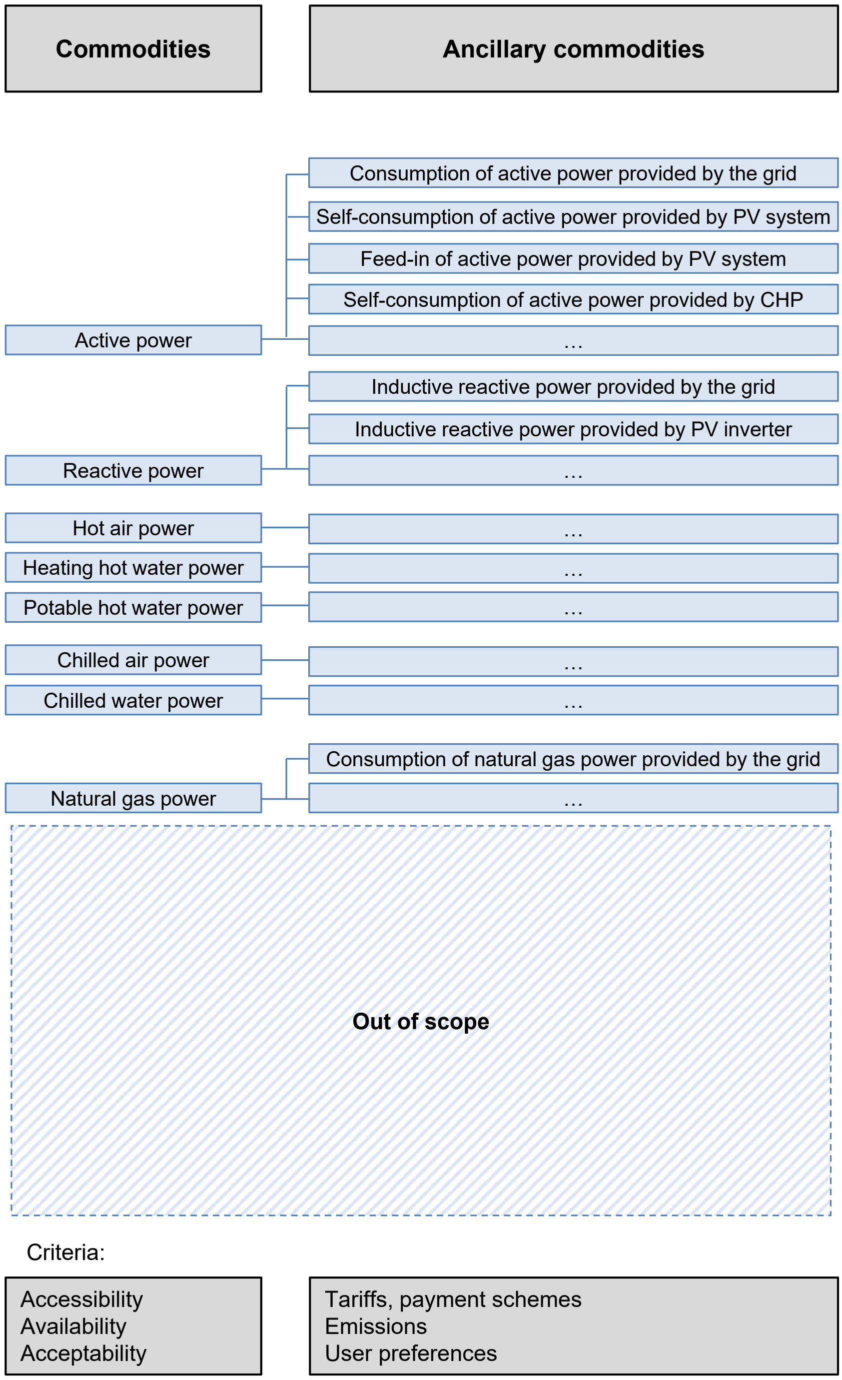


Figure A.12: From commodities to ancillary commodities

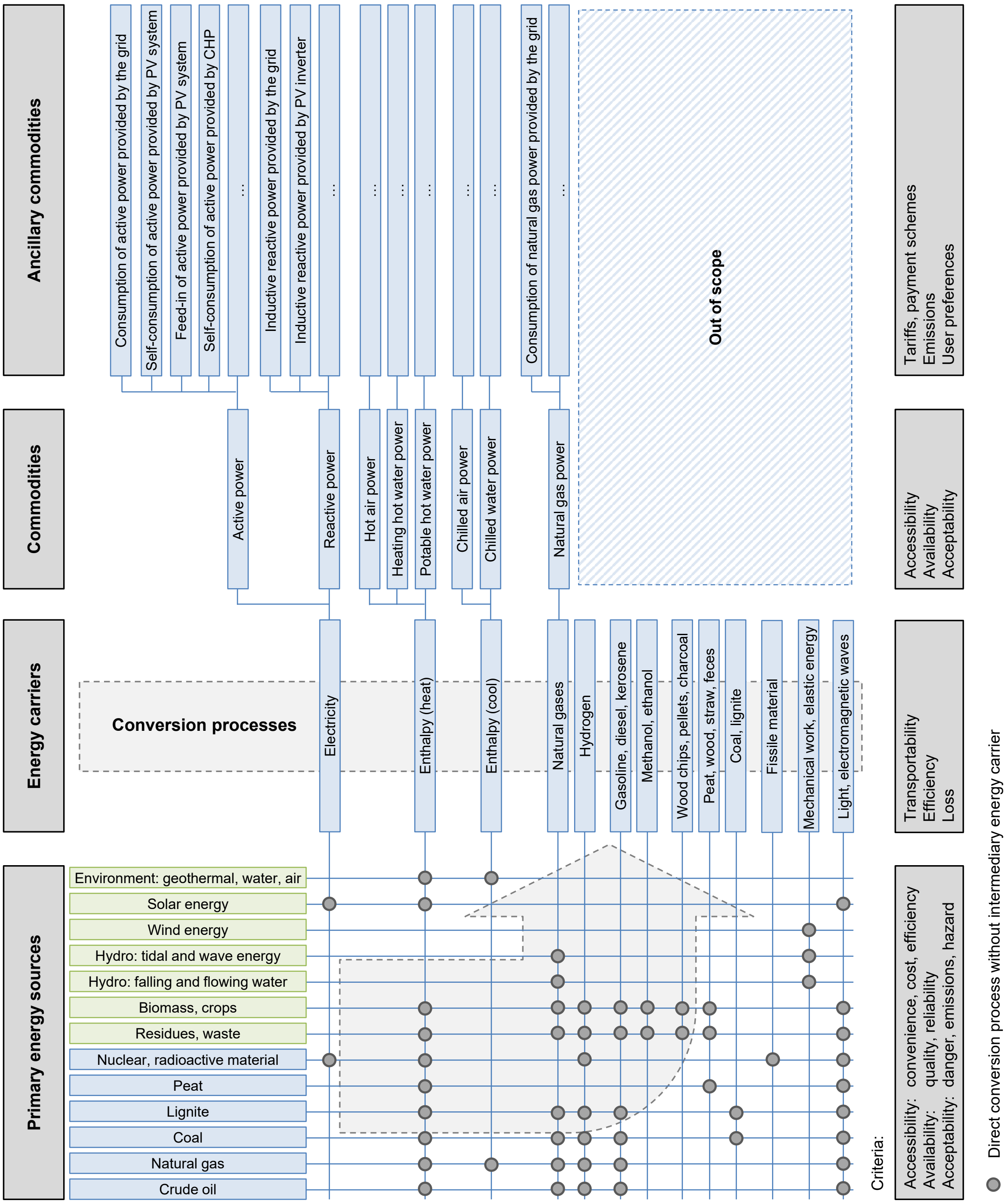


Figure A.13: From energy sources to ancillary commodities, partly based on [334, 652]

A.3 Energy-related Standards and Guidelines

Table A.2: Relevant energy-related standards and guidelines in buildings

Standard / Guideline	Title	Relevant content
DIN 4701	Energy efficiency of heating and ventilation systems in buildings	Heating systems
DIN 4708	Central heat-water-installations	DHW systems and demand
DIN 18599	Energy efficiency of buildings	Energy efficiency assessment, reference values
EN 12309	Gas-fired sorption appliances for heating and/or cooling with a net heat input not exceeding 70 kW	Hybrid appliances
EN 12831	Heating systems in buildings	Heating systems, statistics, DHW load profiles
EN 12977	Thermal solar systems and components – Custom built systems	Heating systems and storages, simulation
EN 13203	Gas-fired domestic appliances producing hot water	Exemplary DHW load profiles
EN 15316	Heating systems in buildings	Heating systems
EN 15450	Heating systems in buildings – Design of heat pump heating systems	Exemplary DHW load profiles
EN 16147	Heat pumps with electrically driven compressors – Testing and requirements for marking of domestic hot water units	Exemplary DHW load profiles
ISO 13370	Thermal performance of buildings – Heat transfer via the ground – Calculation methods	Definitions, fundamentals, building simulation
ISO 13789	Thermal performance of buildings – Transmission and ventilation heat transfer coefficients – Calculation method	Definitions, fundamentals, building simulation
VDI 2067	Economic efficiency of building installations	Statistics, DHW and heating energy consumption
VDI 3807	Characteristic consumption values for buildings	Energy carriers, statistics, energy and water consumption
VDI 3808	Assessment of energy efficiency of buildings and building services	Energy efficiency assessment
VDI 3812	Home automation technologies	Home automation domains
VDI 3922	Energy Consulting for Industry and Business	Definitions, fundamentals
VDI 4645	Design and dimensioning of heating plants with heat pumps in single and multi-family houses	Definitions, fundamentals, reference load profiles
VDI 4655	Reference load profiles of single-family and multi-family houses for the use of CHP systems	Reference load profiles
VDI 4661	Energetic characteristics	Definitions, fundamentals
VDI 4700	Terminology of civil engineering and building services	Definitions, fundamentals
VDI 4710	Meteorological data for technical building services purposes	Statistics
VDI 6002	Solar heating for potable water	Statistics, DHW load profiles
VDI 6007	Calculation of transient thermal response of rooms and buildings	Building simulation
VDI 6009	Facility Management	Definitions, fundamentals
VDI 6018	Cooling in building services – Planning, erection and operation	Air-conditioning, space cooling
VDI 6020	Requirements on methods of calculation to thermal and energy simulation of buildings and plants	Building simulation

A.4 Explanation of Properties in Evaluation Tables

Table A.3: Explanation of properties in the evaluation tables

Aspect	**Detail**	**Explanation**
Category	Productive system	Can be used in productive systems in real buildings
	Simulation	Can be used to perform simulations
	BEMS concept/architecture	Provides a consistent concept or architecture
	BOS	Has the character of a BOS and may run, e. g., “apps” or widgets by third parties
Applicability	Connectivity	Provides device drivers/connectors to real hardware or approaches to device abstraction
	Building automation	Supports building automation functionality, such as room temperature control
	Energy monitoring	Supports energy monitoring, e. g., energy data recording and evaluation
	Automated EMS	Supports automated energy management
	DR	Supports measures of DSM, such as physical and market-based automated DR
	VPP participation	Supports the participation in VPPs
Devices	*All details*	Devices are supported by real systems or demonstrated in simulations, respectively
Appliance load profiles	Real appl. profiles	Realistic load profiles of real appliances are used
	Temporal resolution	Temporal resolution of the load profiles
	Multiple per appl.	Multiple load profiles per appliance are used
Simulation	User behavior	Simulation of (randomized) user behavior based on statistical values or user/occupancy models
	Thermal load profile	Simulation of (usually static) thermal load profiles
	Thermal model	Simulation of thermal (building) models
	Horizon	Period that is typically simulated
	Temporal resolution	Temporal resolution of the simulation
Control	Closed-loop	Support of closed-loop control in operation or optimization
Optimization	Horizon	Duration of the typical optimization horizon, i. e., the time period that is optimized
	Temporal resolution	Temporal resolution of the optimization horizon
	Algorithm	Optimization algorithm that is used
	Rolling horizon	Support of a rolling optimization horizon
	Multi-objective	Support of multi-objective optimization
	Scalarized multi-objective	Reduction of multiple objectives to a single objective
Objective	*All objectives*	Support of the respective optimization objective
Energy carriers	*All energy carriers*	Support of the respective energy carrier in simulation and optimization of buildings
Tariff/pricing	Time-variable prices	Support of tariffs that have prices depending on time, e. g., time-of-use or real-time pricing
	Power-variable prices	Support of tariffs having prices depending on the power
	Power limit (hard)	Support of hard power limits

B

Residential and Commercial Building Data and Statistics

B.1 Classifications and Categorizations of Devices

Table B.1: Classification of appliances according to Allerding and Schmeck (2011) [13]

Class	Observable	Controllable	Examples
Un-predictable	yes	no	Multimedia, lighting, small appliances
Predictable	yes	no	Oven, hob, small appliances
Timed service	yes	yes	Dishwasher, washing machine, dryer
Permanent service	yes	yes	Freezer, electric heating, air-conditioning, water boiler

Table B.2: Categories of appliances according to Althaher et al. (2015) [14]

Category	Description	Examples
Nonflexible deferrable	Starting time of non-interruptible profile may be shifted	Washing machine
Flexible deferrable	Starting time of flexible profile that has a required energy may be shifted and adjusted	Electric vehicle
Thermal	Controllable within certain temperature limits	Heater, air-conditioning
Curtailable	May be switched off according to priorities	Oven, iron
Critical	Uncontrolled operation that has to be preserved	Lights, computer

Table B.3: Classification of appliances according to Damm et al. (2011) [146]

Class	Description	Examples
Variable service	User-variable service based on sensor input	Illuminance-controlled lighting, dimmable lighting, blinds
Virtual storage service	Virtual storage with user-variable service	Heating and cooling devices: fridge, freezer, HVAC, water boiler
Schedulable service	Service scheduled within a certain time-frame	Washing machine, tumble dryer, dishwasher, baking machine
Event-timeout service	Service controlled by sensor events and timers	Sensor-controlled lighting
Charge control	Storage in a device that may be removed	Battery chargers, vacuum cleaner, uninterruptible power supply
Complete control	Controllable storage	Robot vacuum cleaner and lawnmower
Custom control	Does not fit into other classes	Hi-fi equipment, TV, PC, oven

Table B.4: Classification of loads according to Dethlefs et al. (2014) [165]

Class	Description	Control	Examples
User-driven	Loads that satisfy the users demand directly	User-controlled	Light, TV
Program-driven	The user starts the device but it may not run immediately	Semi-automatic	Washing machines, dishwasher
Fully-automated	These devices have actuators and sensors to maintain a certain state	Automatic, parameter driven	Electrical heating or cooling (fridge)

Table B.5: Categories of smart appliances in EF-Pi [601]

Category	Description	Examples
Uncontrollable	Has no flexibility, is measurable and may provide forecast	Solar panel, wind turbine, TV, indoor lighting
Time shiftable	Operation can be shifted in time, has a deadline	Washing machine, dishwasher
Buffer	Flexible in operation for either generation and/or consumption and operation is bound by a buffer	Freezer, heat pump, CHP, battery storage, electric vehicle, cooling systems
Unconstrained	Flexible in operation for generation and the operation is not bound by a buffer	Gas/diesel generator

Table B.6: Categories of appliances according to Gottwalt et al. (2011) [255]

Category	Description	Examples
Automatic	Inherent storage and discontinuous operation	Refrigerator, freezer, storage heater
Semi-automatic	User interaction is required	Washing machine, dishwasher, tumble dryer
Not-controllable	DSM would have severe negative impact on user comfort or is not possible at all	Lighting, TV

Table B.7: Exemplary devices in two dimensions of the classification according to Ha et al. (2006) and Ha et al. (2012) [268, 272]

	Time and availability	
Relation to the user	Temporary or timed services	Permanent services
Support services	Photovoltaic panels	Power provider, grid connection
Intermediate services	–	Energy storage
End-user services	Washing machine, hob	HVAC systems

Table B.8: Categories of consumer load types according to He et al. (2011) [284]

Category	**Description**	**Examples**
Storable	Power consumption and end-use service are decoupled by some energy storage	Electric vehicle, HVAC, BESS
Shiftable	Power consumption is not decoupled but can be moved in time without affecting the end-use service	Washing machine, dishwasher, tumble dryer, vacuum cleaner, stove
Curtailable	Power consumption cannot be shifted but the end-use service can be interrupted instantly	Lighting, TV, handyman tools, computer
Base	End-use service is not decoupled from consumption and cannot be interrupted or shifted in time	Burglary alarm, building automation, TV, lighting
Self-generation	Distributed power generation at the premises of the consumer	PV system, solar thermal system, CHP, wind power

Table B.9: Classes of appliances according to Kok et al. (2005) [358]

Device class	**Description**	**Examples**
Stochastic operation	Uncontrolled, stochastic output	PV system, wind power
Shiftable operation	Operation is shiftable within certain temporal limits	Washing machine, dryer, pool pump, ventilation system
External resource buffering	Buffered energy other than electricity	Electrical heating, heat pump, CHP
Electricity storage	Electrical energy storage	BESS, flywheels, super-capacitors
Freely-controllable	Controllable within certain limits	Diesel generator
User-action	Unpredictable user action	Audio, TV, lighting, computer

Table B.10: Types of control according to Soares et al. (2012) [558]

Type of Control	**Description**	**Appliances**
Uncontrollable loads	Not controllable since it may depreciate the quality of energy services and cause discomfort to the user	Lighting, office and entertainment equipment, cooking appliances
Reparameterizable loads	Loads thermostatically controlled that can have thermostat parameters re-set without depreciation of the energy service provided	Cold appliances, air-conditioning systems, electric water heaters
Interruptible loads	Loads that can be the target of short period interruptions without depreciation of the energy service provided	Cold appliances, air-conditioning systems, electric water heaters [again, sic!]
Shiftable loads	Working cycle that may be deferred or anticipated while respecting user preferences	Washing machines, dryers, dishwashers, electric water heaters

B.2 Electricity Tariffs

Table B.11: *Erneuerbare-Energien-Gesetz (EEG) 2014*: Feed-in compensation in Germany for PV systems on residential buildings having a maximum power of 10 kW [103]

Month	10/2015	11/2015	12/2015	01/2016	02/2016	03/2016
Tariff in cent/kWh	12.31	12.31	12.31	12.31	12.31	12.31

Table B.12: *Kraft-Wärme-Kopplungsgesetz (KWKG) 2012* and *2016*: Feed-in compensation in Germany for microCHP systems [167, 168]

	Compensation in cent/kWh	
Scheme	Self-consumption	Feed-in
KWKG 2012	5.41	5.41
KWKG 2016	4.00	8.00

Table B.13: This thesis: fictional power limit signal for electricity

	Limit and penalty factor τ	
Commodity	Feed-in / capacitive	Consumption / inductive
Active power	3000 W, $\tau_{\mathrm{a}}^{\mathrm{lower}} \in 0, 1$	3000 W, $\tau_{\mathrm{a}}^{\mathrm{upper}} = 1$
Reactive power	Unlimited	Unlimited

Table B.14: Characteristic values of the fictional time-of-use tariff based on the German standard load profile H0 proposed by Mauser (2012) [405] and Allerding (2013) [10]

	Characteristic values		
Tariff in cent/kWh	c_a^{min}	c_a^{avg}	c_a^{max}
Mauser (2012) [405], **Allerding (2013)** [10]	5.00	25.00	45.00
Fictional time-of-use tariff used in this thesis	10.00	30.00	50.00

Table B.15: Fictional time-of-use tariff based on [374] and adapted to an average price of 30 cent/kWh

	Hour of day						
Tariff in cent/kWh	22-06 h	06-12 h	12-13 h	13-17 h	17-19 h	19-22 h	**Avg.**
Liebe et al. (2015) [374]	24.50	32.87	37.15	29.55	32.87	29.55	29.29
This thesis	25.10	33.66	38.06	30.27	33.66	30.27	30.00

Table B.16: This thesis: fictional time-of-use tariffs having alternating prices of 20 and 40 cent/kWh or of 10 and 50 cent/kWh, respectively, and an average price of 30 cent/kWh

	Hour of day						
Tariff in cent/kWh	00-02 h	02-04 h	04-06 h	06-08 h	...	22-24 h	**Avg.**
Variant A	20.00	40.00	20.00	40.00	...	40.00	30.00
Variant B	10.00	50.00	10.00	50.00	...	10.00	30.00

Table B.17: Fictional compensation schemes for PV and microCHP systems

	Compensation in cent/kWh	
Generator	Self-consumption	Feed-in
PV system	0.00	10.00
microCHP	5.00	9.00

B.3 Households and Household Energy Consumption

Table B.18: Appliances: average yearly electrical energy consumption in kWh/a, depending on the size of the household, the electrical generation of domestic hot water (DHW; yes: with DHW utilizing electricity, no: without DHW, all: average of all households), and the correction of the appliance penetration

	Number of persons						
Reference	1	2	3	4	5	**DHW**	**Corrected**
Bost et al. (2011) [90]	1734	2952	3892	4506	–	all	no
Energieagentur.NRW (2011) [191]	2256	3248	4246	5009	5969	all	no
Energieagentur.NRW (2015) [192]	2229	3202	4193	4955	5928	all	no
Energieagentur.NRW (2011) [191]	2818	3843	5151	6189	7494	yes	no
Energieagentur.NRW (2015) [192]	2880	3781	5053	6103	7310	yes	no
Grießhammer et al. (2012) [263]	2750	4140	5030	5950	7170	yes	no
Energieagentur.NRW (2011) [191]	1798	2850	3733	4480	5311	no	no
Energieagentur.NRW (2015) [192]	1714	2812	3704	4432	5317	no	no
Grießhammer et al. (2012) [263]	1750	3140	3630	4150	4970	no	no
Corrected data based on [192]	1908	3023	3970	4726	5558	no	**yes**
This thesis	2000	3100	4000	4700	5200	no	(yes)

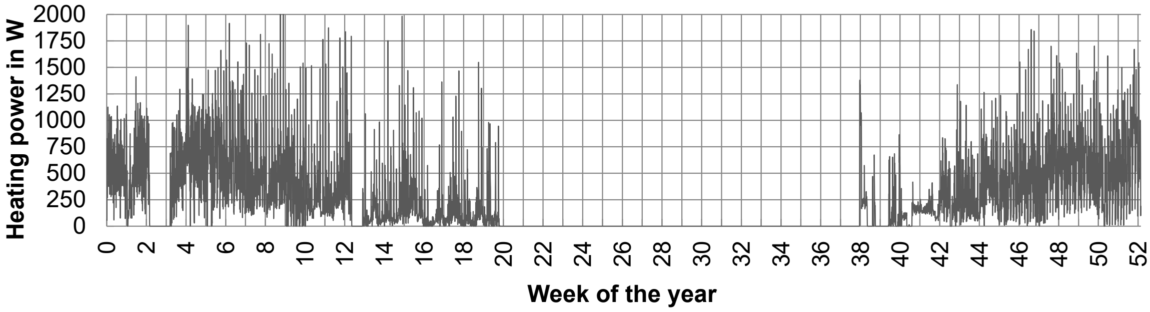
Table B.19: Appliances: 1. Degree of equipment in Germany in the year 2015, data from [164]; 2. Share of the average yearly electrical energy consumption of activities in households without electrical generation of domestic hot water, data from [192]; 3. Share of the average yearly electrical energy consumption of the five major appliances in this thesis, depending on the household size

		Number of persons				
	Appliance	1	2	3	4	5
1. Degree of equipment	Dishwasher	48.9 %	79.8 %	88.0 %	91.0 %	96.7 %
	Hob	–	–	–	–	–
	Oven	–	–	–	–	–
	Tumble dryer	22.9 %	46.3 %	54.5 %	60.3 %	69.2 %
	Washing machine	88.8 %	96.9 %	98.0 %	98.9 %	98.6 %
2. Consumption share ↪ (activities)	Dish washing	2.8 %	5.1 %	6.3 %	6.9 %	7.0 %
	Cooking/baking	11.1 %	12.2 %	10.8 %	10.7 %	9.7 %
	Drying	2.3 %	5.2 %	7.4 %	8.9 %	9.4 %
	Washing machine	4.2 %	4.8 %	5.4 %	5.7 %	6.1 %
	Total	20.4 %	27.3 %	30.0 %	32.3 %	32.3 %
3. Consumption share ↪ (appliances)	Dishwasher	4.9 %	5.6 %	6.5 %	7.1 %	7.1 %
	Hob	5.6 %	6.4 %	5.8 %	5.6 %	5.3 %
	Oven	4.4 %	5.0 %	4.5 %	4.4 %	4.1 %
	Tumble dryer	9.6 %	10.8 %	12.6 %	13.8 %	12.9 %
	Washing machine	4.3 %	4.6 %	5.0 %	5.4 %	5.7 %
	Total	28.7 %	32.3 %	34.3 %	36.3 %	35.2 %

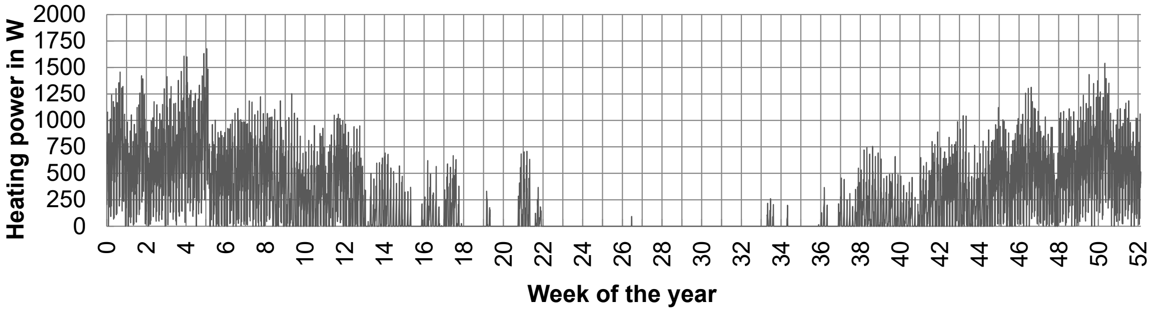
B.4 KIT Energy Smart Home Lab

Table B.20: *KIT Energy Smart Home Lab*: technical data, partly based on [355]

Device/system	**Specification/details**	**Manufacturer and type**
PV system	Electrical peak power: 4.68 kW_p	–
PV panels	24x 195 W, polycrystalline	*Sovello SV-T-195*
PV inverter	10 kVA, 3-phase	*SMA Tripower STP10000TL-10*
MicroCHP	Electrical power: 5.5 kW, thermal power: 12.5 kW, LPG power: 20.5 kW	*SenerTec Dachs G 5.5 standard*, liquefied petroleum gas (LPG)
Electrical IHE	Electrical power: 9.0 kW	*Eltra 2NP 5635-290*
Hot water storage tank	750 liters	*SenerTec SE 750*
Air-conditioning system	Cooling power: 6 kW	*Mitsubishi PUHZ-RP60VHA4*
Chilled water storage tank	200 liters	Custom-made
Phase change material	Melting temperature: 22–28 °C	*DeltaSystems DELTA-COOL 24*
HVAC controller	Climate controller	*Kieback & Peter BMR410*, *FBU410*
Appliance gateway	Power-line Communication (PLC)	*Miele XGW 2000 Miele@home*
ditto	*ZigBee*	*Miele XGW 3000 Miele@home*
Dishwasher	PLC, *ZigBee*	*Miele G 1834 SCi*
Induction hob	PLC, *ZigBee*	*Miele KM 5956*
Electrical oven	PLC, *ZigBee*	*Miele H 5681 BL*
Conventional tumble dryer	PLC, *ZigBee*	*Miele T 8687 C*
Washing machine	PLC, *ZigBee*	*Miele W 3985 WPS*
Automated coffee machine	PLC, *ZigBee*	*Miele CVA 5065*
Refrigerator	No communication	*Liebherr IKS 1720*
Deep-freezer	RS485	*Liebherr GN 3056*
Building automation	*WAGO-I/O-SYSTEM 750* Relay output module Digital in/out module	*WAGO 750-8204* *WAGO 750-523* *WAGO 750-430/530*
BEMS	OSH gateway	*Raspberry Pi 3 Model B*
Phasor measurement unit	3-phase power quality, 25 kHz	*Electrical Data Recorder* [388]
Electric metering system	*WAGO-I/O-SYSTEM 750*	*WAGO 750-8204*
Electric meter	3- &4-phase metering	*WAGO 750-494*, *750-495*
ditto	Smart plugs	*Plugwise Circle*
Thermal metering system	KNX gateway	*Lingg & Janke eibSOLO*
Thermal meter	Cooling meters	*Kamstrup MULTICAL 601*
Air quality sensors	USB, volatile organic compounds	*AppliedSensor AS-MLV-P*
Radio beacons	*Bluetooth LE / Smart* (BLE) BLE gateway	*blukii SmartSensor / S* Proprietary gateway
4-quadrant amplifier	+30 kVA/-15 kW ($U \leq 270V_{RMS}$)	3x *Spitzenberger&Spies* ↪ *PAS 10000/RL 4000*
Grid switching box	Interruption-free ↪ supply system switching	Custom-Made
DC source	PV simulator	*ET System LAB/SMS 31000*
Firewall	Dedicated server	*IPFire 2*
Access Point	Wireless access point	*Ubiquiti UniFi AP-Pro*



(a) Real consumption in the year 2014; data obtained by the thermal metering system; the building's original consumption was 4146 kWh/a



(b) Simulated consumption of an average year; based on a TRNSYS simulation by Gräßle et al. (2011) [256] and Allerding (2013) [10]

Figure B.1: *KIT Energy Smart Home Lab*: real and simulated heating demands of the building, both scaled to a yearly consumption of 2000 kWh

B.5 FZI House of Living Labs

Table B.21: *FZI House of Living Labs*: technical data, partly based on [62]

Device/system	**Specification/details**	**Manufacturer and type**
PV-battery system	Electrical peak power: 15.1 kW$_p$, storage capacity: 15.0 kWh	
PV panels	108 x 140 W$_p$, CIS-thin-film	*Würth Solar WSF0002E140*
Batteries	6 x 5.0 kWh, lead-acid	*BAE AK40012*
PV and battery inverter	3 x 5.0 kVA	*Nedap PowerRouter PR50SB*
MicroCHP	Electrical power: 5.5 kW, gas power: 20.5 kW, thermal power: 12.5 kW	*SenerTec Dachs G 5.5 standard*, natural gas
Condensing boiler	Max. thermal power: 95 kW	*Elco THISION L 100*
Electrical IHE	Electrical power: 0.0, 0.5 ... 3.5 kW	*E.G.O. EGO Smart Heater*
Hot water storage tank	1 x 1650 & 1 x 1600 liters	*Maatz Christensen*, custom-made
Electric vehicle	Max. charging power: 22 kW, capacity: 15.1 kWh	*Smart Fortwo Electric Drive*
ditto	Max. charging power: 3.6 kW, capacity: 40.0 kWh	*Peugeot 3008* (modified)
Adsorption chiller	Nominal cooling power: 9.0 kW	*InvenSor LTC 09*
Dry cooler	Nominal recooling power: 24.0 kW	*InvenSor BE 24*
Chilled water storage tank	2 x 1500 liters	*Maatz Christensen*, custom-made
Ceiling cassette	Cooling power: 2 x 2.2 kW	*Remko KWD 30*
HVAC controller	System controller	*SolarNext chillii*
Thermal metering system	KNX gateway	*Aquametro AMBUS Net*
Thermal meter	Heat, cool meters	*Aquametro CALEC ST*
Electric meter	Metering of electricity	*Landis+Gyr E750*
ditto	Submetering	*B-Control EM210*
ditto	Smart plugs	*E.G.O. Smart Plug*
ditto	Smart plugs	*Plugwise Circle*
Appliance gateway	*ZigBee*, *EnOcean*, *KNX-RF*	*E.G.O. Smart Gateway*
Dishwasher	–	*Neff S42T69N3EU/4*
ditto	–	*Asko DW 90.2*
Induction hob	–	*Gutmann Induktion*, 6 zones
Electrical oven	–	*Stoves SEB900MFSe*
ditto	–	*Bosch HBR78B751*
Conventional dryer	–	*Bosch WTL6500*
Heat pump dryer	–	*Bosch WTW86562*
Washing machine	–	*Hyundai WFC1047D10*
Coffee machine	–	*Siemens EQ.5*
Microwave	–	*Bosch HMT75M451*
Fridge-freezer	–	*Liebherr ICBN 3066*
Automation	*Bluetooth LE / Smart*	Proprietary gateway (PG)
ditto	*EEBus*	*E.G.O. Smart Gateway* (EGW)
ditto	*EnOcean*	EGW, PG
ditto	*HabiTeq*	*GE HabiTeq CTD Controller*
ditto	*KNX*, *KNX-RF*	*tebis KNX*, EGW
ditto	*ZigBee*	EGW

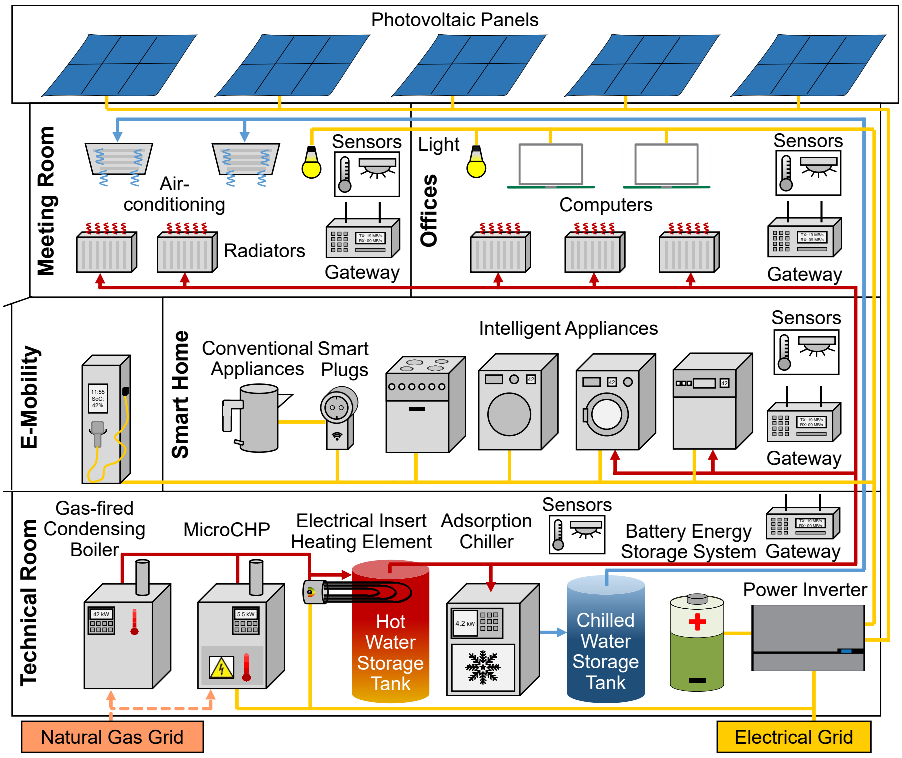


Figure B.2: *FZI House of Living Labs*: overview of the devices and systems in the local energy system, based on [62, Fig. 1]

