Engineering Information Systems for Integrated Energy Communities

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LIST OF ABBREVIATIONS

AC air conditioner

ANN artificial neural network

ANOVA analysis of variance

BEV battery electric vehicle

BSS battery storage system

CEC citizen energy community

CHP combined heat and power plant

CNN convolutional neural network

COP coefficient of performance

DHN district heating network

DPS direct policy search

DSS decision support system

EMODPS evolutionary multi-objective direct policy search

EU emission units

FFN feed-forward neural network

GRU gated recurrent unit

HP heat pump

IS	information systems
IT	information technology
LSTM	long-short term memory
MAPE	mean absolute percentage error
MOEA	multi-objecitve evolutionary algorithm
MU	monetary units
NREL	National Renewable Energy Laboratory
PV	photovoltaic
PVT	photovoltaic/thermal
RBF	radial basis function
RMSE	root-mean-square error
SD	standard deviation
TSS	thermal storage system

Part I.

Fundamentals

CHAPTER 1

INTRODUCTION

The mitigation of climate change caused by carbon emissions is becoming the greatest challenge of the 21^{st} century. Energy-related emissions are responsible for 84% of the carbon emissions in Germany (Umweltbundesamt, 2022b) and households play an important role in this context, as they account for 28.3% of the total energy demand (Umweltbundesamt, 2023). Citizens are already significantly contributing to investments for the decarbonization of electricity supply, currently owning 30.2% of the renewable generation capacity and 68% of the installed storage capacity for battery storage systems (BSSs) (AEE, 2020; Figgener et al., 2021). However, the majority of residential energy consumption is related to heat demand that is primarily covered by fossil fuels (Umweltbundesamt, 2023). One way to decarbonize residential heat supply is by deploying sector-coupling technologies, for example heat pumps (HPs). The expansion of sector coupling technologies requires further investments in renewable electricity generation to cope with the rising electricity demand. As calculated in (Weniger et al., 2018), every second single-family home needs to be equipped with a solar photovoltaic (PV) and BSS by 2050 to reach the German emission reduction targets.

In addition to high investment costs (Figgener et al., 2022), the complexity of the decision-making process can inhibit residential energy technology investment decisions (Maciosek et al., 2022). One way to support citizens in the investment decision process is through the development and application of information systems (IS). However, existing IS solutions often lack application relevance in the fight against climate change (Gholami et al., 2016; Watson et al., 2010).

A regulatory element to support household investments in residential energy technologies is the implementation of a citizen energy community (CEC) concept in Germany. The concept and term CEC was introduced by the European Union in 2019 as a "cooperation of citizens and local actors" that engages in energy generation, distribution, storage or efficiency services to provide "environmental, economic or social community benefits to its members" (European Parliament and Council of the European Union, 2019). In this thesis, CECs are viewed as a community where participants can buy electricity from their neighbors or sell excess electricity, for example, if they own a rooftop PV system (Mengelkamp et al., 2018). CECs offer financial benefits for participants and can increase incentives for investments in residential energy technologies (Coelho et al., 2017). However, the exact effects of CEC regulation on residential energy technology investments have not yet been quantified.

Increased investments in renewable generation can lower carbon emissions in the residential sector. Given the volatile nature of renewable generation and consumer demand, operation strategies are needed to harness the potential of renewables in energy communities. In combination with operation and control strategies, sector coupling technologies can support the mitigation of volatile generation and help to promote decarbonization in all sectors of the energy community. To address the challenges mentioned above, this thesis presents IS for the support of citizen investments in residential energy technologies and the operation of such technologies with a focus on sector coupling.

1.1 Motivation

Despite a 39% reduction of greenhouse gas emissions compared to 1990, Germany has a long way to go to reach the goal of net-zero emissions by 2045 (Deutsches Bundesamt für Justiz, 2021). As a milestone, the German government has proclaimed to achieve an 80% share of renewable electricity generation by 2030 (Deutscher Bundestag, 2022). Germany aims to increase the PV expansion rate to 22GW per year and the onshore wind power expansion rate to 10GW per year (BMWK, 2022). This translates to a tripling of the current expansion rate. However, renewable expansion is not distributed evenly across the three energy sectors electricity, heat and mobility. As displayed in Figure 1.1, the share of renewable electricity generation has almost doubled since 2010, despite a small reduction in 2021. At the

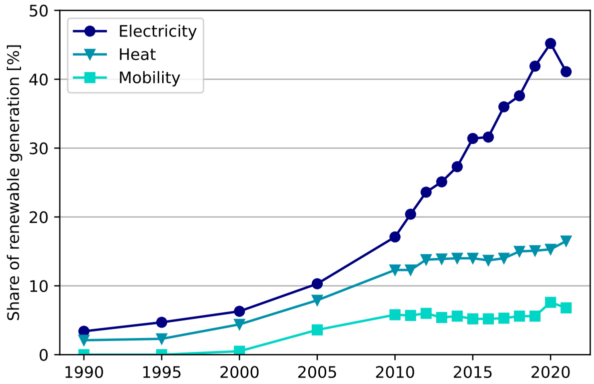

Figure 1.1.: German renewable generation by sector, based on (AGEE-Stat, 2022).

same time, the share of renewable heat generation has increased by only 18%. In an energy system with a coupled heat and electricity sector, renewable electricity could be used in sector coupling technologies to increase the share of renewable heat supply. This leads to an integrated view of the energy system that can support its decarbonization (Mancarella, 2014). In this context, the term "integrated energy system" refers to a connection of the energy sectors heat, electricity and mobility into a holistic energy system (Bründlinger et al., 2018). Sector coupling technologies are technologies that enable the purposeful connection and interaction of energy sectors (Fridgen et al., 2020), for example, conversion technologies like HPs or hybrid generation devices, such as photovoltaic/thermal (PVT). An expansion of sector coupling technology can help to reach the German emission reduction goals. This potential has been recognized by policymakers in Germany (Bundesregierung, 2021). The first steps toward an increased expansion of sector coupling between the heat and electricity sectors are visible. For example, 154,000 heat pumps for space heating were installed in Germany in 2021, an increase of 28% compared to 2020 (BWP, 2022).

By both consuming and producing energy, for example, through the installation of residential PV systems, households become prosumers, actively participating in the energy transition (Ritzer et al., 2012). A successful energy transition will have a positive impact on living quality for citizens due to better living conditions, i.e.,

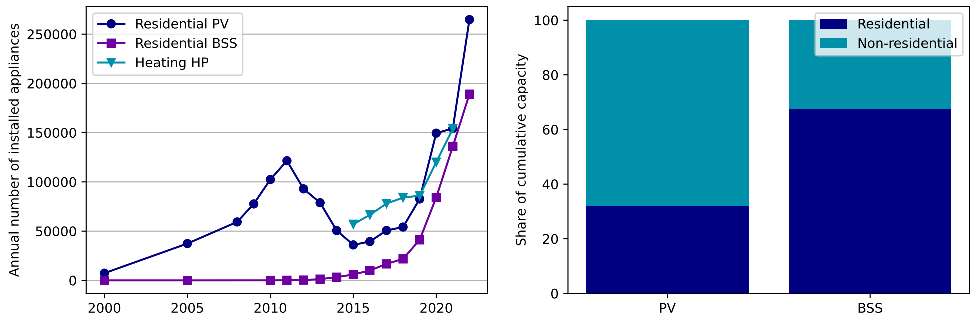

Figure 1.2.: Annual installations of residential energy technologies. Own representation based on data from (Bundesnetzagentur, 2022; Figgener et al., 2022; Tepe et al., 2021; BWP, 2022; AEE, 2020).

a reduced impact of climate change or less air pollution (Mathiesen et al., 2011). To reduce emissions, a change in individual lifestyle and behavior is necessary (Nisa et al., 2019).

In the residential energy sector, investment decisions for residential energy technologies such as PV and BSSs have a high impact on the annual energy bill of households (Al Khafaf et al., 2022). In this thesis, residential energy technologies are understood as energy technologies that can be installed as part of a household or CEC and used for the generation, conversion and storage of (renewable) energy. These technologies include, for example, PV and PVT systems, HPs, BSSs and thermal storage systems (TSSs). Private individuals already significantly contribute to investments in residential energy technologies, as displayed in Figure 1.2. In 2020, 30.2% of the installed PV capacity was owned by private individuals (AEE, 2020) and residential BSSs accounted for about two thirds of the total installed battery storage capacity in Germany (Figgener et al., 2022; Tepe et al., 2021). Weniger et al. (2018) state that 8 million coupled residential PV and BSS need to be installed by 2050 to support climate protection. This means, that despite previous efforts, much more citizens need to become active participants in the energy transition.

However, there is a gap between people wanting to contribute to the energy transition and practical action (Blake, 1999). Aside from high investment costs for residential energy technologies (Weniger et al., 2014), different studies indicate a lack of energy literacy among residential households (Brounen et al., 2013; Blasch et al., 2018), or a lack of action despite reasonable knowledge (Sovacool and Blyth, 2015). Energy literacy is defined in (DeWaters and Powers, 2011) as the domain of basic energy-related knowledge, linked with an understanding of the impacts of energy production and consumption on the environment. While other definitions exist and there is no consensus on a common definition (Martins et al., 2020), the definition in (DeWaters and Powers, 2011) is used in this thesis due to its broad focus on energy-related knowledge. Greenleaf and Lehmann (1995) name lack of information as one of eight main reasons to delay consumption decisions. Other reasons in this context are lack of time, lack of enjoyment, risk exposure, requirement to obtain third-party advice, procedural uncertainty, the expectation of falling prices and expected improvements of the decision quality. This leads to situations of uncertainty regarding investment decisions. In such situations, individuals tend to make sub-optimal decisions, as probable outcomes are underweighted compared to certain outcomes, leading to higher risk aversion (Kahneman and Tversky, 1979). As a result, individuals tend to delay environmental actions such as investments in residential energy technologies (Blake, 1999). In a survey among 1,721 Dutch households, 40% of the participants did not appropriately evaluate investments in energy efficiency equipment (Brounen et al., 2013).

Decision support systems (DSSs) have the ability to overcome some of these shortcomings. As a sub-field of IS, DSSs support and improve decision-making (Arnott and Pervan, 2014). Through provision of knowledge, DSSs can overcome the lack of information (Arnott and Pervan, 2005). Furthermore, DSSs can provide recommendations based on optimization or forecasting (Arnott and Pervan, 2014), thus mitigating risk exposure and expectations regarding falling prices or expected improvements. DSSs have the potential to improve decision quality (Arnott and Pervan, 2014), that is the deviation of the decision from a normative solution that maximizes value or utility (Todd and Benbasat, 1992).

In the context of citizen participation in the energy transition, DSSs can be used to support household investment decisions. The attitude of citizens towards investments in residential energy technologies is influenced by their preferences, for example, with regard to their financial and environmental impact. In the context of home BSSs in Germany, various purchasing motivations representing household preferences are presented in (Kairies et al., 2019). The authors identify motives with environmental (e.g., contribution to the energy transition), financial (e.g., hedging electricity costs), or other background (e.g., interest in technology). In a broader context of green energy, (Hojnik et al., 2021) find that the willingness to pay for green energy is positively influenced by the acceptance and knowledge of green energy, social norms and moral obligations. As described in (Bergmann et al., 2008), individual preferences are heterogeneous and can also vary for differing socio-economic settings, such as rural and urban living areas. To provide residential energy technology investment recommendations for citizens, DSSs must be able to evaluate and reflect these preferences.

For the determination of investment recommendations, these preferences can be translated into multiple objectives that are optimized. To consider a trade-off between different objectives, for example, with regard to costs and emissions in the investment decision, multi-objective optimization can be used for the determination of investment alternatives in households and CECs (Ahmad Khan et al., 2016; Zia et al., 2018). In integrated energy communities, the availability and size of energy generation, conversion and storage technologies has a significant impact on the resulting feasible energy flows (Zhao et al., 2014). This motivates the design of integrated approaches that regard both energy technology investments and system simulation. The solutions from these methods can in turn be used to provide decision support for households in preference-based DSSs, as described above.

The development of preference-based decision support alone is not enough to incentivize households to actively participate in the energy transition. Stern (2020) argues that a combination of behavioral and other incentives, e.g., subsidies or beneficial regulation, is most effective. Gatzert and Kosub (2017) agree that increasing investments in renewable energy requires further policy support. Such support is typically granted through subsidy payments encompassing the lifetime of the energy technology, e.g., through feed-in tariffs, net metering or tax incentives (Lee and Zhong, 2014; REN21, 2022). Another approach is the establishment and regulatory promotion of energy communities. As mentioned above, these communities might enable consumers and prosumers in close proximity to trade or share energy with each other (Mengelkamp et al., 2018). Energy communities further enable and incentivize investments in renewable generation and foster the development of self-sustained neighborhoods (Coelho et al., 2017; Mengelkamp et al., 2018). The potential of CECs has been investigated in a number of pilot projects, for example, the "Quartierstrom" Project in the Swiss city of Walenstadt (Ableitner et al., 2020) or the "Landau Microgrid Project" in the German city of Landau (Richter et al., 2021). However, the integration of sectors has been neglected in CEC projects so far, as most pilot projects of local energy communities in Germany, Austria and Switzerland focus on electricity only (Weinhardt et al., 2019). Furthermore, the impact of CEC regulation on residential energy technology investments has not yet been quantified. This motivates an evaluation of the financial and environmental benefits of integrated CECs for households and neighborhoods.

Investments in renewable generation technologies foster a transition of energy supply. However, increasing the generation capacity through investments is not enough. Renewable generation, especially wind and solar power fluctuates and often does not align with household demand profiles (Hansen et al., 2019). The discrepancies happen during the day, when electricity demand is highest in the morning and evening, while solar generation is higher during daytime (Marszal-Pomianowska et al., 2016; Muenzel et al., 2015). Supply and demand further vary across seasons, for example, when more heat is required in the winter season, but solar generation is higher in the summer (Fischer et al., 2016; Phinikarides et al., 2015). The application of sector coupling technologies can integrate volatile supply and increase the utilization of renewable generation (Su et al., 2014; Liu et al., 2018). Using HPs or PVT systems, sector coupling can contribute to the decarbonization of the heat sector in residential areas. This complicates the energy supply of CECs and requires the development of operation strategies that go beyond simple heuristics (Su and Wang, 2012). Hansen et al. (2019) stress the need for the development of cross-sectoral approaches for the operation of energy systems.

In CECs, the operation of sector coupling technologies can contribute to the decarbonization of the heat sector, for example, through the electrification of heat demand through HP deployment (Backe et al., 2022). Through the development of district heating networks (DHNs) towards lower temperatures (Lund et al., 2014), residential HP or PVT systems can be connected to such networks and supply heat to other households in the CEC. The developed operational strategies can further be used in integrated approaches for the determination of investment recommendations, as described above. By deploying technologies more efficiently during operation, the required generation capacity can be reduced, thus lowering investment costs and capacity-related emissions (Urbanucci and Testi, 2018).

This thesis presents a contribution to the decarbonization of integrated energy communities through the development of preference-based investment recommendations and operation strategies for CECs. The results include implications for the design of preference-based IS for municipalities and policymakers and support citizens to take an active role in the energy transition through investment in residential energy technologies. The presented operation strategies for sector coupling technologies can be applied by municipal utilities and system operators as part of integrated CECs. In summary, the concepts can be used to promote the decarbonization of the heat and electricity sector in CECs and thereby contribute to the goal of limiting global warming to 1.5°C. The case studies described in this thesis use load and generation data from Germany, Denmark, the UK and the US and are applicable to energy systems worldwide. The contributions are structured in three parts, which are presented in Part II, Part III and Part IV of this thesis. These parts are described in the following.

Part II investigates the influence of household preferences on energy technology investment decisions. As mentioned above, individuals often lack information and the means to propose and implement joint infrastructure projects like shared investments in energy-related technologies. In this part, the elements of a platform-based DSS that supports residential energy technology investments in CECs are determined. The information that is required to configure local energy infrastructure is described and a coordination mechanism is conceptualized that merges diverging preferences of participants. The functionality of the tool is demonstrated in a case study using data from a microgrid in Landau, Germany. The results show that an application of the residential energy technologies suggested by the decision support tool can reduce community costs and emissions.

As the performance benefits of IS depend on individual willingness to accept and use a system (Venkatesh et al., 2003), the acceptance factors of preference-based DSSs for individual energy technology investments are assessed in an online experiment with 324 participants. The results show, that preference-based recommendations increase the recommendation acceptance rate by 22 percentage points.

Part III of this thesis focuses on the determination of investment recommendations for residential energy technologies and the impact of CEC regulation on their adoption and potential cost savings and emission reductions in a community. First, a multi-objective optimization for the integrated sizing and simulation of residential energy technologies in a CECs is developed with regard to the preferences addressed in Part II. The optimization provides a set of non-dominated investment alternatives from which one can be selected as DSS recommendation based on the user preferences. The model is then applied to a community with 30 households, where the implementation of residential investment decisions is simulated based on preference-based recommendations and their impact on energy-related costs and emissions in the community. In a comparison of scenarios with and without CEC regulation, the results show that CEC regulation increases the speed and amount of decarbonization and is especially beneficial in communities with a heterogeneous preference distribution regarding costs and emissions.

Finally, the operation of different sector coupling technologies for heating and cooling in CECs is evaluated in Part IV. Operation strategies for sector coupling technologies in CECs can help to mitigate the effects of volatile renewable generation and uncertain demand (Hansen et al., 2019; Liu et al., 2018). Such operation strategies can, for example, use load forecasts to increase the integration of renewables or decrease operational costs. The effects of global warming are expected to increase the distribution of residential cooling systems in Europe (Day et al., 2009). In a first use case, I therefore develop and evaluate an approach to satisfy heat and cooling demand in buildings through hybrid PVT generation and absorption cooling. The results of a case study for a large research facility in Colorado show that the approach can save 74% of operational costs when compared to a system with PV and conventional cooling.

In the second use case, I assess the application of an adaptable rolling-horizon online optimization for the operation of an HP and a TSS in a DHN. The online optimization of the HP operation uses a 24-hour heat load forecast based on a convolutional neural network (CNN). The performance of the operation strategy is evaluated in two case studies using data from the Flensburg DHN. In the first case study (maximization of the share of renewables), a share of renewable offshore generation of 10.90% is achieved (lower benchmark: 9.05%; upper benchmark: 10.93%). In the second case study (minimization of electricity costs), an average electricity price of 20.93€ /MWh is achieved (lower benchmark: 24.00€ /MWh; upper benchmark: 20.91€ /MWh).

1.2 Research Questions

The ability to install residential energy technologies enables citizens to play an active role in the energy transition by becoming prosumers. However, participants of CECs often lack the additional information or the means to propose and implement joint infrastructure projects like shared electricity consumption and generation technologies. Therefore, Research Question 1 addresses the required information for a platform-based DSS to support the decision-making process of households with regard to residential energy technologies in CECs.

Research Question 1 *What are the required elements to provide investment recommendations to CECs through a platform-based decision support system in order to coordinate financial and ecological interests of participants?*

The benefit of such a platform depends on the acceptance of the recommendations by its users. To investigate acceptance factors for preference-based recommendations in DSSs and answer Research Questions 2 and 3, an online experiment with 324 participants is conducted. In the experiment, participants are asked to make an investment decision in the context of energy technologies. They are provided with an investment recommendation that points out the alternative with the lowest costs or emissions or an alternative based on the individual participant's preferences to answer Research Question 2. When making investments in residential energy technologies, households face uncertainty, for example regarding future energy prices and volatile renewable generation or energy demand. Therefore, the experiment is conducted in treatments with and without uncertainty to answer Research Question 3.

Research Question 2 *To what extent does providing recommendations that take into account the trade-off between individual cost and emission preferences in a DSS for residential energy technology investments increase the recommendation acceptance compared to recommendations that consider either costs or emissions?*

Research Question 3 *What is the effect of uncertainty on recommendation acceptance and the perceived usefulness of the DSS?*

To provide such preference-based investment recommendations for residential energy technologies to households, it is necessary to identify possible investment alternatives with respect to the trade-off between participant's preferences, for example, costs and emissions. Furthermore, energy technology sizing and operation in a CEC influence each other and should therefore be regarded simultaneously to derive profound recommendations. Based on the work by Gupta et al. (2020), a direct policy search algorithm is adapted and developed further to address these challenges. The model combines a multi-objective evolutionary algorithm and an energy system simulation to determine a set of non-dominated recommendations for the integrated sizing and operation of residential energy technologies in a CEC. The model is compared to an optimization with perfect foresight as an upper benchmark that regards each of the two objectives costs and emissions individually to answer Research Question 4.

Research Question 4 *What is the financial (cost) and environmental (emission) performance of a multi-objective evolutionary optimization of the integrated sizing and operation of energy technologies in a CEC relative to an upper benchmark optimization with perfect foresight that optimizes the objectives individually?*

As residential energy technology investments in a CEC usually do not happen all at once but depend on household decisions, a period of several years needs to be regarded when evaluating the impact of such investments on cost and emission reduction. The ability to buy or sell excess energy generation within the community affects the ability of neighborhoods to benefit from CECs. Policymakers need to develop corresponding CEC regulation, while municipal utilities have to implement CEC concepts in suitable neighborhoods. The influence of such regulation on long-term cost and emission reductions through residential energy technology investments in an exemplary community with 30 households is evaluated over a period of 10 years with and without CEC regulation to answer Research Question 5. The case study is conducted in scenarios with strong, weak and heterogeneous cost and emission preference distributions among the households in the community to answer Research Question 6.

Research Question 5 *What are the long-term financial (cost) and environmental (emission) effects of CEC regulation on the development of a community with respect to electrification and the investment in residential energy technologies?*

Research Question 6 *To what extent does the spread of individual household preferences in a community impact the potential of CEC regulation for a faster decarbonization?*

For the operation of residential energy technologies, efficient strategies for sector-coupled systems are necessary to integrate volatile renewable generation and foster the decarbonization of heat and electricity supply in CECs. This thesis demonstrates the potential of sector coupling by presenting two use cases in Part III. The presented operation strategies can be implemented as part of a CEC energy management system, for example. While the presented case studies evaluate the adoption in a building complex and on a city level, an implementation on a community level is possible, as well. The first use case regards the operation of a hybrid PVT plant in combination with absorption cooling to provide both heating and cooling. Using the example of powering a research facility in Colorado, Research Question 7 examines the economic benefits of this model compared to a system using a PV plant and conventional cooling over a period of one year.

Research Question 7 *What are the financial benefits of a sector-coupled PVT installation in combination with absorption cooling compared to conventional compression cooling with a PV installation?*

As future supply from renewable generation and household energy demand in a CEC are subject to uncertainty, the second use case focuses on the real-time operation of an HP and a TSS that is connected to a DHN. An online operation optimization is developed that uses a 24-hour rolling horizon heat load forecast to derive an operation strategy for the HP. The strategy optimizes the HP operation with respect to the objectives "integration of renewables" and "minimization of operational costs" and is compared to a global optimization with perfect foresight to answer Research Question 8.

Research Question 8 *What is the performance of an online operation strategy for a district heating system with an HP and a TSS that uses a 24-hours rolling horizon heat load forecast compared to (i) a naive approach and (ii) benchmarked against the global optimum with respect to the integration of renewables and cost minimization?*

1.3 Thesis Structure

As depicted in Figure 1.3, this thesis is structured in five parts along the research questions described above. Following the introduction, the fundamentals of integrated energy systems are introduced in Chapter 2. Chapter 3 introduces the fundamentals of IS in the context of CECs and presents an exemplary implementation of a CEC structured along the house of market engineering framework (Weinhardt and Gimpel, 2007). This constitutes Part I.

The three main parts of the thesis follow: Part II focuses on citizens in CECs and investigates the impact of individual preferences on energy technology investments.

Part I Fundamentals	**Chapter 1** Introduction	**Chapter 2** Integrated Energy Systems	**Chapter 3** IS for Integrated Energy Systems
Part II Household Preferences	**Chapter 4** Scaling the Concept of Decision Support in CECs	**Chapter 5** Evaluation of Decision Support for Energy Technology Investment	
Part III Energy Technology Investment	**Chapter 6** Direct Policy Search for Multi-objective Optimization of the Sizing and Operation of CECs	**Chapter 7** Evaluating the Impact of Regulation on the Path of Electrification for CECs	
Part IV Energy System Operation	**Chapter 8** Combining PVT Generation and Air Conditioning: A Cost Analysis of Surplus Heat Utilization	**Chapter 9** An Operational Strategy for District Heating Networks	
Part V Finale	**Chapter 10** Contributions and Implications	**Chapter 11** Outlook	

Figure 1.3.: The structure of this thesis.

In Chapter 4, I determine the necessary elements to provide preference-based decision support for citizens and develop a decision support tool for CECs. To evaluate the acceptance of such a preference-based DSSs, the results of an online experiment with 324 participants are presented in Chapter 5.

The generation of optimal investment recommendations with regard to individual preferences and the effects of their implementation are addressed in Part III. First, I evaluate the generation of optimal sizing solutions in a CEC with regard to the objectives cost decrease and emission reduction in a multi-objective optimization in Chapter 6. In Chapter 7, the recommendation of investment alternatives and the effects of their implementation are investigated. I analyze the development of cost and emission reductions through household investments in a CEC with 30 households over a period of 10 years and compare the results to a community without CEC regulation.

Part IV of this thesis introduces two use cases for sector coupling applications between the heat and electricity sector. First, the operation of coupled electricity, heat and cooling systems is investigated in Chapter 8. Second, an operational strategy for HP scheduling in a DHN with a TSS that uses a rolling-horizon forecast and can integrate different objectives is presented in Chapter 9.

Finally, Part V summarizes the key findings of the research presented in this thesis in Chapter 10. In Chapter 11, an outlook for further research is provided.

Chapters 4 and 6 to 9 rely on or comprise published articles. In all cases, I disclaim this clearly at the beginning of the respective chapter. Within those chapters, I consistently refer to the authors as “we”, since I collaborated with fellow researchers for these articles.

CHAPTER 2

INTEGRATED ENERGY SYSTEMS

In integrated energy systems, different energy sectors (electricity, heat and mobility) interact with each other on the household, community and city level and beyond (Mancarella, 2014). The operation of integrated energy systems is necessary to distribute renewable generation between sectors and thereby utilize the full potential of renewable generation. Compared to the other sectors, the electricity sector has the highest share of renewables (IEA, 2021). Renewable electricity technologies like wind power plants, PV or hydropower have already been integrated in the energy system and electricity is expected to be the first sector to be decarbonized (Papadis and Tsatsaronis, 2020). Deploying sector coupling technologies for electrification of the heat and mobility sector can help to support the decarbonization in the entire energy system (Baruah et al., 2014). In this chapter, sector coupling applications between different components of a multi-energy system are described, as shown in Figure 2.1. The focus is on applications that can be used in the context of CECs.

2.1 Coupling of the Heat and Electricity Sector

On the way to decarbonize the energy system, the residential heat sector is a decisive factor, as described in Chapter 1.

Aside from building better insulation, the transformation of heat supply through DHNs is expected to play a large role in the decarbonization of the heat sector, as they provide an efficient way to supply heat (Connolly et al., 2014). Due to improvements in heat pipe and building insulation and an effort to increase the energy efficiency of DHNs, the flow and return temperatures have gradually been decreased since the introduction of the first generation of district heating (Lund et al., 2014).

