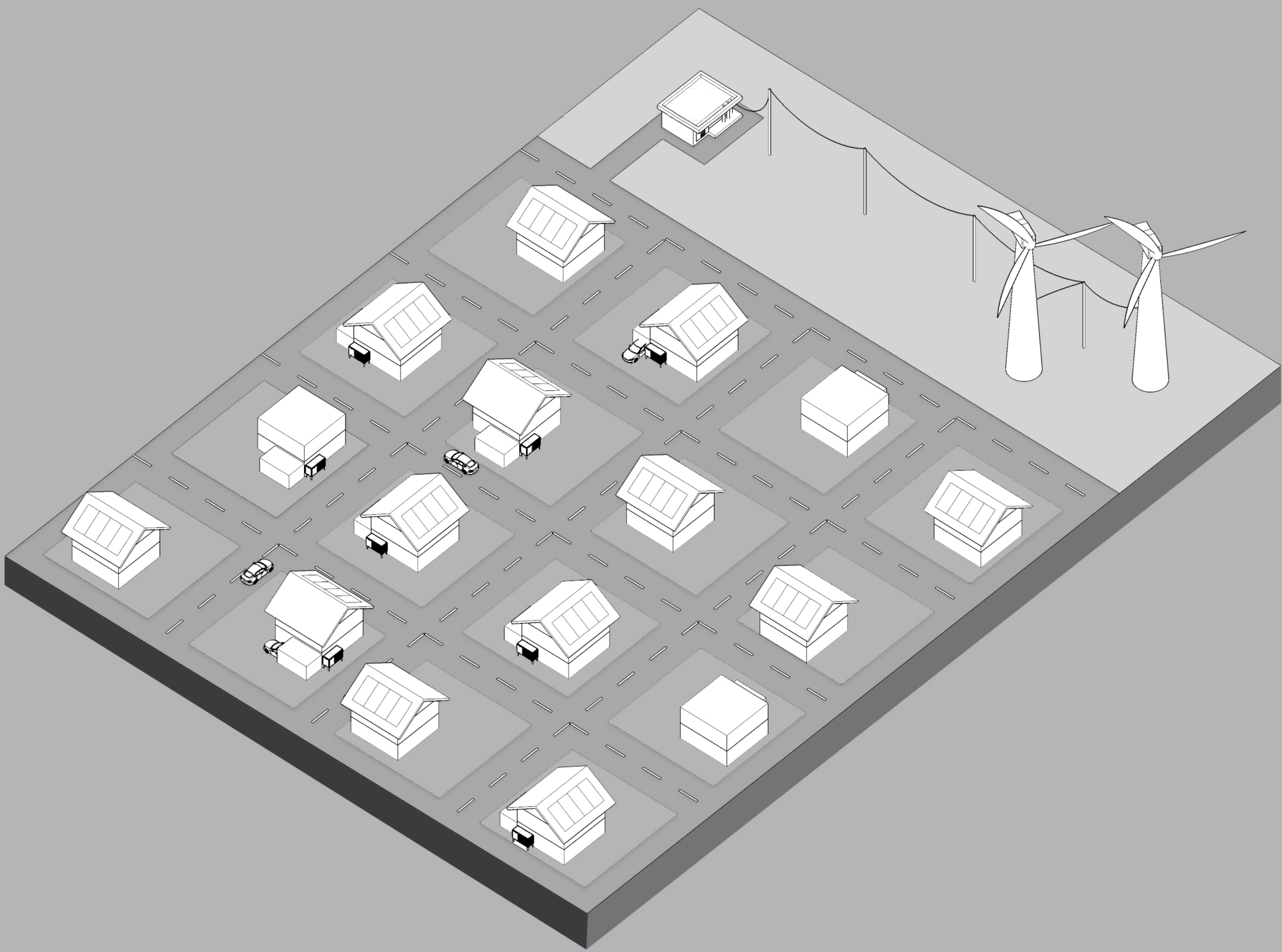
Optimization approaches for exploiting the load flexibility of electric heating devices in smart grids



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Optimization approaches for exploiting the load flexibility of electric heating devices in smart grids

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Abstract

Energy systems all over the world are undergoing a fundamental transition to tackle climate change and other environmental challenges. The share of electricity generated by renewable energy sources has been steadily increasing. In order to cope with the intermittent nature of renewable energy sources, like photovoltaic systems and wind turbines, the electrical demand has to be adjusted to their power generation. To this end, flexible electrical loads are necessary. Moreover, optimization approaches and advanced information and communication technology can help to transform the traditional electricity grid into a smart grid.

To shift the electricity consumption in time, electric heating devices, such as heat pumps or electric water heaters, provide significant flexibility. In order to exploit this flexibility, optimization approaches for controlling flexible devices are essential. Most studies in the literature use centralized optimization or uncoordinated decentralized optimization. Centralized optimization has crucial drawbacks regarding computational complexity, privacy, and robustness, but uncoordinated decentralized optimization leads to suboptimal results. In this thesis, coordinated decentralized and hybrid optimization approaches with low computational requirements are developed for exploiting the flexibility of electric heating devices. An essential feature of all developed methods is that they preserve the privacy of the residents. This cumulative thesis comprises four papers that introduce different types of optimization approaches.

In Paper A, rule-based heuristic control algorithms for modulating electric heating devices are developed that minimize the heating costs of a residential area. Moreover, control algorithms for minimizing surplus energy that otherwise could be curtailed are introduced. They increase the self-consumption rate of locally generated electricity from photovoltaics. The heuristic control algorithms use a privacy-preserving control and communication architecture that combines centralized and decentralized control approaches. Compared to a conventional control strategy, the results of simulations show cost reductions of between 4.1% and 13.3% and reductions of between 38.3% and 52.6% regarding the surplus energy. Paper B introduces two novel coordinating decentralized optimization approaches for scheduling-based optimization. A comparison with different decentralized optimization approaches from the literature shows that the developed methods, on average, lead to 10% less surplus energy. Further, an optimization procedure is defined that generates a diverse solution pool for the problem of maximizing the self-consumption rate of locally generated renewable energy. This solution pool is needed for the coordination mechanisms of several decentralized optimization approaches. Combining the decentralized optimization approaches with the defined procedure to generate diverse solution pools, on average, leads to 100 kWh (16.5%) less surplus energy per day for a simulated residential area with 90 buildings.

In Paper C, another decentralized optimization approach that aims to minimize surplus energy and reduce the peak load in a local grid is developed. Moreover, two methods that distribute a

central wind power profile to the different buildings of a residential area are introduced. Compared to the approaches from the literature, the novel decentralized optimization approach leads to improvements of between 0.8% and 13.3% regarding the surplus energy and the peak load. Paper D introduces uncertainty handling control algorithms for modulating electric heating devices. The algorithms can help centralized and decentralized scheduling-based optimization approaches to react to erroneous predictions of demand and generation. The analysis shows that the developed methods avoid violations of the residents' comfort limits and increase the self-consumption rate of electricity generated by photovoltaic systems.

All introduced optimization approaches yield a good trade-off between runtime and the quality of the results. Further, they respect the privacy of residents, lead to better utilization of renewable energy, and stabilize the grid. Hence, the developed optimization approaches can help future energy systems to cope with the high share of intermittent renewable energy sources.

List of included papers

Paper A

Dengiz T, Jochem P, Fichtner W (2019): Demand response with heuristic control strategies for modulating heat pumps. Applied Energy 238:1346-60.
DOI: https://doi.org/10.1016/j.apenergy.2018.12.008

Paper B

Dengiz T, Jochem P (2020): Decentralized optimization approaches for using the load flexibility of electric heating devices. Energy 193:116651.
DOI: https://doi.org/10.1016/j.energy.2019.116651

Paper C

Dengiz T, Jochem P, Fichtner W (2020): Demand response through decentralized optimization in residential areas with wind and photovoltaics. In: Working Paper Series in Production and Energy (No. 42).
DOI: https://doi.org/10.5445/ir/1000118359

Paper D

Dengiz T, Jochem P, Fichtner W (2019): Uncertainty handling control algorithms for demand response with modulating electric heating devices. 2019 IEEE PES Innovative Smart Grid Technologies Europe (ISGT-Europe). p. 1-5.
DOI: https://doi.org/10.1109/ISGTEurope.2019.8905448

Contents

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Abbreviations

CH_4	Methane
CHPs	Combined heat and power systems
CO_2	Carbon dioxide
DHW	Domestic hot water
EA	Evolutionary algorithms
EMS	Energy management system
EVs	Electric vehicles
HVAC	Heating, ventilation, and air-conditioning system
IDA	*Iterative Desync Algorithm*
LP	Linear programming
MA	Memetic algorithms
MILP	Mixed-integer linear programming
MIQP	Mixed-integer quadratic programming
MPC	Model-predictive control
NLP	Non-linear programming
PSCO	*Parallel Successive Cluster Optimization*
PSCO-IDA	*Parallel Successive Cluster Optimization with IDA*
PSO	Particle swarm optimization
PV	Photovoltaics
QP	Quadratic programming
RES	Renewable energy sources
SEPACO-IDA	*Sequential Parallel Cluster Optimization with IDA*

Part I: Overview

1 Introduction

1.1 Motivation

To mitigate the effects of climate change, most countries in the world have signed the *Paris Agreement* of the *United Nations* from 2015 [1]. The nations have agreed on "*holding the increase in the global average temperature to well below 2° C above pre-industrial levels and pursuing efforts to limit the temperature increase to 1.5° C above pre-industrial levels*" [1]. In order to achieve this aim, it is vital to reduce the emission of greenhouse gases, like carbon dioxide (CO_2) and methane (CH_4), significantly. Burning fossil fuels, such as coal, oil, and gas, is the primary source of greenhouse gas emissions from human activities [2]. The use of renewable energy sources (RES) for generating electricity is a major factor for the transition to a sustainable energy system that is independent of fossil fuels. RES cover photovoltaics (PV), solar thermal energy, wind energy, hydro energy, geothermal energy, and all types of biomass [3]. RES have crucial benefits for the energy system and the society such as [3, 4]:

- Reduction of greenhouse gas emissions
- Reduction of environmental problems (e.g., acid rain)
- Slower depletion of the world's nonrenewable energy sources
- Reduction of the dependency on fuel imports from other countries

The share of RES in Europe has continually been increasing during the last years. Figure 1 shows the share of renewable energy in gross final energy consumption of Europe (EU 27) between the years 2009 and 2018. During this period, the share has increased by more than 5% in total. The goal for the year 2020 was set to 20% [5], and in 2030, 32% of the final energy consumption in Europe is aimed to be served by RES [6]. The change to a sustainable energy system with high penetration of RES has been taking place around the world. In the United States, the share of RES in the total energy consumption rose from 5% in 2001 to 11% in 2018 [7], and in China, the installed capacity of RES between 2009 and 2017 tripled [8].

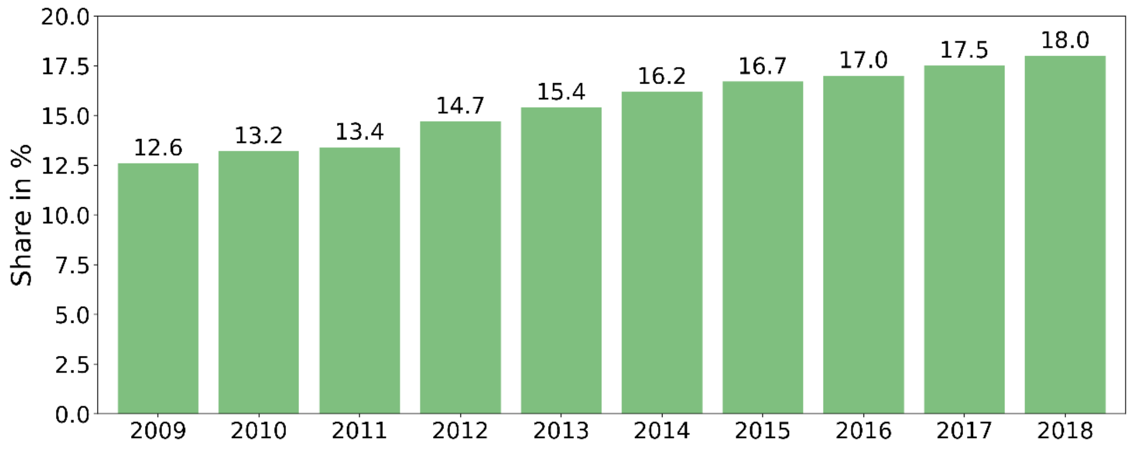

Figure 1: Share of renewable energy in gross final energy consumption of Europe [5]

The proportion of RES in Germany's electricity production mix for the year 2018 was 35% and thus slightly higher than the one in Europe as a whole (33%) [9]. Wind energy generated by far most of the RES-based electricity in Germany (17%). The expansion of the installed capacity for wind power and PV has been the main reason for the increasing share of RES in the electricity generation of Europe [5, 9]. The *European Commission* expects the energy from wind and PV to proceed to grow significantly and thus to be the main drivers for achieving Europe's sustainability goals for 2030 [9]. The generation of electricity in Europe is increasingly decentralized due to the large-scale penetration of RES.

Although having significant benefits, RES bring about crucial challenges to the energy system due to the weather-dependent power generation of wind turbines and PV systems. As their power output can only be partially controlled, the energy system has to realize a paradigm shift. While in the past energy system the electricity generation followed the demand, in the future the electricity demand has to be adjusted to the power supply of the volatile RES. To this end, flexible electrical devices are necessary that can shift their time of operation or vary their power consumption. Besides, advanced information and communication technology can help to transform the traditional electricity grid into a smart grid that can react to the intermittent supply by RES and keep the system reliable.

In a smart grid, the electrical consumption can be automatically adjusted to the volatile electricity generation [10]. For this purpose, the components of the grid have to be able to exchange information about the load in the (local) grid and their flexibility in real-time. There are smart meters currently being rolled out in Germany that can not only monitor electricity demand and generation at high temporal resolution but also communicate with other components in the grid [11]. Until 2032, each traditional meter will have to be replaced by an advanced metering device [11].

Besides batteries for storing electricity from RES, flexible electrical loads will play an integral part in the transition of the energy system. Some of the electrical devices will have to adjust their demand for electricity based on external information. Demand response describes a direct or indirect change in the electricity usage of the customers in response to specific signals [12]. These signals might be based on a price or a generation profile. The signal might also be a command for changing or shifting the operation of the flexible electrical devices.

Adjusting the electricity demand can also stabilize the grid and increase its efficiency. There are several ways how demand response can contribute. Flexible electrical loads can control the voltage in the distribution grid and manage the congestion by providing ancillary services [13]. Moreover, reserve capacity can be provided to ensure a stable frequency in the grid. Demand response can also reduce the peak load (peak shaving) in local grids and consequently limit the stress on transformers and other grid components. Another application for utilizing flexible loads is to purchase electricity from the energy markets at low prices. An aggregator can pool multiple flexible devices and shift their main electrical load to periods with low electricity prices or place bids in the balancing power market [14].

The flexibility of electrical loads can be used in residential areas, in non-residential buildings, and industrial applications. Some industrial sectors can provide flexibility on a large scale, like the aluminum production industry, the cement manufacturing industry, or the paper and wood industry [15]. In the residential sector, several devices are suitable for demand response [16]. The operation of washing machines, tumble dryers, and dishwashers can be shifted in time, making their electrical loads deferrable. Furthermore, electric vehicles (EVs) can be charged in the residential area and thus provide flexibility to the system.

Another significant source of load flexibility in residential areas is seen in thermostatically controlled loads, such as electric heating devices, refrigerators, freezers, and air conditioners [16]. Thermostatically controlled loads can also be utilized in non-residential buildings and in industrial applications (e.g., cooling in the food industry [15]) to shift the electrical consumption in time. Since heating accounts for the largest part of household energy consumption [17], electric heating devices can play a pivotal role in providing flexibility. The goal of this thesis is to develop optimization approaches for exploiting the flexibility of electric heating devices in smart grids. The optimization approaches should yield a good trade-off between the quality of the results and computational time while not infringing on the residents' privacy.

1.2 Structure of the thesis

This thesis consists of two parts. Part I motivates and summarizes the research. To this end, Section 1 introduces and motivates the topic of this thesis. Section 2 describes the techno-economic background of electric heating. It explains the significance of integrating flexible electrical loads into the energy system and lists the most common electric heating devices. Based on three motivational case studies, Section 3 defines the research goals of this thesis. The case studies demonstrate the benefits of optimally shifting the operation of electric heating devices. A comprehensive literature review is given in Section 4. The relevant optimization approaches for electric heating devices from the literature are grouped into different non-disjunctive categories. Section 5 gives an overview of the four included papers of this thesis. It summarizes the main aspects of the developed optimization methods for each paper and the results of simulations. The first part of the thesis ends with conclusions in Section 6. Moreover, the section describes the limitations of this thesis and shows possible directions for future research. Part II includes the four papers this thesis is based on.

2 Techno-economic background of electric heating

This section explains the importance of electric heating for future energy systems. It describes the techno-economic background for using the flexibility of electric heating devices. In order to exploit electrical load flexibility, the buildings need information and communication technology and an energy management system (EMS). Buildings with an EMS are referred to as smart buildings. They can control the flexible devices and optimize their operation based on internal information (e.g., from the local PV system) or external signals from the grid. To this end, the devices themselves require to have interfaces that allow the EMS to observe them and adjust their electrical load.

In particular electric heating devices coupled with thermal storage can provide flexibility. In [18], Gils assesses the theoretical demand response potential of electric heating devices in Europe. The analysis estimates a load shifting potential for 2010 of more than 140 GW for residential buildings. Fehrenbach et al. [19] predict that the capacity of thermal storage in Germany's residential areas will amount to levels between 40 and 78 GWh in 2030. Based on their study, this figure could increase up to 252 GWh until the year 2050.

Figure 2 shows the global energy-related CO_2 emissions of the different sectors in 2015. The industry sector contributed most to the global CO_2 emissions with 41%, followed by the building sector and the transport sector. The building sector can be subdivided into residential and non-residential buildings. Residential buildings were responsible for higher CO_2 emissions (17%) compared to non-residential buildings (11%). The diagram shows that the building sector caused more than a quarter of global emissions in 2015. Thus, a significant reduction of its CO_2 emissions is essential to achieve the climate goals.

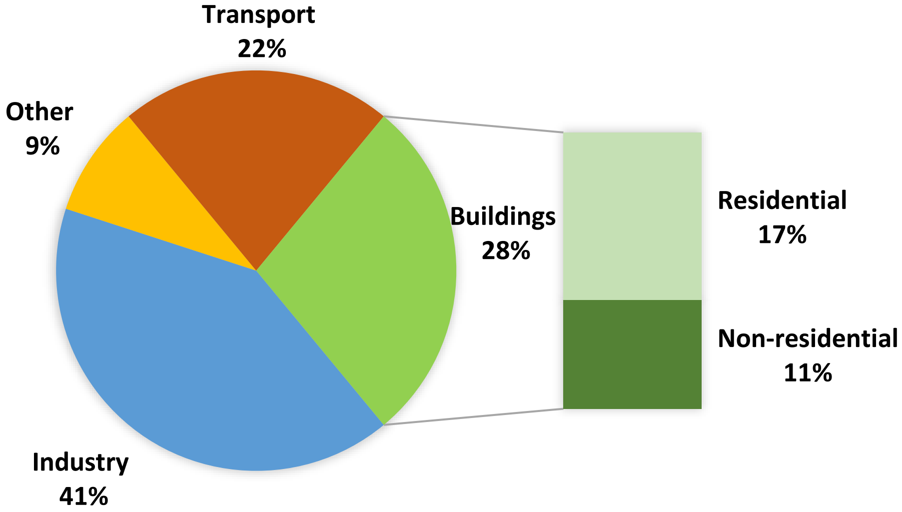

Figure 2: Share of global energy-related CO_2 emissions by sector in 2015 [20]

In Europe, the household sector accounted for 27.2% of the final energy consumption in 2017 [17]. Fossil fuels mainly generated the energy needed for the household sector, whereas RES accounted for merely 17.5% [17]. Figure 3 illustrates the energy consumption of European households in 2017, grouped by the type of application it was used for. Space heating constituted by far the most significant part with more than 64%. Domestic hot water (DHW) accounted for 14.8% of the final energy consumption and was thus the second most energy-intensive application in households, followed by lighting and electrical appliances with 14.4%. Electric heating devices can be used for both space heating and DHW preparation. As heating applications make up approximately 80% of the end energy consumption in households, there is a strong need to decarbonize them by using RES. At the same time, there is an opportunity to make the energy consumption of residential areas flexible when integrating more electric heating devices.

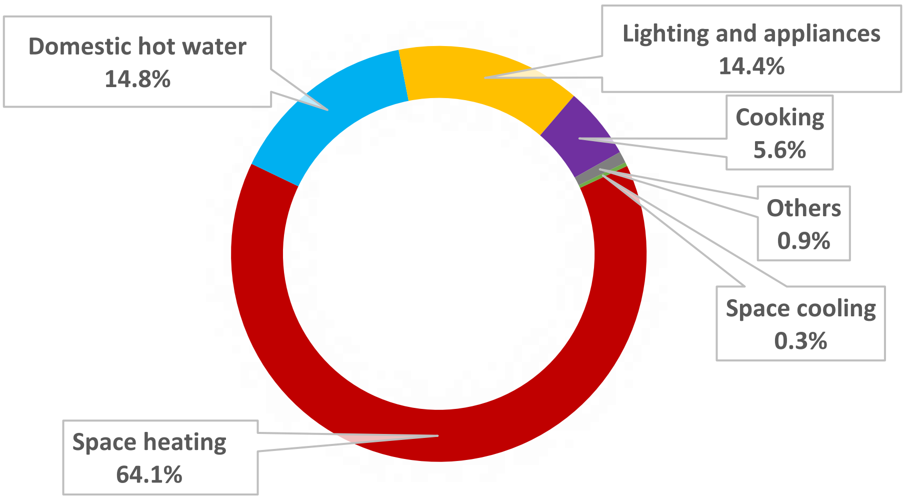

Figure 3: Energy consumption of European households in 2017 [17]

The most common electric heating devices that have already been utilized for demand response are:

- Heat pumps (see for example [13])
- Electric water heaters/electric heating elements in hot water tanks (see for example [21])
- Air conditioners (see for example [22])
- Ventilation fans for heating (see for example [23])
- Electric storage heaters (see for example [24])

Closely related to electric heating devices are combined heat and power systems (CHPs). They usually use gas or other fossil fuels to generate heat and electricity simultaneously. CHP systems can also use hydrogen or renewable biomass to generate electricity. Due to the increased efficiency of the cogeneration process, small heat and power systems (micro CHPs) are expected to play a significant role in curbing CO_2 emissions of residential areas [25].

In order to decouple heat generation and usage in buildings and provide flexibility, a heat storage system is needed. Thus, the heating devices can, for instance, run whenever there is a high generation of electricity by RES or there is a need to increase the load for ancillary services to stabilize the grid. In contrast, during periods with low generation by RES, thermal storage allows the electric heating devices to reduce their load without affecting the residents' comfort negatively. The following types of thermal storage are common for buildings in residential areas [13, 24, 26]:

- Thermal inertia of the building mass
- Hot water tanks (for DHW and as buffer storage for space heating)
- Phase change materials
- High-density bricks (for electric storage heaters)

One crucial advantage of electric heating devices is their capability to use the building mass for thermal storage and thus provide flexibility. Every building has thermal inertia due to the construction materials of its envelope and floors. Consequently, load flexibility can be provided without additional investments in storage systems. In [27], Hedegaard et al. investigate different thermal storage options for demand response with heat pumps. They conclude that the use of the buildings' thermal mass offers the most cost-effective solution. Electric heating devices can primarily provide flexibility on an intra-day time scale [28]. Various factors influence the electro-thermal flexibility of residential buildings such as:

- Outside temperature
- Occupant behavior and comfort limits
- Thermal power of the heating device
- Capacity of the thermal storage

In particular, heat pumps are considered to play a pivotal role in future energy systems because of their comparatively high efficiency and their flexibility [29, 30]. Depending on the heat source, heat pumps are classified into air-source, ground-source, and water-source systems. In Europe, the most common types are air-source heat pumps, followed by ground-source heat pumps [31]. Due to the strong variations of the ambient temperature, the efficiency of air-source heat pumps changes significantly during a day and shows seasonality [13]. Although the main period of use for electric heating devices falls into winter and transition periods, heat pumps and electric heating elements inside hot water tanks generate DHW during the whole year. Generally, heat pumps can be used not only for space heating in winter but also for space cooling in summer if their mode of operation is reversible [32]. Hence, they can provide load shifting potentials for demand response throughout the whole year.

More and more manufacturers offer heat pumps that can be integrated into a smart grid [33]. In Germany, the *Federal Association for Heat Pumps* (*Bundesverband Wärmepumpe*) assigns a label (*smart-grid-ready-label* [34]) to heat pumps whose control units can react to external signals and thus to the volatile electricity generation by RES. Most of today's offered heat pumps in Germany have this label [35]. Especially beneficial for smart grids are modulating heat pumps that not only can be switched on and off but also regulate their power consumption by varying the compressor speed. The majority of air-source heat pumps offered in Germany are assumed to be modulating heat pumps in 2020 [33].

In Germany, the most common fuels for heating systems were natural gas (48%) and oil (30%) in 2019 [36]. Electric heating devices only play a minor role in today's heating system. The share of electric storage heaters is 2.3% and heat pumps account for merely 3.4% [36]. In Europe, the share of heat pumps is slightly less than 10% and thus significantly higher compared to Germany [37]. France, Italy, and Spain are the countries with the biggest heat pump markets in Europe. Norway has the highest share of buildings that are equipped with a heat pump (44%), followed by the other Scandinavian countries Sweden (35%) and Finland (28%) [31].

Figure 4 shows the development of heat pump sales in Europe between the years 2009 and 2018. During the last four years, the European heat pump market has achieved a yearly growth of over 10%. By 2018, almost 12 million heat pumps had been installed across Europe. If the market proceeds to grow similarly, a doubling of the sales is expected by 2024 compared to the figure of 2018 [37]. Heat pumps are especially popular in modern buildings as their high insulation standards reduce the heating system's supply temperature (sink temperature of the heat pump), which results in increased efficiency for space heating [13].

Many newer buildings use an underfloor heating system to decrease the heat pump's sink temperature. The generated heat energy is stored in the concrete of the floor and thus in the building mass. In Germany, heat pumps have become the primary heating technology for newly built residential buildings with a share of about 44% in 2018 [38]. Heat pumps and other electric heating devices can also be utilized for demand response in district heating networks with powerful heat generation units [39, 40].

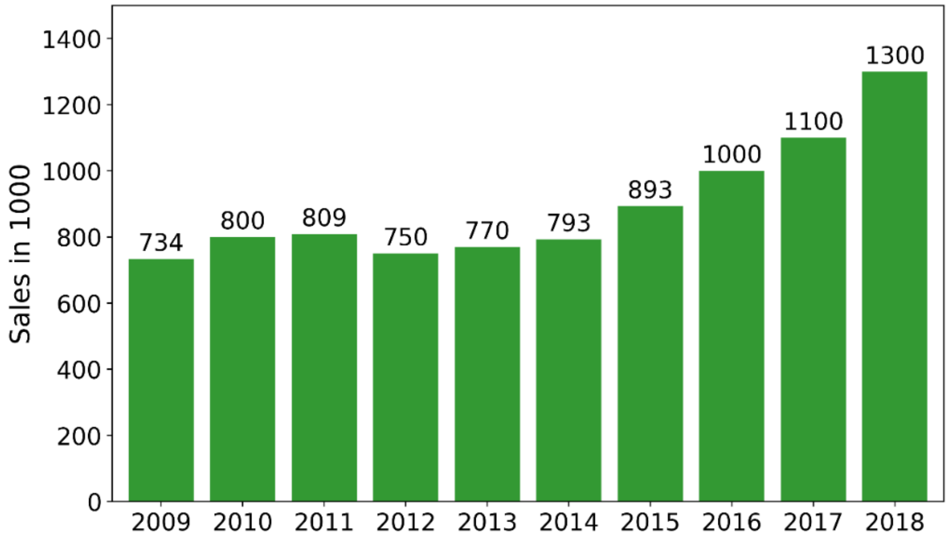

Figure 4: Sales of heat pumps in Europe [37]

To exploit the flexibility of electric heating devices, the heat generation has to be decoupled from the heat demand by using intelligent control algorithms. The used control approach strongly influences the flexibility [41]. Currently, it is common practice to use a conventional hysteresis based control method [42, 43]. The conventional control approach starts heating the thermal storage when the storage's lower temperature limit is reached, and the heating stops as soon as the temperature reaches the upper level. Such a control approach does not exploit the flexibility of thermal storage and is not suitable for demand response.

Heat pumps have already been used to some degree for demand response. In Germany, for example, the operation of most heat pumps can be blocked three times a day for a maximum of two hours by the grid operator [28, 44]. The aim of decreasing their loads is to lower the stress on the grid in return for reduced grid fees for the customers. More advanced control strategies that optimally use the load shifting potentials can react to the current situation in the power system and lead to better utilization of RES.

3 Motivational case studies and research goals

This section illustrates three motivational case studies (Section 3.1) that demonstrate the benefits of shifting electrical loads. Based on these case studies, Section 3.2 identifies the research goals of this thesis.

3.1 Motivational case studies

The benefits of using the flexibility of electric heating devices for the energy system are shown by three case studies. The objective of the first case study is to reduce the curtailment of wind power (Section 3.1.1), and the second case study illustrates the benefits of shifting loads to minimize electricity costs (Section 3.1.2). The third motivational case study shows the reduction of the peak load in a residential area by optimally scheduling the operations of the electric heating devices (Section 3.1.3). The days which are used in each case study are randomly chosen from the heating period in Germany (October – March).

3.1.1 Reducing curtailment of wind power

In Germany, around 5.4 GWh of the electricity generation from RES were curtailed in 2018 due to congestions in the transmission grid [45]. Wind turbines (97%) contributed most to the total curtailment. More than half (53%) of Germany's total energy curtailment in 2018 could be attributed to the federal state of Schleswig-Holstein (North of Germany). One possibility to reduce the curtailment is to react to the wind turbines' volatile power generation by using flexible electrical loads. This case study considers one grid node in Schleswig-Holstein with significant curtailment (in the district of Nordfriesland). The objective is to analyze to what extent electric heating devices could have reduced the curtailed energy during one day in February 2015.

To this end, an optimization model of a residential area in Schleswig-Holstein is set up. The goal of the optimization problem is to minimize curtailment for this grid node. The model incorporates the properties of the German building stock regarding the distribution of different building types and insulation levels [46] and is run with 100 buildings. Afterward, the results are scaled up to the total number of buildings that were connected to the investigated grid node (about 15,000 buildings).

All buildings utilize the building mass for thermal storage. The thermal capacity of the building mass is based on the values specified in *EN ISO 13790* [47]. The electric heating devices can exploit a specific temperature range to optimally react to the electricity generation by RES. This temperature range has to be defined before the optimization by the residents. It ensures that their comfort is not affected negatively by the flexible operation of the electric heating device. A higher permissible temperature range leads to higher flexibility. For this case study, the assumption is made that the buildings' residents have a comfort range of 2° K (20° C to 22° C). Moreover, all buildings have a hot water tank for DHW that serves as a second thermal storage system.

The buildings are either single-family houses, multi-family houses, or terraced buildings. Figure 5 shows the curtailed electrical power during February 15th, 2015, for one grid node in the district of Nordfriesland. The curtailment data from Figure 5 is the output of a transmission grid model by Schermeyer [48]. The curve of the curtailed electrical power strongly correlates with the power generated by RES. It can be seen that electricity is curtailed from 04:00 to 15:00. The demand data for this case study is based on *CREST*, a high-resolution stochastic model that generates load profiles (space heating, electricity, and DHW) for residential buildings [49].

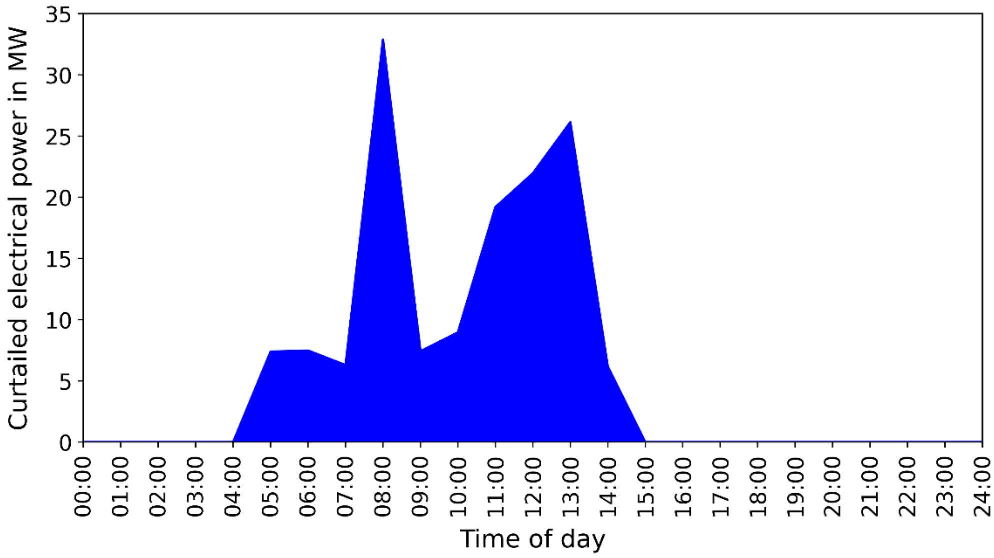

Figure 5: Curtailed electrical power during February 15th, 2015 for one grid node in the district of Nordfriesland [48]

Different scenarios are used to investigate the effects of flexible electrical loads on the curtailment. The share of buildings equipped with electric heating devices is exogenously increased in the optimization model. Depending on the buildings' ages and their insulation levels, either a modulating air-source heat pump is used or an electric heating element in addition to a gas boiler. The electric heating element only runs if electricity generated by RES is available. The gas boiler serves as the primary heating system. Heat pumps can only be efficient in buildings with high insulation standards due to the reduced supply temperatures of their heating systems [13]. Therefore, heat pumps are not used for older buildings in this case study. In the base case scenario, no electric heating devices are used in the buildings. Instead, the buildings use fossil-fuel based heating systems (gas or oil).

The flexible electric heating devices have to react to the supply curve of RES or the predicted curtailment profile to minimize the curtailment. Figure 6 illustratively shows the electrical load of a heat pump and thus its heating activity (yellow curve) and the resulting temperature profile (red curve) of one single-family house during the investigated day. The heat pump has a maximum electrical power of 2500 W, which can be modulated continuously. As an air-source heat pump is used for this building, the efficiency strongly depends on the outside temperature.

It can be seen in Figure 6 that during periods with high curtailment (and thus high generation of electricity by RES), the heat pump operates with high modulation degrees. This results in an increased room temperature (07:00 to 14:00). In periods with less or no RES generation, the power consumption of the heat pump is strongly reduced, leading to a drop in the room temperature (before 07:00). The optimization problem includes a constraint that forces the room temperature at the end of the day to be at 21° C. Therefore, the heat pump increases its load at the end of the day to heat up the building to the desired temperature.

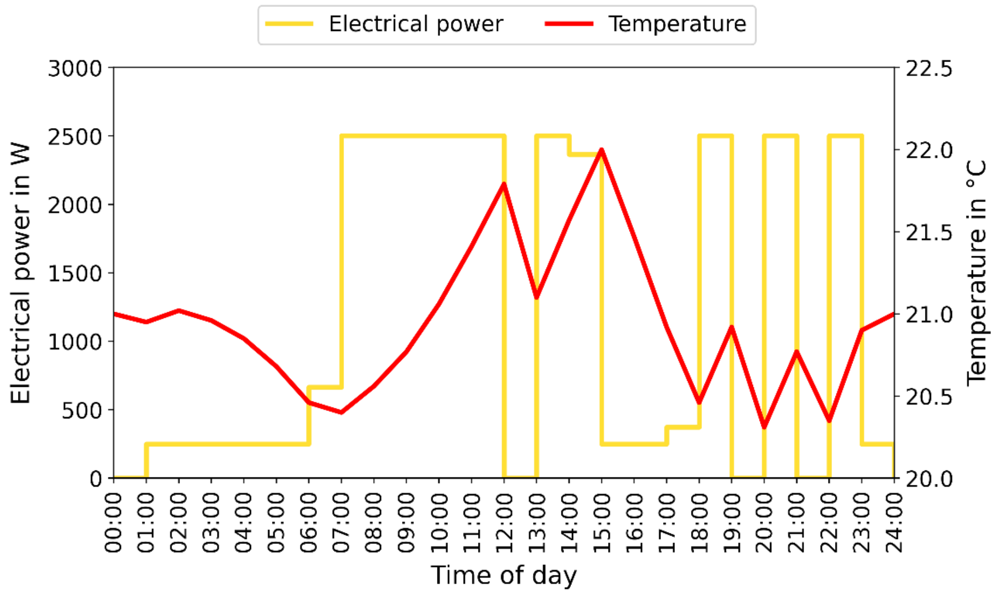

Figure 6: Electrical power of a heat pump and the resulting temperature profile of one building

Figure 7 depicts the curtailed energy depending on the share of buildings with electric heating devices. The diagram is based on multiple runs of the optimization problem for the residential area with varying input parameters. As expected, a higher penetration of electric heating devices reduces the curtailment. A share of 10% leads to reductions of more than 30% (from 144 MWh to 100 MWh). If one out of five buildings is equipped with an electric heating device, the curtailed energy can be halved in the case study. The highest investigated share is 40%, which leads to diminishing the curtailment by more than 125 MWh (89%) compared to the base case scenario with no electric heating devices.

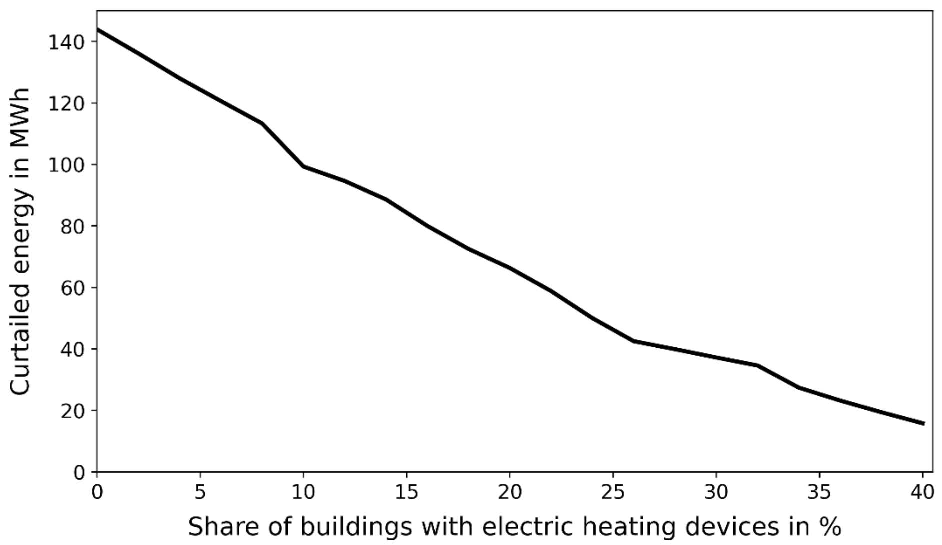

Figure 7: Curtailed energy depending on the share of buildings with electric heating devices

Increasing the share of electric heating devices on all grid nodes in Schleswig-Holstein would not always reduce the curtailment significantly. A reason for this is that the number of buildings that are connected to the nodes with high curtailment was rather low in 2015 [48]. Nevertheless, this case study demonstrates the capability of electric heating devices to reduce curtailment of RES. This leads to a higher self-consumption rate of locally generated and climate-friendly electricity from RES. Thus, a large-scale penetration of flexible electric heating devices can reduce greenhouse gas emissions and help to decarbonize the building sector.

3.1.2 Minimizing electricity costs

The objective of this case study is to show that an optimal operation of flexible electrical devices can reduce electricity costs. An optimization problem is defined for a residential area. The goal of the optimization is to minimize the residential area's electricity costs under the assumption of a time-dependent price for electricity. The optimal control strategy should shift the load of the electric heating devices into periods with low prices in the electricity market.

Demand data (heat, electricity, and DHW) generated by the software tool *synPRO* [50] from *Fraunhofer Institute for Solar Energy Systems* [51] is used for this and the following (Section 3.1.3) case study. This tool combines a thermal resistance-capacity model (*5R1C* model) for space heating, as described in *EN ISO 13790* [47], with a behavioral model, which is based on the *Harmonized European Time of Use Survey* [52]. The models used by *synPRO* are explained and validated against measured data in [50].