Table B.22: Information about the dry cooler model data set

	Property	Value
Cooler data set	Source:	HoLL
	Temporal resolution:	1 minute
Temperature data ↪ set Karlsruhe	Source:	*Deutscher Wetterdienst* [169]
	Temporal resolution:	1 hour
Resulting data set	Number n of observations:	$n = 43\,268$
	Date of first observation in data set:	2014-04-30T16:59:00+00:00
	Date of last observation in data set:	2015-11-09T20:06:00+00:00
Data cleansing	Volumetric flow rate Q of cooler:	$0.1\,\mathrm{m}^3/\mathrm{h} < Q$
	Thermal power P of the cooler:	$0\,\mathrm{kW} < P < 30\,\mathrm{kW}$
	Temperature θ_r of return is smaller ↪ than temperature of flow θ_f:	$\theta_\mathrm{r} < \theta_f$
	see also Listing F.12 on p. 443	

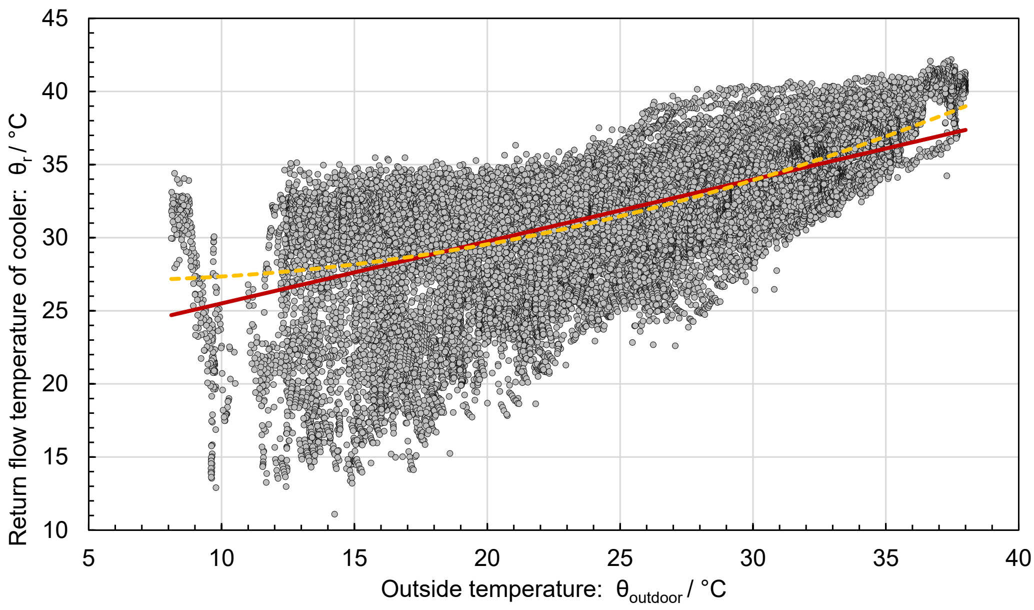


Figure B.3: *FZI House of Living Labs*: scatter plot of the outdoor temperature and the return flow temperature of the dry cooler (solid red line: first degree polynomial regression, dashed yellow line: second degree polynomial regression), data set is described in Table B.22 on p. 390

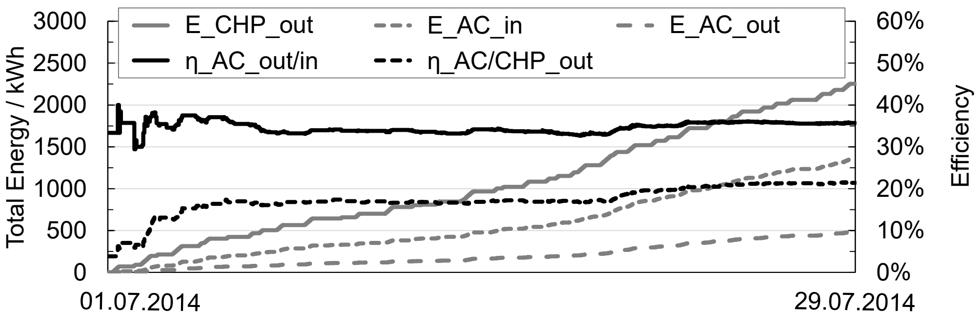


Figure B.4: *FZI House of Living Labs*: development of the cumulative energy of the hot water generation “E_CHP_out” by the microCHP as well as the consumption “E_AC_in” and the chilled water generation “E_AC_out” by the adsorption chiller, resulting in the calculated efficiencies (i. e., COPs) “η_AC_out/in” of the adsorption chiller and “η_AC/CHP_out” of the overall trigeneration system in July 2014

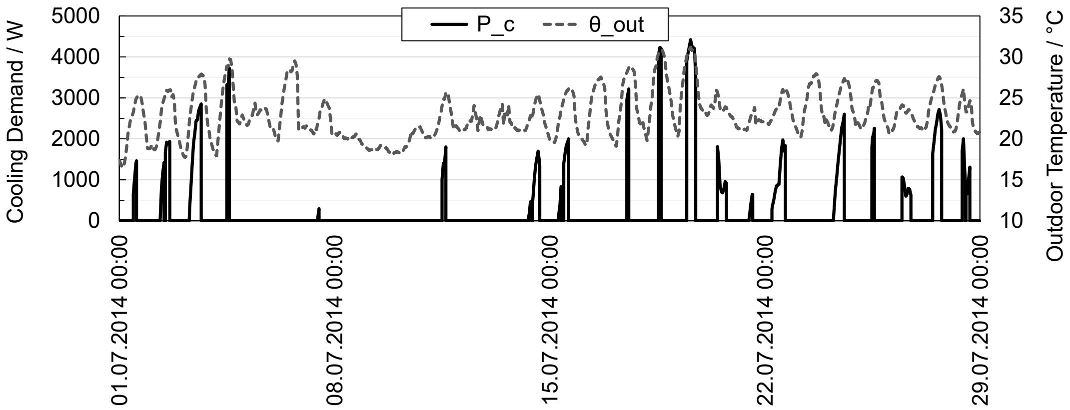


Figure B.5: *FZI House of Living Labs*: simulated space cooling demand "P_c" and outdoor temperature "θ_out" in July 2014

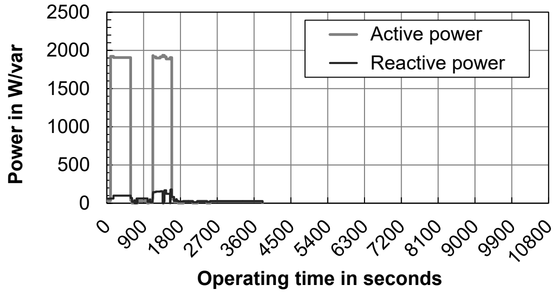
Table B.23: Data set: list of the used real reservations in the *FZI House of Living Labs*

Date	**Duration in s**
2014-07-01T05:30:00+00:00	7200
2014-07-01T11:00:00+00:00	9000
2014-07-02T06:00:00+00:00	18000
2014-07-02T12:00:00+00:00	12600
2014-07-03T06:00:00+00:00	36000
2014-07-04T12:00:00+00:00	7200
2014-07-07T08:30:00+00:00	12600
2014-07-08T05:30:00+00:00	34200
2014-07-09T11:30:00+00:00	12600
2014-07-10T12:00:00+00:00	21600
2014-07-11T12:00:00+00:00	10800
2014-07-14T07:30:00+00:00	31500
2014-07-15T05:30:00+00:00	12600
2014-07-15T11:00:00+00:00	13500
2014-07-17T12:15:00+00:00	5400
2014-07-18T13:00:00+00:00	7200
2014-07-19T11:00:00+00:00	25200
2014-07-20T11:00:00+00:00	25200
2014-07-21T10:00:00+00:00	16200
2014-07-22T05:30:00+00:00	37800
2014-07-24T05:00:00+00:00	32400
2014-07-25T11:30:00+00:00	7200
2014-07-26T11:00:00+00:00	25200
2014-07-27T11:00:00+00:00	25200
2014-07-28T10:00:00+00:00	9000
2014-07-28T13:00:00+00:00	10800
2014-07-29T05:30:00+00:00	7200
2014-07-29T11:00:00+00:00	10800
2014-07-30T04:30:00+00:00	10800
2014-07-30T08:00:00+00:00	7200
2014-07-30T11:30:00+00:00	7200
2014-07-31T11:00:00+00:00	16200

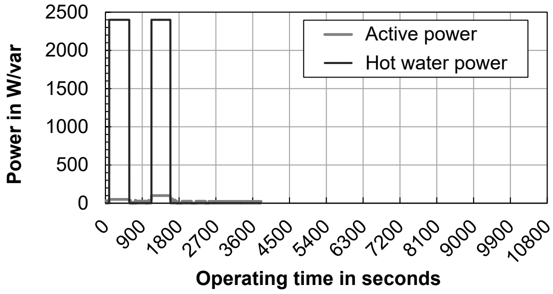
C Future Appliance Data, Analysis, and Integration

C.1 Appliance Load Profiles

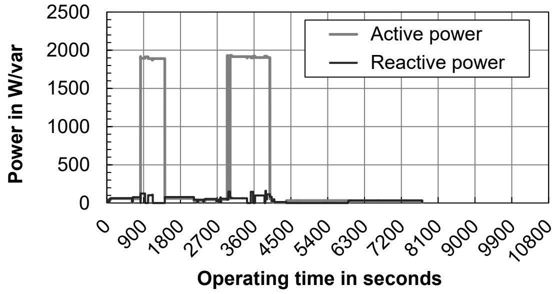
The following load profiles of exemplary appliances have been recorded in the ESHL and the HoLL. They comprise values for active and reactive power.



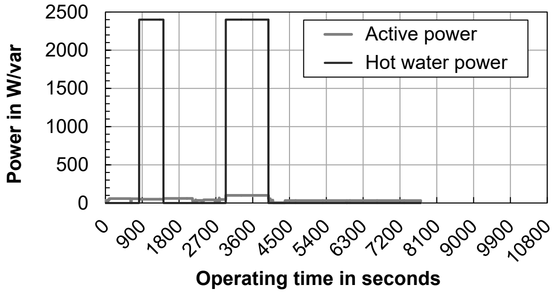
(a) DW_0



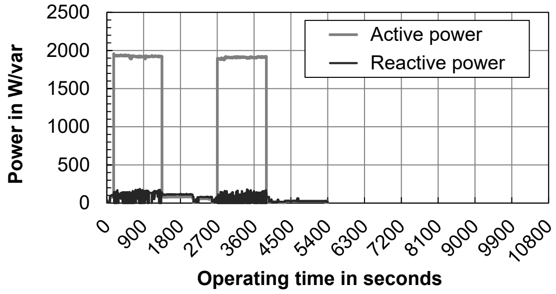
(b) DW_0_hybrid



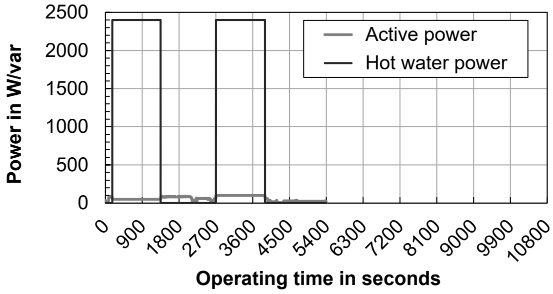
(c) DW_1



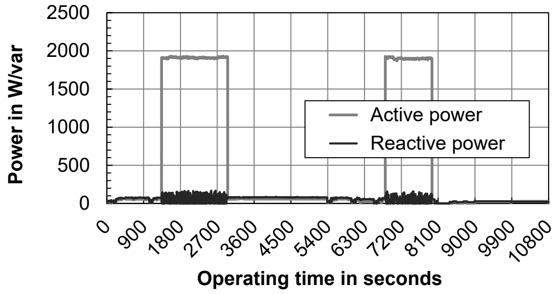
(d) DW_1_hybrid



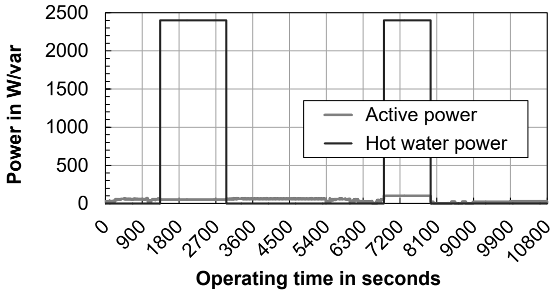
(e) DW_2



(f) DW_2_hybrid



(g) DW_3



(h) DW_3_hybrid

Figure C.1: Load profiles of the simulated dishwasher

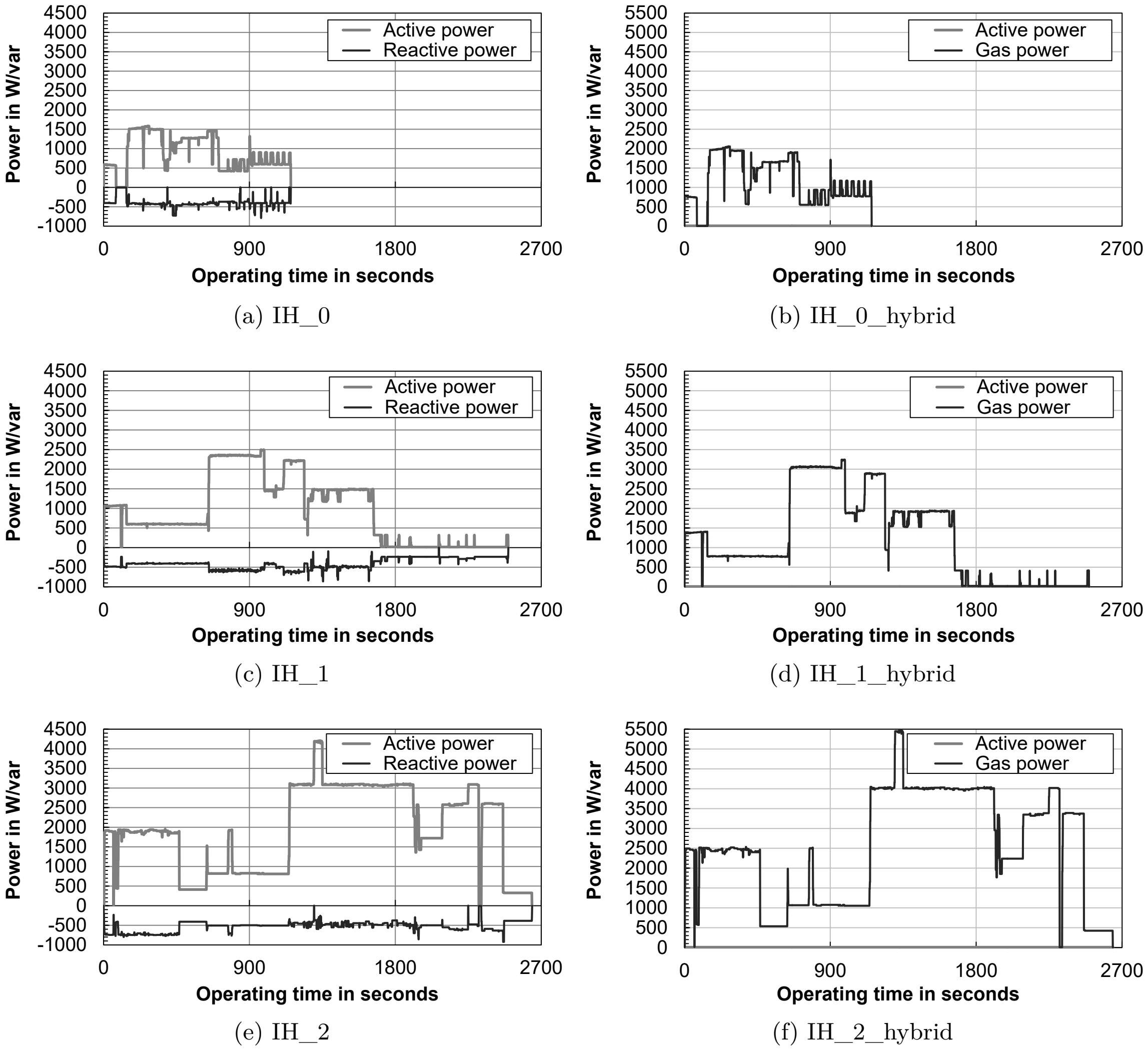
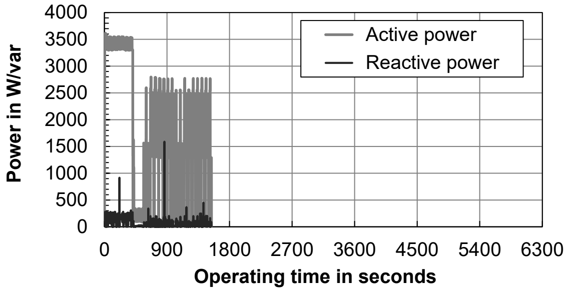
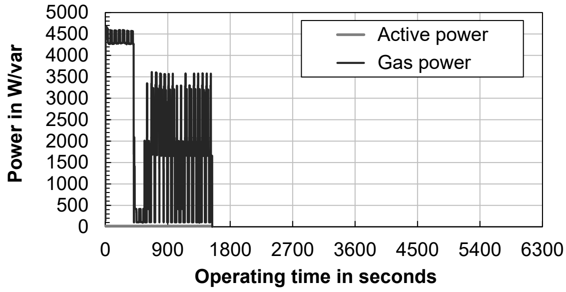


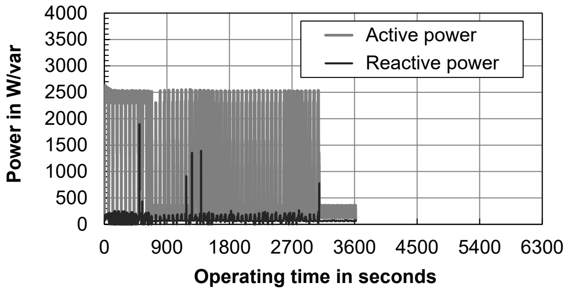
Figure C.2: Load profiles of the simulated hob



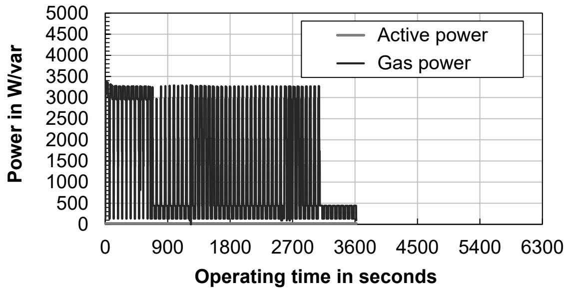
(a) OV_0



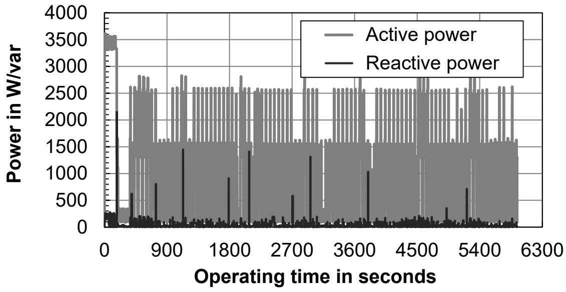
(b) OV_0_hybrid



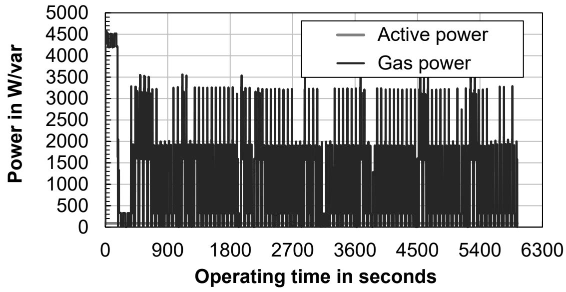
(c) OV_1



(d) OV_1_hybrid

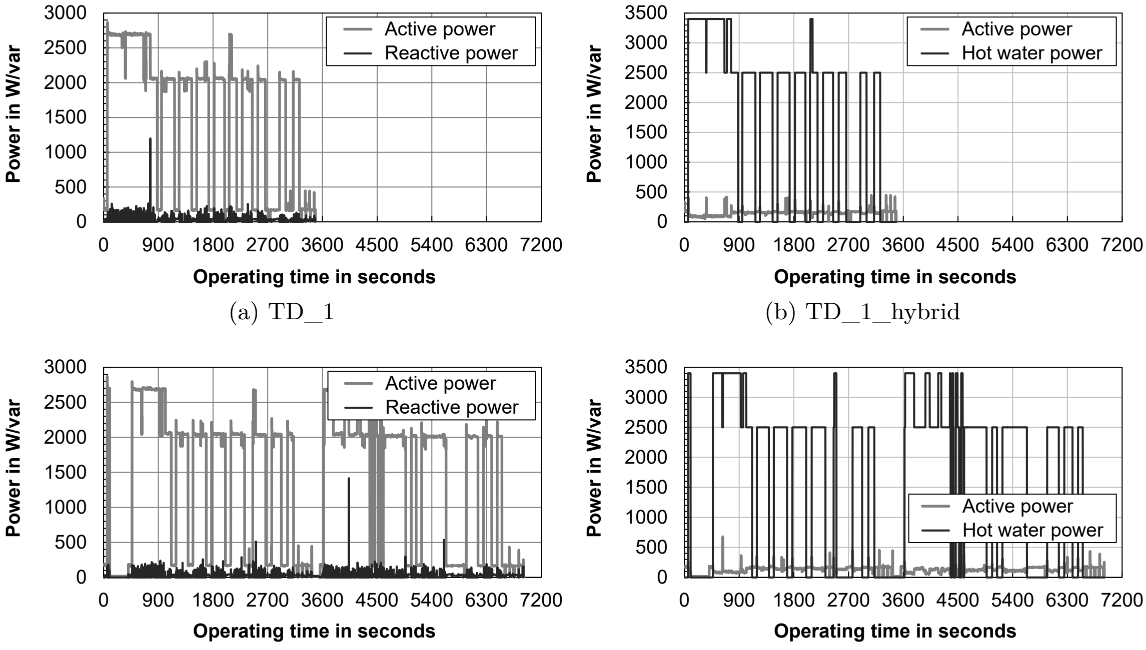


(e) OV_2



(f) OV_2_hybrid

Figure C.3: Load profiles of the simulated oven



(a) TD_1

(b) TD_1_hybrid

(c) TD_2

(d) TD_2_hybrid

Figure C.4: Load profiles of the simulated tumble dryer

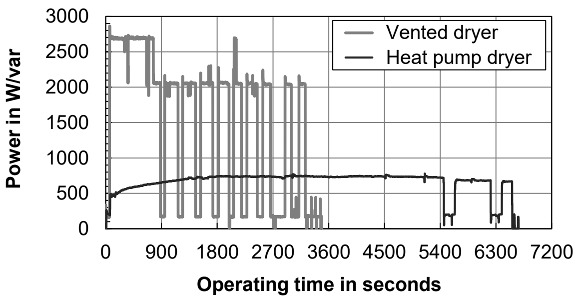
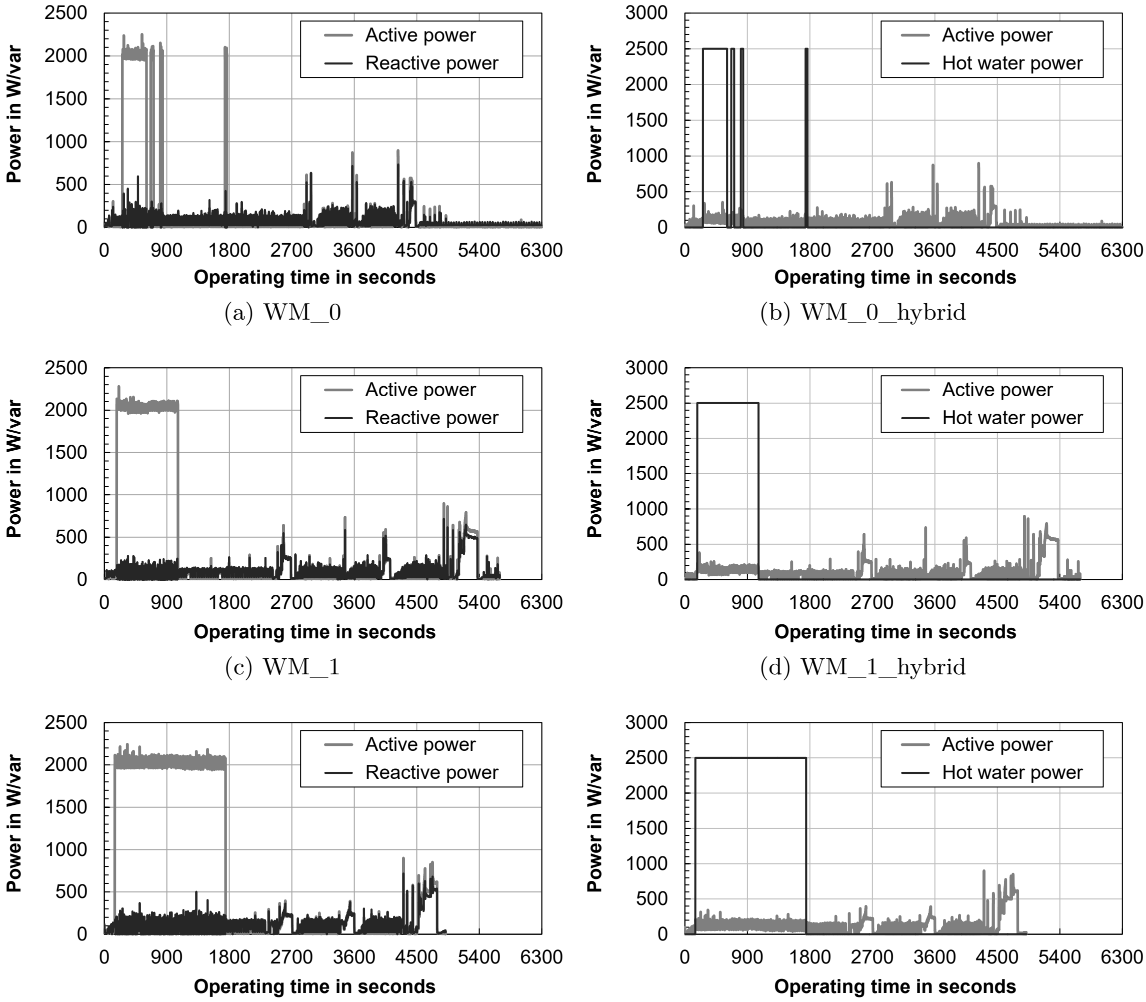


Figure C.5: Exemplary load profiles of a vented and a heat pump dryer



(a) WM_0
(b) WM_0_hybrid
(c) WM_1
(d) WM_1_hybrid
(e) WM_2
(f) WM_2_hybrid

Figure C.6: Load profiles of the simulated washing machine

C.2 Appliance Usage

Table C.1: Future appliances: electricity consumption per program and average number of operation cycles per year, household size, operation mode, and program of dishwasher (DW), hob (IH), oven (OV), tumble dryer (TD), and washing machine (WM)

							Energy consumption per cycle in kWh		
		Number of persons					Conventional mode	Hybrid mode	
Program ID	**Share**	1	2	3	4	5	Electricity	Electricity	Hot water / gas
DW_0	0.2	18	32	48	62	68	0.523	0.037	0.636
DW_1	0.3	27	48	72	93	102	0.927	0.100	1.091
DW_2	0.3	27	48	72	93	102	1.303	0.087	1.587
DW_3	0.2	18	32	48	62	68	1.547	0.140	1.839
Total	1.0	90	160	240	310	340	1.083	0.091	1.298
IH_0	0.4	68	120	140	160	168	0.290	0.003	0.377
IH_1	0.4	68	120	140	160	168	0.648	0.006	0.843
IH_2	0.2	34	60	70	80	84	1.421	0.006	1.847
Total	1.0	170	300	350	400	420	0.659	0.004	0.858
OV_0	0.4	34	60	70	80	84	0.757	0.008	0.974
OV_1	0.4	34	60	70	80	84	1.094	0.020	1.396
OV_2	0.2	17	30	35	40	42	1.435	0.145	1.677
Total	1.0	85	150	175	200	210	1.027	0.040	1.284
TD_1	0.2	16	28	42	54	56	1.457	0.144	1.724
TD_2	0.8	64	112	168	216	224	2.628	0.251	3.010
Total	1.0	80	140	210	270	280	2.394	0.230	2.753
WM_0	0.3	24	40	56	72	82	0.363	0.125	0.314
WM_1	0.5	60	100	140	180	210	0.654	0.188	0.613
WM_2	0.2	36	60	84	108	126	1.039	0.197	1.108
Total	1.0	120	200	280	360	420	0.644	0.178	0.702

Table C.2: Future appliances: overview of the load profiles of dishwasher (DW), hob (IH), oven (OV), tumble dryer (TD), and washing machine (WM), showing whether there is a non-deferrable (n-d), a deferrable (d), non-interruptible (n-i), interruptible (i) profile and the number of interruptions if there are any; the number of phases is given in brackets

		Conventional mode			Hybrid mode			
Appliance	Appliance Program Configuration ID	n-d n-i	d n-i	d i	n-d n-i	d n-i	d i	Number of interruptions
DW	DW_0	✓(1)	✓(3)	✓(5)	✓(1)	✓(3)	✓(5)	1
DW	DW_1	✓(1)	✓(3)	✓(5)	✓(1)	✓(3)	✓(5)	1
DW	DW_2	✓(1)	✓(3)	✓(5)	✓(1)	✓(3)	✓(5)	1
DW	DW_3	✓(1)	✓(3)	✓(5)	✓(1)	✓(3)	✓(5)	1
IH	IH_0	✓(1)	✗	✗	✓(1)	✗	✗	–
IH	IH_1	✓(1)	✗	✗	✓(1)	✗	✗	–
IH	IH_2	✓(1)	✗	✗	✓(1)	✗	✗	–
OV	OV_0	✓(1)	✗	✗	✓(1)	✗	✗	–
OV	OV_1	✓(1)	✗	✗	✓(1)	✗	✗	–
OV	OV_2	✓(1)	✗	✗	✓(1)	✗	✗	–
TD	TD_1	✓(1)	✓(3)	✓(9)	✓(1)	✓(3)	✓(9)	3
TD	TD_2	✓(1)	✓(3)	✓(9)	✓(1)	✓(3)	✓(9)	3
WM	WM_0	✓(1)	✓(3)	✓(5)	✓(1)	✓(3)	✓(5)	1
WM	WM_1	✓(1)	✓(3)	✓(5)	✓(1)	✓(3)	✓(5)	1
WM	WM_2	✓(1)	✓(3)	✓(5)	✓(1)	✓(3)	✓(5)	1

Table C.3: Appliance usage probability: Weekday (dishwasher (DW), induction hob (IH), electrical oven (OV), tumble dryer (TD), washing machine (WM))

Hour of day	DW	IH	OV	TD	WM	Weighted average
00:00	0.008	0.001	0.001	0.004	0.006	0.004
01:00	0.006	0.000	0.000	0.002	0.005	0.003
02:00	0.005	0.000	0.000	0.002	0.005	0.003
03:00	0.005	0.000	0.000	0.002	0.005	0.003
04:00	0.007	0.000	0.000	0.002	0.011	0.004
05:00	0.010	0.005	0.005	0.005	0.015	0.008
06:00	0.020	0.034	0.020	0.014	0.029	0.022
07:00	0.028	0.036	0.023	0.020	0.043	0.028
08:00	0.047	0.025	0.033	0.032	0.066	0.039
09:00	0.052	0.031	0.039	0.049	0.084	0.050
10:00	0.052	0.052	0.061	0.083	0.090	0.070
11:00	0.053	0.077	0.085	0.085	0.084	0.078
12:00	0.047	0.121	0.125	0.082	0.070	0.086
13:00	0.054	0.099	0.103	0.092	0.064	0.083
14:00	0.068	0.043	0.044	0.100	0.060	0.070
15:00	0.066	0.039	0.040	0.067	0.057	0.057
16:00	0.046	0.055	0.060	0.050	0.057	0.053
17:00	0.045	0.058	0.063	0.049	0.054	0.052
18:00	0.069	0.117	0.104	0.058	0.048	0.075
19:00	0.081	0.113	0.101	0.056	0.052	0.076
20:00	0.095	0.044	0.043	0.042	0.043	0.052
21:00	0.081	0.029	0.029	0.045	0.033	0.045
22:00	0.036	0.013	0.013	0.037	0.013	0.026
23:00	0.019	0.007	0.007	0.024	0.006	0.015

Table C.4: Appliance usage probability: Saturday (dishwasher (DW), induction hob (IH), electrical oven (OV), tumble dryer (TD), washing machine (WM))

Hour of day	DW	IH	OV	TD	WM	Weighted average
00:00	0.011	0.001	0.001	0.007	0.009	0.006
01:00	0.009	0.001	0.001	0.005	0.007	0.005
02:00	0.008	0.001	0.001	0.003	0.006	0.004
03:00	0.006	0.001	0.001	0.004	0.006	0.004
04:00	0.008	0.006	0.006	0.004	0.012	0.007
05:00	0.012	0.009	0.009	0.007	0.017	0.010
06:00	0.021	0.030	0.017	0.017	0.032	0.022
07:00	0.029	0.038	0.025	0.028	0.042	0.032
08:00	0.046	0.027	0.034	0.037	0.067	0.041
09:00	0.056	0.034	0.041	0.043	0.082	0.049
10:00	0.057	0.052	0.061	0.066	0.087	0.064
11:00	0.058	0.073	0.081	0.076	0.084	0.074
12:00	0.046	0.110	0.114	0.081	0.068	0.082
13:00	0.053	0.093	0.098	0.078	0.063	0.077
14:00	0.069	0.038	0.039	0.082	0.058	0.062
15:00	0.063	0.047	0.048	0.086	0.056	0.065
16:00	0.043	0.061	0.066	0.055	0.054	0.055
17:00	0.050	0.064	0.069	0.066	0.052	0.061
18:00	0.065	0.122	0.109	0.061	0.048	0.077
19:00	0.070	0.116	0.104	0.060	0.050	0.076
20:00	0.083	0.039	0.038	0.053	0.043	0.053
21:00	0.080	0.024	0.023	0.037	0.034	0.040
22:00	0.037	0.010	0.010	0.029	0.016	0.023
23:00	0.021	0.003	0.003	0.017	0.008	0.012