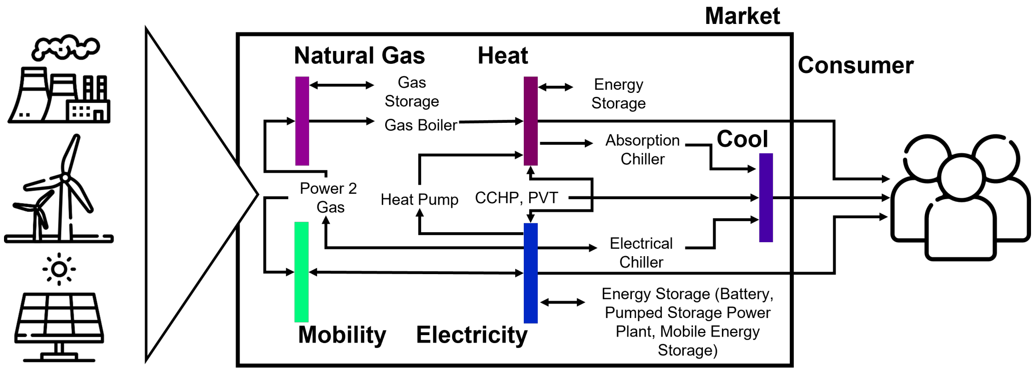

Figure 2.1.: A sustainable multi-energy system, own depiction, based on (Mancarella, 2014).

The decrease of flow and return temperatures in DHNs also allows low caloric heat providers such as geothermal plants or HPs to contribute to the heat supply of communities and cities. In the 4^{th} generation of district heating, according to the taxonomy in (Lund et al., 2014), the integration of renewable energy systems and both short-term and long-term or seasonal TSSs facilitates the utilization of volatile energy generation of solar thermal, PV and wind power plants. An overview on the taxonomy is presented in Figure 2.2. Through the addition of sector coupling technologies, both heat and electricity storage are important for the electrification of the heat sector. While BSSs are becoming more popular in combination with residential PV systems, TSSs in residential areas exist but are not yet widely employed (Alva et al., 2018). The most prominently applied BSS technology in residential areas is the lithium-ion battery (Bundesnetzagentur, 2019). In comparison to BSS, TSSs are based on water or gravel storage systems and therefore less expensive (Mangold, 2007).

The distribution of sector coupling technologies plays an important role in the decarbonization of the heat sector. For this purpose, HPs are a promising technology that is already used in many residential areas (Buffa et al., 2019).

In CECs, combining electricity and heat generation has the potential to increase the degree of self-sufficiency as well as to allow for load-shifting between different energy sectors. PVT systems produce heat and electricity in one integrated system (Chow, 2010). Similarly, combined heat and power plants fueled with gas can supply residential areas at much higher efficiency rates than decoupled electricity and heat generation (Rolfsman, 2004).

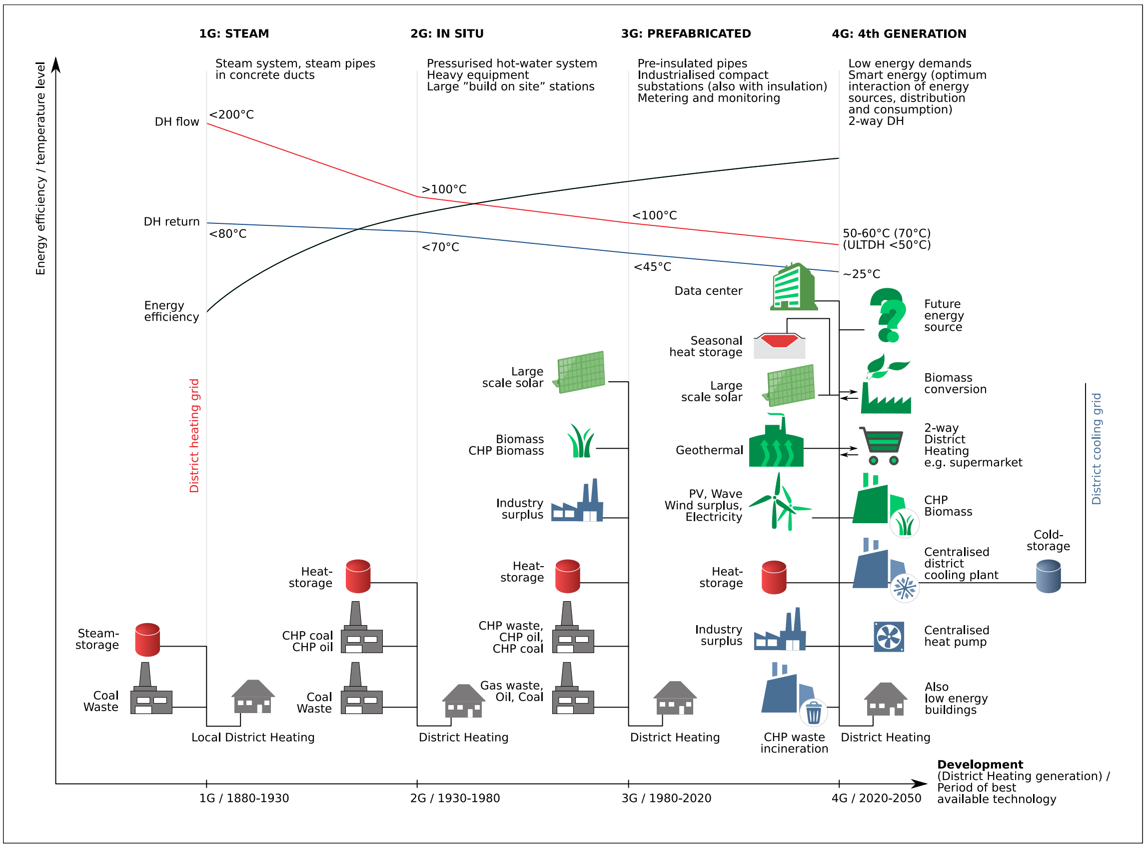

Figure 2.2.: Generations of district heating (Lund et al., 2014).

In recent years and as a consequence of global warming and the thus growing need for residential cooling, district cooling has emerged in the district heating concept (Lund et al., 2014). An overview of district cooling technology and possible enhancements is given in (Rezaie and Rosen, 2012). The authors classify district energy systems by different characteristics such as the circulating fluid, thermal applications and network size. Lake et al. (2017) provide a review on the implementation of district heating and district cooling systems in various case studies. Kato et al. (2008) propose a new heat load prediction model for district heating and district cooling systems using recurrent neural networks. A specific application of district heating and cooling systems with seawater in the city of Daian is evaluated in (Zhen et al., 2007). Especially in the last decade, more work on cooling and district cooling systems has been published. An exergoeconomic concept designed specifically for district cooling systems is applied in (Čož et al., 2017). The performance of a district cooling system in the city of Hong Kong is evaluated in (Gang et al., 2015). The authors compare a district cooling system to conventional in-building cooling. In (Hanif et al., 2014), the correlation of radiative cooling power and the temperature difference between environment and sky is investigated. The authors also evaluate the potential for a radiative cooling system in Malaysia and find that radiative cooling can save up to 11% of the power consumption required for cooling.

2.2 Coupling of the Mobility and Electricity Sector

Transportation is one of the largest carbon-emitting sectors in Germany, accounting for 19% of the total emissions (Umweltbundesamt, 2022a). Between 1990 and 2021, carbon emissions in the transportation sector have been reduced by only 9.4% (Umweltbundesamt, 2022a) A rapid transformation of the transportation sector is necessary, if the 40% emission reduction target should be within reach by 2030. One approach to this challenge is the distribution of battery electric vehicles (BEVs). BEVs are becoming more popular due to several factors, including the price reduction of lithium-ion batteries, popularity of BEV brands and a public increase of climate and environmental awareness (Sanguesa et al., 2021). As mentioned in Chapter 1, this is also the case in Germany, where BEVs made up 13.6% of annual car sales in 2021, an 83.3% increase to 2020 (KBA, 2022). Hybrid BEVs make up a share of 28.8% and it is reasonable to believe that soon the majority of newly sold cars in Germany will be hybrid or full BEVs.

As they use and store electricity, BEVs can be used as coupling technologies between the sectors electricity and mobility. A number of studies investigate the integration of smart charging strategies to provide flexibility in sector-coupled energy systems. Three exemplary studies are presented in the following.

Heinisch et al. (2021) evaluate the integration of the mobility, electricity and heat sector in a city energy system with a focus on BEV charging. The authors evaluate different charging strategies of BEVs for private use and public transport and find that 85% of the private BEV electricity demand is flexible. Using smart charging strategies, this flexibility can be used to increase the utilization of PV generation and reduce the need for investments in stationary BSSs.

A similar approach is considered in (Sterchele et al., 2020). The authors investigate the representation of BEVs in a large-scale simulation of a near-emission-free German energy system. The findings suggest that the integration of BEVs increases energy system costs due to simultaneous vehicle charging. The energy system costs can be lowered through the application of controlled charging strategies and vehicle-to-grid technology.

The provision of flexibility through BEVs in energy communities is investigated in (Backe et al., 2021). The authors investigate energy exchange between local communities and the central power system while considering heat supply and BEV charging in Norway. In a case study addressing the expansion of BEV charging capacity and building heat supply in Norway between 2020 and 2060 they find that building heat flexibility is able to partly substitute a need for BEV charging flexibility.

The decarbonization of the mobility sector is an important task for the energy transition. The adoption of BEVs influences the consumption profile of households when being charged at home. As BEVs are not part of the residential energy technologies as determined in Chapter 2, they are not explicitly considered in the remainder of this thesis. The developed DSSs for investments in residential energy technology and the subsequent operation strategies focus on a coupling of the heat and electricity sector in CECs.

2.3 Citizen Energy Communities

As mentioned in Chapter 1, individuals have the potential to play an important role in the energy system of the future. According to a recent study by the German Institute for Ecological Economic Research, 90% of all households in Germany could be supplied by electricity from energy sharing (Aretz et al., 2022). This potential has been recognized by the European Union, who promotes decentralized energy communities through the European CEC regulation (European Parliament and Council of the European Union, 2019).

2.3.1 Development of Citizen Energy Communities

The idea of CECs has already been discussed for some years in various forms and referred to as 'local energy communities' (Orozco et al., 2019), 'renewable energy community' (Soeiro and Ferreira Dias, 2020), 'sustainable energy community' (Romero-Rubio and de Andrés Díaz, 2015), 'renewable energy cooperative' (Capellán-Pérez et al., 2018), 'citizen energy cooperative' (REScoop, 2022), or 'community microgrid'

	Voluntary participation	Energy sharing	Energy investment	Physical connection
Energy cooperatives	x		x	
Collective energy projects	x		x	
Community microgrids		(x)		x
Island microgrids		x		x
Local energy communities	x	x		(x)
Local energy markets	x	x		(x)
Citizen energy communities	x	x	x	x

Table 2.1.: Classification of energy community concepts.

(Warneryd et al., 2020). Walker and Devine-Wright (2008) investigate the variations of CECs and identify two key concepts to describe them. The authors find that communities must provide a high level of participation and community benefits must be distributed among its participants to qualify as a CEC. Gui and MacGill (2018) provide a typology that distinguishes between centralized, distributed and decentralized communities. The authors define energy communities as a social structure fostering a sustainable energy supply. They also extend the community focus to other commodities like heat, transportation, water, or waste management, in line with (Romero-Rubio and de Andrés Díaz, 2015). Participation in these communities should be voluntary and the generated benefits are not required to be monetary. The common ground for all concepts mentioned above is the focus on connecting individuals in a neighborhood or community within the context of energy generation and consumption, but the concepts may vary in characteristics and priorities. An overview on the classification of concepts related to CECs is presented in Table 4.1. Walker and Devine-Wright (2008) describe the concept of 'energy cooperatives', that focuses exclusively on financing renewable generation capacity in a community without the aspect of energy exchange. The authors distinguish between investments in commercial power plants or joint financing of residential facilities. In line with communities that do not necessarily require a physical connection, 'collective and politically motivated renewable energy projects' are described in (Kunze and Becker, 2015). The authors stress the political purpose of these communities where participation should generate benefits for each member. The concept of 'community microgrids' is described as a group of interconnected load and generation sources acting as a single entity towards the larger grid in (Warneryd et al., 2020). This is in line with (Cornélusse et al., 2019), who mention the concept as a community where all members are connected to the external electricity network through the same bus. The members of the community are able to exchange electricity among each other. 'Community microgrids' are described in (Gui et al., 2017) as self-contained systems that are connected to a central grid or are independent, also referred to as 'island microgrids'. All connection points in the microgrid, e.g., households, small businesses, prosumers are part of the community. Participation is not voluntary and tied to the grid topology (Perger et al., 2021). The application of community or island microgrids focus on a physical interconnection of its participants.

In the 'local energy community' concept, one key point is the aspect of voluntary participation, thus linking them closely to CECs. Orozco et al. (2019) describe local energy communities as a set of residential and industrial actors connected to the same distribution network to form a community on a voluntary basis. Romero-Rubio and de Andrés Díaz (2015) emphasize the sustainability aspect of energy communities through the installation of private renewable generation capacity. While most other ideas focus solely on electricity, their concept of 'sustainable energy communities' also regards heat and expands to other sectors such as water. 'Local energy markets' are a sub-concept of local energy communities and focus on electricity trading on peer-to-peer platforms. This concept has been implemented in pilot projects, for example, in the city of Walenstadt, Austria (Ableitner et al., 2020) or Landau, Germany (Richter et al., 2021).

The concepts mentioned above are based on a more detailed description that can be found in (Richter, 2022). While these concepts all contribute to the general idea of energy sharing and energy communities, their definitions are ambiguous and there is a general lack of a definition that summarizes the different concepts into a comprehensive model. As it provides a clear guideline for energy communities and is the current standard established by the European Union, the CEC concept defined by the European Union as described in Chapter 1 is used in this thesis. Germany was obliged to transform the European CEC regulation guidelines into national law by June 6^{th}, 2021. As of now, the measures taken by the German government to comply with these guidelines remain inadequate (Aretz et al., 2022; Boos, 2021).

2.3.2 Sector Coupling in Citizen Energy Communities

Some work has been published on the operation of microgrids with multi-energy systems from a technical perspective and with a focus on distributed energy generation. For an overview, see (Mancarella, 2014), for example. In examples for more recent studies, the influence of sector coupling in microgrids on residual electricity demand is investigated in (Kida et al., 2022). Li and Roche (2020) investigate the scheduling of multiple microgrids with sector coupling. An energy management system for multi-microgrid networks with sector coupling is presented in (Zhong et al., 2022). However, only a few studies address the topic of sector coupling in CECs with a focus on energy sharing among the participants. Existing studies often focus on the benefits of added flexibility in the CEC through the application of sector coupling that helps to increase the utilization of local renewable generation and reduce load peaks from the external grid.

An overview of existing trends and key issues in sector-coupled energy communities is presented in (Koirala et al., 2016). The authors present a concept for an 'integrated community energy system' that is used for balancing supply and demand within the community but can also provide services to the external grid. The model regards technologies on a household level, e.g., PV, PVT, HPs and BEVs, and technologies on the community level, e.g., community BSS or community PV. Local generation, consumption and collective purchasing of residential energy technologies is mentioned among the key activities in the integrated community energy system.

Regarding applications of sector coupling in CECs, a market mechanism for peer-to-peer trading in sector-coupled energy systems is proposed in (Wang et al., 2022). The market mechanism allows participants to trade both heat and electricity. Furthermore, trading coalitions are introduced. Participants can trade with each other within their coalition and the coalitions as a whole interact with the external grid and heat network. The authors conduct a case study based on a neighborhood in the Netherlands. The results show that peer-to-peer trading increases the overall benefits for the participants and almost all participants benefit individually, as well.

The effects of electricity trading in sector-coupled CECs is investigated in (Wanapinit et al., 2022). The authors evaluate the interaction of market participants and price developments using a mixed complementary problem formulation. A simulated case study for a CEC with twelve participants is conducted. The findings show that the sector coupling technologies in combination with TSSs provide additional flexibility to the community and thereby increase the consumption of local renewable generation.

The integration of storage systems and sector coupling technologies in CECs with high shares of renewable generation is evaluated in (Bartolini et al., 2020). The authors apply a mixed integer linear programming optimization model that minimizes installation and operation costs to determine the optimal residential energy technology size and dispatch strategy. Based on a case study with a real-world residential district they find that sector coupling in combination with storage systems can help to increase the utilization of local electricity generation and mitigate demand ramps on the electricity grid.

In summary, the applications of a coupling between the energy sectors heat, electricity and mobility show their potential to distribute renewable generation between sectors. The electrification of the heat and mobility sector supports decarbonization by increasing the use of renewable electricity resources like wind or PV power plants. As described in Chapter 1, IS can help individuals to apply sector coupling in their households through investments in renewable energy technologies. An introduction to IS is provided in the following chapter.

CHAPTER 3

INFORMATION SYSTEMS FOR INTEGRATED ENERGY SYSTEMS

The development and application of IS presents one way to support citizens in the investment decision process for renewable energy technologies. IS comprise the organized combination of people, hardware, software, communications, networks, data resources, policies and procedures that store, retrieve, transform and disseminate information (O'Brien and Marakas, 2009). IS are primarily used to guide processes and support decision-making within companies (Al-Mamary et al., 2014).

3.1 The Development of Green Information Systems

In this section, a brief outline of the relevant literature with regard to Green IS is presented. The first section sheds light on the contribution of the IS community to sustainability movements in general. In the following, an overview of existing work on DSS in Green IS in the context of (multi-)energy systems and CECs is given.

Green IS represents a subdivision of IS concentrated on the sustainable development of organizations and society with the aim of reducing carbon emission (Watson et al., 2010). Cho et al. (2014) identify three dimensions of environmental sustainability: 1) the economics of energy efficiency; 2) total cost of ownership, and 3) social imperatives. Based on these dimensions, Singh and Sahu (2020) identify five Green IS research areas. An overview of these research areas is presented in Figure 3.1. *Understanding of Green IS* comprises an introduction to the topic and is split in three subcategories: Evolution of Green IS, definitions and concepts of Green IS and dimensions of Green IS. *Green IS adoption* focuses on the acceptance of

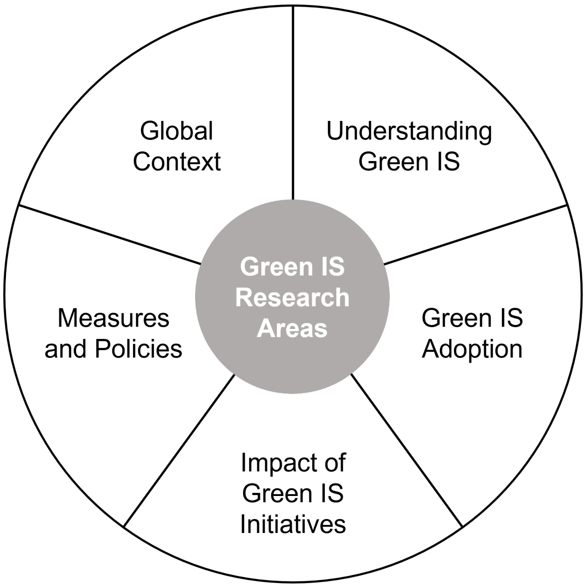

Figure 3.1.: Green IS research area classification (Singh and Sahu, 2020).

Green IS, critical success factors and the required hardware and software. *Impact of Green IS initiatives* investigates the introduction of Green IS concepts in industry, government and society. *Green IS measures and policies* focuses on performance measures, policies and regulatory compliance of Green IS. Studies located in the *global context* research area investigate Green IS for developed, underdeveloped and developing countries. Following this classification, the concepts presented in this thesis are located in fields *Green IS adoption* and *Green IS measures and policies.*

3.2 A Market Platform for Coupled Local Heat and Electricity Markets

As discussed in Section 2.3, different approaches for local energy markets, a subgroup of CECs, where participants can buy or sell electricity directly from their neighbors or residential power plants, have been discussed in previous studies (Ableitner et al., 2020; Richter et al., 2021). Existing approaches focus on buying and selling electricity, only. In an integrated CEC with sector coupling technologies such as HPs or PVT, both heat and electricity could be traded on the market platform, for example, as proposed in (Wang et al., 2022). Based on the market design and its outcome, the implementation of such a market can increase incentives for participants to in-

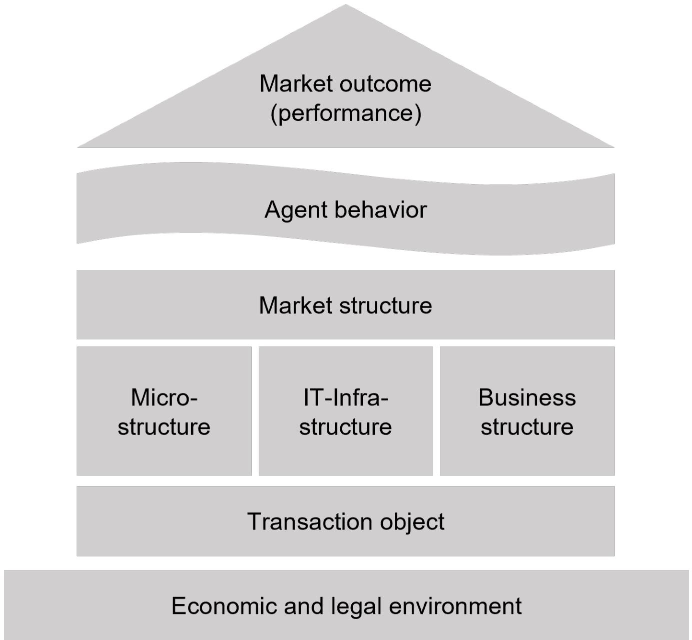

Figure 3.2.: House of Market Engineering (Weinhardt and Gimpel, 2007).

vest in residential energy technologies In this Chapter, I explain the principles of a market for heat and electricity trading in a CEC along the Market Engineering framework by Weinhardt and Gimpel (2007) consisting of five components: The economic and legal environment, the transaction object, the market structure consisting of microstructure, (IT-) infrastructure, and business structure, the agent behavior and the market outcome. The components are illustrated in Figure 3.2.

3.2.1 Economic and Legal Environment

With regard to electricity markets, the framework for CEC platforms in the European Union is the "Directive on Common Rules for the Internal Market for Electricity" (European Commission. Directorate General for Energy., 2019) that is described in Section 2.3. Since its introduction in 2019, the European member states were obliged to implement the regulation into national law. The German government has passed this deadline and has not yet introduced sufficient changes to the regulatory framework for forming CECs (Wiesenthal et al., 2022). Currently, there is a possibility to implement CECs under the regulatory system of a customer system ("Kundenanlage") for households that are in close proximity to each other and are insignificant for market competition on the electricity or gas market (§3 No. 24a EnWG). Following a court decision, an area can be declared as a customer system if the number of households does not exceed a few hundred, the area covers 10,000 m^2 or less, the transmitted energy is below 1,000 MWh and the local network is connected to the external grid through a singular point (Gabler and Pennekamp-Jost, 2020).

In comparison to electricity markets, the regulatory and legal environment for district heating markets varies strongly across European countries (Bacquet et al., 2022). DHN systems are natural monopolies (Bacquet et al., 2022) and therefore require some kind of regulation. As there is currently no uniform regulation within the European Union, the application of sector coupling services for district heating has to be evaluated for each country individually. Focusing on Germany, the current regulation favors heat network operators, allowing them to enforce a compulsory connection to the district heating network, effectively cutting off alternative heat sources that are not part of a DHN. Additionally, prices are liberalized and there is currently no third-party access regulation in place (Bacquet et al., 2022).

3.2.2 Transaction Object

The transaction objects on the market platform are heat and electricity. In general, the amount of consumption [kWh] is the relevant measurement unit. Electricity and heat power [kW] are regarded if network congestion could be an issue or capacity-based market mechanisms are implemented, e.g., a critical peak pricing tariff. The DHN flow supply and return temperatures can be measured for monitoring purposes. While heat itself is a homogeneous good, it can be priced differently based on a number of criteria, for example, its carrier medium (steam or water), temperature and carbon footprint. In contrast to electricity networks, the distribution of heat is rather slow. The transport of heat from one point of the DHN to another thus may take several hours. In addition to congestion, this must be accounted for in the market design. Electricity is a homogeneous good as well. Price differences may occur if customers value factors like renewable or local generation. The pricing of each good, necessary infrastructure, product properties and risk parameters can be specified in the contracts between retailer and consumer (Salah et al., 2017).

3.2.3 Microstructure

The microstructure comprises the design of a coordination mechanism for the allocation of the transaction object. The objective of mechanism design is to find and implement a mechanism that is compatible with individual incentives. These should simultaneously result in efficient decisions maximizing the total welfare, voluntary participation of individuals and balanced transfers across the agents (Jackson, 2014). Thereby, mechanism design aims to provide a system-wide solution to a decentralized optimization problem that provides self-interested agents with incentives to truthfully reveal private information about their preferences for different outcomes (Parkes, 2001). In a local electricity and heating market this is especially important, as the tendency towards a natural monopoly needs to be accounted for in the designed mechanism. The currently dominant microstructure in district heating systems and electricity networks are tariffs. These tariffs are usually flat with an invariant price per kWh. However, the decentralization of energy supply and the integration of intermittent renewable energy generation encourage the use of different mechanisms, such as time-varying tariffs or auction mechanisms. Tariffs with time-varying prices are time-of-use tariffs, real-time pricing tariffs and critical peak pricing tariffs that already exist in the electricity sector. An advantage of tariff systems is that they do not require active participation by the users. Another opportunity is the use of an auction system to coordinate supply and demand. According to the auction classification in (Parsons et al., 2011), auctions can be classified along several independent properties: single-dimensional or multi-dimensional, one-sided or two-sided, open outcry or sealed bid, first price or kth price, single-unit or multi-unit and single-item or multi-item. Heat and electricity auction mechanisms generally comprise single-dimensional, single-item, multi-unit auctions, while the other parameters can be determined according to circumstances. Possible auction formats are first-price-sealed-bid, Vickrey, Dutch, English call auction or a continuous double auction. The long-term analysis of an application of auction formats shows that participant activity that is necessary in the bidding process decreases over time (Richter et al., 2022). The automation of the bidding process, e.g., by the application of bidding agents can help to overcome this issue.

In the context of local energy markets, different market mechanisms have been applied for trading electricity. One popular approach is the application of a double-call auction (Block et al., 2008; Da Goncalves Silva et al., 2014; Ampatzis et al., 2014; Mengelkamp et al., 2018). Mengelkamp et al. (2019) provide an overview on existing market designs for local electricity markets. Another aspect in the design of the coordination mechanism are the differing preferences of participants in a CEC that may influence their willingness to pay (Perger et al., 2021). These preferences can be regarded in the auction design. Zade et al. (2022) propose an auction-based approach to satisfy participant's preferences in the CEC through the introduction of a price premium.