Figure 8 shows the prices for electricity on the day-ahead market of the *European Energy Exchange* on December 4th, 2017 [53]. For every hour of the day, there is a different price, ranging from about 12 to 51 € per MWh. It is assumed that the buildings have a time-dependent electricity tariff based on these prices. This means that the shown prices are directly forwarded to the customers. Duties and taxes are assumed to be fixed. An aggregator controls the electric heating devices of the residential area, intending to minimize the electricity costs. To this end, the aggregator runs an optimization problem (optimal control).

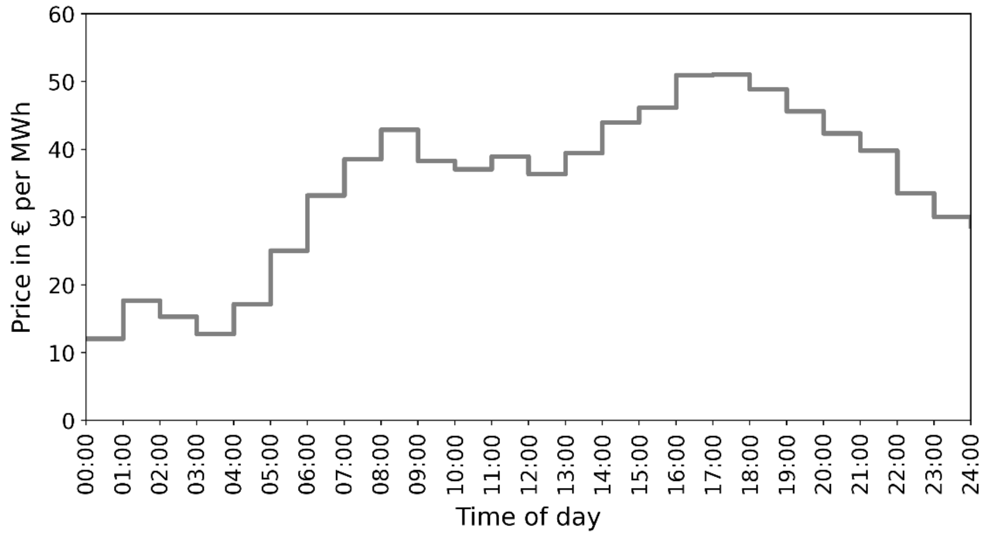

Figure 8: Prices for electricity at the day-ahead market of the European Energy Exchange on December 4th, 2017 [53]

In this case study, only one scenario is analyzed. The residential area consists of 40 single-family houses that are located in Braunschweig (Germany). All buildings have air-source heat pumps that can continuously vary their power consumption. Further, they use an underfloor heating system for thermal storage (the heat is stored in the concrete) and a hot water tank for DHW.

Figure 9 illustrates the combined electrical power of the heat pumps and the resulting costs for the conventional control and the optimal control strategy. The costs do not comprise duties (e.g., renewable energy surcharge) and taxes. It can be seen that the optimal control – as opposed to the conventional control – avoids to schedule the heating activities into periods with high prices (16:00 to 19:00). Moreover, the optimal control utilizes the low price between 03:00 and 04:00 by increasing the electrical loads of the heat pumps. The electricity consumption of inflexible devices is not considered in this case study.

The optimal control results in electricity costs of 34.30 € for that day, which is 11.60 € lower compared to the conventional control (45.90 €). The higher the fluctuations and the ranges of the prices, the more cost savings can be realized by using the optimal control strategy for a residential area on a given day. Besides, the cost savings strongly depend on the number of flexible devices considered in the optimization.

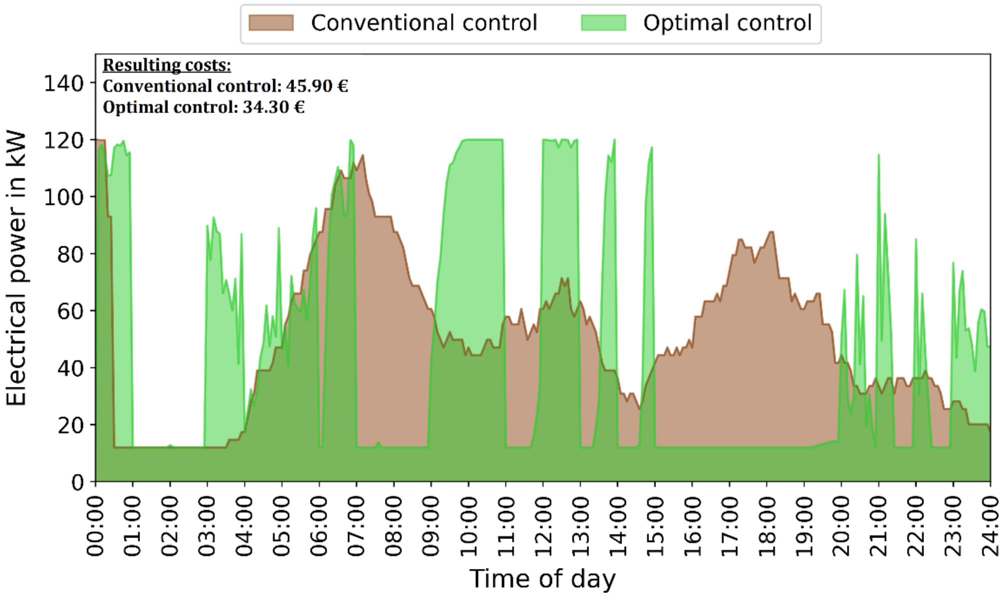

Figure 9: Total electrical load of the heat pumps and resulting costs with conventional and optimal control

This simple case study shows that shifting electrical loads can reduce electricity costs significantly when having time-dependent electricity tariffs. The buildings in this case study do not have a PV system. Considering PV generation in the residential area could lead to higher cost savings for the optimized control compared to conventional control.

3.1.3 Minimize peak load (peak shaving)

Another application for flexible electrical loads is reducing the peak load in a local grid. This decreases the stress on the transformers and other grid components. Moreover, peak shaving can prevent costly grid extensions due to new electrical loads such as EVs and heat pumps. The objective of the optimization problem is to minimize the peak electrical load of all buildings combined.

For this case study, three types of buildings are considered that are all single-family houses. The buildings have different insulation levels and heating systems (modulating air-source heat pumps, ground-source heat pumps, and electric heating elements). Analogous to the previous case study of Section 3.1.2, the buildings that are equipped with a heat pump use an underfloor heating system and a DHW tank for thermal storage. Buildings with gas heating devices have a combined hot water tank that serves for both space heating and DHW. The overall number of buildings is 40.

Figure 10 shows the resulting electrical power of the modeled residential area during one day in January. The load profile of the conventional control shows multiple high peaks, whereas the optimal control strongly flattens the load curve. The conventional control leads to a peak load of 70.3 kW, which is more than 27 kW higher than the resulting peak load of the optimal control strategy. In the analysis, whose results are displayed in Figure 10, merely electric heating devices are used as flexible loads. An inclusion of 5 EVs into the model of the residential area leads to a 35 kW difference between the conventional and the optimal control regarding the peak load. In this and the previous case study (Section 3.1.2), the optimal control leads to reduced electrical energy consumption for heating (the areas of the green curves in Figure 9 and Figure 10 are smaller than the ones of the brown curves). The reason for this is that the optimal control incorporates the volatile efficiency of the air-source heat pumps into its decision making. Therefore, the air-source heat pumps primarily operate during periods with high outside temperatures as this increases their efficiency.

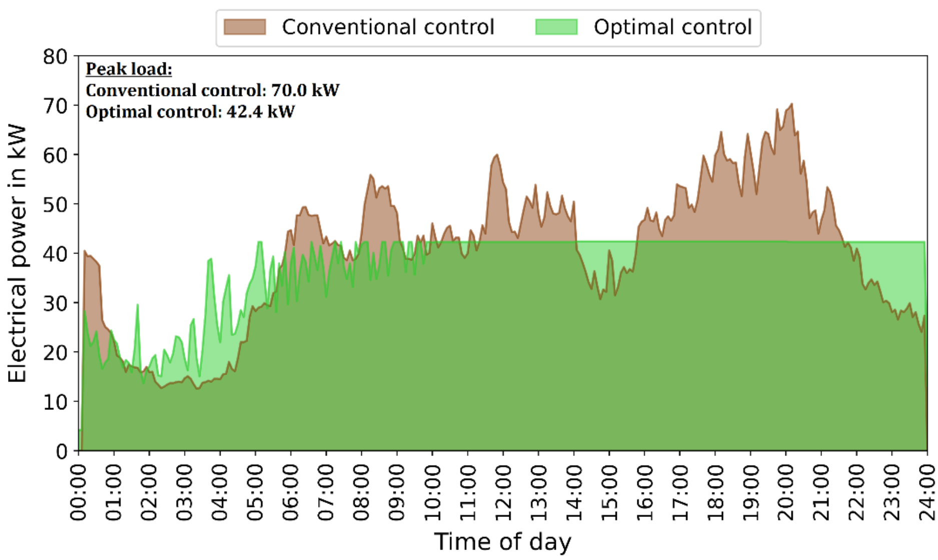

Figure 10: Total electrical load of the modeled residential area with conventional and optimal control

In the modeled residential area of this and the previous case study (Section 3.1.2), each building uses an electric heating device. While this is not representative of today's heating systems in Germany, this configuration is used to show the benefits of exploiting thermoelectric flexibility.

The buildings use heat pumps and electric heating elements as it is assumed that these technologies will have significant market share in the future. To keep the runtime of the optimization low in all case studies, the number of buildings with electric heating devices does not exceed 40.

3.2 Research goals

The three case studies from the previous section demonstrate the benefits of optimally exploiting the load flexibility of electric heating devices. However, in all case studies, a centralized optimization approach is used to control the decentral flexible devices. Centralized optimization approaches are based on a central control unit that needs data from each building for demand and generation forecasts. This data is used as input to a centralized optimization problem that generates optimal schedules for each flexible device in the residential area. The central control unit then either controls the devices directly or sends the schedules to the EMS of the different buildings.

Centralized optimization leads to the overall best result for the residential area but has several crucial drawbacks that limit its applicability in real-world environments [54]. A centralized optimization approach strongly infringes on the privacy of the residents as personal data (e.g., electricity profiles, heating profiles, and DHW usage patterns of the households) has to be collected and processed continuously. Moreover, the computational complexity of centralized optimization problems is fairly high due to the NP-hardness of scheduling problems [55]. Hence, applying centralized optimization to larger residential areas or districts with high numbers of flexible devices can be computationally infeasible. Another disadvantage is the low level of robustness against single-point failures and cyber-attacks due to the necessity of a central control unit [56]. The whole energy system can incur immense damage if the central controller fails due to technical problems or an external cyber-attack.

The goal of this thesis is to develop novel optimization approaches that exploit the flexibility of electric heating devices in smart grids and tackle the fundamental problems of centralized optimization. The designed approaches should have strongly reduced computational complexity such that they are applicable to larger districts. Further, the optimization approaches must preserve the residents' privacy by avoiding to collect and process personal data. Also, the level of robustness of the developed methods should be increased compared to centralized optimization.

To this end, several heuristic optimization algorithms are designed in this thesis that fulfill the properties mentioned above and can thus be applied to larger residential areas. The algorithms should lead to results that are close to the optimal solution of the centralized optimization. Moreover, approaches that can either directly or indirectly handle uncertainties in the optimization are developed. While the focus of this thesis is to design algorithms for electric heating devices, some of the developed methods can also be used for other types of flexible electrical loads.

4 Literature review

Many approaches for exploiting electrical load flexibility can be found in the literature. The following sections list the relevant literature that deals with optimization and control approaches for utilizing the flexibility of electric heating devices and other residential loads in smart grids (algorithms for scheduling flexible loads in the industry can be found in [57]). The optimization approaches can be predictive or non-predictive (Section 4.1). Another way of clustering the approaches is whether the optimization is performed in a centralized or decentralized way (Section 4.2). Besides, the approaches can be distinguished by the method for solving the resulting optimization problem itself (Section 4.3). In Section 4.4, uncertainty handling approaches are explained that are capable of dealing with erroneous predictions. As the used partitions of the relevant literature are not disjunctive, Table 6 in the appendix lists all reviewed approaches of this section with additional information.

Table 1 to Table 4 contain information about the objectives of the different optimization and control approaches, the flexible devices, and the case studies. Most reviewed algorithms aim to minimize the electricity costs given a time-dependent price for electricity. The other most common objectives of the analyzed literature are the maximization of PV self-consumption rates and the reduction of peak loads. Also, other objectives, such as minimizing the carbon emissions, providing ancillary services, or smoothening the fluctuations in the grid, are used.

Most studies use heat pumps as their primary source of load flexibility, followed by electric water heaters and stationary batteries. In several studies, the heating, ventilation, and air-conditioning system of a building is summarized by HVAC. A few of the reviewed studies do not consider electric heating devices but use other flexible devices instead (e.g., CHPs, EVs, refrigerators). Still, they are included in the literature review since the basic approaches explained in those studies are also applicable to electric heating devices. As there are many studies dealing with optimization approaches for demand response in smart grids, the reviewed literature is confined to the most relevant approaches for this thesis.

4.1 Predictive vs. non-predictive approaches

Optimization approaches for exploiting load flexibility in smart grids can be distinguished by their need for incorporating predictions into the control of the flexible device. Today, most (electric) heating devices are controlled by using non-predictive methods [13]. The majority of non-predictive methods, which aim at utilizing the flexibility of electric heating devices, are rule-based control approaches [58-66]. They consist of a set of if-then rules that are based on expert knowledge. Averaged or real-time values from temperature sensors, PV systems, grid frequency, or electricity prices are used to continuously derive a control action [13]. Some non-predictive approaches just use a predefined schedule to control flexible devices [67].

The main advantages of non-predictive approaches are their simplicity and low computational requirements. However, as they do not incorporate any information about the future into their decision making, non-predictive approaches are unlikely to result in optimal control actions.

Furthermore, the design of appropriate rules under frequently changing conditions (e.g., demand and generation patterns, price structures) can be challenging [13].

Predictive approaches, in contrast, make use of forecasted future values and incorporate them into the decision making. Both internal information about the building (like the demand for heat, DHW, and electricity or the PV generation) and external signals (like prices, loads in the grid, and wind generation) can be predicted. The vast majority of the reviewed papers apply predictive approaches that calculate a schedule by solving an optimization problem [42, 54, 62, 68-103]. This optimal schedule defines control actions for the optimization horizon of the flexible devices that can be implemented by their local control systems. To this end, most of the scheduling approaches rely on a model of the system that maps input parameters (e.g., heating power of a heat pump) to outputs (e.g., temperature of a building). However, there are also predictive approaches that do not calculate an optimal schedule but instead use rule-based control methods that consider predictions of future values [104, 105]. Table 1 contains a list of several predictive and non-predictive approaches.

Table 1: List of predictive and non-predictive approaches

Source	Predictive vs. non-predictive	Objective	Flexible devices	Case study
Salpakari et al. 2016 [65]	Non-predictive	Maximize PV self-consumption	Heat pump, battery, shiftable appliances	1 low-energy house in Finland
Rodríguez et al. 2018 [64]	Non-predictive	Minimize electricity costs	Heat pump, battery	1 low-energy house in Germany
Arteconi et al. 2013 [58]	Non-predictive	Minimize electricity costs	Heat pump	1 detached house in Northern Ireland
Thygesen et al. 2014 [66]	Non-predictive	Maximize PV self-consumption	Heat pump	1 energy-efficient building in Sweden
Lee et al. 2015 [67]	Non-predictive	Minimize peak load	Heat pump	1 low-energy house in Korea
Nolting et al. 2019 [63]	Predictive and non-predictive	Minimize electricity costs	Heat pump	1 building in Germany
Buchmann et al. 2017 [60]	Predictive and non-predictive	Maximize utilization of RES	Battery, electric heating	Real prototype
Dar et al. 2014 [104]	Predictive	Maximize PV self-consumption, minimize peak load	Heat pump	1 zero-energy building in Norway
Sichilalu et al. 2014 [96]	Predictive	Minimize electricity costs, maximize PV self-consumption	Heat pump water heaters	1 hotel building in South Africa
Rogers et al. 2011 [92]	Predictive	Minimize carbon emissions	Heat pump	1 building in the UK
Vrettos et al. 2013 [100]	Predictive	Minimize electricity costs	Heat pump, electric water heater, battery	1 average Swiss residential building
Ali et al. 2014 [68]	Predictive	Minimize electricity costs	Electric storage heater	1 building in the Nordic energy market's area
Wang et al. 2014 [106]	Predictive	Smoothing power fluctuations	Heat pumps, batteries	1,000 flexible devices in a residential area
Pedersen et al. 2011 [90]	Predictive	Minimize costs for electricity purchase	Heat pumps	10 buildings in Denmark

4.2 Centralized vs. decentralized approaches

Optimization approaches for demand response can also be distinguished by grouping them into centralized and decentralized methods. As mentioned before, in centralized optimization approaches, a central entity solves an optimization problem for the whole residential area. It then directly or indirectly controls the flexible devices of the buildings based on the calculated optimal schedules [14, 70, 71, 73, 75, 81, 82, 85, 89, 95, 101]. Also, rule-based control strategies for multiple buildings can be applied in a centralized way [105]. Decentralized approaches only depend on local information of the building. Most decentralized approaches merely consider single buildings for the optimization [42, 58, 62-69, 76, 80, 84, 90, 92-94, 96, 99, 100, 104, 107]. However, there are also several decentralized approaches that aim to optimize multiple buildings [54, 60, 61, 78, 79, 82, 83, 86, 91, 98, 101, 102, 108, 109].

Combinations of centralized and decentralized optimization approaches are called hybrid methods [72, 74, 77, 87, 88, 103, 110]. Analogous to the decentralized optimization approaches for multiple buildings, the control actions of the individual buildings are mainly based on local information. However, a central unit influences these decisions by considering the situation of the entire residential area or local grid. A selection of centralized, decentralized, and hybrid methods can be found in Table 2.

Table 2: List of centralized, decentralized, and hybrid approaches

Source	Centralized vs. decentralized	Multiple buildings	Objective	Flexible devices	Case study
Biegel et al. 2013 [14]	Centralized	Yes	Minimize costs for electricity purchase	Heat pumps	10,000 heat pumps in Denmark
Korkas et al. 2016 [111]	Centralized	Yes	Matching demand and supply	HVAC systems	Microgrid with 3 buildings
Biegel et al. 2013 [73]	Centralized	Yes	Provision of ancillary services	Heat pumps, refrigerators, freezers	10,000 flexible on/off devices
Hao et al. 2015 [105]	Centralized	Yes	Provision of frequency control (ancillary services)	Air-conditioners	1,000 devices in the USA
Kolen et al. 2017 [54]	Decentralized	Yes	Minimize peak-to-valley distance of grid load	Heat pumps, CHPs	146 single-family houses
Ramchurn et al. 2011 [91]	Decentralized	Yes	Minimize peak load	Heat pumps, shiftable appliances	5,000 agents in the United Kingdom
Chang et al. 2014 [78]	Decentralized	Yes	Minimize costs for electricity purchase	Air-conditioners, batteries	400 customers
Menon et al. 2019 [86]	Decentralized	Yes	Minimize electricity costs	Heat pumps	12 buildings in Switzerland
Fischer et al. 2017 [62]	Decentralized	No	Minimize electricity costs, Maximize PV self-consumption	Heat pump, electric back-up heater	1 multi-family house in Germany
De Coninck et al. 2014 [61]	Centralized and decentralized	Yes	Provision of voltage control, minimize curtailment	Heat pumps for DHW	33 buildings in a moderate climate (Europe)

Source	Centralized vs. decentralized	Multiple buildings	Objective	Flexible devices	Case study
Ogston et al. 2007 [88]	Hybrid	Yes	Minimize peak load	Refrigerators, general flexibility	200,000 households in Australia
Blaauwbroek et al. 2015 [74]	Hybrid	Yes	Matching demand and supply	Heat pumps, CHPs	500 appliances
Braun et al. 2015 [77]	Hybrid	Yes	Matching demand and supply	Batteries	300 residential customers in Australia
Bao et al. 2015 [110]	Hybrid	Yes	Provision of frequency control	On/off appliances	100 appliances
Bhattarai et al. 2014 [72]	Hybrid	Yes	Minimize electricity costs	Heat pumps	Test case network in Denmark

4.3 Different methods for solving the optimization problem

Several methods exist to solve the resulting optimization problem for controlling flexible electrical devices. Exact methods can guarantee to find the global optimum of the scheduling problem [14, 62, 68, 70, 73-75, 77-79, 83-86, 90-92, 96, 99-101, 103, 107, 112]. Depending on the mathematical formulation and the structure of the problem, the exact methods can be divided into linear programming (LP) [62, 68, 77, 78, 90, 96, 112], non-linear programming (NLP) [99], quadratic programming (QP) [79, 83, 101], mixed-integer linear programming (MILP) [73, 75, 85, 86], mixed-integer quadratic programming (MIQP) [74, 91, 92, 100, 103] and dynamic programming (DP) [107]. Specific algorithms exist to solve the different types of problems.

Some studies apply decomposition methods [78, 79, 83]. These methods break down a large optimization problem into several smaller problems that can be solved by distributed agents with reduced computational effort. Model-predictive control (MPC) is also used in many studies [62, 70, 77, 79, 84, 86, 100, 101, 103, 112]. MPC approaches iteratively solve an optimization problem and successively implement the result for the first time slot of the rolling-horizon to control the flexible device. The relevant input data for the optimization problem (such as demand, generation, and prices) is predicted at the beginning of each iteration.

Many studies use problem-specific heuristics for the optimization [58-67, 69, 71, 74, 88, 94, 104-106, 108]. In contrast to exact optimization methods, heuristics cannot guarantee to find the globally optimal solution of the optimization problem. However, they are usually significantly faster than the exact algorithms. Further, they often require less information about the optimization problem itself (e.g., no explicit mathematical model of the electric heating device). Most of them need no (or very little) information about future values (particularly the rule-based control heuristics [58-60, 62-66, 104-106]).

Metaheuristic optimization methods define a generic search principle for approximately solving an optimization problem by using randomness and local search techniques [113]. As they are heuristics, the quality of the found solutions cannot be guaranteed. Since metaheuristics are not problem-specific, they can be applied to a wide variety of problems. In the context of demand response, population-based metaheuristics are used in the literature, like evolutionary algorithms (EA) [42, 76, 80], memetic algorithms (MA) [82], and particle swarm optimization (PSO) [95].

Several studies apply dynamic demand control [85, 109, 110]. Approaches from this field use algorithms integrated into flexible appliances to regulate their energy consumption and thus their electrical load. Based on the current frequency of the grid, the algorithms use a rule-based control approach to adjust the electrical power of the flexible devices with the aim of stabilizing the grid frequency or the voltage [114].

Algorithmic game theory, in combination with exact optimization methods, is also applied to exploit the load flexibility in smart grids [87, 102]. Game theory generally studies the interaction between competing or cooperating rational individuals [115]. The reviewed game-theoretic approaches for demand response use a decentralized or hybrid communication system. The distributed agents generate schedules by solving a local optimization problem. These schedules are then negotiated among the agents and adjusted using methods from algorithmic game theory.

In recent years, methods from the field of reinforcement learning have increasingly been used for demand response [93, 97]. Reinforcement learning is an area of machine learning that does not require mathematical models of the environment or any specific knowledge. The different agents learn the optimal control actions from past experience. The objective is to find out which actions maximize the cumulative reward. Table 3 shows studies that apply different optimization methods for solving the resulting optimization problems.

Table 3: List of different optimization methods

Source	Optimization method	Objective	Flexible devices	Case study
Juelsgaard et al. 2014 [83]	Exact (QP, Decomposition)	Minimize active losses in the grid	Heat pumps, EVs	342 buildings in Denmark
Verhelst et al. 2012 [99]	Exact (NLP)	Minimize electricity costs	Heat pump	1 residential building
Worthmann et al. 2015 [101]	Exact (decentralized and centralized MPC)	Minimize peak load	Batteries	300 buildings in Australia
Favre et al. 2014 [107]	Exact (DP)	Minimize electricity costs and carbon emissions	Electric heating devices	1 building in France
Brahman et al. 2015 [75]	Exact (MILP)	Minimize energy costs	CHPs, EVs, shiftable appliances	Residential energy hub
Hong et al. 2012 [108]	Heuristic	Matching demand and supply	Heat pump	2 buildings with different insulation levels
Sánchez et al. 2019 [94]	Heuristic	Maximize PV self-consumption	Heat pump	1 single-family house in Switzerland
Brunner et al. 2013 [59]	Heuristic (rule-based)	Minimize peak load	Heat pumps	Low voltage distribution grid in Germany

Source	Optimization method	Objective	Flexible devices	Case study
Sepulveda et al. 2010 [95]	Metaheuristic (PSO)	Minimize peak load	Electric water heaters	200 buildings in Saint John (Canada)
Lösch et al. 2014 [42]	Metaheuristic (EA)	Minimize electricity costs	Heat pump	1 building in Germany
Braun et al. 2016 [76]	Metaheuristic (EA)	Minimize electricity costs, emissions, and wear, maximize comfort	CHP, shiftable devices	1 building in Germany
Hu et al. 2012 [82]	Metaheuristic (MA)	Minimize electricity costs, maximize autarky	HVAC systems, batteries	2 buildings in Arizona (USA)
Kim et al. 2015 [116]	Dynamic demand control (centralized)	Provision of frequency control	Heat pumps	Test system
Molina-García et al. 2011 [109]	Dynamic demand control (decentralized)	Provision of frequency control	HVAC systems, refrigerators, freezers	Residential load scenarios
Zhu et al. 2011 [102]	Game theory and MILP	Minimize peak load	EVs, water heaters, shiftable appliances	4 households
Nguyen et al. 2012 [87]	Game theory and LP	Minimize peak-to-average ratio	Battery, shiftable appliances, EVs	Smart grid with 10 users
Ruelens et al. 2017 [93]	Reinforcement learning	Minimize electricity costs	Heat pump, electric water heater	1 building in Belgium
De Somer et al. 2017 [97]	Reinforcement learning	Maximize PV self-consumption	Electric water heaters	6 residential buildings

4.4 Uncertainty handling methods

The predictive approaches rely on forecasts about the demand, the RES generation, or electricity prices. Because of deviations between predicted and real load profiles and prices, methods that can handle the uncertainties of forecasts are essential for predictive approaches in real-world applications. Schedule correcting algorithms [80, 98] overrule the actions of a previously calculated schedule if a constraint violation is about to occur or if there are substantial deviations between predicted and measured values. MPC approaches can immediately react to changes in the input parameters of the optimization as they iteratively solve an optimization problem using new predictions for every iteration. They only implement the first actions of the calculated schedule. Due to their ability to react to erroneous forecasts, MPC approaches are popular for demand response with electric heating devices [62, 70, 77, 79, 84, 86, 100, 101, 103, 112]. Another way of dealing with uncertainties is to observe the measured value for the demand and generation and to trigger a rescheduling in case of significant deviations between forecasted values and actual measurements [69, 71, 103].

A way to directly consider uncertainties in the optimization problem is to apply stochastic [81, 89] or robust optimization [79, 85]. In robust optimization, the solutions of the optimization problems should remain feasible in all cases of erroneous predictions. However, in real-world applications, it is necessary to have a reasonable trade-off between robustness and optimality. In stochastic optimization, the probability distribution of the input parameters can either be predicted or is assumed to be known before the optimization procedure. The goal is to generate a solution that is feasible for all realizations of the input data. This solution maximizes an objective function that can contain random variables. Table 4 lists several studies that apply uncertainty handling methods.

Table 4: List of uncertainty handling methods

Source	Uncertainty handling method	Objective	Flexible devices	Case study
Gao et al. 2015 [80]	Schedule correcting algorithm	Minimize electricity costs	Air-conditioners	1 commercial building in Hong Kong
Stoyanova et al. 2014 [98]	Schedule correcting algorithm	Ensure grid stability, reduce expenses of customers	Heat pumps, CHPs	62 households
Kajgaard et al. 2013 [84]	MPC	Minimize energy costs	Heat pump	1 typical Danish single-family house
Zwickel et al. 2019 [112]	MPC	Minimize energy costs and energy consumption	HVAC system (with heat pump)	1 office building in Germany
Diekerhof et al. 2018 [79]	Robust MPC	Minimize electricity costs and peak load	Heat pumps	2,000 buildings
Arnold et al. 2011 [70]	MPC with soft and hard constraints	Minimize overall operation costs	CHPs	Energy-hub
Stoyanova et al. 2020 [103]	MPC and rescheduling	Integration of RES, minimize residual deviation	Heat pumps, CHPs	10 buildings in a city district
Barbato et al. 2012 [71]	Rescheduling	Minimize energy costs	Shiftable appliances, battery	Residential building
Allerding et al. 2011 [69]	Rescheduling, real-time reaction	Minimize electricity costs, improvement of grid state	Shiftable appliances, CHP	1 smart building in Germany
Good et al. 2015 [81]	Stochastic optimization	Minimize energy costs, discomfort	Heat pumps, CHPs	50 residential flats
Ottesen et al. 2015 [89]	Stochastic optimization	Minimize peak load	Electric water heater, fans, lights	1 university building in Norway
Kim et al. 2013 [85]	Robust optimization	Minimize energy costs	Shiftable devices	50 devices

5 Summary of the included papers

In this section, the four embedded papers of this thesis are summarized. In all papers, the developed optimization approaches are compared to an exact centralized optimization approach (MILP) that serves as a benchmark. The optimization horizon for the case studies of all papers is one day. Paper A (Section 5.1) and Paper D (Section 5.4) use a rolling horizon approach with non-overlapping time horizons to optimize one week with seven iterations. The data for all papers is provided by the software tool *synPro* (see Section 3.1.2).

The time resolution for all studies is five minutes. This time resolution is recommended by Salom et al. [117] and Cao et al. [118] to capture the short-term fluctuations of PV systems. A fundamental part of all optimization problems is the model of thermal storage. A uniform temperature model with an energy difference equation is used in all papers. These types of thermal models are frequently used in the literature (see for example [65, 119, 120]).

It is assumed that all buildings in the residential area have an EMS that can utilize an existing communication network to exchange information with other buildings. Further, the EMS can monitor and control all flexible devices in the building by either using rule-based control methods (Paper A) or solving a local optimization problem (Paper B, C, D). Table 5 gives an overview of the four included papers.

Table 5: Overview of the included papers

	Paper A	Paper B	Paper C	Paper D
Predictive vs. non-predictive	Predictive and non-predictive	Predictive	Predictive	Predictive
Centralized vs. decentralized	Decentralized and hybrid (centralized MILP as benchmark)	Decentralized (centralized MILP as benchmark)	Decentralized (centralized MILP as benchmark)	Decentralized (also applicable to centralized)
Multiple buildings	Yes	Yes	Yes	No (but possible)
Uncertainty considered	Not necessary for the non-predictive approaches	No	No	Yes (schedule correction)
Solving method	Heuristics (rule-based)	Exact (MILP) combined with heuristic coordination	Exact (MILP) combined with heuristic coordination	Exact (MILP) combined with heuristic corrections
Objective	Minimize electricity costs and surplus energy	Minimize surplus energy	Minimize surplus energy and peak load	Minimize surplus energy
Flexible devices	Heat pumps	Heat pumps, electric heating elements	Heat pumps, electric heating elements, EVs	Heat pump
Case study	40 residential buildings in Germany	30 to 150 residential buildings in Germany	15 to 75 residential buildings in Germany	1 residential building in Germany
Thermal storage for space heating	Underfloor heating systems	Underfloor heating systems, hot water tanks	Underfloor heating systems, combined storage systems	Underfloor heating system
Thermal storage for domestic hot water	Hot water tanks	Hot water tanks	Hot water tanks, combined storage systems	Hot water tank
Considered renewable energy sources	PV systems	PV systems	PV systems, wind turbine	PV system

5.1 Paper A: Demand response with heuristic control strategies for modulating heat pumps

In this paper [121], three heuristic control algorithms are developed for demand response with modulating heat pumps. Two of them aim at minimizing the electricity-based heating costs (*Past Value Heuristic* and *Future Value Heuristic*). The objective of the third heuristic is to minimize surplus energy from PV in a residential area that otherwise could be curtailed (*Incremental Control Heuristic*). All heuristic control strategies are rule-based approaches that do not require a model of the building or the heating device (model-free). They successively calculate a control action for every time slot and do not specify a schedule of future control actions. Both cost minimization heuristics are decentralized optimization approaches. The *Past Value Heuristic* is a non-predictive method that infers its control actions from current and past electricity prices and the current state of the thermal storage. The *Future Value Heuristic* requires a forecast of future electricity prices and is therefore a predictive approach.

The *Incremental Control Heuristic* for minimizing surplus energy (and thus maximize the self-consumption rate) of locally generated PV energy is a non-predictive and hybrid optimization approach. It uses a control and communication architecture that preserves the privacy of the residents. The communication architecture is based on a central control unit that sends unidirectional control advice to the internal controllers of the buildings, which then decide about the execution of control actions.

None of the three heuristic control algorithms breaches the privacy of the residents as they do not collect or process load profiles of the buildings. Besides, they exploit the flexibility of heat pumps without using powerful computational devices. For both of the non-predictive approaches, there is no need to consider uncertainties as they do not require any forecasts. The uncertainties of future electricity prices are not considered in this study for the predictive *Future Value Heuristic*.

Thermal systems for 40 buildings are modeled to compare the heuristics with a centralized optimization and a conventional control approach. The flexibility comes from the inertia of an underfloor heating system and from a hot water tank for DHW. To analyze the developed approaches, the case study covers 12 weeks from the heating period of Germany. Two price scenarios are defined for the cost minimization heuristics. The results reveal that in all weeks the control heuristics lead to reduced heating costs compared to a conventional control strategy. The average improvements are between 4.1% and 13.3%. The improvements strongly depend on the volatility and ranges of the prices on the electricity markets (day-ahead and intraday market). The centralized optimization approach leads to improvements of between 20.7% and 33.3%.

In the problem of surplus energy minimization, the heuristic control strategies perform surprisingly well. Analogous to the cost minimization problem, two scenarios are defined with different peak powers of the buildings' PV systems. For PV systems with 10 (7) kW peak power, the reduction of surplus energy is 38.3% (52.6%). The centralized optimization approach leads to another 13% improvement while having strongly increased runtimes and requiring complete information about future demand and generation.

On average, the centralized optimization needs more than four minutes for the optimization of one week, whereas the heuristic control and the conventional control strategies require three seconds (including the simulations). This study demonstrates the suitability of a privacy-preserving communication and control architecture combined with heuristic control strategies for shifting electrical loads in residential areas. The developed control approaches can be modified for virtual power plant operators, aggregators, or the provision of ancillary services.

5.2 Paper B: Decentralized optimization approaches for using the load flexibility of electric heating devices

In this paper [122], two novel coordinating decentralized optimization approaches for utilizing electrical load flexibility are developed. The two introduced algorithms, called *Parallel Successive Cluster Optimization* (*PSCO*) and *Parallel Successive Cluster Optimization with IDA* (*PSCO-IDA*), are based on the *Iterative Desync Algorithm* (*IDA*) by Kolen et al. [54]. *IDA* is a privacy-preserving and effective algorithm for decentralized optimization. It defines a heuristic coordination mechanism for the buildings in the residential area. For the coordination, all buildings need to have a solution pool with multiple diverse schedules. Analogous to *IDA*, the developed algorithms *PSCO* and *PSCO-IDA* are predictive scheduling-based optimization approaches. *PSCO-IDA* also requires the buildings to have a solution pool. All investigated decentralized approaches use heuristic coordination mechanisms. However, the basic local optimization problem can be solved by using exact methods (as it is done in this study), heuristics, or metaheuristics. The goal of the optimization is to minimize surplus energy in the residential area. Uncertainties are not considered in this study.

Another contribution of this paper is the definition of a new optimization procedure that generates the required solution pools for the coordination in a systematic way. The new optimization procedure iteratively uses a specific optimization problem that outputs a diverse schedule for the problem of minimizing surplus energy from locally generated renewable energy.

For the case study, a base case scenario is defined with 90 buildings. Three types of buildings with different insulation levels and heating systems are used (non-modulating ground source heat pumps, modulating air-source heat pumps, and a gas heating system with additional electric heating elements). The buildings utilize hot water tanks and the inertia of underfloor heating systems for thermal storage. All buildings have a PV system. The analysis is done for 15 days of Germany’s heating period. Different scenarios with changing peak powers of the PV systems and changing numbers of buildings are defined to evaluate the developed optimization approaches.

For the base case scenario, *IDA*, with the introduced optimization procedure to systematically generate diverse solutions, is compared to *IDA* with the automatically created solution pools of the commercial solver *CPLEX* [123]. The solver creates the solution pool by simply storing the found solutions during the optimization process. The developed optimization procedure can improve the results of *IDA* significantly. On average, it leads to about 100 kWh less surplus energy per day.

Moreover, the case study shows that *PSCO-IDA* outperforms *IDA* in all scenarios and, on average, is about 10% closer to the optimal solution. The *PSCO* algorithm yields similar results as *IDA* while having reduced data exchange requirements. All investigated decentralized optimization approaches (*IDA*, *PSCO*, and *PSCO-IDA*) lead to significant improvements compared to an uncoordinated decentralized optimization approach. Although centralized optimization leads to better results, this study shows that it has strongly increased runtimes and is not applicable to larger residential areas. In contrast to the developed decentralized optimization approaches, centralized optimization does not scale well with the number of buildings as its runtimes grow exponentially.

5.3 Paper C: Demand response through decentralized optimization in residential areas with wind and photovoltaics

This paper [124] develops a novel coordination mechanism for the optimal use of flexible electrical loads on a decentralized level. The aim is to react to the volatile supply from RES in a residential area and to reduce the peak load. The *Sequential Parallel Cluster Optimization with IDA (SEPACO-IDA)* is a privacy-preserving approach that combines two coordination algorithms from the literature for decentralized optimization (*PSCO-IDA* [122] and *IDA* [54]). *SEPACO-IDA* is a scheduling-based predictive approach that uses a heuristic coordination mechanism for decentralized optimization. Analogous to *PSCO-IDA* and *IDA*, a solution pool with multiple diverse schedules is created during the optimization. This paper uses the optimization procedure introduced in [122] to generate diverse solution pools for the buildings.

For the analysis, a residential area is modeled with three types of buildings that have different insulation levels and electric heating systems (ground source heat pumps, modulating air-source heat pumps, and a gas heating system with additional modulating electric heating elements). Some of the buildings have a PV system, and some use EVs that are charged at home. Moreover, a small wind turbine (100 kW) is connected to the local grid. The buildings use underfloor heating systems and hot water tanks for thermal storage. Several scenarios are generated for the analysis by using a *Monte Carlo* sampling method. This method generates different combinations of parameters for the residential area (e.g., number of buildings, number of EVs, power of wind turbine, share of buildings with PV).

Each building's EMS solves an optimization problem with two objectives. The first objective is to minimize the surplus energy, which simultaneously maximizes the self-consumption rate of locally generated electricity from RES. Besides, the buildings intend to minimize their peak load. A weighted sum approach is used with different weight combinations to transform the two-dimensional objective space of the optimization problem into a one-dimensional space. *SEPACO-IDA* coordinates the decentralized optimization problems of the buildings and the selection of the schedules from the solution pool to optimize the two goals for the residential area as a whole. Uncertainties are not considered in this study.

The results show that *SEPACO-IDA* outperforms the other approaches for scheduling-based decentralized optimization from the literature. The differences in optimality compared to *PSCO-IDA* are small (between 0.8% and 2.4%). However, *SEPACO-IDA* has additional advantages over *PSCO-IDA* regarding the level of privacy as no direct information from another single building is used. The improvements compared to *IDA* are significant (between 11.1% and 13.3%). Moreover, this study clearly illustrates the suboptimal results of uncoordinated decentralized optimization and, consequently, the strong need for coordination mechanisms.

The development and evaluation of two methods for distributing a central wind power profile to the local optimization problems of distributed buildings (*Equal Distribution* and *Score-Rank-Proportional Distribution*) is another contribution of this paper. The different decentralized optimization approaches are combined with the methods for wind profile assignment. The results reveal the dependency of the most suitable wind profile assignment method on the used decentralized optimization approach.

5.4 Paper D: Uncertainty handling control algorithms for demand response with modulating electric heating devices

To exploit the flexibility of electric heating devices, scheduling-based optimization uses demand and generation predictions to calculate an operative schedule of the heating devices. Due to deviations between predicted and real energy profiles, additional uncertainty handling methods are necessary that adjust the actions imposed by the schedule to the current situation.