Table C.5: Appliance usage probability: Sunday (dishwasher (DW), induction hob (IH), electrical oven (OV), tumble dryer (TD), washing machine (WM))

Hour of day	DW	IH	OV	TD	WM	Weighted average
00:00	0.011	0.001	0.001	0.007	0.009	0.006
01:00	0.008	0.001	0.001	0.005	0.007	0.004
02:00	0.008	0.001	0.001	0.003	0.006	0.004
03:00	0.007	0.001	0.001	0.003	0.006	0.004
04:00	0.008	0.006	0.006	0.003	0.012	0.006
05:00	0.013	0.009	0.009	0.007	0.017	0.010
06:00	0.022	0.028	0.015	0.017	0.031	0.022
07:00	0.027	0.036	0.023	0.021	0.040	0.028
08:00	0.045	0.030	0.037	0.029	0.058	0.038
09:00	0.053	0.043	0.050	0.037	0.074	0.048
10:00	0.055	0.063	0.072	0.068	0.085	0.068
11:00	0.055	0.096	0.105	0.077	0.085	0.081
12:00	0.050	0.122	0.126	0.091	0.068	0.090
13:00	0.049	0.083	0.087	0.080	0.061	0.073
14:00	0.069	0.032	0.033	0.072	0.058	0.057
15:00	0.059	0.041	0.042	0.058	0.056	0.053
16:00	0.047	0.055	0.060	0.056	0.054	0.054
17:00	0.052	0.058	0.063	0.068	0.053	0.060
18:00	0.071	0.118	0.105	0.066	0.054	0.079
19:00	0.070	0.112	0.100	0.067	0.055	0.078
20:00	0.082	0.036	0.035	0.050	0.046	0.051
21:00	0.080	0.021	0.020	0.051	0.036	0.045
22:00	0.037	0.006	0.006	0.040	0.019	0.026
23:00	0.022	0.002	0.002	0.024	0.010	0.015

C.3 Future Appliances, Miele Appliances, and Baseload

Table C.6: Major Future and Miele appliances: analysis

Aspect		Details
Utilization	Source	Grid connection point, local storage
	Energy carrier	Electricity, natural gas, hot water
Distribution	Carrier	–
Conversion	From	–
	To	–
Storage	Storage	–
	Energy carrier	–
Provision	Energy carrier	–
	Energy service	Household functions
Interdependencies	Relations	Local electricity grid (voltage), hot water storage tank (temperature), ambient temperature
	Connections	Local electricity grid, natural gas grid, hot water storage tank
Control	Internal logic	Appliance program logic
	Parameters	Appliance program, selected extras of appliance program
User	Interaction	Appliance program, selected extras of appliance program
	Preferences	Maximum deferral (TDoF)
Energy management	Settings (from EMS)	Start time, program alternative (EDoF), temperature set points
	Commands (from EMS)	Start, pause/interrupt, stop
	Predictions (from EMS)	–
	Predictions (to EMS)	Appliance usage, energy consumption, expected load profile
	Information (to EMS)	Remaining operating time, remaining load profile, available load profiles
Model	Input	User interaction, commands
	Output	Device state
	Efficiency	–
Availability/presence	Temporal	Program driven

Table C.7: Future appliances: integration into the *Organic Smart Home*

Parameter / Property		**Details**
Driver	Simulation device driver	`class GenericFutureApplianceSimulationDriver`
	Device driver	`abstract class GenericApplianceDriver`
	Bus driver	–
Local O/C-unit	Local Observer	`class FutureApplianceLocalObserver`
	Local Controller	`class FutureApplianceLocalController`
	Observer Exchange	`class FutureApplianceMOX`
	Model of Observation Exchange	`class FutureApplianceObserverExchange`
	Controller Exchange	`class FutureApplianceControllerExchange`
IPP	Non-controllable	`class FutureApplianceNonControllableIPP`
	Controllable	`class FutureApplianceIPP`
	Optimization horizon $\mathcal{H}$ (duration)	$\lvert\mathcal{H}\rvert = t^{\text{dof,max}} + t^{\text{o}}$
	Trigger optimization	Change of device state (on, programmed, ...), change of TDoF orEDoF
IPP control model	Encoding of bit string B	$B = [0,1]^b$
	Length b of bit string	$b = b^{\text{tdof}} + b^{\text{edof}}$ $\hookrightarrow = \lceil \log_2 \left(t^{\text{dof,max}}\right) \rceil \cdot p + \lceil \log_2 (a) \rceil$
	Number of time slots p	–
	Selected TDoF	$t^{\text{dof}} = \max(t_i^{\text{min}},$ $\hookrightarrow\ \min(t_i^{\text{max}}, \lceil \frac{\text{gray}^{-1}(B_i)}{\sum_{i=1}^{p} \text{gray}^{-1}(B_i)} \cdot t^{\text{dof,max}} \rceil))$
	Selected EDoF	$k = \lfloor \lvert B\rvert \cdot \frac{a}{2^b} \rfloor$
	Control sequence $\mathcal{C}$	$\mathcal{C} = \left(T^{\text{dof}}, k\right) = \left((t_1^{\text{dof}} \ldots t_p^{\text{dof}}), k\right)$
	Finite-state machine $\mathcal{F}$	–
	Additional penalty $\mathcal{P}$	$\mathcal{P}$ based on starting time
	Operating strategy / control logic	–
IPP entity model	Original devices	–
	Model	`ApplianceProgramConfigurations.xsd,` `ApplianceProgramConfigurationStatus.java`

Table C.8: Miele appliances: integration into the *Organic Smart Home*

Parameter / Property		**Details**
Driver	Simulation device driver	`class GenericMieleApplianceSimulationDriver`
	Device driver	`class MieleApplianceDriver`
	Bus driver	`class MieleGatewayBusDriver`
Local O/C-unit	Local Observer	`class MieleApplianceLocalObserver`
	Local Controller	`class MieleApplianceLocalController`
	Observer Exchange	`class MieleApplianceMOX`
	Model of Observation Exchange	`class MieleApplianceObserverExchange`
	Controller Exchange	`class MieleApplianceControllerExchange`
IPP	Non-controllable	`class MieleApplianceNonControllableIPP`
	Controllable	`class MieleApplianceIPP`
	Optimization horizon $\mathcal{H}$ (duration)	$\lvert\mathcal{H}\rvert = t^{\text{dof,max}} + t^{\text{o}}$
	Trigger optimization	Change of device state (on, programmed, ...), change of TDoF
IPP control model	Encoding of bit string B	$B = [0, 1]^b$
	Length b of bit string	$b = b^{\text{tdof,max}} = \lceil \log_2 \left(t^{\text{dof,max}}\right) \rceil$
	Number of time slots p	–
	Selected TDoF	t^{dof}
	Selected EDoF	–
	Control sequence $\mathcal{C}$	$\mathcal{C} = t^{\text{dof}}$
	Finite-state machine $\mathcal{F}$	–
	Additional penalty $\mathcal{P}$	–
	Operating strategy / control logic	–
IPP entity model	Original devices	See Table B.20 on p. 387
	Model	–

Table C.9: Baseload: integration into the *Organic Smart Home*

Parameter / Property		**Details**
Driver	Simulation device driver	`class BaseloadSimulationDriver`
	Device driver	–
	Bus driver	–
Local O/C-unit	Local Observer	`class BaseloadLocalObserver`
	Local Controller	–
	Observer Exchange	–
	Model of Observation Exchange	`class BaseloadObserverExchange`
	Controller Exchange	–
IPP	Non-controllable	`class BaseloadNonControllableIPP`
	Controllable	–
	Optimization horizon $\mathcal{H}$ (duration)	$\lvert\mathcal{H}\rvert = 0\,\text{h}$
	Trigger optimization	–
IPP control model	Encoding of bit string B	$B = \emptyset$
	Length b of bit string	$b = 0$
	Control sequence $\mathcal{C}$	–
	Finite-state machine $\mathcal{F}$	–
	Additional penalty $\mathcal{P}$	–
	Operating strategy / control logic	–
IPP entity model	Original devices	–
	Model	–

D Other Entity Data, Analysis, and Integration

D.1 Micro Combined Heat and Power Plant

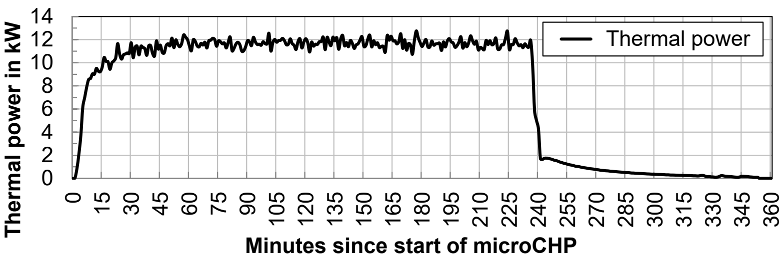


Figure D.1: Exemplary thermal load profile of the *SenerTec Dachs G 5.5 standard*, measured at the *FZI House of Living Labs* in 2015

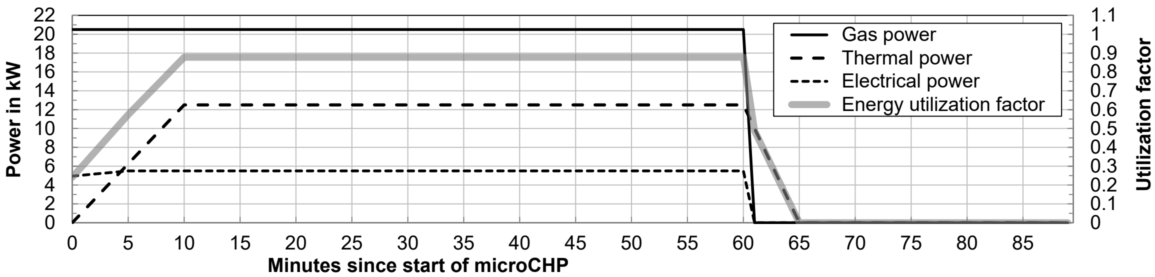


Figure D.2: Model of the microCHP: Gas power, thermal power, electrical power and resulting energy utilization factor for an operation cycle of 60 min

Table D.1: Micro combined heat and power plant: analysis

Aspect		**Details**
Utilization	Source	Grid connection point, local storage
	Energy carrier	Natural gas, liquid gas
Distribution	Carrier	–
Conversion	From	Natural/liquid gas
	To	Electricity, hot water
Storage	Storage system	–
	Energy carrier	–
Provision	Energy carrier	Electricity, hot water
	Energy service	–
Interdependencies	Relations	Grid connection point (voltage, frequency), hot water storage tank (temperature), outdoor temperature
	Connections	Hot water storage tank, local electricity grid
Control	Internal logic	On-off control (hysteresis), operating time control, device overheating protection, legionella protection
	Parameters	Min./max. operating time, min./max. off time, min./max. temperature (tank) min./max. temperature (device)
User	Interaction	–
	Preferences	Temperature settings, execution time of legionella protection
Energy management	Settings (from EMS)	Heat-/electricity-led, operating point
	Commands (from EMS)	Switch on/off, change operating point
	Predictions (from EMS)	Heating demand, electricity demand
	Predictions (to EMS)	–
	Information (to EMS)	Remaining min./max. times
Model	Input	Parameters, commands, operating point
	Output	Device state, primary energy input, thermal and electrical efficiency
	Efficiency	Non-linear, depending on operating point and time
Availability/presence	Temporal	Practically always, depending on the state of the storage

Table D.2: Micro combined heat and power plant: integration into the *Organic Smart Home*

Parameter / Property		**Details**
Drivers	Simulation device driver	`class DachsChpSimulationDriver`
	Device driver	`class DachsChpDriver`
	Bus driver	–
Local O/C-unit	Local Observer	`class DachsChpLocalObserver`
	Local Controller	`class DachsChpLocalController`
	Observer Exchange	`class ChpObserverExchange`
	Model of Observation Exchange	`class DachsChpMOX`
	Controller Exchange	`class ChpControllerExchange`
IPP	Non-controllable	`class DachsChpNonControllableIPP`
	Controllable	`class DachsChpIPP`
	Optimization horizon $\mathcal{H}$ (duration)	$\lvert\mathcal{H}\rvert = 24\,\mathrm{h}$
	Update	At least every 1 h
	Trigger optimization	Forced turn on/off, at least every 4 / 3 hours (residential/commercial)
IPP control model	Encoding of bit string B	$B = [0, 1]^b$
	Length b of bit string	$b = 4 \cdot p$ / $b = 5 \cdot p$ (residential/commercial)
	Number of time slots p	$p = \lvert\mathcal{H}\rvert$ / 5 min
	Control sequence $\mathcal{C}$	$B \xrightarrow{\mathcal{F}} \mathcal{C} = \left(t_1^{\text{toggle}} \ldots t_{i,\max}^{\text{toggle}}\right)$
	Finite-state machine $\mathcal{F}$	$\mathcal{F}_c$
	Overall control sequence $\mathcal{C}$'	$B \xrightarrow{\mathcal{F}'} \mathcal{C}' = \left(t_1^{\text{toggle}} \ldots t_{i,\max}^{\text{toggle}}\right)'$
	Finite-state machine $\mathcal{F}$'	$\mathcal{F}$'
	Additional penalty $\mathcal{P}$	$\mathcal{P}$ for forced turn on/off
	Operating strategy / control logic	On-off control (hysteresis)
IPP entity model	Original device	*SenerTec Dachs G 5.5 standard*
	Model	`class GenericChpModel`
	Nominal active power P_a	$P_\mathrm{a} = -5500\,\mathrm{W}$
	Reactive power	$\mathrm{Cos}(\varphi) = 0.9$, inductive
	Nominal hot water power P_h	$P_\mathrm{h} = -12500\,\mathrm{W}$
	Nominal natural gas power P_n	$P_\mathrm{n} = 20500\,\mathrm{W}$
	Min. operating time	15 min
	Max. operating time	24 h
	Ramp-up: active power	5 min (linear)
	Ramp-down: active power	0 min (linear)
	Ramp-up: hot water power	10 min (linear)
	Ramp-down: hot water power	5 min (linear)
	Min. hot water set temp. $\theta_{\mathrm{h,min}}$	$\theta_{\mathrm{h,min}} = 60 / 55\,^\circ\mathrm{C}$ (residential/commercial)
	Max. hot water set temp. $\theta_{\mathrm{h,max}}$	$\theta_{\mathrm{h,max}} = 80 / 75\,^\circ\mathrm{C}$ (residential/commercial)

D.2 Adsorption Chiller

Table D.3: Adsorption chiller: analysis

Aspect		Details
Utilization	Source	Grid connection point, local storage, (district heating)
	Energy carrier	Hot water, (electricity)
Distribution	Carrier	–
Conversion	From	Hot water, (electricity)
	To	Chilled water
Storage	Storage system	–
	Energy carrier	–
Provision	Energy carrier	Chilled water
	Energy service	–
Interdependencies	Relations	Hot water storage tank (temperature), chilled water storage tank (temperature), outdoor temperature
	Connections	Hot water storage tank, chilled water storage tank, (local electricity grid)
Control	Internal logic	On-off control (hysteresis), operating time control
	Parameters	Min./max. operating time, min./max. off time, min./max. temperature
User	Interaction	–
	Preferences	–
Energy management	Settings (from EMS)	–
	Commands (from EMS)	Switch on/off
	Predictions (from EMS)	Cooling demand
	Predictions (to EMS)	–
	Information (to EMS)	Remaining min./max. times
Model	Input	Parameters, commands
	Output	Device state, primary energy input, efficiency
	Efficiency	Non-linear, depending on outdoor temperature, hot water temperature, chilled water temperature, operating time (cooling cycle)
Availability/presence	Temporal	Practically always, depending on the state of the storage

Table D.4: Adsorption chiller: integration into the *Organic Smart Home*

Parameter / Property		**Details**
Drivers	Simulation device driver	`class AdsorptionChillerSimulationDriver`
	Device driver	–
	Bus driver	–
Local O/C-unit	Local Observer	`class AdsorptionChillerLocalObserver`
	Local Controller	`class AdsorptionChillerLocalController`
	Observer Exchange	`class AdsorptionChillerObserverExchange`
	Model of Observation Exchange	`class ChillerMOX`
	Controller Exchange	`class ChillerControllerExchange`
IPP	Non-controllable	`class AdsorptionChillerNonControllableIPP`
	Controllable	`class AdsorptionChillerIPP`
	Optimization horizon $\mathcal{H}$ (duration)	$\lvert\mathcal{H}\rvert = 24\,\mathrm{h}$
	Update	At least every 30 min
	Trigger optimization	Forced turn on/off, at least every 3 hours
IPP control model	Encoding of bit string B	$B = [0,1]^b$
	Length b of bit string	$b = 5 \cdot p$
	Number of time slots p	$p = \lvert\mathcal{H}\rvert\,/5\,\mathrm{min}$
	Control sequence $\mathcal{C}$	$B \xrightarrow{\mathcal{F}} \mathcal{C} = \left(t_1^{\mathrm{toggle}} \ldots t_{i,\max}^{\mathrm{toggle}}\right)$
	Finite-state machine $\mathcal{F}$	$\mathcal{F}$
	Final control sequence $\mathcal{C}$'	$\mathcal{C} \xrightarrow{\mathcal{F}'} \mathcal{C}' = \left(t_1^{\mathrm{toggle}} \ldots t_{i,\max}^{\mathrm{toggle}}\right)'$
	Finite-state machine $\mathcal{F}$'	$\mathcal{F}$'
	Additional penalty $\mathcal{P}$	$\mathcal{P}$ for forced turn on/off
	Operating strategy / control logic	On-off control (hysteresis)
IPP entity model	Original devices	*InvenSor LTC 09* [321], *InvenSor BE 24* (dry cooler)
	Model	`class AdsorptionChillerModel`
	Nominal cooling power P_{c}	$P_{\mathrm{c}} = -9000\,\mathrm{W}$
	Nominal re-cooling power P_{r}	$P_{\mathrm{r}} = -24000\,\mathrm{W}$
	Nominal hot water power P_{h}	$P_{\mathrm{h}} = 15000\,\mathrm{W}$
	Active power standby P_{h}	$P_{\mathrm{a}} = 10\,\mathrm{W}$
	Active power on P_{h}	$P_{\mathrm{a}} = 420\,\mathrm{W}$
	Min. chilled water set temp. $\theta_{\mathrm{c,min}}$	$\theta_{\mathrm{h,min}} = 14\,°\mathrm{C}$
	Max. chilled water set temp. $\theta_{\mathrm{c,max}}$	$\theta_{\mathrm{h,max}} = 18\,°\mathrm{C}$
	Min. hot water temperature $\theta_{\mathrm{h,min}}$	$\theta_{\mathrm{h,min}} = 50\,°\mathrm{C}$
	Max. hot water temperature $\theta_{\mathrm{h,max}}$	$\theta_{\mathrm{h,max}} = 80\,°\mathrm{C}$
	Cooler model A	$\theta_{\mathrm{r}} = 21.0182\,°\mathrm{C} + 0.4321 \cdot \theta_{\mathrm{outdoor}}$
	Cooler model B	$\theta_{\mathrm{r}} = 10.5091\,°\mathrm{C} + 0.8642 \cdot \theta_{\mathrm{outdoor}}$

D.3 Gas-fired Condensing Boiler

Table D.5: Gas-fired condensing boiler: analysis

Aspect		**Details**
Utilization	Source	Natural gas grid connection point, local storage, electricity grid connection point
	Energy carrier	Natural gas, liquid gas, (electricity)
Distribution	Carrier	–
Conversion	From	Natural gas, liquid gas, (electricity)
	To	Hot water
Storage	Storage system	–
	Energy carrier	–
Provision	Energy carrier	Hot water
	Energy service	–
Interdependencies	Relations	Hot water storage tank (temperature), outdoor temperature
	Connections	Hot water storage tank, (electricity grid connection point)
Control	Internal logic	On-off control (hysteresis) device overheating protection, legionella protection
	Parameters	Min./max. operating time, min./max. off time, min./max. tank temperature (hysteresis)
User	Interaction	–
	Preferences	–
Energy management	Settings (from EMS)	Min./max. tank temperature
	Commands (from EMS)	–
	Predictions (from EMS)	Heating demand
	Predictions (to EMS)	Expected load profile
	Information (to EMS)	Remaining min./max. times
Model	Input	Parameters, settings, commands
	Output	Device state, primary energy input, efficiency
	Efficiency	Non-linear, depending on outdoor temperature, hot water temperature,s and gas quality
Availability/presence	Temporal	Practically always, depending on the state of the storage

Table D.6: Gas-fired condensing boiler: integration into the *Organic Smart Home*

Parameter / Property		**Details**
Drivers	Simulation device driver	`class GasBoilerSimulationDriver`
	Device driver	–
	Bus driver	–
Local O/C-unit	Local Observer	`class GasBoilerLocalObserver`
	Local Controller	–
	Observer Exchange	`class GasBoilerObserverExchange`
	Model of Observation Exchange	–
	Controller Exchange	–
IPP	Non-controllable	`class GasBoilerNonControllableIPP`
	Controllable	–
	Optimization horizon $\mathcal{H}$ (duration)	–
	Update	At least every 1 hour
	Trigger optimization	–
IPP control model	Encoding of bit string B	$B = \emptyset$
	Length b of bit string	$b = 0$
	Control sequence $\mathcal{C}$	–
	Finite-state machine $\mathcal{F}$	–
	Additional penalty $\mathcal{P}$	–
	Operating strategy / control logic	On-off control (hysteresis)
IPP entity model	Original device	–
	Model	`class GasBoilerModel`
	Nominal active power P_{a}	$P_{\mathrm{a}} = 100\,\mathrm{W}$
	Reactive power	$\mathrm{Cos}(\varphi) = 1.0$
	Nominal hot water power P_{h}	$P_{\mathrm{h}} = -P_{\mathrm{n}}$
	Nominal natural gas power P_{n}	$P_{\mathrm{n}} = 15\,000\,\mathrm{W}$
	Ramp-up: hot water power	0 min (linear)
	Ramp-down: hot water power	0 min (linear)
	Min. hot water temperature $\theta_{\mathrm{h,min}}$	$\theta_{\mathrm{h,min}} = 60\,^{\circ}\mathrm{C}$
	Max. hot water temperature $\theta_{\mathrm{h,max}}$	$\theta_{\mathrm{h,max}} = 80\,^{\circ}\mathrm{C}$

D.4 Electrical Insert Heating Element

Table D.7: Electrical insert heating element: analysis

Aspect		**Details**
Utilization	Source	Electricity grid connection point
	Energy carrier	Electricity
Distribution	Carrier	–
Conversion	From	Electricity
	To	Hot water
Storage	Storage system	–
	Energy carrier	–
Provision	Energy carrier	Hot water
	Energy service	–
Interdependencies	Relations	Hot water storage tank (temperature), electricity grid connection point (voltage)
	Connections	Hot water storage tank, local electricity grid, (electricity grid connection point)
Control	Internal logic	On-off control (hysteresis), control loop (net electrical power), device protection legionella protection
	Parameters	Min./max. operating time, min./max. off time, min./max. tank temperature (hysteresis), min./max. electrical power
User	Interaction	–
	Preferences	–
Energy management	Settings (from EMS)	Min./max. tank temperature min./max. electrical power
	Commands (from EMS)	Switch on/off (power value)
	Predictions (from EMS)	Heating demand
	Predictions (to EMS)	Expected load profile
	Information (to EMS)	Remaining min./max. times
Model	Input	Parameters, settings, commands
	Output	Device state, primary energy input, efficiency
	Efficiency	Nearly linear, depending on tank temperature and electricity grid connection point (voltage)
Availability/presence	Temporal	Practically always, depending on the state of the storage

Table D.8: Electrical insert heating element: integration into the *Organic Smart Home*

Parameter / Property		**Details**
Drivers	Simulation device driver	`class SmartHeaterSimulationDriver`
	Device driver	–
	Bus driver	–
Local O/C-unit	Local Observer	`class SmartHeaterLocalObserver`
	Local Controller	–
	Observer Exchange	`class SmartHeaterObserverExchange`
	Model of Observation Exchange	–
	Controller Exchange	–
IPP	Non-controllable	`class SmartHeaterNonControllableIPP`
	Controllable	–
	Optimization horizon $\mathcal{H}$ (duration)	–
	Update	At least every 1 hour
	Trigger optimization	–
IPP control model	Encoding of bit string B	$B = \emptyset$
	Length b of bit string	$b = 0$
	Number of time slots p	–
	Control sequence $\mathcal{C}$	–
	Finite-state machine $\mathcal{F}$	–
	Additional penalty $\mathcal{P}$	–
	Operating strategy / control logic	Control loop (net power at ↪ electricity grid connection point)
IPP entity model	Original device	*E.G.O. EGO Smart Heater*
	Model	`class SmartHeaterModel`
	Nominal active power P_a	$P_\mathrm{a} = 0.0 \ldots 3.5\,\mathrm{kW}$ in steps of 500 W
	Active power threshold $P_\mathrm{a,grid}$	$P_\mathrm{a,grid} \geq 100\,\mathrm{W}$
	Reactive power	$\mathrm{Cos}(\varphi) = 1.0$
	Nominal hot water power P_h	$P_\mathrm{h} = -P_\mathrm{a}$
	Min. operating time	10 s (all heating elements)
	Max. operating time	110/170/230 s (0.5/1.0/2.0 kW heating element)
	Ramp-up: hot water power	0 min (linear)
	Ramp-down: hot water power	0 min (linear)
	Max. hot water temperature $\theta_\mathrm{h,max}$	$\theta_\mathrm{h,max} = 80\,^\circ\mathrm{C}$

D.5 Thermal Energy Storage System: Water Storage Tank

Table D.9: Water storage tank: analysis

Aspect		**Details**
Utilization	Source	*Multiple devices and systems*
	Energy carrier	Hot/chilled water
Distribution	Carrier	–
Conversion	From	–
	To	–
Storage	Storage system	–
	Energy carrier	Hot/chilled water
Provision	Energy carrier	Hot/chilled water
	Energy service	–
Interdependencies	Relations	*Multiple devices and systems*, room / installation site
	Connections	*Multiple devices and systems*
Control	Internal logic Parameters	– –
User	Interaction	–
	Preferences	–
Energy management	Settings (from EMS)	–
	Commands (from EMS)	–
	Predictions (from EMS)	–
	Predictions (to EMS)	Expected temperature curve
	Information (to EMS)	–
Model	Input	Volume, geometry, thermal transmittance tank temperature, ambient temperature
	Output	Device state, primary energy input, efficiency
	Efficiency	Nearly linear, depending on tank temperature and ambient temperature
Availability/presence	Temporal	Always

Table D.10: Water storage tank: integration into the *Organic Smart Home*

Parameter / Property		**Details**
Drivers	Simulation device driver	`class WaterTankSimulationDriver`
	Device driver	–
	Bus driver	–
Local O/C-unit	Local Observer	`class WaterTankLocalObserver`
	Local Controller	–
	Observer Exchange	`class WaterTankObserverExchange`
	Model of Observation Exchange	–
	Controller Exchange	–
IPP	Non-controllable	`class WaterTankNonControllableIPP`
	Controllable	–
	Optimization horizon $\mathcal{H}$ (duration)	–
	Update	At least every 1 hour
	Trigger optimization	$\lvert\theta_{\text{real}} - \theta_{\text{predicted}}\rvert > 0.25\,\text{K}$
IPP control model	Encoding of bit string B	$B = \emptyset$
	Length b of bit string	$b = 0$
	Number of time slots p	–
	Control sequence $\mathcal{C}$	–
	Finite-state machine $\mathcal{F}$	–
	Additional penalty $\mathcal{P}$	$\mathcal{P}$ based on the final tank temperature
	Operating strategy / control logic	–
IPP entity model	Original device	–
	Tank model	`class BasicWaterTank`
	Volume V (residential), ESHL	750 L
	Volume V (commercial), HoLL	3250 L
	Heat loss P_{transfer} (hot water)	$P_{\text{transfer}} = a \cdot (12 + 5.93\,\frac{1}{\text{L}} \cdot (\frac{1000}{\text{m}^3} \cdot V)^{0.4})$ $\hookrightarrow \cdot \frac{(\theta_{\text{outside}} - \theta_{\text{inside}})}{40\,\text{K}}\,\text{W}$
	Heat loss P_{transfer} (hot water), ESHL	$P_{\text{transfer}} = 1 \cdot (12 + 5.93\,\frac{1}{\text{L}} \cdot (\frac{1000}{\text{m}^3} \cdot V)^{0.4})$ $\hookrightarrow \cdot \frac{(\theta_{\text{outside}} - \theta_{\text{inside}})}{40\,\text{K}}\,\text{W}$
	Heat loss P_{transfer} (hot water), HoLL	$P_{\text{transfer}} = 8 \cdot (12 + 5.93\,\frac{1}{\text{L}} \cdot (\frac{1000}{\text{m}^3} \cdot V)^{0.4})$ $\hookrightarrow \cdot \frac{(\theta_{\text{outside}} - \theta_{\text{inside}})}{40\,\text{K}}\,\text{W}$
	Heat gain P_{transfer} (chilled water), HoLL	$P_{\text{transfer}} = 8 \cdot (12 + 5.93\,\frac{1}{\text{L}} \cdot (\frac{1000}{\text{m}^3} \cdot V)^{0.4})$ $\hookrightarrow \cdot \frac{(\theta_{\text{outside}} - \theta_{\text{inside}})}{40\,\text{K}}\,\text{W}$
	Ambient temperature $\theta_{ambient}$ (residential)	$\theta_{ambient} = 20\,°\text{C}$
	Ambient temperature $\theta_{ambient}$ (commercial)	$\theta_{ambient} = 24\,°\text{C}$

D.6 Electrical Energy Storage Systems

Table D.11: Battery Electrical Energy Storage System: analysis

Aspect		Details
Utilization	Source	Electricity grid connection point
	Energy carrier	Electricity
Distribution	Carrier	–
Conversion	From	–
	To	–
Storage	Storage system	*Various battery technologies*
	Energy carrier	Electrochemical
Provision	Energy carrier	Electricity
	Energy service	–
Interdependencies	Relations	*Multiple devices and systems*, room / installation site
	Connections	*Multiple devices and systems*
Control	Internal logic Parameters	Control loop (net electrical power) Min./max. electrical charge power, min./max. electrical discharge power, min./max. state of charge
User	Interaction	–
	Preferences	–
Energy management	Settings (from EMS)	Parameters for control and operation logic
	Commands (from EMS)	Charge, discharge, parameters for control and operation logic
	Predictions (from EMS)	Expected net electrical power
	Predictions (to EMS)	Expected state of charge
	Information (to EMS)	Current state of charge
Model	Input	Battery efficiency (charge, discharge), ambient temperature
	Output	Device state, electrical power
	Efficiency	Nonlinear, depending on cell temperature, electrical power
Availability/presence	Temporal	Practically always, depending on the state of the storage

D.7 Photovoltaic system

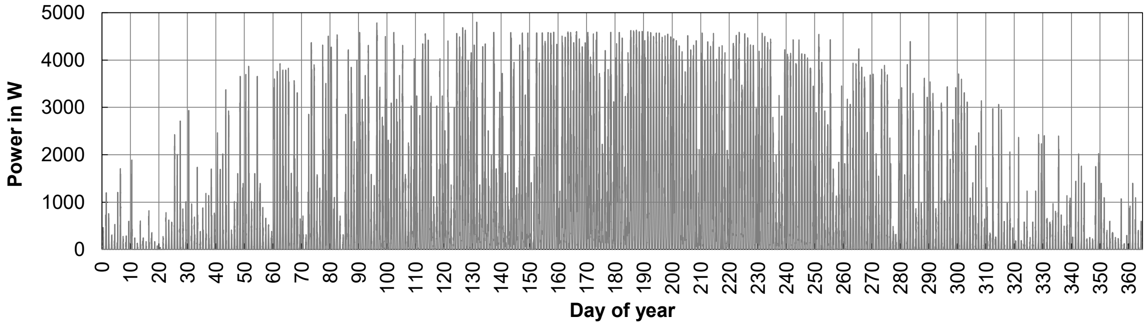


Figure D.3: *FZI House of Living Labs*: PV system generation profile recorded in the year 2013

Table D.12: *FZI House of Living Labs*: total PV system generation per month in the year 2013

Month	Jan	Feb	Mar	Apr	May	Jun	
Generation in kWh	72	159	385	495	593	841	
Generation share	1.4 %	3.0 %	7.3 %	9.3 %	11.2 %	15.9 %	
	Jul	Aug	Sep	Oct	Nov	Dec	Total
	957	762	510	332	121	77	5,305
	18.0 %	14.4 %	9.6 %	6.3 %	2.3 %	1.5 %	100 %

Table D.13: Photovoltaic systems: analysis

Aspect		**Details**
Utilization	Source	Sun
	Energy carrier	Solar radiation/irradiance
Distribution	Carrier	Electricity (DC, system internal)
Conversion	From	Solar irradiance
	To	Electricity
Storage	Storage system	–
	Energy carrier	–
Provision	Energy carrier	Electricity (AC)
	Energy service	–
Interdependencies	Relations	Electricity grid connection point (voltage, frequency),
	Connections	Local electricity grid, electricity grid connection point
Control	Internal logic Parameters	Control loop (active and reactive power) Max. electrical active power, min./max. electrical reactive power, reactive power control strategy (e. g., $Q(U)$)
User	Interaction	–
	Preferences	–
Energy management	Settings (from EMS)	Parameters for control and operation logic
	Commands (from EMS)	Max. electrical active power, electrical reactive power
	Predictions (from EMS)	Expected solar irradiance, outdoor temperature
	Predictions (to EMS)	Expected active and reactive power
	Information (to EMS)	Current active and reactive power
Model	Input	Solar irradiance, outdoor temperature
	Output	Device state, electrical power
	Efficiency	Nonlinear, depending on cell temperature, solar irradiance, outdoor temperature
Availability/presence	Temporal	Practically always (day time), depending on solar irradiance