In a local heat and electricity market, both transaction objects can be regarded separately or in an integrated approach. Especially when sector coupling technologies, e.g., an HP are installed in the CEC, heat and electricity demand influence each other and require an integrated coordination. An example for coordination of heat and electricity allocation using a merit order is presented in (Maurer et al., 2021). When coupled with other services, e.g., the provision of a heat pump, the auctions become multi-dimensional, which could be addressed using a complex service auction (Blau et al., 2010).

The choice of the coordination mechanism should depend on the market environment, for example, the risk aversion of participants, available information, computational capabilities and communication costs (McAfee and McMillan, 1987). Due to its simplicity and behavioral incentives for participants, the application time-of-use tariffs or a real-time-pricing tariff, as implemented in the research project "Smart Microgrids as a Service" (SMaaS)[1] would be recommended in this Section.

3.2.4 IT-Infrastructure

The required software and technical components for the market platform are described in the IT-infrastructure. The digitization of energy supply increases the importance of this element. In Germany, the ongoing large-scale distribution of intelligent metering systems, the *Smart-Meter Rollout*, creates an important basis for the distribution and scalability of local energy market concepts. Intelligent metering hardware is required for the coordination of supply and demand accord-

[1] smaas.iism.kit.edu

ing to the implemented market or tariff mechanisms. The smart meter hardware records application and household load and generation data and is thus part of the data transmission system (Richter et al., 2021). Furthermore, secure communication protocols, encryption and firewall mechanisms that preserve data privacy and data preparation services are required to ensure a smooth and reliable platform operation. The user interface of the market platform is directed towards households and involved in user identification and verification, request and visualization of individual load data and interaction or feedback by the users to the platform operator, e.g., through the submission of bids (Richter et al., 2021). A database is required to store and deploy the preprocessed data generated in the community where the market platform is implemented. This comprises load and generation data but can be expanded to include data from additional services through sensors, e.g., using the LoRaWAN (*Long-Range Wide-Area Network*) technology. The database further integrates market and allocation data within the market platform.

3.2.5 Business Structure

The business structure refers to the business model of the platform operator. In case of the local heat and electricity market platform, the platform operator is usually the operator of the local electricity grid and gas network or the DHN. This could, for example, be the municipal utility or an external contractor. The business model includes pricing and transaction costs which in this case comprise the compensation for the provision of heat and electricity through a carrier medium. Aside from generation costs, this compensation may also include network charges and rent for the used technology, e.g., if an HP or a combined heat and power plant (CHP) plant is installed by the municipal utility. For the municipal utility, the lease of sector coupling technologies like an HP or a CHP plant can help to mitigate risk and decrease capital commitment.

In a sector-coupled market with prosumer participation, the business model becomes more complex. Other participants can now purchase the required electricity directly from the prosumers. If the prosumers own multi-sector generation plants, e.g., PVT modules, they can also supply heat directly to the community. Market participants may also share power plants within the community. The market operator is responsible for the organization of this process and the allocation of energy within the community. Furthermore, the market operator can offer additional services to the CEC, e.g., by providing a platform for shared investments in renewable generation and storage infrastructure. For a market platform with a sector-coupled heat and electricity market, a combination of services could represent the most promising approach.

3.2.6 Agent Behavior

As the market platform relies on the interaction of individuals, the agent behavior is a central part of its design. Three types of agents, namely professional agents, non-professional agents and automated agents could exist on the platform. Professional agents, i.e., the market operator will try to increase their revenue on the platform. On the other hand, non-professional agents, i.e., residents within a CEC have varying interests ranging from economic benefits to ecologic considerations. Furthermore, residential agents are not necessarily intrinsically motivated to actively participate in the market and have time restrictions regarding their availability. Previous analyses show that residential customers are reluctant to actively participate in the energy transaction process and bidding activity decreases rapidly over time (Richter et al., 2022). This puts non-professional agents in a disadvantage compared to professional agents. One way to overcome this imbalance is the application of automated agents that take over active bidding for the participants. In an empirical study, Richter (2022) shows, that such agents are able to exploit static bidding prices by other non-professional participants, but that the advantages are negated when all non-professional participants employ automated agents. It is also possible to employ strategies that require only limited active participation of the non-professional agents in the market, e.g., through the application of time-varying tariffs.

3.2.7 Market Outcome

The market outcome or performance is based on its economic and legal environment, the market structure and agent behavior. It can be measured based on a variety of indicators with different backgrounds, e.g., from an economic, ecological or societal perspective. In the context of a local electricity and heat market in a CEC, the market outcome can be evaluated with regard to revenue (economic), emission reduction or dependency on fossil fuels (ecological) and total participant utility (societal).

The principles described in this section represent one possible implementation of a market platform for a local coupled heat and electricity market. The remainder of this thesis focuses on supporting citizens in investing in renewable energy technologies and operation strategies for sector-coupled systems. In addition, the proposed market platform could support the coordination of energy supply and demand in integrated energy communities. As mentioned in the introduction of this section, such a market can be designed so that the market outcome can increase the incentives for participants to invest in residential energy technologies and thereby become prosumers. The support of participants in such investment decisions through preference-based DSSs is addressed in Part II of this thesis.

Part II.

Household Preferences in Energy Communities

INTRODUCTION TO PART II

As outlined in Part I, household investments in residential energy technologies are important for the success of the energy transition in Germany. However, citizens often lack the means or information to make such investment decisions. They can be supported through the development of preference-based DSSs for citizens in CECs.

The design of these DSSs can enable citizens to take an active role in the energy transition and thereby contribute to the mitigation of climate change. In Part II, I first determine the elements of a preference-based decision support tool for residential energy technology investments in CECs (Chapter 4). Furthermore, I evaluate acceptance factors of preference-based recommendations in a DSS for energy technology investments in comparison to naive recommendations in an online experiment (Chapter 5).

CHAPTER 4

SCALING THE CONCEPT OF DECISION SUPPORT IN CITIZEN ENERGY COMMUNITIES

This chapter introduces a platform-based DSS that enables residential consumers and prosumers to create CECs. The necessary information is determined to configure a local energy infrastructure and conceptualize a coordination mechanism that merges diverging preferences of participants. The application of the proposed framework is demonstrated using empirical data from the Landau Microgrid Project to provide a proof of concept. The developed platform facilitates the transition of citizen energy communities from a niche phenomenon to a large-scale concept. It is therefore an implementable solution from the IS domain toward the mitigation of climate change.

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4.1 Introduction

The shift towards a renewable energy sector causes a change of paradigm in energy systems across the globe. The widespread installation of renewable generation plants is leading to a decentralization of energy supply (Brauner, 2016). As a result of this development, local and individual decision-makers have the potential to play an important role in the energy system of the future. As mentioned in Part I, this potential has been recognized by the European Union through the introduction of the concept of CECs (European Parliament and Council of the European Union, 2019). This is not solely limited to electricity. To achieve the emission reduction goals of the European Union, all sectors responsible for emissions have to be further decarbonized. In residential areas, this includes electricity consumption, but also heat demand of buildings and mobility of residents (Brauner, 2016; Bründlinger et al., 2018). Until now, these sectors have usually been considered as separate systems, but research suggests that the desired emission reductions can be better achieved through an integrated approach (Bründlinger et al., 2018). In this chapter, we therefore emphasize the importance of a multi-energy approach in the context of CECs. The authors of this chapter conclude that the scaling of CECs from an experimental state to a mainstream movement is an important driver of sustainability developments. In the spirit of (Gholami et al., 2016), we therefore propose a communication-driven DSS as a solution to support the development and implementation of decentralized energy systems. We emphasize the requirement of i) a platform that offers the possibility for agents (local consumers, prosumers or investors) to find each other and to cooperate, ii) a coordination mechanism that aligns diverging preferences and iii) a support mechanism that provides recommendations in terms of technology investment and supply systems as well as their economic and environmental implications. We therefore answer the following research question:

RQ 1: What are the required elements to provide investment recommendations to CECs through a platform-based DSS in order to coordinate financial and ecological interests of participants?

To answer the research question, we provide a framework for a DSS in a CEC. To contribute to the scalability of CECs, we create a system that integrates participant preferences through the formulation of a corresponding optimization problem. We demonstrate the functionality of the proposed framework through a case study presented in Section 4.5. The case study shows potential local financial savings and potential carbon emission reductions caused by a concrete implementation of the platform.

4.2 Related Work

In this section, we briefly outline the relevant literature. In the first section, we shed light on the contribution of the IS community to sustainability movements in general. We then give an overview of existing work on DSS in Green IS in the context of (multi-)energy systems and CECs.

4.2.1 Information Systems and Sustainability

Watson et al. (2010) address the need for the IS community to be more involved in the development of IS that support a transition towards a more sustainable society. The authors introduce energy informatics as a sub-field of Green IS that “is concerned with analyzing, designing, and implementing systems to increase the efficiency of energy demand and supply systems” (Watson et al., 2010, p.24). Gholami et al. (2016) add that not enough feasible solutions for the challenges of the global climate change crisis are proposed by the IS community, in spite of the fact that it offers great potential. The authors state that “a major research gap seems to exist between what is needed to solve problems associated with climate change and what IS scholars have done despite the huge potential contribution of IS knowledge and skills” (Gholami et al., 2016, p.524). The positive influence of Green IS on environmental orientation and behavior has been demonstrated by several authors both on an individual and organizational level (Henkel and Kranz, 2018). The effects of IS-supported green initiatives in municipalities are studied in (Bengtsson and Ågerfalk, 2011), concluding that IS can optimize processes through the provision of information and thus influence the sustainability performance of a municipality. Jenkin et al. (2011) find that Green IS has the most positive impact when it provides feedback on environmental effects, reduces barriers to participate in actions and contains engaging features such as an entertaining interface. Seidel et al. (2018) identify the most significant design principles for Green IS as provision of novel information, the possibility to store and categorize ideas, interactive communication and the provision of action alternatives. In a review of the role of DSS in Green IS Research, Klör (2016) identifies research contributions along five theoretical concepts, namely the type of DSS (e.g., data-driven, knowledge-driven, communication-driven), the information technology (IT) artifact (e.g., constructs, models, instantiations), IS research method (e.g., conceptual research, empirical research), supported life cycle (first-, second- and end-of-life) and Green IS paradigm (green by IS versus green in IS). The author finds that communication-driven DSSs as well as conceptual research are underrepresented. While models are the most often found IT artifact, less than half also provide an instantiation and thus the intended implementation remains questionable.

4.2.2 Decision Support Systems for Citizen Energy Communities

As previously defined, a CEC is an association of local consumers and prosumers who cooperate in generating, storing and consuming distributed energy resources. While a certain degree of self-sufficiency is sometimes aspired, a CEC might still have access to external energy sources. One hurdle for CECs is bringing together several individuals on a local scale so that they can enhance local energy structures by taking joint investment decisions and by combining their energy infrastructures (Soshinskaya et al., 2014). This is made more difficult by the complexity of the decisions that have to be reached before any investment is made, including the choice and scale of renewable energy sources, infrastructures and the environmental impact that results from these choices. A further obstacle is the regulation of CECs that is changing rapidly and differs by country (Soshinskaya et al., 2014). The design of a DSS for the technological and infrastructural coordination of a multi-energy system, specifically aiming at residential neighborhoods targets a sub-task of DSS in Green IS that can be categorized along two dimensions. The first dimension is the target group of the DSS in terms of expertise in the energy domain. We divide this dimension into "experts" (i.e., utilities, project planners, service providers, policymakers) and "non-experts" (i.e., residents or private investors without expertise in the energy domain). The second dimension is the research perspective which can be either a "specific technology" or a holistic "system view". The transition between these two approaches can be somewhat blurred. In general, researchers either target the in-depth configuration of a particular technology using a unique method, or the integration and interaction of several technologies and infrastructures on a more superficial level. Table 4.1 shows a selection of DSS research on energy system design categorized into the two dimensions and helps in describing the identified research gap. In a technology-specific approach, Hopf et al. (2017) estimate the potential for PV. Wang et al. (2017) develop strategies for the installation and operation of CHPs in district heating networks. Rickenberg et al. (2013) evaluate optimal locations for car-sharing stations. Using a holistic approach, Liang et al. (2006) investigate

	Experts	Non-experts
Specific technology	(Hopf et al., 2017) (Wang et al., 2017), (Rickenberg et al., 2013)	(Azzopardi et al., 2013)
System view	(Liang et al., 2006), (Eickenjäger and Breitner, 2013), (Rager et al., 2013)	(Brandt et al., 2013), (Cherni et al., 2007)

Table 4.1.: Research on DSS in Green IS in the context of the design of an energy system.

optimal choices for electricity generation projects. Eickenjäger and Breitner (2013) consider the interaction of various exogenous and endogenous factors for political decisions regarding the replacement of fossil fuels in the mobility sector. Rager et al. (2013) describe a web-based DSS for multi-energy utilities.

In line with (Brauer et al., 2015) who find that smart city research is primarily directed at city planners, both the technology-specific and system perspective are mainly addressed at the expert level, i.e., project planning in the government or industry. One research that targets non-experts for a specific technology is presented by Azzopardi et al. (2013) who design a DSS for ranking PV technologies for households. A multi-criteria DSS to support the selection of an appropriate set of energy options for remote rural areas in Colombia is introduced in (Cherni et al., 2007). In an effort to address individual needs, the developed tool considers resources that are available to the community as well as group priorities. However, individual preferences of residents as well as the corresponding communicative coordination process are not included. The objective of designing a remote rural energy system in a developing country also differs substantially in terms of available technologies and prerequisites that weigh into the decision process. In conclusion, most hands-on research related to CECs either considers only a single energy sector or investigates a very specific use case with a fixed choice of technologies and limited parameter variability, which is in line with the findings presented in (Mancarella, 2014). Since the transition towards a more sustainable energy system is driven by local actors who become actively involved in energy generation and consumption, this is a shortcoming in existing research. Given the provided literature, a lack of research exists in regards to DSS for “non-expert” decision makers with a “system view”.

4.3 Scalability of Citizen Energy Communities

As described in the first part of this chapter, CECs hold the potential to propel the movement towards a sustainable energy system. Combined with the abilities of Green IS to promote participation, to provide access to information and to enhance pro-environmental behavior, this potential motivates our research proposal: We propose a DSS that unites potential participants, coordinates preferences of local consumers and prosumers and provides recommendations of energy investments that meet these preferences. Through this platform, the concept of CECs can be extended to other locations more easily. Scalability of CECs can be measured in two dimensions (Seyfang and Haxeltine, 2012; Ruggiero et al., 2018). First, a concept should have the potential to be replicated in other locations, that is, effective IS enable the concept of CECs to be easily adapted by others. This issue is addressed in our research through the consideration of local infrastructure characteristics, existing technologies and assets. Our model thus has the potential of disseminating CECs regardless of location and facilitates the emergence of CECs by uniting local decision-makers and enabling informed decisions. Second, the scalability of an existing CEC in a given location can be measured by the extent of participation from local individuals. A successful model therefore should be able to extend the size of a community by facilitating the coordination of large groups and the addition of new participants. In this respect, participation in CECs is investigated in (Seyfang and Haxeltine, 2012). The authors find that scaling up community projects beyond "committed environmentalists" is a problem for the majority of investigated projects. This issue is addressed in the proposed DSS through the incorporation of economic and environmental preferences, targeting a wide circle of potential users. By demonstrating economic advantages, the system addresses potential participants who are not driven by ecological motives. Additionally, a mechanism that coordinates diverging preferences further advances extended participation in CECs. The potential of transferring the concept of CECs to a global scale is high. For example, the potential of renewable energy-based systems on small islands is analyzed in (Blechinger et al., 2016). In spite of good conditions for the implementation of renewable energy technologies, many of these isolated energy systems still mainly use diesel generators today. Such systems especially exist in third-world countries and emerging markets.

The primary concern for isolated systems is to increase the autonomy of the system and from a socially conscious point of view, to raise the standard of living for the inhabitants of an isolated system. Nonetheless, the same incentives and market models as for CECs apply as well. Blechinger et al. (2016) conclude that missing knowledge is a significant problem that hinders a more widespread application.

4.4 Platform Design

To address the research gap derived in Section 4.2, we describe the design of a platform-based group DSS for CECs. First, we define the possible components of CECs that are taken into account for the recommendations of our proposed platform. Subsequently, we introduce the platform, its coordination mechanism and the resulting recommendation cycle in detail.

4.4.1 Components of Citizen Energy Communities

In the first part of this research, we emphasize the importance of an integrated approach in the deployment of CECs. The components of a residential integrated energy system include renewable generation, combined electricity and heat generation and energy storage systems. An overview of the components can be found in Chapter 2. The components and their connections are displayed in Figure 2.1.

4.4.2 Decision-Support Platform for Citizen Energy Communities

The overview on IS for CECs presented in Section 4.2 shows that while there are many examinations and optimizations of specific cases of CECs or its components, existing (IS) research does not include a holistic approach that considers individual preferences and existing resources of local residents in the design of CECs. We address the need of IS that enable the participation and coordination of agents in a local multi-energy community. In the following, we therefore design a user-centric platform that considers the preferences and characteristics of individuals participating in a CEC to support joint decisions, e.g., by giving recommendations. We define the required information as well as the coordination mechanism that merges individual preferences. Figure 4.1 shows the framework of the proposed DSS, which is based on the four design principles for sensemaking support systems derived from (Seidel

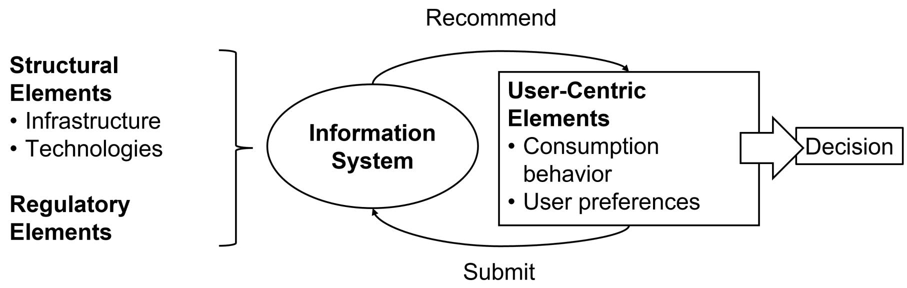


Figure 4.1.: Conceptual design of a CEC platform.

et al., 2018): We provide environmental facts in the form of possible CO_2 emission reductions (design principle 1). Our platform registers structural, regulatory and user-centric elements to support the decision making process (design principle 2). Merged and individual preferences are visible to all users during the recommendation cycles, providing a feature for communication (design principles 3a and 3b). Through the recommendation of applicable technologies, we provide action alternatives for the CEC (design principle 4). In the following, we describe the steps that lead to a recommendation for a CEC, starting with the initial input of the participants' data, preferences and assets, followed by the determination of feasible solutions through an optimization. Finally, we describe the recommendation cycle consisting of one or more recommendations that are given to the participants as feedback whereupon preferences can be adjusted gradually until a joint decision is reached.

4.4.3 Platform Initialization

Potential participants on the platform include consumers, prosumers and potential investors that do not have to be part of the local residents of a CEC. Each participant registers on the platform and receives an account. In the first step, she enters all relevant data on **Structural Elements** for a CEC:

- Geographic location: To join participants that live in geographic proximity, users need to enter their location of residence.
- Existing technologies: This includes all previously installed energy-related technologies that can be incorporated in a CEC, including but not limited

to renewable generation sources, CHP or storage units, HPs and BEVs.

- Existing infrastructure in the district: Structural restrictions must be taken into account when selecting alternatives. It is crucial that participants provide information on this infrastructure such as district heating or gas networks that require participation of residents.

The second input are the **User-Centric Elements** that disclose personal preferences and characteristics:

- Heat and electricity load profiles (if known) or consumption patterns: The issue of missing real historic load profiles can be overcome by including a synthetic load profile based on consumption patterns. When no real data is available, participants enter consumption characteristics, including household size (number of residents and living space), daily work routines (e.g. part-time vs. full-time employment, shift work vs. "9 to 5") and energy intensive appliances (e.g. BEVs or HPs). Based on this information, synthetic load profiles can be generated as shown in (Pflugradt et al., 2013).

- Weighting of economic vs. ecological preferences: In some cases, citizens are willing to pay a surplus on their energy consumption if this has a beneficial environmental effect (e.g. for electricity from renewable energy sources) (Mengelkamp et al., 2017b). However, economic considerations are the most prominent concern for most consumers. We introduce a weighting parameter α that can be adjusted from 0 (only environmental concern) to 1 (only economic concern) on a continuous scale. Environmental costs are expressed as costs of additional carbon emissions in Euro per ton and can therefore be compared to the economic impact of CEC solutions.

- Preferred degree of minimum self-sufficiency: This value can be adjusted on a continuous scale from 0 to 100% by each participant. It reflects a minimum aspired level of self-sufficiency and is integrated into the optimization problem as a constraint.

- Investment costs: The financial possibilities of residents may be limited. Therefore, participants may enter their maximum willingness to invest which is added to the optimization as a constraint.

- Preferences regarding preferred technologies: Here, a participant can select technologies from a multi-choice selection that she wants to see considered in the analysis. This does not mean that the selected technology has to be installed but it rather serves as a benchmark for participants who are interested in certain specific technologies.

- Intentions regarding planned technologies: Similarly to the previous point, participants can pick technologies from a multi-choice selection. However, this differs in the respect that there is already a pronounced intention to make the said investment in the foreseeable future. Thus, the planned time before installation is also required for this aspect to be included in the optimal recommendation. One example would be the planned purchase of a BEV.

These are the required elements to coordinate the financial and ecological interests of participants. From here on we determine how these elements can be used to provide investment recommendations to CECs through a platform-based DSS. For a specific intended CEC, multiple participants can join a project on the platform. Suitable projects for interested participants can be recommended based on geographic location. A project can either be initiated by an existing CEC or by individuals (consumers, prosumers or investors) with the objective of creating a CEC. The initiator of a project can make several choices during the set-up. She can select whether external investments are desired, thus making the project accessible for potential investors. A project can be created “open”, i.e., granting access to all interested individuals or “closed” in case a physical community exists and wants to use the application for recommendations only. However, even in open projects, the initiator may decide, whether an interested agent is allowed to join the project. For the adoption of CEC projects, regulation plays a major role. Even though the European Union has issued a directive for the promotion of CECs (European Parliament and Council of the European Union, 2019), the regulation is still inconsistent between most countries and the implementation is only underway. For instance, the German regulator has established the use of so called *customer systems* in which local trading of energy is possible under certain circumstances and with certain financial benefits (Bundesministerium für Justiz, 2011). Another approach is to link customers and appliances 'behind' the meter to allow for shared generation and consumption in-

Variable	**Unit**	**Description**
A^{CO_2}	kg	Overall amount of CO_2 produced by an appliance
b^{el}, b^{ht}		Battery status
c^{CO_2}	€ /t	Specific CO_2 costs
C^{el}, C^{ht}	€	Investment and operating costs for a electricity or heat technology
c^{el}, c^{ht}	€ /kWh	Electricity / heat costs
$c^{g,el}, c^{g,ht}$	€ /kWh	Grid electricity / heat costs
d^{el}, d^{ht}	kWh	Electricity / heat demand
db^{el}, db^{ht}	kWh	Storage electricity / heat demand
$f^{g,el}, f^{g,ht}$	kWh	Electricity / heat fed into the grid
$F^{c,el}, F^{c,ht}$		Cost function electricity / heat
$F^{c,env}$		Environmental cost function
$F^{r,el}, F^{r,ht}$		Revenue function electricity / heat
i		Appliance index
j		Participant index
K		Set of available technology specifications
M		Number of appliances
N		Number of participants
$r^{f,el}, r^{f,ht}$	€	Feed-in revenue electricity / heat
s^{el}, s^{ht}	kWh	Electricity / heat supplied by an appliance
$s^{g,el}, s^{g,ht}$		Electricity / heat supplied by the grid
t	h	Time step index
T		Time series
X	kW,kWh	Matrix of applied technology specifications
X_i	kW,kWh	Vector of specifications for technology i
α	%	Weighting factor
α^m	%	Merged weighting factor
β	%	Degree of self-sufficiency
β^m	%	Merged degree of self-sufficiency
ϕ	%	Percentage of self-sufficiency

Table 4.2.: Nomenclature.

dependently of the energy network as self-consumption (Mengelkamp et al., 2017a). A uniform regulation approach would nonetheless help to improve the scalability of CECs on a European and global stage as business models could be exported and transferred more easily.

4.4.4 Deriving an Optimal Solution

From the user-centric preferences and the structural and regulatory input, we derive an optimal solution for the development of a CEC. In a new project, the participants' preferences are merged to generate one set of preferences. As explained in Section 4.4, the individual tendency towards an economic or environmental optimization of the community project is expressed by α. The merged α^m includes the mean of all set preferences α_j and is given by:

$$\alpha^m = \frac{1}{N}\sum_{j=1}^{N}\alpha_j \tag{4.1}$$

Here, N is the number of participants. The full nomenclature is given in Table 4.2. The time step index t is omitted in the table. Whenever it is added in a formula, the variable changes over time. The merged minimum self-sufficiency β^m is also derived as a mean of all individual self-sufficiency preferences β_j and given by:

$$\beta^m = \frac{1}{N}\sum_{j=1}^{N}\beta_j \tag{4.2}$$

The revenue $F^{r,el}_{t,i}, F^{r,ht}_{t,i}$ and costs $F^{c,el}_{t,i}, F^{c,ht}_{t,i}$ in the electricity and heat sector are calculated for every time step t in Equations (4.3) to (4.6). The revenue and cost functions are given by:

$$F^{r,el}_{t,i}(X_i) = s^{el}_{t,i}(X_i)\cdot c^{el} + f^{g,el}_{t,i}(X_i)\cdot r^{f,el} \qquad \forall\,(t,i)\in(T\times M) \tag{4.3}$$
$$F^{r,ht}_{t,i}(X_i) = s^{ht}_{t,i}(X_i)\cdot c^{ht} + f^{g,ht}_{t,i}(X_i)\cdot r^{f,ht} \qquad \forall\,(t,i)\in(T\times M) \tag{4.4}$$
$$F^{c,el}_{t,i}(X_i) = d^{el}_{t,i} + db^{el}_{t,i}(X_i)\cdot c^{el} + s^{g,el}_{t,i}\cdot c^{g,el} + C^{el}_{t,i}(X_i) \qquad \forall\,(t,i)\in(T\times M) \tag{4.5}$$
$$F^{c,ht}_{t,i}(X_i) = d^{ht}_{t,i} + db^{ht}_{t,i}(X_i)\cdot c^{ht} + s^{g,ht}_{t,i}\cdot c^{g,ht} + C^{ht}_{t,i}(X_i) \qquad \forall\,(t,i)\in(T\times M) \tag{4.6}$$

Here, X_i denotes a vector where every entry contains information about the applicable technology $i \in M$ such as power, storage capacity and cycle efficiency. Equation (4.7) denotes the environmental costs $F^{c,env}$, measured in CO_2 equivalents, which are given by:

$$F^{c,env}_{t,i}(X_i) = c^{CO_2} \cdot A^{CO_2}(X_i, s^{el}_{t,i}, s^{ht}_{t,i}) \; \forall \, (t,i) \in (T \times M) \tag{4.7}$$

For each technology that is available in the project, the optimization given in Equation (4.8) returns an optimal value. Thus, the project owners have the ability to implement the recommended system. The optimization constraints consist of two functions for balanced supply and demand in the heat and electricity sector, two equations for storage system updates, the calculation of the self-sufficiency ratio over the entire time series, the technology restrictions and a limitation for the minimum self-sufficiency. The entire optimization is given by:

$$\begin{aligned}
\min_X - &\left[\alpha^m \left(\sum_{i=1}^{M} \sum_{t=1}^{T} F^{r,el}_{t,i}(X_i) + F^{r,ht}_{t,i}(X_i) - F^{c,el}_{t,i}(X_i) \right.\right. \\
&\left.\left. - F^{c,ht}_{t,i}(X_i) \right) - (1-\alpha^m) \left(\sum_{i=1}^{M} \sum_{t=1}^{T} F^{c,env}_{t,i}(X_i) \right) \right] \\
&w.r.t. \\
&s^{g,el}_{t,i} + \sum_{i=1}^{M} s^{el}_{t,i}(X_i) - f^{g,el}_{t,i} - d^{el}_{t,i} - db^{el}_{t,i}(X_i) && = 0 \; \forall \, (t,i) \in (T \times M) \\
&s^{g,ht}_{t,i} + \sum_{i=1}^{M} s^{ht}_{t,i}(X_i) - f^{g,ht}_{t,i} - d^{ht}_{t,i} - db^{ht}_{t,i}(X_i) && = 0 \; \forall \, (t,i) \in (T \times M) \\
&b^{el}_{t-1}(X_i) + s^{el}_{t,i}(X_i) - db^{el}_{t,i}(X_i) - b^{el}_{t,i}(X_i) && = 0 \; \forall \, (t,i) \in (T \times M) \\
&b^{ht}_{t-1}(X_i) + s^{ht}_{t,i}(X_i) - db^{ht}_{t,i}(X_i) - b^{ht}_{t,i}(X_i) && = 0 \; \forall \, (t,i) \in (T \times M) \\
&\sum_{i=1}^{M} \sum_{t=1}^{T} \frac{s^{el}_{t,i}(X_i) - f^{g,el}_{t,i} + s^{ht}_{t,i}(X_i) - f^{g,ht}_{t,i}}{s^{g,el}_{t,i} + s^{el}_{t,i}(X_i) - f^{g,el}_{t,i} + s^{g,ht}_{t,i} + s^{ht}_{t,i}(X_i) - f^{g,ht}_{t,i}} && - \phi = 0 \\
&X_i \in K_i \; \forall \, i \in M \\
&\beta^m < \phi
\end{aligned} \tag{4.8}$$

The optimal solution is not to be understood in such a way that on a continuous scale all possible alternatives (e.g., arbitrarily large storage units, an HP etc.) are calculated. Instead, a predefined set of alternatives, which is based on the described possible components, available sizes (e.g., commercially available BSS size) and the preferences and restrictions are analyzed and lead to a mixed integer linear programming formulation. From this set, the optimal possibility is then recommended to the participants.