In this paper [125], two simple but effective corrective control algorithms for buildings in smart grids with modulating heating devices are developed (*Storage Correction algorithm* and *PV Correction algorithm*). These schedule correcting algorithms are rule-based approaches that can cope with the uncertainties of predictions. In contrast to other uncertainty handling approaches, the algorithms introduced in this paper are specially designed for modulating heating devices. Another essential feature of the developed approaches is that they combine a corrective mechanism with elements from robust optimization.

The *Storage Correction algorithm* strongly decreases the likelihood and degree of constraint violations of the thermal storage. Thermal constraint violations result in a loss of comfort for the residents and can cause technical problems. The heuristic algorithm overrules the control actions of the previously calculated optimal schedule if a constraint violation is about to occur. Uncertainties in the PV forecast and the prediction of the building's electrical demand do not lead to constraint violations of the thermal storage but to suboptimal decisions. Hence, the *PV Correction algorithm* adjusts the recommended actions of the optimal schedule by reacting to the measured power generation of the PV system. The goal is to maximize the self-consumption rate of locally generated PV energy.

For the analysis, only one building is considered to show the applicability of the developed correction algorithms in general. The building has a PV system and uses a modulating air-source heat pump coupled to an underfloor heating system and a hot water tank. The developed algorithms can be used with both centralized and decentralized optimization approaches in smart grids.

The analysis shows that the developed approaches lead to a higher usage of locally generated electricity from PV systems while avoiding violations of the residents' comfort limits. Further, the results reveal that erroneous predictions of electricity demand and generation diminish the capability of electric heating devices to react to the volatile generation by the RES. Higher predictions errors lead to higher numbers of necessary corrections to avoid constraint violations. Even a low prediction error of only 2% makes, on average, 76 corrections necessary in the schedule for one simulated week.

Moreover, using the *Storage Correction algorithm* in combination with the *PV Correction algorithm* leads to better results than only using the *Storage Correction algorithm*. As expected, the results for the uncertainty handling methods are in all investigated weeks better than those of the conventional control approach (11 to 15 kWh less surplus energy) but worse than those of the optimization with perfect foresight (7 to 10 kWh more surplus energy).

6 Conclusions, critical appraisal and outlook

This section concludes the thesis. Section 6.1 summarizes the main characteristics of the developed optimization approaches and draws conclusions. Several simplifications and assumptions were necessary for this study. Hence, the limitations of this thesis are discussed in Section 6.2. As there is still a need for research in the field of load flexibility in smart grids, Section 6.3 points out possible directions for future research.

6.1 Conclusions

The flexibility of electric heating devices can help to overcome the challenges caused by increasing shares of intermittent renewable energy sources in the energy system. In this thesis, several novel optimization approaches that exploit the flexibility of electric heating devices and other electrical loads in smart grids are developed. The primary goal of the introduced algorithms is to adjust the electrical consumption of multiple devices in a coordinative way. Thus, the electrical load can react to the intermittent electricity generation from renewable energy sources. For the evaluation of the developed approaches, residential areas with different building types are modeled. The buildings use different electric heating devices. The main flexibility comes from underfloor heating systems, which utilize the building mass to store heat energy, and from hot water tanks.

The introduced algorithms tackle the disadvantages of centralized optimization approaches regarding privacy, computational complexity, and robustness. Basically, three types of optimization approaches are developed in this thesis. The first type comprises model-free and rule-based control heuristics for modulating electric heating devices (Paper A). They use decentralized or hybrid control and communication architectures that preserve the privacy of the residents. Two of the developed approaches are non-predictive approaches that do not need forecasts of future demand and electricity generation. Simulations show up to 52.6% less surplus energy and up to 13.3% lower costs compared to a conventional control approach.

The second type comprises predictive scheduling-based methods (Paper B and Paper C). They use heuristic coordination mechanisms for decentralized optimization that are based on solution pools with diverse schedules. The approaches make use of a newly defined optimization procedure that generates these diverse schedules for the problem of minimizing surplus energy from locally generated renewable energy (Paper B). Furthermore, methods for distributing a central wind power profile to the local optimization problems of distributed agents are developed and evaluated (Paper C). The introduced decentralized optimization approaches from Paper B and Paper C are not restricted to electric heating devices but can be used with every type of flexible electrical load. They outperform an effective and privacy-preserving approach for decentralized optimization from the literature by generating solutions that are, on average, between 10% and 13% closer to the optimum.

The third type of developed methods comprises uncertainty handling control algorithms for modulating electric heating devices (Paper D). Corrective control algorithms for scheduling-based predictive optimization are introduced and evaluated. They can cope with the uncertainties of demand and generation predictions by adjusting the recommended actions of a previously calculated schedule. These supplementary methods can be used with both centralized and decentralized optimization approaches.

All introduced methods preserve the privacy of the residents and yield good results. This thesis shows the suboptimality of the currently used conventional control approaches for electric heating devices and the advantages of coordinated decentralized optimization. The differences between all introduced optimization approaches to a conventional control strategy are remarkable. In contrast to centralized optimization, the developed algorithms have low computational complexity and scale well with the number of buildings in the residential area. Hence, they can be applied to larger residential areas with many buildings or even to whole regions. Sustainable energy systems with high shares of renewable energy sources can profit from applying the developed optimization approaches, as they are capable of adjusting the electrical demand to the volatile electricity generation.

6.2 Critical appraisal

For the analysis, several simplifications were made to reduce the model complexity and to deal with data availability problems. The efficiency of the modulating heat pump in the used models does not depend on the modulation degree. However, in reality, the modulation degree has a non-negligible impact on the heat pump's efficiency [62]. Considering the dependency of the heat pump's efficiency on the modulation degree makes the model nonlinear. This would result in strongly increased runtimes. Moreover, the heating system's supply temperature is assumed to be constant. In reality, the supply temperature of the heating system depends on the outside temperature.

Another assumption is the exact and immediate heat energy transfer from the thermal storage systems (underfloor heating system and hot water tanks) to the rooms of the buildings. The heat demand data for the case studies is given externally. It quantifies the heating energy that is necessary to keep the room temperature at 21° C. In the optimization models of the buildings the exact amount of heat energy, which is predefined by the external time series data for space heating, is immediately transferred from the thermal storage. Modeling a realistic heat transfer would require a detailed thermal model of the building and the hot water tank, which was not in the scope of this thesis. Incorporating such a model in an optimization problem would strongly increase the computational effort to solve it. In particular, the centralized optimization problems, which served as a benchmark for all developed optimization approaches, would become computationally challenging. Moreover, such a model would be based on many assumptions regarding the buildings' heat transfer coefficients and geometry. Further, information or assumptions about the geometry of the underfloor heating system would be required to model a realistic heat transfer from the thermal storage to the building. Due to the lack of real-world data, synthetic load profiles (demand for electricity, space heating, and domestic hot water) and photovoltaic generation time series were used in this thesis. The synthetic data was generated by the software tool *synPRO*.

For the scheduling-based decentralized optimization approaches (Paper B and Paper C) and all centralized optimization approaches, no uncertainties were considered. However, in reality, forecasts of future demand and supply are always erroneous. Consequently, the results of all predictive optimization approaches represent upper bounds for the realizable improvements. The consideration of uncertainties will affect the results and will require uncertainty handling optimization approaches that can deal with erroneous predictions. Schedule correcting algorithms are introduced in this thesis (Paper D). These methods can be applied to the developed scheduling-based optimization approaches of Paper B and Paper C. They overrule the actions imposed by a previously calculated optimal schedule to avoid violations of the resident's comfort levels caused by erroneous predictions. However, other uncertainty handling approaches found in the literature, like stochastic optimization, (purely) robust optimization, model predictive control, and rescheduling were not investigated.

In this thesis, different optimization approaches for exploiting the electrical load flexibility in smart grids were investigated from a system perspective. Market mechanisms for incentivizing building owners to use their flexibility (see for example [126]) or special market designs for locally trading electricity (see for example [127, 128]) were not analyzed as the energy market itself was neglected in this thesis. The simplifying assumption was made that all building owners agree to participate in the optimization procedures without any incentive. Further, the building owners allow other buildings to use their locally generated photovoltaic energy without any payments, as costs for selling electricity were not considered. Designing market strategies that can be combined with decentralized optimization approaches was not in the scope of this thesis.

The developed optimization approaches are all investigated in simulations and not in real-world environments. Not all existing electric heating devices can directly use the developed methods in real-world applications. Their local control units might not fit to the methods or might interfere with them. Although many heat pumps can react to external signals (*smart-grid-ready-*

label [34]), it might be necessary to adjust the introduced optimization approaches to the specific control units of the used heating devices.

In all case studies, multiple days or weeks were randomly chosen from the heating period of Germany to evaluate the developed optimization approaches. A more sophisticated way of selecting days or weeks for the case studies is to use representative time series. For instance, self-organizing maps, a specific type of artificial neural network, seem promising for the task of finding representative days for energy-related optimization models [129].

6.3 Outlook

Additional research is necessary to successfully integrate electric heating devices into smart grids and exploit their flexibility. The different optimization approaches should be investigated and compared in real-world experiments to evaluate their practicability. Rule-based non-predictive approaches are easier to implement and do not rely on a thermal model of the building. In contrast, predictive scheduling-based approaches use a thermal model of the building and the flexible devices. Further, they incorporate predictions into their decision making, which can be an advantage. For model-based approaches, exact methods to solve the resulting optimization problem can be used that guarantee to find the optimal solution. In simulations that are based on the assumption of perfect foresight, they lead to the best results.

However, fundamental questions arise regarding model-based predictive approaches in real-world experiments. One core question is how detailed the thermal model has to be in order to capture the thermal dynamics of buildings accurately. A more detailed building model increases the computational complexity of scheduling-based optimization problems. This might make exact optimization methods infeasible.

Another vital question arises concerning the accuracy of the needed predictions in reality. Related to this, research has to be conducted to infer which uncertainty handling methods should be used to cope with erroneous predictions. The model-based scheduling approaches should be compared to both rule-based approaches and to methods from the field of reinforcement learning in experiments with different types of buildings and electric heating devices.

The incorporation of other flexible devices into the simulations and real-world experiments, such as combined heat and power systems or cooling devices, constitutes another direction for future work. As the demand for space cooling is going to increase due to global warming [130], air conditioners can provide significant flexibility in the future. Especially in periods with low electricity generation by renewable energy sources, combined heat and power systems can contribute to the security of supply by generating electricity.

In addition to real-world applications, large-scale energy system models can significantly profit from the developed optimization approaches. Energy system models typically use centralized optimization for large regions (e.g., countries or continents). They are frequently used to analyze economic and technical pathways for the optimal transition of energy systems and to infer policy advice [131]. Integrating the volatile electricity generation from photovoltaics and wind turbines, drastically increases the computational cost of energy system models, as the renewable energy sources have to be modeled with high temporal and spatial resolution [131-133]. Since the developed optimization approaches yield good results while having strongly reduced runtimes compared to centralized optimization, they can be used for large energy system models to answer different research questions. In particular, the developed approaches can be used for a detailed analysis of electrical load flexibility in different regions. The scheduling-based optimization methods presented in Paper B, C, and D can be combined to calculate a realistic load shifting potential of electric heating devices. These numbers can then be compared to the resulting potentials when using the rule-based control strategies of Paper A.

Another important research field is the design of market mechanisms that incentivize the building owners to participate in optimization approaches like the ones developed in this thesis. The optimization approaches maximize the self-consumption rate of locally generated renewable energy for residential areas from the perspective of the whole system. Further, they can reduce the peak load in local grids. The combination of such optimization approaches with suitable market designs constitutes a crucial task for the transition of the energy system.

Closely related to the market design is the question of user acceptance. This is important for all types of flexible loads in residential and non-residential areas. Both the optimization approaches and the market mechanisms have to be in line with data protection laws and should not lead to any inconvenience for the residents. Thus, future energy systems with high shares of renewable energy sources can significantly contribute to achieving the climate goals and to minimize the harmful impact on the environment while satisfying the energy needs of humanity.

Appendix

Literature Review

Table 6: List of the relevant studies found in the literature

Source	Predictive vs. non-predictive	Centralized vs. decentralized	Multiple buildings	Solving method	Uncertainty considered
Salpakari et al. 2016 [65]	Non-predictive	Decentralized	No	Heuristic (rule-based)	Not necessary (rule-based)
Rodríguez et al. 2018 [64]	Non-predictive	Decentralized	No	Heuristic (rule-based)	Not necessary (rule-based)
Arteconi et al. 2013 [58]	Non-predictive	Decentralized	No	Heuristic (rule-based)	Not necessary (rule-based)
Thygeses et al. 2014 [66]	Non-predictive	Decentralized	No	Heuristic (rule-based)	Not necessary (rule-based)
Lee et al. 2015 [67]	Non-predictive	Decentralized	No	Heuristic (predefined schedule)	No
Nolting et al. 2019 [63]	Both	Decentralized	No	Heuristic (rule-based)	Not necessary (rule-based)
Buchmann et al. 2017 [60]	Both	Decentralized	Yes	Heuristic (rule-based, swarm intelligence)	Not necessary
Dar et al. 2014 [104]	Predictive	Decentralized	No	Heuristic (predictive rule-based)	Not necessary (rule-based)
Sichilalu et al. 2014 [96]	Predictive	Decentralized	No	Exact (LP)	No
Rogers et al. 2011 [92]	Predictive	Decentralized	No	Exact (MIQP)	No
Vrettos et al. 2013 [100]	Predictive	Decentralized	No	Exact (MPC with MIQP)	Yes (MPC)
Ali et al. 2014 [68]	Predictive	Decentralized	No	Exact (LP)	No
Wang et al. 2014 [106]	Predictive	Centralized	Yes	Heuristic	Yes (rule-based reaction)
Pedersen et al. 2011 [90]	Predictive	Decentralized	No	Exact (LP)	No
Biegel et al. 2013 [14]	Predictive	Centralized	Yes	Exact	No
Korkas et al. 2016 [111]	Predictive	Centralized	Yes	Exact (Optimal control theory)	Yes
Biegel et al. 2013 [73]	Predictive	Centralized	Yes	Exact (MILP)	No
Hao et al. 2015 [105]	Predictive	Centralized	Yes	Heuristic (predictive rule-based)	Not necessary (rule-based)
Kolen et al. 2017 [54]	Predictive	Decentralized	Yes	Exact combined with heuristic	No
Ramchurn et al. 2011 [91]	Predictive	Decentralized	Yes	Exact (MIQP) and heuristic	No
Chang et al. 2014 [78]	Predictive	Decentralized	Yes	Exact (LP Decomposition)	No
Menon et al. 2019 [86]	Predictive	Decentralized	Yes	Exact (Distributed MPC with MILP)	Yes (MPC)

Source	Predictive vs. non-predictive	Centralized vs. decentralized	Multiple buildings	Solving method	Uncertainty considered
Fischer et al. 2017 [62]	Both	Decentralized	No	Heuristic (rule-based), MPC with LP	Not necessary (rule-based), MPC
De Coninck et al. 2014 [61]	Non-predictive	Both	Yes	Heuristic (rule-based)	Not necessary (rule-based)
Ogston et al. 2007 [88]	Predictive	Hybrid	Yes	Heuristic	No
Blaauwbroek et al. 2015 [74]	Predictive	Hybrid	Yes	Exact (MIQP) and heuristic	No
Braun et al. 2015 [77]	Predictive	Hybrid	Yes	Exact (MPC with LP)	MPC
Bao et al. 2015 [110]	Non-predictive	Hybrid	Yes	Dynamic Demand Control (Hybrid)	Not necessary
Bhattarai et al. 2014 [72]	Predictive	Hybrid	Yes	Exact and heuristic	Yes (schedule correction)
Juelsgaard et al. 2014 [83]	Predictive	Decentralized	Yes	Exact (QP Decomposition)	No
Verhelst et al. 2012 [99]	Predictive	Decentralized	No	Exact (NLP)	No
Worthmann et al. 2015 [101]	Predictive	Both	Yes	Exact (MPC with QP)	MPC
Favre et al. 2014 [107]	Predictive	Decentralized	No	Exact (DP)	No
Brahman et al. 2015 [75]	Predictive	Centralized	Yes	Exact (MILP)	No
Sepulveda et al. 2010 [95]	Predictive	Centralized	Yes	Metaheuristic (PSO)	No
Lösch et al. 2014 [42]	Predictive	Decentralized	No	Metaheuristic (EA)	No
Braun et al. 2016 [76]	Predictive	Decentralized	No	Metaheuristic (EA)	No
Hu et al. 2012 [82]	Predictive	Both	Yes	Metaheuristic (MA)	No
Hong et al. 2012 [108]	Non-predictive	Decentralized	Yes	Heuristic	Not necessary
Sánchez et al. 2019 [94]	Predictive	Decentralized	No	Heuristic	No
Brunner et al. 2013 [59]	Non-predictive	Centralized	Yes	Heuristic (rule-based)	Not necessary (rule-based)
Kim et al. 2015 [116]	Non-predictive	Centralized	Possible	Dynamic Demand Control (Centralized)	Not necessary
Molina-García et al. 2011 [109]	Non-predictive	Decentralized	Yes	Dynamic Demand Control (Decentralized)	Not necessary
Ruelens et al. 2017 [93]	Predictive	Decentralized	No	Reinforcement learning	Not necessary
De Somer et al. 2017 [97]	Predictive	Decentralized	Yes	Reinforcement learning	Not necessary
Zhu et al. 2011 [102]	Predictive	Decentralized	Yes	Game theory and MILP	No
Nguyen et al. 2012 [87]	Predictive	Hybrid	Yes	Game theory and LP	No

Source	Predictive vs. non-predictive	Centralized vs. decentralized	Multiple buildings	Solving method	Uncertainty considered
Gao et al. 2015 [80]	Predictive	Decentralized	No	Metaheuristic (EA)	Yes (schedule correction)
Stoyanova et al. 2014 [98]	Predictive	Decentralized	Yes	Heuristic adjustments	Yes (schedule correction)
Kajgaard et al. 2013 [84]	Predictive	Decentralized	No	Exact (MPC)	Yes (MPC)
Diekerhof et al. 2018 [79]	Predictive	Decentralized	Yes	Exact (Decomposition, MPC with QP)	Yes (Robust MPC)
Arnold et al. 2011 [70]	Predictive	Centralized	Energy-hub	Exact (MPC)	Yes (MPC)
Barbato et al. 2012 [71]	Predictive	Centralized	No	Heuristic	Yes (Rescheduling)
Allerding et al. 2011 [69]	Predictive	Decentralized	No	Heuristic	Yes (Rescheduling)
Good et al. 2015 [81]	Predictive	Centralized	Yes	Exact with uncertainties (SP)	Yes (Stochastic optimization)
Ottesen et al. 2015 [89]	Predictive	Centralized	Yes	Exact with uncertainties (SP)	Yes (Stochastic optimization)
Kim et al. 2013 [85]	Predictive	Centralized	Yes	Exact (MILP)	Yes (Robust optimization)
Zwickel et al. 2019 [112]	Predictive	Decentralized	No	Exact (MPC with LP)	Yes (MPC)
Stoyanova et al. 2020 [103]	Predictive	Hybrid	Yes	Exact (Distributed MPC with MIQP)	Yes (MPC and rescheduling)

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Demand response with heuristic control strategies for modulating heat pumps

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HIGHLIGHTS

- Control strategies for using flexibilities of modulating heat pumps are developed.
- A privacy preserving control and communication architecture is used.
- Combination of central and decentralized control approaches.
- Comparison to a conventional control and exact optimization approaches.
- Results reveal a good trade-off between quality and computational time.

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ABSTRACT

The flexibility of electrical heating devices can contribute to overcoming the challenges caused by increasing shares of volatile renewable energy sources in the energy system. Especially modulating heat pumps are suitable for using intelligent control strategies that vary the pumps' power output based on demand response signals. In this paper, we define optimization problems for minimizing the heating costs and the surplus energy of a residential area, and we introduce novel heuristic control strategies for modulating heat pumps to solve these problems. The heuristic control strategies make use of a privacy preserving control and communication architecture that combines central and decentralized control approaches. All buildings use an underfloor heating system and a domestic hot water tank as thermal storages. Compared to a conventional control strategy, the results show average cost reductions of between 4.1% and 13.3% for the cost minimization heuristics, and average improvements of between 38.3% and 52.6% for the surplus energy minimization heuristic. Contrary to approaches for finding the globally optimal solution, the introduced heuristic control strategies have significantly lower computational times and do not require perfect foresight regarding future demands and electricity generation.

1. Introduction

To diminish the effects of climate change caused by increasing amounts of CO_2 in the atmosphere, the European countries have agreed to decarbonize the power system. As a result, the share of environment-friendly renewable energy sources in Europe has been steadily increasing. Between 2004 and 2016, the share of energy from renewable sources in gross final consumption of energy increased from 8.5% to 17% in Europe [1]. This development will continue as the target for the year 2020 is 20%, and 27% for the year 2030. Due to these high shares, generating energy is increasingly decentralized. A crucial challenge brought about by renewable energy sources like wind turbines and photovoltaic systems (PV) is their intermittent character. As noted in [2], wind and PV contributed about 12% of Europe's electricity supply in 2016. That study, carried out by the Joint Research Centre of the European Commission, concludes that this contribution needs to be tripled in order to reach the 2030 target.

To cope with these problems, energy systems have to realize a paradigm shift in future. The electrical demand will continuously have to be adjusted based on the current power outputs of the fluctuating renewable energy sources. Flexible electrical loads will become essential to deliver demand response which directly or indirectly describes implemented changes in customers' electric usage in response to certain signals [3]. Incentive based signals like direct load control or price-based signals can be used for shifting the electrical demand [4]. In the residential sector several technologies, such as thermostatically

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Nomenclature

ΔE_t^{UFHsoc}	energy difference between current SOC and target SOC
Δt	time resolution
ΔT_t	temperature difference between sink and source temperature of the heat pump
ρ	density
B	number of buildings
b	index for buildings
C	total heating costs
c	heat capacity
COP_t	coefficient of performance
d^{Update}	interval between updating time slots
$F_l(p)$	empirical distribution function
$h_t^{positive}$	binary auxiliary variable for the big-M approach
$h_{t,b}$	binary auxiliary variable
l	number of past or future values for the cost minimization heuristics
M_t^+, M_t^-	big-M parameters
$mDeg_t$	advised modulation degree by the central controller
P^{HPmax}	maximal electrical power of the heat pump
p_t	price for electricity
$P_t^{PVtotal}$	total PV generation
P_t^{ResAux}	auxiliary residual load
$P_t^{ResReal}$	measured residual load
$P_t^{Surplus+}$	positive part of surplus power
$P_t^{Surplus-}$	negative part of surplus power
$P_t^{Surplus}$	surplus power
P_t^{total}	total demand
$P_{t,b}^{Demand}$	conventional electrical demand
$P_{t,b}^{PV}$	PV generation by one building
P_t^{LoadHP}	electrical load of all heat pumps
$Q^{LossesDHW}$	losses of the domestic hot water tank
$Q^{LossesSH}$	losses of the space heating
$Q_t^{DemandSH}$	demand for space heating
$Q_t^{HP,DHW}$	heating energy of the heat pump for domestic hot water
$Q_t^{HP,SH}$	heating energy of the heat pump for space heating
SE	surplus energy
$SOC_{t,b}^{DHW}$	state of charge of the domestic hot water tank
	state of charge of the underfloor heating system
t	index for time slots
T^{DHW}	temperature of the domestic hot water
T^{Sink}	sink temperature of the heat pump
t_i^{Update}	updating time slot for the cost minimization heuristics
T_t^{Source}	source temperature of the heat pump
T_t^{UFH}	temperature of the underfloor heating system
V_t^{DHWuse}	usable volume of the domestic hot water tank
V^{UFH}	volume of the underfloor heating system
x_t	modulation degree of the heat pump for space heating
x_t^*	necessary modulation for keeping the SOC of the UFH
y_t	modulation degree of the heat pump for domestic hot water
Z	number of time slots

controlled loads, electric vehicles, and deferrable loads (washing machine, dish washer, and tumble dryer) are suitable for demand response [5].

Especially electrical heating devices (e.g. heat pumps, electric storage heaters, and electric heating elements) in combination with thermal storage can provide significant flexibility. In 2016, space heating accounted for about 65% of the end energy consumption in EU households and domestic hot water (DHW) preparation for more than 14% [6]. Considering suitable heating technologies for demand response, heat pumps can play a significant role in providing flexibilities, due to their high efficiencies [7]. Between 2006 and 2016, the number of buildings equipped with a heat pump in Europe has increased fivefold [8] having installed more than 10 million by the end of 2017 [9].

Heat pumps can efficiently use existing infrastructure for thermal storage by decoupling heat production and usage in buildings. The thermal mass of the building [10] and a hot water tank [11] can be utilized for shifting the operation of the heat pump without affecting the inhabitants' comfort negatively. Currently, the practice is to use a conventional control for heating devices coupled to thermal storages. The conventional control strategy starts heating up the thermal storage with full power if the lower temperature limit is reached, and the heating stops when the storage's energy level reaches its upper limit. However, this control approach does not exploit the flexibility of thermal storage. Alternative strategies can optimize the use of the electrical heating devices making them suitable for demand response.

In this paper we introduce novel heuristic control strategies for modulating heat pumps. These types of heat pumps can not only be switched on and off, but are capable of adjusting their electrical power continuously. In 2020, the majority of air-source heat pumps offered in Germany are assumed to be modulating heat pumps [12]. In contrast to other control strategies for heat pumps, our control strategies make specific use of the continuously adjustable power of modulating heat pumps to minimize the heating costs of a residential area or the surplus energy. The heat pumps are connected with two storages (see Fig. 1). An underfloor heating (UFH) system stores the energy for space heating and a hot water tank is used for DHW preparation. The goal is to use the flexibility of the heating system to minimize the heating costs and the surplus energy. The computational effort for exactly solving the corresponding scheduling problems is fairly high as scheduling problems are generally NP-hard [13]. Another drawback of exact optimization approaches is that they require perfect input data. We have therefore developed heuristics for controlling the electrical heating devices trying to achieve a certain goal. The heuristic control strategies can be implemented easily, as there is no need for powerful computing devices. We compare the results of the heuristic control strategies to the optimal solution in order to quantify the differences between the approaches.

Further, we use a special control and communication architecture in this paper (see Fig. 3). It consists of a central controller which sends control advice to the internal controllers of the buildings. The internal controllers then decide on the control actions locally without giving feedback to the central controller. As there is no necessity for centrally monitoring and directly controlling the buildings, this control architecture will not breach the privacy of the inhabitants. The remainder of the paper is organized as follows: Section 2 gives a literature review. Section 3 describes the model of the residential area and defines two optimization problems for making use of modulating heat pumps. We explain the two heuristic control strategies and the control architecture we use in Section 4. In Section 5 we discuss results, and the paper ends with a summary and conclusion in Section 6.

2. Related work

The relevant literature mentions several different approaches that have been applied to make use of flexible electrical heating devices. They can be roughly subdivided into four overlapping categories: metaheuristic optimization, conventional (exact) optimization, model predictive control (MPC) and (problem-specific) heuristic control strategies. Metaheuristic optimization methods define a generic search principle for approximately solving an optimization problem by using randomness and local search (without guaranteeing the quality of the found solutions) [14]. They can be applied in a wide variety of problems as they are not problem-specific. In [15–17] different metaheuristics are used for scheduling flexible heating loads of buildings. In contrast to heuristics, conventional (exact) optimization methods can guarantee finding the globally optimal solution. The authors of [15,18–20] illustrate applications of exact optimization methods in exploiting the flexibility of electrical heating devices. MPC is an approach used for controlling dynamic systems by iteratively solving a finite-horizon optimization problem based on predicted input parameters. The authors of [21–23,7] use MPC approaches to control the heating activities of heat pumps in residential buildings.

We call methods which consist of problem-specific control laws that iteratively try to achieve a certain goal, *heuristic control strategies* (some authors refer to these approaches as rule-based control). As these methods are heuristics, they are not able to guarantee the quality of the control actions. Opposed to the above-mentioned methods, heuristic control strategies do not require perfect information regarding the future. Most of them need no (or very little) information about future values. Table 1 compares the different heuristic control strategies for using the flexibility of electrical heating devices found in the literature. The aim of all these strategies is to minimize the heating costs or to maximize the consumption of power generated by renewable energy sources (PV and wind). While most of the publications consider a conventional heat pump that can merely be switched on and off, De Coninck et al. [24], Fischer et al. [25], and Salpakari et al. [26] define control strategies that are specified for modulating heat pumps. Besides Hong et al. [27] and De Coninck et al. [24], the heuristic control strategies are designed for only one building. As none of the essential information for the control strategies (electrical power of the building, temperatures of the storages, heat demand, etc.) is sent to others, all approaches for controlling one building are privacy friendly.

In [27] Hong et al. investigate a heat pump for space heating in one building, which is powered by a wind turbine. A distributed demand side control algorithm groups the electrical demands of the building in three clusters depending on their control availability. When the demand exceeds the supply, the algorithm controls the flexible demands progressively from cluster 1 (highest load availability) to 3 (lowest load availability). If the supply is higher than the demand, the algorithm initiates a load recovery program beginning from cluster 3. Although their study used only one building, the approach can be applied to multiple buildings and different types of flexible loads. As the algorithm continuously needs current temperature data of the storages to quantify their load availability, it will infringe on the privacy of the inhabitants if it is used for centrally controlling multiple buildings.

De Coninck et al. [24] analyze several control strategies for DHW production with heat pumps in a zero-energy neighborhood of 33 buildings, aiming to reduce PV curtailment. Besides some decentralized control strategies for single buildings, the authors introduce an approach which necessitates a central controller with access to the voltage and temperature of the DHW tank in each building. When the voltage exceeds a threshold value anywhere in the grid, the central controller increases the temperature set point of the DHW tank with the lowest temperature. However, such a central monitoring and control approach is not privacy friendly.

All the heuristic control strategies are compared to a conventional control approach. Only Fischer et al. [25] use an MPC approach as an upper optimal benchmark for their strategies. Salpakari et al. [26] define a cost-optimal control approach and approximate the global optimal solution using a dynamic programming algorithm. Moreover, they develop a rule-based control strategy for one building that can cope with different kinds of flexible loads as in electrical heating devices, shiftable appliances, and batteries.

As far as the authors know, no heuristic control strategy that is specially designed for modulating heating devices, combines the benefits of a central control system with the privacy friendliness of a decentralized control system. Optimizing a single building without interacting with the other buildings or with a central controller can lead to suboptimal decisions for the entire system. Therefore, we introduce a communication and control architecture that takes its decisions based on the entire system without the drawback of breaching the privacy of the inhabitants. While the introduced control strategies are only designed for modulating heating devices, the basic approach regarding communication and control can be used for other flexible loads, especially electric vehicles and batteries.

3. Optimization problems for a residential area

In this section we explain the model of a residential area by describing the heating system and the thermal storages of the buildings in Section 3.1 and the data and parameters for the case studies in Section 3.2. After that, we introduce two central optimization problems in Sections 3.3 and 3.4. The first problem aims at minimizing the heating costs for the residential area, while the second one aims to minimize surplus energy.

3.1. Heating system and thermal storages

Fig. 1 illustrates a schematic view of the heating system and the corresponding energy flows. The only heating device is a heat pump that can either heat up the UFH system or the DHW tank. A switching valve controls the hot water flow from the heat pump to either the UFH system or to the DHW tank. The water stored in the DHW tank is not directly used by the inhabitants of the building. Instead, whenever there is demand for DHW, hot water flows from the DHW tank into a fresh water station. Simultaneously, fresh cold water passes into the fresh water station and a heat exchanger transfers the heating energy to the fresh water for use by the inhabitants. Such a fresh water station allows for reducing the supply temperature of the DHW tank while ensuring a small likelihood of hygienic problems caused by Legionella bacteria [33].

For modeling the temperature of the UFH system we use a uniform temperature model with an energy difference equation that has been used frequently in similar form for modeling thermal storages (for example in [34,35,26]):

$$T_t^{UFH} = T_{t-1}^{UFH} + \frac{Q_t^{HP,SH} - Q_t^{DemandSH} - Q^{LossesSH}}{V^{UFH} \cdot \rho^{Concrete} \cdot c^{Concrete}} \tag{1}$$

The temperature T_t^{UFH} of the UFH system at time t is calculated by adding the energy difference at time t to the temperature T_{t-1}^{UFH} at time $t-1$ and dividing that by the volume of the UFH system V^{UFH}, the density of the concrete $\rho^{Concrete}$ and the heat capacity of the concrete $c^{Concrete}$. The heating energy of the heat pump for space heating $Q_t^{HP,SH}$ increases the energy level of the UFH system while both the demand for space heating $Q_t^{DemandSH}$ and the losses of the space heating $Q^{LossesSH}$ decrease it. The difference in energy for the UFH system can be positive or negative. A positive difference results in a temperature increase while a negative difference leads to reduced temperatures.

For modeling the usable volume of the DHW tank V_t^{DHWuse} at time t

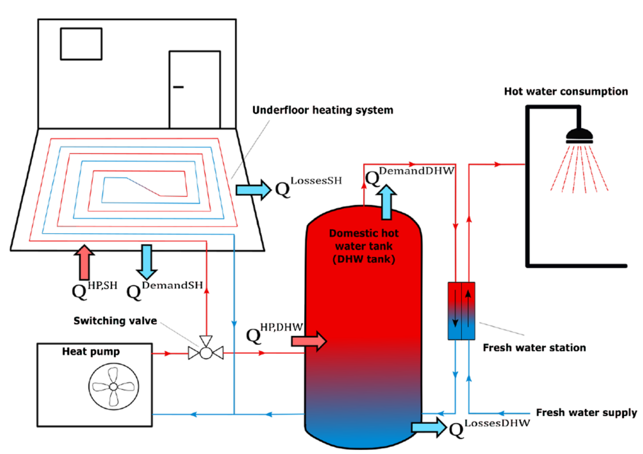

Fig. 1. Schematic view of the heating system.

Table 1
Comparison of various heuristic control strategies for electrical heating devices in work related to our approach.

	De Coninck et al. [28]	Nolting et al. [29]	Alimohammadisagvand et al. [30]	Hong et al. [27]	Schibuola et al. [31]	De Coninck et al. [24]	Fischer et al. [25]	Salpakari et al. [26]	Rodriguez et al. [32]	Our approach
Consideration of modulating heating device						✓	✓	✓		✓
Central control of multiple buildings				(✓)		✓				✓
Privacy friendly	✓	✓	✓		✓		✓	✓	✓	✓
Comparison to optimal solution							✓	(✓)		✓
Comparison to conventional control	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Other flexible loads				(✓)				✓		

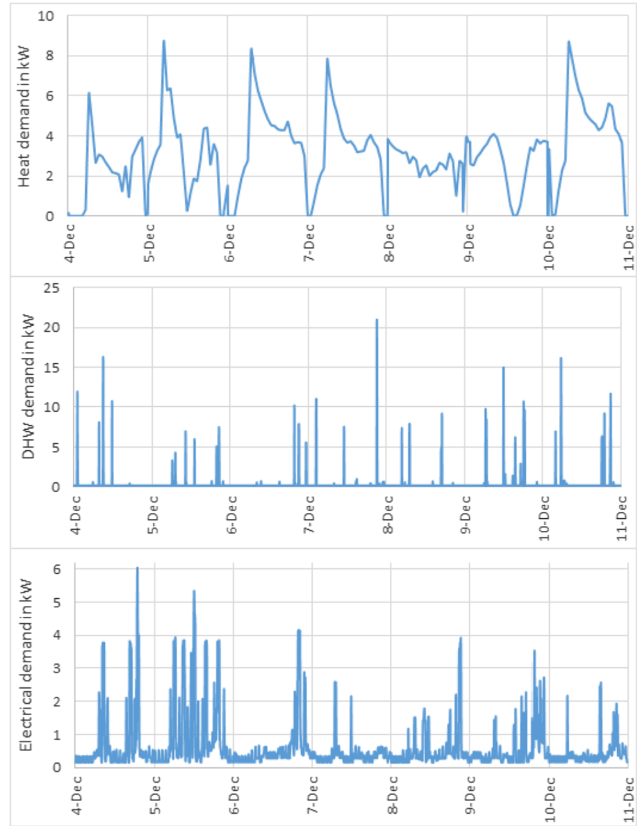

Fig. 2. Heat, DHW and electrical demand of one building with 4 inhabitants during one week.

we use the same difference equation for the energy stored, but in this case the temperature of the domestic hot water T^{DHW} is fixed and the usable volume itself is variable:

$$V_t^{DHWuse} = V_{t-1}^{DHWuse} + \frac{Q_t^{HP,DHW} - Q_t^{DemandDHW} - Q^{LossesDHW}}{T^{DHW} \cdot \rho^{Water} \cdot c^{Water}} \tag{2}$$

Analogous to the UFH system, the demand for DHW $Q_t^{DemandDHW}$ and the standing losses of the DHW tank $Q^{LossesDHW}$ decrease the usable volume of the DHW tank while the heating energy of the heat pump for DHW $Q_t^{HP,DHW}$ increases it. As water is the storage medium of the DHW tank, the difference in energy is divided by the density of water ρ^{Water}, the heat capacity of water c^{Water} and the temperature of the hot water T^{DHW}.

To calculate the heating energy of the heat pump for space heating $Q_t^{HP,SH}$ the constant maximal electrical power of the heat pump P^{HPmax} is multiplied by the time resolution Δt and the coefficient of performance COP_t (Eq. (3)). The coefficient of performance (COP) is an indicator of the heat pump's efficiency and is not constant over time since it depends on the difference ΔT_t between sink T^{Sink} and source temperature T_t^{Source} of the heat pump. In this study, we use a linear relationship between the COP and ΔT_t (see Section 3.2) which is similar to the way it was done in [36]. We choose an air source heat pump as the heating system, since air source heat pumps account for about 50% of the entire heat pumps in Europe [8]. The modulation degree of the heat pump for space heating x_t determines which fraction of the maximal heating energy is used for space heating at time t. The heating energy of the heat pump $Q_t^{HP,DHW}$ for DHW is calculated in the same way with y_t being the variable for quantifying the fraction of the maximal heating energy that is used (Eq. (4)).

$$Q_t^{HP,SH} = x_t \cdot P^{HPmax} \cdot \Delta t \cdot COP_t \tag{3}$$

$$Q_t^{HP,DHW} = y_t \cdot P^{HPmax} \cdot \Delta t \cdot COP_t \tag{4}$$

For a conventional heat pump that can merely be switched on and off, x_t and y_t would be binary variables. For our analysis we use a modulating heat pump which can vary its electrical power from 0% to 100% making x_t and y_t continuous variables with ranges between 0 and 1.

3.2. Data and parameters for the case studies

For our analysis, we model a residential area with 40 single-family houses located in Braunschweig, Germany. Of these, 30 are inhabited by four persons, whereas the remaining 10 buildings have two persons living in each. Having been built after 2001, the buildings have a high energy efficiency level. We use the same type of building for all single-family houses. Its heat related parameters are presented in Table A1 in the appendix. For the load profiles (demand for electricity, space heating, and DHW) and for the PV generation we use data that was generated by the tool *synPRO* from *Fraunhofer Institute for Solar Energy Systems* [37]. The tool combines a behavioral model, based on the Harmonised European Time of Use Survey (HETUS [38]), and a 5R1C building model for space heating, as described in DIN EN ISO 13790 [39]. The used models are explained and validated against measured data in [40]. Fig. 2 illustrates the heat, DHW and electrical (not flexible loads) demand of one building with four inhabitants during a week in December.

To determine the maximal power of the heat pumps P^{HPmax}, we scaled up the maximal heat demand of the year to an outside temperature of $-14\,^{\circ}C$ and added 100 W per person for the DHW preparation. This value was chosen to ensure that the heat pump itself can cover the whole demand for space heating and DHW without needing an additional heating element. The resulting maximal electrical power was 3000 W for each heat pump. The maximal temperature of the UFH system T^{UFHmax} is set to $22\,^{\circ}C$ and the minimal temperature T^{UFHmin} to $20\,^{\circ}C$ [41]. For the buildings with four inhabitants, we use a DHW tank volume of 200 l and for the buildings with two inhabitants, we use 150 l following the recommendations of the heat pump manufacturer *Viessmann* [42].