Table D.14: Photovoltaic system: integration into the *Organic Smart Home*

Parameter / Property		**Details**
Drivers	Simulation device driver	`class PvSimulationDriver`
	Device driver	–
	Bus driver	–
Local O/C-unit	Local Observer	`class PvLocalObserver`
	Local Controller	`class PvLocalController`
	Observer Exchange	`class PvObserverExchange`
	Model of Observation Exchange	`class PvMOX`
	Controller Exchange	`class PvControllerExchange`
IPP	Non-controllable	`class PvNonControllableIPP`
	Controllable	`class PvControllableIPP`
	Optimization horizon $\mathcal{H}$ (duration)	$\lvert\mathcal{H}\rvert = 6$ hours
	Update	At least every 1 hour
	Trigger optimization	–
IPP control model	Encoding of bit string B	$B = \emptyset$
	Length b of bit string	$b = 0$
	Number of time slots p	–
	Control sequence $\mathcal{C}$	–
	Finite-state machine $\mathcal{F}$	–
	Additional penalty $\mathcal{P}$	–
	Operating strategy / control logic	–
IPP entity model	Original device	–
	Available (recorded) profiles	SLP EV0 (resolution: 15 min), ↪ HoLL (resolution: 1 min), ↪ ESHL (resolution: 1 s)

D.8 Space Heating

Table D.15: Space heating (energy service): analysis

Aspect		Details
Utilization	Source	*Various devices and systems*
	Energy carrier	Hot water/air, electricity
Distribution	Carrier	Hot water/air
Conversion	From	Hot water/air, electricity
	To	Space heating
Storage	Storage system	–
	Energy carrier	–
Provision	Energy carrier	Heated air
	Energy service	Space heating
Interdependencies	Relations	Outside temperature, irradiance, indoor temperature, ventilation
	Connections	Local heating system
Control	Internal logic Parameters	On-off control (hysteresis) Min./max. indoor temperatures, temporal temperature adjustments (e. g., night-time)
User	Interaction	Ventilation
	Preferences	Temperature set points
Energy management	Settings (from EMS)	Parameters for control and operation logic
	Commands (from EMS)	Temporal temperature adjustment
	Predictions (from EMS)	Expected solar irradiance, outdoor temperature, occupancy
	Predictions (to EMS)	Expected hot water power
	Information (to EMS)	Current hot water power
Model	Input	Solar irradiance, outdoor temperature
	Output	Thermal power
	Efficiency	Nearly linear, depending on solar irradiance, outdoor temperature indoor temperature
Availability/presence	Temporal	Always

Table D.16: Space heating: integration into the *Organic Smart Home*

Parameter / Property		**Details**
Drivers	Simulation device driver	`class SpaceHeatingSimulationDriver`
	Device driver	–
	Bus driver	–
Local O/C-unit	Local Observer (simulation)	`abstract class ThermalDemandLocalObserver`
	Local Observer (simulation)	`class SpaceHeatingLocalObserver`
	Local Observer (application)	`class ESHLSpaceHeatingLocalObserver`
	Local Controller	`class ThermalDemandLocalController`
	Observer Exchange	`class ThermalDemandObserverExchange`
	Model of Observation Exchange	–
	Controller Exchange	–
IPP	Non-controllable	`class SpaceHeatingNonControllableIPP`
	Controllable	–
	Optimization horizon $\mathcal{H}$ (duration)	$\lvert\mathcal{H}\rvert = 6$ hours
	Update	At least every 1 hour
	Trigger optimization	–
IPP control model	Encoding of bit string B	$B = \emptyset$
	Length b of bit string	$b = 0$
	Number of time slots p	–
	Control sequence $\mathcal{C}$	–
	Finite-state machine $\mathcal{F}$	–
	Additional penalty $\mathcal{P}$	–
	Operating strategy / control logic	–
IPP entity model	Generic building model	`class BuildingThermalModel`
	Simulated heating demand model	`class ThermalDemandSimulation`
	Simulated profiles	ESHL (recorded TRNSYS simulation)
	Simulated heating demand P_h in W	$P_h = \text{Random}(0,1) \cdot P_{h,\text{TNRSYS}} + \frac{P_{h,\text{TNRSYS}}}{2}$
	Real building model ESHL	`class ESHLThermalModel`
	Predicted heating demand P_h in W	$P_h = \max(0, -68.3333 \cdot \theta_{\text{outdoor}} + 1230)\,\text{W}$

D.9 Space Cooling

Table D.17: Space cooling (energy service): analysis

Aspect		**Details**
Utilization	Source	*Various devices and systems*
	Energy carrier	Cooling fluid, chilled water/air, electricity
Distribution	Carrier	Cooling fluid, chilled water/air
Conversion	From	Cooling fluid, chilled water/air, electricity
	To	Space cooling
Storage	Storage system	–
	Energy carrier	–
Provision	Energy carrier	Chilled air
	Energy service	Space cooling
Interdependencies	Relations	Outside temperature, irradiance, indoor temperature, ventilation
	Connections	Local cooling system
Control	Internal logic Parameters	On-off control (hysteresis) Min./max. indoor temperatures, temporal temperature adjustments (e. g., night-time)
User	Interaction	Ventilation
	Preferences	Temperature set points
Energy management	Settings (from EMS)	Parameters for control and operation logic
	Commands (from EMS)	Temporal temperature adjustment
	Predictions (from EMS)	Expected solar irradiance, outdoor temperature, occupancy
	Predictions (to EMS)	Expected chilled water power
	Information (to EMS)	Current chilled water power
Model	Input	Solar irradiance, outdoor temperature
	Output	Thermal power
	Efficiency	Nearly linear, depending on solar irradiance, outdoor temperature indoor temperature (set point)
Availability/presence	Temporal	Always

Table D.18: Space cooling: integration into the *Organic Smart Home*

Parameter / Property		**Details**
Drivers	Simulation device driver	`class SpaceCoolingSimulationDriver`
	Device driver	–
	Bus driver	–
Local O/C-unit	Local Observer	`class SpaceCoolingLocalObserver`
	Local Controller	–
	Observer Exchange	`class SpaceCoolingObserverExchange`
	Model of Observation Exchange	–
	Controller Exchange	–
IPP	Non-controllable	`class ChilledWaterNonControllableIPP`
	Controllable	–
	Optimization horizon $\mathcal{H}$ (duration)	–
	Update	At least every 1 hour
	Trigger optimization	–
IPP control model	Encoding of bit string B	$B = \emptyset$
	Length b of bit string	$b = 0$
	Number of time slots p	–
	Control sequence $\mathcal{C}$	–
	Finite-state machine $\mathcal{F}$	–
	Additional penalty $\mathcal{P}$	–
	Operating strategy / control logic	–
IPP entity model	Generic building model	`class BuildingThermalModel`
	Real building model HoLL	`class FZIThermalModel`
	Predicted cooling demand P_c in W	$P_c = \max(0, 274.8\ \mathrm{W}/°\mathrm{C} \cdot \theta_{\mathrm{outdoor}} - 5143)\ \mathrm{W}$
	Real building model HoLL	Indoor temperature set point: 22 °C.
	Real reservations	HoLL July 2014
	Simulated reservations	Randomly generated (see Section 4.3.2)
	Outdoor temperature	*DWD WESTE-XL*, Rheinstetten, Germany
	Real building model ESHL	`class ESHLThermalModel`

D.10 Domestic Hot Water

Table D.19: Domestic hot water: used draw off profiles, data partly based on [200]

Profile	Duration	Avg. power	Total energy	Probability	Consumption share
DHW_00	9 s	6.00 kW	0.015 kWh	0.684	0.077
DHW_01	60 s	6.30 kW	0.105 kWh	0.098	0.077
DHW_02	40 s	9.45 kW	0.105 kWh	0.098	0.077
DHW_03	90 s	12.60 kW	0.315 kWh	0.033	0.077
DHW_04	120 s	12.60 kW	0.420 kWh	0.024	0.077
DHW_05	200 s	9.45 kW	0.525 kWh	0.020	0.077
DHW_06	210 s	12.60 kW	0.735 kWh	0.014	0.077
DHW_07	400 s	9.45 kW	1.050 kWh	0.010	0.077
DHW_08	268 s	18.90 kW	1.407 kWh	0.007	0.077
DHW_09	347 s	18.90 kW	1.822 kWh	0.006	0.077
DHW_10	412 s	31.50 kW	3.605 kWh	0.003	0.077
DHW_11	506 s	31.50 kW	4.428 kWh	0.002	0.077
DHW_12	466 s	50.40 kW	6.524 kWh	0.002	0.077
				1.000	1.000

Table D.20: Domestic hot water: correction factors of the monthly consumption, data based on [613, Fig. D1]

Month	Jan	Feb	Mar	Apr	May	Jun
Correction factor	1.12	1.13	1.12	1.02	1.04	0.94
	Jul	Aug	Sep	Oct	Nov	Dec
	0.75	0.90	0.95	0.90	1.05	1.08

Table D.21: Domestic hot water: consumption share in weekly total consumption and correction factors per day of week, data based on [613, Fig. D2]

Day of week	Mon	Tue	Wed	Thu	Fri	Sat	Sun
Consumption share	0.138	0.138	0.138	0.138	0.138	0.150	0.160
Resulting correction factor	0.966	0.966	0.966	0.966	0.966	1.050	1.120

Table D.22: Domestic hot water: consumption share per day of week, data based on [613, Fig. D3, D4, D5]

Hour of day	**Mon**	**Tue**	**Wed**	**Thu**	**Fri**	**Sat**	**Sun**
00:00	0.016	0.016	0.016	0.016	0.016	0.017	0.019
01:00	0.008	0.008	0.008	0.008	0.008	0.011	0.012
02:00	0.003	0.003	0.003	0.003	0.003	0.005	0.007
03:00	0.003	0.003	0.003	0.003	0.003	0.003	0.005
04:00	0.008	0.008	0.008	0.008	0.008	0.006	0.004
05:00	0.025	0.025	0.025	0.025	0.025	0.007	0.004
06:00	0.073	0.073	0.073	0.073	0.073	0.010	0.005
07:00	0.077	0.077	0.077	0.077	0.077	0.022	0.010
08:00	0.065	0.065	0.065	0.065	0.065	0.051	0.035
09:00	0.053	0.053	0.053	0.053	0.053	0.091	0.070
10:00	0.047	0.047	0.047	0.047	0.047	0.088	0.083
11:00	0.043	0.043	0.043	0.043	0.043	0.085	0.092
12:00	0.042	0.042	0.042	0.042	0.042	0.071	0.085
13:00	0.040	0.040	0.040	0.040	0.040	0.054	0.071
14:00	0.036	0.036	0.036	0.036	0.036	0.052	0.058
15:00	0.032	0.032	0.032	0.032	0.032	0.048	0.049
16:00	0.037	0.037	0.037	0.037	0.037	0.048	0.043
17:00	0.049	0.049	0.049	0.049	0.049	0.055	0.047
18:00	0.056	0.056	0.056	0.056	0.056	0.056	0.058
19:00	0.073	0.073	0.073	0.073	0.073	0.058	0.063
20:00	0.077	0.077	0.077	0.077	0.077	0.053	0.065
21:00	0.073	0.073	0.073	0.073	0.073	0.046	0.052
22:00	0.040	0.040	0.040	0.040	0.040	0.036	0.040
23:00	0.024	0.024	0.024	0.024	0.024	0.027	0.023

Table D.23: Domestic hot water (energy service): analysis

Aspect		**Details**
Utilization	Source	*Various devices and systems*
	Energy carrier	DHW, (electricity)
Distribution	Carrier	DHW
Conversion	From	Potable water
	To	DHW
Storage	Storage system	–
	Energy carrier	–
Provision	Energy carrier	DHW
	Energy service	DHW
Interdependencies	Relations	Outside temperature, irradiance, indoor temperature, ventilation
	Connections	Local heating system
Control	Internal logic Parameters	On-off control (hysteresis) Min./max. indoor temperatures, temporal temperature adjustments (e. g., night-time)
User	Interaction	Ventilation
	Preferences	Temperature set points
Energy management	Settings (from EMS)	Parameters for control and operation logic
	Commands (from EMS)	Temporal temperature adjustment
	Predictions (from EMS)	Expected solar irradiance, outdoor temperature, occupancy
	Predictions (to EMS)	Expected DHW power
	Information (to EMS)	Current DHW power
Model	Input	Solar irradiance, outdoor temperature
	Output	Thermal power
	Efficiency	Nearly linear, depending on solar irradiance, outdoor temperature indoor temperature
Availability/presence	Temporal	Always

Table D.24: Domestic hot water: integration into the *Organic Smart Home*

Parameter / Property		**Details**
Drivers	Simulation device driver	`class VDI6002DomesticHotWater` ↪ `SimulationDriver`
	Device driver	`class VDI6002DomesticHotWaterDriver`
	Bus driver	–
Local O/C-unit	Local Observer	`class VDI6002DomesticHotWater` ↪ `LocalObserver`
	Local Controller	–
	Observer Exchange	`class HotWaterDemandObserverExchange`
	Model of Observation Exchange	–
	Controller Exchange	–
IPP	Non-controllable	`class DomesticHotWater` ↪ `NonControllableIPP`
	Controllable	–
	Optimization horizon $\mathcal{H}$ (duration)	–
	Update	At least every 1 hour
	Trigger optimization	–
IPP control model	Encoding of bit string B	$B = \emptyset$
	Length b of bit string	$b = 0$
	Number of time slots p	–
	Control sequence $\mathcal{C}$	–
	Finite-state machine $\mathcal{F}$	–
	Additional penalty $\mathcal{P}$	–
	Operating strategy / control logic	–
IPP entity model	Original demand	–
	Available profile (based on)	VDI Guideline 6002 [613]
	Draw off profiles (based on)	Energy labeling of space heaters of the ↪ European Commission [200]

E

Optimization and Energy Simulation Core

The following figures provide additional information about the optimization module and the *Energy Simulation Core*.

Table E.1: Possible shortcomings in the optimization of the devices used in this thesis and the inherent considerations or penalties that are used to tackle them in the heuristic optimization

Device	**Shortcoming**	**Inherent consideration**	**Additional penalty $\mathcal{P}$**
Appliance	Deferred start of appliance may benefit from potential future starts of other devices	–	Penalty for the device start that is gradually decreasing over time, which is leading to a delay of the start in case of otherwise equal costs
Hybrid appliance	Hot water from storage tank is virtually free and causes only indirect costs that arise later on, leading to an incentive to always use the operation mode utilizing hot water	Longer duration of optimization horizon	*see hot water storage tank*
MicroCHP	Device uses on-off control, i. e., hysteresis control, instead of scheduled device operation periods	–	Forced turn on/off because of on-off control causes a penalty
MicroCHP	Starting the device causes additional energy loss that is not considered and leads to frequent device starts	Thermal power requires some minutes to increase to the nominal power (see also Figure D.1 on p. 405)	–
MicroCHP	Wear caused by device start is not considered and leads to frequent device starts	*see previous row*	–
MicroCHP	Earlier starts of the microCHP increase the standing loss of the hot water storage tank due to higher average tank temperatures	Standing loss of hot water storage tank depends on the tank temperature	–
Adsorption chiller	Device uses on-off control, i. e., hysteresis control, instead of scheduled device operation periods	–	Forced turn on/off because of on-off control causes a penalty
Hot water storage tank	Hot water from storage tank is virtually free and causes only indirect costs that arise later on, leading to an incentive to prefer hot water over electricity	Longer duration of optimization horizon	Penalty for a temperature of the hot water storage tank at the end of the optimization horizon that is lower than the temperature at the beginning (and vice versa)
Chilled water storage tank	*see hot water storage tank*	*see hot water storage tank*	*see hot water storage tank*
BESS	*see hot water storage tank*	*see hot water storage tank*	*see hot water storage tank*

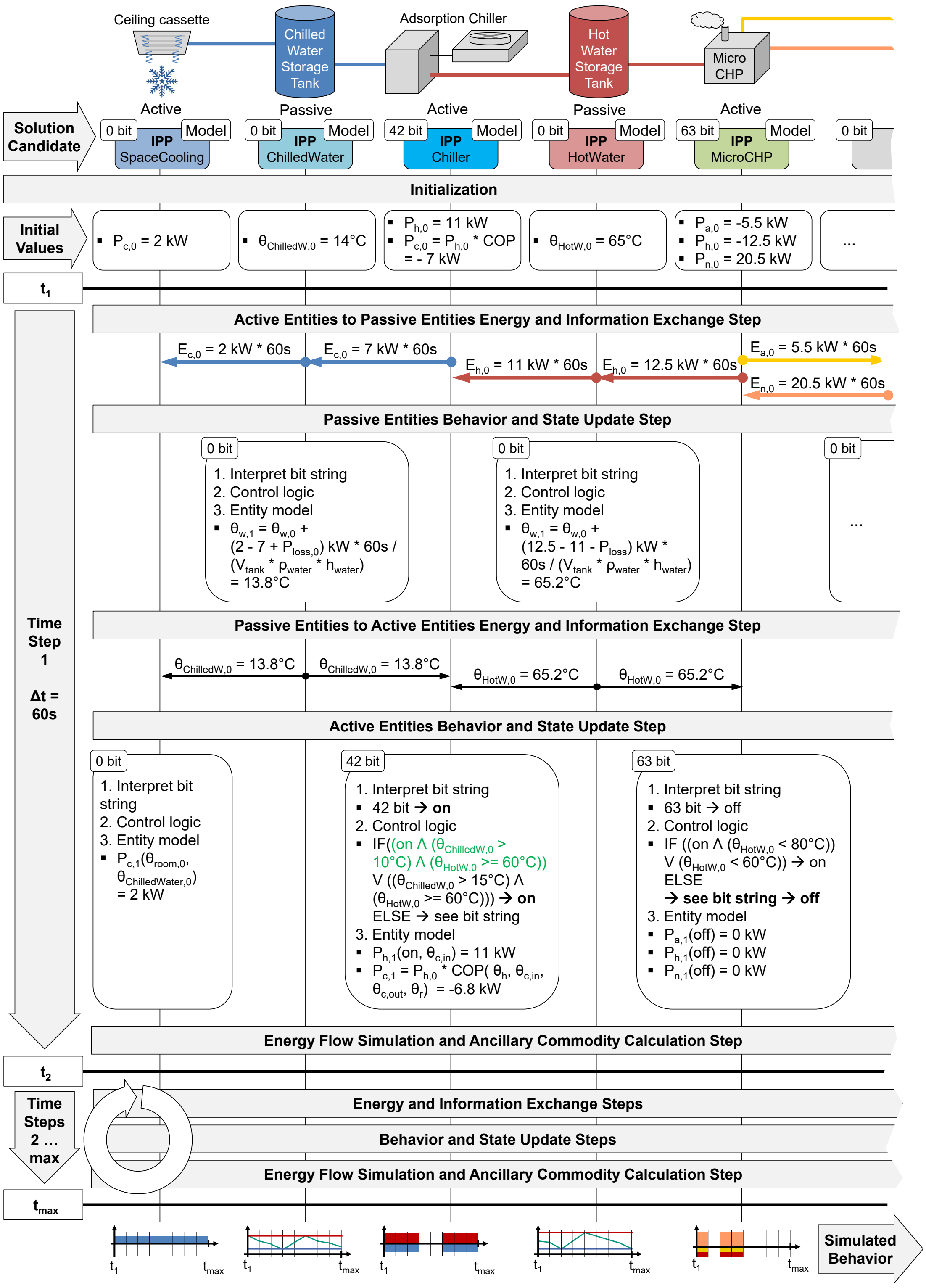


Figure E.1: *Energy Simulation Core*: Interpretation of a solution candidate by means of the *Interdependent Problem Parts* (detailed figure)

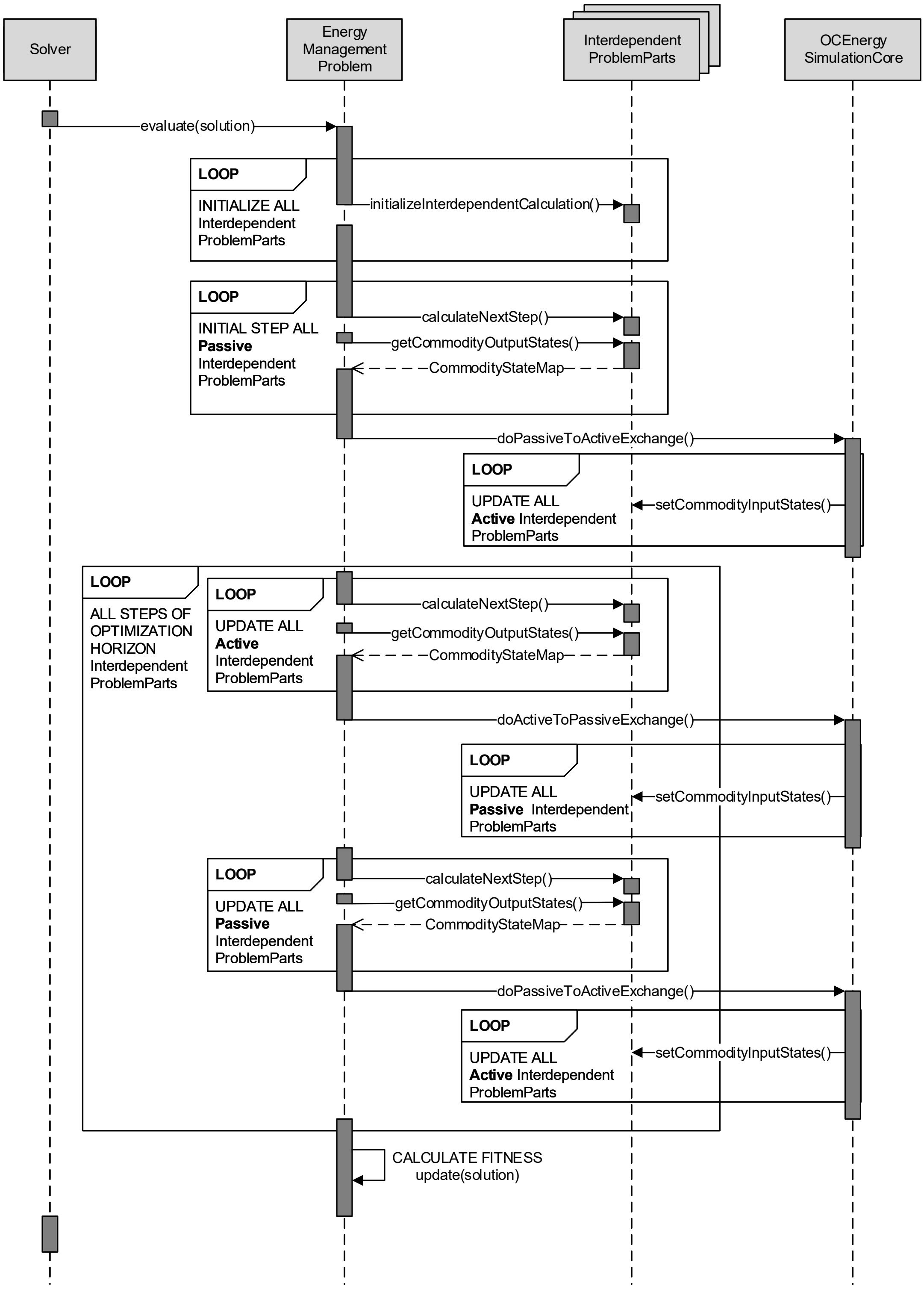


Figure E.2: *Energy Simulation Core*: UML sequence diagram showing the interactions between the solver of the optimization module, the energy management problem that is solved by the optimization module, the *Interdependent Problem Parts*, and the Energy Simulation Core of the global O/C-unit

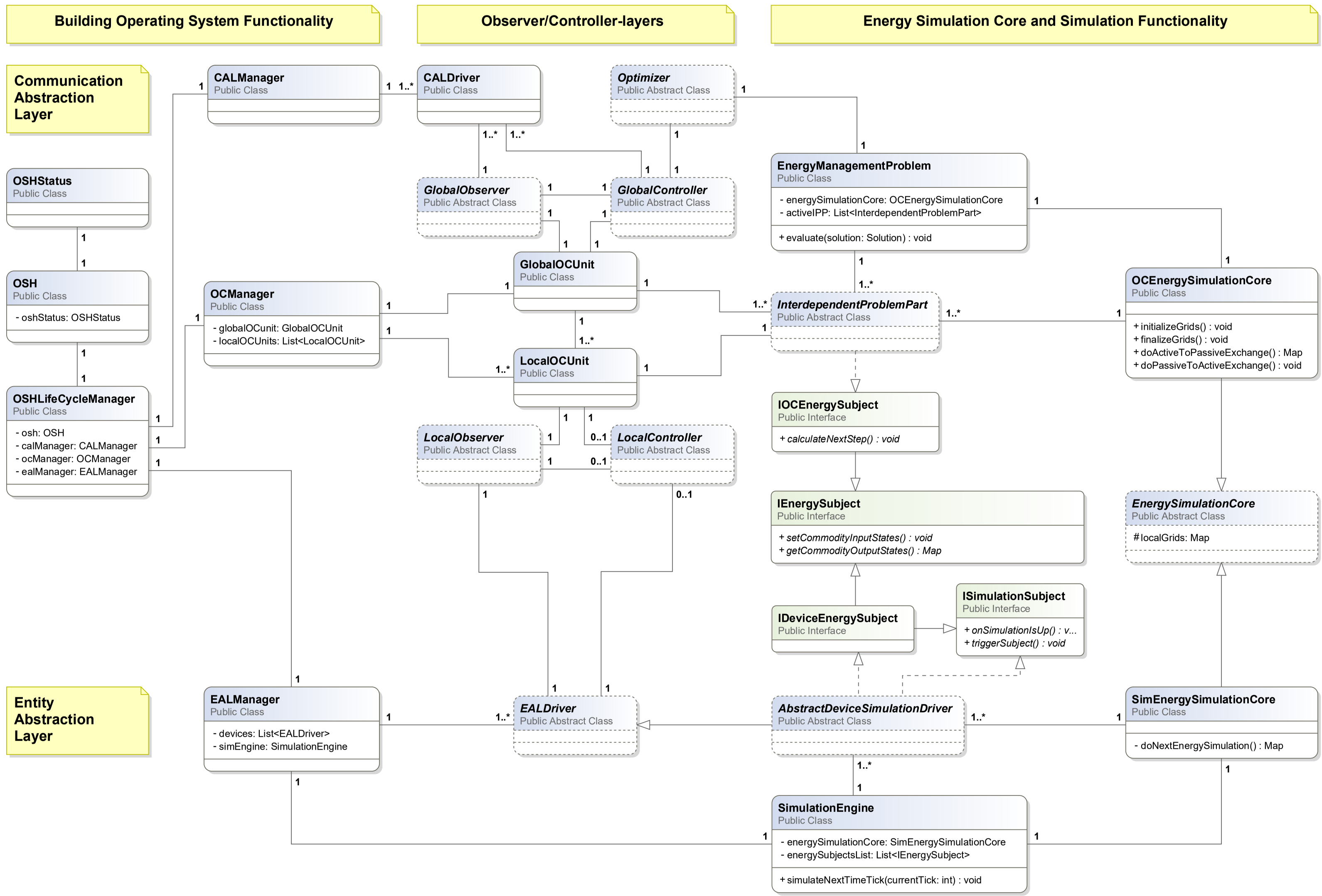


Figure E.3: *Energy Simulation Core*: UML class diagram of the core components in the *simulation mode* (simplified diagram)

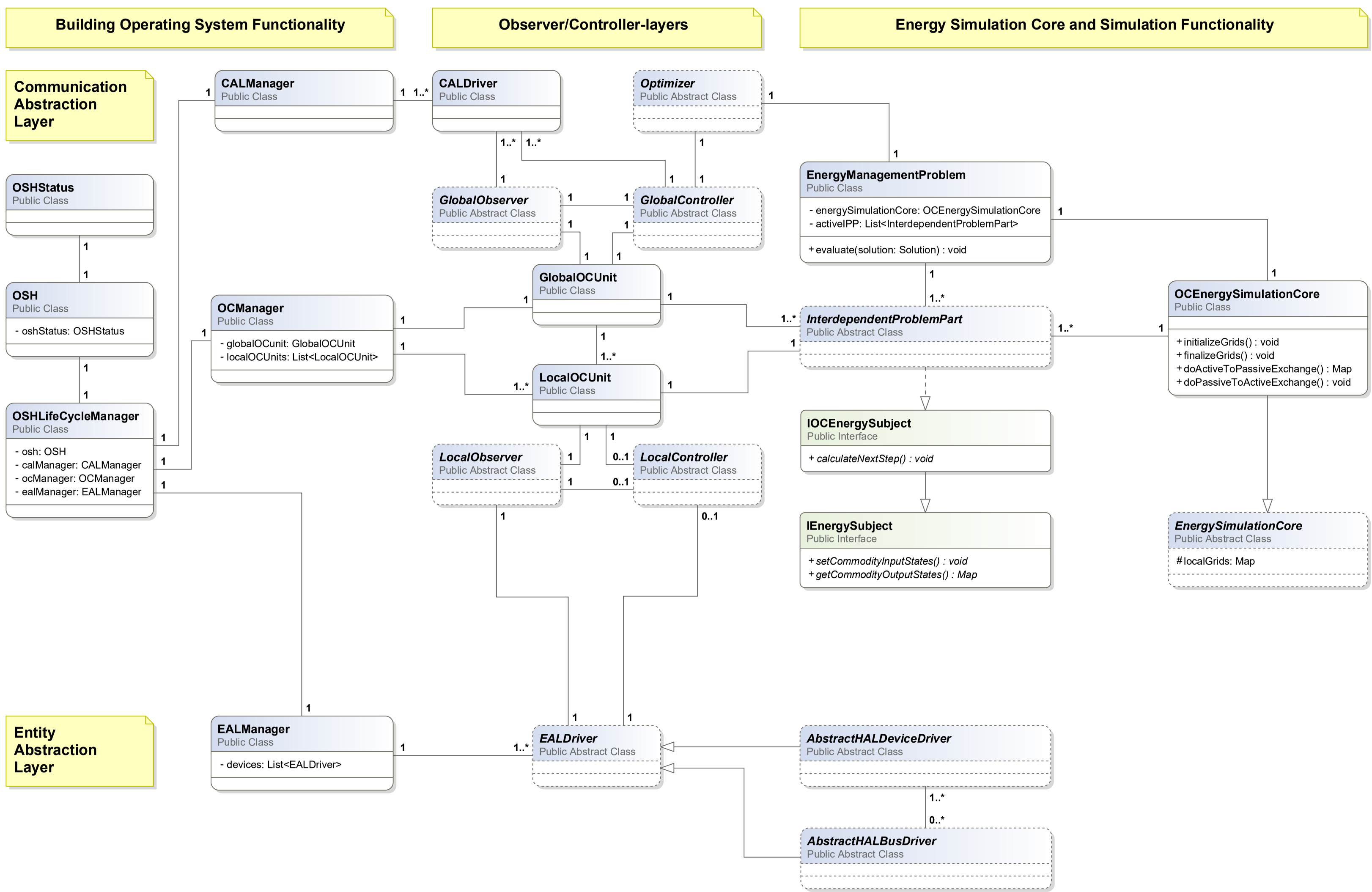


Figure E.4: *Energy Simulation Core*: UML class diagram of the core components in the *application mode* (simplified diagram)

F Files and Algorithms

F.1 Generic Evolutionary Algorithm

Algorithm 1 Generic Evolutionary Algorithm [154, 247]

procedure EVOLUTIONARYALGORITHM
    $i \leftarrow 0$
    population(i) $\leftarrow$ GeneratedInitialIndividuals()
    Evaluate(*population(i)*)
    while not StoppingCriterionIsReached(*population(i)*) **do**
        offspring(i) $\leftarrow$ Variation(*population(i)*)
        Evaluate(*offspring(i)*)
        population$(i+1)$ $\leftarrow$ Update(*population(i)*, *offspring(i)*)
        $i \leftarrow i + 1$

F.2 Relevant XSD Files

Listing F.1: `GridLayout.xsd`

```xml
<?xml version="1.0" encoding="UTF-8"?>
<schema targetNamespace="http://OSH/energy/grid/configuration" elementFormDefault="qualified" xmlns="http://www.w3.org/2001/XMLSchema" xmlns:tns="http://OSH/Energy/Grid/Configuration">
  <element name="GridLayout">
    <complexType>
      <sequence>
        <element minOccurs="0" maxOccurs="unbounded" name="connections" type="tns:LayoutConnection"></element>
        <element minOccurs="0" maxOccurs="unbounded" name="meterUUIDs" type="string"></element>
        <element minOccurs="0" maxOccurs="unbounded" name="deviceMeterMap" type="tns:devicePerMeter"></element>
      </sequence>
    </complexType>
  </element>
  <complexType name="LayoutConnection">
    <sequence>
      <element name="activeEntityUUID" type="string"></element>
      <element name="passiveEntityUUID" type="string"></element>
      <element name="activeToPassiveCommodity" type="string"></element>
      <element name="passiveToActiveCommodity" type="string"></element>
    </sequence>
  </complexType>
  <complexType name="devicePerMeter">
    <sequence>
      <element name="meterUUID" type="string"></element>
      <element name="deviceUUID" type="string"></element>
      <element name="deviceType" type="string"></element>
    </sequence>
  </complexType>
</schema>
```

Listing F.2: `ApplianceProgramConfigurations.xsd`

```xml
<?xml version="1.0" encoding="UTF-8"?>
<xs:schema xmlns:xs="http://www.w3.org/2001/XMLSchema" xmlns:wp="http://osh/configuration/appliance" targetNamespace="http://osh/configuration/appliance" elementFormDefault="qualified" attributeFormDefault="unqualified">
  <xs:include schemaLocation="CommonDatatypes.xsd" />
  <xs:complexType name="ConfigurationParameter">
    <xs:sequence>
      <xs:element name="ParameterName" type="wp:name" />
      <xs:element name="ParameterValue" type="xs:string" />
    </xs:sequence>
  </xs:complexType>
  <xs:complexType name="ConfigurationParameters">
    <xs:sequence>
      <xs:element name="Parameter" type="wp:ConfigurationParameter" minOccurs="0" maxOccurs="255" />
    </xs:sequence>
  </xs:complexType>
  <!-- Program has a ProgramID, a name, and a description -->
  <xs:complexType name="Program">
    <xs:sequence>
      <xs:element name="ProgramID" type="wp:byte" minOccurs="1" maxOccurs="1" />
```

```
      <xs:element name="ProgramName" type="wp:name" minOccurs="0" maxOccurs="1" />
      <xs:element name="Descriptions" type="wp:XsdDescriptions" minOccurs="0" maxOccurs="1" />
    </xs:sequence>
  </xs:complexType>
  <!-- One configuration with one or multiple alternative LoadProfiles -->
  <xs:complexType name="ApplianceProgramConfiguration">
    <xs:sequence>
      <xs:element name="ConfigurationID" type="wp:nonNegativeInt" minOccurs="1" maxOccurs="1" />
      <xs:element name="ConfigurationName" type="wp:name" minOccurs="0" maxOccurs="1" />
      <xs:element name="Program" type="wp:Program" minOccurs="1" maxOccurs="1" />
      <xs:element name="Parameters" type="wp:ConfigurationParameters" minOccurs="0" maxOccurs="1" />
      <xs:element name="LoadProfiles" type="wp:XsdLoadProfiles" minOccurs="1" maxOccurs="1" />
    </xs:sequence>
  </xs:complexType>
  <!-- Sequence of all possible configurations of an appliance -->
  <xs:element name="ApplianceProgramConfigurations">
    <xs:complexType>
      <xs:sequence>
        <xs:element name="ApplianceProgramConfiguration" type="wp:ApplianceProgramConfiguration" minOccurs="1" maxOccurs="unbounded" />
      </xs:sequence>
    </xs:complexType>
  </xs:element>
</xs:schema>
```