4.4.5 Recommendation Cycle

When a group of participants initiates a community project, they may choose to receive a recommendation based on their entered preferences, assets and restrictions. To derive the optimal solution, the platform analyzes a predefined set of alternatives as described in Section 4.4.4. For each alternative, the platform calculates the CEC's benefits in terms of financial and environmental impact. An optimal technology set is then recommended based on the target function. The recommendation is displayed with all relevant information such as investment costs, duration of amortization and emission reductions. Along with the recommendation, this information is displayed for all considered alternatives to ensure the adherence to the design principles established by Seidel et al. (2018). It may happen that the constraints (e.g., degree of self-sufficiency) are not achievable within the given parameters or only at unreasonable costs. This is the case if the issued recommendation exceeds investment costs or a minimum threshold for the rate of utility of a technology. Then, participants receive recommendations on how a change in preferences might result in a more favorable outcome. It is encouraged to adjust the user-centric elements gradually to receive alternative optimal scenarios and improve the coordination between participants who may interact during the process.

4.5 Case Study

To demonstrate the functionality of the proposed platform, we present a case study based on data of the Landau Microgrid Project (LAMP) (Richter et al., 2021). For the case study, we use consumption data of eight households from September to October 2019 and a 23 kW PV plant that is already installed at the location. The eight participants form a CEC that utilizes the power generated by the PV panel. The main objectives are to reduce energy costs and increase the revenues generated by the PV panel. The reduction of local carbon emissions and a degree of self-sufficiency are not of major concern. We show that for a rising number of participants, the overall cash flow increases and the amortization time decreases, thus giving the incentive to scale up the system and include more members. This speaks to the spirit of the proposed solution that is intended to increase local engagement in CECs.

4.5.1 Implementation

For the case study, we assume that the PV panel is owned by the eight participants and feed-in revenues are split equally between all parties. To extend the CEC, the community has the option to install a BSS and an HP that is connected to the local DHN. For the optimization, consumer data and preferences are derived from the IS platform. The CEC participants submit individual consumption profiles and the PV generation profile. Since there are no actual heat load profiles available for the CEC, we use data generated with a load profile generator (Pflugradt et al., 2013). The optimization is carried out with three available batteries and two HP sizes. The rated capacity of the BSS is 4.6 kW, the load efficiency is 96% and the storage efficiency is 98% for all models. The usable capacities are 16 kWh, 18 kWh and 20 kWh and the corresponding investment costs are 23,790€, 26,360€ and 28,930€. The HP that can be installed has a coefficient of performance (COP) of 3.5 and is available in two sizes (10 and 15 kWp) and resulting investment costs of 16,500€ and 18,400€. All participants agree to pay the same amount for the installed appliances and share costs and revenues equally. The electricity purchasing costs are set to 0.30€ per kWh, heat purchasing costs at 0.08€ per kWh and the PV feed-in tariff is set according to German feed-in regulation for 2019 at 0.0959€ per kWh.

4.5.2 Results

The different scenarios are compared with regard to cash flow and amortization time. The results show that a solution can be found where the investments are amortized within the lifetime of the installed objects. For the case study, the installation of both a BSS and an HP is considered. The scenarios are benchmarked against a

Cash flow base case: -1,725.14€	**BSS 16 kWh**	**BSS 18 kWh**	**BSS 20 kWh**
HP 10 kWp	528.88 (12.70)	551.85 (12.94)	574.83 (13.17)
HP 15 kWp	564.90 (**12.45**)	587.87 (12.69)	**610.61** (12.92)
	Δ Cash flow [€] (Amortization [years])		

Table 4.3.: Economic calculation of HP & BSS scenario including heating costs.

base case without further additions. In the base case, the entire cash flow of the CEC amounts to -1,725.14€ of operating costs for heat and electricity demand. An overview of the case study results is presented in Table 4.3. In a combined scenario, a larger HP is favorable both with regard to the cash flow difference and the amortization time. For the BSS, the recommendation differs depending on the optimization goal. A 16 kWh BSS is favored when only considering the amortization time. The recommendation for a project with focus on a low amortization time would be the combination of a 16kWh BSS together with a 15kWp HP. The investment per participant is 5,273.75€ and the return on investments per year is 8.0% or 423.68€. With the implementation of both HP and the PV plant, the CEC can save 1.30 tonnes of CO_2 emissions in the regarded period (Considering $510g/kWh^{el}$ as estimated for the German electricity mix (Icha and Kuhs, 2019)) and achieve a degree of self-sufficiency of 31%. For a project with focus on large cash flow generation, the recommendation is the installation of a 20kWh BSS and a 15kWp HP. Here, the investment per participant rises to 5,916.25€ and the return on investments decreases to 7.7% or 457.96€ per year. The implementation can save 1.42 tonnes of CO_2 in the regarded period and achieves a degree of self-sufficiency of 34%. A main objective of this work is to create incentives for a decentrally organized participation in the energy transition through CECs. To show the overall improvement that can be achieved with a higher participation rate in a project, we vary the number of agents participating in the energy community for the combined scenario with a 16kWh BSS and a 15kWp HP. By calculating the amortization time and yearly cash flow difference, we demonstrate the effects of different participation rates. An overview is presented in Figure 4.2. The results show that a higher number of participants has a strictly positive effect on both the amortization time and yearly difference in cash flow. This indicates, that our proposed model creates an

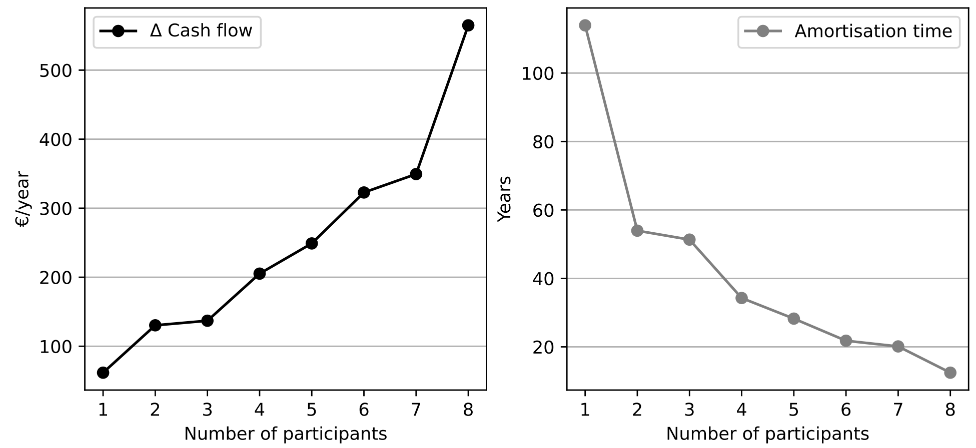


Figure 4.2.: Amortization time and cash flow with varying numbers of participants.

incentive for households to participate in CEC projects and also for existing projects to motivate new participants.

4.5.3 Discussion

In the previous sections, we define the basic components, requirements and mechanisms for IS that enable the formation of CECs. However, some aspects remain that would need to be taken into account before implementing the proposed platform. One point is the application design. We suggest an easy-to-access application, that is web-based or distributed through a mobile application. An important aspect would be, for example, the "engaging features" proposed by Jenkin et al. (2011). Further, the possible roles of the participants, their rights, obligations and restrictions must be defined in detail. An investor, for example, is a special type of participant who does not have to live in proximity to a potential CEC but is willing to provide financial resources. We do not go into further detail about the possibilities and implications of investors but note that this is an important participant that should be included and needs to be further elaborated in future work. In addition, it should be investigated how joint revenues are divided among participants. This is especially important when an external investor participates in the CEC, but it is also relevant for residents who may jointly invest in technologies (e.g., a BSS). Then the question arises as to whether the revenue should be divided solely according to the share of the investment or whether it should also be rewarded if one behaves economically beneficial, for example by providing flexible demand. Furthermore, questions regarding the ownership and responsibility for the technology, e.g., if repairs are necessary, need to be settled. Another interesting consideration could be a reward scheme for bringing in new participants. As additional consumption might have a similar effect to a storage system, this can save investment costs. A further point of consideration are amount and quality of available consumer data. In our use case, we rely on real consumption data instead of synthetic generated load profiles over a longer period of time. The use of sparse data to give recommendations regarding optimal electricity tariffs is investigated in (vom Scheidt et al., 2019), suggesting that even small samples of real data are suitable for this task. Further research could be done on a comparison between real and synthetic data sets for different use cases. While the overall design of the proposed DSS is finalized, the specification of detailed platform components is beyond the scope of this chapter and remains subject to future research. The proposed DSS can be further enhanced using the design science research cycle presented in (Hevner et al., 2004). As proposed in (Staudt et al., 2019), behavioral research is required within the design cycle to assess participant preferences and requirements. Besides the context of CECs, the proposed DSS can also be applied by decision makers in companies that want to establish more sustainable energy practices. The requirements of such applications are subject to further research.

4.6 Conclusion

In this chapter, we develop a platform-based DSS for CECs and show its principal functionality in a case study for a microgrid in Landau, Germany. The necessity of the developed DSS arises from the high potential of Green IS to contribute to sustainable development and to promote environmentally beneficial behavior. CECs in particular offer a solution to integrate renewable energy sources in a decentralized energy system. To overcome obstacles to the emergence of CECs, we design a generally applicable platform that considers individual and diverging preferences and supports complex group decision making. We thus answer the research question introduced in the first section: To coordinate financial and ecological interests of participants, a combination of structural elements (geographic location, existing technologies, existing infrastructure), user-centric elements (load profiles, weighting of preferences, preferred degree of self-sufficiency, investment costs, technology preferences, intentions regarding planned technologies) and regulatory elements is required. With an optimization that regards these elements we provide investment recommendations to CECs through a platform-based DSS. We define the information required within a platform-based DSS to initiate a project and generate a recommendation, consisting of structural elements and participant's consumption patterns and preferences. We introduce a coordination mechanism that takes into account economic and ecological preferences through a weighting parameter in the target function of the optimal technology assessment. For the case study, we show that a 15 kW HP and 16 kWh BSS generate the highest cash flow, leading to an investment amortization within less than 13 years and carbon emission reductions of 1.4 tons over a period of two months. The proposed platform has the potential to positively influence the scaling of CECs by facilitating participation and supporting interaction, providing comprehensible information on environmental impact and by presenting different paths of actions and their economic and ecological consequences. With the help of the use case, we show how the model is applied and its potential effects. We provide a system that integrates participant preferences through an optimization formulation. Our research is thus a tangible contribution of the IS community towards a decarbonized energy system. The acceptance of preference-based DSSs as proposed in this chapter is evaluated in Chapter 5.

CHAPTER 5

EXPERIMENTAL EVALUATION OF DECISION SUPPORT FOR RESIDENTIAL ENERGY TECHNOLOGY INVESTMENTS

The results of the previous chapter support the development of preference-based DSSs that provide recommendations for citizens regarding investments in residential energy technologies. The success of such IS depends on the acceptance of the recommendations by the users. To evaluate the acceptance factors for preference-based recommendations in DSSs, the results of an online experiment (n = 324) are presented in this chapter. In three treatment groups with a total of six treatments and a between-subject, one-shot design, participants choose from 20 investment alternatives for residential energy technologies with or without uncertainty about the outcome. For comparison, the first two groups are presented with a naive recommendation indicating the lowest cost or the lowest emission alternative. In a third treatment group, participants receive a preference-based recommendation based on their individual cost or emission preference as determined in a rank-based conjoint analysis. According to the results of the experiment, the acceptance rate of the recommendation is on average 22 percentage points higher in the treatments with preference-based recommendations.

5.1 Introduction

Scaling up renewable energy generation, storage and sector coupling technologies supports the transformation of the energy system on the pathway towards decarbonization (Hansen et al., 2019). As argued in Chapter 1, individuals play a large role in this transformation through investments in these technologies (Yildiz, 2014).

These investments need to be further increased to reach the German emission reduction targets (Weniger et al., 2018). However, citizens often lack energy-related knowledge (Martins et al., 2020). In a general context, such a lack of knowledge in combination with competing interests, for example with regard to costs and emissions and uncertainty regarding future payoffs can lead to a delay in individual investment decisions (Blake, 1999; Morwitz and Schmittlein, 1992).

Households therefore need assistance in making decisions about residential energy technology investments. While other studies follow the approach of educating citizens by increasing energy literacy (Martins et al., 2020), this chapter focuses on directly assisting citizens by means of a DSS with preference-based recommendations. As argued in Chapter 1, DSSs aim to support and improve decision making (Arnott and Pervan, 2014) and thus can help to overcome some of the problems with regard to investment in residential energy technologies. Such a concept of a platform-based DSS for citizens is presented in Chapter 4.

Venkatesh et al. (2003) state that the performance benefits of IS often depend on the individual willingness to accept and use an available system. One example, where support systems for residential energy investments have been implemented with a focus on energy efficiency are "residential energy audits" in the US. Residential energy audits are professional home assessments to identify energy efficiency investments and provide estimates of the expected monthly savings (Gillingham and Tsvetanov, 2018). Similar to the investments in residential energy technologies, households face uncertainty regarding future payoff due to imperfect information about energy costs and product-specific attributes (Gillingham and Palmer, 2014; Allcott, 2016). Participation in energy audits remains at a low level and only 4% of households in the US have participated in an energy audit (Palmer et al., 2015).

A similar support system using preference-based recommendations for residential energy technology investments could be implemented based on the findings presented in Chapter 4. The impact of such a system on the reduction of carbon emissions in a household or a CEC depends on the acceptance of the proposed investment recommendations by its users. Acceptance factors for preference-based recommendations in DSSs in the context of energy technology investments are, therefore, evaluated in this chapter. The experiment further investigates the perceived usefulness of the recommendation, as it is a fundamental determinant of user acceptance (Davis, 1989).

When making investment decisions for residential energy technologies, households are faced with uncertainty, for example regarding the development of energy prices or future generation and consumption patterns. Phillips-Wren and Adya (2020) identify uncertainty as one stressor of the decision-making process in general which can be mitigated through the application of DSSs. Therefore, the impact of uncertainty on acceptance and the perceived usefulness of the DSS recommendation is investigated. Thereby, the following research questions are answered:

RQ 2: To what extent does providing recommendations that take into account the trade-off between individual cost and emission preferences in a DSS for residential energy technology investments increase the recommendation acceptance compared to recommendations that consider either costs or emissions?

RQ 3: What is the effect of uncertainty on recommendation acceptance and the perceived usefulness of the DSS?

The research questions are addressed by means of an online experiment (n = 324). Participants take the role of residential investors and decide between 20 different investment alternatives for residential energy technologies. The investment alternatives differ in investment and operation costs and carbon emissions. To support the investment decision of the participants, they are presented with an investment recommendation. Depending on the treatment, the recommendation indicates the alternative with the lowest costs or emissions or an investment alternative based on the participant's preferences. These preferences are determined using a rank-based conjoint analysis. To evaluate the impact of uncertainty on the acceptance and perceived usefulness of the recommendation, the experiment is conducted both with and without uncertainty regarding operation costs and emissions.

The remainder of this chapter is structured as follows: First, an overview of related work in the context of DSSs for energy investments is provided in Section 5.2. The structure of the online experiment as well as the derivation of participant preferences and determination of the investment recommendations are presented in Section 5.3. The results of the online experiment are described in Section 5.4. The findings are discussed in Section 5.5 and summarized in Section 5.6.

5.2 Related Work

A general overview on DSS applications in the context of CECs is presented in Section 4.2.2. In this section, further applications of DSSs for decision-making in the context of energy consumption and energy investments are introduced with a focus on the acceptance of these tools.

A number of studies have investigated factors and measures that impact individual decisions for residential energy investments. Colasante et al. (2021) conduct an online survey to investigate the willingness of individuals to shift their intraday energy use to maximize self-consumption and reduce energy consumption. While most study participants (95%) did not own residential PV systems, 85% expressed a positive opinion about a potential installation. According to the survey results, monetary incentives are the main driver for the installation of a residential PV system. For participants with an awareness of the emission reduction through PV compared to fossil fuels, the authors reported a higher willingness to increase self-consumption. Furthermore, individuals who were oriented on reducing their own carbon footprint were less influenced by monetary subsidies. The authors, therefore, suggest a combination of monetary and non-monetary incentives to support investments in residential energy technologies. While the study focuses on the motivations of individuals to invest in residential PV, the authors did not consider a combination of residential energy technologies or recommendations regarding the optimal decision for the participants. Gillingham and Tsvetanov (2018) investigate the effect of information provision as a nudge to influence the acceptance of residential energy audits in a randomized field experiment. The authors examine the effectiveness of information provided during the audit uptake process when the households face the decision of whether or not to complete an already scheduled audit visit. The results show that an information notecard containing individual information can increase the acceptance rate by 1.1 percentage points. The experiment in (Gillingham and Tsvetanov, 2018) focuses on the general use of recommendation systems, in this case efficiency audits, and not on the outcomes of such audits.

The investment recommendations presented to the participants in the online experiment in this chapter could also be viewed as a form of nudging, as the outcome of the investment decision is not influenced by the recommendation, only by the participant investment decision itself. Nudging represents the implementation of measures to alter individual behavior in a predictable way without explicitly excluding any options or changing economic incentives significantly (Thaler and Sunstein, 2009). For a general overview of nudging applications, please refer to (Hummel and Maedche, 2019).

Actual investment decisions resulting from such an energy audit are investigated in (Holladay et al., 2019). The authors compare the effects of monetary incentives, randomly varied subsidies and information nudges through a comparison of monthly consumption, expenditures and carbon emissions on the likelihood of a household participating in an energy audit and subsequently making an investment in energy-efficient appliances. Comparing point estimates, the authors estimate the worth of nudges at 50$ to 70$. The authors consider individual household data but do not include household preferences in their recommendations. According to the results of the study, price subsidies and nudges increase participation in audits, but have no significant effect on subsequent energy efficiency investments.

To further contribute to the understanding of acceptance factors for DSSs, the study presented in this chapter investigates the provision of preference-based recommendations in the context of residential energy technology investments. The results can be used to support the design of application-oriented DSSs. In the following section, the design of the online experiment is presented.

5.3 Experimental Study

In this section, the experimental procedure and the treatment design, the determination of participant preferences and the derivation of the investment recommendations are presented. Furthermore, the sample characteristics are introduced.

5.3.1 Procedure

The experimental procedure is displayed in Figure 5.1. There are six treatments. These are differentiated by the type of recommendation during the investment and the application of uncertainty regarding future costs and emissions of the investment alternatives. The treatments are explained in more detail in Section 5.3.3. The study is designed as an online experiment using a between-subject design and consists of five parts that took participants approximately 20 minutes to complete. In Part I, participants are given information on the overall structure of the experiment (for details see Appendix Table A.1). Part II consists of a pre-experimental survey, where participants are asked to state their individual cost and emission importance in a general behavioral context and in the context of energy consumption decisions on a 5-point Likert scale (e.g.: *What role do costs play in connection with decisions affecting your energy consumption?* For details, see Appendix Table A.2). The results of this pre-experimental survey are used in the analysis to validate the results of the conjoint analysis and investigate the impact of cost and emission preferences on investment decisions.

5.3.2 Determination of Individual Preferences

In Part III of the experiment, a rank-based conjoint analysis is used to quantify the trade-off between the cost and emission preferences of each participant. This information is later used for the recommendation in the "preference" treatment in the investment decision. The conjoint analysis is widely used in marketing research for analyzing consumer trade-offs (Green et al., 2001). As one of the established conjoint analysis methods besides rating-based conjoint analysis, rank-based conjoint analyses can be generally applied in contexts where individuals need to make decisions with regard to multi-attributive objects (Eggers et al., 2022; Homburg et al., 2022). In the experiment, participants are tasked with ranking nine electricity tariffs (see Appendix Table A.1). The tariffs are presented to them all at once in a randomized order and differ with regard to costs and emissions that are caused by the generation technology. The conjoint alternatives are presented in Table 5.1. Figure 5.2 shows the appearance

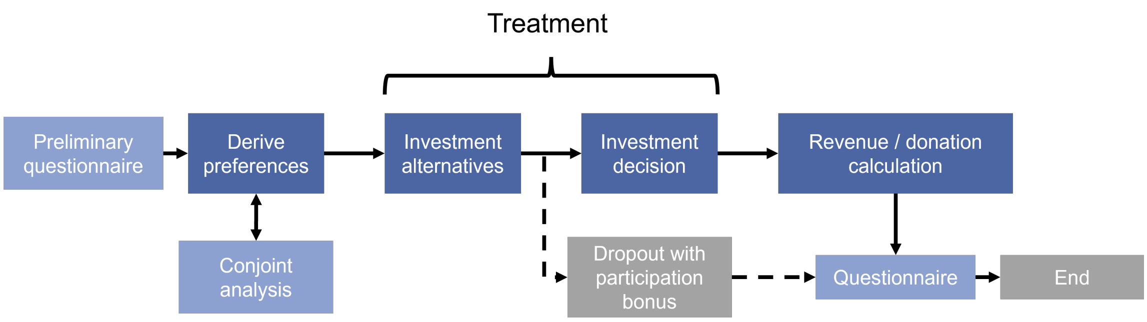


Figure 5.1.: Chronological structure of the online experiment.

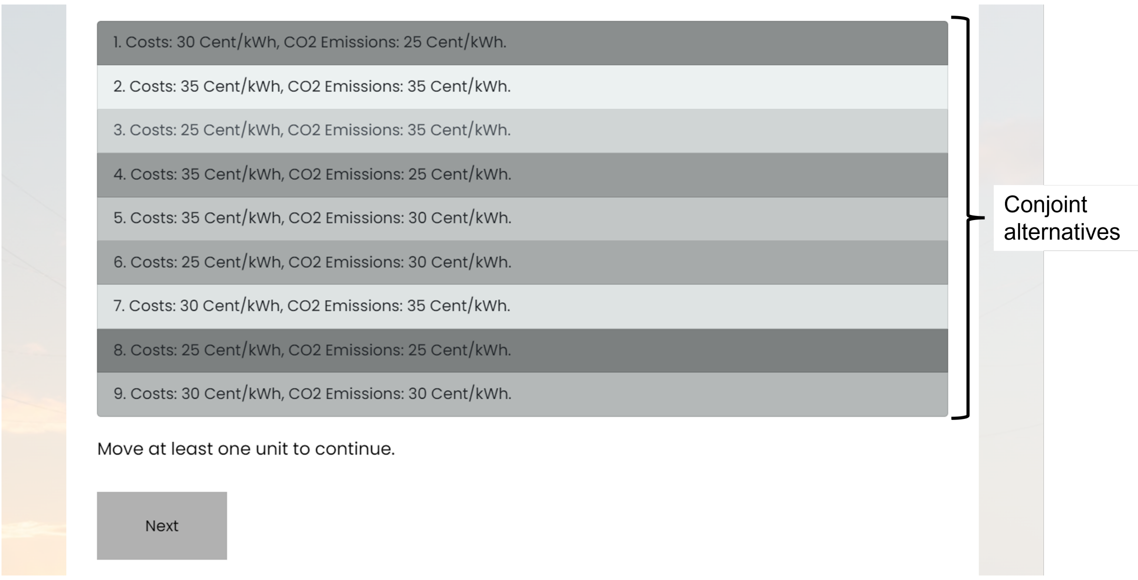


Figure 5.2.: Appearance of the rank-based conjoint analysis in the online experiment. Translated from original German.

of the conjoint alternatives in the experiment. The participants are then instructed to rank the nine electricity tariffs according to their preferences. They can change the order of the presented tariffs using a drag-and-drop mechanism and have to change at least one rank (that they can then change back) to continue the experiment. Using an ordinary least squares regression, the part-worth utilities for costs and emissions are calculated based on the ranking of the alternatives. These are used to calculate the cost and emission weights. The weights are normalized, so that *weight emission* + *weight cost* = 1.0 to reflect the trade-off between costs and emissions. A higher cost weight represents a stronger valuation for changes in economic costs while a higher emission weight represents a stronger emission valuation. Please refer to (Homburg et al., 2022) for a detailed description of the conjoint analysis.

Element	**Unit**	**Dimensions**
Cost	€$/kWh$	0.25, 0.30, 0.35
Emission Costs	€$/kWh$	0.25, 0.30, 0.35

Table 5.1.: Rank-based conjoint analysis components (3×3 design).