The source temperature for the calculation of the COP is equal to the current outside temperature. For the UFH system, we assume a supply temperature (sink temperature) of $30\,^{\circ}C$, which is 5 K lower than the temperature mentioned in [36], and we use $45\,^{\circ}C$ [43,33] for the temperature of the DHW. The parameters for calculating the COP are similar to the ones of the model *LA 28TBS* of the heat pump manufacturer *Glen Dimplex* ($\Delta T = 28$ K$\rightarrow$ $COP = 3.8$, $\Delta T = 42$ K$\rightarrow$ $COP = 2.8$) [44]. We use a common minimal modulation degree $mDeg^{min}$ of 0.1 for all heat pumps. These heat pump specific parameters calibrate Eqs. (5) and (6) that are used in our study. The higher supply temperature for DHW decreases the COP when heating up the DHW tank by 1.07 compared to the UFH system. Table A2 in the appendix contains all relevant parameters of the heating system we used.

$$COP_t(\Delta T_t) = max\left\{5.8 - \frac{1}{14}\cdot\Delta T_t,\ 0\right\} \tag{5}$$

$$\Delta T_t = T^{Sink} - T_t^{Source} \tag{6}$$

3.3. Cost minimization problem

In the first central optimization model a central controller intends to minimize the heating costs for a residential area. The buildings b are all equipped with the heating system explained in Section 3.1. The central controller determines when to heat up which thermal storage by solving the following optimization problem:

$$min\ \ C = \sum_{t=1}^{Z}\sum_{b=1}^{B}((x_{t,b} + y_{t,b})\cdot P_b^{HPmax})\cdot\Delta t\cdot p_t \tag{7}$$

subject to:

$$T_b^{UFHmin} \leqslant T_{t,b}^{UFH} \leqslant T_b^{UFHmax} \quad \forall\ \ t,\ b \tag{8}$$

$$V_b^{DHWmin} \leqslant V_{t,b}^{DHWuse} \leqslant V_b^{DHWmax} \quad \forall\ \ t,\ b \tag{9}$$

$$x_{t,b} + y_{t,b} \geqslant mDeg^{min} \quad \forall\ \ t,\ b \tag{10}$$

$$x_{t,b} \leqslant h_{t,b}^{Aux} \quad \forall\ \ t,\ b \tag{11}$$

$$y_{t,b} \leqslant 1 - h_{t,b}^{Aux} \quad \forall\ \ t,\ b \tag{12}$$

$$x_{t,b} \in [0,\ 1],\ \ y_{t,b} \in [0,\ 1],\ \ h_{t,b}^{Aux} \in \{0,\ 1\} \quad \forall\ \ t,\ b \tag{13}$$

To determine the total cost (Eq. (7)) of heating C, the electrical power of the heat pump, which is obtained by multiplying the modulation degree of the heat pump with its maximal power, is summed up for all buildings b and all time slots t. The overall power for each time slot is multiplied by the time resolution and the time dependent price for electricity p_t. Constraints (8) ensure that the temperature of the UFH system is always between a lower limit T_b^{UFHmin} and an upper limit T_b^{UFHmax} while constraints (9) force the usable volume of the DHW tank always to be greater than (or equal to) a minimal value V_b^{DHWmin} and smaller than (or equal to) a maximal value V_b^{DHWmax} for all buildings. These constraints are vital for guaranteeing the inhabitant's maximal comfort and to ensure that certain technical limitations are not violated. To avoid the heat pump being switched on and off too frequently constraints (10) force the heat pump never to switch off completely. Instead, it goes into a "standby-mode" with a minimal modulation degree of $mDeg^{min}$. This constraint can be eliminated or adjusted as it is not vital in the model. Since excluding this constraint leads to frequent stops and starts of the heat pump, we inserted it to avoid additional stress on the compressors. Constraints (11) and (12) introduce the binary variable $h_{t,b}^{Aux}$ which makes sure that only one storage can be heated up in every time slot. Having both continuous and binary variables makes this model a Mixed-Integer Linear Programming (MILP) problem.

3.4. Surplus energy minimization problem

For the second central optimization problem, the residential area's buildings additionally have PV systems on their roofs. The controller's objective is to schedule the heating activities of the buildings in a way that will minimize the overall surplus energy SE for the residential area. To reduce the surplus energy the surplus power $P_t^{Surplus}$ has to be minimized. But if the surplus power is negative due to higher electricity demand than generation by the PV systems, a value of 0 should be assigned to the surplus power $P_t^{Surplus}$. This prevents the central controller from minimizing negative surplus power by scheduling the heat pumps' heating activities into time periods with no or low PV generation. The corresponding optimization problem to be solved is:

$$min\ \ SE = \sum_{t=1}^{Z} P_t^{Surplus+}\cdot\Delta t \tag{14}$$

subject to:

$$P_t^{PVtotal} = \sum_{b=1}^{B} P_{t,b}^{PV} \quad \forall\ \ t \tag{15}$$

$$P_t^{total} = \sum_{b=1}^{B}((x_{t,b} + y_{t,b})\cdot P_b^{HPmax} + P_{t,b}^{Demand}) \quad \forall\ \ t \tag{16}$$

$$P_t^{Surplus} = P_t^{PVtotal} - P_t^{total} \quad \forall\ \ t \tag{17}$$

$$P_t^{Surplus} = P_t^{Surplus+} - P_t^{Surplus-} \quad \forall\ \ t \tag{18}$$

$$P_t^{Surplus+} \leqslant M_t^{+}\cdot h_t^{positive} \quad \forall\ \ t \tag{19}$$

$$P_t^{Surplus-} \leqslant M_t^{-}\cdot(1 - h_t^{positive}) \quad \forall\ \ t \tag{20}$$

$$h_t^{positive} \in \{0,\ 1\},\ \ P_t^{Surplus+} \geqslant 0,\ \ P_t^{Surplus-} \geqslant 0 \quad \forall\ \ t \tag{21}$$

and the constraints 8–13 *of the previous model* 3.3

The total PV generation of all buildings $P_t^{PVtotal}$ at time t is defined in Eq. (15) as the sum of the PV generation of each building $P_{t,b}^{PV}$. Similarly, the total demand for every time slot P_t^{total} comprises the conventional electrical demand of each household $P_{t,b}^{Demand}$ and the electrical power of the heat pump (Eq. (16)). The conventional electrical demand sums up the power for all electrical appliances in a building excepting the power for the heat pump. We assume that these electrical loads are inflexible and thus cannot be controlled. However, as this demand influences the operative schedule of the heat pump, it has to be incorporated in the objective function. The surplus power $P_t^{Surplus}$ is defined in Eq. (17). It is calculated by subtracting the total electrical demand from the total PV generation. In order to assign the value 0 to the objective function if we have negative surplus power, the variable surplus power is subdivided in Eq. (18) into a positive part $P_t^{Surplus+}$ and a negative part $P_t^{Surplus-}$. Only the positive part is considered in the objective function.

We use the big-M approach to model the problem as a disjunctive MILP program, similar to how it is done in [45,46]. Eqs. (19) and (20) are the big-M constraints which use the two big-M parameters M_t^+ and M_t^- and an additional binary auxiliary variable $h_t^{positive}$. If $h_t^{positive}$ has the value 0, the positive surplus power $P_t^{Surplus+}$ will also take the value 0 because it is a positive variable. However, if $h_t^{positive}$ is 1 and if the big-M parameter M_t^+ is sufficiently large, the positive surplus power $P_t^{Surplus+}$ can take every positive value smaller than the big-M parameter M_t^+. The same is valid for the negative part of the surplus power $P_t^{Surplus-}$ with opposite values of $h_t^{positive}$. This modeling approach solves the initially mentioned problem of assigning a value of 0 to the surplus power in the objective function if the total demand exceeds the generated electricity. Further, we also include the constraints (8)–(13) from the *cost minimization problem* of Section 3.3 in this problem.

4. Heuristic control strategies

In this section we introduce heuristic control strategies for approximately solving the optimization problems of Section 3. In contrast to algorithms for exactly solving the corresponding optimization problems, these heuristics have low computational complexities and do not require perfect information about future input data. The heuristics use a special communication and control architecture with a central and several internal controllers being available. A building's internal controller has the function of implementing the control actions of the central controller. We describe the communication architecture and outline the basic principles of the internal controller in Section 4.1. Section 4.2 describes a heuristic for the cost minimization problem, and Section 4.3 a heuristic for the surplus energy minimization problem.

4.1. Communication and control architecture

Fig. 3 shows the local grid and the information flows of an illustrative residential area which consists of only six buildings in this case (our case studies use 40 buildings). All buildings are equipped with the heating system described in Section 3.1 and have a PV system on their roofs. The net meter measures the residual load of the residential area, and the local grid is connected to a transformer. The dashed green[1] lines show the unidirectional information flows. Each building has an internal controller (IC) that receives information from the central controller, but does not send anything back to it. The net meter sends information about the current residual load to the central controller.

The internal controllers of the buildings are a fundamental part of the proposed control system. Opposed to the central optimization problems of Sections 3.3 and 3.4, the central controller is not directly controlling the heat pumps but merely sends modulation advice to the buildings. The internal controller has to decide whether the advised modulation degree is applicable or not, and which storage (UFH system or DHW tank) to heat up. Eq. (22) calculates the state of charge (SOC) of the UFH system and Eq. (23) the one of the DHW tank $SOC_{t,b}^{DHW}$:

$$SOC_{t,b}^{UFH} = \frac{T_{t,b}^{UFH} - T_b^{UFHmin}}{T_b^{UFHmax} - T_b^{UFHmin}} \tag{22}$$

$$SOC_{t,b}^{DHW} = \frac{V_{t,b}^{DHWuse} - V_b^{DHWmin}}{V_b^{DHWmax} - V_b^{DHWmin}} \tag{23}$$

To calculate the SOC, the minimal temperature (or volume) is subtracted from the current temperature (or volume). This difference is then divided by the difference between the corresponding maximal and minimal values. If the SOC of both storages is higher than a certain threshold (we use 95%), the internal controller will use the minimal modulation degree for the storage with the lower SOC. Likewise, if the SOC of only one storage is under a certain threshold (we use 10% for the UFH system and 25% for the DHW tank) the internal controller heats up the storage by using the full power of the heat pump. Otherwise, if none of the storages has reached its upper or lower threshold, the internal controller heats up the storage, which was heated up during the last time slot, with the modulation degree $mDeg_t$ advised by the central controller. After one storage reaches its upper limit, the internal controller switches to the other storage. By doing so, frequent switching between the two storages is minimized while ensuring that no technical violations occur. Table 2 shows the rules of the internal controller for the just described normal operation. The rules are listed in descending priority, meaning that the internal controller starts to check the condition of the first rule. If the condition is fulfilled the corresponding action will be implemented. Otherwise the internal controller checks the condition of the next rule.

Rules 1–5 ensure the avoidance of constraint violations. For both storages threshold values are used that incorporate a safety buffer to the temperature and volume limits. For the upper threshold values, we choose 95% for both storages. Since a minimal modulation degree is considered, heating up a storage until its limit (100% SOC) can cause a constraint violation if the SOC of the other storage is also near 100%. Switching to heat up the other storage if a 95% SOC is reached, does not guarantee removal of a violation risk, but it makes it less likely. In our studies the upper limit was never violated with a minimal modulation degree of 10% for the heat pump. If a minimal modulation degree of 0% is used (meaning that the heat pump can be switched off) there is no need for a safety buffer to the upper limits. The use of a safety buffer to the lower limits assure that no constraint violation will occur in times of high demand for both DHW and space heating. For the UFH system 10% and for the DHW tank 25% were sufficient in our studies. However, if there is demand for DHW and $SOC_{t,b}^{DHW}$ is smaller than 40%, the DHW tank should be heated up with full power. A reduction of these safety buffers resulted in constrain violations in our study. This is why we choose these values. The thresholds should be adjusted if another heating system is used as they depend on the technical parameters of the heating system. Nonetheless, we think that the chosen values can be used as a rough estimate for other heating systems. Further, it should be noted that small violations of the limits potentially bring about reduced comfort, but do not result in technical problems.

Our control approach, with both central and internal controllers, combines the benefits of a central and a decentralized control architecture. On the one hand, the control advice is calculated centrally by considering the whole residential area; on the other hand, decentralized

[1] For interpretation of color in Fig. 1, the reader is referred to the web version of this article.

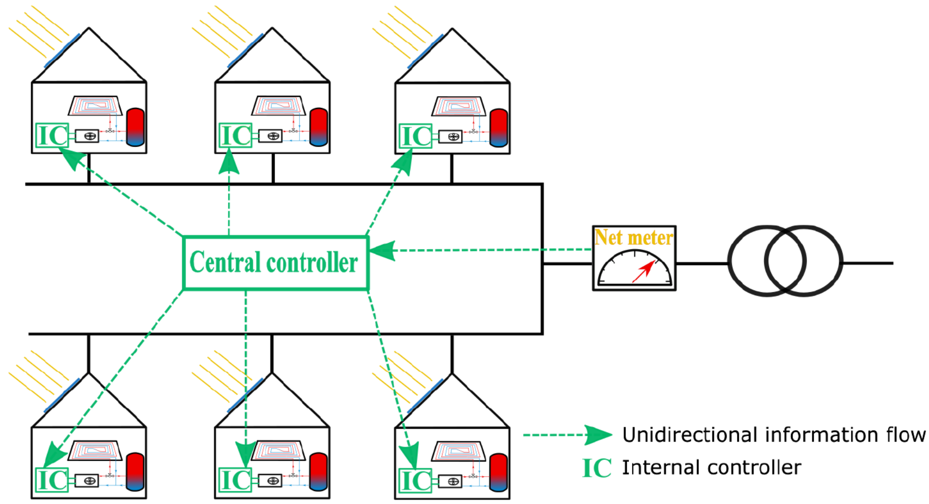

Fig. 3. Local grid and information flows of the residential area.

internal controllers assure control of the flexible devices. The central controller neither directly controls the load, nor measures private data of the households (e.g. electrical load, temperature of the storages). Consequently, our control approach in using the described control and communication architecture, will not be in conflict with the inhabitants' privacy.

4.2. Heuristic for cost minimization

The *Past Value Heuristic* aims at setting the modulation degrees of the heat pumps at every time slot t such that the total heating costs are as low as possible. In this case the buildings do not have a PV system on their roofs, and there is no need for a net meter. Fig. 4 depicts the flowchart of the cost minimization heuristic. To initialize, we have to define updating time slots t_i^{Update}. The intervals between these time slots ($d^{Update} = t_{i+1}^{Update} - t_i^{Update}$) can be for instance one day, half a day or only a few hours. At each updating time slot ($t = =t_i^{Update}$) the central controller calculates the empirical distribution function $F_l(p)$ of the last l price values.

Fig. 5 illustrates this step. Both the number of past price values and the interval between the updating time slots are adaptable parameters of the introduced heuristic. In the shown case the number of past price values l is equal to the interval between the updating time slots. This does not necessarily have to be the case, as l can be larger or smaller. After having updated the empirical distribution function, the central controller increments i such that the next time slot for updating is changed.

Within two updating time slots ($t \neq t_i^{Update}$) the value of the empirical distribution function $F_l(p_t)$ is calculated for the current price p_t at time t. Next, the central controller sets the advised modulation degree to $mDeg_t = 1 - F_l(p_t)$ and broadcasts this to the internal controllers of the buildings. The advised modulation degree will be high if the price is relatively low, and it will be low if the price is relatively high. The internal controllers now try to either heat the UFH system with the advised modulation degree ($x_t = mDeg_t$) or the DHW tank ($y_t = mDeg_t$). Since a violation of the volume or temperature constraint is possible, the internal controller will not directly heat up the storages with $mDeg_t$. An internal control approach determines whether heating up (or cooling down) according to the advised modulation is possible or

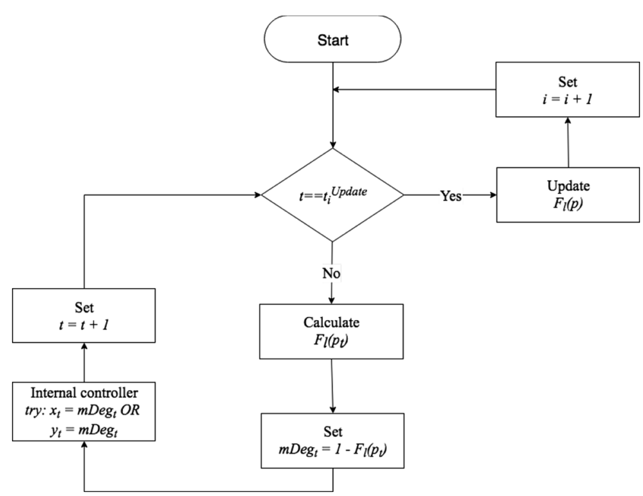

Fig. 4. Flowchart of the cost minimization heuristic.

Table 2
Internal controller rules (normal operation) in descending priority.

No.	Condition	Action
1	IF demand for DHW AND $SOC_t^{DHW} < 40\%$	Heat up DHW tank with full modulation ($y_t = 1$)
2	IF $SOC_t^{UFH} \geqslant 95\%$ AND $SOC_t^{DHW} \geqslant 95\%$ AND $SOC_t^{UFH} \geqslant SOC_t^{DHW}$	Heat up DHW tank with minimal modulation ($y_t = mDeg^{min}$)
3	IF $SOC_t^{UFH} \geqslant 95\%$ AND $SOC_t^{DHW} \geqslant 95\%$ AND $SOC_t^{UFH} < SOC_t^{DHW}$	Heat up UFH with minimal modulation ($x_t = mDeg^{min}$)
4	IF $SOC_t^{DHW} < 25\%$	Heat up DHW tank with full modulation ($y_t = 1$)
5	IF $SOC_t^{UFH} < 10\%$	Heat up UFH with full modulation ($x_t = 1$)
6	IF DHW tank heated up in *t-1* AND $SOC_t^{DHW} < 95\%$	Heat up DHW tank with advised modulation ($y_t = mDeg_t$)
7	IF DHW tank heated up in *t-1* AND $SOC_t^{DHW} \geqslant 95\%$	Heat up UFH with advised modulation ($x_t = mDeg_t$)
8	IF UFH heated up in *t-1* AND $SOC_t^{UFH} < 95\%$	Heat up UFH with advised modulation ($x_t = mDeg_t$)
9	IF UFH heated up in *t-1* AND $SOC_t^{UFH} \geqslant 95\%$	Heat up DHW tank with advised modulation ($y_t = mDeg_t$)

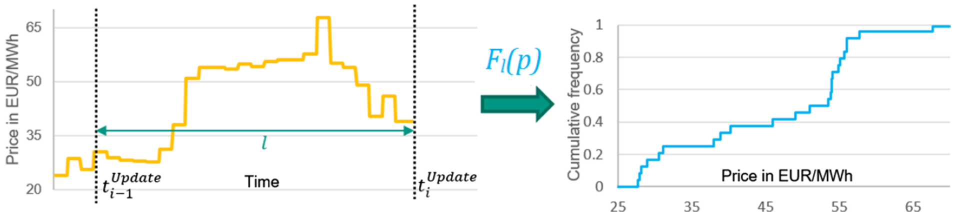

Fig. 5. Calculation of the empirical distribution function $F_l(p)$ at updating time slot t_i^{Update}.

not (see Table 2). Due to the use of past values for updating the empirical distribution function we call this approach *Past Value Heuristic*. If information about future electricity prices are available, the upcoming l values can be used for calculating $F_l(p)$. The *Future Value Heuristic* is equivalent to the *Past Value Heuristic* with the only difference that is uses future values for updating the empirical distribution function. Both heuristics have two parameters: the number of past (or future) price values l and the interval between two updating time slots d^{Update}. As these heuristics are control strategies, there does not necessarily have to be an end. When these strategies are used for solving the optimization problem defined in Section 3.3, the control ends whenever the current time t is equal to the number of time slots Z.

4.3. Heuristic for surplus energy minimization

The objective of the *Incremental Control Heuristic* is to shift the operation of the heat pumps to times with high PV generation and thus to minimize the surplus energy in the residential area. Fig. 6 shows the flowchart of the *Incremental Control Heuristic*. At the beginning of each iteration, the net meter measures the current residual load $P_t^{ResReal}$ and sends this information to the central controller. If the current residual load is higher than 0, meaning that the demand of the residential area exceeds the supply, the central controller instructs each internal controller to implement its *Keep-SOC-Strategy* for this time slot. The goal of this strategy is to have the SOC of the two storages (UFH system and DHW tank) at certain levels. Afterwards the time slot is incremented and the next iteration starts. If the supply is higher than the demand, the measured residual load $P_t^{ResReal}$ will be negative. The advised modulation degree $mDeg_t$ is then initially set to the minimum $mDeg^{min}$. Next, the central controller calculates a help value, which we call auxiliary residual load, P_t^{ResAux} with the following equations:

$$P_t^{ResAux} = P_t^{ResReal} - P_{t-1}^{LoadHP} + \sum_{b=1}^{B} P_b^{HPmax} \cdot mDeg_t \tag{24}$$

$$P_{t-1}^{LoadHP} = \sum_{b=1}^{B} P_b^{HPmax} \cdot mDeg_{t-1} \tag{25}$$

Eq. (25) determines the electrical load of all heat pumps from the previous time slot $t-1$ if all used the advised modulation degree $mDeg_{t-1}$ from the previous time slot. The central controller subtracts this load from the measured residual load $P_t^{ResReal}$ and adds the new hypothetical load of the heat pumps for this time slot to it (Eq. (24)). The new hypothetical load depends on the advised modulation degree $mDeg_t$. If the auxiliary residual load is negative and the advised modulation degree has not reached the maximum value of 1, the central controller increments the modulation degree by 0.01 (1%). Following this, the new auxiliary residual load is recalculated. This loop stops either if the auxiliary residual load is negative, or if $mDeg_t$ has reached its maximum value. The central controller now sends the value of the advised modulation degree to all internal controllers which try to use this value for heating up the UFH system or the DHW tank (see Table 2). At the end of the iteration, the time slot t is increased by one and the whole procedure starts from the beginning. Analogous to the cost minimization heuristics in Section 4.2, an end is not essential, as this is a real time control approach. However, considering the corresponding optimization problem of Section 3.4, the control heuristic will end if t is equal to the number of time slots Z.

This control approach does not need to monitor the individual buildings. Only the constant maximal electrical power of the heat pumps P_b^{HPmax} has to be known by the central controller. If the heat pumps have different minimal modulation degrees, the approach has to be slightly modified. In such a case, the central controller will not send one common advised modulation degree $mDeg_t$ to the internal controllers. Instead, it will calculate a specific advised modulation degree for each heat pump, which has to be considered in Eqs. (24) and (25).

When applying the *Incremental Control Heuristic*, the central controller can instruct the internal controllers to use their *Keep-SOC-Strategy*. The aim of this strategy is to keep the SOC of the storages at a certain level by dynamically adjusting the modulation degrees. The internal controller uses the necessary modulation degree x_t^* (Eqs. (26) and (27)) to maintain the UFH system's at a certain predefined target level (we use 25%). Simultaneously, the internal controller checks at every time slot whether the SOC of the DHW tank $SOC_{t,b}^{DHW}$ is under a predefined value (we use 25%). If it is below that value, the heat pump starts heating up the DHW tank with maximal power until it has reached an upper threshold for this strategy (we use 35%). Afterwards, the UFH system is heated up until having reached its target level. Subsequently, the internal controller proceeds to maintain the UFH system's SOC at this target level while checking the SOC of the DHW tank.

$$x_t^* = max\left\{mDeg^{min}, \frac{\Delta E_t^{UFHsoc} + Q_t^{DemandSH} + Q^{LossesSH}}{P^{HPmax} \cdot COP_t \cdot \Delta t}\right\} \tag{26}$$

$$\Delta E_t^{UFHsoc} = (T^{Target} - T_t^{UFH}) \cdot V^{UFH} \cdot \rho^{Concrete} \cdot c^{Concrete} \tag{27}$$

Table 3 summarizes the rules of the internal controller when using their *Keep-SOC-Strategy*. Rules 1–5 are equal to the ones of the normal operation. We obtained these thresholds by trying out different values in many runs of a simulation, eventually using the values that, on

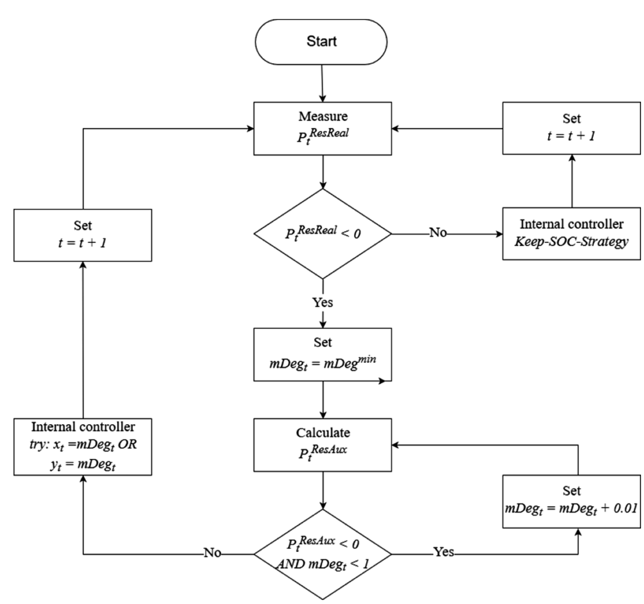

Fig. 6. Flowchart of the heuristic for surplus energy minimization.

Table 3
Internal controller rules (Keep-SOC-Strategy) in descending priority.

No.	Condition	Action
1	IF demand for DHW AND $SOC_t^{DHW} < 40\%$	Heat up DHW tank with full modulation ($y_t = 1$)
2	IF $SOC_t^{UFH} \geqslant 95\%$ AND $SOC_t^{DHW} \geqslant 95\%$ AND $SOC_t^{UFH} \geqslant SOC_t^{DHW}$	Heat up DHW tank with minimal modulation ($y_t = mDeg^{min}$)
3	IF $SOC_t^{UFH} \geqslant 95\%$ AND $SOC_t^{DHW} \geqslant 95\%$ AND $SOC_t^{UFH} < SOC_t^{DHW}$	Heat up UFH with minimal modulation ($x_t = mDeg^{min}$)
4	IF $SOC_t^{DHW} < 25\%$	Heat up DHW tank with full modulation ($y_t = 1$)
5	IF $SOC_t^{UFH} < 10\%$	Heat up UFH with full modulation ($x_t = 1$)
6	IF UFH heated up in *t-1* AND $SOC_t^{DHW} \geqslant 25\%$	Heat up UFH with necessary modulation for keeping SOC_t^{UFH} ($x_t = min\{1, x_t^*\}$)
7	IF DHW tank heated up in *t-1* AND $SOC_t^{DHW} < 35\%$	Heat up DHW tank with full modulation ($y_t = 1$)
8	IF DHW tank heated up in *t-1* AND $SOC_t^{DHW} \geqslant 35\%$	Heat up UFH with necessary modulation for keeping SOC_t^{UFH} ($x_t = min\{1, x_t^*\}$)

average, yielded the best results. The thresholds depend on the goal of the used control strategies and on the heating system. These values can also serve as rough estimates for other heating systems if the goal is to minimize surplus energy in a residential area.

5. Results

For our study, we chose 12 weeks of the year 2017 by randomly picking two weeks for each month of the heating period (October – March). We used a rolling-horizon-approach for the optimization with a time horizon of one day and consequently seven iterations (one for each day of the week). The time resolution Δt was five minutes. Most of the studies in the reviewed literature used a lower time resolution. Salom et al. [47] strongly recommend a time resolution of between one to five minutes to analyze the interaction between the grid and individual buildings. In [48] it is shown that using a 1-h resolution can lead to errors of up to 60% compared to a 1-min resolution if the objective is to match the electrical demand of a building with its PV production. As the basic aim of our control approaches is to react to the volatile supply of renewable energy sources, and thus to balance the grid, we choose a time resolution of five minutes. The optimization problem was modeled with the modeling language *GAMS* and we used *Cplex 12.8* as the solver. The heuristics and the simulations were implemented in *Java*. All computations were carried out on an *Intel Core i5-6200U* system with 2.3 GHz, 2 cores, and 8 GB RAM. We discuss the results of the optimization and the heuristic control strategies in Sections 5.1 and 5.2. This chapter ends with a critical appraisal in Section 5.3.

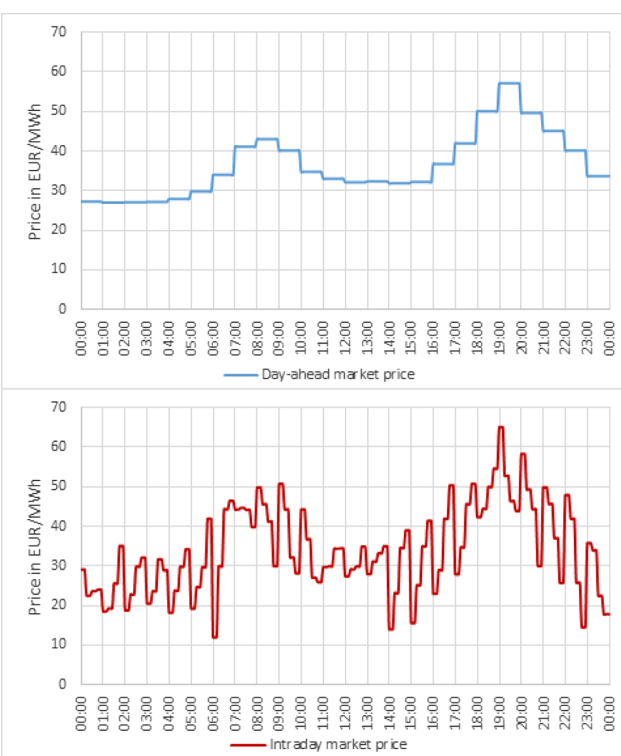

Fig. 7. Prices of the day-ahead market and the intraday market for March 13th, 2017.

5.1. Cost minimization

We both solved an optimization problem and ran simulations for applying the *Past Value Heuristic*, the *Future Value Heuristic*, and a conventional control approach. For the *Past Value Heuristic*, we used half a day (770 min) for both the interval between updating time slots d^{Update} and the number of past values l for calculating the empirical distribution function. We chose these values after having tried out different parameter combinations. Regarding the *Future Value Heuristic*, an updating frequency of 40-min intervals with 440 min of future values, yielded good results. Data from the day-ahead market and the intraday market (average price of the auctions) of the *European Energy Exchange* were used as the time dependent price for electricity p_t. Fig. 7 illustratively shows these prices for March 13th, 2017.

Fig. 8 shows the heating costs for the different control approaches when we used price data from the day-ahead market. The *Past Value Heuristic* led to reduced costs compared to the conventional control approach in every week. The *Future Value Heuristic* outperformed the *Past Value Heuristic* in 10 weeks, whereas surprisingly, in weeks 41 and 46 the application of the *Past Value Heuristic* led to reduced costs. As expected, the central optimization approach yields the best results across all weeks. Generally, the differences between the methods are rather small. The main reason for that is the relatively small variability of the day-ahead markets prices. The prices have a time resolution of one hour which is significantly smaller than the 5-min time resolution of all the control approaches. We maintained the time resolution of five minutes although the price signals have a lower time resolution, as this leads to increased decision options for the controller for exploiting the flexibility of the heating devices. Moreover, the COP of the heat pumps depends on the outside temperature and slightly changes every five minutes. This results in changing costs for generating a certain amount of heat even if the price for electricity is constant.

The used average prices of the intraday market auctions have a time resolution of 15 min. The results for the intraday market prices are displayed in Fig. 9. The diagram looks similar to the one of the day-ahead market prices. In this case, the *Future Value Heuristic* always yields better results than the *Past Value Heuristic*. As the price fluctuations are higher due to the increased time resolution, the difference between the conventional control and the other control approaches are higher. Fig. 10 illustrates the average percentage improvements of the different approaches compared to the conventional control for the 12 weeks. When we used day-ahead market prices, the average improvement of the *Past Value Heuristic* for the 12 weeks was 4.1% and for the *Future Value Heuristic* 7.5%. The increased volatility of the intraday market prices almost doubles the improvements of the two heuristic

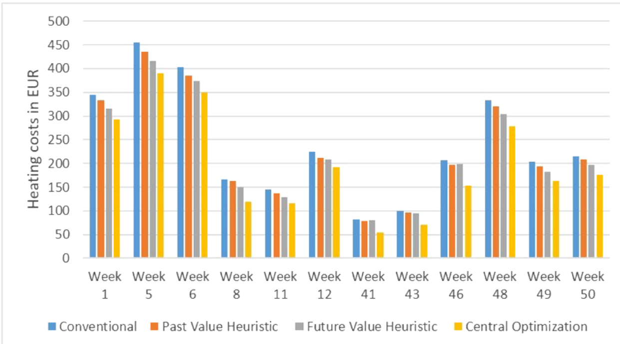

Fig. 8. Heating costs for the different approaches when using day-ahead market prices.

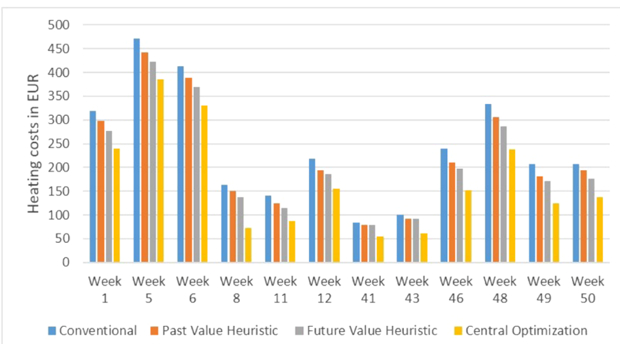

Fig. 9. Heating costs for the different approaches when using intraday market prices.

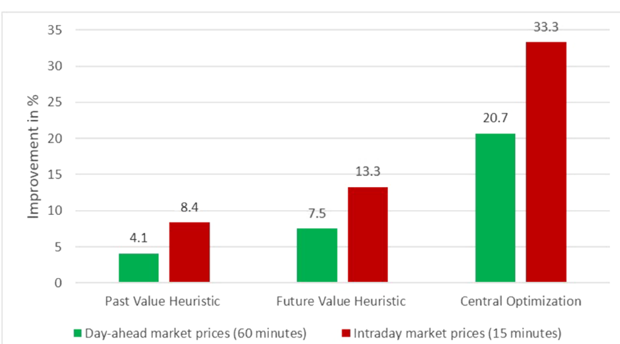

Fig. 10. Average improvement of the different approaches for cost minimization compared to using the conventional control.

control strategies. The central optimization leads to improvements of 20.7% for the day-ahead price scenarios and 33.3% for intraday market prices.

The results show that using flexible electrical loads for decreasing the heating costs is beneficial if the price fluctuations are high enough. Wide differences between the maximal and minimal prices and a high temporal resolution of the price signal leads to increased saving potential when heuristic control strategies and central optimization are applied. Considering a big utility company which has to buy energy for all its customers, heat costs saving in the range of 4–13% can be a significant amount. Figs. A1 and A2 in the appendix show how often the advised modulation degree could be used when applying the different heuristics. On average the internal controllers were able to use the advised modulation 60% of the time if the central controller used the *Past Value Heuristic*. For the *Future Value Heuristic* this figure is 64%. We also ran all scenarios without considering a minimal modulation degree to quantify its impact on the results. Fig. A4 in the appendix depicts the average alterations of the results. The changes for the central optimization are 2.5% if day-ahead market prices are used and 5.8% for intraday market prices. These numbers are much smaller for both heuristics ranging from 0.1% to 1%.

Another advantage of the proposed heuristic control strategies is the enormously reduced computational effort. For each iteration of the rolling-horizon-optimization, 57,600 variables were necessary, among which 11,520 were binary variables. The optimization needed on average 2:17 min for the scenarios with day-ahead market prices and 3:47 min for the intraday market scenarios when an MIP gap of 0.5% was chosen. The computational time for the heuristic control strategies and the conventional control was merely three seconds, even including the simulations.

5.2. Surplus energy minimization

We used the same weeks as in the cost minimization problem for analyzing the effects of the *Incremental Control Heuristic* on the surplus energy minimization. We defined two scenarios. In the first scenario, all the buildings had a PV system with 10 kW peak power, whereas in the second scenario the peak power was 7 kW. Fig. 11 shows the surplus energy of the residential area for the 10 kW scenarios. Besides in week 12, the results reveal significantly reduced surplus energy in almost every week compared to the conventional control approach when we used the *Incremental Control Heuristic*. The PV production in week 12 is much higher than that of the other weeks we investigated. In this week the total electricity demand of the buildings was not sufficient to match the PV production, resulting in only moderate improvements. In week 8, using both the *Incremental Control Heuristic* and the central optimization led to no surplus energy.

The results for the 7 kW scenarios are shown in Fig. 12. The improvements we found in using the *Incremental Control Heuristic* were even higher than those in the 10 kW scenarios. Analogous to the previous scenarios, the improvements were lower in week 12. As expected, the surplus energy is lower when the PV systems have reduced peak powers. Fig. 13 illustrates the average improvements of the *Incremental Control Heuristic* and the central optimization compared to the conventional control. When the buildings are equipped with a 10 kW PV system, the improvement of the heuristic control strategy is more than 38%. Reducing the peak power to 7 kW increases the improvement to 52.6%. Applying the central optimization leads to 14.3% higher improvements for the 7 kW scenarios and to 12.6% for the 10 kW scenarios. The usage of the advised modulation degrees for the *Incremental Control Heuristic* is shown in Fig. A3 in the appendix. The internal controller were on average able to use the advised modulation in about 72% of the time. The values range from 53% in week 12–89% in week 8. The result alteration when not considering a minimal modulation degree are on average between 0.5% and 3% (see Fig. A5 in the appendix).

Besides requiring perfect information about the future for the

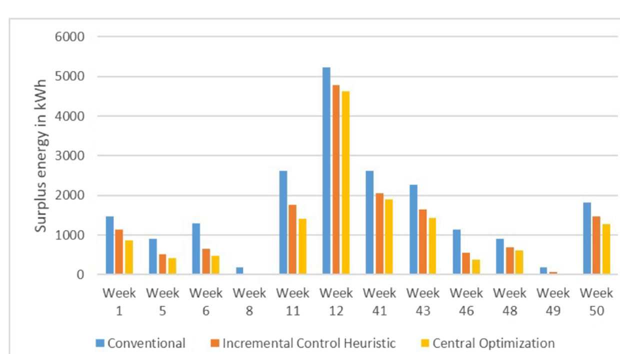

Fig. 11. Surplus energy of the residential area with PV peak power of 10 kW.

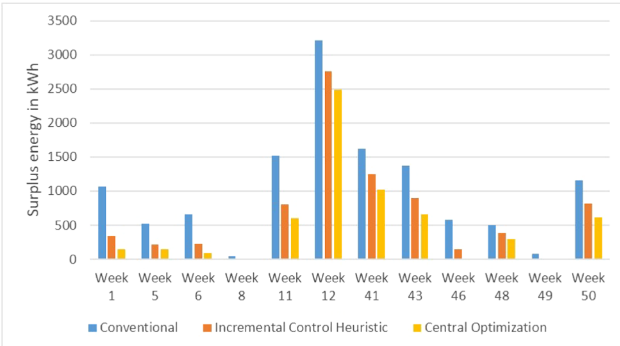

Fig. 12. Surplus energy of the residential area with PV peak power of 7 kW.

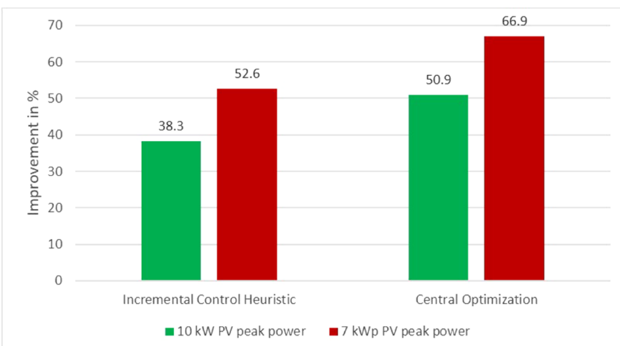

Fig. 13. Average improvement of the different approaches for surplus energy minimization compared to using the conventional control.

central optimization, the computational effort is much higher compared to the heuristic control strategy. As for the cost minimization problems, we used a rolling-horizon-approach for the central optimization (one day time horizon and seven iterations). This required 103,680 variables (23,040 binary variables) for each iteration. The average computational time for the 10 kW scenarios was 02:19 min with an MIP gap of 0.5%. The reduced power of the PV system increased the computational times to 09:03 min. Both the conventional control and the *Incremental Control Heuristic* needed, on average, three seconds for the control and the simulations.

5.3. Critical appraisal

For our study we simplified some features to reduce the model complexity and to deal with data availability problems. One reason why the prospects for modulating heat pumps are bright is their increased part-load efficiency compared to conventional heat pumps [12]. However, considering the dependency of the COP on the modulation degree, makes the model nonlinear with heavily increased computational times. Because of this, the COP in our study does not depend on the power output of the heat pump, as it does in [49]. We used a constant supply temperature for the heating system. In reality, the supply temperature is affected by the heat output of the heating device (and consequently by the outside temperature). This would, similarly, lead to non-linearities [35].