Listing F.3: CommonDatatypes.xsd

```
<?xml version="1.0" encoding="UTF-8"?>
<xs:schema xmlns:xs="http://www.w3.org/2001/XMLSchema" xmlns:osh="http://osh/configuration/appliance" targetNamespace="http://osh/configuration/appliance" elementFormDefault="qualified" attributeFormDefault="unqualified">
  <xs:simpleType name="byte">
    <xs:restriction base="osh:nonNegativeInt">
      <xs:maxInclusive value="255" />
    </xs:restriction>
  </xs:simpleType>
  <xs:simpleType name="nonNegativeInt">
    <xs:restriction base="xs:int">
      <xs:minInclusive value="0" />
    </xs:restriction>
  </xs:simpleType>
  <xs:simpleType name="name">
    <xs:restriction base="xs:token">
    </xs:restriction>
  </xs:simpleType>
  <xs:complexType name="XsdDescription">
    <xs:sequence>
      <xs:element name="Value" type="xs:string" minOccurs="1" maxOccurs="1" />
    </xs:sequence>
    <xs:attribute name="language" type="xs:string" use="required" />
  </xs:complexType>
  <xs:complexType name="XsdDescriptions">
    <xs:sequence>
      <xs:element name="description" type="osh:XsdDescription" minOccurs="1" maxOccurs="255" />
    </xs:sequence>
  </xs:complexType>
```

```
  <xs:complexType name="XsdLoad">
    <xs:sequence>
      <xs:element name="Value" type="xs:int" minOccurs="1" maxOccurs="1" />
      <xs:element name="MinValue" type="xs:int" minOccurs="0" maxOccurs="1" />
      <xs:element name="MaxValue" type="xs:int" minOccurs="0" maxOccurs="1" />
    </xs:sequence>
    <xs:attribute name="commodity" type="xs:string" use="required" />
  </xs:complexType>
  <xs:complexType name="XsdTick">
    <xs:sequence>
      <xs:element name="Load" type="osh:XsdLoad" minOccurs="1" maxOccurs="unbounded"
          ↪ />
    </xs:sequence>
  </xs:complexType>
  <xs:complexType name="XsdPhase">
    <xs:sequence>
      <xs:element name="Tick" type="osh:XsdTick" minOccurs="1" maxOccurs="unbounded"
          ↪ />
    </xs:sequence>
    <xs:attribute name="id" type="osh:nonNegativeInt" use="required" />
    <xs:attribute name="name" type="osh:name" use="optional" />
    <xs:attribute name="minLength" type="osh:nonNegativeInt" use="required" />
    <xs:attribute name="maxLength" type="osh:nonNegativeInt" use="required" />
  </xs:complexType>
  <xs:complexType name="XsdPhases">
    <xs:sequence>
      <xs:element name="Phase" type="osh:XsdPhase" minOccurs="1" maxOccurs="
          ↪ unbounded" />
    </xs:sequence>
  </xs:complexType>
  <xs:complexType name="XsdLoadProfile">
    <xs:sequence>
      <xs:element name="Phases" type="osh:XsdPhases" minOccurs="1" maxOccurs="1" />
    </xs:sequence>
    <xs:attribute name="id" type="osh:nonNegativeInt" use="required" />
    <xs:attribute name="name" type="osh:name" use="optional" />
  </xs:complexType>
  <xs:complexType name="XsdLoadProfiles">
    <xs:sequence>
      <xs:element name="LoadProfile" type="osh:XsdLoadProfile" minOccurs="1"
          ↪ maxOccurs="unbounded" />
    </xs:sequence>
  </xs:complexType>
</xs:schema>
```

F.3 Relevant Java Source Files

Listing F.4: EnergyRelation.java

```java
public class EnergyRelation<T extends ConnectionType> {
  // # Variables #
  private T activeToPassiveConnection;
  private T passiveToActiveConnection;
  private EnergySourceSink activeEntity;
  private EnergySourceSink passiveEntity;
  // # Constructors #
  public EnergyRelation(EnergySourceSink activeEntity, EnergySourceSink
     ↪ passiveEntity, T activeToPassiveConnection, T passiveToActiveConnection) {
    super();
    this.activeEntity = activeEntity;
    this.passiveEntity = passiveEntity;
    this.activeToPassiveConnection = activeToPassiveConnection;
    this.passiveToActiveConnection = passiveToActiveConnection;
  }
  // # Methods #
  public T getActiveToPassive() {
    return activeToPassiveConnection;
  }
  public T getPassiveToActive() {
    return passiveToActiveConnection;
  }
  public EnergySourceSink getActiveEntity() {
    return activeEntity;
  }
  public EnergySourceSink getPassiveEntity() {
    return passiveEntity;
  }
}
```

Listing F.5: ConnectionType.java

```java
public abstract class ConnectionType {}
```

Listing F.6: RealConnectionType.java

```java
public abstract class RealConnectionType extends ConnectionType {
  // # Variables #
  private Commodity commodity;
  // # Constructors #
  public RealConnectionType(Commodity commodity) {
    super();
    this.commodity = commodity;
  }
  // # Methods #
  public Commodity getCommodity() { return commodity; }
}
```

Listing F.7: VirtualConnectionType.java

```java
public abstract class VirtualConnectionType extends ConnectionType {
  // # Variables #
  private AncillaryCommodity commodity;
```

```java
  // # Constructors #
  public VirtualConnectionType(AncillaryCommodity commodity) {
    super();
    this.commodity = commodity;
  }
  // # Methods #
  public AncillaryCommodity getAncillaryCommodity() {
    return commodity;
  }
}
```

Listing F.8: `IEnergyGrid.java`

```java
public interface EnergyGrid {
  // # Methods #
  /** Initialize grid by loading all relations into lists */
  public void initializeGrid(Set<UUID> allActiveNodes, Set<UUID> activeNeedsInputNodes, Set<UUID> passiveNodes);
  /** Finalize grid by unloading all relations */
  public void finalizeGrid();
  /** Simulation (bottom-up): Do grid calculation and update states */
  public void doCalculation(Map<UUID, EnumMap<Commodity, RealCommodityState>> commodityStates, Map<UUID, EnumMap<Commodity,RealCommodityState>> totalInputStates, Map<UUID, EnumMap<AncillaryCommodity, AncillaryCommodityState>> totalAncillaryInputStates);
  /** O/C-Simulation (optimization) (1): Do active to passive part update */
  public void doActiveToPassiveCalculation(Set<UUID> passiveNodes, Map<UUID, EnumMap<Commodity, RealCommodityState>> activeStates, Map<UUID, EnumMap<Commodity, RealCommodityState>> totalInputStates, Map<UUID, EnumMap<AncillaryCommodity, AncillaryCommodityState>> totalAncillaryInputStates);
  /** O/C-Simulation (optimization) (2): Do passive to active part update */
  public void doPassiveToActiveCalculation(Map<UUID, EnumMap<Commodity, RealCommodityState>> passiveStates, Set<UUID> activeNodes, Map<UUID, EnumMap<Commodity, RealCommodityState>> totalInputStates);
  /** Get UUIDs of virtual meters */
  public Set<UUID> getMeterUUIDs();
  /** Get UUIDs of active IPPs */
  public Set<UUID> getActiveUUIDs();
  /** Get UUIDs of passive IPPs */
  public Set<UUID> getPassiveUUIDs();
}
```

Listing F.9: `ElectricalEnergyGrid.java` (shortened)

```java
public class ElectricalEnergyGrid extends EnergyGrid {
  // # Variables #
  private final Set<EnergySourceSink> sourceSinkList = new HashSet<EnergySourceSink>();
  private final Set<UUID> meterUUIDs = new HashSet<UUID>();
  private final List<EnergyRelation<Electrical>> relationList = new ArrayList<>();
  private List<EnergyRelation<Electrical>> initializedActiveToPassiveRelationList = new ArrayList<>();
  private List<EnergyRelation<Electrical>> initializedPassiveToActiveRelationList = new ArrayList<>();
  private boolean hasBeenInitialized = false;
  private final Set<UUID> activeUUIDs = new HashSet<UUID>();
  private final Set<UUID> passiveUUIDs = new HashSet<UUID>();
  private final Map<UUID, Map<String, Set<UUID>>> devicesByTypePerMeter = new HashMap<UUID, Map<String, Set<UUID>>>();
  // # Constructors #
```

```
public ElectricalEnergyGrid(String layoutFilePath) throws JAXBException, FileNotFoundException {
  // Unmarshal XML providing the grid layout
  ...
}
// # Methods #
@Override
public void initializeGrid(...) {...}
@Override
public void finalizeGrid() {...}
/** Simulation (bottom-up): Do grid calculation and update states */
@Override
public void doCalculation(...) {
  for (EnergyRelation<Electrical> rel : relationList) {
    ...
    updateActivePart(activeMap, localPassiveState, passiveCommodity);
    ...
    updatePassivePart(passiveMap, localActiveState, activeCommodity);
    ...
  }
  calculateMeter(localCommodityStates, totalInputStates, totalAncillaryInputStates);
}
/** O/C-Simulation (optimization) (1): Do active to passive part update */
public void doActiveToPassiveCalculation(Set<UUID> passiveNodes, Map<UUID, EnumMap<Commodity, RealCommodityState>> activeStates, Map<UUID, EnumMap<Commodity, RealCommodityState>> totalInputStates, Map<UUID, EnumMap<AncillaryCommodity, AncillaryCommodityState>> totalAncillaryInputStates) {
  ...
  for (EnergyRelation<Electrical> rel : realList) {
    ...
    updatePassivePart(passiveMap, localActiveState, activeCommodity);
    ...
  }
  calculateMeter(activeStates, totalInputStates, totalAncillaryInputStates);
}
/** O/C-Simulation (optimization) (2): Do passive to active part update */
public void doPassiveToActiveCalculation(Map<UUID, EnumMap<Commodity, RealCommodityState>> passiveStates, Set<UUID> activeNodes, Map<UUID, EnumMap<Commodity, RealCommodityState>> totalInputStates) {
  ...
  for (EnergyRelation<Electrical> rel : realList) {
    ...
    updateActivePart(activeMap, localPassiveState, passiveCommodity);
    ...
  }
}
private void calculateMeter(Map<UUID, EnumMap<Commodity, RealCommodityState>> localCommodityStates, Map<UUID, EnumMap<Commodity, RealCommodityState>> totalInputStates, Map<UUID, EnumMap<AncillaryCommodity, AncillaryCommodityState>> totalAncillaryInputStates) {
  // calculate ancillary commodities
  ...
}
private void updateActivePart(EnumMap<Commodity, RealCommodityState> activeMap, ealCommodityState localPassiveState, Commodity passiveCommodity) {
  ...
}
private void updatePassivePart(
    EnumMap<Commodity, RealCommodityState> passiveMap, RealCommodityState localActiveState, Commodity activeCommodity) {
  ...
}
```

```
  ...
}
```

Listing F.10: `IEnergySubject.java`

```java
public interface IEnergySubject {
  /**
   * Is invoked by the EnergySimulationCore at every time step
   * to GET the energy commodity states of the subject
   * (i.e., obtain new state and thus energy exchange)
   */
  public EnumMap<Commodity, RealCommodityState> getCommodityOutputStates() throws
      ↪ EnergySimulationException;
  /**
   * Is invoked by the EnergySimulationCore at every time step
   * to SET the energy commodity states of the subject
   * (i.e. provide new states and thus energy exchange in order
   * to calculate the next state in onNextTimeTick()
   * called by triggerSubject() or calculateNextStep(), respectively) */
  public void setCommodityInputStates(EnumMap<Commodity, RealCommodityState>
      ↪ inputStates, EnumMap<AncillaryCommodity, AncillaryCommodityState>
      ↪ ancillaryInputStates) throws EnergySimulationException;
  public UUID getDeviceID();
}
```

Listing F.11: `LoadProfile.java`

```java
public abstract class LoadProfile<C extends Enum<C>> implements ILoadProfile<C>,
    ↪ Serializable {
  ...
  // # Methods #
  /** Add only a new sample if there is a discontinuity greater than |powerEps| */
  protected void getCompressedProfileByDiscontinuities(final double powerEps,
      ↪ LoadProfile<C> compressed) {
    for (C c : getEnumValues()) {
      TreeMap<Long, Tick> map = commodities.get(c);
      double lastValueSaved = Double.MAX_VALUE;
      long lastValueSavedKey = Long.MIN_VALUE;
      double momentaryAvg = Double.MAX_VALUE;
      double momentaryAvgMax = Double.MIN_VALUE;
      double momentaryAvgMin = Double.MAX_VALUE;
      Tick lastLookedAtTick = null;
      long lastLookedAtKey = Long.MIN_VALUE;
      long counter = 0;
      for (Iterator<Map.Entry<Long, Tick>> it = map.entrySet().iterator(); it.
          ↪ hasNext();) {
        Entry<Long,Tick> e = it.next();
        // if last sample -> store sample
        if (it.hasNext() == false) {
          compressed.setLoad(c, e.getKey(), e.getValue().value);
          if (lastLookedAtTick != null) {
            // write previous average value...
            compressed.setLoad(c, lastValueSavedKey, (int) Math.round(momentaryAvg))
                ↪ ;
          }
        }
        // store first value
        else if (lastLookedAtTick == null) {
          compressed.setLoad(c, e.getKey(), e.getValue().value);
          lastValueSavedKey = e.getKey();
          lastValueSaved = e.getValue().value;
```

```
          lastLookedAtTick = e.getValue();
          lastLookedAtKey = e.getKey();
          momentaryAvg = lastValueSaved;
          momentaryAvgMax = lastValueSaved;
          momentaryAvgMin = lastValueSaved;
          counter = 0;
        }
        //if difference of avg to min/max/lastValue/nowValue > powerEps --> store
            ↪ new sample
        else if (Math.abs(momentaryAvg - momentaryAvgMax) > powerEps
            || Math.abs(momentaryAvg - momentaryAvgMin) > powerEps
            || Math.abs(momentaryAvg - lastValueSaved) > powerEps
            || Math.abs(momentaryAvg - e.getValue().value) > powerEps) {

          long diffToLastKey = e.getKey() - lastLookedAtKey;
          momentaryAvg = (lastLookedAtTick.value * diffToLastKey + momentaryAvg *
              ↪ counter) / (diffToLastKey + counter);

          compressed.setLoad(c, lastValueSavedKey, (int) Math.round(momentaryAvg));
          lastValueSavedKey = e.getKey();
          lastValueSaved = e.getValue().value;
          lastLookedAtTick = e.getValue();
          lastLookedAtKey = e.getKey();
          momentaryAvg = lastValueSaved;
          momentaryAvgMax = lastValueSaved;
          momentaryAvgMin = lastValueSaved;
          counter = 0;
        }
        // difference is to small, update avg/min/max etc.
        else {
          long diffToLastKey = e.getKey() - lastLookedAtKey;
          momentaryAvg = (lastLookedAtTick.value * diffToLastKey + momentaryAvg *
              ↪ counter) / (diffToLastKey + counter);
          lastLookedAtKey = e.getKey();
          lastLookedAtTick = e.getValue();
          if (e.getValue().value > momentaryAvgMax) {
            momentaryAvgMax = e.getValue().value;
          }
          else if (e.getValue().value < momentaryAvgMin) {
            momentaryAvgMin = e.getValue().value;
          }
          counter = counter + diffToLastKey;
        }
      }
    }
    compressed.setEndingTimeOfProfile(this.getEndingTimeOfProfile());
  }
  ...
}
```

F.4 Relevant Python Source Files

Listing F.12: `Cooler_Model_BE24.py`

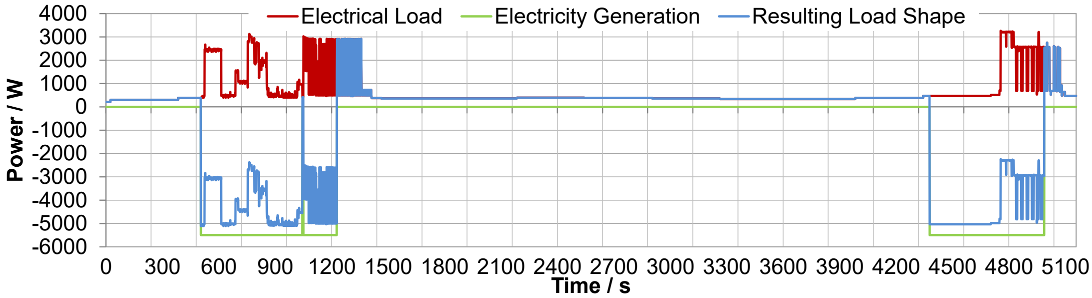
```
# coding: utf-8

import pandas as pd
import numpy as np
```

```
import matplotlib.pyplot as plt

get_ipython().magic('matplotlib notebook')

df = pd.read_csv('weste_data.csv', header=0, sep=';', usecols=(2,3), parse_dates=[0])

# remove constant values (most probably errors)
df = df.loc[df["T_out"].shift() != df["T_out"]]

df.set_index('Date', drop=True, inplace=True)
df2 = df.resample('1min').interpolate()

rk_th = pd.read_csv('wmz_be24_Th.csv', header=0, sep=',', usecols=(2,5),parse_dates=[0])
rk_tc = pd.read_csv('wmz_be24_Tc.csv', header=0, sep=';', usecols=(2,5),parse_dates=[0])
rk_q =  pd.read_csv('wmz_be24_Q.csv',  header=0, sep=',', usecols=(2,5),parse_dates=[0])
rk_p =  pd.read_csv('wmz_be24_P.csv',  header=0, sep=',', usecols=(2,5),parse_dates=[0])

rk_th.set_index('time', drop=True, inplace=True)
rk_tc.set_index('time', drop=True, inplace=True)
rk_q.set_index('time', drop=True, inplace=True)
rk_p.set_index('time', drop=True, inplace=True)
rk_th.index.names = ['Date']
rk_tc.index.names = ['Date']
rk_q.index.names = ['Date']
rk_p.index.names = ['Date']
rk_th.index = rk_th.index.map(lambda x: x.replace(second=0))
rk_tc.index = rk_tc.index.map(lambda x: x.replace(second=0))
rk_q.index = rk_q.index.map(lambda x: x.replace(second=0))
rk_p.index = rk_p.index.map(lambda x: x.replace(second=0))
t = pd.merge(rk_th, rk_tc, left_index=True, right_index=True)
t = pd.merge(t, rk_q, left_index=True, right_index=True)
t = pd.merge(t, rk_p, left_index=True, right_index=True)

t.columns = ['RK_Th', 'RK_Tc', 'RK_Q', 'RK_P']

# remove constant values (most probably errors)
t = t.loc[t["RK_Th"].shift() != t["RK_Th"]]

t2 = t2[t2.RK_Q > 0.1]
t2 = t2[t2.RK_P > 0]
t2 = t2[t2.RK_P < 30]

final = pd.merge(df2, t2, left_index=True, right_index=True)
final2 = pd.merge(df2, final, left_index=True, right_index=True)
final2 = final2[final2.RK_Th > final2.RK_Tc]

import statsmodels.api as sm

# first degree
regression1st = sm.OLS(final2['RK_Tc'], sm.add_constant(final2['T_out'])).fit()
regression1st.summary()

#second degree
X = np.column_stack((final2['T_out'], final2['T_out']**2))
X = sm.add_constant(X)
regression2nd = sm.OLS(final2['RK_Tc'], X).fit()
regression2nd.summary()
```

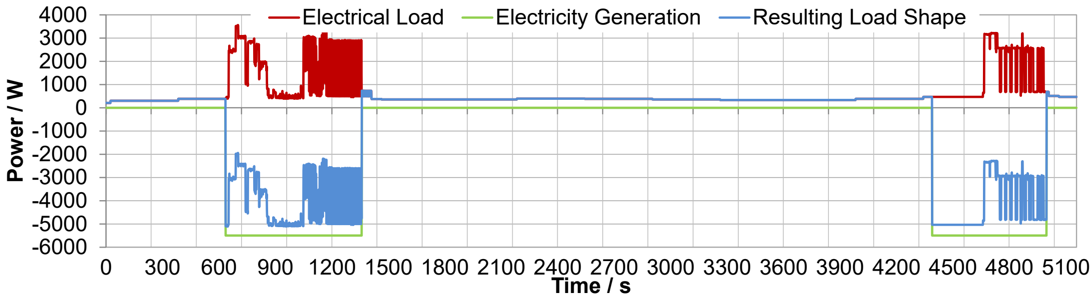
G

Simulations, Configurations, and Results

G.1 Simulation: Calibration of Parameters



(a) Optimization using default parameters



(b) Optimization using calibrated parameters

Figure G.1: Simulation results of a residential building comprising appliances and a microCHP using the default and the calibrated parameters, respectively, leading to different behavior and thus temporal synchronization of the appliances ("electrical load") and the microCHP ("electricity generation"), based on [406, Fig. 11]

G.2 Simulation: Typical Computation Time of Simulations

Table G.1: Overview of the simulated time, the typical time required for simulations, and the typical number of runs of the optimization module; without the additional stopping criterion, for abbreviations see Table G.3 on p. 447

Appliances	**MicroCHP**	**IHE**	**Adsorption chiller**	**Simulated time**	**Computation time**	**Optimization runs**
Smart Residential Building Scenario (four-person household, FLAT-30):						
C	–	–	–	364 days	12 min	0
D	–	–	–	364 days	95 min	3082
I	–	–	–	364 days	176 min	6107
H	–	–	–	364 days	137 min	2092
HD	–	–	–	364 days	233 min	3387
HI	–	–	–	364 days	484 min	6660
C	NO	–	–	364 days	12 min	0
D	NO	–	–	364 days	93 min	2965
I	NO	–	–	364 days	181 min	6074
H	NO	–	–	364 days	142 min	2071
HD	NO	–	–	364 days	266 min	3450
HI	NO	–	–	364 days	493 min	6644
C	O	–	–	364 days	296 min	5006
D	O	–	–	364 days	384 min	5708
I	O	–	–	364 days	621 min	8544
H	O	–	–	364 days	325 min	4999
HD	O	–	–	364 days	395 min	5806
HI	O	–	–	364 days	682 min	8654
Smart Commercial Building Scenario (FLAT-30):						
–	NO	–	NO	28 days	1 min	n/a
–	O	–	NO	28 days	35 min	n/a
–	NO	–	O	28 days	34 min	n/a
–	O	–	O	28 days	34 min	n/a

All simulations have been performed on the following personal computer:

	DELL PowerEdge T20
OS:	*Windows 10 Professional 64 bit*
Processor:	*Intel Xeon E3-1225v3*
RAM:	2x 4 GB DDR 3 ECC, 2x 8 GB DDR 4
HDD:	*Samsung 840 Evo*, SSD, 250 GB
Java RE:	*Oracle JDK 8 Update 111*

G.3 Configurations: Smart Residential Building Scenario

Table G.2: Smart residential building scenario: details of parameters and tariffs

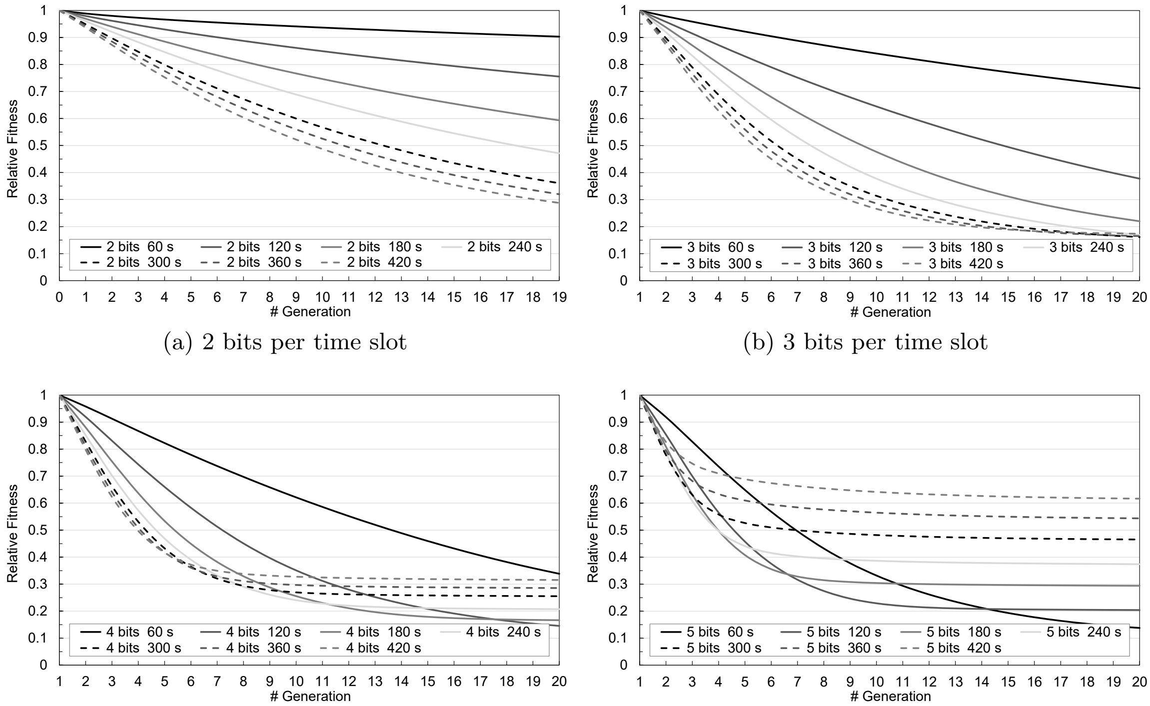
Future appliances	Operation modes:	Conventional/hybrid
	TDoF:	see Table 4.6 on p. 140
	EDoF:	see Table 4.7 on p. 142
	Simulation driver:	`class GenericFutureApplianceSimulationDriver`
MicroCHP	Nominal hot water power:	12.5 kW
	Nominal active power:	5.5 kW
	Nominal natural gas power:	20.5 kW
	Model:	`class GenericChpModel`
Hot water storage tank	Heat loss factor a:	$a = 1$
	Capacity:	750 liters
	Initial temperature:	70.0 °C
	Min./max. temperature:	60.0 °C/80.0 °C
	Ambient temperature:	20.0 °C
	Model:	`class BasicWaterTank`
Tariffs	Electricity tariff:	*various*
	Natural gas tariff:	8 cent/kWh
	PV feed-in:	10 cent/kWh
	MicroCHP feed-in:	9 cent/kWh
	MicroCHP self-consumption:	5 cent/kWh
	Power limit signal:	$\tau_a^{\text{upper}} = 1$, $\tau_{\text{a}}^{\text{lower}} = 0$, $P_{\text{a}}^{\text{upper}} = 3000\,\text{W}$

G.4 Simulation: Abbreviations in the Evaluations

Table G.3: Overview of the abbreviations that are used in Table 6.13 on p. 284, Table G.4 on p. 449, and Tables G.7 to G.10 on pp. 477 ff.

Device	**Abbrev.**	**Meaning**
Appliance	–	Not available
	C	Conventional appliance
	D	Deferrable appliance
	I	Interruptible appliance
	H	Hybrid appliance
	HD	Hybrid deferrable appliance
	HI	Hybrid interruptible appliance
MicroCHP	–	Not available, i. e., condensing gas boiler
	NO	Not optimized, i. e., non-controlled
	O	Optimized, i. e., controlled
Adsorption chiller	–	Not available
	NO	Not optimized, i. e., non-controlled
	O	Optimized, i. e., controlled

G.5 Evaluation: Encoding of the MicroCHP



(a) 2 bits per time slot

(b) 3 bits per time slot

(c) 4 bits per time slot

(d) 5 bits per time slot

Figure G.2: Relative convergence of the normalized fitness of the tested microCHP encodings using a generation size of 100 in a four-person household without PV system (Tariff: H0-30, $n = 10$)

G.6 Evaluation: Stopping Criterion

See Table G.4 on p. 449.

Table G.4: Average annual total cost of conventional (C), hybrid (H), deferrable (D), and interruptible (I) appliances and a non-optimized (NO) or an optimized (O) microCHP or without it (–), using the additional stopping criterion (ASC) to the normal stopping criterion of 200 generations in a four-person household having a 4 kW_p PV system (Tariff: WIK-30, $n = 10$)

Appliances	**MicroCHP**	**Avg. costs in EUR/a**			**Avg. # of generations**		
		normal	ASC		normal	ASC	
		20 generations having $\Delta_{\text{fitness}} < 5 \cdot 10^{-15}$					
C	–	1711	1711	–	–	–	–
D	–	1669	1669	+0.0 %	200	35.5	-82 %
I	–	1669	1669	+0.0 %	200	47.1	-76 %
H	–	1440	1440	+0.0 %	200	21.0	-90 %
HD	–	1437	1438	+0.1 %	200	34.2	-83 %
HI	–	1439	1440	+0.1 %	200	47.6	-76 %
C	NO	1730	1730	–	–	–	–
D	NO	1631	1631	+0.0 %	200	34.5	-83 %
I	NO	1625	1626	+0.1 %	200	49.2	-75 %
H	NO	1506	1506[a1]	+0.0 %	200	21.0	-90 %
HD	NO	1483	1483[b1]	+0.0 %	200	33.2	-83 %
HI	NO	1486	1487	+0.1 %	200	50.7	-75 %
C	O	1621	1648	+1.7 %	200	60.0	-70 %
D	O	1563	1589	+1.7 %	200	83.7	-58 %
I	O	1568	1589	+1.3 %	200	111.2	-44 %
H	O	1494	1509[a2]	+1.0 %	200	62.0	-69 %
HD	O	1479	1496[b2]	+1.2 %	200	84.9	-58 %
HI	O	1480	1491	+0.7 %	200	118.4	-41 %
		35 generations having $\Delta_{\text{fitness}} < 5 \cdot 10^{-15}$					
C	O	1621	1634	+0.8 %	200	96.3	-52 %
D	O	1563	1576	+0.8 %	200	120.9	-40 %
I	O	1568	1577	+0.6 %	200	145.4	-27 %
H	O	1494	1501[a3]	+0.5 %	200	99.1	-50 %
HD	O	1479	1485[b3]	+0.4 %	200	121.6	-39 %
HI	O	1480	1485	+0.3 %	200	149.8	-25 %
		50 generations having $\Delta_{\text{fitness}} < 5 \cdot 10^{-15}$					
C	O	1621	1629	+0.5 %	200	125.6	-37 %
D	O	1563	1570	+0.5 %	200	144.5	-28 %
I	O	1568	1572	+0.3 %	200	162.6	-19 %
H	O	1494	1498[a4]	+0.3 %	200	129.3	-35 %
HD	O	1479	1482[b4]	+0.3 %	200	145.5	-27 %
HI	O	1480	1482	+0.1 %	200	166.0	-17 %

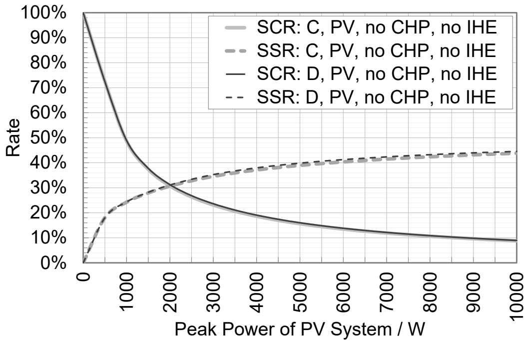
G.7 Validation: Self-consumption and Self-sufficiency Rates

Table G.5: Comparison of the self-consumption and self-sufficiency rates in simulated residential building scenarios to values given in the literature

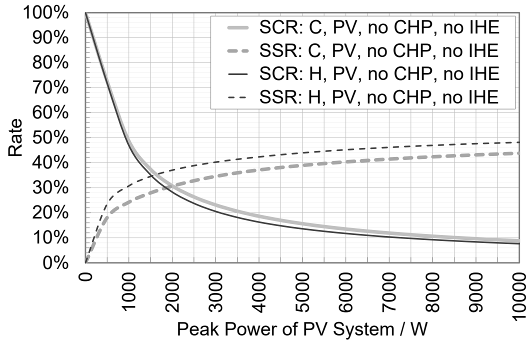
Source	Consump.	PV system	Self-consumption rate	Self-sufficiency rate
[626]	1000 kWh/a	1.0 kW_p, 1000 kWh/a	~38 %	~39 %
[636, 637]	4700 kWh/a	2.0 kW_p, 2000 kWh/a	50 %	22 %
This thesis	4700 kWh/a	2.0 kW_p, 2000 kWh/a	54.7 %	23.0 %
[636, 637]	2000 kWh/a	3.0 kW_p, 3000 kWh/a	22 %	34 %
This thesis	2000 kWh/a	3.0 kW_p, 3000 kWh/a	23.1 %	34.6 %
This thesis	4700 kWh/a	3.0 kW_p, 3000 kWh/a	43.7 %	27.6 %
[212]	2336 kWh/a	2.9 kW_p, 3456 kWh/a	16 %	24 %
[212]	4992 kWh/a	2.9 kW_p, 3456 kWh/a	44 %	32 %
This thesis	2000 kWh/a	3.5 kW_p, 3500 kWh/a	20.6 %	36.0 %
This thesis	4700 kWh/a	3.5 kW_p, 3500 kWh/a	39.8 %	29.3 %
[667]	4449 kWh/a	4.0 kW_p, 3698 kWh/a	31.6 %	26.3 %
[646]	3900 kWh/a	? kW_p, 3900 kWh/a	~37 %	~37 %
This thesis	4000 kWh/a	4.0 kW_p, 4000 kWh/a	32.4 %	32.2 %
[534]	4338 kWh/a	4.1 kW_p, ? kWh/a	~31 %	~31 %
[636, 637]	4700 kWh/a	4.0 kW_p, 4000 kWh/a	33 %	29 %
This thesis	4700 kWh/a	4.0 kW_p, 4000 kWh/a	36.5 %	30.7 %
This thesis	4700 kWh/a	5.0 kW_p, 5000 kWh/a	31.4 %	33.1 %
[95]	5500 kWh/a	5.0 kW_p, 5000 kWh/a	~35 %	?
[438]	4510 kWh/a	5.0 kW_p, 5280 kWh/a	20.0 %	?
[98]	3514 kWh/a	6.0 kW_p, 5844 kWh/a	29 %	48 %
This thesis	3100 kWh/a	6.0 kW_p, 6000 kWh/a	19.6 %	37.8 %
This thesis	4000 kWh/a	6.0 kW_p, 6000 kWh/a	24.3 %	36.2 %
This thesis	4700 kWh/a	9.0 kW_p, 9000 kWh/a	20.4 %	38.6 %
[636, 637]	4700 kWh/a	9.0 kW_p, 9000 kWh/a	18 %	36 %
[473]	4752 kWh/a	8.6 kW_p, 9050 kWh/a	24.8 %	47.5 %