5.3.3 Investment Decision

In Part IV, each participant is assigned to one of the six treatment groups. Participants are unaware of the other treatment groups. After an introduction to the topic and an explanation of the investment procedure, which differs between treatments with and without uncertainty, the participants are asked to make an investment in a residential energy technology. The investment options themselves only differ in costs and emissions to avoid a technology-preference bias. However, participants are being told that such an investment could be, for example, the installation of a rooftop PV plant or a residential heating system. For their investment, all participants have a cost budget of 500 monetary units (MU) and an emission budget of 500 emission units (EU). Each of the 20 investment alternatives consists of an initial monetary investment and yearly costs (i.e., operation and maintenance). Additionally, there are emissions that occur every year and reduce the carbon emission budget as a result of the chosen investment. The considered period is five years. The values for cost and emission of each investment alternative are drawn randomly and independent from each other. The initial monetary investment is between 0 and 100 MU, the yearly costs are between 0 and 80 MU and the yearly CO_2 emissions are between 0 and 100 EU.

In the treatments with uncertainty, an uncertainty level μ for each participant is determined through random selection from a normal distribution ($\varnothing = 10$, standard deviation (SD) $= 5$). Using this uncertainty level, the annual cost and annual emission interval is determined by:

$$I_n^{c,o} = (c_n^o - \mu, c_n^o + \mu) \,\forall\, n \in (1, .., N) \tag{5.1}$$

$$I_n^{e,o} = (e_n^o - \mu, e_n^o + \mu) \,\forall\, n \in (1, .., N) \tag{5.2}$$

Here, $I_n^{c,o}$ is the interval for the annual costs, $I_n^{e,o}$ is the interval for the annual emissions, c_n^o is the basic annual cost value and e_n^o is the basic annual emission value determined in the same way as for the treatments without uncertainty for investment alternative n and N is the set of investment alternatives. From each interval, one value is randomly selected each year as annual cost or emission.

Treatment	Recommendation	Uncertainty
1: Pref-A	Preference-based	no
2: Pref-U	Preference-based	yes
3: Co-A	Cost	no
4: Co-U	Cost	yes
5: Em-A	Emission	no
6: Em-U	Emission	yes

Table 5.2.: Overview on the six experimental treatments.

In the non-preference treatments (Co-A, Co-U, Em-A, Em-U, see Table 5.2), the recommendation is not based on individual preferences. The recommendation in the "cost" treatments (Co-A, Co-U) points out the alternative with the lowest overall (expected) costs (*Alternative X has the lowest (expected) financial cost.*). In the "emission" treatments (Em-A, Em-U), the recommendation points out the lowest overall (expected) emissions (*Alternative X leads to the lowest (expected)* CO_2 *emissions per year.*) In the "preference" treatments (Pref-A, Pref-U), the alternative with the highest individual decision quality is recommended to the participant (*An optimization software has calculated a recommendation for you based on the information you provided in Part 1. According to your preferences, you are advised to choose alternative X to invest.*).

The quality of a decision can be characterized by two dimensions in general: The decision-making process (how was the decision derived) and the outcome (decision goals) (Phillips-Wren et al., 2009). Todd and Benbasat define decision quality as the deviation of the decision from a solution "provided by a normative strategy, such as expected value maximization or utility maximization" (Todd and Benbasat, 1992, p. 375). Following this definition, decision quality is measured as the relative and rank-based deviation from the optimal decision alternative available for each participant. The highest utility among the investment alternatives is derived by using the following formulation:

$$u' = max(u_1, .., u_N) \tag{5.3}$$

$$u_n = w^c \cdot (b^c - c_n^i - p \cdot c_n^o) + w^e \cdot (b^e - p \cdot e_n^o) \; \forall \, n \in (1, .., N) \tag{5.4}$$

Here, u' is the utility of the alternative that is recommended to the participant, u_n

is the utility of one investment alternative, N is the number of alternatives. The cost weight is given by w^c, the emission weight by w^e, b^c is the monetary budget of a participant and b^e is the emission budget of a participant, c^i are the initial and c^o the annual investment costs, e^o are the annual emissions and p is the number of years considered in the evaluation.

In the experiment, 100 MU are equal to 1€ of monetary payout and 100 EU are equal to 1€ of carbon emission compensation via the carbon offsetting company "atmosfair"[2]. While this allows for an integration of monetary and emission budget into one utility value, it has to be noted that the substitution between monetary and emission budget is not perfect and remains subject to further discussion.

Participants see the recommendation at the top of the investment page and directly above the input field where they have to submit their investment decision. The recommendation at the top is highlighted in blue as displayed in Figure 5.3 and participants are required to confirm that they have seen the presented recommendation before proceeding. In treatments with uncertainty, the recommendations are based on the expected values for costs and emissions.

As mentioned in the introduction, individuals tend to delay investment decisions due to a lack of knowledge or uncertainty regarding the investment outcome (Blake,

[2]atmosfair gGmbH: www.atmosfair.de

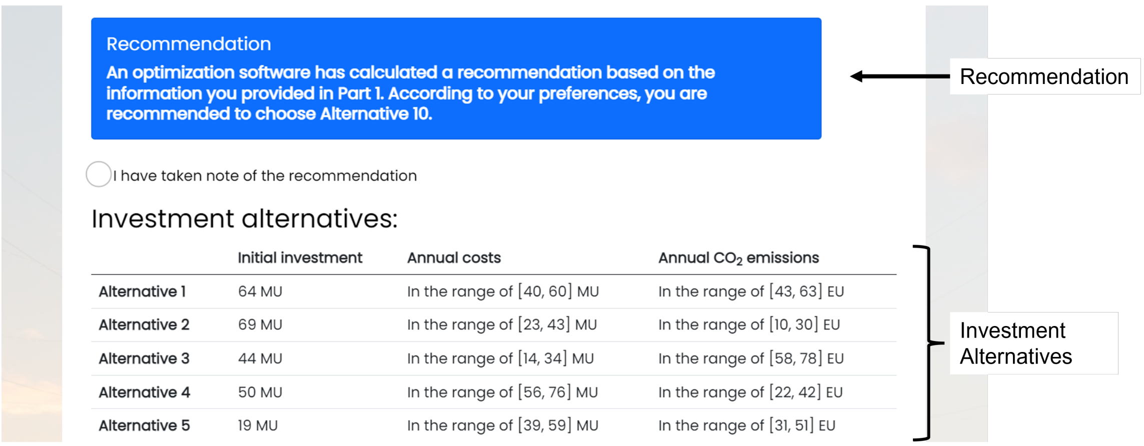


Figure 5.3.: Appearance of the recommendation (blue background) and the first five of 20 investment alternatives in the "preference" treatment with uncertainty. Translated from original German.

1999). To evaluate this behavior, participants are given the option to decide against an investment after seeing the investment alternatives and the recommendation. If the participants do not want to make an investment decision, they can leave the investment page and go directly to the post-experimental questionnaire. In such a case, they receive a monetary compensation of 2.50€ as a participation bonus. If the participants choose to make an investment decision, they are presented with the results of their decision regarding cost and emission. The initial investment costs and the annual costs and emissions are then deducted from their budget. The payoff and emission compensation are calculated based on the remaining cost and emission budget.

The final Part V consists of a demographic evaluation and a post-experimental survey using a 5-point Likert scale (see Appendix Table A.3). In the post-experimental survey, the general self-perceived knowledge of the participants with regard to renewable energy is assessed (i.e., *I am very well acquainted with the subject "renewable energy"*), as well as the perceived information load (i.e., *The number of choices on the investment page overwhelmed me*) and perceived usefulness of the investment recommendation (i.e., *The recommendation on the investment page helped me make my decision*). Furthermore, the participant is asked to evaluate, whether the decision resembles their behavior in a real-world investment decision (i.e., *The decisions within the experiment reflect my actual investment behavior*) and about the trust in the company "atmosfair" to compensate the emission savings in a sensible way (i.e., *I trust that my emission savings will be sensibly compensated via atmosfair*). The survey also includes an attention check, where participants are asked to mark a specific answer in the survey.

5.3.4 Sample

Participants were recruited from the student pool at a large German university using the software *hroot* (Bock et al., 2014). The monetary reward amounted to 3.44€ per person on average. The greenhouse gas compensation via atmosfair amounted to 3.90€, equivalent to 167kg CO_2 per person on average. The experiment was conducted in German, all quotes from experimental descriptions in this chapter are

Mean (SD)	**All**	**Pref-A**	**Pref-U**	**Co-A**	**Co-U**	**Em-A**	**Em-U**
Female	0.343	0.339	0.327	0.308	0.234	0.333	0.456
Age	25.3 (5.2)	24.8 (4.8)	25.7 (5.2)	26.0 (7.4)	25.2 (3.9)	24.7 (3.6)	25.4 (5.6)
Weight Cost	0.58 (0.20)	0.58 (0.20)	0.56 (0.20)	0.59 (0.20)	0.60 (0.21)	0.58 (0.20)	0.56 (0.20)

Table 5.3.: Demographics of the sample and results of the conjoint analysis.

translated from German. The experiment was fully completed including the successful passing of an attention check by 324 participants. The sample characteristics are summarized in Table 5.3. About one third of all participants (34.3%) are female (one non-binary participant) and the average age is 25.3 years (SD=5.16). According to the conjoint analysis, participants have a higher valuation for costs than for emissions (0.58, SD=0.20). Only a small number of participants (n = 6) chose not to make an investment decision across all treatments. Reasons for that could be the low financial reward if participants did not make an investment and the overall low monetary value compared to real-world investments. Due to the low number of dropouts, these were not further investigated.

5.4 Results

This section provides a closer insight into the findings of the online experiment to answer the research questions presented in Section 5.1. Before evaluating the results of the investment recommendations, the cost and emission weights obtained in the conjoint analysis are analyzed to assess whether this method is suitable for capturing individual preferences in the experimental context.

5.4.1 Conjoint Analysis Evaluation

To analyze the results of the conjoint analysis, the participants are divided into three groups based on the determined cost and emission weights. Participants with a cost weight above 0.66 are assigned to the "price-sensitive" group, participants with a cost weight below 0.33 are assigned to the "emission-sensitive" group and participants with a cost weight between 0.33 and 0.66 are assigned to the "neutral"

Item Mean (SD)	**Overall**	**Price-sensitive**	**Neutral**	**Emission-sensitive**	**ANOVA**
General importance cost (C1)	4.38 (0.72)	4.54 (0.54)	4.32 (0.81)	4.11 (0.77)	F=7.94 p<0.001***
Energy importance cost (C2)	4.19 (0.89)	4.38 (0.81)	4.13 (0.84)	3.81 (1.03)	F=8.49 p<0.001***
General importance emission (E1)	3.37 (0.99)	2.91 (1.08)	3.60 (0.78)	4.00 (0.61)	F=34.21 p<0.001***
Energy importance emission (E2)	3.71 (1.03)	3.16 (1.05)	3.99 (0.81)	4.43 (0.62)	F=47.74 p<0.001***

Table 5.4.: Comparison of the cost and emission importance in the preference groups.

group. Across all treatments, 43% of the participants belong to the “price-sensitive” group, 17% belong to the “emission-sensitive” group and 39% belong to the “neutral” group.

Table 5.4 shows the answers from the preliminary questionnaire that was conducted in Part II of the experiment, before the conjoint analysis (For details see Appendix Table A.2). Responses are measured on a 5-point Likert scale from not at all important to very important. The importance of costs is highest in the “price-sensitive” group, while the importance of emissions is highest in the “emission-sensitive” group. The analysis of variance (ANOVA) between the three groups confirms significant differences for each item. This indicates that the weights determined in the rank-based conjoint analysis are an adequate representation of the participant preferences. Overall, the importance of costs is higher than the importance of emissions, which matches the average cost weight from the conjoint analysis (0.58, SD=0.20). The importance of costs decreases in the energy context, while the importance of emissions increases. A reason for this phenomenon could be the impact of the ongoing political and public debate regarding the decarbonization of the energy sector on the individual valuations of emissions in this context. Notably, the spread between the “price-sensitive” and “emission-sensitive” groups is much higher in the emission importance items (E1, E2) than in the cost importance items (C1, C2). The median of the “emission sensitive” group still values costs as rather important, while the median of the “price-sensitive” group values emissions as neither important nor unimportant. These results indicate that costs play a role for the participants regardless of their emission preferences, but that this is not the case for emissions. As the "neutral" and "price-sensitive" groups are also considerably larger than the "emission-sensitive" group, this indicates that costs are still a dominant factor for most individuals in the decision for energy technology investments.

5.4.2 Recommendation Acceptance

This section describes the factors affecting the acceptance of the recommendation in each of the treatment groups "cost", "emission" and "preference".

In the cost treatments, 47% of the participants accept the recommendation (with uncertainty: 43%, without uncertainty: 52%). The results of the post-experimental questionnaire are presented in Table A.4. The items can be found in the Appendix in Table A.3. The perceived usefulness of the recommendation is higher for individuals who accepted the recommendation (P5, t-test=5.34, $p<0.001$***).

Like in the cost treatments, 47% of the participants accepted the recommendation in the emission treatments (with uncertainty: 51%, without uncertainty: 42%). The results of the post-experimental questionnaire are presented in Table A.5. The perceived usefulness of the recommendation is rated lower if participants accept the recommendation (P4, t-test=0.08, $p=0.027$*). Participants seem to find the emission recommendation less useful than the recommendation in the cost treatments and the results of the conjoint analysis indicate that costs are on average more important to the participants than emissions. Even though the participants have a higher valuation of costs as described in Section 5.4.1, the recommendation acceptance rate is the same in both treatment groups. This could indicate, that emission recommendations can be useful in the design of DSSs as a nudge to support investments in low-emission technologies. However, this phenomenon needs to be further investigated, for example, with regards to the accuracy of the cost and emission weight determined in the conjoint analysis. Furthermore, a field experiment would be necessary to investigate the external validity of this assumption.

In the "preference" treatments with a recommendation based on the cost and emission weights determined in the conjoint analysis, the acceptance rate is almost 50% higher than in the other treatment groups. In total, 69% of the participants accepted the recommendation (uncertainty treatment: 70%, no uncertainty treatment:

Treat-ment	Preference group	With uncertainty	ANOVA	Without uncertainty	ANOVA
Cost	c n e	0.61 (0.24) 0.17 (0.15) 0.43 (0.24)	F=4.16, p=0.02*	0.71 (0.21) 0.28 (0.20) 0.57 (0.24)	F=4.52, p=0.02*
Emission	c n e	0.50 (0.25) 0.43 (0.24) 0.66 (0.22)	F=0.85, p=0.43	0.44 (0.25) 0.44 (0.25) 0.28 (0.20)	F=0.27, p=0.76
Preference	c n e	0.70 (0.21) 0.69 (0.21) 0.72 (0.19)	F=0.01 p=0.98	0.73 (0.19) 0.58(0.24) 0.75(0.19)	F=0.72, p=0.49

c: “price-sensitive”, n: “neutral”, e: “emission-sensitive”

Table 5.5.: Comparison of the recommendation acceptance rates with regard to the preference groups.

67%). The cost weight determined in the conjoint analysis is lower for participants accepting the preference-based recommendation (t-test=-2.05, p=0.045*). The results of the post-experimental questionnaire are presented in Table A.6. The perceived usefulness of the recommendation is rated higher if participants accept the recommendation (P4, t-test=5.79, p<0.001***).

To provide a deeper understanding of the recommendation acceptance factors, the acceptance rates in the preference groups derived in Section 5.4.1 are compared. The results are presented in Table 5.5. The number of participants for each subsample is between 16 and 26 for the “price-sensitive” and “neutral” groups and between 7 and 12 for the “emission-sensitive” groups. Across all samples, there are no significant differences between the acceptance rate in the treatments with and without uncertainty. The ANOVA displayed in the table shows the analysis between the “price-sensitive”, “neutral” and “emission-sensitive” participants.

In both cost treatments, the acceptance rates differ significantly between the treatment groups. As to be expected, “price-sensitive” participants have the highest recommendation acceptance rate, both with and without uncertainty. Participants with “neutral” sensitivity have the lowest acceptance rate overall. This could indicate that individuals with a balanced cost and emission weight make a more conscious effort to balance out costs and emissions in their investment decision compared to participants with less heterogeneous preferences. However, such an assumption is difficult to make due to the low number of "emission-sensitive" participants in all treatments and requires further evaluation.

In both emission treatments, the acceptance rates do not show a significant difference in the preference groups. A larger number of participants would be necessary in this group to create more robust results. Notably, almost half of the "price-sensitive" and "neutral" participants accept the emission recommendation despite different preferences. Displaying emission recommendations might therefore be an effective nudge, if the aim of the DSS is the reduction of emissions. Furthermore, the acceptance rate for "neutral" participants is about twice as high as in the treatments with cost recommendation.

In the treatments with preference-based recommendations, the acceptance rates are distributed evenly across the preference groups. The acceptance rates are higher in all preference groups, meaning that participants benefit from preference-based recommendations regardless of their cost and emission sensitivity. On the other hand, preference-based recommendations might be less useful, if the goal of the DSS is to maximize the emission reduction. In the case of investments in residential energy technologies, emission reduction is the priority from a governmental perspective to achieve the carbon emission reduction goals. As almost any form of residential energy technology will help to achieve that goal, the challenge is to persuade households to make an investment. Due to the higher acceptance rates, preference-based recommendations can be an important tool in this process.

5.4.3 Investment Outcome

Regarding the preference groups introduced above, Figure 5.4 gives an overview on the remaining cost and emission budgets. The remaining cost budget is highest in the "price-sensitive" group (Mean=355.56, SD=37.85) and lowest in the "emission-sensitive" group (Mean=323.55, SD=39.57), while the remaining budget of the "neutral" group are between the other two (Mean=345.72, SD=41.59). The results are reversed for the remaining emission where the participants in the "price-sensitive" group have the lowest remaining emission budget (Mean=373.01, SD=87.48) and

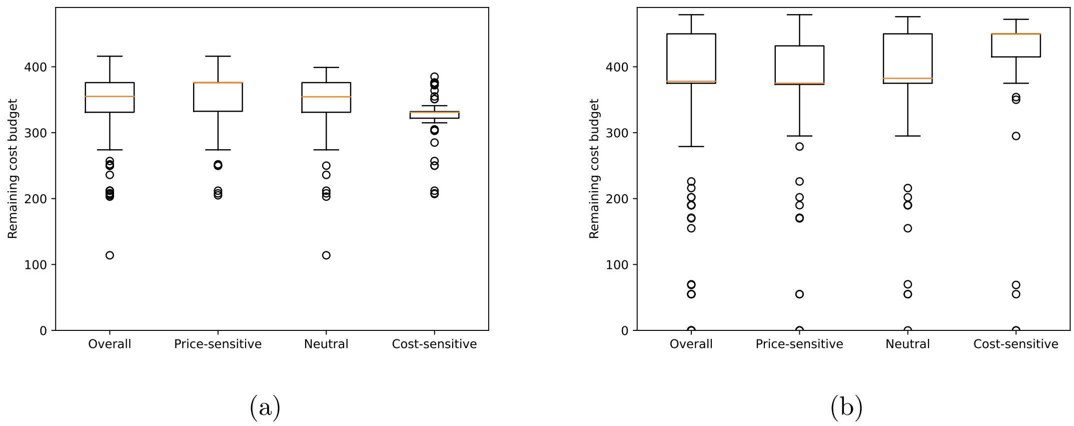
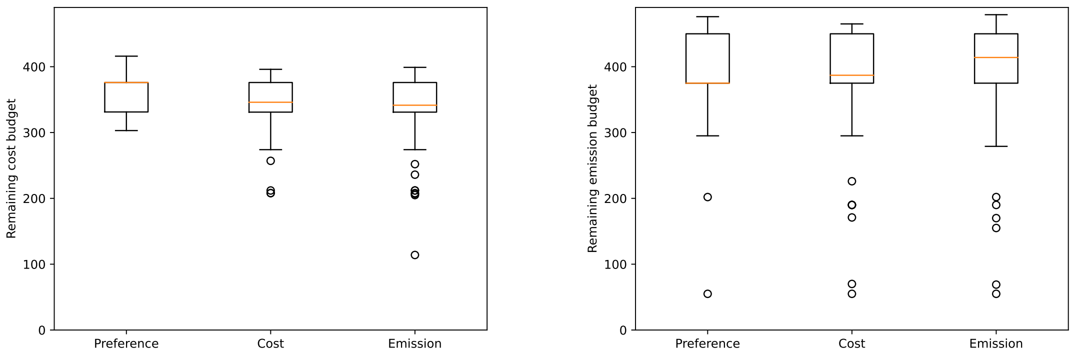


Figure 5.4.: Overview on the remaining cost (a) and emission (b) budgets in the preference groups.

participants in the “emission-sensitive” group have the highest remaining emission budget (Mean=402.55, SD=111.91). The remaining emission budget in the “neutral” group is again between the other groups (Mean=384.38, SD=88.59). An ANOVA between the three preference groups reveals a significant difference between the remaining cost budgets (F=12.26, p<0.001***) but no significant difference between the remaining emission budgets (F=1.95, p=0.14). The lack of significance between the remaining emission budgets despite larger differences in the mean values can be explained through the larger standard deviations that are more than twice the size of the standard deviations for the remaining cost budgets.

Regarding the experiment treatments, an overview of the remaining carbon and emission budgets in the different treatments after the investment decisions is displayed in Figure 5.5. An ANOVA between the treatments preference, cost and emission reveals a significant effect for the differences in the remaining cost budget (F=5.84, p=0.003**), but no significant effect for the difference in the remaining emission budget (F=0.03, p=0.97). There is no significant difference between the results in the treatments with uncertainty and without uncertainty regarding the remaining cost and emission budget. This could mean that the level of uncertainty or the monetary value of the investment decision was not large enough to impact the investment decision of the participants.



(a) (b)

Figure 5.5.: Overview on the remaining cost (a) and emission (b) budgets after the investment decision.

5.4.4 Perceived usefulness of the recommendation

The individual perceived usefulness of the recommendation in the “cost”, “emission” and “preference” treatments is measured through P4 (*The recommendation on the investment page helped me make my decision*). The results are displayed in Table 5.6. Overall, the perceived usefulness is highest in the “preference” treatments. An ANOVA reveals a significant difference between the treatments (F=4.050, p=0.019*). The effect is higher in the treatments with uncertainty (F=4.335, p=0.014*) than in the treatments without uncertainty (F=3.224, p=0.04*). This could indicate that individuals benefit more from preference-based recommendations in situations with uncertainty. Overall, the perceived usefulness is on average 0.34 points higher in treatments with uncertainty (t-test=2.190, p=0.029*).

In the “emission” treatments, the perceived usefulness is lower than in the “cost” treatments (t-test=2.31, p=0.022*). In the cost treatment, there is a positive correlation between the cost weight and the perceived usefulness of the recommendation (t-test=0.437, p<0.001***). As expected, the correlation between cost weight and perceived usefulness of the recommendation is negative in the “emission” treatments (t-test=-0.222, p=0.027*). Based on these results, a recommendation regarding costs is more beneficial for individuals in the energy investment context if these individuals have stronger monetary preferences, as is the case in the experiment sample.

The results are in line with the findings of section 5.4.2. Preference-based rec-

Mean (SD)	DSS treatment	Cost treatment	Emission treatment
Overall	3.82 (1.38)	3.67 (1.39)	3.21 (1.37)
With uncertainty	3.93 (1.23)	3.83 (1.24)	3.42 (1.31)
No uncertainty	3.72 (1.50)	3.51 (1.48)	2.93 (1.38)

Table 5.6.: Perceived usefulness of the recommendation (P4) in each treatment combination, measured on a 5-point Likert scale.

ommendations offer increased usefulness for the participants, which strengthens the argument of developing and implementing DSSs for residential energy technology investments that regard preferences of individuals. If the goal of the DSS is to reduce emissions, the recommendation could be supplemented by potential cost savings to increase the usefulness of the recommendation to the users of the DSS.

5.5 Discussion

The experiment presented in this chapter aims to investigate acceptance factors for preference-based recommendations in DSSs. While the analysis of the experiment results provides some indicators regarding the acceptance of preference-based recommendations and their usefulness to participants, further research is necessary to explain these effects. While online experiments can have external validity (Horton et al., 2011), there are significant differences between the investment decision in the experiment and a real-world investment in residential energy technologies. These differences include, for example, actual investment costs and the time between investment and payoff. Therefore, the external validity of the identified indicators for the acceptance of preference-based recommendations is currently low. To determine, how well the observed behavior translates to real-world investment decisions, observation in a field experiment is necessary. In cooperation with a municipal utility, such an experiment could accompany actual investment decisions for residential energy technologies, for example.

As determined in Section 5.4.4, participants view the recommendation as more useful in the treatments with uncertainty compared to treatments without uncertainty. While this gives an indication that the support of citizen investment decisions through recommendations is more important in scenarios with uncertainty, further evaluation of perceived usefulness along the construct presented in (Davis, 1989) is necessary to explain this effect. Furthermore, this indication should be tested in a field experiment as described above, to improve its external validity.

The results of the online experiment indicate that a ranking-based conjoint analysis is a suitable solution to assess the trade-off between the cost and emission preferences of individuals in this context. For validation, the results of the conjoint analysis are compared to the self-reported importance of costs and emissions in Section 5.4.1. The self-reported importance of costs and emissions match the results of the conjoint analysis. The experiment did not control for any form of stereotype consistency bias, i.e., the tendency to convey stereotype-consistent information (Clark and Kashima, 2007). In the proposed experiment, participants might, for example, deliberately choose investment alternatives to confirm their answers in the conjoint analysis. This might be addressed by a longer gap between the conjoint analysis and the investment decision in future research. The occurrence of social desirability bias in an environmental context such as the one used in the experiment is low, but cannot be completely disregarded (Vesely and Klöckner, 2020). Previous studies have shown, that a fully randomized conjoint design can reduce the social desirability bias (Horiuchi et al., 2022), which supports the use of conjoint analyses in the context of this experiment.

5.6 Conclusion

This chapter presents the results of an online experiment (n=324) to assess the acceptance of preference-based recommendations in decision support systems in the context of energy-related investments. In six treatment groups [("cost", "emission", "preference") × ("no uncertainty", "uncertainty")], participants were asked to choose between 20 investment alternatives. With regard to Research Question 2, the acceptance rate of preference-based recommendations in the experiment is 22 percentage points higher than in treatments without preference-based recommendations that regard only costs or emissions.

Regarding Research Question 3, the treatments with uncertainty had no significant effect on the recommendation acceptance rates and experiment outcome, i.e., the monetary payoff and emission compensation for the participants. This is contrary to the findings of other studies, for example, (Kahneman and Tversky, 1979) and may be explained by the relatively low monetary value compared to a real-world scenario and the experimental setting, where the participants could not lose money. The perceived usefulness of the recommendation is 0.34 points higher in the treatments with uncertainty (t-test=2.190, p=0.029*).

Overall, this chapter contributes to the understanding of acceptance factors for preference-based recommendations in decision support systems. The results can be used in the development of application-oriented information systems to support the decarbonization of the energy system.

The determination of optimal investment alternatives for residential energy technologies that can be recommended to users of the decision support system is also a challenge. The optimal sizing of a residential energy technology is influenced by the consumption patterns and existing technologies in the citizen energy community in addition to the preferences of a household. This challenge is addressed in Part III of this thesis.

Part III.