Another assumption is the possibility of an exact and immediate energy transfer from the UFH system to the rooms of the building. The externally given demand for space heating $Q_t^{DemandSH}$ quantifies the heating energy that is necessary to have a room temperature of 21 °C. In our model, the exact amount of heat energy is immediately taken from the UFH system. Modeling a realistic heat transfer would require a detailed thermal model of the building and the DHW tank which was not in the scope of this study. Incorporating such a model in an optimization problem would drastically increase the computational effort making a study like ours computationally fairly challenging. Further, such a model would be based on many assumptions regarding several heat transfer coefficients, the geometry of the building, the geometry of the UFH system, and its pipe system. A minor simplification is the assumption of constant losses of the DHW tank and the UFH system. These losses basically depend on the temperature difference between the inside and the outside of the storages. Compared to the much higher heat demands for space heating and DHW, the temperature dependency of such losses is negligible.

We did not consider uncertainties for the central optimization approaches. As in reality we cannot assume that perfect information about future demand and supply is obtainable, the results of the central optimization are upper bounds for the realizable improvements. Incorporating uncertainties will affect the results and will require adjusted optimization approaches that are capable of dealing with uncertainties.

Even having used several simplifications, we are convinced that the proposed control strategies and architecture are useful for effectively using modulating electrical heating devices for demand response. The control strategies themselves are independent of the thermal model of the building. Because of this, we assume more complex models for the simulations will deliver similar results. Regarding the cost minimization heuristics, we expect even better results, due to the increased part-load efficiency of the heat pumps.

6. Summary and conclusion

We developed heuristic control strategies for two optimization problems for demand response with modulating heat pumps. The goal of the first problem was to minimize the heating costs whereas the second problem aimed at minimizing surplus energy from PV within a residential area. For comparing the results from the heuristics with a central optimization approach, we modeled a simplified thermal system of 40 buildings based on empirical heat demand patterns. The flexibilities come from an UFH system and a DHW tank. The developed heuristic control strategies use a control and communication architecture that preserves the privacy of the inhabitants. The communication architecture is based on a central controller that sends control advice to the internal controllers of the buildings which then decide about the execution of control actions.

For the cost minimization problem, we defined two price scenarios. The results show that in all weeks the application of the control heuristic led to reduced heating costs compared to a conventional control strategy. The average improvements were between 4.1% and 13.3% and depend strongly on the price spread on the electricity markets. The central optimization approach could improve this value by another 20%. In the second problem on surplus energy minimization, the heuristic control strategies performed surprisingly well. For PV systems with 10 (7) kW peak power the reduction of surplus energy was 38.3% (52.6%). The central optimization approach led to another 13% improvement while having strongly increased computational times and requiring perfect information about the future.

Our study demonstrates the suitability of a privacy preserving communication and control architecture in combination with heuristic control strategies for demand response in residential areas. As the decisions of each building depend on the situation of the whole grid, the proposed approach is capable of balancing demand and volatile supply without the need to install powerful computational devices or to breach the privacy of the inhabitants. The difference to a conventional control strategy is remarkable. Further, the implementation effort is relatively small which makes the heuristic control strategies applicable for real devices. The developed control approach can be modified for aggregators, virtual power plant operators, or the provision of ancillary services. Especially sustainable energy systems with high shares of renewable energies can benefit from incorporating basic principles of our approach.

Future work could analyze larger residential areas and the interaction between different areas in a region. While the heuristic control strategies in this study are only applicable to modulating heating devices, strategies for other flexible non-modulating heating devices (e.g.non-modulating heat pumps, electric storage heaters, and electric heating elements) can be investigated. A combination of different additional flexibility options like electric vehicles and stationary batteries should also be considered in future research.

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Appendix A

Tables A1 and A2
Figs. A1,A2,A3,A4,A5

Table A1
Heat related parameters of the used building.

Parameter	Value
Specific heat demand	81 $\frac{\text{kWh}}{\text{m}^2\text{a}}$
Usable area of the building	160.1 m^2
Ceiling height of the building	2.5 m
Air exchange rate	0.5 $\frac{1}{h}$
Heat transfer coefficient (U-value) of the windows	1.3 $\frac{\text{W}}{\text{m}^2\text{K}}$
Energy transmittance (g-value) of the windows	0.75
Window area on the south facade	20.8 m^2
Window area on the west facade	4.7 m^2
Window area on the north facade	3.7 m^2
Window area on the east facade	4.7 m^2
Heat transfer coefficient of the external walls	0.24 $\frac{\text{W}}{\text{m}^2\text{K}}$
Area of the external walls	226.9 m^2
Heat transfer coefficient of the roof	0.22 $\frac{\text{W}}{\text{m}^2\text{K}}$
Area of the roof	103.2 m^2
Heat transfer coefficient of the bottom plate	0.23 $\frac{\text{W}}{\text{m}^2\text{K}}$
Area of the bottom plate	95.9 m^2
Heat transfer coefficient of the door	2 $\frac{\text{W}}{\text{m}^2\text{K}}$
Area of the door	2 m^2

Table A2
Parameters of the heating system.

Parameter	Value	Source	Comment
Maximal power of heat pump	3000 W	[25]	Sized for mono energetic operation at norm ambient temperature − 14 °C
Heated area of the buildings	140 m^2	[37]	Assumption: Not all rooms in the cellar are heated
Concrete width (for the UFH)	7 cm	[39]	DIN standard 18560 for screeds in building construction
Density of concrete	2400 $\frac{\text{kg}}{\text{m}^3}$	[50]	European standards for concrete EN 206-1
Heat capacity of concrete	1000 $\frac{\text{J}}{\text{kg} * \text{K}}$	[50]	European standards for concrete EN 206-1
Temperature range of the UFH	20–22 °C	[41]	Assumptions for optimal comfort
DHW tank volume	150 l, 200 l	[42]	200 l for 4 inhabitants and 150 l for 2 inhabitants
Losses of DHW tank	35 W	[51]	2nd highest efficiency class (EU regulation 814/2013)
Losses of space heating	45 W		Assumption[a]
Supply temperature UFH	30 °C	[41,36]	
Supply temperature DHW tank	45 °C	[33,43]	
COP of the heat pump for ΔT = 28 K	3.8	[44]	Similar value as model *LA 28TBS* from *Glen Dimplex*
COP of the heat pump for ΔT = 42 K	2.8	[44]	Similar value as model *LA 28TBS* from *Glen Dimplex*

[a] For the losses of space heating $Q^{LossesSH}$ we assumed 45 W. It is difficult to find reliable values for $Q^{LossesSH}$, as the losses of an UFH system contribute to heating up the desired rooms of the buildings. The losses quantified by $Q^{LossesSH}$ are only the losses of the UFH system's pipes that do not contribute to heating up the desired rooms. They should not be confused with the much higher transmission heat losses of the building which are included in the demand for space heating $Q_t^{DemandSH}$.

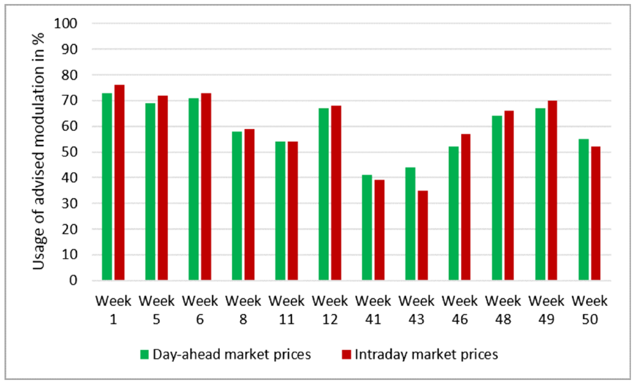

Fig. A1. Average usage of the advised modulation when applying the *Past Value Heuristic*.

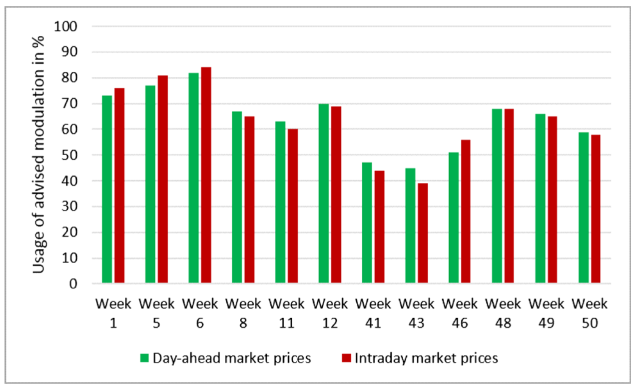

Fig. A2. Average usage of the advised modulation when applying the *Future Value Heuristic*.

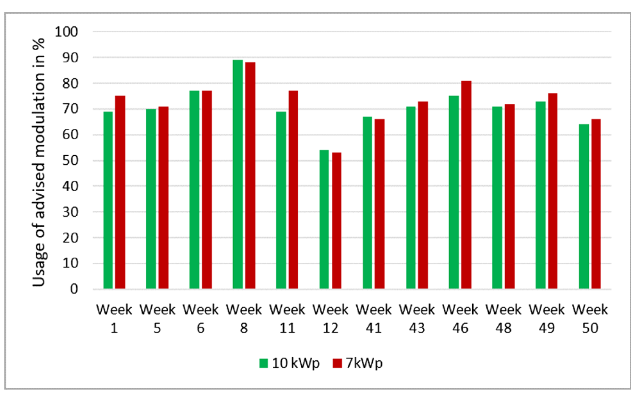

Fig. A3. Average usage of the advised modulation when applying the *Incremental Control Heuristic*.

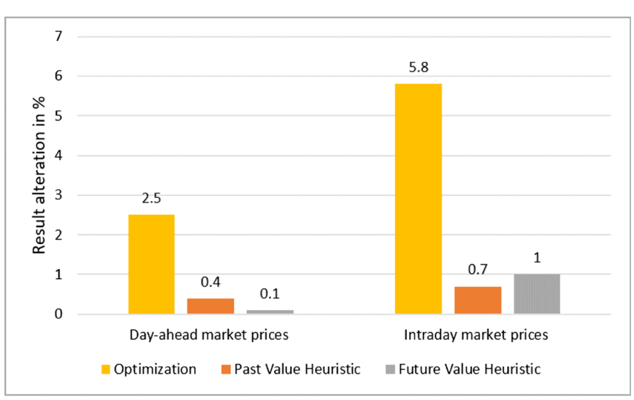

Fig. A4. Average changes in the results for the cost minimization when not using a minimal modulation degree.

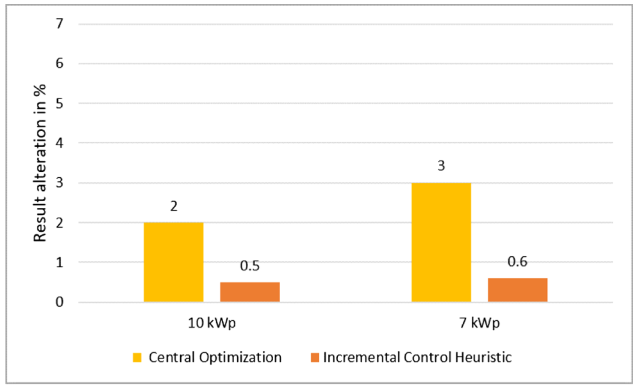

Fig. A5. Average changes in the results for the surplus power minimization when not using a minimal modulation degree.

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Decentralized optimization approaches for using the load flexibility of electric heating devices

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A B S T R A C T

Electric heating devices can provide the needed load flexibility for future energy systems with high shares of renewable energies. To exploit these flexibilities, the literature often suggests centralized scheduling-based optimization. However, centralized optimization has crucial drawbacks regarding complexity, privacy and robustness while uncoordinated decentralized optimization approaches yield non-optimal results for the entire system. In this paper, we develop two novel coordinating decentralized optimization approaches, PSCO and PSCO-IDA. Furthermore, we define an optimization procedure to generate a solution pool with diverse schedules for the coordinating approaches. The results show that all investigated approaches for coordinated decentralized optimization lead to lower surplus energy and thus to higher self-consumption rates of locally generated renewable energy compared to the uncoordinated approach. Moreover, using solution pools generated by our optimization procedure strongly improves the Iterative Desync Algorithm (IDA), an effective and privacy-preserving algorithm for decentralized optimization. A comparison of the different decentralized optimization approaches reveals that PSCO-IDA leads to an average improvement of 10% compared to IDA while PSCO leads to similar results with reduced communication effort. All decentralized approaches have significantly reduced runtimes compared to centralized optimization. Our study reveals the strong advantages of coordinated decentralized optimization approaches for using flexible electrical loads.

1. Introduction

The energy system is undergoing a fundamental transition, as more and more energy is generated by intermittent renewable energy sources like wind turbines and photovoltaic systems (PV). Flexible electric loads can cope with the challenges brought about by the volatile electricity supply. The main flexibility options which are currently discussed in the literature for residential areas come from electric vehicles, batteries, deferrable loads (e.g. washing machine, dish washer, and tumble dryer) and thermostatically controlled loads [1]. As heat is the main energy demand in residential areas in most parts of the world, electric heating devices coupled with thermal storage can provide significant flexibility. Furthermore, they are comparatively cheap as they can utilize existing infrastructures like the mass of the building or hot water tanks as thermal storage to shift the operation of the flexible devices without affecting customer's comfort.

Different concepts have been analyzed in the literature to use the flexibilities in residential areas with multiple buildings. When using centralized optimization (CO) approaches, a central unit collects data from each building for demand and generations forecasts that are used as input to a central optimization problem. The central control unit then directly controls the flexible devices of the buildings based on the calculated optimal schedule. CO leads to the overall best solution for the residential area. However, CO also has crucial drawbacks that strongly limit its applicability [2]. First, a CO approach infringes on the privacy of the inhabitants. Moreover, CO approaches have a high computational complexity as scheduling problems are generally NP-hard [3]. Another disadvantage is the low level of robustness due to the central controller. If the central controller fails, for example due to technical problems or an external cyber-attack, tremendous damage could be done to the whole energy system.

When decentralized optimization (DO) approaches are used, each building optimizes its own goal and controls its own devices. Compared to CO approaches, DO approaches have advantages

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Nomenclature

Δt	time resolution
η	efficiency
ρ	density
$buffer^{Deviaton}$	buffer value for the deviation maximization problem
BT1, BT2, BT2	building types 1, 2, 3
c	specific heat capacity
COP_t	coefficient of performance
D	total diversity of two load profiles
h_t^{Aux}	binary auxiliary variable
$h_t^{Diverstiy+}$	binary auxiliary variable for the big-M approach
$h_t^{positive}$	binary auxiliary variable for the big-M approach
$mDeg^{min}$	minimal modulation degree of the heat pump
M_t^+	M_t^- big-M parameters
P_t^{Demand}	inflexible electrical demand
$P_t^{Diversity+}$	positive deviation in power
$P_t^{Diversity-}$	positive deviation in power
$P_t^{Diversity}$	diversity in power between two load profiles
$P^{ElectricDHW}$	power of the electrical heating device for domestic hot water
$P^{ElectricSH}$	power of the electrical heating device for space heating
P^{HP}	maximal electrical power of the heat pump
$P_t^{Optimal}$	power value of the optimal load profile
P_t^{PV}	PV generation
P^{PvPeak}	peak generation of the building's PV system
$P_t^{Surplus+}$	positive part of surplus power
$P_t^{Surplus-}$	negative part of surplus power
$P_t^{Surplus}$	surplus power
P_t^{total}	total electrical demand
$Q_t^{DemandDHW}$	demand for domestic hot water
$Q_t^{DemandSH}$	demand for space heating
Q_t^{DHW}	heating energy for domestic hot water
$Q_t^{LossesDHW}$	losses of the domestic hot water tank
$Q_t^{LossesSH}$	losses of space heating
Q_t^{SH}	heating energy for space heating
$\mathrm{r_t}$	auxiliary vector for generating diversity
SE	surplus energy
$SE^{optimal}$	surplus energy of the optimal solution
t	index for time slots
T_t^{BS}	temperature of the buffer storage
V^{BS}	volume of the buffer storage
V_t^{DHWuse}	useable volume of the domestic hot water tank
x_t	modulation degree of the heat pump for space heating
$x_t^{Electric}$	modulation degree of the electric heating element for space heating
x_t^{Gas}	heating variable of the electric heating element for space heating
y_t	modulation degree of the heat pump for domestic hot water
$y_t^{Electric}$	modulation degree of the electric heating element for domestic hot water
y_t^{Gas}	heating variable of the electric heating element for domestic hot water
Z	number of time slots

regarding computational complexity, data privacy and robustness [2]. But if the buildings in the residential area merely optimize their own goal without interacting with the other buildings, the results will be sub-optimal for the whole residential area. Because of this, coordination mechanisms for DO are essential for using flexible devices for reacting to the volatile electricity generation by renewables.

In this paper, we develop novel coordination approaches for DO and improve existing ones by defining a new optimization procedure for generating a diverse solution pool for the local optimization problems of buildings. We compare the coordinating DO approaches to CO approaches and non-coordinating DO approaches. Further, we show the sub-optimality of DO without coordination. This paper is structured as follows: In Section 2, we review the relevant literature. Section 3 defines the optimization problems for the residential area. We describe the used DO approaches in Section 4 and show the results of our analysis in Section 5. The paper ends with a summary and conclusion in Section 6.

2. Related work

In this study, we focus on scheduling-based approaches to use the flexibility of electric heating devices. In contrast to rule-based approaches for controlling multiple buildings (see for example [4,5]), an optimization algorithm uses a model and information about future demand and generation to generate an operative schedule for the flexible devices. Different studies exist in the literature that use DO for demand response (cf. Table A.1 in the Appendix A).

While most studies merely investigate one coordinating DO approach, Braun et al. [6] compare model-predictive control to a decomposition approach. Many studies apply decomposition methods [6–10] which break down a single optimization problem into several smaller problems that can be solved by distributed agents [6]. A crucial drawback of decomposition approaches is the necessity of a central controller which coordinates the procedure and which infringes on the privacy of the inhabitants. When using decomposition, the decentralized solutions of the agents are created in a systematic way, as they are outputs of different adjusted optimization problems. Kolen et al. [2] introduce a two-stage scheduling approach for clusters of flexible devices. In a first step, all agents optimize their own local goal creating a set of multiple schedules. Next, the agents coordinate the selection of their individual schedule with the aim of optimizing a common goal. The commercial solver *Cplex* automatically creates the solution pool of schedules by storing the found solutions of the basic optimization problem during optimization procedure. Ramchurn et al. [11] use an approach with a time-dependent price signal which is sent to the buildings. The goal is to create schedules of the flexible devices that reduce the peak power.

In the algorithm proposed by Ogston et al. [12], the buildings of a residential area create a set of local schedules for their flexible devices and send them to a central control unit. The central controller uses a simple heuristic by sequentially choosing the schedule of an agent that best fits to the current resulting load. Blaauwbroek et al. [13] use a similar approach. However, the set of possible schedules is not generated immediately. The buildings successively solve an adjusted optimization problem to create a set of schedules in a systematic way. Hu et al. [14] define a facilitator agent for a cluster of multiple buildings aiming to coordinate the buildings. The central facilitator agent classifies the decision variables into local variables which are controlled by each building and coupled variables which are jointly controlled by multiple buildings. While most of the listed studies use an approach where a central control unit is essential, the coordination approaches by Kolen et al. [2] and Ramchurn et al. [11] do not need a central control unit.

Worthmann et al. [15] use a hierarchical model-predictive control approach for coordinated DO. A central entity broadcasts a cost function that influences the local optimization problems of the decentralized buildings. After receiving the schedules of each building, the central entity iteratively updates the cost function to achieve a network-wide objective. Chang et al. [16] introduce a DO approach that converges to the solution of the CO problem and that does not need a central controller. However, their approach requires exchanging consumption and generation data among neighbors, which breaches the privacy of the inhabitants [6,15]. Furthermore, it is assumed that each agent can estimate its contribution to the global coupled constraint which is difficult to realize in real-world applications.

We introduce novel coordinating DO approaches and compare them to existing ones. To the best of our knowledge, this is the only study that compares different coordinating DO approaches that do not need a central control unit and that are privacy-friendly. Another contribution of this paper is the definition of an additional optimization problem that generates diverse schedules for the problem of minimizing surplus energy of locally generated renewable energy. A set of schedules is required for the coordination approaches introduced in Refs. [2,12,13]. We use the additional optimization problem to generate diverse schedules for the *Iterative Desync Algorithm* (*IDA*) by Kolen et al. [2], as it is the only privacy-preserving approach that is based on a set of schedules and does not require a central control unit. In contrast to Kolen et al., we create these schedules in a systematic way by introducing a novel optimization procedure that makes use of the additional optimization problem. Moreover, we compare the used DO approaches to both CO and non-coordinating DO.

3. Optimization problems for a residential area

In this section, we introduce the optimization problems for a residential area. At first, Section 3.1 describes the different types of buildings and heating systems that are used for our case study. Afterwards, we define the basic optimization problem for minimizing surplus energy in a residential area with locally generated PV in Section 3.2. The optimization problem for generating a set of diverse schedules that are used as input to the coordinating DO approaches is explained in Section 3.3.

3.1. Different building types and heating systems for the case study

The residential area consists of three types of buildings, which have different insulation levels and heating systems. All of them are single-family houses that are inhabited by either two or four persons. Table 1 shows an overview of the different types of buildings. Building type 1 has a very high insulation standard and consequently low heat demand. A ground-source heat pump with constant electrical power generates the heat. Buildings from the second category have a relatively low specific heat demand. For these buildings, a modulating air-source heat pump is used for heating. Building type 3 has the lowest insulation standard resulting in the highest specific heat demand among the three building types. The main heating device is a gas heater. Two additional electric heating elements (one for the buffer storage and one for the domestic hot water (DHW) tank) are used. All buildings in the residential area use two thermal storages: a buffer storage for space heating and a hot water tank for DHW. For the buildings with heat pumps, an underfloor heating system is used for buffer storage, as this allows low supply temperatures for space heating which increases the heat pumps' efficiencies [17]. The residential buildings are located in Braunschweig (Germany) and have a PV system.

While the overall market share of heat pumps in Germany was only 2% [18] in 2017, the majority (43%) of new buildings built in 2017 were equipped with a heat pump [19]. Heating systems based on gas have the highest market share (around 50%) among all buildings in Germany [18]. In our modeled residential area, every building uses an electric heating device. While this is not representative of today's heating systems in Germany, we use this residential area to investigate different optimization approaches that exploit thermoelectric flexibilities. We use heat pumps and electric heating elements as we think that these technologies will have significant market shares in the future. Especially heat pumps can play a fundamental role for providing the needed flexibilities in future energy systems with high shares of renewables [20].

We use data that was generated by the software tool *synPRO* provided by *Fraunhofer Institute for Solar Energy Systems* [21] for the different load profiles (electric demand, space heating, DHW, PV generation). The tool generates synthetic data by using a behavioral model and a resistance-capacitance model for space heating as described in DIN EN ISO 13790 [23]. We scaled up the maximum heat demand of the year for the different building types to an outside temperature of -14 °C (standard outside temperature in Braunschweig [24]) for determining the power of the heating devices as is done in Ref. [25]. Table B.1 in the Appendix B lists the additional parameters of the heating systems.

3.2. Surplus energy minimization problem

The basic goal for each building is to minimize its surplus energy *SE* and thus to maximize the self-consumption rate of locally generated PV. To determine an optimal schedule for the electric heating devices, the buildings solve an optimization problem. The following equations define the mixed-integer linear program for building type 2. The main decision variables are the modulation degree of the heating device when heating up the buffer storage x_t and the modulation degree when heating up the DHW tank y_t.

Table 1
Overview of the different types of buildings.

	Building type 1	Building type 2	Building type 3
Specific heat demand	26 $\frac{kWh}{m^2a}$	81 $\frac{kWh}{m^2a}$	140 $\frac{kWh}{m^2a}$
Heating device	Ground-source heat pump	Air-source heat pump	Gas heater
Power of heating device	1.200 W	3.000 W (modulating)	12.000 W
Power of additional electric heating elements	–	–	2 * 2.000 W (modulating)
Buffer storage	Underfloor heating system	Underfloor heating system	Hot water tank
DHW storage	Hot water tank	Hot water tank	Hot water tank
PV system	Yes	Yes	Yes

$$\min SE = \sum_{t=1}^{Z} P_t^{Surplus+} \cdot \Delta t \tag{1}$$

subject to

$$T^{min} \le T_t^{BS} \le T^{max} \quad \forall\ t \tag{2}$$

$$V^{DHWmin} \le V_t^{DHWuse} \le V^{DHWmax} \quad \forall\ t \tag{3}$$

$$T_1^{BS} \le T_Z^{BS} \le T_1^{BS} \quad \forall\ t \tag{4}$$

$$V_1^{DHWuse} \le V_Z^{DHWuse} \le V_1^{DHWuse} \quad \forall\ t \tag{5}$$

$$x_t + y_t \ge mDeg^{min} \quad \forall\ t \tag{6}$$

$$x_t \le h_t^{Aux} \quad \forall\ t \tag{7}$$

$$y_t \le \left(1 - h_t^{Aux}\right) \quad \forall\ t \tag{8}$$

$$P_t^{total} = (x_t + y_t) \cdot P^{HP} + P_t^{Demand} \quad \forall\ t \tag{9}$$

$$P_t^{Surplus} = P_t^{PV} - P_t^{Total} \quad \forall\ t \tag{10}$$

$$P_t^{Surplus} = P_t^{Surplus+} - P_t^{Surplus-} \quad \forall\ t \tag{11}$$

$$P_t^{Surplus+} \le M_t^{+} \cdot h_t^{positive} \quad \forall\ t \tag{12}$$

$$P_t^{Surplus-} \le M_t^{-} \cdot \left(1 - h_t^{positive}\right) \quad \forall\ t \tag{13}$$

$$\begin{aligned} &x_t \in [0,1],\ y_t \in [0,1],\ h_t^{Aux} \in \{0,1\}, h_t^{positive} \in \{0,1\}, \\ &P_t^{Surplus+} \ge 0,\ P_t^{Surplus-} \ge 0 \quad \forall\ t \end{aligned} \tag{14}$$

Constraints (2) and (3) ensure that the temperature of the buffer storage T_t^{BS} and the useable volume of the DHW tank V_t^{DHWuse} are always between two limits. Moreover, the values of these two variables at the end of the optimization horizon have to be equal to their starting values (constraints (4) and (5)). Constraint (6) introduces a minimal modulation degree for the air-source heat pump, whereas constraints (7) and (8) forbid the heating device to heat up both the buffer storage and the DHW tank simultaneously. The total electrical demand P_t^{total} is defined in Eq. (9); it consists of the flexible load of the heat pump (P^{HP} is the maximal power of the heat pump) and the inflexible load of the other household appliancesP_t^{Demand}. We subtract the total electrical demand from the PV generation P_t^{PV} to determine the surplus power $P_t^{Surplus}$ in Eq. (10). To ensure that only positive surplus power is minimized and thus prevent to schedule the heat pump's activities into times with low PV generation, we use the big-M approach [26,27] by adding Eq. (11)-(13). A more detailed description of this optimization problem can be found in Ref. [4]. The corresponding optimization problems for building types 1 and 3 are defined in the Appendix C.

A fundamental part of these optimization problems is the model for the buffer storage and the DHW tank. For modeling the buffer storage's temperature T_t^{BS}, we use a uniform temperature model with an energy difference equation (Eq. (15)). This approach is often used in the literature [28].

$$T_t^{BS} = T_{t-1}^{BS} + \frac{Q_t^{SH} - Q_t^{DemandSH} - Q_t^{LossesSH}}{V^{BS} \cdot \rho^{BS} \cdot c^{BS}} \tag{15}$$

The difference in energy at time t is divided by the volume of the buffer storage V^{BS}, the density ρ^{BS} of the storage medium and heat capacity c^{BS} and is then added to the temperature of the previous time slot. While the demand for space heating $Q_t^{DeamandSH}$ and the losses $Q_t^{LossesSH}$ decrease the temperature of the buffer storage, the generated thermal energy of the heating devices Q_t^{SH} increases it. The storage medium for building types 1 and 2 is concrete, since these buildings use an underfloor heating system. A hot water tank serves as buffer storage for the buildings of type 3.

$$V_t^{DHWuse} = V_{t-1}^{DHWuse} + \frac{Q_t^{DHW} - Q_t^{DemandDHW} - Q_t^{LossesDHW}}{T^{DHW} \cdot \rho^{Water} \cdot c^{Water}} \tag{16}$$

For the useable volume of the DHW tank V_t^{DHWuse}, we use the same difference equation (Eq. (16)). The difference is that the volume itself is variable whereas the temperature for T^{DHW} is fixed and that water is used as the storage medium for all buildings. We use Eq. (17) and Eq. (18) to calculate the generated energy of the heating device in building type 2 for space heating and DHW. As an air-source heat pump is used, the coefficient of performance (COP) quantifying the heat pump's efficiency is not constant over time. To incorporate its dependency on the outside temperature, we use a linear relationship as it is done in Ref. [4].

$$Q_t^{SH,BT2} = x_t \cdot P^{HP} \cdot COP_t \cdot \Delta t \tag{17}$$

$$Q_t^{DHW,BT2} = y_t \cdot P^{HP} \cdot COP_t \cdot \Delta t \tag{18}$$

The equations of the other buildings can be found in the Appendix C. For building type 1, we assume the COP of the ground-source heat pump to be constant, since the temperature variations in the ground are strongly reduced compared to the ones of outside air [29]. Building type 3 has three heat sources. A gas heating device with the power P^{Gas} and the constant efficiency η^{Gas} can heat up both the buffer storage and the DHW tank. Furthermore, these types of buildings have additional electric heating elements for space heating and DHW with constant efficiencies. We add an additional penalty term to the objective function of building type 3. This term penalizes the use of the electric heating devices to a certain extent. This prevents the buildings to use electricity instead of gas for heating in times with no PV generation.

3.3. Optimization problem for generating diverse schedules

The DO approaches described in Section 4 need a diverse pool of optimal or near-optimal schedules. When using an exact solver, there is the possibility to specify certain parameters of the solver to trigger a generic approach for creating a pool of diverse solutions. However, as these solutions are not problem-specific, we define an additional optimization problem to generate diverse solutions for the problem of minimizing surplus energy. This optimization problem needs the solution from the surplus energy minimization problem of the previous Section 3.2 as an input. All buildings can run this additional optimization problem after having obtained the results from the previous problem in a first step. For building type 2, the diversity maximization problem to be solved is:

$$\max D = \sum_{t=1}^{Z} \left(P_t^{Diversity+} + P_t^{Diversity-}\right) \cdot \mathrm{r_t} \tag{19}$$

subject to:

$$P_t^{Diversity} = P_t^{Optimal} - P_t^{Total} \quad \forall\ t \tag{20}$$

$$P_t^{Diversity} = P_t^{Diversity+} - P_t^{Diversity-} \quad \forall\ t \tag{21}$$

$$P_t^{Diversity+} \leq M_t^{+} \cdot h_t^{Diverstiy+} \quad \forall\ t \tag{22}$$

$$P_t^{Diversity-} \leq M_t^{-} \cdot \left(1 - h_t^{Diverstiy+}\right) \quad \forall\ t \tag{23}$$

$$SE = \sum_{t=1}^{Z} P_t^{Surplus+} \cdot \Delta t \tag{24}$$

$$SE \leq SE^{optimal} + \left(SE^{optimal} \cdot buffer^{Deviaton}\right) \quad \forall\ t \tag{25}$$

$$h_t^{Diverstiy+} \in \{0,1\},\ P_t^{Diversity+} \geq 0,\ P_t^{Diversity-} \geq 0 \quad \forall\ t \tag{26}$$

and the constraints (2)–(14).

At its core, this optimization problem is equivalent to the surplus energy minimization problem, including all of its constraints. However, the goal now is to maximize the diversity D between the load profile of a new schedule and the given load profile of the optimal schedule from the previous optimization problem. For calculation of the diversity in power $P_t^{Diversity}$ (Eq. (20)), the total demand of the new schedule P_t^{Total} is subtracted from the value of the optimal load profile of the previous surplus energy minimization problem $P_t^{Optimal}$. As we intend to maximize the absolute value between the load profiles, Eq. (21) subdivides $P_t^{Diversity}$ into a positive $P_t^{Diversity+}$ and a negative $P_t^{Diversity-}$ part. We use the big-M approach again to incorporate this into our model (Eq. (22) and Eq. (23)). To ensure that the surplus energy of the new solution SE that is calculated by using Eq. (24) only differs to a certain small degree $buffer^{Deviaton}$ from the optimal value of the initial optimization problem $SE^{optimal}$, we add Eq. (25).

In the objective function, we use the exogenous binary parameter vector r_t. This vector specifies the time slots at which the new load profile shall differ from the previous optimal load profile. Solving this optimization problem with different r-vectors generates multiple (near) optimal diverse schedules. Fig. 1 shows an exemplary output load profile (P_t^{total}) of the surplus energy minimization problem for a building with a modulating heat pump (building type 2). This profile and the corresponding value of the objective function SE are used as inputs to the diversity maximization problem.

Fig. 2 illustrates the resulting load profiles when using two different r-vectors. For the left load profile, the r-vector has the value 1 for the last third of the timespan in which the PV system has produced energy. For the right profile, a certain amount of 1-entries are equally distributed over the timespan with PV generation. As only the time slots which are specified in the r-vector affect the objective function, the optimization algorithm primarily tries to increase or decrease the load of these time slots. Consequently, using specific r-vectors makes it possible to specify desired time slots for generating diversity in the load profiles. The 1-entries should be placed within the timespan of the volatile generation. In Section 5.2, we compare the systematically generated solution pool of this approach with the automatically generated solution pool during the optimization procedure of a commercial solver.

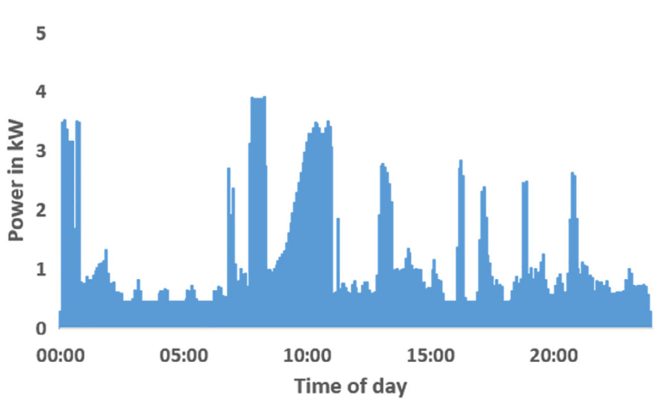

Fig. 1. Output load profile of the surplus minimization problem.

The corresponding optimization problems of the other building types for generating diverse schedules can be found in the Appendix D.

The surplus energy minimization problem of Section 3.2 and the diversity maximization problem of this section are combined to generate a pool of different schedules for the local optimization problems of the buildings. The DO approaches of the following Section 4 need this solution pool. Fig. 3 illustrates a flowchart of the optimization procedure to generate a diverse solution pool. First the surplus energy minimization problem is solved whose output is an optimal schedule. This schedule builds the first solution of the solution pool and serves as input for the diversity maximization problem.

The other essential input for the diversity maximization problem is a set of different r-vectors. Basically, the r-vectors can have any shape as they merely indicate the timeslots in which diversity is favored to be created. In Section 5.2 we list the used r-vectors for our case study that led to the best results. One of the r-vectors is used for the diversity maximization problem which outputs another schedule that is stored in the solution pool. If the number of generated schedules is smaller than the desired number, another different r-vector is used as input for the diversity maximization problem. Every run of the diversity maximization problem with a different r-vector creates a further solution. This procedure is repeated until the desired number of solutions are stored in the solution pool.

4. Decentralized optimization approaches

In this section, we describe three different approaches for decentralized optimization. In Section 4.1, an effective algorithm from the literature for decentralized optimization without a central control instance is explained. Afterwards, we introduce a novel approach in Section 4.2 and a combination of these two methods in Section 4.3. A prerequisite for applying decentralized coordination mechanisms is the existence of a communication network that enables the buildings to exchange messages.

4.1. Iterative Desync Algorithm (IDA)

The basic version of the *Iterative Desync Algorithm* (*IDA*) is described by Kolen et al. in Ref. [2]. We use a slight modification of this algorithm to coordinate the DO of several buildings with the aim of reducing surplus energy in a residential area. Fig. 4 shows the DO approach *IDA* for an illustrative residential area, which consists of only six buildings in this case. As a perquisite for *IDA* (1st step), all buildings must have a pool of different schedules for their local optimization problem. The buildings use their energy management system (EMS) to run the local optimization problem and to control the flexible heating devices. Depending on the used optimization method, several ways exist for generating a pool of schedules. For our case study, we use the optimization problems

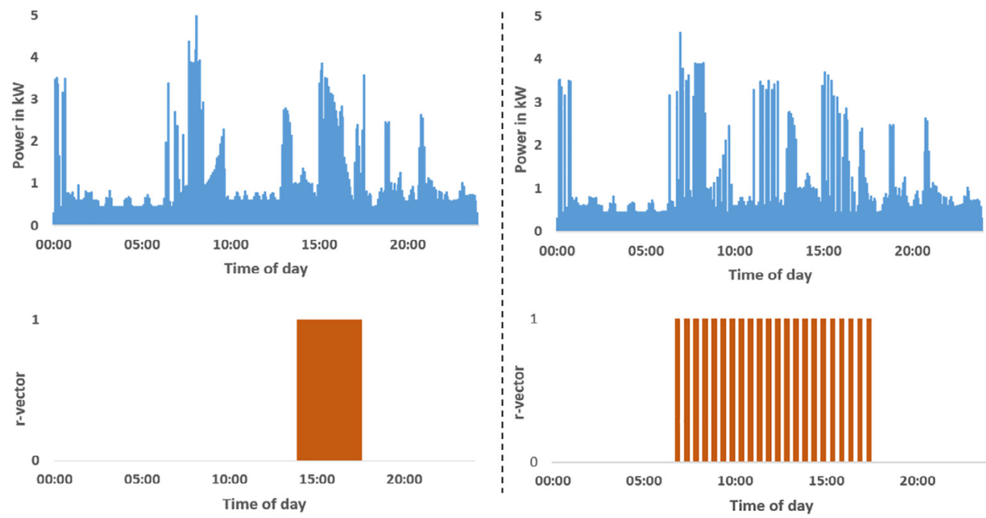

Fig. 2. Output load profiles of the optimization problem for generating diverse schedules with two different r-vectors.

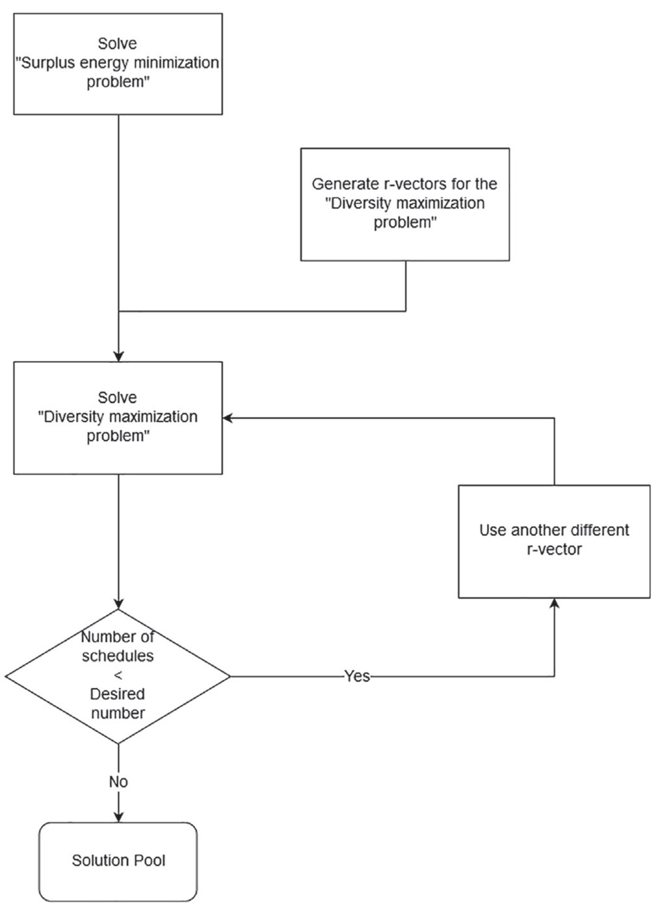

Fig. 3. Flowchart of the optimization procedure to generate a solution pool.

described in Section 3 to generate a diverse set of feasible schedules. This is done simultaneously for all buildings. In the residential area shown in Fig. 4, the solution pool of each building consists of three schedules.