'?': value not given or calculated

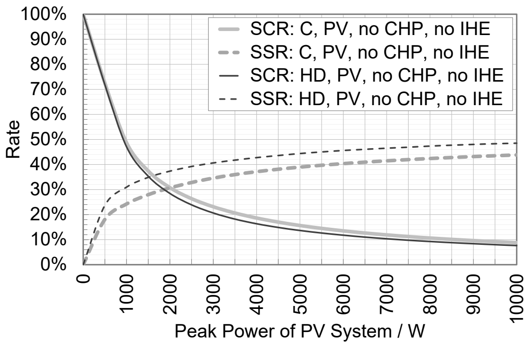
G.8 Results: Smart Residential Building Scenarios



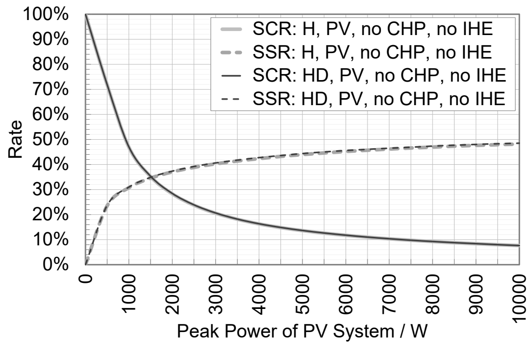
(a) Conventional (C) and deferrable appliances (D), no microCHP



(b) Conventional (C) and hybrid appliances (H), no microCHP

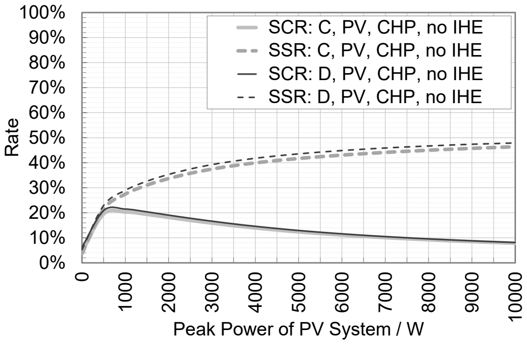


(c) Conventional (C) and hybrid deferrable appliances (HD), no microCHP

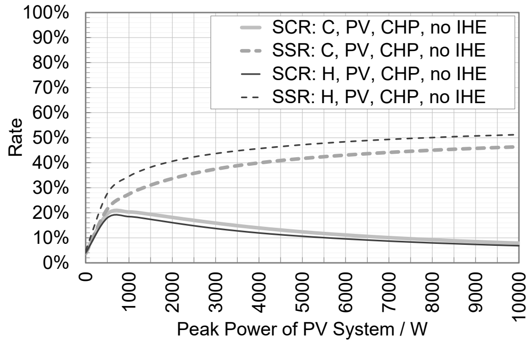


(d) Hybrid (H) and hybrid deferrable appliances (HD), no microCHP

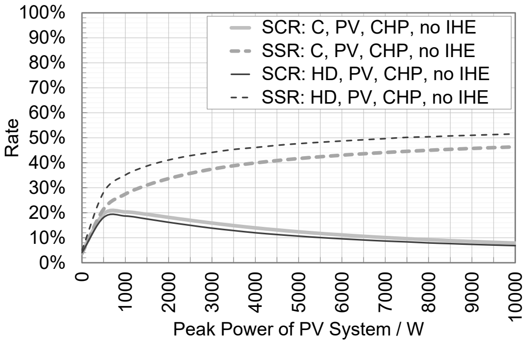
Figure G.3: Comparison of self-consumption (SCR) and self-sufficiency rates (SSR): one-person household, part 1 (a) (Tariff: FLAT-30, $n = 10$)



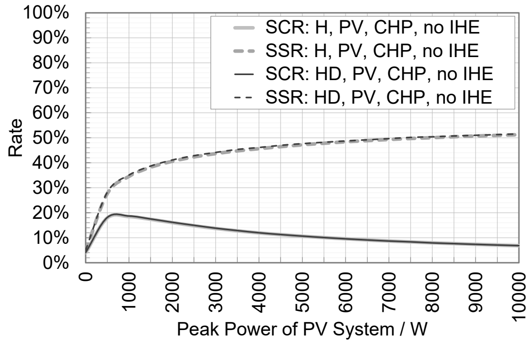
(e) Conventional (C) and deferrable appliances (D), non-optimized microCHP



(f) Conventional (C) and hybrid appliances (H), non-optimized microCHP

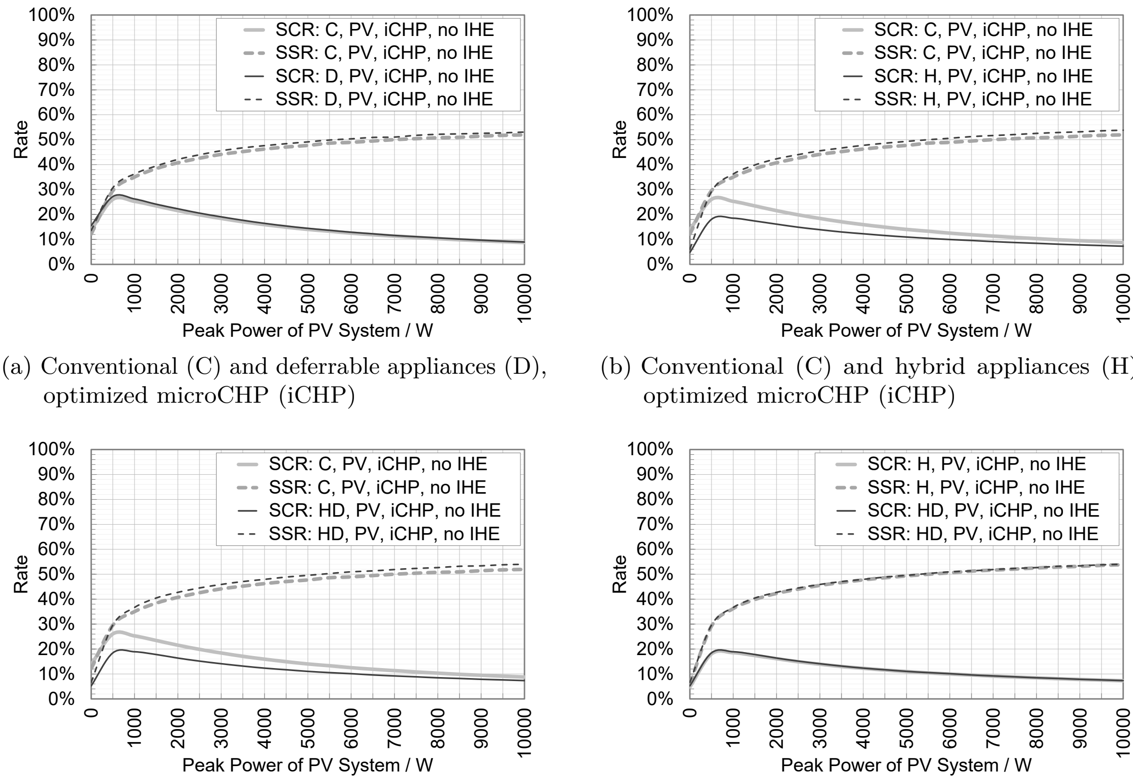


(g) Conventional (C) and hybrid deferrable appliances (HD), non-optimized microCHP



(h) Hybrid (H) and hybrid deferrable appliances (HD), non-optimized microCHP

Figure G.4: Comparison of self-consumption (SCR) and self-sufficiency rates (SSR): one-person household, part 1 (b) (Tariff: FLAT-30, $n = 10$)



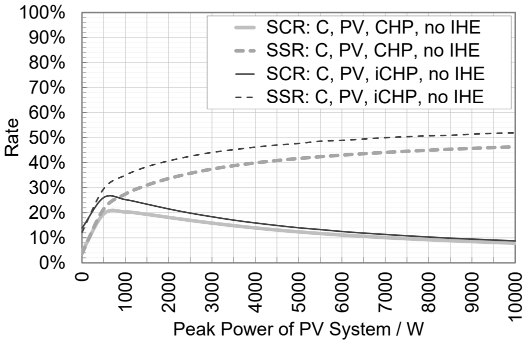
(a) Conventional (C) and deferrable appliances (D), optimized microCHP (iCHP)

(b) Conventional (C) and hybrid appliances (H), optimized microCHP (iCHP)

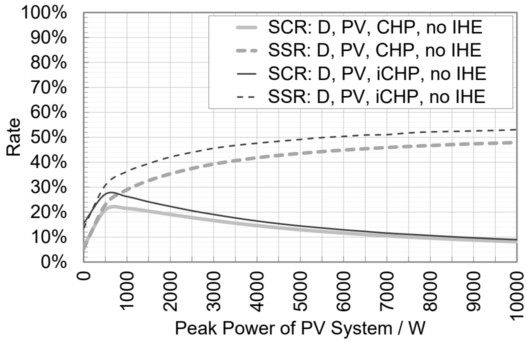
(c) Conventional (C) and hybrid deferrable appliances (HD), optimized microCHP (iCHP)

(d) Hybrid (H) and hybrid deferrable appliances (HD), optimized microCHP (iCHP)

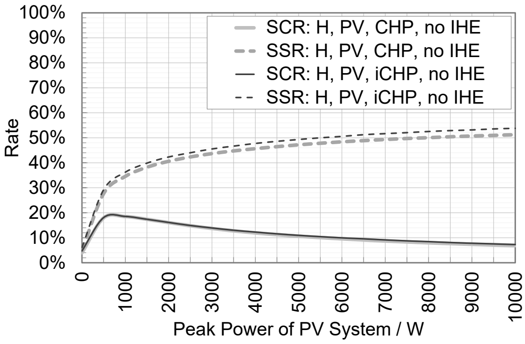
Figure G.5: Comparison of self-consumption (SCR) and self-sufficiency rates (SSR): one-person household, part 2 (a) (Tariff: FLAT-30, $n = 10$)



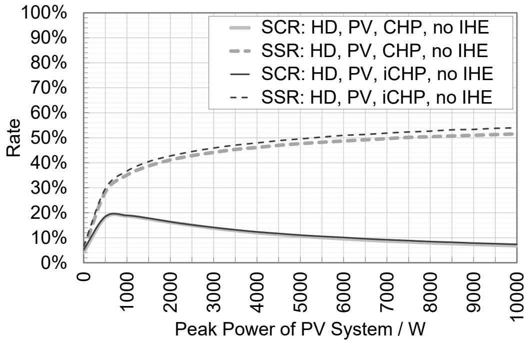
(e) Conventional (C) appliances (D), (non-)-optimized microCHP (CHP/iCHP)



(f) Deferrable appliances (D), (non-)optimized microCHP (CHP/iCHP)

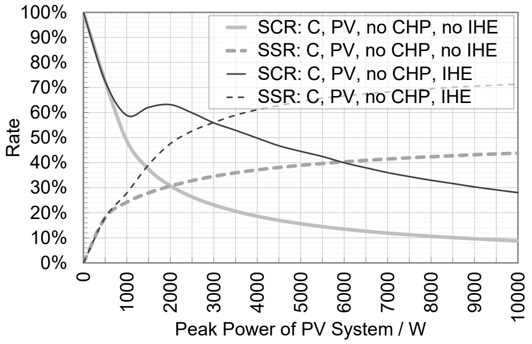


(g) Hybrid appliances (H), (non-)optimized microCHP (CHP/iCHP)

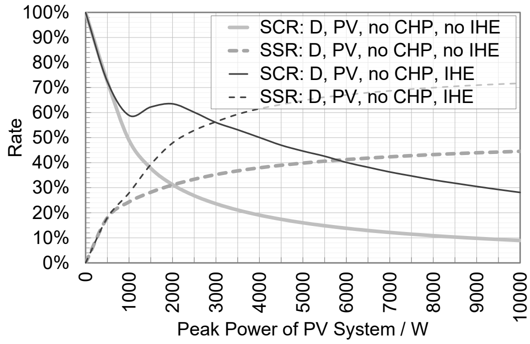


(h) Hybrid deferrable appliances (HD), (non-)optimized microCHP (CHP/iCHP)

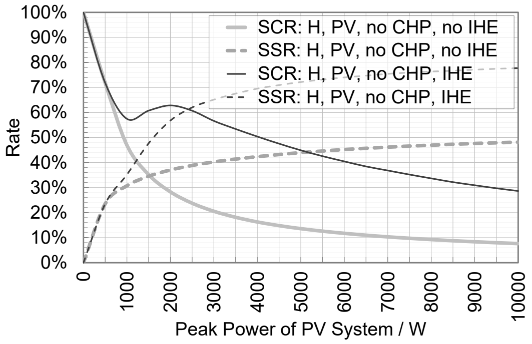
Figure G.6: Comparison of self-consumption (SCR) and self-sufficiency rates (SSR): one-person household, part 2 (b) (Tariff: FLAT-30, $n = 10$)



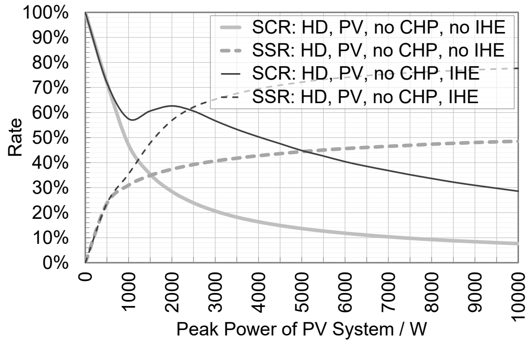
(a) Conventional appliances (C), no microCHP (CHP)



(b) Deferrable appliances (D), no microCHP (CHP)

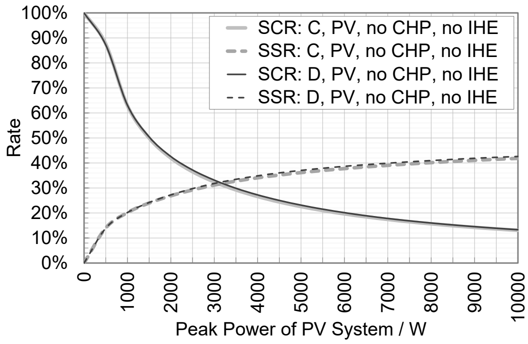


(c) Hybrid appliances (H), no microCHP (CHP)

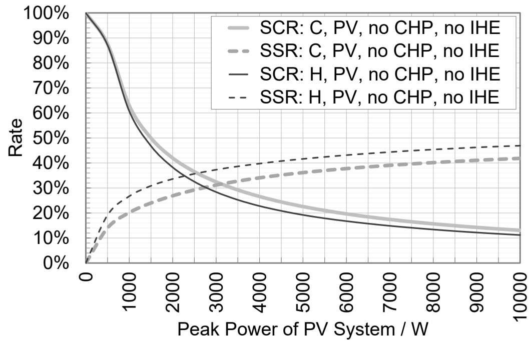


(d) Hybrid deferrable appliances (HD), no microCHP (CHP)

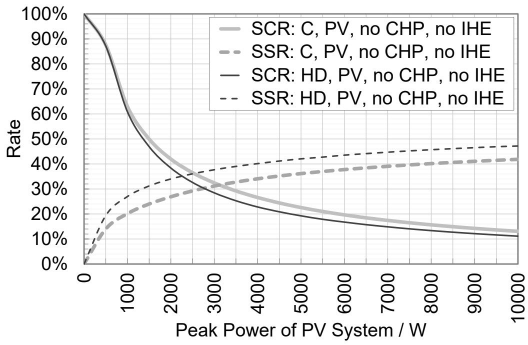
Figure G.7: Comparison of self-consumption (SCR) and self-sufficiency rates (SSR): one-person household, part 3 (Tariff: FLAT-30, $n = 10$)



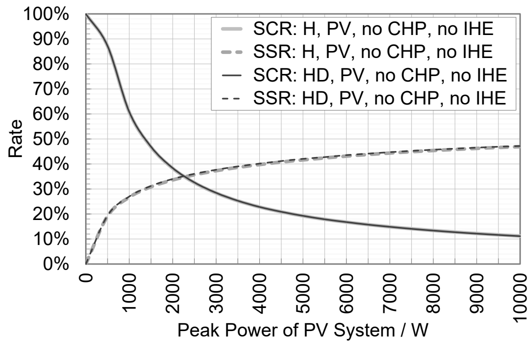
(a) Conventional (C) and deferrable appliances (D), no microCHP



(b) Conventional (C) and hybrid appliances (H), no microCHP

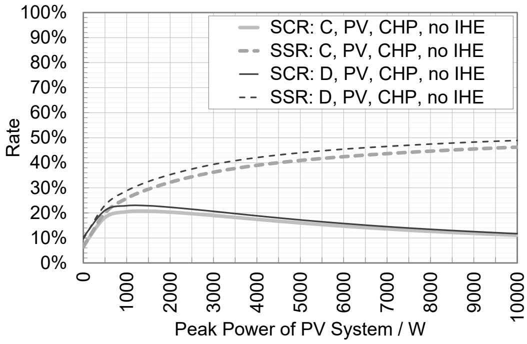


(c) Conventional (C) and hybrid deferrable appliances (HD), no microCHP

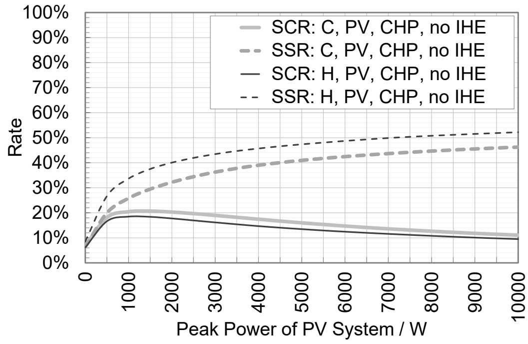


(d) Hybrid (H) and hybrid deferrable appliances (HD), no microCHP

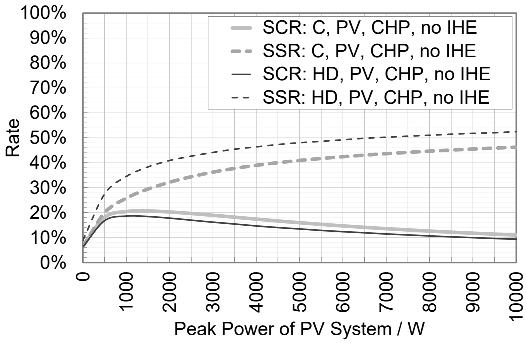
Figure G.8: Comparison of self-consumption (SCR) and self-sufficiency rates (SSR): two-person household, part 1 (a) (Tariff: FLAT-30, $n = 10$)



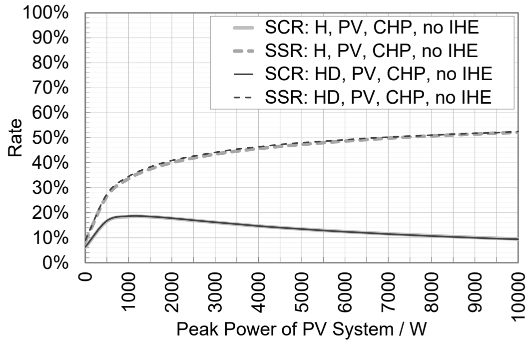
(e) Conventional (C) and deferrable appliances (D), non-optimized microCHP



(f) Conventional (C) and hybrid appliances (H), non-optimized microCHP

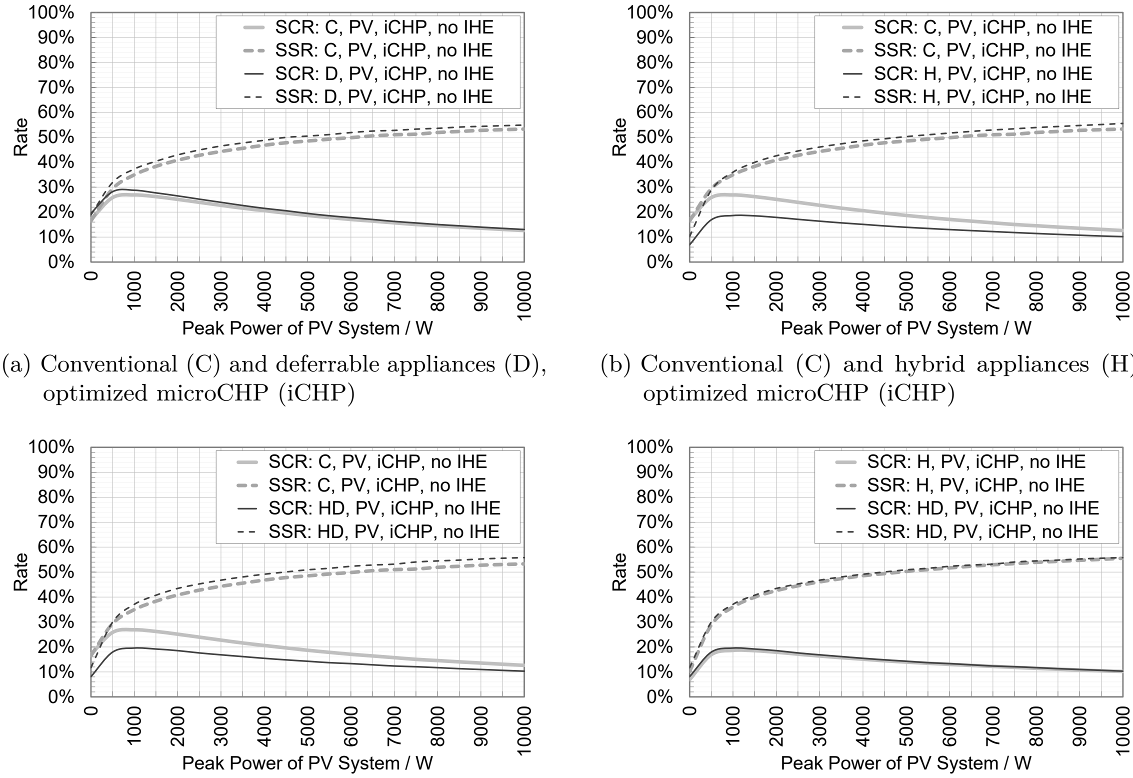


(g) Conventional (C) and hybrid deferrable appliances (HD), non-optimized microCHP



(h) Hybrid (H) and hybrid deferrable appliances (HD), non-optimized microCHP

Figure G.9: Comparison of self-consumption (SCR) and self-sufficiency rates (SSR): two-person household, part 1 (b) (Tariff: FLAT-30, $n = 10$)



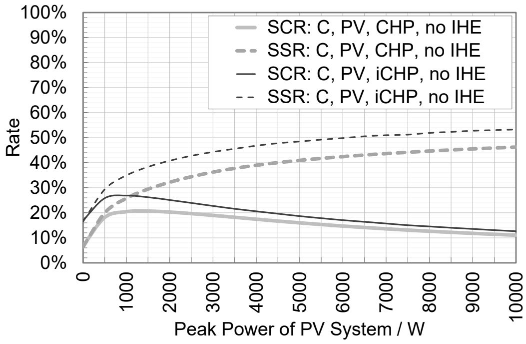
(a) Conventional (C) and deferrable appliances (D), optimized microCHP (iCHP)

(b) Conventional (C) and hybrid appliances (H), optimized microCHP (iCHP)

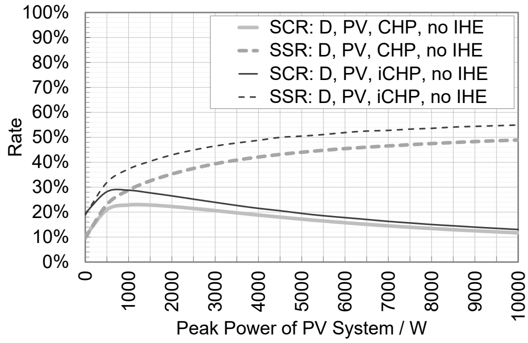
(c) Conventional (C) and hybrid deferrable appliances (HD), optimized microCHP (iCHP)

(d) Hybrid (H) and hybrid deferrable appliances (HD), optimized microCHP (iCHP)

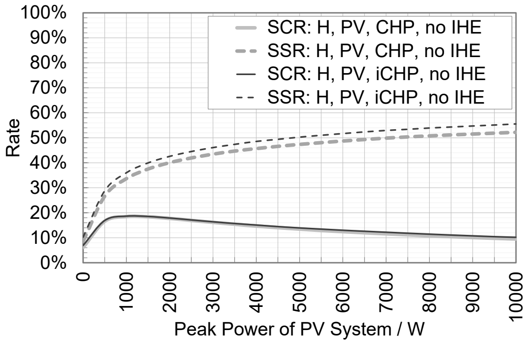
Figure G.10: Comparison of self-consumption (SCR) and self-sufficiency rates (SSR): two-person household, part 2 (a) (Tariff: FLAT-30, $n = 10$)



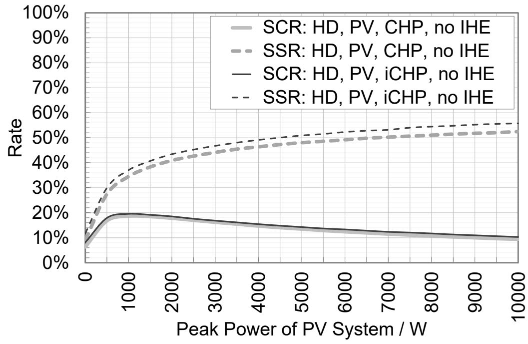
(e) Conventional (C) appliances (D), (non-)optimized microCHP (CHP/iCHP)



(f) Deferrable appliances (D), (non-)optimized microCHP (CHP/iCHP)

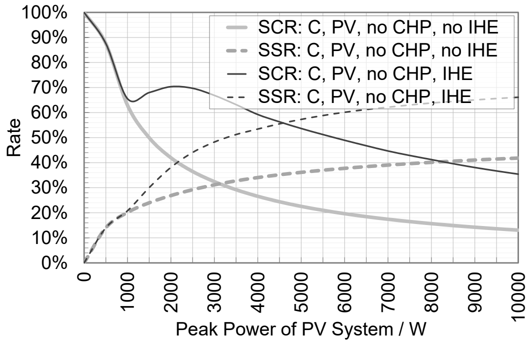


(g) Hybrid appliances (H), (non-)optimized microCHP (CHP/iCHP)

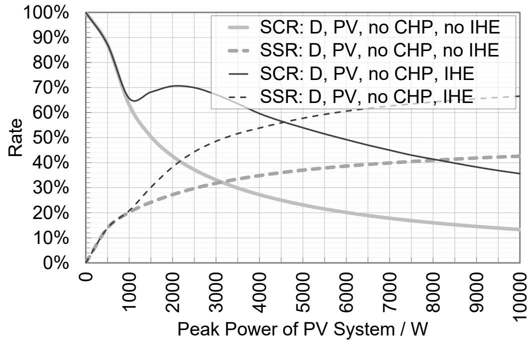


(h) Hybrid deferrable appliances (HD), (non-)optimized microCHP (CHP/iCHP)

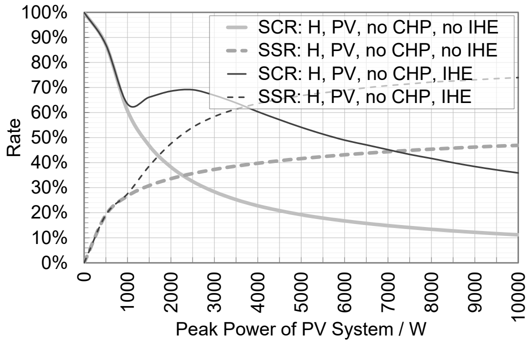
Figure G.11: Comparison of self-consumption (SCR) and self-sufficiency rates (SSR): two-person household, part 2 (b) (Tariff: FLAT-30, $n = 10$)



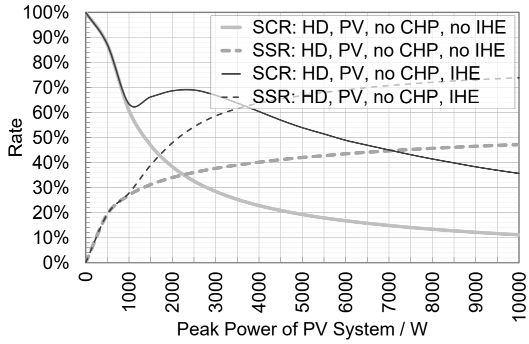
(a) Conventional appliances (C), no microCHP (CHP)



(b) Deferrable appliances (D), no microCHP (CHP)

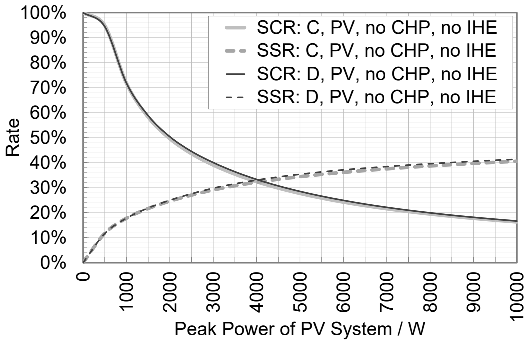


(c) Hybrid appliances (H), no microCHP (CHP)

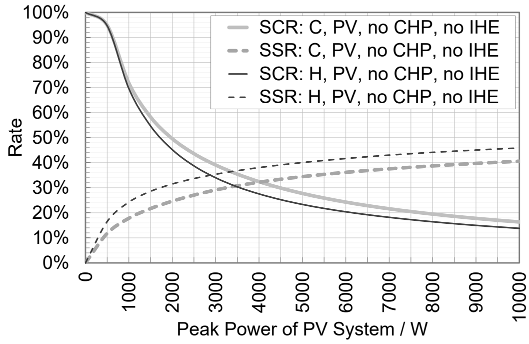


(d) Hybrid deferrable appliances (HD), no microCHP (CHP)

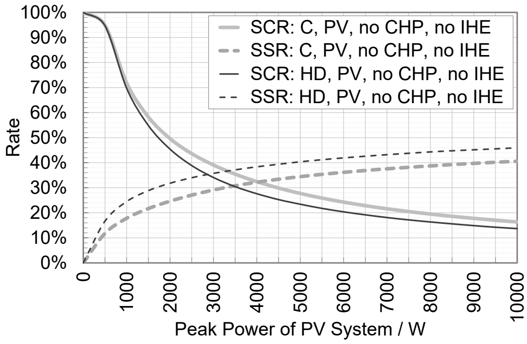
Figure G.12: Comparison of self-consumption (SCR) and self-sufficiency rates (SSR): two-person household, part 3 (Tariff: FLAT-30, $n = 10$)



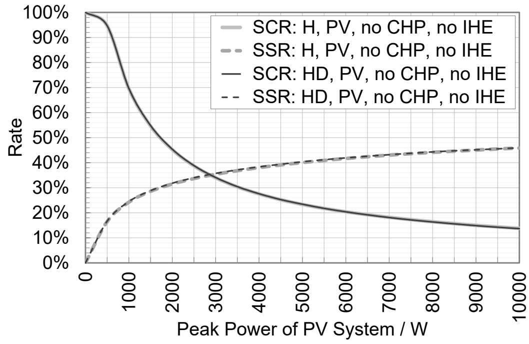
(a) Conventional (C) and deferrable appliances (D), no microCHP



(b) Conventional (C) and hybrid appliances (H), no microCHP

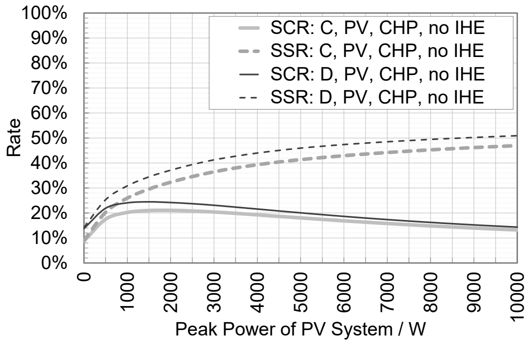


(c) Conventional (C) and hybrid deferrable appliances (HD), no microCHP

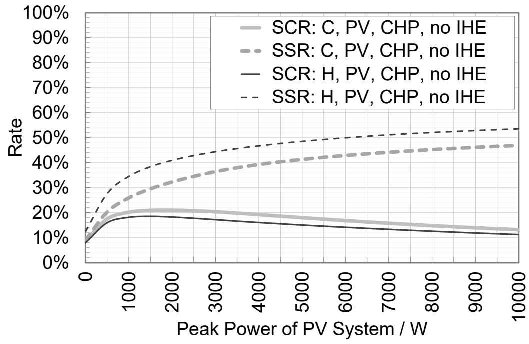


(d) Hybrid (H) and hybrid deferrable appliances (HD), no microCHP

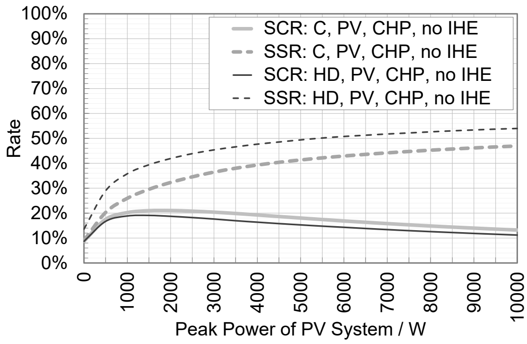
Figure G.13: Comparison of self-consumption (SCR) and self-sufficiency rates (SSR): three-person household, part 1 (a) (Tariff: FLAT-30, $n = 10$)