Residential Energy Technology Investment

INTRODUCTION TO PART III

As demonstrated in Part II, preference-based DSSs can support citizens in investments in residential energy technologies. To provide recommendations to citizens, it is first necessary to determine the optimal energy technology sizing decisions with regard to a reduction of costs and emissions. Aside from personal preferences, the optimal investment decision depends on the individual energy consumption patterns of a household, existing residential energy technologies and the possibility to sell or buy energy to or from neighbors in a CEC. In addition, interactions between the sectors electricity and heat must be considered when building sector coupling technologies.

In Part III, the generation of optimal sizing solutions of residential energy technologies in a CEC with regard to the objectives cost and emission are investigated (Chapter 6). The solution space of sizing alternatives for residential energy technologies can be used to determine individual recommendations based on household preferences towards costs and emissions. I evaluate the implementation of these recommendations in a community and their impact on household investments in residential energy technologies with and without the application of CEC regulation (Chapter 7).

CHAPTER 6

DIRECT POLICY SEARCH FOR MULTI-OBJECTIVE OPTIMIZATION OF THE SIZING AND OPERATION OF CITIZEN ENERGY COMMUNITIES

The first step to providing preference-based investment recommendations to citizens is the determination of a solution space of possible and non-dominated investment alternatives. This chapter presents an evolutionary algorithm that has previously been used for a multi-objective operation of microgrids. We extend this model by including the perspective of heat provision and investment decisions. This way, the developed tool can be used by CEC planners to integrate conflicting objectives of residents in the installation phase. The algorithm formulation and a demonstration of its functionality on a case study for different ambient conditions is introduced in the following sections. The results show the opportunities to size and operate CECs using the presented algorithm. The solution space can be used to determine investment recommendations based on individual preferences.

This chapter comprises the published article: Golla, Armin; Meinke, Robin-Joshua; Liu, M. Vivienne; Staudt, Philipp; Anderson, C. Lindsay; Weinhardt, Christof (2021): Direct Policy Search for multi-objective Optimization of the Sizing and Operation of Citizen Energy Communities. In: Hawaii International Conference on System Sciences (HICSS) 54, p. 3263–3272.

6.1 Introduction

The international transition to more renewable energy sources and the associated subsidy schemes as well as the cost degradation of household-sized renewable generation capacity, especially PV, lead to an increased power generation on a household level (Barzegkar-Ntovom et al., 2020). Such small scale generation was originally a solution for microgrids that would sustain service in case of an outage for small communities or serve remote or island communities (Olivares et al., 2014). The increasing electrification of the transport and heat sector as well as the availability of residential battery solutions provides the flexibility to compensate volatile renewable generation. This increases the ability of such microgrid communities to supply themselves with electricity and allows them to become increasingly independent of the transmission grid (Baldinelli et al., 2020).

As mentioned in Part II, operating such microgrids is a challenge as multiple, sometimes conflicting objectives of the microgrid community need to be considered (Gupta et al., 2020). Furthermore, the optimal operation of BSSs given uncertain generation and demand is a constant subject of research (Nguyen and Crow, 2016). First approaches to the operation of microgrids have been published (Karimi and Jadid, 2019). The authors are mostly focusing on an optimization of the available resources subject to one objective function. Recently, a study emerged that focuses on multiple objectives in a microgrid using evolutionary algorithms, presenting only non-dominated strategies (Gupta et al., 2020). However, with an increasing interest in microgrid communities, specifically in the European Union under the term CECs (European Parliament and Council of the European Union, 2019), it becomes more important to not only focus on the operation but also the installation of such microgrids and to take different objectives and individual preferences such as financial considerations or local carbon emissions into account. Therefore, in this chapter, we apply the Borg multi-objecitve evolutionary algorithm (MOEA) (Hadka and Reed, 2013) that is used to co-optimize conflicting objectives, to integrate the decisions on the installation of resources and the decisions within the operation strategy with regards to multiple objectives into one problem. As a result, we are able to provide microgrid stakeholders with multiple courses of action based on non-dominant strategies. In doing so, we contribute to the advancement of applications of evolutionary algorithms and provide a practical tool for planners and residents to design microgrids in their neighborhoods. With this chapter, we answer the following research question:

RQ 4: What is the financial (cost) and environmental (emission) performance of a multi-objective evolutionary optimization of the integrated sizing and operation of energy technologies in a CEC relative to an upper benchmark optimization with perfect foresight that optimizes the objectives individually?

We begin by reviewing relevant literature and then move on to the model and a corresponding case study.

6.2 Sector Coupling and Evolutionary Algorithms in Microgrid Implementations

The existing related literature can be classified into three different streams: (1) microgrid sizing and operation, (2) sector coupling in microgrids and (3) evolutionary algorithms in microgrid optimization.

6.2.1 Microgrid Sizing and Operation

The concept of microgrids has become an active field of research in recent years as it enables the connection and integration of the rising share of decentralized energy resources. Olivares et al. (2014) analyze the operational challenges that these complex energy systems create. They point out that advanced control strategies are necessary to coordinate the supply and demand in those decentralized systems, especially if several energy carriers are involved. Zhao et al. (2014) see the design and operation of a microgrid as a joint-optimization problem and apply their theory to islanded microgrids in remote geographic areas. To solve their multi-objective sizing and operation problem, Zhao et al. (2014) use a method based on a genetic algorithm to find an optimal solution for electricity generation devices in microgrids. This chapter extends the microgrid optimization to the provision of heat for residential households in CECs. Like other studies, (Gupta et al., 2020) and (Berendes et al., 2018) acknowledge that the objectives of a community when operating a microgrid are multidimensional and they therefore perform a multi-objective analysis that includes a minimization of emissions and a maximization of self-consumption. Due to the computational complexity, the use of heuristics are proposed in (Berendes et al., 2018) for microgrid optimization. In their study, the authors design a software-based tool for sizing and operation of microgrid systems. The open source software tool micrOgridS provides a set of optimal solutions for the configuration and the control of decentralized electricity systems from a multi-objective perspective. In this chapter, we follow this direction and use an evolutionary algorithm to solve this problem.

6.2.2 Sector Coupling in Microgrids

In this chapter, we consider a sector-coupled microgrid sometimes also referred to as multi-energy microgrid. Zhao et al. (2014), Gupta et al. (2020) and Berendes et al. (2018) are optimizing the design and operation of microgrids but are solely focusing on electricity, neglecting the demand for heat in their analysis. Zhang et al. (2015) introduce micro CHP applications as an effective technology to couple electricity and heat generation on a local level. Gu et al. (2014) state that the implementation of cogeneration technologies (e.g., micro CHPs) through single applications has several benefits to fulfill energy carrier demands (such as cooling, heating and power). These applications act as reliable sources of electricity generation in microgrids with a high penetration of fluctuating renewable energy from, e.g., PV systems, which stabilize the supply and increase the overall system efficiency. This chapter considers two cogeneration technologies, CHP and PVT applications, to fully enable the potential of synergies in parallel heat and power generation. Besides parallel generation, power-to-x technologies play a major role in the development of CECs. In Chapter 3 of this thesis, HPs are used to configure optimal CEC setups in which electricity can be used as a resource for heat generation. Alongside BSSs, HPs can be an efficient application for the utilization of excess electricity either for fulfilling the heat demand directly or using a thermal storage system, as presented in Chapter 9. Li and Xu (2018) provide a comprehensive analysis of microgrid operation with multi-energy systems. The implementation of several forms of energy storage (TSS, ice storage tank and BSS) allows for high flexibility and efficient coordination between the energy carriers. In this chapter, we exploit the full potential of sector coupling in microgrids through the combined implementation of cogeneration and power-to-x technologies as well as energy storage systems for both heat and power. In line with (Gu et al., 2014) and the findings presented in Chapter 3, this chapter takes a comprehensive approach and optimizes the sizing and operation of sector-coupled CECs. The chapter extends existing research on sector-coupled operation in microgrids by using an evolutionary algorithm to approximate multi-objective optimization.

6.2.3 Evolutionary Algorithms in Microgrid Optimization

Using the principle of combining mutation and recombination, evolutionary algorithms provide a process of approximating the solution to global optimization problems (Bäck, 1996). As outlined in the previous two sections, microgrid operation and sizing can be seen as such a problem with multidimensional objectives. Fadaee and Radzi (2012) review research that uses evolutionary algorithms to solve multi-objective optimizations for the control and sizing of microgrids. The authors conclude that heuristic evolutionary algorithms are the most suitable for microgrid optimization. Gupta et al. (2020) address the multidimensional objectives of microgrid energy management with a simulation-based optimization to identify efficient control strategies that are non-dominated by other strategies. The authors are using the evolutionary computing framework Borg MOEA, which is designed for the optimization of multi-objective, multidimensional problems. The Borg MOEA uses auto-adaptive operators which provide several advantages compared to other MOEAs: identification of search stagnation, avoidance of local optima through randomized restarts and efficient recombination of dominant operators (Hadka and Reed, 2013).

This chapter is based on this approach and uses the Borg MOEA framework for an evolutionary multi-objective direct policy search (EMODPS) to determine the optimal application sizing and operation parameters that can be presented to CEC planners and participants.

6.3 Enhancing Citizen Energy Community Development with EMODPS

In the following section, the methodology of the proposed EMODPS is introduced. Direct policy search (DPS) is used as a control strategy that searches directly in the solution space (Heidrich-Meisner and Igel, 2009). The DPS method parametrizes the policies and reduces the computational complexity when using a simulation-based optimization method. The strategy is particularly suited for problems including multiple objectives because they can be coupled with true MOEAs such as Borg. DPS can be directly coupled with the simulation model and does not add new constraints to the overall structure (Giuliani et al., 2016). The structure of the EMODPS presentation used in this chapter is based on the approach proposed in (Gupta et al.,

Variable	**Unit**	**Description**
O_i		Objective
Θ		Set of applications θ
		(BSS, TSS, PV, PVT, CHP, HP)
a_1, a_2		Phase shifts on $[0,2\pi]$
b^s	kWh/kW	Normalized PV generation
$c^{el,g}$	€/ kWh	Grid electricity costs
$c^{ht,CHP}$	€/ kWh	CHP heat costs
$c^i, c^{i,\theta}$	€/ kW, €/ kWh	Investment costs (for θ)
cop^{HP}		Coefficient of performance HP
e^θ	kg	CO_2 emission factor for application θ
D^{el}, D^{ht}	kWh	Total electricity/heat demand
$d^{el,HH}$	kWh	Household electricity demand
$d^{el,HP}$	kWh	HP electricity demand
$d^{ht,HH}$	kWh	Household heat demand
$f^{el,r}$	kWh	Renewable electricity fed into the grid
$f^{el,c}$	kWh	Conventional electricity fed into the grid
$F(O_1, O_2)$		Objective function
g^{el}	kWh	Electricity supplied by the grid
i, j		Counting variables
k^{ht}	kWh	Heat released into the environment
l^θ	years	Lifetime of application θ
$n^{RBF,\alpha,\beta}$		Number of RBFs
$r^{el,c}$	€/ kWh	Feed-in tariff for CHP electricity
$r^{el,r}$	€/ kWh	Feed-in tariff for PVT and PV electricity
s^θ	kW,kWh	Size of application θ
$s^{\theta,max}$	kW,kWh	Maximum size of application θ
t		Current time step
T		Number of time steps
X^{el}, X^{ht}	kWh	Total electricity/heat supply
$x^{el,\theta}$	kWh	Electricity generation of θ
$x^{ht,\theta}$	kWh	Heat generation of θ

$\alpha^{BSS}, \alpha^{TS}$	kWh	Storage load for BSS / TSS
η^{BSS}		Cyclic efficiency of BSS
η^{TS}		Calendaric efficiency of TSS
$\lambda^{BSS}, \lambda^{TS}$	kWh	Storage level of BSS / TSS
ϕ^{θ}		Electricity to heat ratio for $\theta \in$ (CHP,PVT)
w, c, r, p		Borg MOEA Parameters

Table 6.1.: Nomenclature.

2020). First, the conflicting objectives and the general optimization model are explained. Afterwards, we introduce the radial basis functions (RBFs) used to model the operational decisions as well as the variables used to model the sizing of the available technologies. In the last step, the simulation used to model the policy effects and its interaction with the Borg MOEA is explained. For the system structure, different generation, storage and sector coupling technologies are considered. The system is connected to the grid to draw or feed in electricity. Besides PV generation, a hybrid PVT plant is considered for both renewable heat and electricity generation. As described in Chapter 8, the technology has the potential to reduce operational costs in sector-coupled scenarios. Besides, a CHP is integrated in the system. An HP possibly enables sector coupling between both the electricity and the heat sector. The option to install a BSS or a TSS is given. For more information on the functionality of the Borg MOEA, please see (Hadka and Reed, 2013).

6.3.1 Objectives

To enable a successful energy transition, public acceptance is a key factor (Staudt et al., 2019). Therefore, it is necessary to include varying CEC participant preferences in the decision making process when determining the system structure and operational strategy of CECs. For the CEC participants, those preferences can be the reduction of carbon emissions, revenue maximization or a high degree of self-sufficiency, among others. In the course of this chapter, we focus on two objectives: Costs and carbon emissions. The cost objective is given by:

$$O_1 = c^i + \sum_{t=1}^{T} (g_t^{el} \cdot c^{el,g} + x_t^{ht,CHP} \cdot c^{ht,CHP} - f_t^{el,r} \cdot r^{el,r} - f^{el,c} \cdot r^{el,c}) \tag{6.1}$$

$$c^i = \sum_{\theta=1}^{N} \frac{c^{i,\theta} \cdot s^{\theta}}{l^{\theta}} \tag{6.2}$$

The objective is the sum of the installation costs for the different appliances as well as the operating costs for electricity and heat supply. For the calculation of CO_2 emissions, both emissions from energy generation, manufacturing and installation are considered. In the case study, emissions of each appliance are approximated through an emission factor. For CHP, PV, PVT and grid electricity, the emissions are calculated with regard to the amount of energy produced. For the devices used to store or convert energy within the system, BSS, TSS and HP, the emissions are calculated with regard to the application size. The emission objective for the entire simulation is measured in kg of CO_2 and is given by:

$$O_2 = \left(s^{HP} \cdot e^{HP} + s^{BSS} \cdot e^{BSS} + s^{TSS} \cdot e^{TSS}\right) \cdot T + \sum_{t=1}^{T} (g_t^{el} \cdot e^{g} + x_t^{ht,CHP} e^{CHP} + x_t^{el,PV} \cdot e^{PV} + x_t^{el,PVT} \cdot e^{PVT}) \tag{6.3}$$

In our case study, the only operational parameter is the HP operation. All other operating decisions are deterministic due to corresponding regulation and are fixed within the simulation. However, the system sizing is subject to optimization as well.

6.3.2 Optimization

For the EMODPS search, both objectives derived in Section 6.3.1 are optimized. The corresponding optimization problem is formulated below. Both objectives are minimized simultaneously in the objective function:

$$\min_{x^{ht,HP},s^{\theta}} F(O_1, O_2) \tag{6.4}$$

The objective function is minimized with regard to Equations (6.5) to (6.14). The first two Equations, (6.5) and (6.6), represent the balance constraints for the electricity and heat sector:

$$\begin{aligned}\sum_{i=1}^{n^{HH}} d_{i,t}^{el,HH} =& x_t^{el,PV} + x_t^{el,PVT} + x_t^{el,CHP} - d_t^{el,HP} \\ &+ g_t^{el} - f_t^{el,r} - f_t^{el,c} + \alpha_t^{BSS} \;\forall\, t \in T \qquad (6.5)\\ \sum_{i=1}^{n^{HH}} d_{i,t}^{ht,HH} =& x_t^{ht,PVT} + x_t^{ht,CHP} + x_t^{ht,HP} - k_t^{ht} \\ &+ \alpha_t^{TSS} \;\forall\, t \in T \qquad (6.6)\end{aligned}$$

The operation and status of the BSS and TSS are modeled in Equations (6.7) and (6.8):

$$\begin{aligned}\lambda_t^{BSS} =& \lambda_{t-1}^{BSS} - \begin{cases}\alpha_t^{BSS}\eta^{BSS}, & \alpha_t^{BSS} \leq 0\\ \alpha_t^{BSS}, & \alpha_t^{BSS} > 0\end{cases} && \forall\, t \in T \qquad (6.7)\\ \lambda_t^{TSS} =& \lambda_{t-1}^{TSS}\eta^{TSS} - \alpha_t^{TSS} && \forall\, t \in T \qquad (6.8)\end{aligned}$$

Equations (6.9) and (6.10) represent the COP for the HP operation and the heat to power ratio for the PVT system and the CHP. The electricity generation of both PV and PVT with regard to the system size is expressed in Equation (6.11). The limitation of the HP load with regard to the system size is stated in Equation (6.12), the CHP system size is restricted through Equation (6.13), the storage levels for BSS and TSS are limited to the respective system size in Equation (6.14) and the maximum system sizes of BSS, HP, PV, PVT and TSS are determined in Equation (6.15):

$$x_t^{ht,HP} = cop^{HP} \cdot d_t^{el,HP} \qquad \forall\, t \in T \tag{6.9}$$

$$x_t^{ht,\theta} = \phi_t^{\theta} \cdot x^{el,\theta} \qquad \forall\, \theta \in (PVT, CHP), t \in T \tag{6.10}$$

$$x^{el,\theta} = b^s \cdot s^{\theta} \qquad \forall\, \theta \in (PV, PVT) \tag{6.11}$$

$$0 \leq d_t^{el,HP} \leq s^{HP} \qquad \forall\, t \in T \tag{6.12}$$

$$0 \leq s^{ht,CHP} \leq max\left(x_t^{ht,CHP}\right) \qquad \forall\, t \in T \tag{6.13}$$

$$0 \leq \lambda_t^{\theta} \leq s^{\theta} \qquad \forall\, \theta \in (BSS, TSS), t \in T \tag{6.14}$$

$$0 \leq s^{\theta} \leq s^{\theta,max} \qquad \forall\, \theta \in (BSS, HP, PV, PVT, TSS) \tag{6.15}$$

6.3.3 Policy Formulation

In the proposed scenario, policies for the HP operation and sizing parameters for different system applications are implemented. The sizes of the TSS and BSS are set with regard to the maximum storage capacity. The size of the PV and PVT plant is set with regard to the installed peak capacity. The size of CHP plant and HP are set with regard to the maximum heat capacity. While the other appliances are set through policy parameters, the CHP size is determined by the maximum heat demand in the period that persists after the remaining sizing decisions have been taken. This is done to ensure that heat demand can be covered at all times, because otherwise, an oversizing of the CHP would always be beneficial due to feed-in tariffs. The capacity sizing policies are given by:

$$s^{\theta} = p^{\theta} \cdot s^{\theta,max}\; \forall\, \theta \in (PV, PVT, BSS, TSS, HP) \tag{6.16}$$

As proposed in (Gupta et al., 2020), cubic RBFs are implemented for the HP operation decisions. Two different types of RBFs are implemented, one with regard to the BSS level and one with regard to the TSS level.

The RBFs are given by:

$$RBF_i^{\alpha} = w_i \left(\left| \frac{\lambda_t^{BSS} - c_i}{r_i} \right| + x_t^2 + y_t^2 \right)^3 \qquad \forall\, t \in T, i \in RBF^{\alpha} \tag{6.17}$$

$$RBF_j^{\beta} = w_j \left(\left| \frac{\lambda_t^{TS} - c_j}{r_j} \right| + x_t^2 + y_t^2 \right)^3 \qquad \forall\, t \in T, j \in RBF^{\beta} \tag{6.18}$$

$$x^{HP,ht} = \sum_{i=1}^{n^{RBF,\alpha}} RBF_i^{\alpha} + \sum_{j=1}^{n^{RBF,\beta}} RBF_j^{\beta} \tag{6.19}$$

Here, x and y are the cyclic representations of the time of the day with $x_t = sin(2\pi t/24 - a_1)$ and $y_t = cos(2\pi t/24 - a_2)$, where a_1 and a_2 are the phase shifts on [0,2π]. A total of four RBFs is used, two considering the BSS storage load λ^{BSS} and two considering the TSS storage load λ_t^{TSS} with parameter limits $w_i \in [-2, 2], c_i \in [-2, 2], r_i \in [-2, 2]$. As defined in (Gupta et al., 2020), the goal of the EMODPS is to present a non-dominated set of parameters that minimizes the system objectives. In this chapter, the weights, centers and radii of the RBFs are used to model the HP operation decisions. The inclusion of both the TSS and BSS storage levels as two different system states enhances previous studies by providing the opportunity to determine operation policies in sector coupled scenarios. Additionally, the sizing parameters offer the ability for local communities to enhance their microgrid by adding new appliances. The sizing parameters are directly included in the objective function and therefore can be set without the use of explicitly modeled RBFs.

6.3.4 Simulation and Implementation

Based on the inputs derived from the policy formulation in Section 6.3.3, the simulation calculates the objective values and thereby enables an evaluation of the policy. The simulation structure is depicted in Figure 6.1. The system loads and device operations are calculated in each time step, while the application size is set once for the entire time horizon. The heat and electricity demand of all households are used as input. Based on the application size, the PV plant supplies a given amount of electricity while the PVT plant supplies both heat and electricity. The HP operation is determined through policy parameters. TSS and BSS are operated based on the

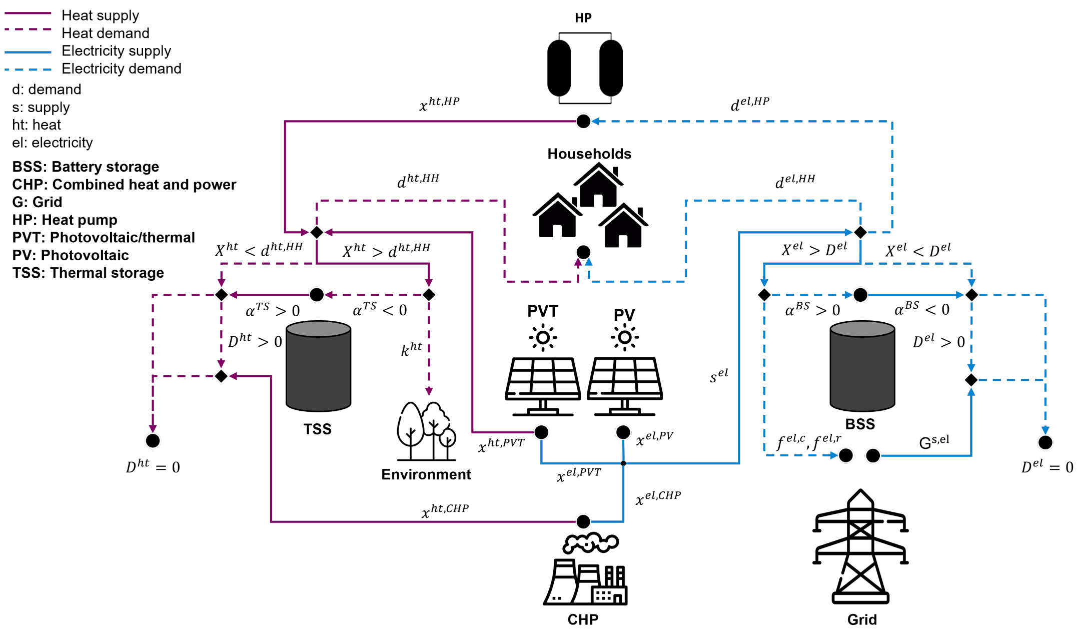


Figure 6.1.: Flowchart of the simulation.

demand or supply in the respective sector. The CHP is used to cover the remaining heat demand, after heat generation of the HP, PVT and the TSS are used. Excess heat cannot be sold, but is instead released into the environment. Electricity produced by the CHP while satisfying the heat demand is consumed locally or fed into the grid if demand is lower than generation. Here, the connected grid is both able to supply electricity in times of high demand or absorb electricity from PV, PVT and CHP in times of excess generation. A renewable energy feed-in tariff is paid for fed-in electricity from the PV and PVT panels, a slightly lower feed-in tariff is paid for electricity from the CHP, following current German regulation.

The general structure of the interaction between simulation and the Borg MOEA is displayed in Figure 6.2. The parameters initially generated by the Borg MOEA are fed into the simulation that returns a set of results for the different objectives that are then reported back to the Borg MOEA. The Borg MOEA uses the information to determine new parameters for the next evaluation using an auto-adaptive multi-operator recombination that is suited for a broad range of problem domains (Hadka and Reed, 2012). The algorithm uses an adaptive configuration of simulated binary crossover, differential evolution, parent-centric crossover, unimodal normal distribution crossover, simplex crossover and uniform mutation to determine new

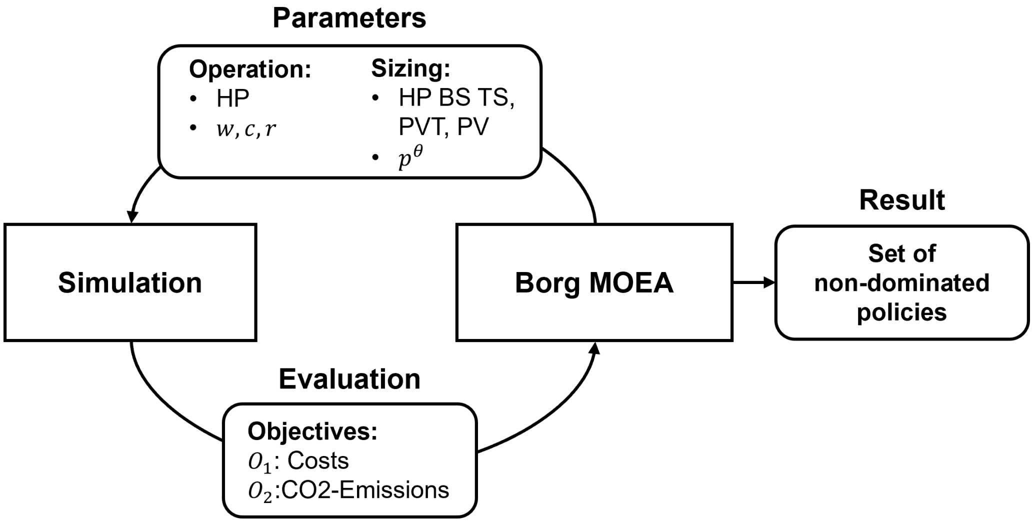


Figure 6.2.: Interaction between the simulation and the Borg MOEA for the EMODPS.

parameters for the next evaluation. Aside from uniform mutation, the offspring produced by the other operators is mutated using polynomial mutation. The results of the recombination are then evaluated and considered for inclusion in the archive (Hadka and Reed, 2013). All dominated policies, i.e., policies that are outperformed by another policy in all objectives considered are discarded. After the final round of evaluation, the DPS system returns a set of non-dominated policies.

The system is able to determine both the application size of the considered technologies and parameters for a corresponding operation policy. The returned set of non-dominated solutions can be used to enable the decision-making process of local community participants based on individual preferences[3].