In the 2nd step, the buildings use *IDA* to coordinate the selection of the individual schedules. The buildings are ordered in a cycle. The order can be random or based on some ranking (e.g. power of the heating devices). Every building has a predecessor and a successor in the circle. Furthermore, the buildings store a local view on the residential area's surplus power. At the beginning, the load profile for the residential area's surplus power has only zero values. For the coordination, every building performs the four following steps:

1. Add the local PV generation to the surplus power profile of the residential area
2. Choose the best schedule for minimizing the surplus power of the residential area
3. Update the surplus power profile of the residential area
4. Forward the new surplus power profile of the residential area to the next building

The first building in the circle chooses the schedule from its solution pool that leads to the lowest surplus power for the entire residential area. The local load profile for the residential area's surplus power has no entries in the beginning. Afterwards, it updates the load profile for the residential area's surplus power and forwards this to the next building. The next building adds its PV generation to this profile and subtracts the total electrical demand of its different schedules from it to determine which of the possible schedules leads to the lowest surplus power for the residential area. If the subtraction of the total electrical demand leads to a negative value for one time slot, a value of 0 will be assigned to this time slot. This is done because merely the (positive) surplus power should be shared among the buildings and not the entire electrical load profiles, since this could infringe on the privacy of the inhabitants. After having chosen the best schedule, the building sends the updated surplus power profile to its successor, which performs the same steps. In the lower part of Fig. 4, the first three buildings have already chosen their temporary schedule and the fourth building is about to perform the four steps of the algorithm. There may be multiple iterations through the circle and the building can deviate from their initially selected schedule in each iteration. It is also possible for each building to add random noise to the load profile in the first iteration and delete that random noise during the second iteration through the cycle. Thus, this approach would have an even higher degree of privacy-friendliness. The algorithm stops, if no building changes its selected schedule for one iteration through the circle. Afterwards the buildings' EMS will implement the selected schedules and control the electric heating devices according to them.

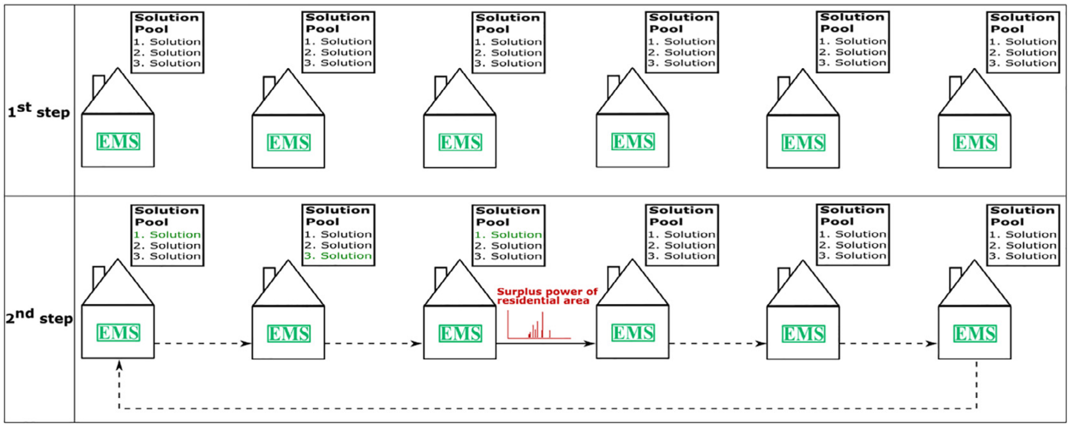

Fig. 4. Decentralized optimization approach IDA in a residential area.

4.2. Parallel Successive Cluster Optimization (PSCO)

Based on the *IDA* idea, we developed a novel coordinating DO approach called *Parallel Successive Cluster Optimization* (*PSCO*), which clusters all buildings of the residential area. The clusters have the same number of buildings (the number for the last cluster may be different). Besides the number of buildings per cluster, the order within the clusters must be defined beforehand. Fig. 5 illustrates *PSCO* for clusters of size two. The number of steps is equal to the number of buildings in a cluster. During the first step, the first buildings of each cluster solve their local optimization problem (in our case, the surplus energy minimization problem of Section 3.2) and send the resulting local surplus power of the cluster to the next building within the cluster. All first buildings of the clusters do this in parallel.

In the second step, the second buildings of the clusters use the profile for the local surplus power of the cluster as an input to their own optimization problem. In contrast to the *IDA* algorithm, the local optimization problem of the building is not solved before having the output of the previous building. Thus, the output of the previous building directly influences the optimization problem of the buildings. Further, no additional schedules are calculated as the buildings do not have a solution pool. As soon as the last buildings of each cluster have solved their local optimization problem, *PSCO* terminates. In our experiments, clusters of size two yielded both the best results and the lowest runtime. This is why we stick to this cluster size for our case study. For other objective functions (e.g. peak shaving), larger clusters may yield better results.

4.3. Parallel Successive Cluster Optimization with IDA (PSCO-IDA)

Our second newly developed approach is the *PSCO-IDA* algorithm, which combines *PSCO* from the previous Section 4.2 and IDA from Section 4.1. Fig. 6 displays a schematic view of *PSCO-IDA* with two buildings per cluster. The first two steps are similar to the ones of *PSCO*. The only difference is that the buildings not only generate one schedule but a solution pool of multiple diverse schedules as it is done at the beginning of *IDA*. After the last building in each cluster has generated its solution pool, the buildings use *IDA* (third step) to coordinate the selections of the profiles that lead to minimal surplus power for the residential area. The main advantage over *IDA* is that the second buildings of the clusters can incorporate the output of the first buildings into their local optimization problem for generating the solution pool.

Besides a random ordering, we use a simple order heuristic to assign buildings to clusters of size two for *PSCO* and *PSCO-IDA*. For this, we calculate a score value for each building by using the following formula:

$$\text{Score} = P^{PvPeak} - P^{ElectricalHeating} \tag{27}$$

The power of the building's electrical heating device is subtracted from the peak power of its PV system. This score roughly quantifies the expected self-consumption rate of locally generated PV for each building. The higher the score, the more surplus energy is expected by this building. We group the building with the highest score and the building with the lowest score into the first cluster. Next, we group the building with the second highest and the

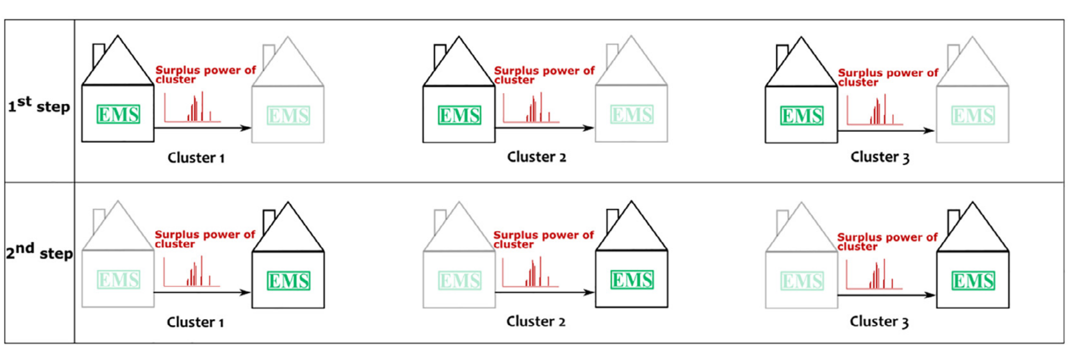

Fig. 5. PSCO algorithm with two buildings per cluster.

Fig. 6. PSCO-IDA algorithm with two buildings per cluster.

second lowest score into the next cluster. We proceed with this procedure until every building belongs to one cluster. If there is an odd number of buildings, the last cluster will consist of one building only. The buildings with the higher score are always the first buildings in the cluster that start with the optimization. The rationale behind this grouping is that the buildings with low PV generation can use the surplus energy of buildings with high PV generation for their electric heating devices. For clusters containing more buildings, this heuristic ordering has to be adjusted. However, for our study, we only used clusters with two buildings, as this led to the best results.

5. Results

The base scenario for the residential area in our case study consists of 90 buildings. Of these, 15 are inhabited by two persons whereas 75 have four persons living in each. We chose 30 buildings for each building type. All buildings have a PV system with an average peak power of 8 kW (equally distributed between the peak powers of 5 kW and 11 kW). The time resolution Δt was 5 min, as this is recommended for capturing the short-term fluctuations of PV [30]. We used the modelling language *GAMS* to implement the optimization problems with *Cplex 12.8* as the solver and a MIP gap of 1% (maximum deviation from the globally optimal solution). The simulation of the interaction between the buildings is implemented in Java. All computations were carried out on an Intel Core i5-2500 K system with 3.3 GHz, 4 cores and 16 GB RAM. At first, we show the difference between CO and uncoordinated DO in Section 5.1. Afterwards, we evaluate our method for generating diverse solutions for the *IDA* algorithm in Section 5.2 and compare different DO approaches in Section 5.3. This section ends with a critical appraisal in Section 5.4.

5.1. Difference between centralized optimization and decentralized optimization without coordination

If every building in a residential area only optimizes its own objective without interacting with other buildings, the resulting solution is going to be suboptimal for the entire system. Fig. 7 shows the difference in surplus energy between centralized and uncoordinated DO for the base scenario during the heating period in Germany (October–March). It can be seen that on many days, the difference between the centralized and the uncoordinated DO are significant. On five days, the difference is even above 300 kWh. Especially on the sunnier and warmer months of the heating period (March and October), the application of an uncoordinated DO approach leads to higher surplus energy. On days with no or less PV generation, the difference does not exist, since even the DO leads to no surplus energy. On average, the difference is about 55 kWh including the days with negligible PV generation. This diagram clearly shows the need for coordination approaches when using DO.

5.2. Evaluation of the solution pool for IDA

When using the *IDA* algorithm, every building needs a solution pool with different schedules. In the reference paper for *IDA* [2], the solution pool is automatically created by the commercial solver *Cplex* in an unsystematic way by storing feasible solutions that satisfy some quality criteria during the optimization procedure. In Section 3.3 we introduced a systematic way of generating diverse solutions for the problem of minimizing surplus energy from renewables by defining an adjusted optimization problem. We run *IDA* with both automatically and systematically created solution pools for 15 different days of the heating period. We randomly picked 5 days with low, 5 days with medium and 5 days with high

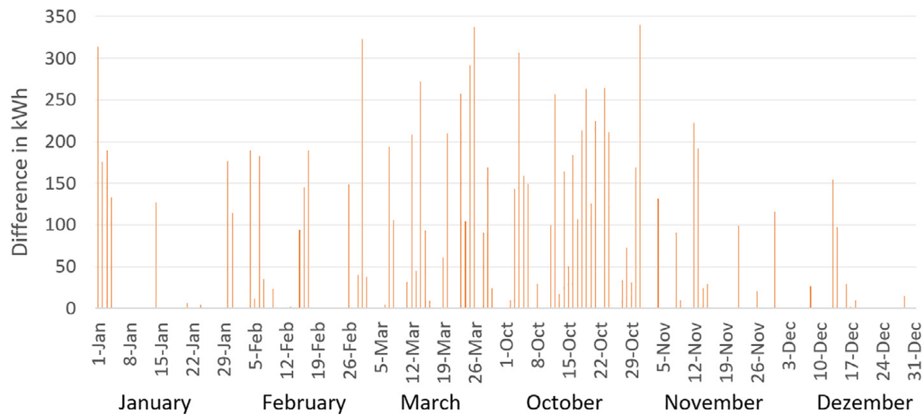

Fig. 7. Difference in surplus energy between centralized and uncoordinated decentralized optimization for the base scenario.

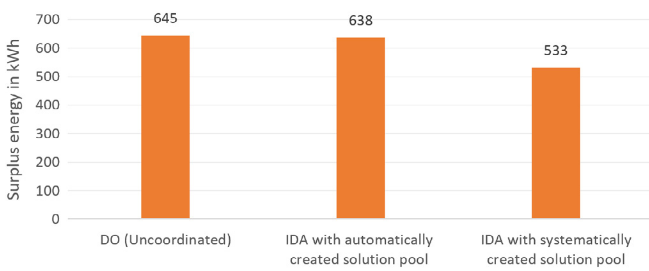

Fig. 8. Surplus energy of the IDA algorithm with differently created solution pools for a day averaged over 15 days of the base scenario.

PV generation for choosing 15 days that are used throughout our following analysis. Fig. 8 illustrates the average surplus energy for *IDA* with differently created solution pools and for the DO approach without any coordination.

While using *IDA* with automatically created solution pools only leads to minor improvements, the application of our introduced approach leads to significant improvements of, in this case, about 20%. We ran the diversity maximization problem of Section 3.3 four times with different r-vectors to generate a solution pool of size five (including the solution of the base problem from Section 3.2). The average time for generating the five solutions was 25 s. We chose a deviation buffer ($buffer^{Deviaton}$) of 5% between the surplus energy of the base problem and the one of the diversity maximization problem, since this led to the best results. When instructing the solver *Cplex* to automatically generate diverse solutions, the number of diverse solutions and the gap to the globally optimal solution have to be specified. We let *Cplex* collect 50 solutions within a gap of 10%. The average time for this was 187 s. We tried out different values for the gap and the size of the solution pool. The impact on the results of *IDA* was fairly small and the chosen values yielded the lowest surplus energy in our experiments. It can be deduced that using our novel optimization procedure to generate a diverse solution pool for *IDA* clearly outperforms a generic and automatically created solution pool.

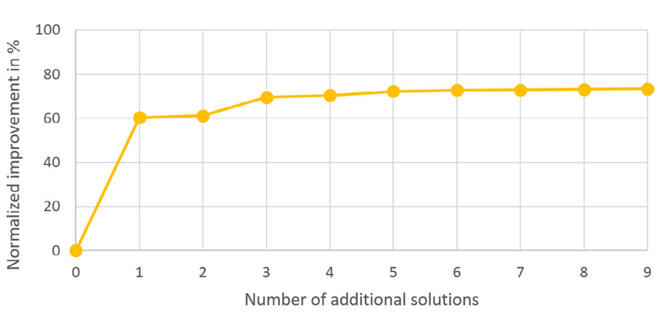

Fig. 9. Normalized improvement of IDA for a day averaged over 15 days of the base scenario depending on the number of additional solutions in the solution pool.

Further, we investigated the effect of the solution pool's size on the results when using *IDA* with our approach to create diverse solutions. Fig. 9 shows the average normalized improvements NI of *IDA* depending on the number of additional solutions. The normalized improvement of a certain approach is calculated by using the following formula:

$$\mathrm{NI}^{Approach} = \frac{SE^{DO} - SE^{Approach}}{SE^{DO} - SE^{CO}} \tag{28}$$

The surplus energy resulting from the application of a certain approach $SE^{Approach}$ is subtracted from the surplus energy of the same scenario when using the uncoordinated DO approach SE^{DO}. This is divided by the difference in surplus energy between the decentralized and the CO approach SE^{CO}. Hence, the normalized improvement is 100% if an approach yields equally good results as the CO. A normalized improvement of 0% means that the used approach leads to an equal amount of surplus energy like the uncoordinated DO. As Fig. 9 displays, adding only one additional solution leads to an average normalized improvement of 60% in the base scenario. Adding further additional solutions enhances the normalized improvement. However, the additional gain decreases with an increasing number of additional solutions. We chose to have four additional solutions for *IDA* and *PSCO-IDA*, because this yielded a good trade-off between improvement and computational time. We tried out different types of r-vectors to generate diverse schedules using the diversity maximization problem of Section 3.3 and chose the following four, as their application resulted in the lowest surplus energy:

1) 1-entries: Whole timespan with PV generation
2) 1-entries for: First third of the timespan with PV generation
3) 1-entries for: Second third of the timespan with PV generation
4) 1-entries for: 40 timeslots equally distributed over the timespan with PV generation

5.3. Comparison of different decentralized optimization approaches

Fig. 10 shows the average normalized improvement of different

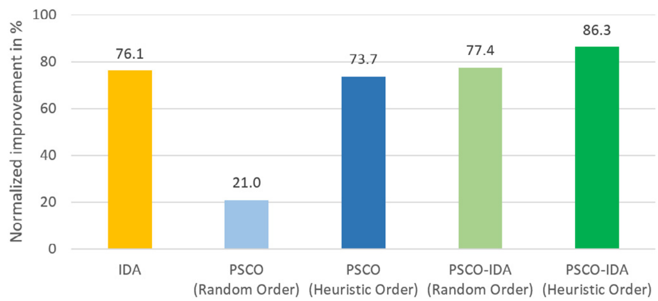

Fig. 10. Normalized improvement of different DO approaches for a day averaged over 15 days of the base scenario.

approaches for 15 days of the base scenario. In addition to *IDA*, two configurations of *PSCO* and *PSCO-IDA* are used for the comparison. In the one configuration, the buildings in the residential area are randomly assigned to clusters and randomly ordered whereas in the other configuration, the heuristic ordering explained in Section 4.3 is used. As expected, all of the five approaches yield better results than an uncoordinated DO approach but worse results compared to the CO. While *PSCO* with random order is clearly outperformed by all other algorithms, the normalized improvements of *IDA*, *PSCO* with heuristic order and *PSCO-IDA* with random order are similarly high (about 75%). Using *PSCO-IDA* with heuristic order leads to significant improvements (more than 86%). It can be further stated that the systematic assignment of buildings to certain clusters and systematic ordering using the proposed order heuristic clearly leads to better results compared to a random ordering.

5.3.1. *PV sensitivity analysis*

We altered the mean peak of the PV system between 5 kW and 10 kW and calculated the average normalized improvement of the different approaches. Fig. 11 illustrates the results. Increased PV generation tends to result in lower improvements for all approaches. A reason for this might be that higher average PV peaks lead to more PV generation whereas the load flexibility potentials do not change. This makes it more difficult for decentralized approaches to use the relatively small load flexibility potential for matching the large-scale PV generation in an optimal way since, opposed to the centralized approaches, the DO itself is not aware of other buildings' situations.

When having buildings with an average PV peak of 5 kW, the normalized improvement for *PSCO-IDA (Heuristic Order)* is about 93% whereas a PV peak of 10 kW leads to improvements of about 80%. For all cases, *PSCO-IDA (Heuristic Order)* yields the best results. The higher the average PV peak, the wider the gap between *PSCO-IDA (Heuristic Order)* and the other algorithms. *PSCO (Heuristic Order)* leads to better results than *IDA* in four of the six investigated cases, and *PSCO-IDA* (Random Order) results in the second highest improvements in all cases. Due to illustrative reasons, Fig. 10 does not include the results for *PSCO* with random order, as the normalized improvement when using this approach is only about 20%.

Further, we used different spreads for the peaks of the buildings' PV systems. For the aforementioned results, a maximum deviation of 3 kW from the mean PV peak was used with an average peak of 8 kW. This means that the peak powers of the PV systems for the 90 buildings are equally distributed between 8 and 3 = 5 kW and 8 + 3 = 11 kW. We varied the maximal deviation from the mean PV peak between 0 and 5 kW while having a mean of 8 kW. Fig. 12 depicts the resulting normalized improvements for different DO approaches (*PSCO (Random Order)* is again not illustrated as it only led to improvements around 20%). A higher spread leads to slightly higher improvements for all approaches. Stronger deviations between the PV generations of the buildings make coordination approaches more useful as they enable the buildings to use balancing effects.

5.3.2. *Runtime analysis*

For the decentralized approaches, the overall runtime is calculated by adding the time for the coordination procedure to the maximum time a building needed to generate the schedules, since the coordination cannot start before each building has generated its schedules. We ran all the optimizations and simulations with different numbers of buildings. Fig. 13 illustrates the average runtime in seconds of different DO approaches depending on the number of buildings. While *PSCO* has similar average runtimes, uncoordinated DO, *IDA* and *PSCO-IDA* have increased runtimes. However, the runtimes are generally rather low (under 50 s) and the number of buildings has a negligible impact on the runtime, making these approaches applicable to larger residential areas. The centralized approach has strongly increased average runtimes that are illustrated in Fig. 14 (runtime is shown in minutes). Furthermore, the CO does not scale well with the number of buildings as the runtime grows disproportionately. Even with the used simple optimization model, the average runtime for a residential area with 150 buildings for one day was above 45 min. These results show that the centralized approach is not applicable to larger residential areas or more complex optimization problems.

5.3.3. *Number of sent messages*

The buildings have to send messages to apply the DO approaches. Fig. 15 shows the average number of sent messages for

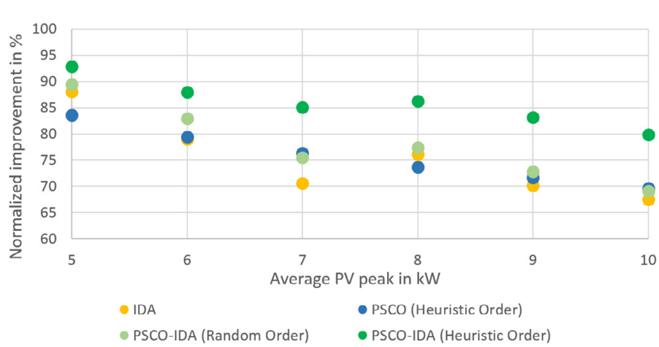

Fig. 11. Normalized improvement of different DO approaches for a day averaged over 15 days depending on the average peak of the buildings' PV system.

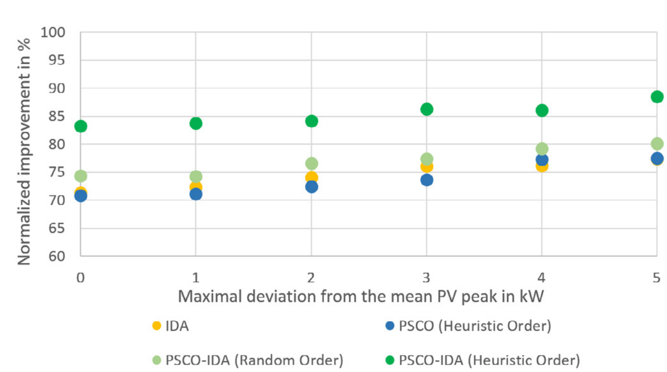

Fig. 12. Normalized improvement of different DO approaches for a day averaged over 15 days depending on the maximum deviation from the mean peak of the buildings' PV system.

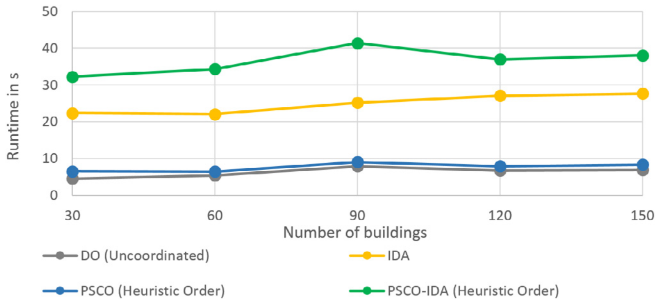

Fig. 13. Runtime in seconds of the different DO approaches for a day averaged over 15 days.

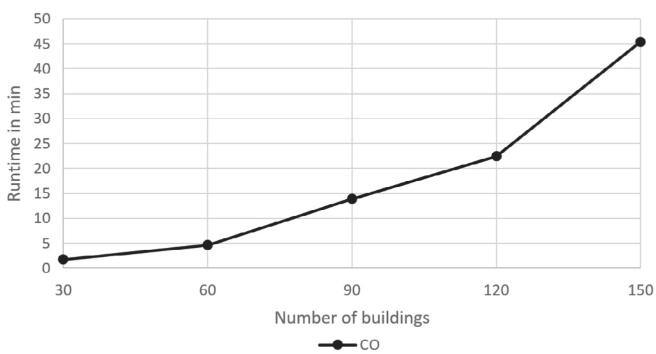

Fig. 14. Runtime in minutes of the centralized optimization approach for a day averaged over 15 days.

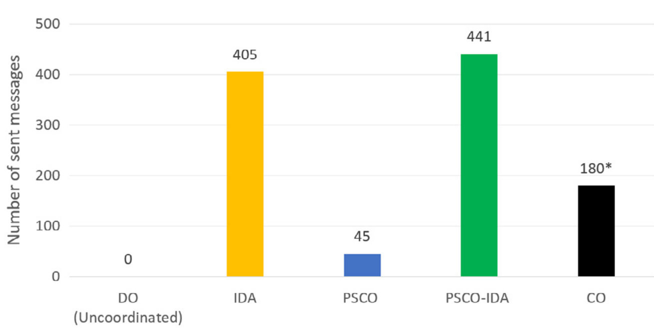

Fig. 15. Number of sent messages for a day averaged over 15 days of the base scenario.

one day averaged over 15 days of the base scenario (90 buildings). *PSCO* only needed 45 messages to be sent while the number for *IDA* and *PSCO-IDA* is strongly increased. However, as one sent message merely contains one profile for the surplus energy, the amount of exchanged data is rather low. When using the *CO* approach, the number of messages is lower than the ones of *IDA* and *PSCO-IDA*. But in this case, each of the 90 buildings have to send the four input data profiles (electrical demand, heat demand, DHW demand and PV generation) to the central controller before the optimization. This leads to 360 (4×90) profiles being sent before the optimization. The output of the *CO* exists of two schedules for each building (one for each thermal storage). This requires sending further 180 (2×90) profiles. While the number of sent messages is lower compared to *IDA* and *PSCO-IDA* when using *CO*, the amount of data that has to be exchanged is higher. The asterisk on the number of sent messages for *CO* indicates this.

5.4. Critical appraisal

We made some simplifications for the building model used in our analysis. Our aim was to compare the decentralized approaches to the centralized approach. Increasing the model's level of detail would lead to strongly increased computational times for the CO making a study like ours infeasible. The coordination part of the DO approaches is independent of the way the schedules are generated. The resulting optimization problem from a complex model can, for example, be solved by (meta) heuristics, which can generate a set of different schedules for the DO approaches within a predefined time span. Using an exact solver is also possible. Moreover, all optimizations were carried out under the assumption of perfect foresight. As in reality all predictions are erroneous, using the investigated approaches in real-world applications requires combining them with uncertainty handling methods like [32–34].

In our study we only investigated the applicability of different optimization approaches to exploit the electrical load flexibility in residential areas from a system perspective. We neither analyzed market mechanisms for incentivizing building owners to use their flexibility, nor did we use market strategies for locally trading electricity. The aim of this study is to show how to optimally use the flexibilities of electric heating devices from a system perspective. The design of market strategies is not in the scope of this paper.

6. Summary and conclusion

In this paper, we developed novel decentralized optimization approaches to exploit the flexibility of electric heating devices of buildings in residential areas. Moreover, we introduced a new optimization procedure that generates the required schedules of flexible devices for the *Iterative Desync Algorithm* (*IDA*) in a systematic way. The new optimization procedure uses an additional optimization problem that outputs diverse schedules for the problem of minimizing surplus energy from locally generated renewable energy. For our case study, we modeled a residential area with 90 buildings that all have a photovoltaic system. We used three types of buildings that have different insulation levels and use different electric heating devices coupled with thermal storage.

First, we showed that if the buildings only optimize for themselves without coordinating with other buildings, the resulting surplus energy of the residential area for one day is on average 55 kWh (at maximum 300 kWh) higher compared to centralized optimization. Using IDA with our approach to systematically generate diverse solutions on average led to 100 kWh less surplus energy compared to using *IDA* with the automatically created solution pool of the commercial solver *Cplex*.

Furthermore, we developed the *Parallel Successive Cluster Optimization* (*PSCO*) algorithm and the *Parallel Successive Cluster Optimization with IDA* (*PSCO-IDA*) algorithm, which is an extension of the *IDA* algorithm. *PSCO-IDA* outperformed *IDA* in all our scenarios and on average led to improvements of about 10%. The *PSCO* algorithm led to similar results as *IDA* while having reduced data exchange requirements. All investigated approaches led to improvements compared to a decentralized optimization approach without coordination. Although centralized optimization yields better results than the decentralized optimization approaches, our analysis shows that it has strongly increased runtimes and is not applicable to larger residential areas. When considering additional flexibility options, the computational complexity of the centralized approaches will be even higher. Furthermore, the centralized approach breaches the privacy of the inhabitants and requires larger amounts of data to be exchanged between the buildings. Our study reveals the strong advantages of applying decentralized optimization approaches in future energy systems with high shares of renewable energy sources.

Future work could analyze the applicability of decentralized optimization approaches to other flexibility options like electric vehicles and stationary batteries. Moreover, generation by wind turbines should be considered in future work. Including wind energy and more flexible loads in the analysis raises the questions of grid stability. In future research, we intend to consider the additional goal of grid stability for the decentralized optimization approaches. Furthermore, the combination of decentralized optimization approaches with uncertainty handling methods for smart grids should be investigated.

Data availability

Datasets related to this article can be found at https://data.mendeley.com/datasets/2krvds8zm2/1, an open-source online data repository hosted at Mendeley Data.

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Appendix

A. Literature review

Table A.1
Comparison of different papers studying approaches for DO

	Different methods for DO	Systematic generation of various solutions	Absence of central control unit	Comparison to DO without coordination	Comparison to CO
Harb et al. [7]	✗	✓ (Decomposition)	✗	✗	✓
Kolen et al. [2]	✗	✗	✓	✓	(✓)
Ramchurn et al. [11]	✗	✓	✓	✗	✓
Ogston et al. [12]	✗	✗	✗	✓	✓
Liu et al. [8]	✗	✓ (Decomposition)	✗	✓	✗
Blaauwbroek et al. [13]	✗	✓	✗	✓	✓
Braun et al. [6]	✓	✓ (Decomposition)	✗	✗	✓
Diekerhof et al. [9]	✗	✓ (Decomposition)	✗	✗	✓
Juelsgaard et al. [10]	✗	✓ (Decomposition)	✗	✗	✓
Hu et al. [14]	✗	✓	✗	✗	✓
Worthmann el al [15].	✓	✓	✗	✓	✓
Chang et al. [16]	✓	✓	✓	✗	✓
Our study	✓	✓	✓	✓	✓

B. Parameters of the heating systems

Table B.1
Parameters of the heating systems

Parameter	Value	Source	Comment
Heated area of the buildings	140 m^2	[21]	Assumption: Not all rooms in the cellar are heated
Concrete width (for the underfloor heating system)	7 cm	[35]	DIN standard 18560 for screeds in building construction
Density of concrete	$2400\ \frac{kg}{m^3}$	[36]	European standards for concrete EN 206-1
Heat capacity of concrete	$1000\ \frac{J}{kg \cdot K}$	[36]	European standards for concrete EN 206-1
Temperature range of the underfloor heating system	20–22 °C	[37]	Assumptions for optimal comfort
Temperature range of the hot water tank (buffer storage)	30–45 °C	[38]	
DHW tank volume	150 l, 200 l	[29]	200 l for 4 inhabitants, 150 l for 2
Losses of space heating	45 W		Assumption
Losses of DHW tank	35 W	[39]	2nd highest efficiency class (EU regulations 814/2013)
Supply temperature underfloor heating system	30 °C	[37]	
Supply temperature hot water tank (buffer storage)	60 °C	[38]	
Supply temperature hot water tank (DHW)	45 °C	[40]	
COP of the air-source heat pump for $\Delta T = 28$ K	3.8	[41]	Similar value as model *LA 28TBS* from *Glen Dimplex*
COP of the air-source heat pump for $\Delta T = 42$ K	2.8	[41]	Similar value as model *LA 28TBS* from *Glen Dimplex*
COP of the ground-source heat pump for $\Delta T = 35$ K	4.7	[42]	Similar value as model *SIK 6TES* from *Glen Dimplex*
COP of the ground-source heat pump for $\Delta T = 45$ K	3.7	[42]	Similar value as model *SIK 6TES* from *Glen Dimplex*

C. Surplus energy minimization problems

Building type 1 (non-modulating ground-source heat pump)

$$\min SE = \sum_{t=1}^{Z} P_t^{Surplus+} \cdot \Delta t \quad (C.1)$$

subject to:

$$T^{min} \leq T_t^{BS} \leq T^{max} \quad \forall t \quad (C.2)$$

$$V^{DHWmin} \leq V_t^{DHWuse} \leq V^{DHWmax} \quad \forall t \quad (C.3)$$

$$T_1^{BS} \leq T_Z^{BS} \leq T_1^{BS} \quad \forall t \quad (C.4)$$

$$V_1^{DHWuse} \leq V_Z^{DHWuse} \leq V_1^{DHWuse} \quad \forall t \quad (C.5)$$

$$x_t \leq h_t^{Aux} \quad \forall t \quad (C.6)$$

$$y_t \leq \left(1 - h_t^{Aux}\right) \quad \forall t \quad (C.7)$$

$$P_t^{total} = (x_t + y_t) \cdot P^{HP} + P_t^{Demand} \quad \forall t \quad (C.8)$$

$$P_t^{Surplus} = P_t^{PV} - P_t^{Total} \quad \forall t \quad (C.9)$$

$$P_t^{Surplus} = P_t^{Surplus+} - P_t^{Surplus-} \quad \forall t \quad (C.10)$$

$$P_t^{Surplus+} \leq M_t^{+} \cdot h_t^{positive} \quad \forall t \quad (C.11)$$

$$P_t^{Surplus-} \leq M_t^{-} \cdot \left(1 - h_t^{positive}\right) \quad \forall t \quad (C.12)$$

$$T_t^{BS} = T_{t-1}^{BS} + \frac{Q_t^{SH,BT1} - Q_t^{DemandSH} - Q_t^{LossesSH}}{V^{BS} \cdot \rho^{BS} \cdot c^{BS}} \quad (C.13)$$

$$V_t^{DHWuse} = V_{t-1}^{DHWuse} + \frac{Q_t^{DHW,\,BT1} - Q_t^{DemandDHW} - Q_t^{LossesDHW}}{T^{DHW} \cdot \rho^{Water} \cdot c^{Water}} \quad (C.14)$$

$$Q_t^{SH,BT1} = x_t \cdot P^{HP} \cdot \mathrm{COP} \cdot \Delta t \quad (C.15)$$

$$Q_t^{DHW,BT1} = y_t \cdot P^{HP} \cdot \mathrm{COP} \cdot \Delta t \quad (C.16)$$

$$x_t \in \{0,1\},\ y_t \in \{0,1\},\ h_t^{Aux} \in \{0,1\},\ h_t^{positive} \in \{0,1\},\ P_t^{Surplus+} \geq 0,\ P_t^{Surplus-} \geq 0 \quad \forall t \quad (C.17)$$

Building type 3 (gas heating device with additional electric heating element)

$$\min SE = \sum_{t=1}^{Z} P_t^{Surplus+} \cdot \Delta t - \sum_{t=1}^{Z} 0.01 \cdot \left(x_t^{Electric} \cdot P^{ElectricSH} + y_t^{Electric} \cdot P^{ElectricDHW}\right) \quad (C.18)$$

subject to

$$T^{min} \leq T_t^{BS} \leq T^{max} \quad \forall t \quad (C.19)$$

$$V^{DHWmin} \leq V_t^{DHWuse} \leq V^{DHWmax} \quad \forall t \quad (C.20)$$

$$T_1^{BS} \leq T_Z^{BS} \leq T_1^{BS} \quad \forall t \quad (C.21)$$

$$V_1^{DHWuse} \leq V_Z^{DHWuse} \leq V_1^{DHWuse} \quad \forall t \quad (C.22)$$

$$x_t^{Gas} \leq h_t^{Aux} \quad \forall t \quad (C.23)$$

$$y_t^{Gas} \leq \left(1 - h_t^{Aux}\right) \quad \forall t \quad (C.24)$$

$$P_t^{Total} = x_t^{Electric} \cdot P^{ElectricSH} + y_t^{Electric} \cdot P^{ElectricDHW} + P_t^{Demand} \quad \forall t \quad (C.25)$$

$$P_t^{Surplus} = P_t^{PV} - P_t^{total} \quad \forall t \quad (C.26)$$

$$P_t^{Surplus} = P_t^{Surplus+} - P_t^{Surplus-} \quad \forall t \quad (C.27)$$

$$P_t^{Surplus+} \leq M_t^{+} \cdot h_t^{positive} \quad \forall t \quad (C.28)$$

$$P_t^{Surplus-} \leq M_t^{-} \cdot \left(1 - h_t^{positive}\right) \quad \forall t \quad (C.29)$$

$$T_t^{BS} = T_{t-1}^{BS} + \frac{Q_t^{SH,BT3} - Q_t^{DemandSH} - Q_t^{LossesSH}}{V^{BS} \cdot \rho^{BS} \cdot c^{BS}} \quad (C.30)$$

$$V_t^{DHWuse} = V_{t-1}^{DHWuse} + \frac{Q_t^{DHW,\,BT3} - Q_t^{DemandDHW} - Q_t^{LossesDHW}}{T^{DHW} \cdot \rho^{Water} \cdot c^{Water}} \quad (C.31)$$

$$Q_t^{SH,BT3} = x_t^{Gas} \cdot P^{Gas} \cdot \eta^{Gas} \cdot \Delta t + x_t^{Electric} \cdot P^{ElectricSH} \cdot \eta^{ElectricSH} \cdot \Delta t \quad (C.32)$$

$$Q_t^{DHW,BT3} = y_t^{Gas} \cdot P^{Gas} \cdot \eta^{Gas} \cdot \Delta t + y_t^{Electric} \cdot P^{ElectricDHW} \cdot \eta^{ElectricDHW} \cdot \Delta t \quad (C.33)$$

$$x_t^{Gas} \in \{0,1\}, y_t^{Gas} \in \{0,1\}, x_t^{Electric} \in [0,1],\ y_t^{Electric} \in [0,1]\ ,$$
$$h_t^{Aux} \in \{0,1\},\ h_t^{positive} \in \{0,1\},\ P_t^{Surplus+} \geq 0,\ P_t^{Surplus-} \geq 0 \quad \forall\ t \tag{C.34}$$

D. Optimization problem for generating diverse schedules.

Building type 1 (non-modulating ground-source heat pump)

$$\max\ D\ =\ \sum_{t=1}^{Z}\left(P_t^{Diversity+} + P_t^{Diversity-}\right) \cdot\ r_t \tag{D.1}$$

subject to:

$$P_t^{Diversity} = \ P_t^{Optimal} - P_t^{Total} \quad \forall\ t \tag{D.2}$$

$$P_t^{Diversity} = \ P_t^{Diversity+} - P_t^{Diversity-} \quad \forall\ t \tag{D.3}$$

$$P_t^{Diversity+} \leq \ M_t^{+} \cdot h_t^{Diverstiy+} \quad \forall\ t \tag{D.4}$$

$$P_t^{Diversity-} \leq \ M_t^{-} \cdot \left(1 - h_t^{Diverstiy+}\right) \quad \forall\ t \tag{D.5}$$

$$SE = \sum_{t=1}^{Z} P_t^{Surplus+} \cdot\ \Delta t \tag{D.6}$$

$$SE \leq SE^{optimal} + \left(SE^{optimal} \cdot buffer^{Deviaton}\right) \quad \forall\ t \tag{D.7}$$

$$h_t^{Diverstiy+} \in \{0,1\},\ P_t^{Diversity+} \geq 0,\ P_t^{Diversity-} \geq 0 \quad \forall\ t \tag{D.8}$$

and the constraints (C.2)-(C.17).

Building type 3 (gas heating device with additional electric heating element)

$$\max\ D\ =\ \sum_{t=1}^{Z}\left(P_t^{Diversity+} + P_t^{Diversity-}\right) \cdot r_t - \sum_{t=1}^{Z} 0.01 \cdot \left(x_t^{Electric} \cdot P^{ElectricSH} + y_t^{Electric} \cdot P^{ElectricDHW}\right) \tag{D.9}$$

subject to:

$$P_t^{Diversity} = \ P_t^{Optimal} - P_t^{Total} \quad \forall\ t \tag{D.10}$$

$$P_t^{Diversity} = \ P_t^{Diversity+} - P_t^{Diversity-} \quad \forall\ t \tag{D.11}$$

$$P_t^{Diversity+} \leq \ M_t^{+} \cdot h_t^{Diverstiy+} \quad \forall\ t \tag{D.12}$$

$$P_t^{Diversity-} \leq \ M_t^{-} \cdot \left(1 - h_t^{Diverstiy+}\right) \quad \forall\ t \tag{D.13}$$

$$SE = \sum_{t=1}^{Z} P_t^{Surplus+} \cdot\ \Delta t \tag{D.14}$$

$$SE \leq SE^{optimal} + \left(SE^{optimal} \cdot buffer^{Deviaton}\right) \quad \forall\ t \tag{D.15}$$

$$h_t^{Diverstiy+} \in \{0,1\},\ P_t^{Diversity+} \geq 0,\ P_t^{Diversity-} \geq 0 \quad \forall\ t \tag{D.16}$$

and the constraints (C.19)-(C.34).