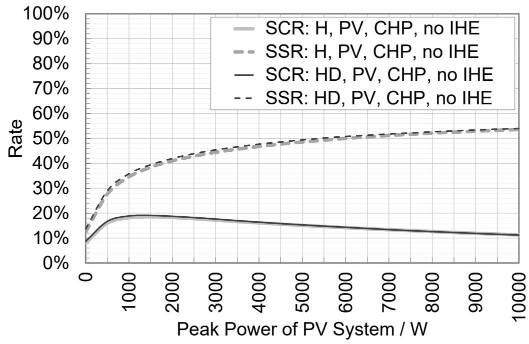
(e) Conventional (C) and deferrable appliances (D), non-optimized microCHP



(f) Conventional (C) and hybrid appliances (H), non-optimized microCHP

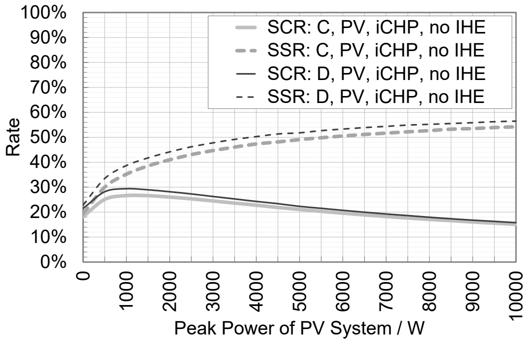


(g) Conventional (C) and hybrid deferrable appliances (HD), non-optimized microCHP

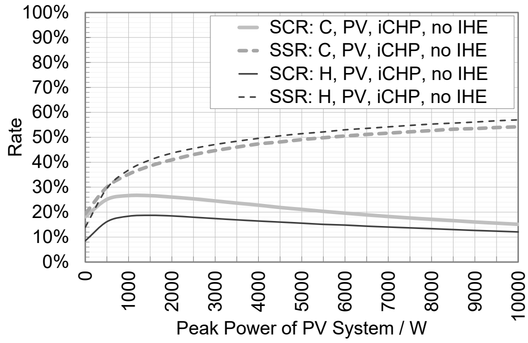


(h) Hybrid (H) and hybrid deferrable appliances (HD), non-optimized microCHP

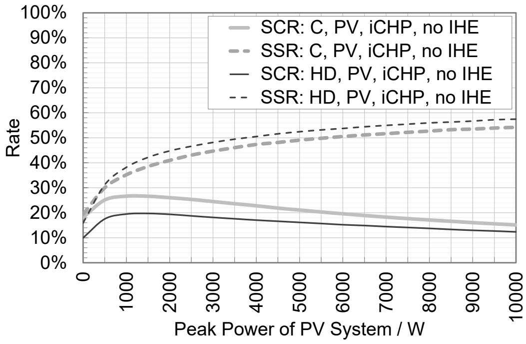
Figure G.14: Comparison of self-consumption (SCR) and self-sufficiency rates (SSR): three-person household, part 1 (b) (Tariff: FLAT-30, $n = 10$)



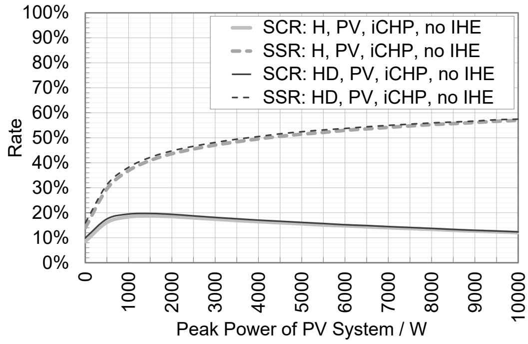
(a) Conventional (C) and deferrable appliances (D), optimized microCHP (iCHP)



(b) Conventional (C) and hybrid appliances (H), optimized microCHP (iCHP)

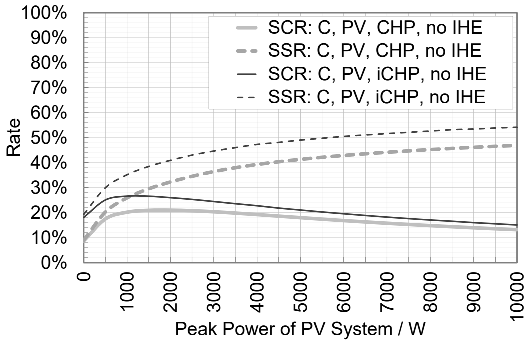


(c) Conventional (C) and hybrid deferrable appliances (HD), optimized microCHP (iCHP)

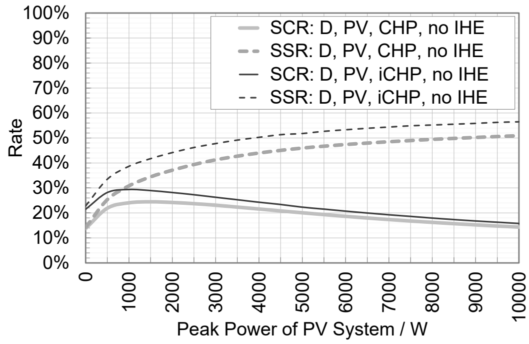


(d) Hybrid (H) and hybrid deferrable appliances (HD), optimized microCHP (iCHP)

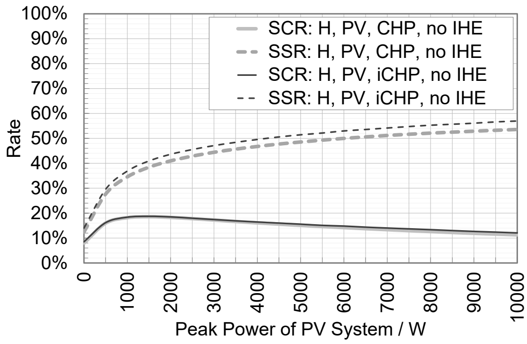
Figure G.15: Comparison of self-consumption (SCR) and self-sufficiency rates (SSR): three-person household, part 2 (a) (Tariff: FLAT-30, $n = 10$)



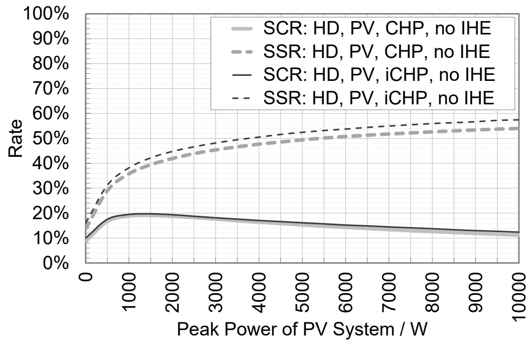
(e) Conventional (C) appliances (D), (non-)-optimized microCHP (CHP/iCHP)



(f) Deferrable appliances (D), (non-)optimized microCHP (CHP/iCHP)

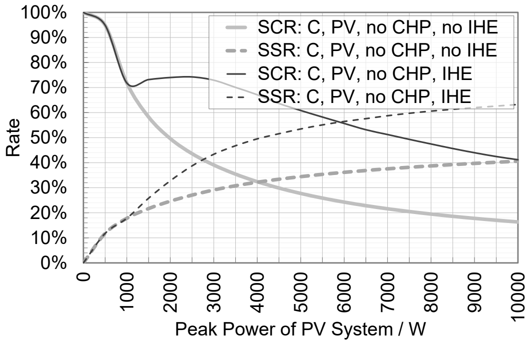


(g) Hybrid appliances (H), (non-)optimized microCHP (CHP/iCHP)

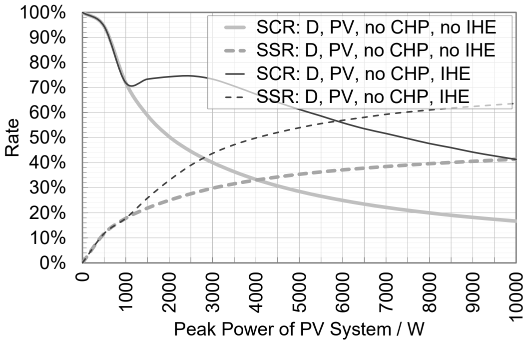


(h) Hybrid deferrable appliances (HD), (non-)-optimized microCHP (CHP/iCHP)

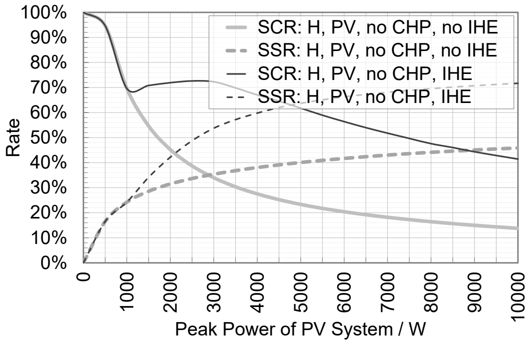
Figure G.16: Comparison of self-consumption (SCR) and self-sufficiency rates (SSR): three-person household, part 2 (b) (Tariff: FLAT-30, $n = 10$)



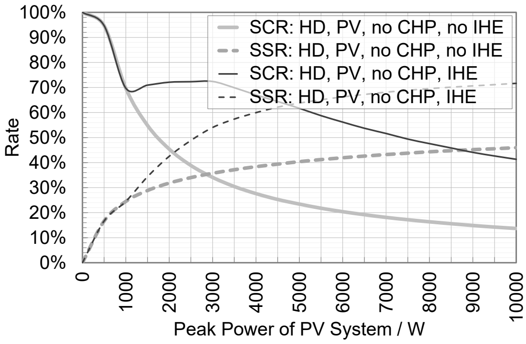
(a) Conventional appliances (C), no microCHP (CHP)



(b) Deferrable appliances (D), no microCHP (CHP)

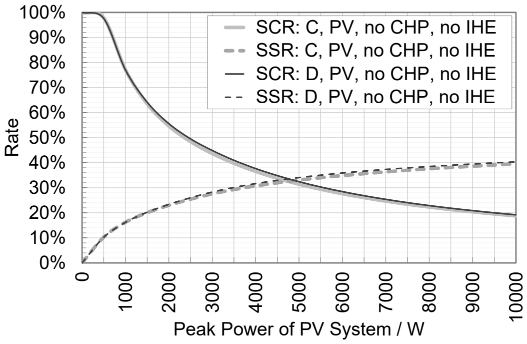


(c) Hybrid appliances (H), no microCHP (CHP)

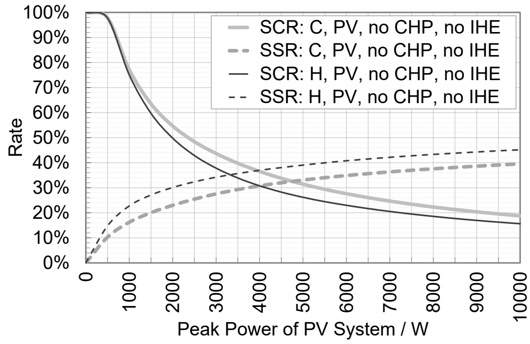


(d) Hybrid deferrable appliances (HD), no microCHP (CHP)

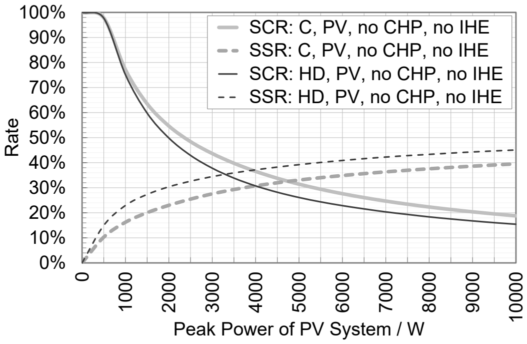
Figure G.17: Comparison of self-consumption (SCR) and self-sufficiency rates (SSR): three-person household, part 3 (Tariff: FLAT-30, $n = 10$)



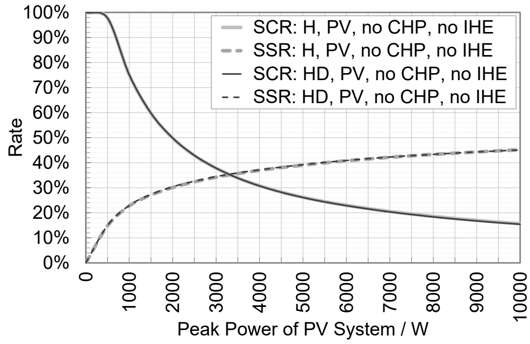
(a) Conventional (C) and deferrable appliances (D), no microCHP



(b) Conventional (C) and hybrid appliances (H), no microCHP

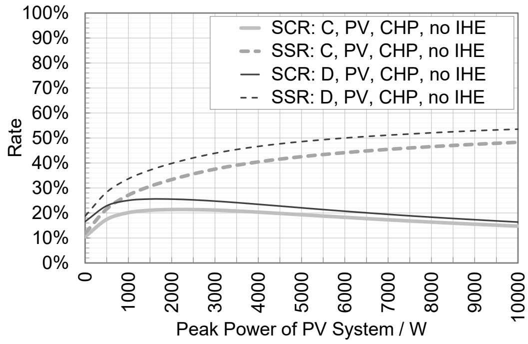


(c) Conventional (C) and hybrid deferrable appliances (HD), no microCHP

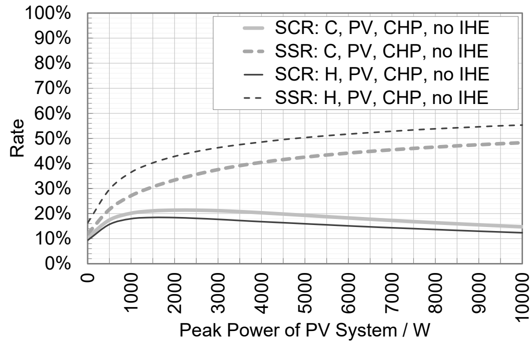


(d) Hybrid (H) and hybrid deferrable appliances (HD), no microCHP

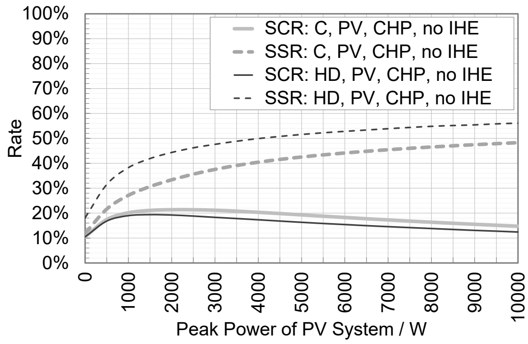
Figure G.18: Comparison of self-consumption (SCR) and self-sufficiency rates (SSR): four-person household, part 1 (a) (Tariff: FLAT-30, $n = 10$)



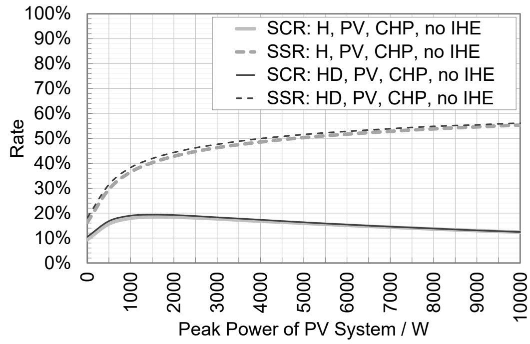
(e) Conventional (C) and deferrable appliances (D), non-optimized microCHP



(f) Conventional (C) and hybrid appliances (H), non-optimized microCHP

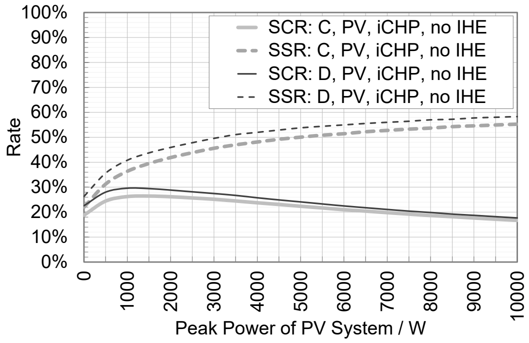


(g) Conventional (C) and hybrid deferrable appliances (HD), non-optimized microCHP

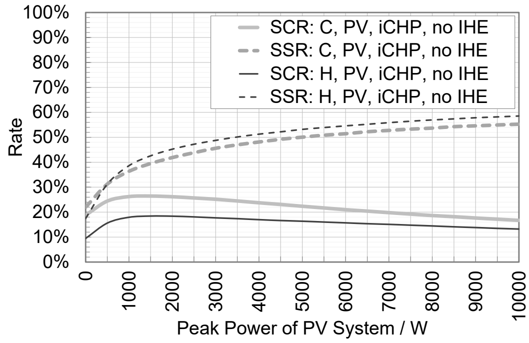


(h) Hybrid (H) and hybrid deferrable appliances (HD), non-optimized microCHP

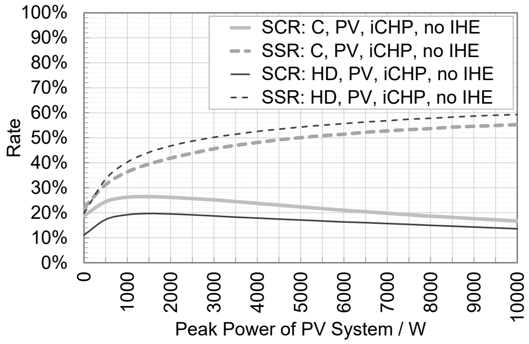
Figure G.19: Comparison of self-consumption (SCR) and self-sufficiency rates (SSR): four-person household, part 1 (b) (Tariff: FLAT-30, $n = 10$)



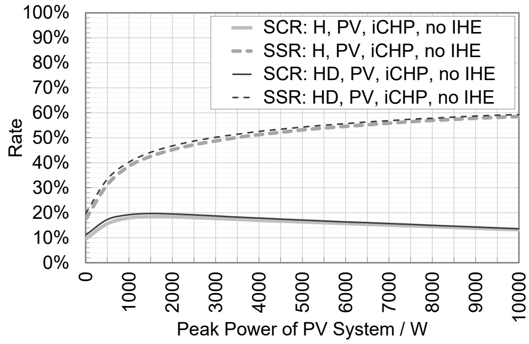
(a) Conventional (C) and deferrable appliances (D), optimized microCHP (iCHP)



(b) Conventional (C) and hybrid appliances (H), optimized microCHP (iCHP)

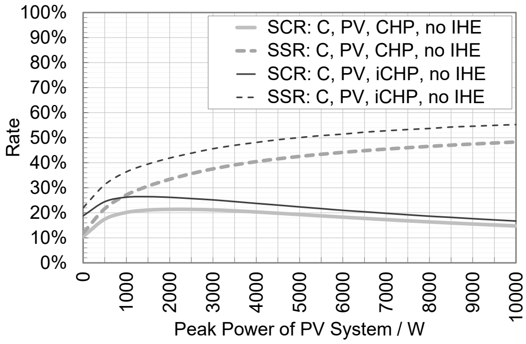


(c) Conventional (C) and hybrid deferrable appliances (HD), optimized microCHP (iCHP)

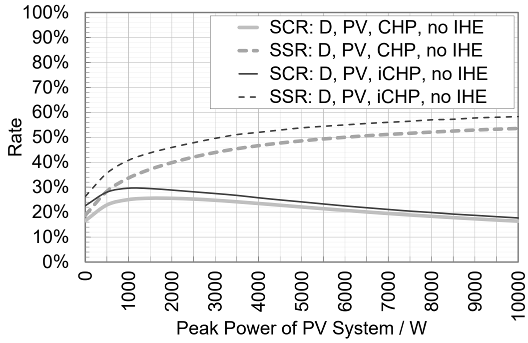


(d) Hybrid (H) and hybrid deferrable appliances (HD), optimized microCHP (iCHP)

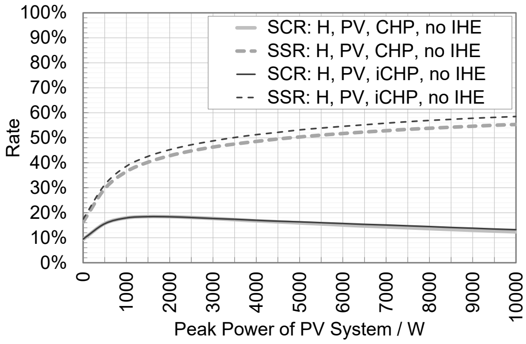
Figure G.20: Comparison of self-consumption (SCR) and self-sufficiency rates (SSR): four-person household, part 2 (a) (Tariff: FLAT-30, $n = 10$)



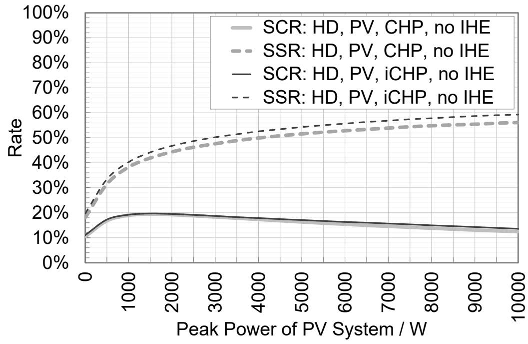
(e) Conventional appliances (D), (non-)optimized microCHP (CHP/iCHP)



(f) Deferrable appliances (D), (non-)optimized microCHP (CHP/iCHP)

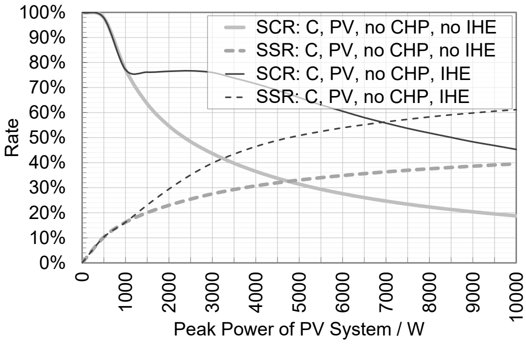


(g) Hybrid appliances (H), (non-)optimized microCHP (CHP/iCHP)

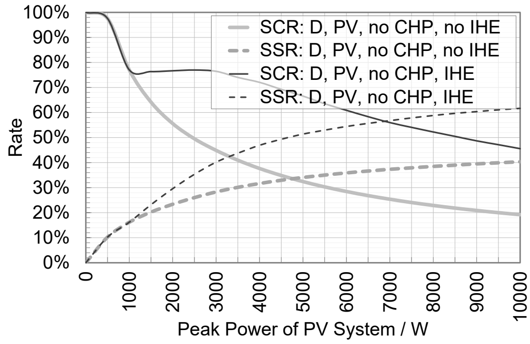


(h) Hybrid deferrable appliances (HD), (non-)optimized microCHP (CHP/iCHP)

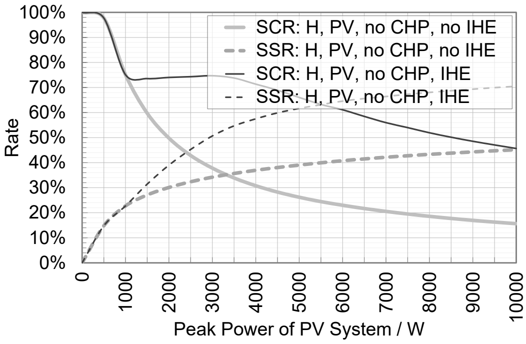
Figure G.21: Comparison of self-consumption (SCR) and self-sufficiency rates (SSR): four-person household, part 2 (b) (Tariff: FLAT-30, $n = 10$)



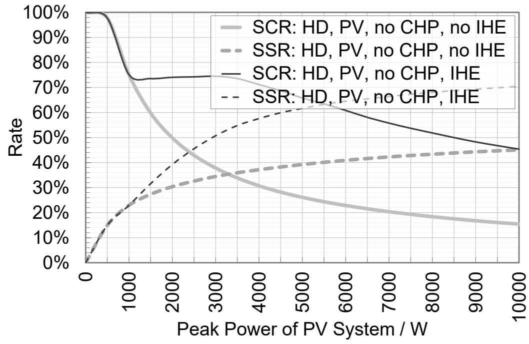
(a) Conventional appliances (C), no microCHP (CHP)



(b) Deferrable appliances (D), no microCHP (CHP)

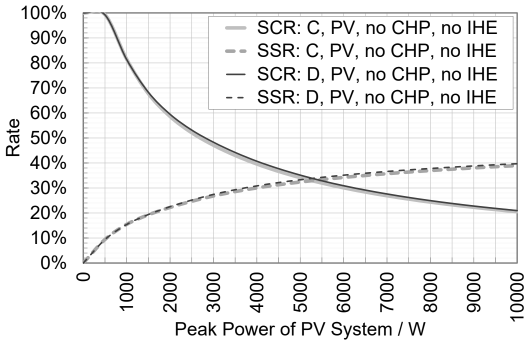


(c) Hybrid appliances (H), no microCHP (CHP)

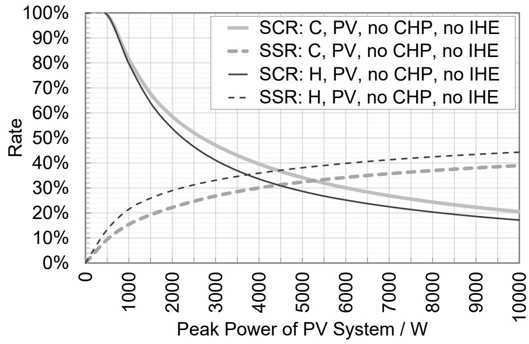


(d) Hybrid deferrable appliances (HD), no microCHP (CHP)

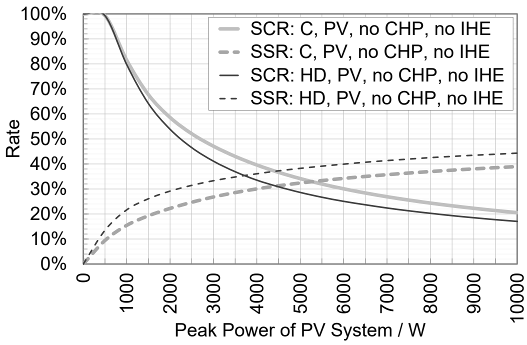
Figure G.22: Comparison of self-consumption (SCR) and self-sufficiency rates (SSR): four-person household, part 3 (Tariff: FLAT-30, $n = 10$)



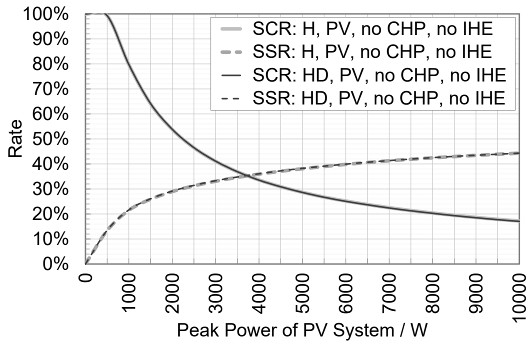
(a) Conventional (C) and deferrable appliances (D), no microCHP



(b) Conventional (C) and hybrid appliances (H), no microCHP

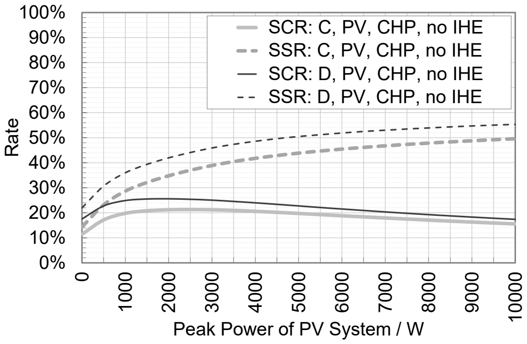


(c) Conventional (C) and hybrid deferrable appliances (HD), no microCHP

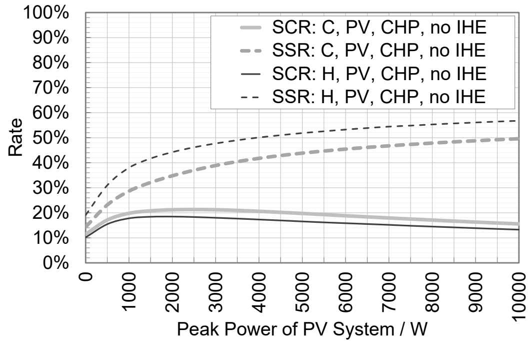


(d) Hybrid (H) and hybrid deferrable appliances (HD), no microCHP

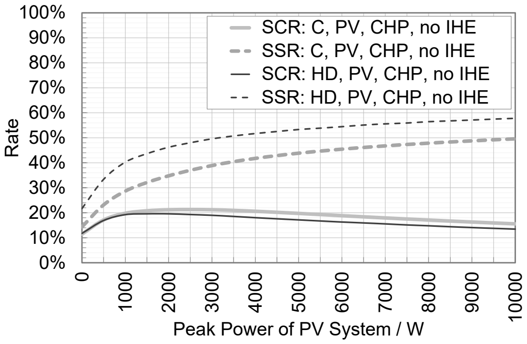
Figure G.23: Comparison of self-consumption (SCR) and self-sufficiency rates (SSR): five-person household, part 1 (a) (Tariff: FLAT-30, $n = 10$)



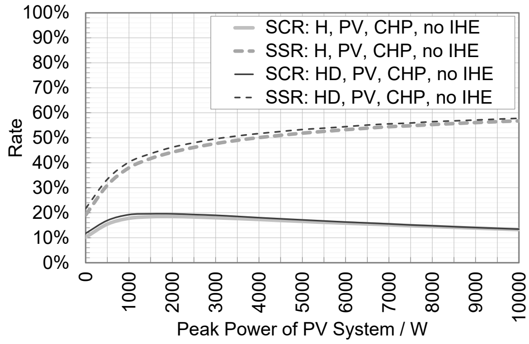
(e) Conventional (C) and deferrable appliances (D), non-optimized microCHP



(f) Conventional (C) and hybrid appliances (H), non-optimized microCHP

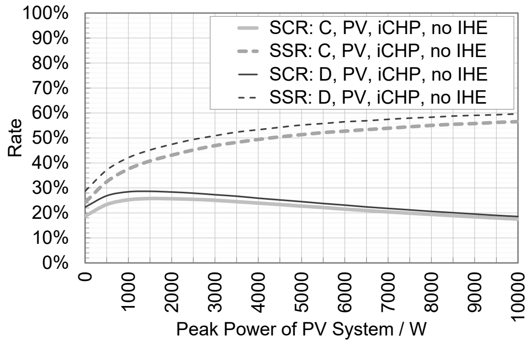


(g) Conventional (C) and hybrid deferrable appliances (HD), non-optimized microCHP

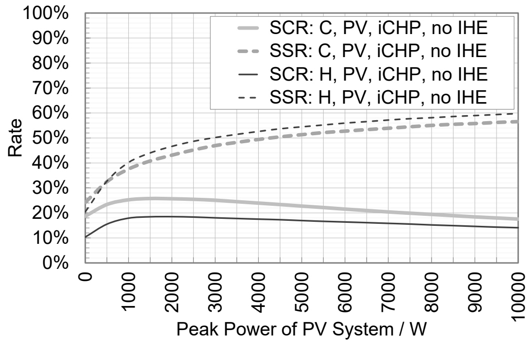


(h) Hybrid (H) and hybrid deferrable appliances (HD), non-optimized microCHP

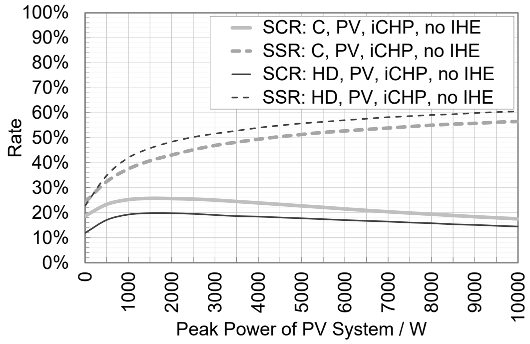
Figure G.24: Comparison of self-consumption (SCR) and self-sufficiency rates (SSR): five-person household, part 1 (b) (Tariff: FLAT-30, $n = 10$)



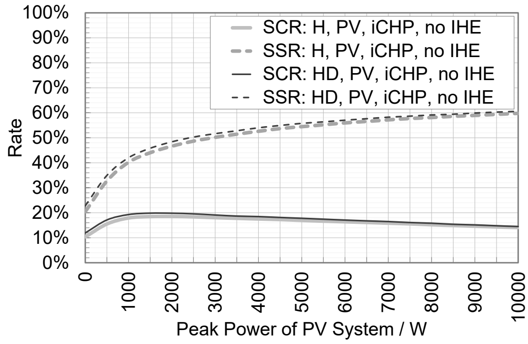
(a) Conventional (C) and deferrable appliances (D), optimized microCHP (iCHP)



(b) Conventional (C) and hybrid appliances (H), optimized microCHP (iCHP)

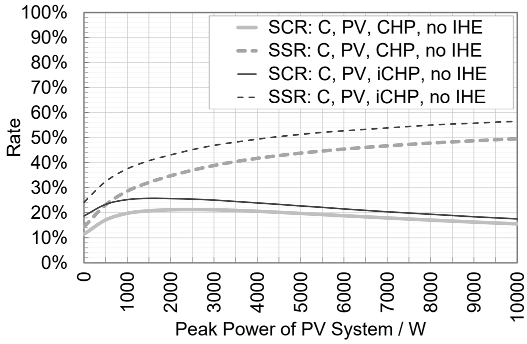


(c) Conventional (C) and hybrid deferrable appliances (HD), optimized microCHP (iCHP)

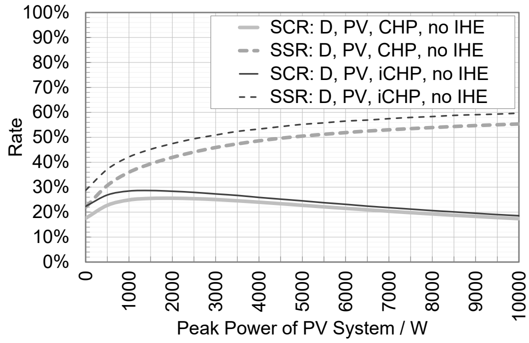


(d) Hybrid (H) and hybrid deferrable appliances (HD), optimized microCHP (iCHP)