6.4 Case Study

To demonstrate the functionality of the EMODPS, we apply the Borg MOEA and the simulation model described in Section 7.3.1 to one year of data including residential heat and electricity consumption in hourly resolution of ten households with an average electricity demand of 3,286 kWh and an average heat demand of 15,237 kWh per year. The individual load profiles are created using the load profile generator (Pflugradt et al., 2013). The solar generation data is simulated for a CEC

[3]The entire simulation code is available at:
`https://github.com/ArminGo/HICSSBorg`

Application	**Investment costs** [€/ kWh]	**Lifetime** [years]	**CO_2 emissions** [kg/kWh]
CHP (Falkenberg et al., 2019)	1700	20	0.207*
PV (Wirth, 2021)	1400	20	0.050*
PVT (Wirth, 2021; Lauf et al., 2019)	1800	20	0.055*
BSS (Figgener et al., 2018)	1700	20	83.5**
TSS (Thess et al., 2015) (Samweber and Schifflechner, 2016)	40	20	12**
HP (Johnson, 2011)	1450	17	1060**

* kg CO_2/kWh production, ** kg CO_2/kWh system size

Tariff	**Costs**	**CO_2 emissions**
g^{el}(Icha and Kuhs, 2019)	0.30	0.401
$x^{ht,CHP}$ (Falkenberg et al., 2019)	0.10	0.207
$f^{el,r}$	0.10	-
$f^{el,c}$	0.08	-

Table 6.2.: Investment costs, CO_2 emissions and lifetime for specific technologies.

located in southern Germany. To show the algorithm performance with regard to different seasons, we evaluate three scenarios: "summer", "winter" and "mid-season". For the summer scenario, the household load and solar generation data between May and August is aggregated to an average week to reduce the necessary computation time. For the winter scenario, we aggregate the data for the months from November to February and the mid-season scenario includes March, April, September and October. The system configuration for investment costs and CO_2-emissions is based on the situation in the German energy market. An overview of the technology parameters for the case study is given in Table 6.2. Energy generation costs, grid charges and feed-in tariffs are based on German regulation and are also shown in Table 6.2. For the analysis, each scenario is run with 30 initial sets of randomly chosen parameters over 200,000 evaluation rounds by the Borg MOEA (Version 1.9). The simulation is carried out over the average week for each scenario. For comparison, each scenario is also analyzed with linear optimization models that regard each objective individually.

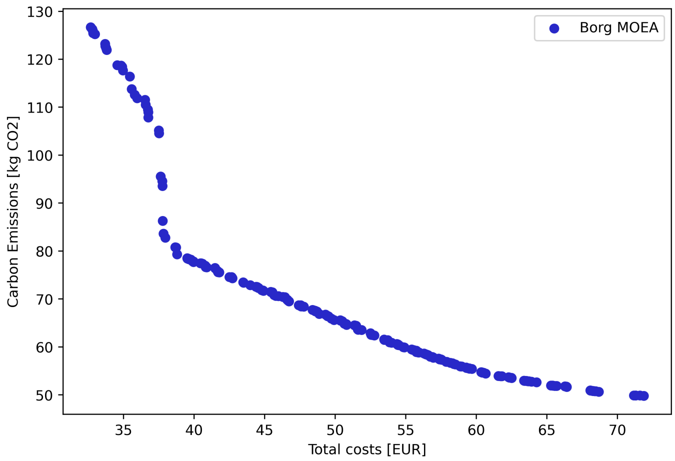


Figure 6.3.: The pareto front for the summer scenario.

6.4.1 Results of the EMODPS

The results indicate a wide range of non-dominated policies that can be used for the sizing and operation of the considered system. Figure 6.3 shows the non-dominated policies for each initial seed for the summer scenario. Each point represents one non-dominated result for a sizing and operation policy. As to be expected, the DPS for the summer scenario returns policies with the lowest overall costs compared to other scenarios. That can be explained by the high PV and PVT generation potential compared to low heating costs in that period. The gap in the pareto front exists due to a change between two general strategies in the application sizing decisions for the summer scenario. In Figure 6.4, each line represents the sizing decisions of one DPS solution with regard to the application sizes relative to their maximum

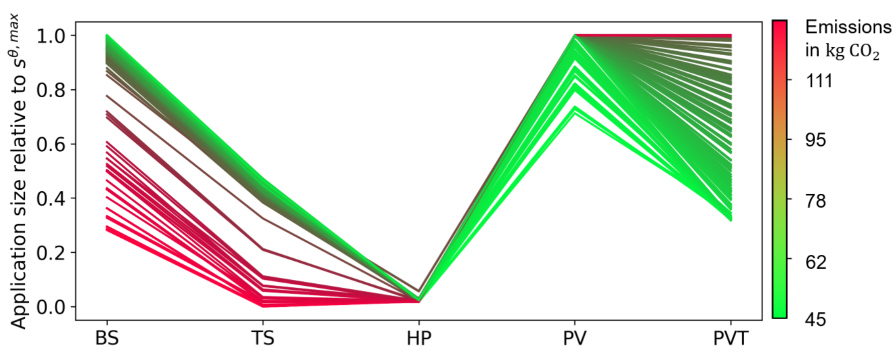


Figure 6.4.: Application sizing decisions for the summer scenario.

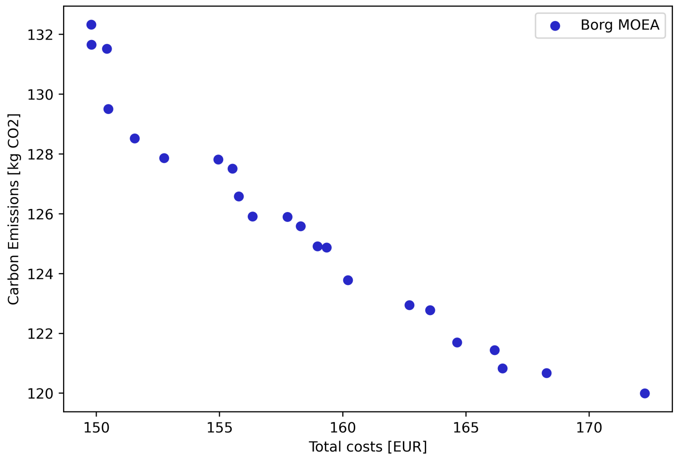


Figure 6.5.: The pareto front for the mid-season scenario.

installation sizes. The two strategies mentioned mainly differ in the sizing of the BSS and the TSS. The DPS solutions that achieve better results for the cost objective favor both large PV and PVT systems, indicating that the current feed-in tariff policy in Germany incentivizes the installation of residential solar PV. The linear optimizations for the summer scenario return costs of 26€ for O_1 and 43 kg CO_2 emissions for O_2 as optimal individual solutions.

The DPS solutions for the mid-season scenario presented in Figure 6.5 result in both higher costs and emissions for a mixed strategy than the summer scenario. Figure 6.6 shows that the policies mainly differ in the sizing of the PV plant, while all other parameters remain similar. The larger TSS system in comparison to both the summer scenario and the winter scenario indicates a higher volatility in the heat demand, as the mid-season scenario already includes days with higher heating de-

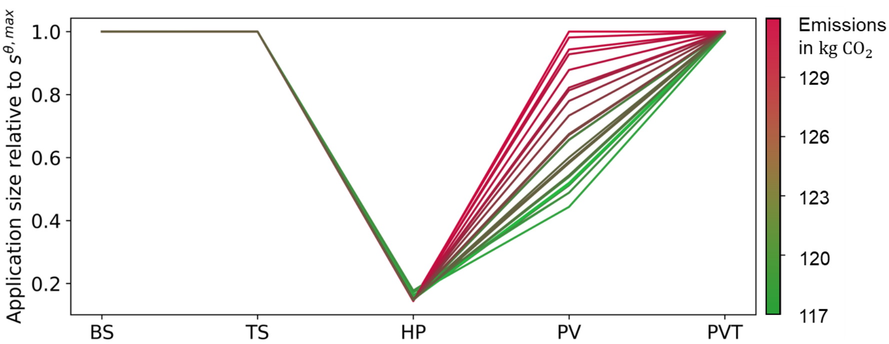


Figure 6.6.: Application sizing decisions for the mid-season scenario.

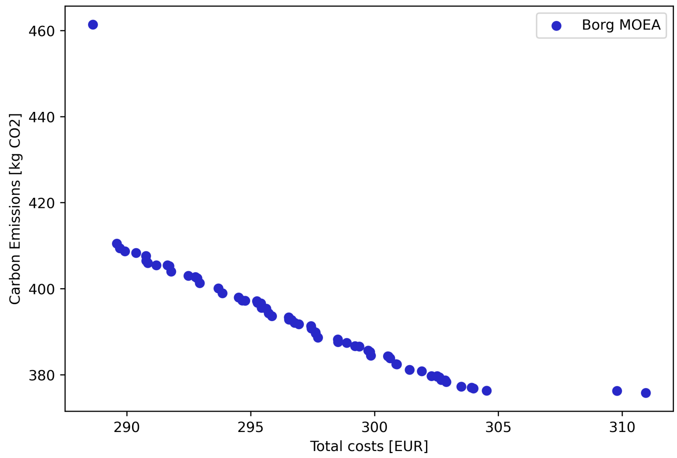


Figure 6.7.: The pareto front for the winter scenario.

mand. For renewable generation, the PVT plant is favored over the PV system with regard to ecological interests. The linear optimization for the mid-season scenario returns costs of 117.5€ for O_1 and 111.7 kg CO_2 emissions for O_2 in the individual optimization.

The results for the EMODPS in the winter scenario return the highest costs and emissions, as depicted in Figure 6.7. Recommendations for the HP size implementation in the winter scenario are distinctly larger then in the other scenarios, but do not exhaust the maximum application size available, as can be seen in Figure 6.8. The PVT plant is again built to the maximum size for all DPS solutions, while the size of the PV plant correlates with the policy emissions. The linear optimization for the winter scenario returns costs of 285€ for O_1 and 371 kg CO_2 emissions for O_2 as individual optima.

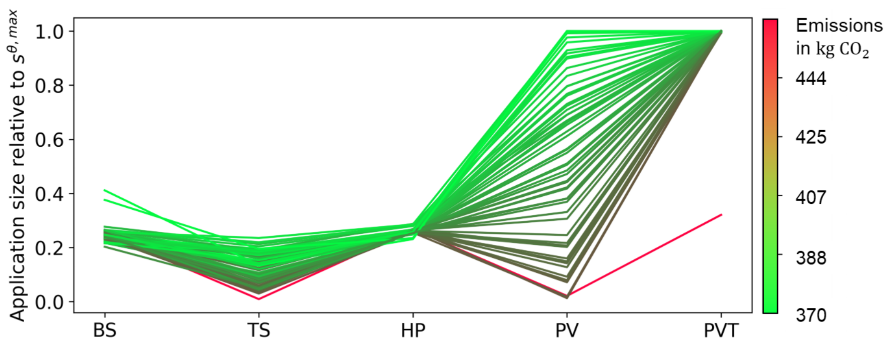


Figure 6.8.: Application sizing decisions for the winter scenario.

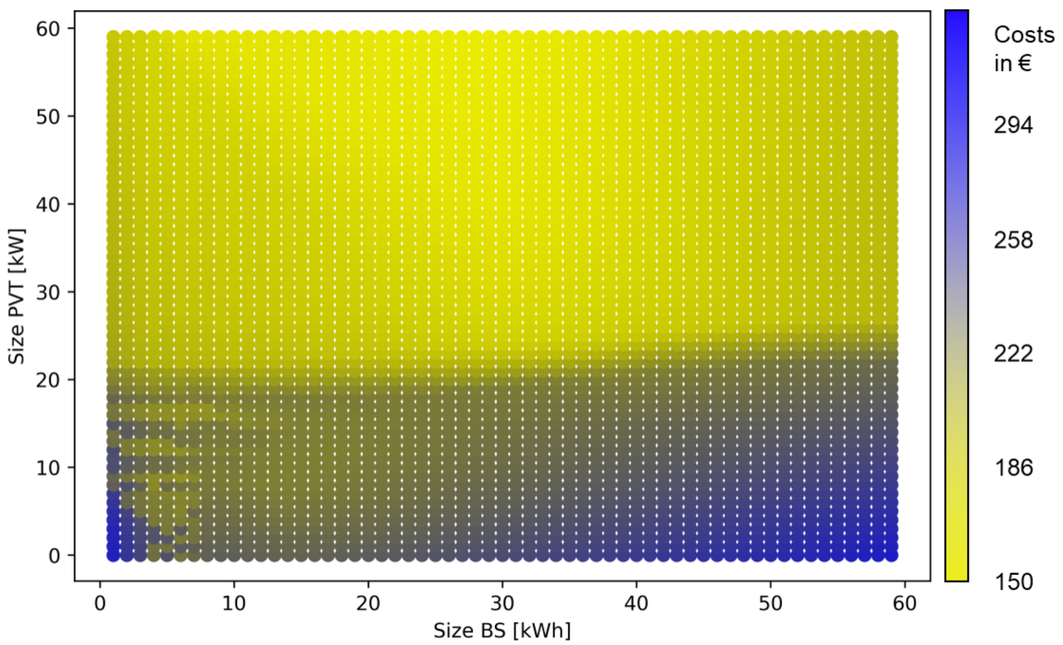


Figure 6.9.: Sensitivity analysis of the cost objective with regard to different system sizes.

The insights provided by the EMODPS on an individual level for each scenario show the different policies that can be used to plan and operate a CEC. Depending on the season in focus, the DPS recommends different strategies and sizing decisions, although some parameters, like a large PVT plant, are recommended through all scenarios. The following section provides further evaluation of the results with variable parameters.

6.4.2 Sensitivity Analysis

Besides the HP operation parameters, the simulation results are very dependent on the application sizing decisions determined by the Borg MOEA. In the in-between scenario, PVT and BSS are built to the maximum size for all policies, resulting in a 25 kW PVT plant and a 30 kWh BSS. To demonstrate the effect of these two system components on the overall outcome for the energy community, the input sizes for the simulation configurations are varied for one exemplary policy in the mid-season scenario with costs of 156€ and CO_2 emissions of 127 kg for the one week period. The operation parameters for the HP and all sizing decisions, except for BSS and PVT remain constant. The BSS size is then varied between one and 60 kWh. The

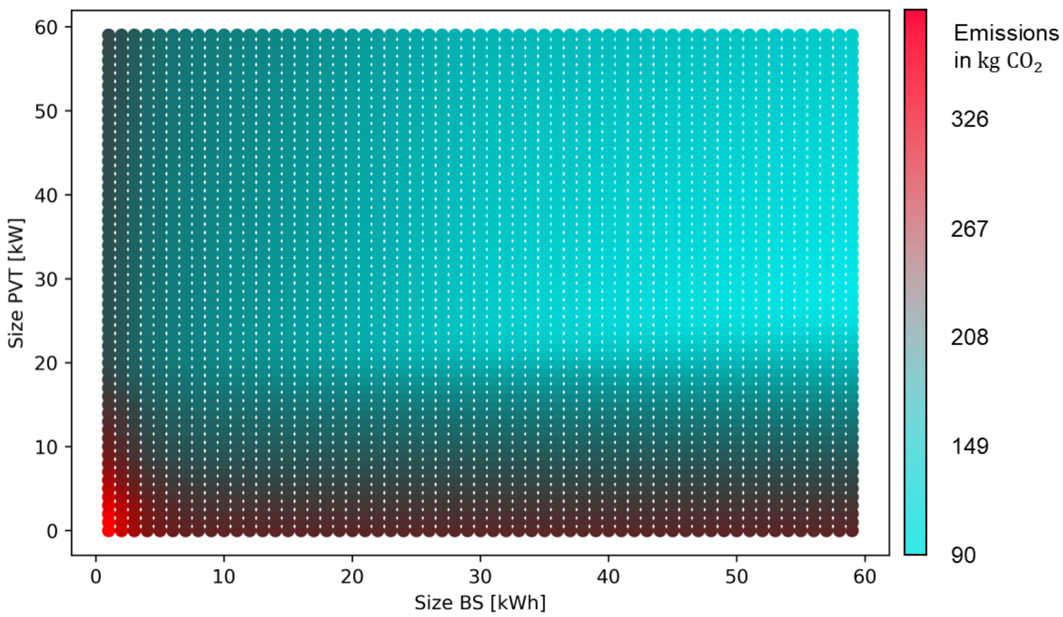


Figure 6.10.: Sensitivity analysis of the emission objective with regard to different system sizes.

PVT size is varied between one and 60 kW. The results for the cost objective are displayed in Figure 6.9. While an increased size of the PVT plant generally leads to reduced costs, the effect of the BSS size depends on the size of the PVT. For a small PVT, a high BSS size increases overall costs, while a smaller BSS is able to utilize excess energy generated by the PVT plant. Figure 6.10 shows the same variations with regard to the emission objective. Here, the turquoise section shows the positive network effects of a simultaneous increase of BSS and PVT. A larger BSS enables the use of generated renewable electricity instead of using electricity from the grid with a higher emission factor.

6.5 Discussion and Outlook

The results of the case study indicate the potential of EMODPS for the operation and sizing of sector-coupled CECs. With DPS, the interested parties can see the effects of different preference selections before needing to specifically state these preferences. Future work needs to investigate group decision processes to select one individual policy based on individual preferences of participants, investors and operators in a CEC. While a general setup for a decision support system has already been provided in Chapter 4, the exact specifications of this system remain subject to further research. With regard to the emission objective, this work focuses on CO_2 emissions that arise through investment and generation within the community and through generation supplied by the grid that is used in the community, represented through the grid emission factor in the case study. The potential emission benefits of feeding in low emission electricity generation from PV, PVT and CHP into the grid and the associated system emission reductions are not considered. As a whole, CECs with renewable generation have the ability to lower emissions system-wide and a system perspective is therefore an important next step. The constrained application sizes in the case study are given as fixed values, as larger appliances require more space and the application size is therefore limited. While some applications are used with the maximum size available in each scenario, namely the PV and PVT panel, other applications like the HP are only used at a fraction of the maximum size available. In reality, technologies like PV and PVT often have competing maximum application sizes for example due to limited roof space. Future research should incorporate joint sizing options for all available applications as interdependent decisions.

6.6 Conclusion

The model for evolutionary, multi-objective, direct policy search in the context of the development and operation of Citizen Energy Communities (CECs) presented in this chapter enables the integrated assessment of operation and application sizing decisions with regard to competing objectives. The model integrates both the demand for heat and electricity on a community level. The policies regard both the thermal storage level and the battery storage level to model the heat pump operation. For the emission objective in all scenarios and the cost objective in the winter scenario, the results are within 0.5% to 4.5% of the linear optimization benchmark. The larger gap of 24.1% and 27.7% for the cost objective in the summer and mid-season scenarios indicates that the solution space must be more thoroughly searched in these settings. The model results might be further improved through a longer evaluation period, e.g., an entire year.

The set of solutions can be used to enable local decision-makers in energy communities to develop their community based on individual preferences. Participants, investors and local operators are able to see the effects of their installation decisions and the energy costs and emissions for the community. The model proposed in this chapter can be integrated into a decision support system that helps residents to participate in CECs and build their own renewable generation technologies. We aim to bridge the interest gap between investors, local residents and energy suppliers and thereby contribute to a successful, decentralized energy transition.

CHAPTER 7

EVALUATING THE IMPACT OF REGULATION ON THE PATH OF ELECTRIFICATION IN CITIZEN ENERGY COMMUNITIES WITH PROSUMER INVESTMENT

Based on the investment alternatives in the solution space determined in Chapter 6, it is possible to provide preference-based residential energy technology recommendations for citizens in CECs. However, the success of such DSSs depends on the willingness of individual households to actively participate in the energy transition by investing in electrification and by becoming prosumers. This willingness is influenced by the return on investments in electrification and preferences towards environmental sustainability. Returns on investment can be supported by a preferential regulation of CECs, i.e., the ability to sell excess electricity directly within the community. However, the exact effect of such regulation is debated and therefore analyzed in this chapter.

A multi-periodic community development model is proposed that determines household investment decisions over a long time horizon, with heterogeneous individual preferences regarding sustainability and heterogeneous energy consumption profiles. The model considers that investment decisions which increase individual utility might be delayed due to inertia in the decision process. Decisions are determined in the model based on personal preferences using a multi-objective evolutionary algorithm embedded in an energy system simulation. In a case study, the development of a neighborhood in Germany consisting of 30 households is investigated in regards to community costs and community emissions with and without CEC regulation as proposed by the European Union. The results show that CEC regulation always reduces overall community costs and emissions, while heterogeneous distributions of economic and ecologic preferences within the community are beneficial in terms of cost and emissions. Furthermore, decision inertia considerably slows down the transformation process. This indicates that policymakers should carefully consider who to target with CEC regulation and that subsidies should be designed such that they counterbalance delayed private investment decisions.

This chapter comprises the published article: Golla, Armin; Röhrig, Nicole; Staudt, Philipp; Weinhardt, Christof (2022): Evaluating the impact of regulation on the path of electrification in Citizen Energy Communities with prosumer investment. In: Applied Energy 319, p. 119241.

7.1 Introduction

The worldwide transition towards clean energy supply through renewable generation leads to a decentralization of energy generation (Alstone et al., 2015). This puts part of the momentum of the energy transition into the hands of individual households. To reach the ambitious climate targets of the Paris agreement (United Nations, 2015), more private investment into sustainable energy technology and electrified energy consumption is required. By installing low emission energy infrastructure in their households, individuals can be part of a successful energy transition. However, such private actions towards a more environmentally friendly energy consumption sometimes stand in contrast to individual preferences, are unattractive due to a lack of financial incentives, or are simply delayed because of inertia in decision-making. This could be improved by allowing neighborhoods to generate and consume electricity as a community and by jointly promoting clean energy investment. For example, prosumers might be able to achieve a higher revenue by selling excess solar generation to their neighbors instead of receiving fixed feed-in tariffs. At the same time, consumers of local electricity from PV panels will benefit from lower emissions compared to grid electricity in such a scenario (Mengelkamp et al., 2018). Studies further suggest peer effects in certain communities in regards to investment in PV panels (Busic-Sontic and Fuerst, 2018). In this scenario, peers are the neighbors living in the community. Due to a growing interest in energy communities that produce and share energy on a local level, the European Union has promoted the concept of CECs, as described in Chapter 1. While other concepts such as smart energy systems as proposed by (Mathiesen et al., 2015) or the energy hub model by (Geidl et al., 2007) are ambiguous, the CEC concept is clearly defined in European regulation. The aim is to provide “an enabling framework, fair treatment, a level playing field and a well-defined catalog of rights and obligations” for CECs, where households are required to be able to choose to participate voluntarily (European Parliament and Council of the European Union, 2019).

The ability to share locally generated electricity on a peer-to-peer basis can increase the sustainability of an energy neighborhood (Mengelkamp et al., 2018), while individual households receive cost and revenue benefits. An implementation of CEC regulation could thereby improve both the acceptance and financial value of private energy generation, conversion and energy storage capacity. This makes it necessary to evaluate the benefits of CECs for communities and individual households. As CEC projects are still primarily in a demonstration phase, simulations are an adequate tool to assess the potential benefits of CEC regulation.

When considering the energy consumption of a community, both heat and electricity sector must be taken into account. While the share of renewable electricity generation is continuing to rise worldwide, the amount of renewable heat remains low (IEA, 2021). Therefore, hybrid PVT systems and HPs are considered in this chapter as electrification technologies linking power generation to sustainable heat provision.

Replacing the energetic equipment of an entire community with renewable energy technologies is typically not performed at once. The capacity in the community over all individual households develops over time. While some inhabitants install solar panels and battery systems right away, others follow later as is the case with many innovations (Beal and Bohlen, 1956). The decision to invest in technology strongly depends on the individual household’s financial endowment, the financial environment and personal preferences. These preferences can sometimes contradict each other, for example, when the most cost-effective decision is not the one with the smallest carbon emissions while both dimensions are important to the household. Even the intent to invest in an energy application does not necessarily mean that the decision is implemented right away. Different factors such as high installation costs, possible alternatives, or simply decision inertia, i.e., the tendency to stick to previous choices regardless of the outcome (Alós-Ferrer et al., 2016), cause a delay in

private investment decisions (Greenleaf and Lehmann, 1995; Morwitz and Schmittlein, 1992).
Therefore, managers in municipal utilities and policymakers face a complex policy design problem: The transformation of a residential microgrid into a CEC and changes in the corresponding regulation influence the community's long-term development. In turn, individual investment decisions affect both the environmental footprint and the community's heat and electricity load profiles. These decisions can be steered using corresponding incentives and regulation. This leads us to the following research questions that we intend to answer in this chapter.

RQ 5: What are the long-term financial (cost) and environmental (emission) effects of CEC regulation on the development of a community with respect to electrification and the investment in residential energy technologies?

RQ 6 To what extent does the spread of individual household preferences in a community impact the potential of CEC regulation for a faster decarbonization?

To answer these questions, we develop a multi-periodic investment decision model that features decentralized energy generation, conversion and storage technology covering the heat and electricity sector and apply it to a case study. In particular, we evaluate the benefits of CEC regulation to support policymakers and municipal utilities. Moreover, we consider the effects of diverging individual preferences between cost savings and sustainable energy consumption on the effectiveness of CEC regulation. Furthermore, we model decision inertia to simulate delays in investment decisions. Figure 7.1 is a schematic representation of the development of investments in a community over time, based on individual decisions without CEC regulation as a residential microgrid and as a CEC. The figure shows how CECs affect energy flows with respect to technology adoption. To identify investment strategies, we use the Borg MOEA that was proposed by (Hadka and Reed, 2013) and has already been implemented in the context of direct policy search for energy communities by (Gupta et al., 2020) and in Chapter 5. The evolutionary algorithm is embedded in a local energy system simulation. The algorithm can be used to provide decision support for individual households with multiple investment objectives and heterogeneous preferences and we apply it to determine an investment plan for

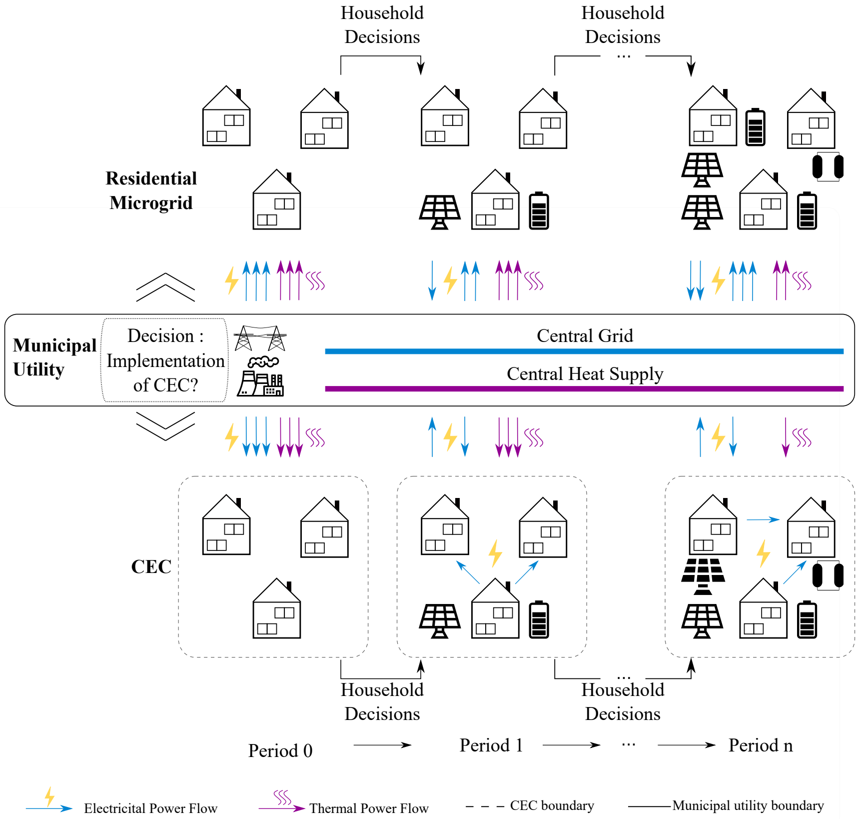


Figure 7.1.: Multi-periodic development of a community with and without a CEC.

sustainable energy technologies from all possible non-dominated investment plans for each household individually.