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Demand response through decentralized optimization in residential areas with wind and photovoltaics

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Demand response through decentralized optimization in residential areas with wind and photovoltaics

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A paradigm shift has to be realized in future energy systems with high shares of renewable energy sources. The electrical demand has to react to the fluctuating electricity generation of renewable energy sources. To this end, flexible electrical loads like electric heating devices coupled with thermal storage or electric vehicles are necessary in combination with optimization approaches. In this paper, we develop a novel privacy-preserving approach for decentralized optimization to exploit load flexibility. This approach, which is based on a set of schedules, is referred to as SEPACO-IDA. The results show that our developed algorithm outperforms the other approaches for scheduling based decentralized optimization found in the literature. Furthermore, this paper clearly illustrates the suboptimal results for uncoordinated decentralized optimization and thus the strong need for coordination approaches. Another contribution of this paper is the development and evaluation of two methods for distributing a central wind power profile to the local optimization problem of distributed agents (*Equal Distribution* and *Score-Rank-Proportional Distribution*). These wind profile assignment methods are combined with different decentralized optimization approaches. The results reveal the dependency of the best wind profile assignment method on the used decentralized optimization approach.

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Abstract

A paradigm shift has to be realized in future energy systems with high shares of renewable energy sources. The electrical demand has to react to the fluctuating electricity generation of renewable energy sources. To this end, flexible electrical loads like electric heating devices coupled with thermal storage or electric vehicles are necessary in combination with optimization approaches. In this paper, we develop a novel privacy-preserving approach for decentralized optimization to exploit load flexibility. This approach, which is based on a set of schedules, is referred to as SEPACO-IDA. The results show that our developed algorithm outperforms the other approaches for scheduling based decentralized optimization found in the literature. Furthermore, this paper clearly illustrates the suboptimal results for uncoordinated decentralized optimization and thus the strong need for coordination approaches. Another contribution of this paper is the development and evaluation of two methods for distributing a central wind power profile to the local optimization problem of distributed agents (*Equal Distribution* and *Score-Rank-Proportional Distribution*). These wind profile assignment methods are combined with different decentralized optimization approaches. The results reveal the dependency of the best wind profile assignment method on the used decentralized optimization approach.

Keywords: Demand response, Decentralized optimization, Smart grid, Wind and PV integration, Electric heating, Electric vehicles

1 Introduction

As the share of volatile renewable energy sources (RES) like photovoltaics (PV) and wind energy has been increasing in Europe, there is a strong need for demand response to balance demand and supply [1]. Especially electric vehicles (EV) and electric heating devices coupled with thermal storage can react to the intermittent electricity production from RES in residential areas by providing the needed flexibility [2, 3]. Coupling the electricity sector with the heat and transport sector is a vital step towards using high shares of RES [4]. The demand for heat is the main energy demand in residential areas in most countries. Electic heating devices can use existing infrastructures like hot water tanks or the inertia of building mass to store energy. Thus, their operation can be shifted to times with high generation by RES without affecting the residents' comfort level.

Advanced measurement devices like smart meters and intelligent monitoring and control strategies transform the conventional electricity grid into a smart grid [5]. A smart grid can reduce the curtailment of RES and thus increase the self-consumption rate of locally generated RES. In the year 2018, around

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5.4 GWh of electricity production from RES were curtailed in Germany [6]. Wind energy caused about 97 % of the curtailed energy, while the share of PV was approximately 2 %. Furthermore, intelligent control approaches can lower the peak load in local grids and thus reduce the stress on the transformers.

Centralized scheduling-based optimization (CO) is often applied in the literature to exploit the electric load flexibilities in residential areas [7]. In CO, a central unit generates schedules for all buildings in a residential area based on demand and generation forecasts and directly controls the flexible devices. While CO leads to the overall best results, it has many significant disadvantages that make its application difficult in real-world scenarios. CO approaches infringe on the privacy of the inhabitants [8, 9] and have a high computational complexity due to the NP-hardness of scheduling problems [10]. Moreover, CO approaches are not robust against single-point failures and cyber-attacks [9, 11]. Decentralized optimization (DO) approaches, on the contrary, do not depend on a central control unit. Each building only optimizes its own goal based on local information. DO approaches have a higher level of robustness and lead to increased data-privacy while having reduced computational complexity [8, 11]. However, uncoordinated DO of the single buildings without any interaction with the other buildings in a residential area leads to results that are far away from the optimum for the entire system [9].

This paper has two main contributions. The first one is the development of a novel coordinating DO approach for scheduling-based optimization. We compare our approach to existing ones from the literature, to CO, and to a conventional control approach that is used nowadays. Moreover, we introduce and investigate methods for assigning central wind power profiles to the local optimization problems of different buildings in a residential area. For a large-scale analysis of the developed methods in a variety of scenarios, we use a multi-objective optimization problem that exploits the flexibility of electric heating devices and EVs. This paper is structured as follows: In Section 2, we sum up the related work, and in Section 3, we describe the residential area for our case study and the optimization problem. Section 4 introduces the novel DO approach and wind assignment methods. We show the results of our case study in Section 5 and summarize the paper in Section 6.

2 Related Work

We use scheduling-based approaches for exploiting the flexibility of electric heating devices and EVs in this study. These approaches determine an optimal schedule for the operation of the flexible device as the output of an optimization problem. We found several DO approaches for demand response in the literature. Commonly used techniques are decomposition methods [12–15]. A single optimization problem is broken down into multiple smaller optimization problems when using decomposition approaches. This process has to be carried out by a central control unit that defines the optimization problems for the decentralized agents.

Braun et al. [12] and Worthmann et al. [16] use hierarchical model predictive control to coordinate the DO of different agents, and Menon et al. [17] use distributed model predictive control for demand response. The authors of [8, 9, 18, 19] use approaches where no central control unit is present. For the approach introduced by Chang et al. [19], the buildings need to exchange consumption and generation data, which interferes with the privacy of the residents [12, 16]. Ramchurn et al. [18] use a time-dependent price signal and a coordinative optimization mechanism to reduce the costs and the peak load of multiple buildings in a decentralized way. The DO algorithms in [8, 9, 20, 21] are based on creating and coordinating a set of schedules for the local optimization problems of different buildings.

While a central control unit is necessary in [20, 21], the DO approaches by Kolen et al. [8] and Dengiz et al. [9] are based on a set of schedules and do not need a central controller. Kolen et al. introduce a two-stage approach to exploit the flexibility of electric heating devices. In the first step, every agent creates a pool of (near-) optimal schedules by solving their local optimization problems. The buildings afterward coordinate the selection of the individual schedules to optimize a common goal in the local grid. Dengiz et al. extend the coordinating algorithm by Kolen et al. and define a procedure to generate a diverse set of schedules for the problem of maximizing the self-consumption rate of locally generated RES. As we saw potential for improvement, we introduce a novel DO approach in this paper that is based on the coordination mechanism by Kolen et al. and the approach by Dengiz et al. for generating diverse solution sets.

Several studies also apply decomposition methods [11, 22, 23] to use wind energy for demand response in a decentralized way. In [24, 25], the authors use load aggregation methods to aggregate the electrical load and the demand response capabilities of multiple residential buildings to participate in the electricity market. Xu et al. [25] use a stochastic day-ahead economic dispatch model to improve the utilization of wind energy. Shao et al. [24] develop a real-time demand response exchange market that is capable of balancing short-term fluctuations of wind power. In addition to the novel approach for coordinating DO, we introduce methods that distribute the whole wind power profile of a residential area to the local optimization problems of different buildings. To the best of our knowledge, this is the only study that investigates methods for assigning wind power profiles to decentralized agents that apply coordinating DO approaches based on a set of schedules.

3 Optimization problem for the residential area of our case study

In this section, we describe the optimization problem for the residential area of our case study. The different building types with their corresponding heating systems are shortly described in Section 3.1, and the multi-objective optimization problem for exploiting the load flexibility potentials is explained in Section 3.2.

3.1 Different building types and heating systems

The residential area in our case studies consists of three different building types that all represent single-family buildings. Building type 1 and building type 2 have a high insulation level and use an underfloor heating system (for space heating) and a hot water tank (for domestic hot water) as thermal storage. Building type 1 uses a non-modulating ground-source heat pump and building type 2 uses a modulating air-source heat pump. Buildings belonging to the third category have a mediocre insulation standard and use a combined storage system for space heating and domestic hot water. Their primary heat source is a gas boiler. In addition to that, a modulating electric heating element is used in the combined hot water tank.

Figure 1 displays a schematic view of the residential area's local grid. Some buildings are equipped with a PV system and some have EVs that are charged at home. Furthermore, a wind turbine is connected to the local grid. All buildings use an energy management system (EMS) for controlling the flexible heating systems and the charging of the EVs. A transformer connects the local grid to other grid levels. Table A.1 (Appendix) lists the parameters of the heating systems and the EVs in the residential area. In Section 5.1, we describe how we generate the scenarios for our case study. We use the software tool *synPRO* that generates realistic synthetic data for the load profiles (demand for electricity, space heating, and DHW) and PV generation [26].

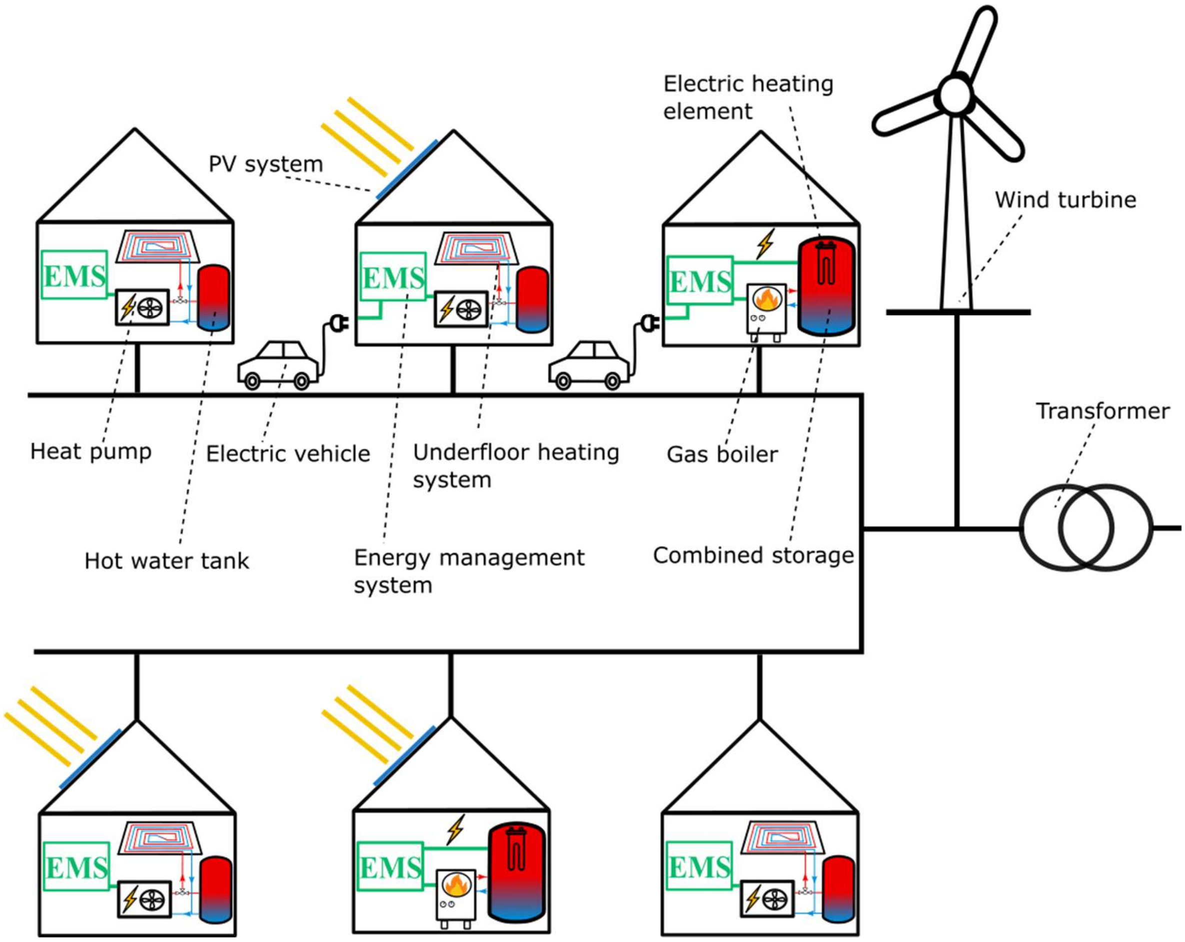

Figure 1: Local grid of the residential area

3.2 Multi-objective optimization problem

The buildings in the residential area solve an optimization problem with two objectives. The first goal is to minimize the surplus energy SE and thus to maximize the self-consumption rate of locally generated RES. Further, the buildings intend to minimize their peak loads P^{Peak}. To determine an optimal schedule for the electric heating devices and the EVs, each building solves a multi-objective optimization problem. Eq. (1) shows the objective function for the individual buildings. We combine the two objectives by using a weighted sum approach. Thus, the objective space is transformed into a one-dimensional space and we can apply conventional algorithms for solving single-objective optimization problems [27]. We multiply the two objectives by the two weights w_1 and w_2 that sum up to one. To avoid biases caused by different scales of the objectives, we divide each of the objective variables (SE and P^{Peak}) by their corresponding normalized values (SE_{Norm} and P^{Peak}_{Norm}). These values represent the optimal solution for each of the two objectives if the weight of the other objective is set to zero. They are obtained by solving two auxiliary single-objective optimization problems separately prior to the basic optimization problem with the two objectives.

$$\min \qquad w_1 \cdot \frac{SE}{SE_{Norm}} + w_2 \cdot \frac{P^{Peak}}{P^{Peak}_{Norm}} \tag{1}$$

The optimization problems have the following constraints:

- Temperature limits of the buffer storage
- Volume limits of the hot water tank
- Heat pump cannot heat up both storages of a building simultaneously (building types 1 and 2)
- Power constraint of the heating device
- Power and availability constraint for charging the EV
- State of charge (SOC) limitation constraints for the EV

The following variable definitions are part of the optimization problem:

- Amount of surplus energy
- Power of RES (wind and PV)
- Peak load
- Difference equation for the temperature of the buffer storage (building types 1 and 2)
- Difference equation for the volume of the hot water tank (building types 1 and 2)
- Difference equation for the energy content of the combined storage (building type 3)
- Difference equation for the SOC of the EV

The coordinating DO approaches of Section 4.2 require the buildings to have not only one schedule but a set of multiple schedules. We use the method introduced in [9] to generate a diverse solution pool that leads to much better results than the conventional procedure of commercial solvers to collect and store the solutions found during the optimization. For this purpose, all buildings have to solve another optimization problem that maximizes the diversity of a new solution to a given optimal schedule. The full commented mathematical representation of the basic problem (described in this section) and the diversity maximization problem (described in [9]) for all three building types can be found at the data repository hosting the supplementary materials for this paper [28]. Moreover, we uploaded the commented code (written in the modeling language *GAMS*) for all optimization problems used in our study.

4 Decentralized optimization

We describe methods for assignment of wind power to buildings in Section 4.1. In Section 4.2, we explain two coordination approaches for decentralized optimization from the literature and introduce a novel approach that is based on the two other ones.

4.1 Methods for assignment of wind power to decentralized agents

To assign a central wind power profile to the local optimization problems of different buildings, we propose and investigate two simple methods. Figure 2 illustrates these two methods for the distribution of an entire wind power profile to five buildings. The upper diagram shows an exemplary profile of a small wind turbine that should be distributed to the different buildings such that they can incorporate the generated wind power into their optimization procedures. The left-hand picture depicts the assignment when using the *Equal Distribution (ED)* method. The entire profile is equally distributed to the five buildings. Eq. (2) shows the formula to calculate the wind power assigned to building i. For every time slot t, the power value of the entire wind power profile $P_t^{WindOverall}$ is divided by the number of buildings. Thus, each building gets an equal share of wind energy. The buildings include these assigned profiles in their local optimization problems by adding the corresponding values to their PV generation profiles.

$$P_{t,i}^{Wind} = \frac{P_t^{WindOverall}}{\# \, Buildings} \qquad \forall \, i \in \{1, \dots, B\}, \forall \, t \tag{2}$$

The picture on the right-hand side of Figure 2 shows the *Score-Rank-Proportional Distribution (SRPD)* method. In the first step, a score is calculated for every building by using Eq. (3). The power of the building's electric heating device $P_i^{ElectricalHeating}$ and the power for the EV charging station $P_i^{EVCharging}$ are subtracted from the peak power of the PV system P_i^{PVPeak}. This score roughly quantifies the expected self-consumption rate of locally generated PV. Buildings that have a high score are more likely to generate surplus energy since their flexible electrical demand might not match their PV generation. As all information from the buildings is static, there is no need to measure any data from the buildings or to monitor demand profiles, which would infringe on the residents' privacy. In the next step, the buildings are ranked according to this score. The building with the highest score gets the highest rank and the building with the lowest score gets the lowest rank. In the example of Figure 2, building 5 has the lowest score and thus the lowest rank ($Rank_5 = 5$) and building 1 has the highest score and thus the highest rank ($Rank_1 = 1$). *SRPD* uses Eq. (4) for assignment of the wind power profiles to the buildings. The entire wind power for each time slot is divided by the sum of ranks (in this example, the sum of ranks is $\sum_i^B Rank_i = 1 + 2 + 3 + 4 + 5 = 15$). This value is then multiplied by the rank of the building which leads to an assignment of more wind power to buildings with lower ranks, as is illustrated in Figure 2. We evaluate the two methods *SRPD* and *ED* in Section 5.2.

$$\text{Score}_i = P_i^{PVPeak} - P_i^{ElectricalHeating} - P_i^{EVCharging} \tag{3}$$

$$P_{t,i}^{Wind} = \frac{P_t^{WindOverall}}{\sum_i^B Rank_i} \cdot Rank_i \qquad \forall \, i \in \{1, \dots, B\}, \forall \, t \tag{4}$$

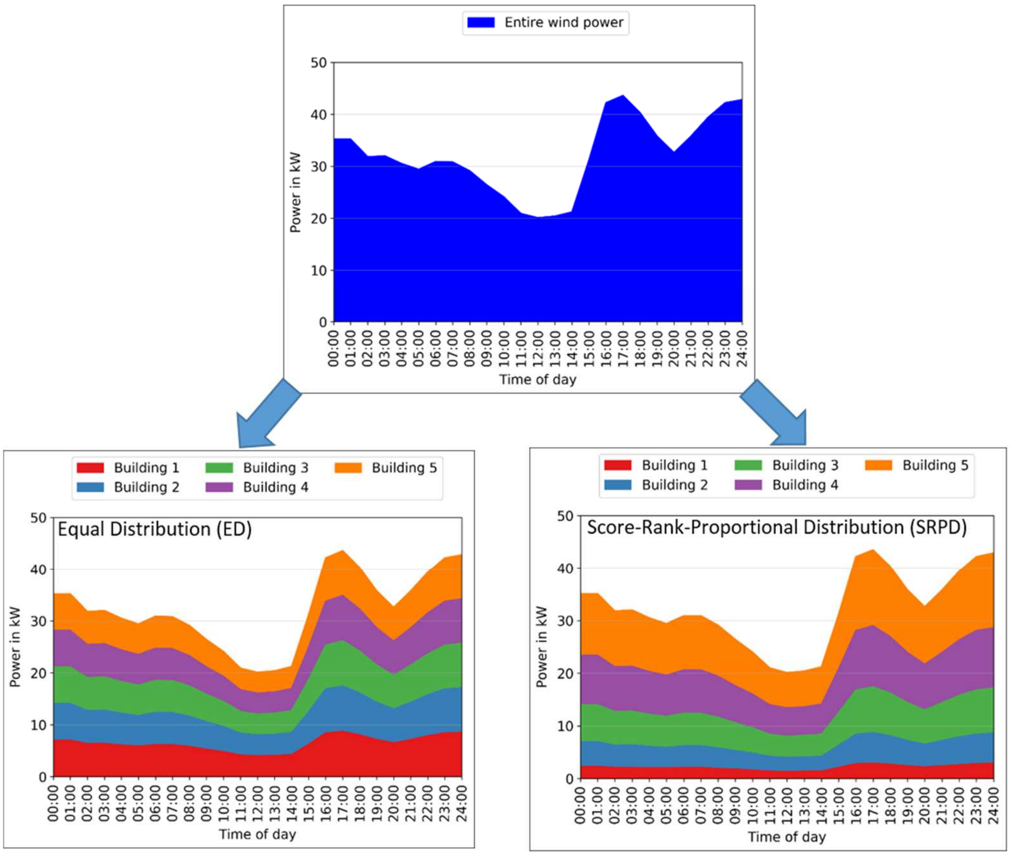

Figure 2: Two methods for assignment of wind power to buildings

4.2 Coordination methods for decentralized optimization

4.2.1 Iterative Desync Algorithm (IDA)

The *Iterative Desync Algorithm* (*IDA*), developed by Kolen et al. [8], is the basic approach for the two other coordinating DO algorithms used in this paper. Figure 3 schematically displays *IDA* in a residential area. In the first step, all buildings simultaneously create a solution pool that consists of multiple schedules by solving their local optimization problems (see Section 3.2). Afterward, the buildings coordinate the selection of the individual schedules. All buildings are ordered in a cycle and have a predecessor and successor each. Furthermore, the buildings store local views on the residential areas' load profiles (profiles resulting from generation and demand). In each iteration, each building successively selects the schedule out of its solution pool that leads to an optimal value of a common objective. This common objective of our study is based on the load profiles of the residential area. It can be calculated by using the weighted sum of the surplus energy in the residential area, and the peak load (see Eq. (1)). The building then updates the common load profiles of the residential area based on their selected schedules (demand profile) and generation profiles. Next, the building forwards the updated profiles to the next building in the cycle, which performs the same procedure. The algorithm terminates if none of the buildings changes its previously selected schedule for one iteration through the cycle.

To guarantee the privacy-friendliness of this algorithm, the first building to start with this process adds a random noise vector to its load and generation profiles during the first iteration and stores this vector. During the second iteration through the cycle, this building removes the previously added random noise from the load profiles of the residential area.

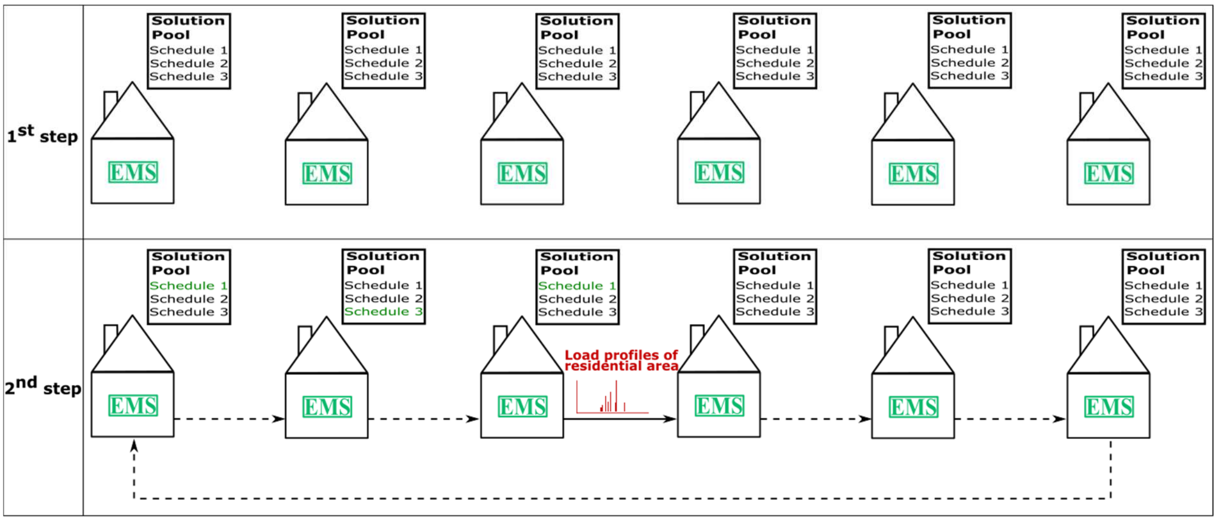

Figure 3: Decentralized optimization approach IDA in a residential area [9]

4.2.2 Parallel Successive Cluster Optimization with IDA (PSCO-IDA)

The *PSCO-IDA* algorithm groups the buildings of the residential area into multiple clusters of a specific size. The number of steps for *PSCO-IDA* is proportional to the number of buildings in a cluster. Figure 4 shows the algorithm for clusters of size two, as this cluster size led to the best results in our experiments. In the first step, only the first of the two buildings in each cluster solve their local optimization problems in parallel and thus generate a solution pool. Afterward, they forward the resulting surplus power profiles to the next buildings in the clusters, which use these as an input to their local optimization problems. In contrast to *IDA*, the results of the first buildings' optimization problems directly influence the solution pool of the second buildings in the clusters. In the last step, all buildings of the residential area use *IDA* to coordinate the selection of the schedules. A more detailed description of *IDA* and *PSCO-IDA* can be found in [8, 9].

Instead of randomly assigning buildings to the clusters, we use a simple ordering heuristic that is introduced in [9] and that led to strongly improved results. For each building, a score is calculated by using Eq. (3). The building with the highest score and the building with the lowest score are grouped into the first cluster. For the second cluster, we use the building with the second-highest and the second-lowest score. We successively do this until each building belongs to one cluster. The basic idea behind this clustering is that the buildings with low PV generation can use the surplus power of buildings with high PV generation for their flexible devices as buildings with higher scores tend to generate more surplus energy.

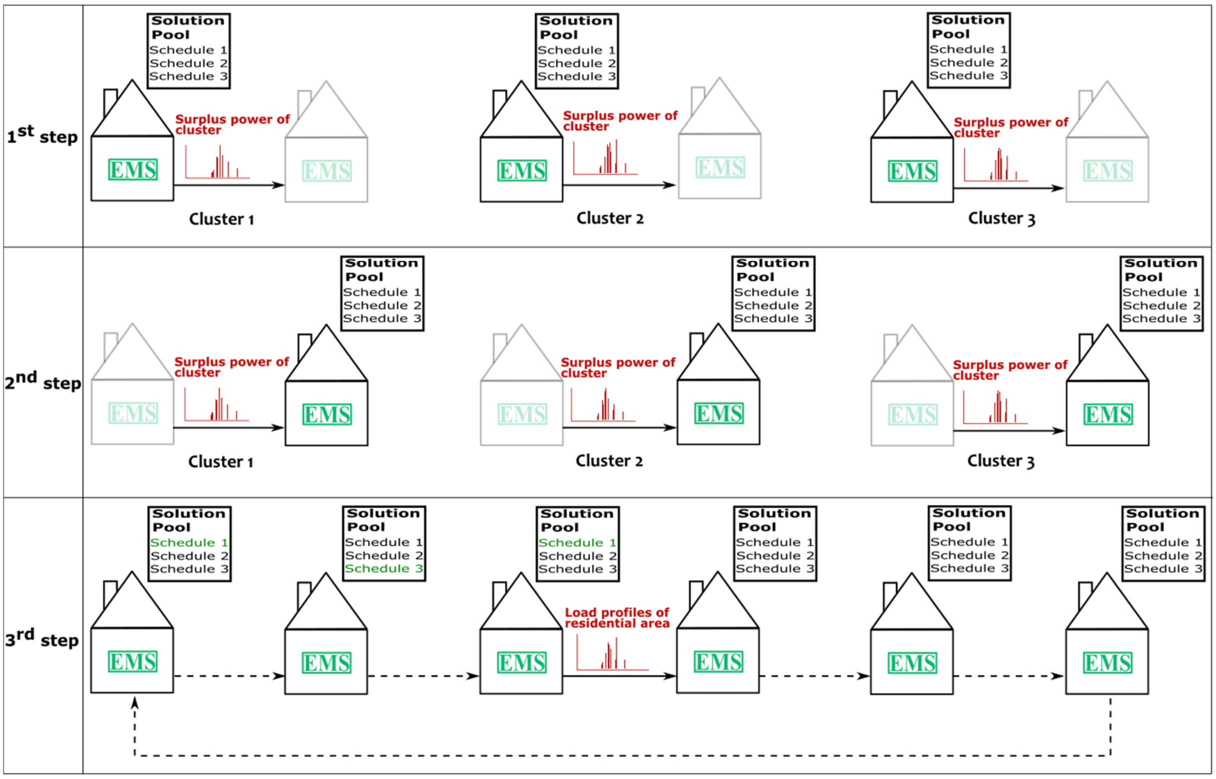

Figure 4: PSCO-IDA algorithm with two buildings per cluster [9]

4.2.3 Sequential Parallel Cluster Optimization with IDA (SEPACO-IDA)

The *SEPACO-IDA* algorithm is one of the two main contributions of this paper. It efficiently combines the *PSCO-IDA* and *IDA* algorithms. As in *PSCO-IDA*, the buildings are divided into an arbitrary number of clusters. In *SEPACO-IDA*, the number of steps is proportional to the number of clusters. Figure 5 illustrates the algorithm for two clusters. We investigated the algorithm with different numbers of clusters, and two clusters led to the best results while having the lowest computational time. In the first step, the buildings of the first cluster simultaneously generate a solutions pool and use *IDA* for selecting individual schedules. Afterward, the resulting load profiles of the cluster are sent to all buildings from the second cluster (2nd step). Next, the buildings of the second cluster likewise generate a solution pool and use *IDA* for coordination. The resulting load profiles of the first cluster influence the local optimization problems of the buildings in the second cluster. The surplus power profile of the previous clusters can be assigned to the building of the new cluster by using the methods explained in Section 4.1 for the wind power assignment. In the last step, all buildings of the residential area use IDA to coordinate the selection of the schedules jointly. The difference to *PSCO-IDA* is that in *SEPACO-IDA*, the buildings in one cluster generate their solution pool simultaneously and not successively. Moreover, the buildings use *IDA* for the coordination within every cluster, and optimization of the different clusters is done sequentially and not in parallel. As no building receives direct information from another single building, *SEPACO-IDA* has a higher level of privacy compared to *PSCO-IDA*.

We investigated different approaches for assigning buildings to the clusters. The best result was obtained when using the score function of Section 4.1 (Eq. (3)) and putting the buildings with high scores into the first cluster and the buildings with low scores into the second cluster. We also tried a random assignment of buildings to the clusters and assignments based on either an increasing sum of scores per cluster or a similar sum of scores per cluster. However, our approach with a decreasing sum of scores per cluster overall led to the best solutions. We analyze the three DO approaches and compare them to CO and a conventional control approach in Section 5.3.

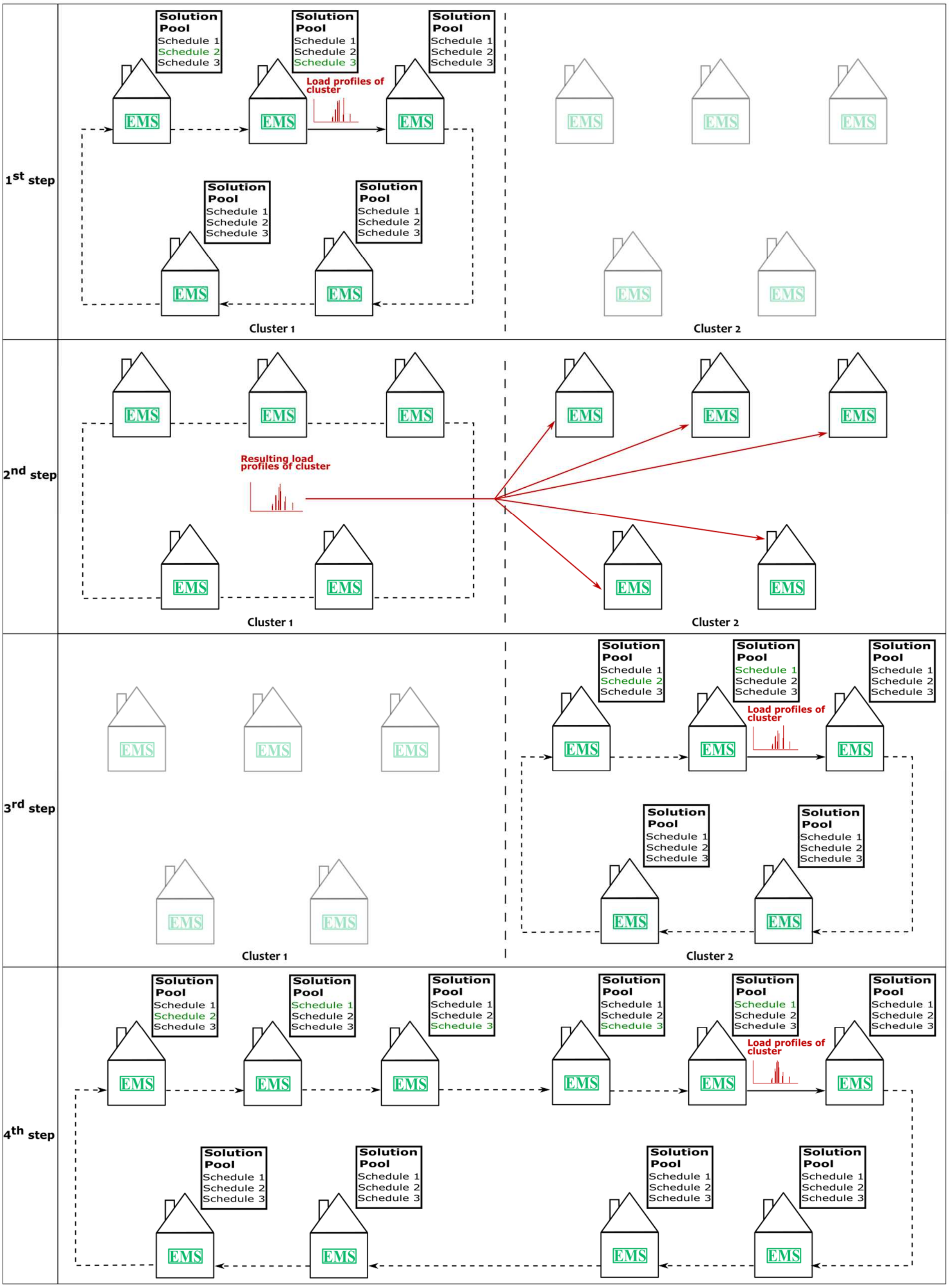

Figure 5: SEPACO-IDA algorithm with two clusters

5 Results

In this section, we evaluate the methods developed in Section 4. Section 5.1 describes the scenarios used for our analysis. In Section 5.2, we compare the two wind assignment methods and in Section 5.3, we show the results for the different optimization approaches.

5.1 Scenarios for the analysis

To analyze the developed methods, we define base case scenarios for 31 days. We randomly choose 31 days with mediocre to high PV or wind energy generation from the heating period in Germany (October – March). In the base case scenarios, we use 15 buildings for each of the three building types, resulting in 45 buildings. Of these, 15 have two residents each, whereas four persons live in each of the other 30 buildings. The average PV peak of buildings which have a PV system on their rooftop is 7 kW with a maximum positive and negative deviation from the average peak power of 3 kW. This means that the values for the PV systems' peak power of the different buildings are uniformly distributed between 4 kW (7 – 3) and 10 kW (7 + 3). The share of buildings with a PV system is 50 % in the base case scenarios. Ten of the buildings have an EV that is charged at home. We choose two types of EVs (*Opel Ampera-e* and *BMW i3*) and assume that at the beginning of the optimization horizon, the SOC of all vehicles is at 0.5 (50 %). This value is also the target SOC for the end of the optimization horizon. We use the driving and availability patters from [29] as mobility data for the EVs. Table A.1 in the Appendix lists the technical parameters of the EVs and the charging stations. For wind generation, we use profiles of the wind turbine *Nordex N27/150* with a capacity of 100 kW generated by the web tool *Renewable.ninja* [30].

In addition to the base case scenarios, we generate several further scenarios for our analysis. To this end, we use a Monte Carlo sampling method for the different parameters. Table 1 lists the relevant parameters of the residential area and their average, minimum, and maximum values. For all scenarios, the optimization horizon is one day with a time resolution of five minutes. We implemented the optimization problems in the modeling language *GAMS* with *Cplex* as the solver and used *Java* for the simulations. The solution pool for all coordinating approaches consists of five different solutions, as this leads to a good trade-off between the quality of the results and computational time [9].

Table 1: Parameters for the Monte Carlo sampling

Parameter	Average	Min	Max
Number of buildings type 1	15	5	25
Number of buildings type 2	15	5	25
Number of buildings type 3	15	5	25
PV peak power [kW]	7	3	11
Maximal deviation from PV peak power [kW]	1.5	0	3
Share of buildings with PV [%]	50	25	75
Number of EVs	11.5	2	21
Power of wind turbine [kW]	140	30	250

5.2 Wind assignment methods

For the evaluation of the two different wind assignment methods of Section 4.1, we use six different optimization approaches in combination with the wind assignment methods for the base case scenarios. Figure 6 shows the optimality percentages of the two wind assignment methods for the different optimization approaches averaged over the 31 base case scenarios with wind. Per definition, CO leads to an optimality of 100 %. In addition to the three coordination methods for DO described in Section 4.2, we include a conventional control approach (hysteresis control) that is current practice for today's heating systems, and a DO approach without any coordination mechanism in the evaluation. The analysis shows that for CO and Conventional Control, the two assignment methods *ED* and *SRPD* lead to similar results since CO and *Conventional Control* do not depend on the assignment of wind power profiles to decentralized entities. The slight difference for *Conventional Control* occurs because of the random decision on whether to heat up or cool down the thermal storage at the beginning of a day.

For the DO approaches, the application of *ED* and *SRPD* leads to different results. While for DO without coordination and for *IDA*, an equal distribution (*ED*) of the centralized wind power profile leads to better results, for *PSCO-IDA* and *SEPACO-IDA*, the *Score-Rank-Proportional Distribution (SRPD)* yields better results. This might be explained by the fact that for *PSCO-IDA* and *SEPACO-IDA*, a score roughly quantifying the expected self-consumption rate of the different buildings is already used for the generation of the clusters. A second assignment based on such a score might interfere with the notion of the initial clustering. *IDA* and *DO* without coordination do not make use of such a score. This might be the reason why consideration of the score brings these optimization approaches closer to optimality, as Figure 6 indicates.

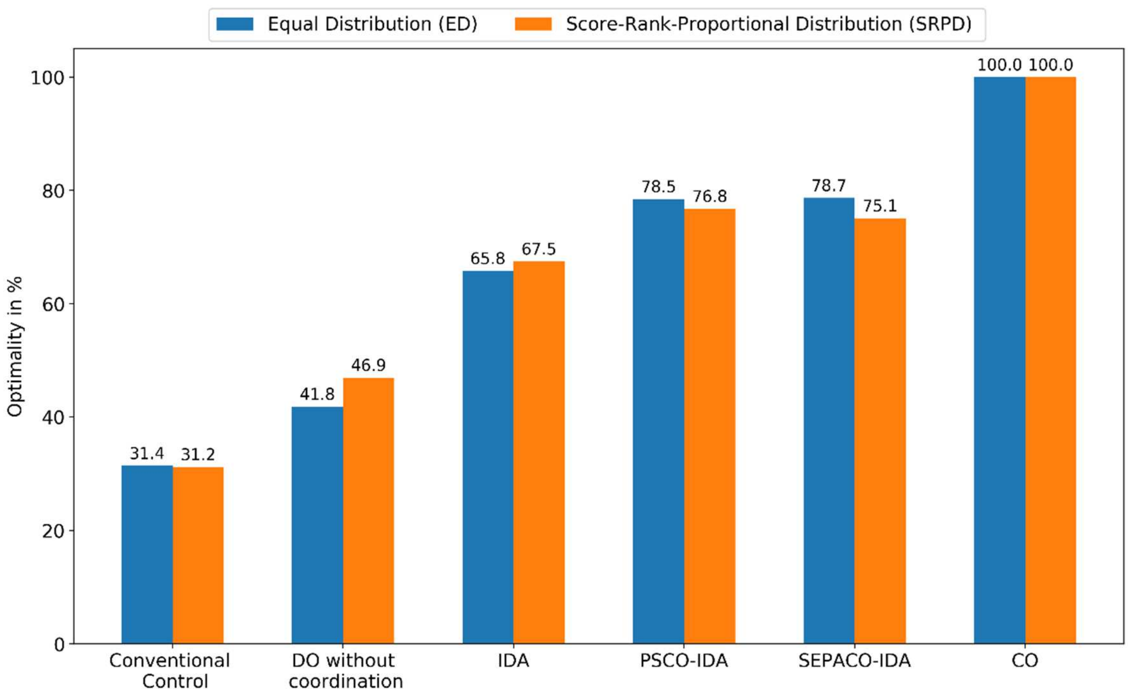

Figure 6: Optimality comparison of the two wind assignment methods for the different optimization approaches averaged over the base case scenarios

5.3 Optimization approaches

To compare and evaluate the coordination methods for DO, we use scenarios with and without wind power generation. PV is included in all scenarios. For the scenarios with wind energy generation, we use the 31 days of the base case and generate four additional scenarios per day by using the Monte

Carlo sampling method. This leads to a total of 155 scenarios. We ran all scenarios with five different combinations of weight coefficients. Figure 7 displays the optimality of the methods used with different weights for the objectives averaged over all scenarios with wind and PV generation. For all weight combinations, *Conventional Control*, as expected, leads to the worst results having optimality percentages of around 30 %. The figure clearly shows that if all buildings only optimize their own goal without interacting with the other buildings, the result is quite far away from the optimal solution. For all weights, DO without coordination leads to optimality percentages below 50 %. The results reveal that *SEPACO-IDA* outperforms the other two coordinating DO approaches *IDA* and *PSCO-IDA* having optimality percentages of between 87 % and 79 %. The differences to *PSCO-IDA* are small (between 0.8 % and 2.4 %), while the improvements compared to *IDA* are significant (between 11.1 % and 13.3 %). Figure 7 shows that the more the emphasis is on the second goal (reducing the peak load), the worse the results become for all three coordinating DO approaches (*IDA*, *PSCO-IDA*, and *SEPACO-IDA*).