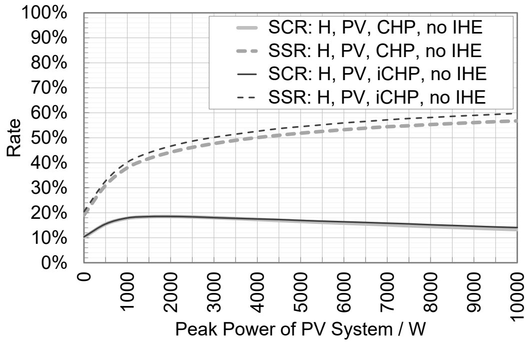
Figure G.25: Comparison of self-consumption (SCR) and self-sufficiency rates (SSR): five-person household, part 2 (a) (Tariff: FLAT-30, $n = 10$)



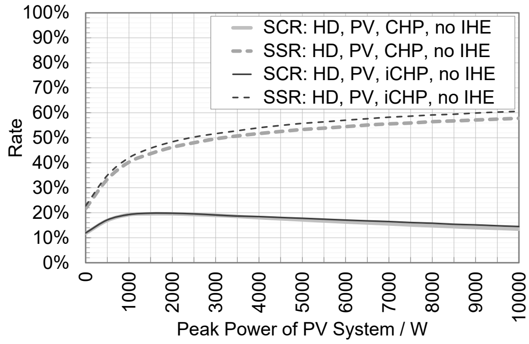
(e) Conventional appliances (C), (non-)optimized microCHP (CHP/iCHP)



(f) Deferrable appliances (D), (non-)optimized microCHP (CHP/iCHP)

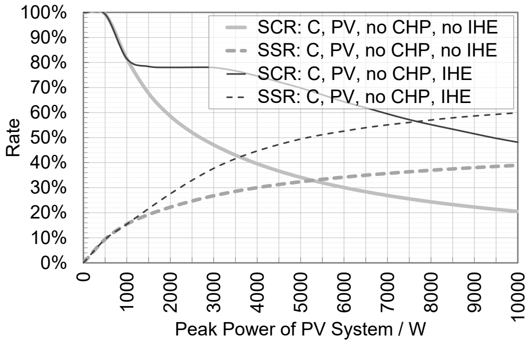


(g) Hybrid appliances (H), (non-)optimized microCHP (CHP/iCHP)

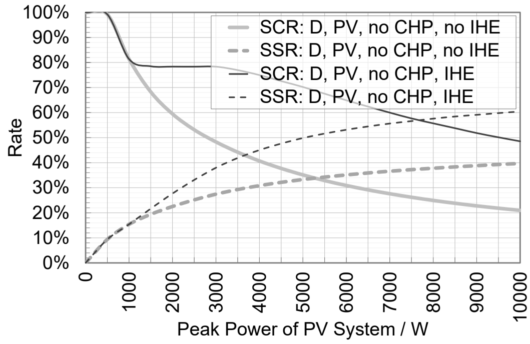


(h) Hybrid deferrable appliances (HD), (non-)optimized microCHP (CHP/iCHP)

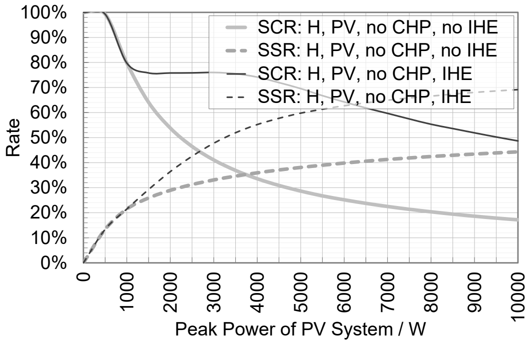
Figure G.26: Comparison of self-consumption (SCR) and self-sufficiency rates (SSR): five-person household, part 2 (b) (Tariff: FLAT-30, $n = 10$)



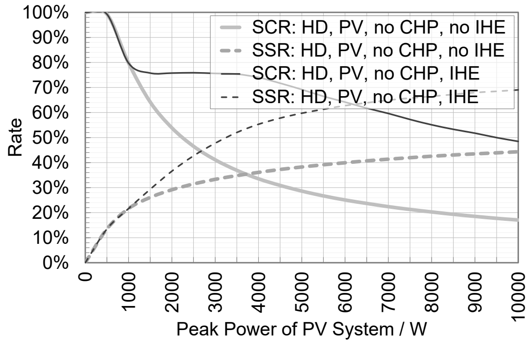
(a) Conventional appliances (C), no microCHP (CHP)



(b) Deferrable appliances (D), no microCHP (CHP)



(c) Hybrid appliances (H), no microCHP (CHP)



(d) Hybrid deferrable appliances (HD), no microCHP (CHP)

Figure G.27: Comparison of self-consumption (SCR) and self-sufficiency rates (SSR): five-person household, part 3 (Tariff: FLAT-30, $n = 10$)

Table G.6: Average yearly total costs, self-consumption rates, and self-sufficiency rates in four-person households having different electricity tariffs, see Table 6.6 on p. 269 for more details about the tariffs and Table G.3 on p. 447 for the used abbreviations ($n = 20$)

		Avg. total costs in EUR				**Avg. self-consumption rate in %**				**Avg. self-sufficiency rate in %**			
Appliances	**IHE**	**FLAT-30**	**H0-30**	**WIK-30**	**ALT-20-40**	**FLAT-30**	**H0-30**	**WIK-30**	**ALT-20-40**	**FLAT-30**	**H0-30**	**WIK-30**	**ALT-20-40**
						no PV system							
C	✗	2394	2634	2459	2502	–	–	–	–	–	–	–	–
D	✗	2387	2490	2405	2346	–	–	–	–	–	–	–	–
H	✗	2085	2222	2117	2153	–	–	–	–	–	–	–	–
HD	✗	2078	2209	2112	2139	–	–	–	–	–	–	–	–
C	✓	2394	2634	2459	2502	–	–	–	–	–	–	–	–
D	✓	2387	2490	2405	2346	–	–	–	–	–	–	–	–
H	✓	2085	2222	2117	2153	–	–	–	–	–	–	–	–
HD	✓	2078	2209	2112	2139	–	–	–	–	–	–	–	–
						2 kW PV system							
C	✗	1970	2142	2000	2045	54.7	54.8	54.7	54.7	23.0	23.1	23.0	23.0
D	✗	1960	2019	1955	1907	55.5	53.8	54.7	53.6	23.3	22.6	23.0	22.5
H	✗	1687	1768	1690	1728	49.8	49.7	49.8	49.8	30.1	30.2	30.2	30.2
HD	✗	1684	1756	1686	1719	49.9	49.7	49.7	49.6	30.3	29.9	30.2	29.9
C	✓	1979	2150	2009	2053	76.4	76.5	76.4	76.4	29.5	29.5	29.5	29.5
D	✓	1968	2028	1964	1917	76.7	76.2	76.3	76.0	29.6	29.3	29.4	29.2
H	✓	1697	1778	1700	1739	74.0	73.9	74.0	74.0	39.1	39.1	39.1	39.1
HD	✓	1694	1767	1696	1730	74.1	74.0	74.0	74.0	39.2	38.8	39.1	38.8
						4 kW PV system							
C	✗	1694	1844	1713	1758	36.5	36.7	36.5	36.5	30.7	30.9	30.7	30.7
D	✗	1680	1732	1671	1645	37.6	37.0	37.2	36.1	31.6	31.1	31.3	30.4
H	✗	1445	1518	1442	1482	30.8	30.8	30.7	30.7	37.0	37.0	37.0	37.0
HD	✗	1441	1505	1438	1474	30.8	30.7	30.7	30.6	37.2	36.7	37.0	36.7
C	✓	1725	1875	1744	1789	71.7	71.5	71.7	71.7	46.5	46.5	46.5	46.5
D	✓	1710	1763	1702	1676	72.1	71.7	72.1	71.6	46.9	46.6	46.8	46.3
H	✓	1479	1552	1477	1517	71.5	71.4	71.5	71.4	57.6	57.7	57.7	57.6
HD	✓	1477	1543	1475	1511	71.1	71.0	71.2	71.3	57.6	57.0	57.5	57.3

Table G.7: Total costs in various four-person households, for abbreviations see Table G.3 on p. 447 (Tariff: FLAT-30, $n = 20$)

	Appliances	MicroCHP	No IHE			With IHE		
	PV system		no PV	2 kW	4 kW	no PV	2 kW	4 kW
January	C	–	286	279	274	286	279	274
	D	–	285	279	273	285	279	273
	H	–	256	249	244	256	249	245
	HD	–	256	250	245	256	250	245
	C	NO	282	276	271	267	261	256
	D	NO	265	260	255	252	247	242
	H	NO	259	254	250	241	236	231
	HD	NO	255	250	245	239	234	230
	C	O	272	267	261	259	254	250
	D	O	262	257	253	251	246	242
	H	O	261	255	251	244	238	234
	HD	O	258	252	248	242	237	232
July	C	–	110	49	9	110	51	15
	D	–	110	48	8	110	50	14
	H	–	92	35	-1	92	37	5
	HD	–	91	35	-1	91	37	5
	C	NO	111	51	11	108	51	15
	D	NO	109	49	9	107	49	14
	H	NO	93	38	2	90	37	5
	HD	NO	92	37	2	89	37	5
	C	O	104	46	7	103	48	13
	D	O	102	45	6	102	48	12
	H	O	92	37	2	89	36	5
	HD	O	92	37	2	88	36	4
Yearly	C	–	2394	1970	1694	2394	1979	1725
	D	–	2387	1960	1680	2387	1968	1710
	H	–	2085	1687	1445	2085	1697	1479
	HD	–	2078	1684	1441	2078	1694	1477
	C	NO	2389	1983	1716	2286	1890	1647
	D	NO	2296	1897	1634	2206	1815	1577
	H	NO	2124	1748	1512	1999	1633	1423
	HD	NO	2096	1723	1490	1985	1622	1414
	C	O	2270	1887	1628	2199	1825	1595
	D	O	2205	1823	1573	2144	1774	1548
	H	O	2120	1743	1509	2003	1634	1428
	HD	O	2102	1725	1492	1994	1626	1421

Average total costs in EUR

Table G.8: Electricity self-consumption rate in various four-person households, for abbreviations see Table G.3 on p. 447 (Tariff: FLAT-30, $n = 20$)

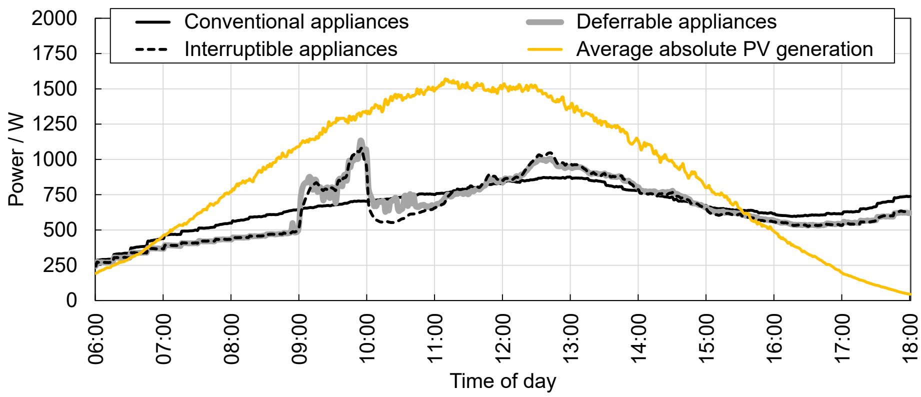
Average electricity self-consumption rate in %								
	Appliances	**MicroCHP**	**No IHE**			**With IHE**		
	PV system		no PV	2 kW	4 kW	no PV	2 kW	4 kW
January	C	–	–	93	82	–	93	90
	D	–	–	92	81	–	92	90
	H	–	–	92	78	–	92	88
	HD	–	–	92	78	–	92	88
	C	NO	12	13	14	73	73	73
	D	NO	19	20	21	76	76	76
	H	NO	11	12	13	73	73	73
	HD	NO	16	17	18	74	74	74
	C	O	17	19	20	75	75	75
	D	O	21	22	23	77	77	77
	H	O	12	13	14	73	73	73
	HD	O	15	17	17	74	74	74
July	C	–	–	40	25	–	73	62
	D	–	–	41	25	–	73	62
	H	–	–	35	19	–	70	64
	HD	–	–	35	19	–	70	64
	C	NO	10	32	22	72	71	62
	D	NO	16	33	22	74	72	62
	H	NO	9	26	17	71	69	64
	HD	NO	11	26	17	72	69	64
	C	O	36	36	24	83	74	45
	D	O	41	37	24	84	74	46
	H	O	10	26	18	72	71	47
	HD	O	13	26	19	74	71	46
Yearly	C	–	–	55	37	–	76	72
	D	–	–	56	38	–	77	72
	H	–	–	50	31	–	74	72
	HD	–	–	50	31	–	74	71
	C	NO	10	21	20	72	72	71
	D	NO	16	25	23	75	74	72
	H	NO	10	19	17	72	71	70
	HD	NO	13	21	19	73	72	71
	C	O	20	27	25	76	75	69
	D	O	25	30	27	78	77	70
	H	O	11	20	18	73	72	69
	HD	O	14	22	20	74	73	70

Table G.9: Electricity self-sufficiency rate in various four-person households, for abbreviations see Table G.3 on p. 447 (Tariff: FLAT-30, $n = 20$)

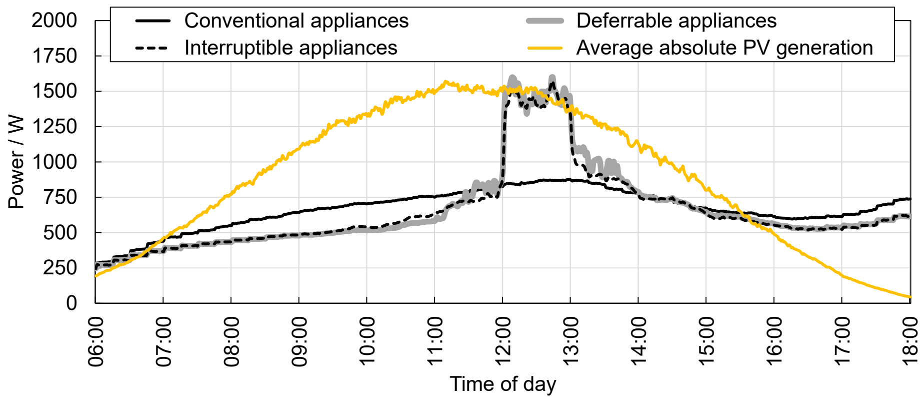
Average electricity self-sufficiency rate in %								
	Appliances	**MicroCHP**	**No IHE**			**With IHE**		
	PV system		no PV	2 kW	4 kW	no PV	2 kW	4 kW
January	C	–	–	5	8	–	5	9
	D	–	–	5	8	–	5	9
	H	–	–	7	11	–	7	13
	HD	–	–	7	11	–	7	13
	C	NO	23	26	29	57	59	61
	D	NO	36	40	42	63	65	67
	H	NO	29	34	38	68	70	72
	HD	NO	38	43	46	69	71	73
	C	O	35	38	41	62	64	66
	D	O	42	46	48	65	67	68
	H	O	33	38	42	69	71	73
	HD	O	38	43	46	69	72	73
July	C	–	–	46	56	–	60	76
	D	–	–	46	57	–	61	77
	H	–	–	56	61	–	72	84
	HD	–	–	56	62	–	72	84
	C	NO	4	48	57	18	63	76
	D	NO	6	49	59	19	64	77
	H	NO	6	58	63	29	76	84
	HD	NO	8	60	64	30	76	84
	C	O	14	55	64	24	66	72
	D	O	17	56	65	25	66	73
	H	O	8	61	67	31	77	81
	HD	O	9	62	67	31	78	81
Yearly	C	–	–	23	31	–	29	47
	D	–	–	23	32	–	30	47
	H	–	–	30	37	–	39	58
	HD	–	–	30	37	–	39	58
	C	NO	12	33	40	42	57	65
	D	NO	19	40	47	45	61	68
	H	NO	17	43	49	53	70	76
	HD	NO	22	47	52	54	70	76
	C	O	24	44	50	47	62	68
	D	O	29	48	54	49	64	70
	H	O	20	47	53	55	72	77
	HD	O	24	50	55	55	72	77

Table G.10: Yearly electricity and natural gas consumption in various four-person households, for abbreviations see Table G.3 on p. 447 (Tariff: FLAT-30, $n = 20$)

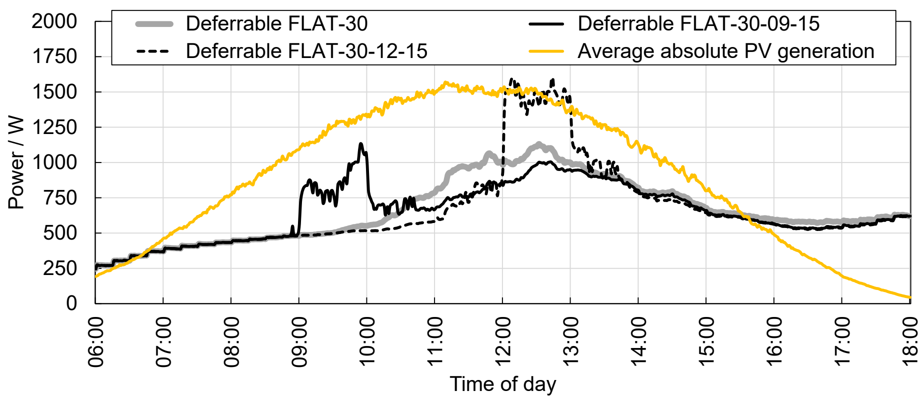
	Appliances	**MicroCHP**	**No IHE**			**With IHE**		
	PV system		no PV	2 kW	4 kW	no PV	2 kW	4 kW
	Average electricity consumption in kWh (without local generation)							
Yearly	C	–	4750	4750	4750	4750	5184	6164
	D	–	4760	4757	4756	4760	5180	6145
	H	–	3299	3302	3327	3299	3788	4961
	HD	–	3265	3288	3307	3265	3774	4939
	C	NO	4671	4671	4671	7246	7582	8344
	D	NO	4679	4676	4676	7118	7464	8238
	H	NO	3372	3384	3415	6177	6549	7463
	HD	NO	3518	3533	3549	6179	6567	7463
	C	O	4671	4671	4671	7129	7532	8115
	D	O	4677	4677	4677	7023	7434	8044
	H	O	3347	3341	3408	6203	6596	7410
	HD	O	3516	3499	3560	6223	6612	7424
	Average natural gas consumption in kWh							
Yearly	C	–	11806	11806	11806	11806	11371	10409
	D	–	11806	11806	11806	11806	11382	10432
	H	–	13695	13691	13659	13695	13203	12028
	HD	–	13735	13708	13683	13735	13219	12051
	C	NO	19816	19816	19816	15614	15047	13792
	D	NO	19816	19816	19816	15835	15248	13974
	H	NO	22285	22259	22203	17726	17092	15579
	HD	NO	21965	21937	21913	17706	17031	15553
	C	O	20580	20581	20523	16463	15732	14761
	D	O	20466	20449	20415	16570	15822	14815
	H	O	22849	22882	22742	18172	17506	16151
	HD	O	22446	22495	22381	18065	17416	16075



(a) Average yearly consumption load profiles using FLAT-30-09-15



(b) Average yearly consumption load profiles using FLAT-30-12-15



(c) Average yearly consumption load profiles

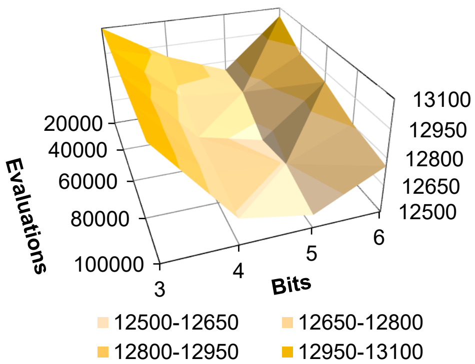
Figure G.28: Average yearly electricity load profiles of a four-person household with a PV system (solid yellow curve) and conventional or interruptible appliances, respectively; using different exemplary tariffs ($n = 100$)

G.9 Configurations: Smart Commercial Building Scenarios

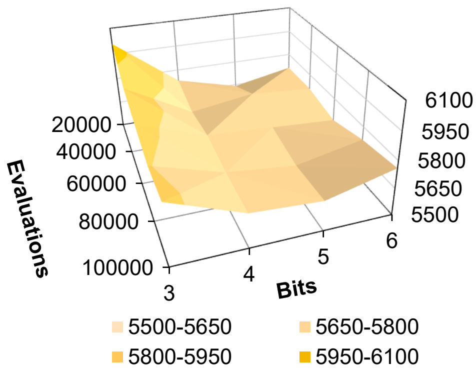
Table G.11: Smart commercial building scenario: details of the devices and tariffs

Adsorption chiller	Nominal cooling power:	9.0 kW	
	Model:	`class AdsorptionChillerModel`	
	Cooler models:	**Model A** (see Table D.4 on p. 409)	
		Model B (see *ibid.*)	
MicroCHP	Nominal hot water power:	12.5 kW	
	Nominal active power:	5.5 kW	
	Nominal natural gas power:	20.5 kW	
	Model:	`class GenericChpModel`	
Hot water storage tank		**High loss**	**Low loss**
	Heat loss factor a:	$a = 8$	$a = 2$
	Capacity:	3250 liters	
	Initial temperature:	57.5 °C	
	Min./max. temperature:	55.0 °C/75.0 °C	
	Ambient temperature:	24.0 °C	
	Model:	`class BasicWaterTank`	
Chilled water storage tank		**High loss**	**Low loss**
	Heat loss factor a:	$a = 8$	$a = 2$
	Capacity:	3000 liters	
	Initial temperature:	17.0 °C	
	Min./max. temperature:	14.0 °C/18.0 °C	
	Ambient temperature:	24.0 °C	
	Model:	`class BasicWaterTank`	
Tariff		**FLAT-30:**	
	Electricity:	30 cent/kWh	
	Natural gas:	6 cent/kWh	
	MicroCHP feed-in:	9 cent/kWh	
	MicroCHP self-consumption:	5 cent/kWh	
	Power limit signal:	–	

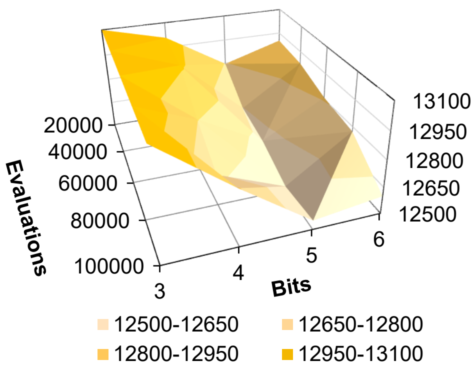
G.10 Evaluation: Parameters in the Smart Commercial Building Scenarios



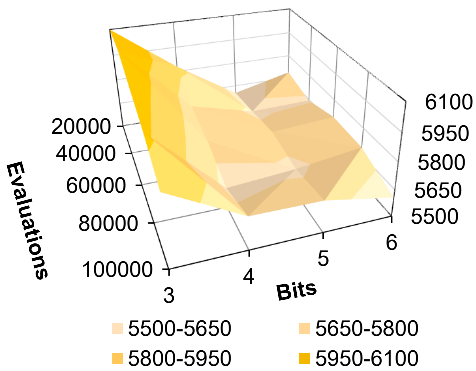
(a) Heat loss factor $a = 8$, cooler model B: mutation factor $m = 15$



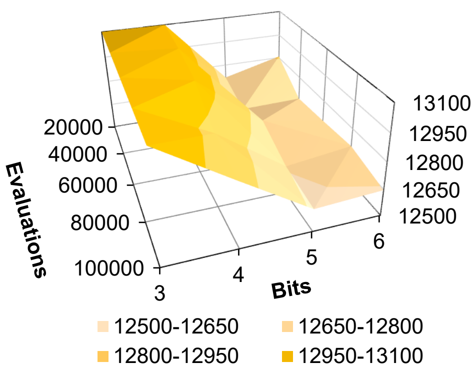
(b) Heat loss factor $a = 2$, cooler model A: mutation factor $m = 15$



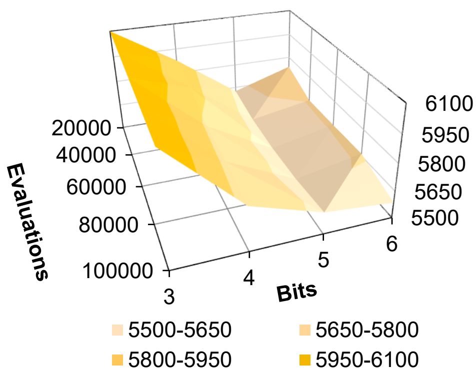
(c) Heat loss factor $a = 8$, cooler model B: mutation factor $m = 21$



(d) Heat loss factor $a = 2$, cooler model A: mutation factor $m = 21$



(e) Heat loss factor $a = 8$, cooler model B: mutation factor $m = 27$



(f) Heat loss factor $a = 2$, cooler model A: mutation factor $m = 27$

Figure G.29: Smart commercial building scenario: average total costs in case of various parameter settings of the genetic algorithm ($n = 5$)

G.11 KIT Energy Smart Home Lab: Evaluation Phase

Table G.12: Device-user interaction in the ESHL at the two consecutive exemplary evaluation days December, 1st and 2nd of 2016

Time (UTC)	Device	Details
Day 1: 01.12.2016 – automated energy management		
07:15	Lighting Room 1	On
07:20	Coffee machine	On
07:25	Lighting Room 2	On
07:25	DHW	Draw off, 2 min
07:40	Dishwasher	Programmed (Auto, extra dry), TDoF: $t^{\mathrm{dof}} = 8\,\mathrm{h}$
07:50	Washing machine	Programmed (40 °C, Cotton, extra rinse), TDoF: $t^{\mathrm{dof}} = 8\,\mathrm{h}$
08:10	Washing machine	TDoF: $t^{\mathrm{dof}} = 4\,\mathrm{h}$
08:15	Washing machine	Started by OSH
09:15	Tumble dryer	Programmed (Extra dry, Cotton), TDoF: $t^{\mathrm{dof}} = 8\,\mathrm{h}$
09:15	Lighting Room 2	Off
12:15	Induction hob	Started (rear left: level 6)
12:15	Electric oven	Started (120 °C, Convection)
12:15	DHW	Draw off, 3 min
12:20	Dishwasher	Started by OSH
12:20	Tumble dryer	Started by OSH
12:35	Electric oven	Off
12:45	Induction hob	Off
14:10	Tumble dryer	Programmed (Extra dry, Cotton), TDoF: $t^{\mathrm{dof}} = 2\,\mathrm{h}$
14:40	Tumble dryer	Programmed (Extra dry, Cotton), TDoF: $t^{\mathrm{dof}} = 10\,\mathrm{h}$
Day 2: 02.12.2016 – no energy management		
07:15	Lighting Room 2	On
07:20	Coffee machine	On
07:25	DHW	Draw off, 2 min
07:40	Dishwasher	Started (Auto, extra dry)
07:50	Washing machine	Started (40 °C, Cotton, extra rinse)
09:10	Tumble dryer	Started (Extra dry, Cotton)
09:15	Lighting Room 2	Off
12:10	Induction hob	Started (rear left: level 6)
12:10	Electric oven	Started (120 °C, Convection)
12:15	DHW	Draw off, 3 min
12:30	Electric oven	Off
12:40	Induction hob	Off
14:10	Tumble dryer	Started (Extra dry, Cotton)
16:10	Lighting Room 1	Off

H Related Publications

Table H.1: List of relevant own publications and their relation to this thesis

Establishing a Hardware-in-the-Loop Research Environment with Hybrid Energy Storage System S. Kochanneck, I. Mauser, B. Bohnet, S. Hubschneider, H. Schmeck, M. Braun, Th. Leibfried 2016 IEEE Power and Energy Society Conference on Innovative Smart Grid Technologies Asia, IEEE	**2016** [355] ✍
This paper introduces the HIL laboratory environment at the KIT and the usage of the new version of the OSH to realize HIL simulations. The latter has been my part in writing it. However, actual HIL simulations are not part of this thesis.	
Comparison of Multi-objective Evolutionary Optimization in Smart Building Scenarios M. Braun, Th. Dengiz, I. Mauser, H. Schmeck Applications of Evolutionary Computation, Springer, LNCS 9597, p. 443–458 *Best paper award (EvoApplications)*	**2016** [96] ✍ ①
This paper compares the results of multi-objective optimization by various EAs in smart building scenarios. The actual multi-objective optimization is not part of this thesis and only provided as an outlook.	
Optimization of Operation and Control Strategies for Battery Energy Storage Systems by Evolutionary Algorithms J. Müller, M. März, I. Mauser, H. Schmeck Applications of Evolutionary Computation, Springer, LNCS 9597, p. 507–522	**2016** [440] ✍
This paper introduces the optimization of the parameters of a control strategy that is used by a BESS. The optimization of the operation of BESSs and electric vehicles is one of the motivations for the development of the ESC that is presented in this thesis. However, the simulation of scenarios using BESSs is not part of thesis and only provided as an outlook.	
Adaptive building energy management with multiple commodities and flexible evolutionary optimization I. Mauser, J. Müller, F. Allerding, H. Schmeck Renewable Energy, Volume 87 (2), Elsevier, p. 911–921	**2016** [410] ✍
This article gives an overview of some concepts and implementations that are described in detail in this thesis. Furthermore, it provides initial results of the smart building scenarios. However, the given data and models have since been revised and thus all simulations and evaluations of this thesis are new. The simulation of scenarios using BESSs is not part of this thesis and only provided as an outlook.	

Optimization of Hybrid Appliances in Future Households **2015**
I. Mauser, H. Schmeck, U. Schaumann [412]
ETG Congress 2015: Die Energiewende – Blueprint for the new energy age, VDE Verlag

This paper introduces the initial optimization of hybrid appliances and an electrical IHE in smart residential buildings and provides first evaluations. However, the given data and models have since been revised and thus all simulations and evaluations of this thesis are new.

Bottom-Up Simulation of Suburban Power Grids **2015**
S. Kochanneck, C. Hirsch, I. Mauser, H. Schmeck, M. Schröder [354]
ETG Congress 2015: Die Energiewende – Blueprint for the new energy age, VDE Verlag

Response of Smart Residential Buildings with Energy Management Systems to Price Deviations **2015**
S. Kochanneck, H. Schmeck, I. Mauser, B. Becker [356]
2015 IEEE Power and Energy Society Conference on Innovative Smart Grid Technologies Asia, IEEE ✍

These two papers demonstrate the bottom-up simulation of buildings that has been developed as part of this thesis. The new version of the OSH enables a multi-building simulation that is combined with an electricity grid calculation of an exemplary low-voltage grid.

Building Energy Management in the FZI House of Living Labs **2015**
B. Becker, F. Kern, M. Loesch, I. Mauser, H. Schmeck [62]
Energieinformatik 2015 D-A-CH, Springer, LNCS 9424, p. 95–112 ✍

This paper describes the HoLL, which provides the basis for the smart commercial building scenario comprising a trigeneration system. This thesis uses some of these descriptions and extends them.

Organic Architecture for Energy Management and Smart Grids **2015**
I. Mauser, C. Hirsch, S. Kochanneck, H. Schmeck [409]
2015 IEEE International Conference on Autonomic Computing (ICAC), IEEE, p. 101–108 ✍

This paper introduces the Extended O/C Architecture that is described in detail in this thesis. My part of this paper has been the proposal and generalization of the CAL, enabling the two-fold abstraction of generic entities.

Evolutionary Optimization of Smart Buildings with Interdependent Devices **2015**
I. Mauser, J. Feder, J. Müller, H. Schmeck; A. M. Mora, G. Squillero (Eds.) [408]
Applications of Evolutionary Computation, Springer, LNCS 9028, p. 239–251 ✍

This paper outlines the ESC, which has been used by Feder (2014) [211] to provide initial results of the optimization of the CCHP in the HoLL. However, the given data and models have since been revised and thus all simulations and evaluations of the trigeneration system that are given in this thesis are new.

A Privacy-Aware Architecture for Energy Management Systems in Smart Grids **2014**
F. Rigoll, C. Hirsch, S. Kochanneck, H. Schmeck, I. Mauser [506]
IEEE 11th Intl. Conf. on Ubiquitous Intelligence and Computing and IEEE 11th Intl. Conf. on Autonomic and Trusted Computing and IEEE 14th Intl. Conf. on Scalable Computing and Communications and Its Associated Workshops (UIC-ATC-ScalCom), IEEE, p. 449–455 ✍

This paper introduces the Data Custodian that is generalized in this thesis, resulting in the generic CAL that enables—in conjunction with the EAL—the two-fold abstraction of generic entities and provides additional functionality.

Tarife zur Flexibilisierung des Stromverbrauchs in Haushalten mit Energiemanagementsystemen **2014**
I. Mauser, H. Schmeck [411]
VDE-Kongress 2014: Smart Cities – Intelligente Lösungen für das Leben in der Zukunft, VDE Verlag

This paper presents the initial results of multi-building simulations by means of the OSH and tariffs having short-term price deviations. The multi-building simulation is briefly outlined in this thesis.

Run-Time Parameter Selection and Tuning for Energy Optimization Algorithms I. Mauser, M. Dorscheid, H. Schmeck; T. Bartz-Beielstein, J. Branke, B. Filipič, J. Smith (Eds.) Parallel Problem Solving from Nature - PPSN XIII, Springer, LNCS 8672, p. 80–89	**2014** [407] ✍
This paper presents the automated calibration and tuning of parameters of the GA by means of the *Calibration Engine*. This thesis provides more information about possible collaborative approaches and proposes to introduce an extra level into the BEMS for automated parameter calibration and tuning.	
Encodings for Evolutionary Algorithms in Smart Buildings with Energy Management Systems I. Mauser, M. Dorscheid, F. Allerding, H. Schmeck 2014 IEEE Congress on Evolutionary Computation (CEC), IEEE, p. 2361–2366	**2014** [406] ✍
This paper presents the encodings of deferrable, interruptible, and hybrid appliances as well as of a microCHP that are used by the GA. This thesis draws on these descriptions when presenting the IPPs.	
Customizable Energy Management in Smart Buildings Using Evolutionary Algorithms F. Allerding, I. Mauser, H. Schmeck Applications of Evolutionary Computation, Springer, LNCS 8602, p. 153–164	**2014** [11] ✍
This paper presents the original version of the OSH using the *Problem Parts* and an evaluation of smart residential buildings. This thesis uses some of the descriptions when outlining the initial OSH and the simulation results in the validation of the novel version.	

✍: peer-reviewed, ①: best paper award