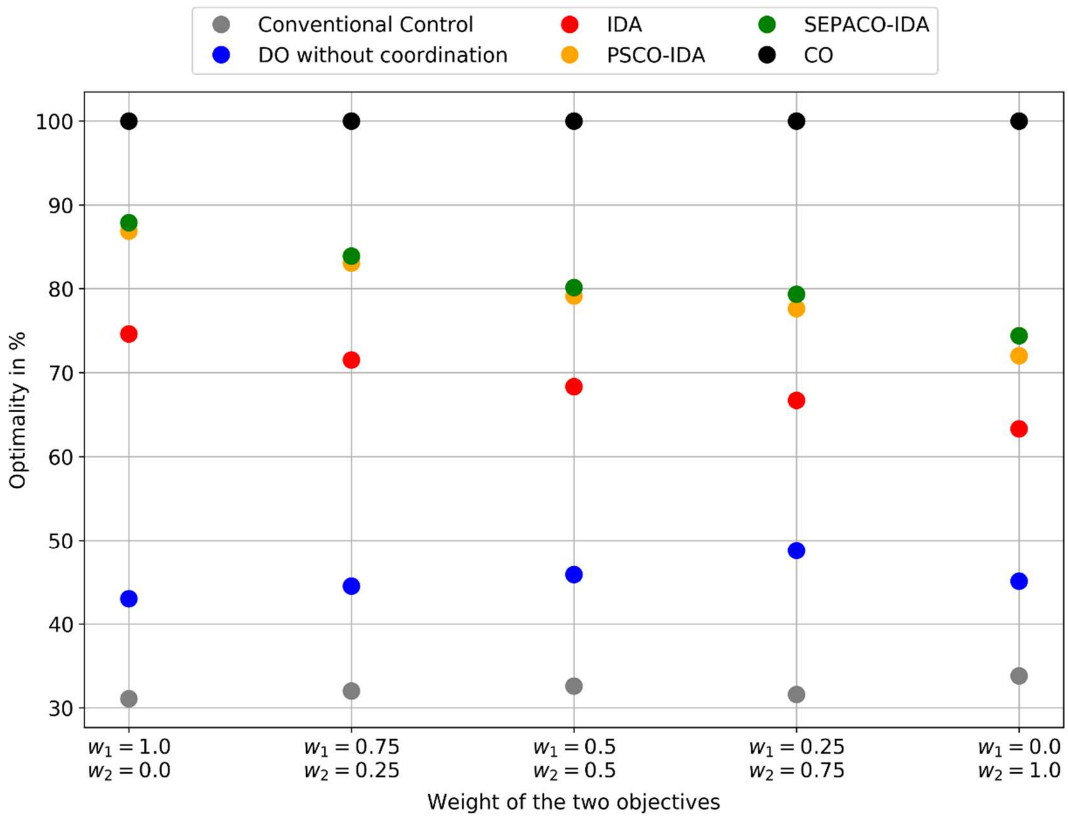

Figure 7: Optimality comparison of the used optimization approaches with different weight combinations for the objectives averaged over all scenarios with wind and PV (w_1: Weight for the Surplus Energy, w_2: Weight for the Maximum Load)

Table 2 lists the average results of the scenarios with wind and PV for different weights of the objectives. For *Conventional Control*, the values of the surplus energy and the maximum load do not depend on the weights of the objectives. For all four DO approaches, the results significantly change for the three weight combinations that have nonzero values for both objectives ([$w_1 = 0.75$, $w_2 = 0.25$], [$w_1 = 0.5$, $w_2 = 0.5$], [$w_1 = 0.25$, $w_2 = 0.75$]). Surprisingly, when putting the whole weight and thus the emphasis only on one objective ([$w_1 = 1.0$, $w_2 = 0.0$] or [$w_1 = 0.0$, $w_2 = 1.0$]), the results for the single objective are worse than the corresponding result for that objective when also considering the other objective to some degree. This means that decreasing the weight for one objective from 1.0 to 0.75 led to better results for that objective. This counterintuitive outcome can be explained by the optimization approach used for creating the solution pool for the DO approaches explained in [9]. A diverse solution pool with different schedules is vital for the DO approaches, as the coordination procedure is not an exact optimization algorithm but a heuristic. Using weights for both objectives leads to higher flexibility for the generation of a solution pool. This eventually can lead to better results for the whole residential area, although the results for the individual buildings might be worse.

For CO, the results among the combined weights ([w_1 = 0.75, w_2 = 0.25], [w_1 = 0.5, w_2 = 0. 5], [w_1 = 0.25, w_2 = 0.75]) are almost identical. The results of the objective *Maximum Load* for the combined weights are equal to the one of the single-objective optimization of the peak load ([w_1 = 0.0, w_2 = 1.0]). The results of the objective *Surplus Energy* are only slightly worse for the combined objectives compared to the single-objective optimization ([w_1 = 1.0, w_2 = 0.0]). This indicates that the objectives in our case studies are not contrary to each other. The surplus energy can simultaneously be minimized with the maximum load because the power of the RES mainly causes the peak load. However, if the full focus is on one objective only, the other objective is neglected, which leads to very poor results for that objective. This is valid for CO and all DO approaches. Thus, for scenarios with high power generation by RES in residential areas where the peak load at the transformer is mainly caused by feeding power of RES from the local grid into the whole grid, the consideration of a combined objective function is highly beneficial.

Table 2: Average results of the scenarios with wind and PV for different weight combinations of the objectives (Surplus Energy in kWh and Maximum Load in kW)

Objectives	Conventional Control	DO with no coordination	IDA	PSCO-IDA	SEPACO-IDA	CO
Surplus Energy (Weight w_1 = 1.0)	666.8	481.8	278.0	238.7	236.0	207.7
Maximum Load (Weight w_2 = 0.0)	111.4	93.2	77.1	72.6	72.5	75.0
Surplus Energy (Weight w_1 = 0.75)	666.8	475.6	276.8	236.8	234.1	210.3
Maximum Load (Weight w_2 = 0.25)	111.4	82.4	64.3	56.9	56.7	37.6
Surplus Energy (Weight w_1 = 0.5)	666.8	477.8	279.5	238.6	237.1	210.3
Maximum Load (Weight w_2 = 0.5)	111.4	78.2	60.9	53.5	52.4	37.5
Surplus Energy (Weight w_1 = 0.25)	666.8	477.8	283.2	239.7	239.6	210.4
Maximum Load (Weight w_2 = 0.75)	111.4	75.7	58.4	50.5	49.1	37.5
Surplus Energy (Weight w_1 = 0.0)	666.8	637.4	361.4	341.0	343.2	370.1
Maximum Load (Weight w_2 = 1.0)	111.4	83.1	59.3	52.1	50.4	37.5

As the authors of [9] only test the algorithm *PSCO-IDA* in scenarios with PV, but without wind energy, we also evaluate the newly developed algorithm *SEPACO-IDA* in scenarios without wind. Figure 8 illustrates the optimality percentages of the used control approaches with different weights for the objectives averaged over all scenarios with PV and no wind. For this purpose, we used the base case scenarios without wind and additionally generated three scenarios for each day, leading to a total of

124 scenarios. The results show that *SEPACO-IDA* again leads to better results compared to *IDA* and *PSCO-IDA* (for the combined weights [$w_1 = 0.25$, $w_2 = 0.75$], *PSCO-IDA* and *SEPACO-IDA* have similar results). The optimality percentages of *PSCO-IDA* and *SEPACO-IDA* do not vary strongly for the different weight combinations. In contrast, the difference to *IDA* becomes smaller with an increasing emphasis on the objective of minimizing the peak load.

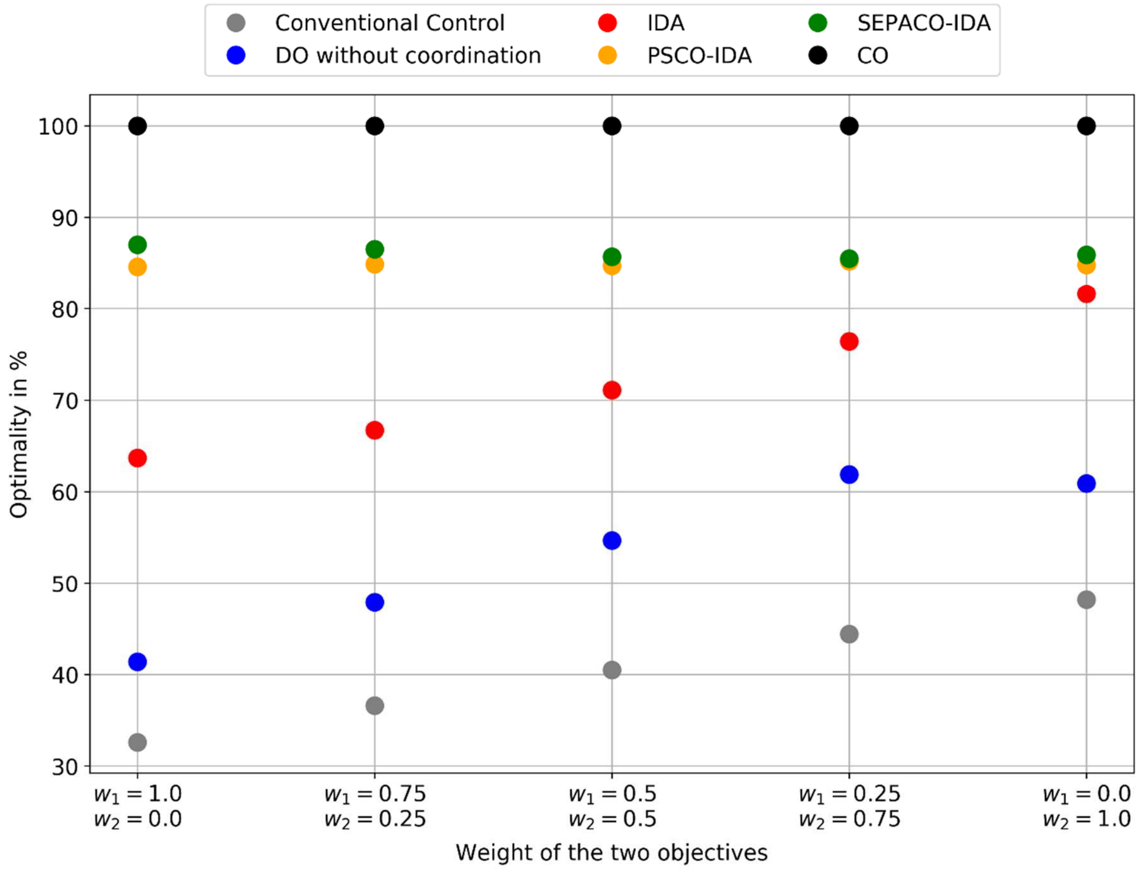

Figure 8: Optimality comparison of the used optimization approaches with different weight combinations for the objectives averaged over all scenarios with PV and no wind (w_1: Weight for the Surplus Energy, w_2: Weight for the Maximum Load)

Table 3 shows the average runtimes and number of coordination rounds of the optimization approaches for the base case scenarios with wind and PV. CO has the highest runtime requiring around 20 times more time than *SEPACO-IDA*. We used an *Intel i7 3930K* system with 3.2 GHz and 64 GB RAM for the analysis. The MIP gap for both the centralized and the decentralized optimization problems was set to 0.1 %. Surprisingly, *SEPACO-IDA* led to a similar number of coordination rounds for selection of the schedules as *IDA* and fewer coordination rounds compared to *PSCO-IDA*. Although *SEPACO-IDA* needs coordination for each cluster, the final *IDA* step converges rather quickly. We included the load profiles of all buildings for all base case scenarios to the uploaded supplementary materials of this paper [28]. Moreover, we added result tables, which include detailed information about the results and the configurations of every single scenario to the supplementary materials.

Table 3: Average runtimes and number of coordination rounds of the optimization approaches for the base case scenarios

Approach	Runtime [s]	Number of coordination rounds
Conventional Control	2	-
DO without coordination	13	-
IDA	47	4.7
PSCO-IDA	76	4.9
SEPACO-IDA	86	4.7
CO	1770	-

5.4 Critical appraisal

For our study, we made some simplifications. We assumed perfect foresight regarding the generation and demand of the buildings for all optimization problems. To apply the investigated methods to real-world scenarios, they have to be combined with forecasts and uncertainty handling methods for scheduling-based optimization like [31, 32]. Furthermore, we assumed that all buildings agree to participate in the decentralized optimization without any incentive. The focus of this study was to investigate different optimization approaches from a system perspective and not to analyze market strategies for incentivizing building owners to use their flexibility or to trade their generated electricity locally.

We merely tested two different methods for wind power assignment. Many other possible criteria for the assignment of wind power profiles to the local optimization problems of decentralized entities exist. Also, for the coordination approach *SEPACO-IDA*, clustering methods based on other score functions or ranking schemes have not been analyzed in detail. Doing a large-scale analysis of different methods for generating the clusters could even improve *SEPACO-IDA*.

6 Summary and conclusion

In this paper, we developed a novel coordination mechanism for optimally using flexible electrical loads in a decentralized way in order to react to the volatile supply from renewable energy sources in a residential area. The *Sequential Parallel Cluster Optimization with IDA (SEPACO-IDA)* combines two coordination algorithms from the literature for decentralized optimization that are based on a set of schedules (*PSCO-IDA* and *IDA*). In a case study that consists of a high number of scenarios, we compared our developed approach to existing approaches for decentralized optimization, to a conventional control approach and a centralized optimization. The load flexibility in the residential areas comes from electric heating devices and electric vehicles. The results reveal the superiority of *SEPACO-IDA* over the other coordinating approaches for decentralized optimization. Further, our analysis demonstrates that uncoordinated decentralized optimization leads to fairly bad results. In addition to that, we investigated the two methods *Equal Distribution* and *Score-Rank-Proportional Distribution* for assigning a wind power profile to the local optimization problems of decentralized agents. These methods are used in combination with decentralized optimization approaches. While for the uncoordinated decentralized optimization and *IDA*, the wind assignment method *Score-Rank-Proportional Distribution* yields better results, the two decentralized optimization approaches *SEPACO-IDA* and *PSCO-IDA* profit more from the *Equal Distribution* method.

All introduced methods are easy to implement and preserve the privacy of the residents. Our study shows the suboptimality of the currently used conventional control approaches and the crucial advantages of coordinating decentralized optimization. Sustainable energy systems with high shares of renewable energy sources can profit from the application of the developed methods. They can help to overcome the challenges brought about by the weather-dependent electricity generation of wind turbines and photovoltaic systems.

Future work could compare the used scheduling-based decentralized optimization approaches to rule-based or to machine-learning-based control approaches. Moreover, different criteria (like the sum of the total electricity consumption) for the assignment of wind power profiles to decentralized optimization problems of buildings should be investigated. Designing novel market mechanisms to offer incentives to building owners to participate in demand response programs is an essential task for exploiting the load flexibilities in residential areas and should be analyzed in future work.

Supplementary materials

We added the following supplementary materials to an open-source online data repository [28] hosted at Mendeley Data (https://data.mendeley.com/datasets/8jx97kfjxg/2):

- Full mathematical description of all optimization problems with explanations of the equations
- Resulting load and temperature profiles of the buildings for the base case scenarios
- Result tables with detailed information about the scenarios and their results
- Commented code (in the modeling language *GAMS*) of the decentralized optimization problems for the different building types and the centralized optimization problem

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Appendix

Parameters of the residential area

Table A.1: Parameters of the residential area

Parameter	Value	Source	Comment
Heated area of the buildings	140 m^2	[33]	Assumption: Not all rooms in the cellar are heated
Concrete width (for the underfloor heating system)	7 cm	[34]	DIN standard 18560 for screeds in building construction
Density of concrete	$2400 \frac{kg}{m^3}$	[35]	European standards for concrete EN 206-1
Heat capacity of concrete	$1000 \frac{J}{kg \cdot K}$	[35]	European standards for concrete EN 206-1
Temperature range of the underfloor heating system	20 – 22 °C	[36]	Assumptions for optimal comfort
Temperature range of the hot water tank (buffer storage)	30 – 45 °C	[37]	
DHW tank volume	150 l, 200 l	[38]	200 l for 4 residents, 150 l for 2
Losses of space heating	45 W		Assumption
Losses of DHW tank	35 W	[39]	2nd highest efficiency class (EU regulations 814/2013)
Supply temperature of the underfloor heating system	30 °C	[36]	
Supply temperature of the hot water tank (buffer storage)	60 °C	[37]	
Supply temperature of the hot water tank (DHW)	45 °C	[41]	
Energy content of the combined storage	14 kWh		
Electrical power of the heating devices	1.2 kW (BT 1), 3 kW (BT 2, BT 3)		Thermal power of the gas heating device: 12 kW
COP of the air-source heat pump for ΔT=28 K	3.8	[40]	Similar value as model *LA 28TBS* from *Glen Dimplex*
COP of the air-source heat pump for ΔT=42 K	2.8	[40]	Similar value as model *LA 28TBS* from *Glen Dimplex*
COP of the ground-source heat pump for ΔT=35 K	4.7	[42]	Similar value as model *SIK 6TES* from *Glen Dimplex*
COP of the ground-source heat pump for ΔT=45 K	3.7	[42]	Similar value as model *SIK 6TES* from *Glen Dimplex*
Battery capacity *BMW i3*	37.9 kWh	[43]	
Charging efficiency *BMW i3*	85 %	[43]	
Energy consumption per 100 km *BMW i3*	13.9 kWh	[43]	
Battery capacity *Opel Ampera-e*	60 kWh	[43]	
Charging efficiency *Opel Ampera-e*	89 %	[43]	

Parameter	Value	Source	Comment
Energy consumption per 100 km *Opel Ampera-e*	17.5 kWh	[43]	
Maximal charging power for home charging	4.6 kW	[44]	Wallbox: *KEBA KeContact P30*
Average length of rides *BMW i3 (Opel Ampera-e)*	35 km (45 km)	[45]	Assumptions inspired by the German Mobility Study

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Uncertainty handling control algorithms for demand response with modulating electric heating devices

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***Abstract*—The flexibility of electric heating devices coupled with thermal storage can help to cope with the increasing share of volatile renewable energy sources in the electricity grid. Scheduling-based demand response approaches for optimally exploiting these flexibilities use demand and generation predictions to calculate an operative schedule of the heating devices. Due to deviations between predicted and real energy profiles, additional uncertainty handling methods are essential which adjust the actions imposed by the schedule to the current situation. In this paper, we introduce corrective control algorithms for buildings in smart grids with modulating heating devices that can compensate the uncertainties of predictions. The results show that our developed approaches avoid violations of the inhabitants' comfort limits and decrease the surplus energy (and thus increase the self-consumption rate) of photovoltaic systems compared to a conventional control strategy. Further, our analysis reveals that uncertainties affect the load shifting potentials of electric heating devices and lead to increased surplus energy.**

***Index Terms*—Demand response, control algorithms, uncertainties, electric heating devices, home automation, smart grids**

I. Introduction

Demand response is becoming more and more important for future energy systems, as it allows to cope with the increasing share of volatile renewable energy sources like wind or photovoltaics (PV). Among the flexible loads that are suitable for demand response in the residential area, electric heating devices (e.g heat pumps, electric storage heaters, electric heating elements) seem promising as they can use existing infrastructure for thermal storage like the mass of the building or a hot water tank. The operation of the flexible devices can thus be shifted in time. Opposed to rule-based control approaches for flexible loads (see for example [1]), scheduling-based approaches use a model and predictions of future demand and generation to calculate a schedule for the flexible devices. However, in reality the predictions are erogenous which makes additional correcting algorithms necessary. These algorithms adjust the recommended actions by previously calculated schedules with the aim of reacting to the current situation.

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In this paper, we develop novel uncertainty handling approaches for buildings in smart grids with modulating electric heating devices. In Germany, most of the offered heat pumps by the year 2020 are assumed to be modulating heat pumps [2] that can not only be switched on and off but have continuously adjustable power outputs and are thus especially suitable for smart grids. The remainder of this paper is structured as follows: Section II summarizes the relevant literature and Section III defines the optimization problem for residential buildings with thermal storage. The two corrective control algorithms are explained in Section IV and the results of our analysis are shown in Section V. This paper ends with a conclusion in Section VI.

II. Literature review

In literature different approaches are used for exploiting the flexibility of electrothermal loads under the consideration of uncertainties. Gao et al. [3] and Stoyanova et al. [4] use corrective algorithms which adjust the control actions of a schedule that was calculated before with the use of predicted input data. The methods only overrule the initial control actions if a constraint violation is about to occur. In [5] and [6] model predictive control (MPC) is used to cope with the uncertainties of demand and generation forecasts. As MPC approaches iteratively solve an optimization problem and merely implement the first results of the optimization, they can immediately react to changes in the input parameters of the optimization. Arnold et al. [7] also apply MPC and use, in addition to hard constraints, soft constraints for the storage which can be violated. The authors of [8] and [9] tackle the problem of uncertainties in predictions by using a two-stage stochastic optimization. Barbato et al. [10] use a control system that triggers a rescheduling of the flexible devices' activities if events which were unexpected when calculating the initial schedule, like wrong weather forecasts or users misbehaviors, occur. Another approach for dealing with uncertainties is robust optimization for demand response [11]. Generally in robust optimization the solutions should remain feasible in all cases of erroneous predictions. However, in real world applications it is necessary to have a reasonable trade-off between optimality and robustness [11].

In contrary to all other approaches, our algorithms, introduced in this paper, are specially designed for modulating heating devices. Another essential feature of our approaches is that we combine elements from robust optimization with an corrective online mechanism. To the best of our knowledge, this is the only study that analyzes the effects of different prediction error degrees on the capability of electric heating devices to react to locally generated renewable energy. Further, our adjusting methods are easy-to-implement and have negligible runtime. They can be used with centralized or decentralized optimization approaches for buildings in smart grids.

III. Optimization Problem

The building used in our case study is equipped with a modulating air-source heat pump and uses a hot water tank for domestic hot water (DHW) and an underfloor heating system for space heating. Furthermore, the building has a 10 kWp PV system on its rooftop. The goal of the building is to minimize its surplus energy SE and thus to maximize the self-consumption rate of locally generated PV. The Mixed-Integer Linear Program to be solved is:

$$min\ SE = \sum_{t=1}^{Z} P_t^{Surplus+} \cdot \Delta t \tag{1}$$

subject to:

$$T^{min} \leq T_t^{BS} \leq T^{max} \qquad \forall\ t \tag{2}$$
$$V^{DHWmin} \leq V_t^{DHWuse} \leq V^{DHWmax} \qquad \forall\ t \tag{3}$$
$$x_t^S + y_t^S \geq mDeg^{min} \qquad \forall\ t \tag{4}$$
$$x_t^S \leq h_t^{Aux} \qquad \forall\ t \tag{5}$$
$$y_t^S \leq 1 - h_t^{Aux} \qquad \forall\ t \tag{6}$$
$$P_t^{total} = (x_t^S + y_t^S) \cdot P^{HP} + P_t^{Demand} \qquad \forall\ t \tag{7}$$
$$P_t^{Surplus} = P_t^{PV} - P_t^{total} \qquad \forall\ t \tag{8}$$
$$P_t^{Surplus} = P_t^{Surplus+} - P_t^{Surplus-} \qquad \forall\ t \tag{9}$$
$$P_t^{Surplus+} \leq M_t^{+} * h_t^{positive} \qquad \forall\ t \tag{10}$$
$$P_t^{Surplus-} \leq M_t^{-} * (1 - h_t^{positive}) \qquad \forall\ t \tag{11}$$
$$x_t^S, y_t^S \in [0,1];\ h_t^{Aux}, h_t^{positive} \in \{0,1\} \qquad \forall\ t \tag{12}$$

The modulation degree of the heat pump when heating up the buffer storage x_t^S and the modulation degree when heating up the DHW tank y_t^S are the main decision variables of this problem. Constraints (2) and (3) make sure that the temperature of the buffer storage T_t^{BS} and the usable volume of the DHW tank V_t^{DHWuse} are bounded. We use a minimal modulation degree for the heat pump by adding (4). Constraints (5) and (6) forbid the heat pump to heat up both the buffer storage and the DHW tank at the same time by using the binary variable h_t^{Aux}. Equation (7) defines the total electrical demand P_t^{total} which comprises the flexible load of the heat pump and the inflexible load of the other household appliances P_t^{Demand}. For the calculation of the surplus power, we subtract the total electrical demand from the PV generation P_t^{PV} in (8). Equations (9) to (11) define the big-M approach [12]. This approach is used to guarantee that merely positive surplus power is minimized and thus prevent to schedule the heat pump's activities into times with low PV generation. The surplus energy SE, defined in (1), is the sum of the positive surplus power $P_t^{Surplus+}$ over all time slots Z multiplied by the time resolution Δt. For the temperature of the buffer storage T_t^{BS} we use a uniform temperature model with an energy difference equation (13) that is often used in literature [13]:

$$T_t^{BS} = T_{t-1}^{BS} + \frac{Q_t^{SH} - Q_t^{DemandSH} - Q^{LossesSH}}{V^{BS} \cdot \rho^{BS} \cdot c^{BS}} \tag{13}$$

The energy of the heat pump for space heating Q_t^{SH} increases the temperature whereas the demand for space heating $Q_t^{DemandSH}$ and losses $Q^{LossesSH}$ decrease it. The difference in energy in divided by the volume of the buffer storage V^{BS} the density of the storage medium ρ^{BS} and its heat capacity c^{BS}. We use the same difference equation for the usable volume of the hot water tank V_t^{DHWuse} with the only difference being that the temperature of the hot water is fixed whereas the volume itself is variable. The generated energy for space heating and for DHW linearly depend on the respective modulation degrees x_t and y_t and on the efficiency of the heat pump. A more detailed description of this optimization problem can be found in [1].

IV. Corrective control algorithms

The output of the optimization problem is a schedule for a day. As the optimization is carried out under the presumption of perfect foresight, the resulting schedule will not be optimal in reality and is likely to cause constraint violations. To cope with the uncertainties of predictions, we introduce two simple supplementary online correction mechanisms that strongly decrease the likelihood and degree of constraint violations and lead to improved results. In our analysis, we only consider one building to generally show the applicability of the developed correction algorithms. When having multiple buildings and a smart grid with a communication infrastructure, a central optimizer could calculate the individual schedules and send them to the buildings, similar to [14]. Alternatively, the buildings could apply a decentralized optimization approach and coordinate the selection of individual schedules via the communication network, as it is done in [15] and [16].

A. Storage Correction algorithm

When using a scheduling-based approach for exploiting flexibilities of electric heating devices coupled with thermal storage, upper and lower limits have to be defined for the optimization problem. Most often the limits for the optimization are identical to the limits for maximal comfort of the thermal storage. The output of the optimization is a schedule of the heat pump for heating up the buffer storage $S_x = \{x_1^S, x_2^S, ..., x_Z^S\}$ and the DHW tank $S_y = \{y_1^S, y_2^S, ..., y_Z^S\}$.

For each of the optimization horizon's Z time slots (typically one day), the schedule specifies one decision variable for each storage. This is based on forecasted demand and generation profiles. However, due to the uncertainty of every prediction, the real values will differ from the predicted ones. Moreover, the used models of the thermal storage and the heating device themselves introduce further uncertainties since they are only a simplification of reality. As a consequence, just following the recommended actions of the optimal schedule will lead to constraint violations as can be seen in Fig. 1. The figure shows the temperature of the buffer storage when no correction mechanism is used. The constraint violations result in a loss of comfort for the inhabitants and can even cause technical problems.

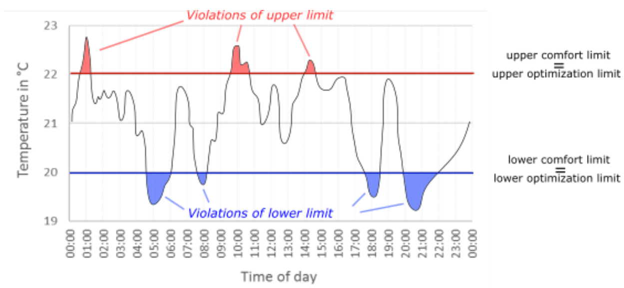

Fig. 1. Temperature of the buffer storage with no correction mechanism

To tackle this problem, we introduce a simple and easy-to-implement online control algorithm that adjusts the recommended actions of the previously calculated schedule. Further, we make the output of the schedule more robust by reducing the temperature range of the buffer storage (and the volume range of the DHW tank) for the optimization. Thus violations of the optimization limits will not necessarily result in violations of the comfort limits, as Fig. 2 illustrates. The control strategy for the buffer storage is described in Algorithm 1. For each time slot ($t < Z$) the control unit of the heating device checks whether the current storage temperature T_t^{BS} is within the comfort limits. If this is the case, the current modulation degree for heating up the buffer storage is set to the one of the calculated optimal schedule ($x_t = x_t^S$). If the temperature is above the upper limit, the current modulation degree is set to the minimal modulation degree ($x_t = mDeg^{min}$) and in case of a lower limit violation, the buffer storage is heated up with full power ($x_t = 1$). Fig. 2 shows a resulting temperature profile when using the *Storage Correction* algorithm. The control algorithm for the DHW tank is analogously defined but is treated with higher priority in case of necessary control actions for both storage types at a certain time slot.

B. PV Correction algorithm

Uncertainties in the PV forecast and in the prediction of the building's electrical demand do not lead to constraint violations but to sub-optimal decisions. Hence, adjusting the initially calculated control actions of the optimal schedule can yield improved results. Algorithm 2 lists the steps of the control mechanism for reacting to errors in the prediction of

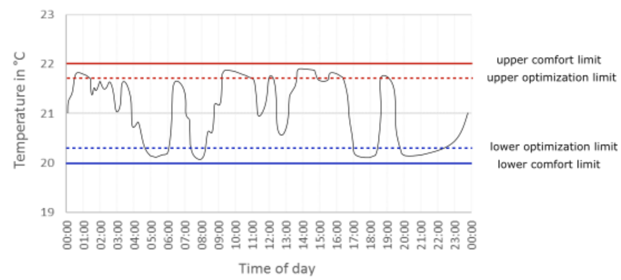

Fig. 2. Temperature of the buffer storage with the *Storage Correction* algorithm

Algorithm 1 Storage Correction for the buffer storage

while $t < Z$ **do**
  if $T^{min} \leq T_t^{BS} \leq T^{max}$ **then**
    Set $x_t = x_t^S$
  end
  if $T_t^{BS} > T^{max}$ **then**
    Set $x_t = mDeg^{min}$
  end
  if $T_t^{BS} < T^{min}$ **then**
    Set $x_t = 1$
  end
  Set $t = t + 1$
end

the PV generation and the electrical demand of the building. For every time slot ($t < Z$), first a preliminary adjusting factor α_t^* is calculated based on the differences between real and forecasted values for the PV generation and the electrical demand. In our analysis it turned out that a strong adjustment of the actions recommended by the optimal schedule is not beneficial. Consequently, we set the limits for the used adjusting factor α_t to 0.5 and 1.5 by using a sectionally defined function, as this led to the best results in our experiments. The limits can be modified for different buildings as they depend on the power of the flexible devices and the PV system. However, we think that the chosen limits can be used as a rough estimate for other buildings. In the last step, the recommended modulation degrees for the storage are updated. The proposed algorithm for reacting to uncertainties in PV generation and in the electrical demand should be used before the Storage Correction algorithms of section IV-A, since a possible constraint violation is critical and its avoidance should have highest priority.

V. Results

For our analysis we use synthetic data created by the tool *synPRO* from *Fraunhofer Institute for Solar Energy Systems* [17]. The tool uses a behavioural model, calibrated with data of the Harmonised European Time of Use Survey (HETUS [18]), and a resistance-capacitance model for space heating, as described in DIN EN ISO 13790 [19]. We apply our methods on a single family house located in Braunschweig, Germany. The building with four inhabitants has a modulating air-source

Algorithm 2 PV Correction

while $t < Z$ **do**

Calculate $\alpha_t^* = \left| \frac{P_t^{PV,real} - P_t^{Demand,real}}{P_t^{PV,forecasted} - P_t^{Demand,forecasted}} \right|$

$$\text{Set } \alpha_t = \begin{cases} 1.5 & \text{for } \alpha_t^* \geq 2 \\ 1.4 & \text{for } 1.8 \leq \alpha_t^* < 2 \\ 1.3 & \text{for } 1.6 \leq \alpha_t^* < 1.8 \\ 1.2 & \text{for } 1.4 \leq \alpha_t^* < 1.6 \\ 1.1 & \text{for } 1.2 \leq \alpha_t^* < 1.4 \\ 1.0 & \text{for } 0.9 \leq \alpha_t^* < 1.2 \\ 0.9 & \text{for } 0.7 \leq \alpha_t^* < 0.9 \\ 0.8 & \text{for } 0.5 \leq \alpha_t^* < 0.7 \\ 0.7 & \text{for } 0.3 \leq \alpha_t^* < 0.5 \\ 0.6 & \text{for } 0.1 \leq \alpha_t^* < 0.3 \\ 0.5 & \text{for } \alpha_t^* < 0.1 \end{cases}$$

Update $x_t^S = x_t^S \cdot \alpha_t$

Update $y_t^S = y_t^S \cdot \alpha_t$

Set $t = t + 1$

end

heat pump with 3 kW of electrical power (minimal modulation degree of 0.1) and a PV system with 10 kW peak generation. Additional to an underfloor heating system, a 200 l hot water tank servers as thermal storage. More information about the building and the used parameters of the heating system are described in [1]. We manually manipulated the load profiles to generate uncertainties by enhancing or lowering the values of the original four load profiles that are used to generate the optimal schedule (electric demand, space heating, DHW, PV generation). The optimization problem was formulated in *GAMS* and solved with *Cplex* using a MIP gap of 0.1%. We implemented a simulation in *Java* that uses the output of the optimization and applies the different control algorithms. The time resolution of the optimization and simulation Δt are five minutes. We used a rolling-horizon-approach for the optimization with a time horizon of one day. This leads to seven iterations for one week.

Fig. 3 shows the surplus energy of the building for the expemplarily choosen 9. week (March) of the year 2017 depending on the prediction error. We compared four approaches: *Storage Correction*, *Storage Correction and PV Correction*, *Optimal Control* with perfect foresight and *Conventional Control* (two-point controller). Since the *Optimal Control* uses input data without any prediction errors (which is not possible in reality) and the *Conventional Control* does not need any prediction, those two approaches are independent from the prediction error. The optimization problem for the *Optimal Control* with perfect foresight exploits the whole temperature range of the buffer storage ($20\,°C$ – $22\,°C$) and the whole volume range of the DHW tank ($0\,l - 200\,l$). This can be done as this approach merely represents a hypothetical scenario without any uncertainties. For the two uncertainty handling control approaches (*Storage Correction*, *Storage Correction and PV Correction*) the optimization limits for the buffer storage were chosen to be between $20.3\,°C$ – $21.7\,°C$ and $50\,l - 175\,l$ for the DHW tank. These adjusted limits, combined with the correction algorithms, led to schedules that were robust enough to avoid constraint violations in all scenarios of our experiments. We used three runs of the uncertainty handling methods with differently manipulated data, for each of the six values of the prediction error. This means that e.g. for a prediction error of 2 %, we created three different input data sets for the optimization that deviate 2 % from the "real" data that was used for the simulations.

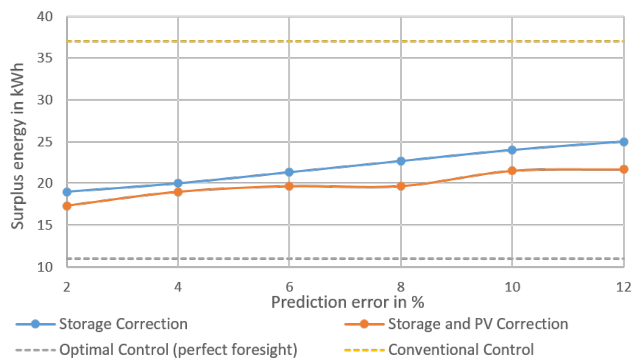

Fig. 3. Surplus energy of the building for week 9 (March) depending on the prediction error

It can be seen that considering uncertainties significantly impact the surplus energy and thus the usable load shifting potentials. Higher prediction errors lead to worse results. Moreover, using the *Storage Correction* algorithm in combination with the *PV Correction* algorithm yields better results than solely using the *Storage Correction* algorithm. As expected, the results for the uncertainty handling methods are in all cases better than the ones of the conventional control approach but worse than the ones of the optimization with perfect foresight. For our analysis, we did not use a forecasting method (like regression or artificial neural networks) but manipulated the data manually to quantify the impact of different prediction errors on the results. We assume that using a forecasting method would enhance the improvement of the *PV Correction algorithm*, because the algorithm can react to wrongly predicted cloudiness.

Fig. 4 depicts the number of necessary corrections of the *Storage Correction* algorithm to avoid constraint violations for week 9 of the year 2017. Even a low prediction error of only 2 % makes on average 76 corrections necessary for this week. A higher prediction error requires more correcting actions, as simply following a schedule that was calculated by using high prediction errors will lead to strong violations of the comfort limits. We analyzed 12 weeks of the year 2017 by randomly picking two weeks for each month of the heating period (October – March). The results look similar for every week. Fig. 5 shows the average surplus energy of the building for the 12 weeks. Generally, the additional computational times of the algorithms are under one second and thus negligible.

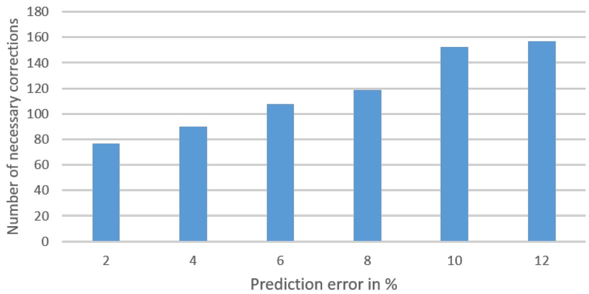

Fig. 4. Number of necessary corrections of the *Storage Correction* algorithm for week 9 (March) depending on the prediction error

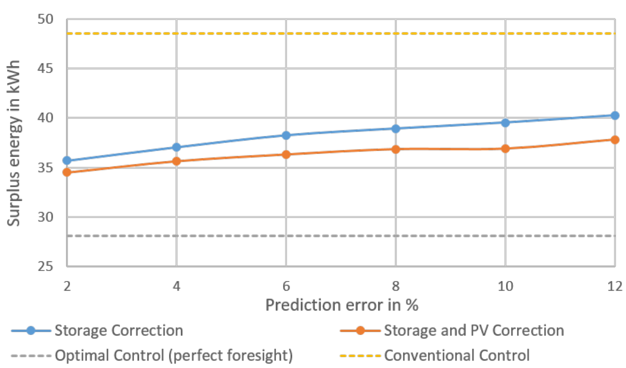

Fig. 5. Average surplus energy of the building for 12 weeks depending on the prediction error

VI. Conclusion

We developed two simple but effective uncertainty handling algorithms for buildings in smart grids with modulating heating devices and thermal storage. The algorithms adjust the recommended actions of an previously calculated schedule. Our analysis shows that the developed approaches avoid violations of the inhabitants' comfort limits and lead to a higher usage of locally generated PV. Moreover, the results reveal that uncertainties in predictions of electricity demand and generation diminish the capability of electric heating devices to react to the volatile generation by the renewable energy sources. Higher predictions errors make more correcting actions necessary to avoid constraints violations. The corrective control algorithms can be easily implemented and combined with both centralized and decentralized optimization approaches in smart grids.

In future work, we will compare our correcting approaches to the other uncertainty handling methods found in literature like MPC, stochastic optimization, (purely) robust optimization and rescheduling in case of strong deviations. Furthermore, we want to adjust the algorithms to non-modulating heating devices. In this study we used synthetic data and only considered one building. We intend to analyze different uncertainty handling approaches using real data and forecasting methods for multiple buildings in future research.

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