To demonstrate our approach, we evaluate the development of a community with 30 households between the years 2020 and 2030 in three preference scenarios in Section 7.4. The first scenario considers a neighborhood that is primarily interested in the economic dimension when investing in electrified energy technology, i.e., cost savings and has weak sustainability preferences. This might, for example, be true for low-income neighborhoods and other neighborhoods with little environmental concern. The second scenario assumes a more substantial ecological concern of the individual households, i.e., the local reduction of carbon emissions. This may apply to residential suburban areas with high-income families, for example. As these preferences might be heterogeneous within a neighborhood in many cases, we consider completely heterogeneous preferences in our last scenario. For all three scenarios, we evaluate the effects on the development of sustainable energy investments in the community with and without CEC regulation. Each household can invest in energy generation, conversion and storage technologies at the end of each period in accordance with the individual cost and emission preferences. The technologies covered in this chapter include PV and PVT systems, BSS and HPs. This then alters the household's heat and electricity load patterns for the subsequent periods. Furthermore, we simulate the effect of decision inertia on the development of the community energy systems by implementing a lag factor. The results of our case study show that a community consisting of households with heterogeneous preferences regarding cost and sustainability objectives profits most from the implementation of a CEC and should be targeted by policy makers. In summary, our approach is the first to consider heterogeneous preferences of individual households through multi-objective optimization in conjunction with realistic inert investment behavior and different regulatory environments.

In the following, we first introduce related literature in Section 7.2. Then, we describe the proposed model in Section 7.3. Next, the model evaluation based on a case study community of 30 households in Germany is described in Section 7.4. Finally, the overall findings of this chapter as well as policy implications are discussed in Section 7.5. The term CEC is used for communities where shared energy consumption is allowed. Communities without such regulation are referred to as residential microgrids. The term community is used to refer to both CECs and residential microgrids at the same time.

7.2 Microgrid Operation and Investment Decisions

This section presents related studies on microgrid operation and approaches for preference-based community investments. For an introduction of the CEC concept and corresponding regulation please see Section 2.3.

Optimization of energy systems and energy infrastructure within buildings and communities has been investigated in detail from a system's point of view, for example, in (Maroufmashat et al., 2016) and (Fina et al., 2019). Liu et al. evaluate the operation of coupled heat and electricity systems in general (Liu et al., 2016) and of BSS and power-to-heat devices in an energy community (Liu et al., 2019a). The authors further address the optimal design of PV and BSS in a multi-energy system with HPs (Liu et al., 2019b). The results indicate that the use of HPs leads to a decrease in the required BSS capacity. Only a few studies consider the effects of individual preferences in the decision process. One example is a multi-criteria decision analysis regarding local preferences proposed by (McKenna et al., 2018) for rural communities. The authors combine energy system analysis with multi-criteria decision analysis to evaluate eight different energy application plans for a municipality in South-Western Germany considering CO_2-emissions and community energy imports. Another example for a multi-criteria decision support system for the installation and operation of combined heat and power plants is presented in (Wang et al., 2017). The study focuses on centralized decision-making and presents a weighting mechanism for different decision criteria. The authors evaluate the implementation of CHP plants for heat and power generation in Daqing, China. The implementation and operation of energy generation, conversion and storage technologies within a CEC are investigated with a focus on decision support in Chapter 4 and direct policy search in Chapter 6. While both studies consider individual household preferences, they cover neither the implementation of a CEC nor do they consider the development of investments in sustainable technology over time. Therefore, decision inertia of households that intend to invest in energy appliances is also not considered.

Aside from the energy sector, many studies have investigated the role of investment decision inertia and investment decision delay. From a game-theoretic perspective, Chamley and Gale (1994) argue that the occurrence of delay is dependent on the reaction time and the number of players in an investment game. In their study, they investigate an n-player game, where each player can either reveal his or her private information or wait to see what other players do. Xiao and Yue (2018) investigate investor decision inertia on crowdfunding platforms. Their findings support the existence of decision inertia for investors with regard to investment timing and reward tier selection. Decision inertia as a form of holding on to sub-optimal investments for too long is reported in (Sandri et al., 2010). In an experimental study, the authors compare divestment choices of entrepreneurs and non-entrepreneurs. They identify two forms of inertia: 'Options-based' inertia based on possible real-option alternatives and behavior-based 'psychological' inertia. They conclude that even though divestment decisions should only be subject to 'options-based' inertia from a rational standpoint, 'psychological' inertia plays a central role in the conducted experiments.

To the best of our knowledge, no study evaluates the value of implementing CEC projects for the sustainable electrification of energy consumption given various scenarios of consumer preferences. Therefore, this chapter is one of the first to inform policymakers and municipal utilities on the value of designing incentive systems for this regulatory concept. In the following, we describe our approach to addressing this research gap.

Index	**Description**	**Index**	**Description**
θ	Technology index	Θ	Set of technologies
a, b	Node indices	N	Set of nodes
i	Household index	I	Set of households
p	Period index	P	Set of periods
t	Time step index	T	Time horizon
Technologies Θ: PV, PVT, BSS, HP			

Variable	**Unit**	**Description**
A	m^2	Available roof space
c^I, c^M, c^O	€	Investment, maintenance, operation costs
$\hat{c}^{I,\theta}$	€ /(kWp, kWh)	Investment costs per unit for technology θ
$\hat{c}^{M,\theta}$	€ /(kWp, kWh)	Maintenance costs per unit for technology θ
$\hat{c}^{g,c,th}$	€ /kWh	Cost parameter for grid, community electricity, centralized heat
d^{el}	kWh	Electricity demand
d^{th}	kWh	Thermal demand
e^{θ}	kg CO_2	Total emissions of technology θ
$\hat{e}^{\theta}$	kg CO_2 / kWh	Emissions of technology θ w.r.t. generation quantity
$\hat{e}^{I,\theta}$	kg CO_2 / kWh	Emissions of technology θ w.r.t. application size

$e^{g,c,th}$	kg CO_2	Emissions of grid, community electricity, centralized heat
$\hat{e}^{g,c,th}$	kg CO_2/kWh	Emission parameters for grid, community electricity, centralized heat
$el_{p,t}^{i,bss(c)}, el_{p,t}^{i,bss(d)}$	kWh	Electricity charge and discharge of the BSS for household i in p,t
$el_{p,t}^{i,d}$	kWh	Electricity demand for household i in p,t
$el_{p,t}^{i,f}, el_{p,t}^{i,f(c)}$	kWh	Electricity feed-in into the grid and the community for household i in p,t
$el_{p,t}^{i,g}, el_{p,t}^{i,g(c)}$	kWh	Electricity supply from the grid and the community for household i in p,t
$el_{p,t}^{i,hp}$	kWh	Electricity demand of the HP for household i in p,t
$el_{p,t}^{i,pv}, el_{p,t}^{i,pvt}$	kWh	Electricity supply from PV and PVT for household i in p,t
l^{θ}	years	Lifetime of technology θ
$\hat{r}^{f}$	€ /kWh	Feed-in tariff (grid)
$\hat{r}^{c}$	€ /kWh	Feed-in tariff (community)
$th_{p,t}^{i,d}$	kWh	Thermal demand for household i in p,t
$th_{p,t}^{i,e}$	kWh	Thermal heat released into the environment, for household i in p,t
$th_{p,t}^{i,g}$	kWh	Thermal supply from the gas network, for household i in p,t
$th_{p,t}^{i,pvt}, th_{p,t}^{i,hp}$	kWh	Thermal supply from PVT and HP for household i in p,t
O^{c}, O^{e}	€, kg CO_2	Cost and emission objective
$W^{\theta,el/th}$	m^2/kWp	Nominal power for technology $\theta \in (PV, PVT)$
X_p	kWp, kWh	Matrix of installed applications in all Households in period p
$\vec{x}_p^{i}$	kWp, kWh	Vector of installed applications in household i in period p

$x^{i,\theta}_{max}$	kWp, kWh	Maximum application size for each household i
$\Delta\vec{x}^{i}_{p}$	kWp, kWh	Investment decisions of household i in period p
α		Fixed parameter representing the decision inertia
$\tilde{\gamma}$	kW/m^2	Solar radiation
μ^i_p	%	Decision probability of household i in period p
η^θ	%	(Inverter) efficiency for technology $\theta \in (PV, PVT, BSS, HP)$
κ	%	Round trip efficiency for BSS
λ	%	State of charge for BSS
δ	%	Depth of discharge for BSS
ξ	%	Self-discharge-rate of BSS
$\rho^{i,c}$, $\rho^{i,e}$	%	Cost, emission preference of household i

Table 7.1.: Nomenclature.

7.3 A Multi-periodic Evaluation of Sustainable Energy Technology Investment Behavior

In this section, we describe the composition and functionalities of the proposed model. We develop a community energy hub model that can simulate the heat and electricity balance within a community considering different energy infrastructures. In this chapter, we consider PV panels, PVT panels, BSS and HPs, as well as centralized heat generation and electricity provision from the public grid. The individual households' energy balance is embedded in a simulation within the Borg MOEA. Using the output of this simulation, the individual decision to invest in sustainable energy technologies with regard to individual household preferences is determined. The Borg MOEA developed by Hadka and Reed is a highly effective evolutionary algorithm for problems with two to eight objectives (Hadka and Reed, 2013). A detailed outline of the technical features of the Borg MOEA can be found in (Hadka and Reed, 2013) and (Hadka and Reed, 2015). An overview on the indices and variables used in this section is displayed in Table 7.1.

7.3.1 Energy System Simulation

To show the effects of implementing CEC regulation in a community, we propose a community development tool that models individual investment decisions over a multi-periodic horizon. The energy simulation required to determine investment alternatives in each period through the Borg MOEA is described in this section. First, we outline the necessary model components, then we describe the energy balance within each household. Finally, the community energy balance for the implementation of CECs is modeled.

Community configuration: To provide a useful contribution for policymakers and managers in municipal utilities, the community development model must be adaptable to various community architectures and configurations. Four types of models are used to specify the system parameters. (i) General settings, which include the simulation periods and the optimization objectives are set in the configuration model. (ii) The technology model summarizes the technical data of all included devices. The investment and maintenance costs, system lifetime, system efficiency and CO_2-manufacturing emissions are specified for all appliances. In addition, the self-discharge rate and maximum depth of discharge are included for BSS and an additional feed-in tariff for locally generated electricity can be determined. (iii) The geographic location is specified in the microgrid model. (iv) For each building in the community, the year of construction, building size, the roof size, tilt and azimuth angle that influence the potential for PV and PVT systems are specified in the household model.

One major objective of this chapter is to include individual household preferences in the simulation. As described in Chapter 4, individual preferences concerning cost and sustainability objectives can influence household investment decisions when considering renewable energy technologies. These decisions influence the individual heat and electricity consumption patterns and the community overall, which usually

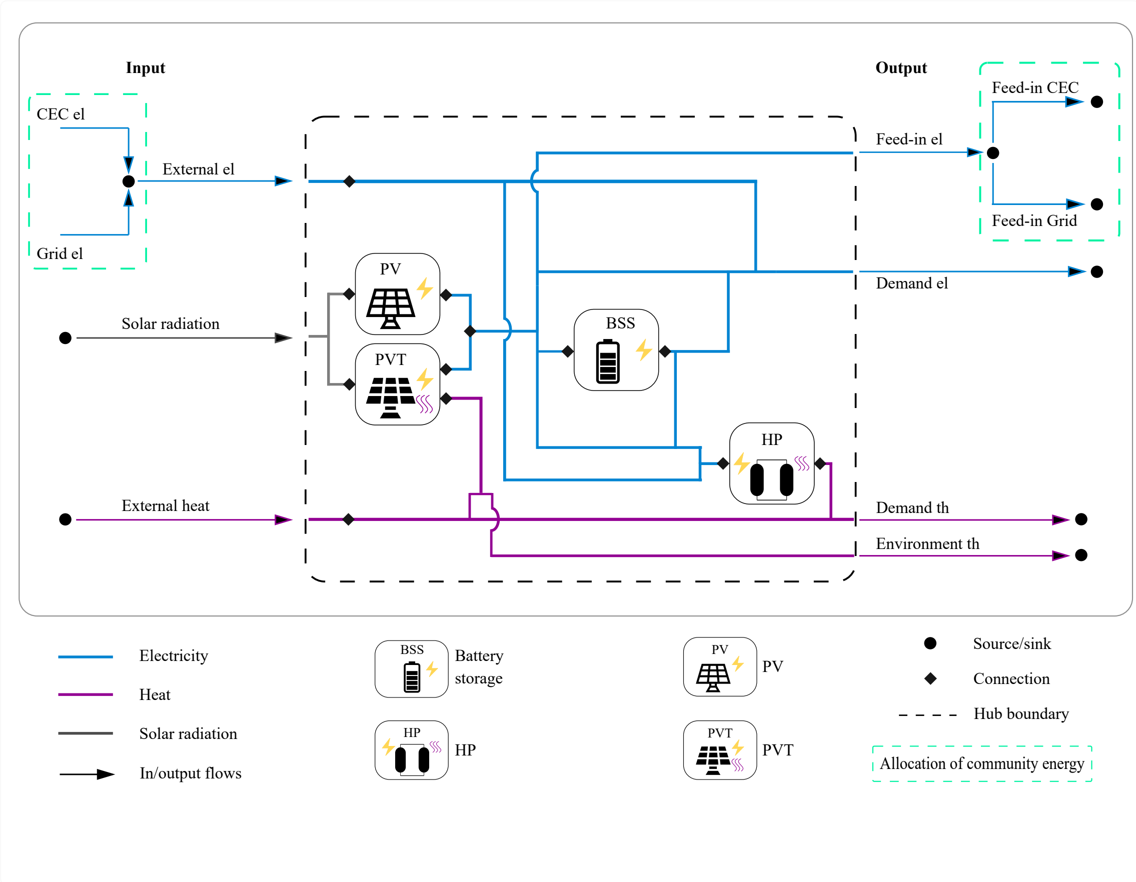


Figure 7.2.: Energy hub from the household's perspective.

does not include more than a few dozen households (Weinhardt et al., 2019). The individual preferences of each household in the microgrid are specified as part of the household model.

Household energy balance: Building on the energy hub model (Geidl et al., 2007), the energy supply and demand in each household of the community is simulated through a set of balance equations. An overview is given in Figure 7.2.

For every household i, prior knowledge of two input types is assumed: (i) The solar radiation and thereby the PV and PVT generation profiles and (ii) the electricity and heat load profiles. The electrical power output of solar PV and the electrical and thermal power output of PVT is given by:

$$\begin{aligned} el_{p,t}^{i,pv} &= x_p^{i,pv} \cdot W^{pv,el} \cdot \eta^{pv} \cdot \gamma_{p,t} && \forall\,(i,p,t) \in I \times P \times T \\ el_{p,t}^{i,pvt} &= x_p^{i,pvt} \cdot W^{pvt,el} \cdot \eta^{pvt} \cdot \gamma_{p,t} && \forall\,(i,p,t) \in I \times P \times T \\ th_{p,t}^{i,pvt} &= x_p^{i,pvt} \cdot W^{pvt,th} \cdot \eta^{pvt} \cdot \gamma_{p,t} && \forall\,(i,p,t) \in I \times P \times T \end{aligned} \tag{7.1}$$

Here, $el_{p,t}^{i,pv}$ is the electricity supply of the PV plant, $el_{p,t}^{i,pvt}$ is the electric and $th_{p,t}^{i,pvt}$ is the thermal power supply of the PVT plant for household i in period p and time step t, $x_p^{i,pv}$ and $x_p^{i,pvt}$ are the application sizes for the PV and PVT plant, $W^{pv,el}$,$W^{pvt,el}$ and $W^{pvt,th}$ are the nominal electric power of the PV and PVT plant and the nominal thermal power of the PVT plant, η^{pv} and η^{pvt} are the inverter efficiencies for PV and PVT and $\gamma_{p,t}$ is the solar radiation in period p at time step t. The allocation of energy within the households follows a simple four-step heuristic described below.

Step 1: If possible, the thermal and electric outputs of PV and PVT are used for self-consumption within the household.

Step 2: If an HP is installed, PV and PVT electricity left from Step 1 is used for HP operation for immediate heat demand. The HP conversion from electricity to heat is given by:

$$el_{p,t}^{i,hp} = \frac{th_{p,t}^{i,hp}}{\eta_t^{i,hp}}, el_{p,t}^{i,hp} \leq x_p^{i,hp}\,\forall\,(i,p,t) \in I \times P \times T \tag{7.2}$$

Here, $el_{p,t}^{i,hp}$ is the electricity consumption and $th_{p,t}^{i,hp}$ is the thermal output of the HP for household i in period p and time step t, $\eta_t^{i,hp}$ is the power-to-heat ratio of the HP with regard to the ambient temperature and $x_p^{i,hp}$ is the size of the HP in period p.

Step 3: The remaining solar electricity generation from the previous two steps is used to charge the BSS. Later, the BSS can be discharged to satisfy the remaining electrical demand. The state of charge of the BSS in every time step is given by:

$$\begin{aligned} \lambda^{i}_{p,t} \quad &= \quad \kappa \cdot el^{i,bss(c)}_{p,t} + \xi \cdot \lambda^{i}_{p,t-1} - el^{i,bss(d)}_{p,t} \\ & \quad\quad \forall\, i,p \in I \times P, t \in \{2,...T\}, \quad \lambda^{i}_{p,1} = 0 \\ with \quad & (1-\delta_{bss}) \leq \lambda^{i}_{p,t} \leq x^{i,bss}_{p} \end{aligned} \tag{7.3}$$

Here, $el^{i,bss(c)}_{p,t}$ and $el^{i,bss(d)}_{p,t}$ represent the electricity used to charge and discharge the BSS for household i in period p and time step t, κ is the round-trip-efficiency, ξ is the self-discharge rate and δ_{bss} is the depth-of-discharge. The initial state of charge $\lambda^{i}_{p,0}$ is set to $(1-\delta_{bss})$ in every period. The operational model does not consider a transfer of the state of charge between two periods p and $p+1$ but of course, it does so between time steps. A simple operation heuristic controls the battery operation. If there is remaining solar electricity and the current state-of-charge does not exceed the upper threshold of λ, the BSS is charged. Discharge is triggered when a household has remaining demand and the BSS state-of-charge does not fall below the maximum depth-of-discharge $(1-\delta_{bss})$. The BSS can also be discharged for the HP operation to satisfy thermal demand.

Step 4: In case any electricity generated by the PV or PVT system is not consumed in the previous steps, it can be fed into the local grid if the community is a CEC. Otherwise, it is fed directly into the public grid. Energy stored in the BSS cannot be used for feed-in. If additional electricity is required, it is obtained from the community in the case of a CEC or the public grid, otherwise. The electricity balance for the entire simulation is given by:

$$\begin{aligned} & el^{i,pv}_{p,t} + el^{i,pvt}_{p,t} - el^{i,d}_{p,t} - el^{i,hp}_{p,t} - el^{i,bss(c)}_{p,t} \\ & \quad + el^{i,bss(d)}_{p,t} - el^{i,f}_{p,t} - el^{i,f(c)}_{p,t} + el^{i,g}_{p,t} + el^{i,g(c)}_{p,t} = 0 \,\forall\, (i,p,t) \in I \times P \times T \end{aligned} \tag{7.4}$$

Here, $el^{i,d}_{p,t}$ is the electricity demand, $el^{i,f}_{p,t}$ is the grid feed-in, $el^{i,f(c)}_{p,t}$ is the electricity fed into the community, $el^{i,g}_{p,t}$ is the grid supply and $el^{i,g(c)}_{p,t}$ is the electricity supplied by the community for household i in period p and time step t. If the thermal generation of the PVT plant is larger than the thermal demand of a household, excess thermal heat $th^{i,e}_{p,t}$ is released into the environment. Additional heat is supplied using the gas distribution network. The heat balance is given by:

$$th^{i,pvt}_{p,t} + th^{i,hp}_{p,t} - th^{i,d}_{p,t} - th^{i,e}_{p,t} + th^{i,g}_{p,t} = 0 \,\forall\, (i, p, t) \in I \times P \times T \tag{7.5}$$

Here, $th^{i,d}_{p,t}$ is the thermal energy demand, $th^{i,e}_{p,t}$ is the excess energy released into the environment, $th^{i,g}_{p,t}$ is the external energy supplied by the gas network for household i in period p and time step t.

CEC simulation: In a CEC, surplus energy from households is locally distributed before it is fed into the public grid. The evaluation of a community both as a CEC and as a residential microgrid allows community planners and policymakers to assess the potential benefits of a CEC implementation. Community trading is prioritized before electricity from the public grid is used, if energy sharing is enabled. After the model is initialized, it is possible to compute the optimal investment decision alternatives over the following years. In the optimization, the simulation model is used to determine the objective outputs for community costs and emissions with regard to the technology application sizes.

7.3.2 Preference-based Optimization of Investment Decision Alternatives

The previous section covers the first operational module, which executes the simulation step and provides an energy balance for each household and within the community. This section describes the optimization module. Based on the simulation results in a period p, the model determines the actions of every household in the microgrid. The action is selected from a set of pareto-optimal options calculated using the Borg MOEA. First, we describe the different objective functions that reflect the individual preferences of the households.

Objective functions: The simulation model proposed in Section 7.3.1 can be used to derive an investment proposition for each household. The proposition is determined based on the household's preferences that are used to weigh the corresponding objectives. In this chapter, we focus on the two objectives community costs and emissions. The cost objective comprises investment costs $c^I(\vec{x}, p, i)$, annual maintenance costs $c^M(\vec{x}, p, i)$ and operation costs $c^O(\vec{x}, p, i)$:

$$O^c(\vec{x}, p, i) = c^I(\vec{x}, p, i) + c^M(\vec{x}, p, i) + c^O(\vec{x}, p, i) \tag{7.6}$$

The investment costs associated with a variable combination $\vec{x}$ represent the sum of yearly equipment depreciation until the end of the considered time horizon:

$$c^I(\vec{x}, p, i) = \sum_{\theta=1}^{\Theta} x_p^{i,\theta} \frac{\hat{c}^{I,\theta}}{l^\theta} \forall (i, p) \in I \times P \tag{7.7}$$

$\hat{c}^{I,\theta}$ are the investment costs per unit of installation and l^θ is the lifetime of technology θ. Maintenance costs summarize the annual costs for service and maintenance of all installed technologies:

$$c^M(\vec{x}, p, i) = \sum_{\theta=1}^{\Theta} x_p^{i,\theta} \cdot \hat{c}^{M,\theta} \forall (i, p) \in I \times P \tag{7.8}$$

$\hat{c}^{M\theta}$ are the maintenance costs of technology θ per unit of installation. The operation costs c^O are derived from the energy consumption costs and the expected feed-in revenues for electricity with the installed energy infrastructure:

$$\begin{aligned} c^O(\vec{x}, p, i) = & \sum_{t=1}^{T} el_{p,t}^{i,g} \cdot \hat{c}^g + el_{p,t}^{i,g(c)} \cdot \hat{c}^c + th_{p,t}^{i,g} \cdot \hat{c}^{th} \\ & -el_{p,t}^{i,f} \cdot \hat{r}^f - el_{p,t}^{i,f(c)} \cdot \hat{r}^c \forall (i, p) \in I \times P \end{aligned} \tag{7.9}$$

$\hat{c}^g$ is the cost parameter for external electricity, $\hat{c}^{th}$ is the cost parameter for external heat, $\hat{r}^f$ is the feed-in tariff for power supplied to the grid and $\hat{r}^c$ is the feed-in tariff for power supplied to the CEC. The emissions objective is measured in kg CO_2 equivalents for the infrastructure combination $\vec{x}^i$ of each household. The total emissions are the sum of all emissions associated with each consumed unit of an energy carrier and the manufacturing emissions of the energy infrastructure. The overall emissions of generation technologies are mapped to the generated kWh for each technology θ:

$$O^e(\vec{x}, p, i) = \sum_{\theta=1}^{\Theta} e^\theta(\vec{x}, p, i) \tag{7.10}$$

e^{θ} are the emissions of technology θ. The manufacturing emissions from PV and PVT are mapped to emissions per kWh of generation, based on the yearly generation and lifetime. The emissions are distributed proportionally between heat and electricity generation for the PVT system. Regarding the electricity sector, only the self-consumed amount of electricity is considered for the household's CO_2 balance:

$$\begin{aligned} e^{i,pv}(\vec{x},p,i) &= (el_p^{i,pv} - el_p^{i,f,pv} - el_p^{i,f(c,pv)})\hat{e}^{pv} && \forall\,(i,p) \in I \times P \\ e^{i,el,pvt}(\vec{x},p,i) &= (el_p^{i,pvt} - el_p^{i,f,pvt} - el_p^{i,f(c,pvt)})\hat{e}^{el,pvt} && \forall\,(i,p) \in I \times P \\ e^{i,th,pvt} &= th_p^{i,pvt} \cdot \hat{e}^{th,pvt} && \forall\,(i,p) \in I \times P \end{aligned} \tag{7.11}$$

$e^{i,pv}$ are the PV emissions, $e^{i,el,pvt}$ and $e^{i,th,pvt}$ are the PVT emissions for household i, $\hat{e}^{pv}$ is the specific PV emission factor, $\hat{e}^{el,pvt}$ and $\hat{e}^{th,pvt}$ are the specific PVT emission factors. This chapter does not consider a possible CO_2-bonus for the feed-in of renewable electricity into the public grid. Emissions from HPs and BSSs are measured based on the manufacturing emissions:

$$\begin{aligned} e^{i,bss}(\vec{x},p,i) &= \frac{\hat{e}^{I,bss}x_p^{i,bss}}{l^{bss}} && \forall\,(i,p) \in I \times P \\ e^{i,hp}(\vec{x},p,i) &= \frac{\hat{e}^{I,hp}x_p^{i,hp}}{l^{hp}} && \forall\,(i,p) \in I \times P \end{aligned} \tag{7.12}$$

$e^{i,bss}$ and $e^{i,hp}$ are the emissions, $x^{i,bss}$ and $x^{i,HP}$ are the sizes of the BSS and HP for household i, $\hat{e}^{I,bss}$ and $\hat{e}^{I,hp}$ are the specific emission factors, l^{bss} and l^{hp} are the lifetime of the BSS and HP. Emissions of external heat supply and grid electricity are measured in kg CO_2 per consumed kWh of each household and are given by:

$$\begin{aligned} e^{i,g}(\vec{x},p,i) &= el_{p,t}^{i,g} \cdot \hat{e}_g^{el} && \forall\,(i,p) \in I \times P \\ e^{i,g(c)}(\vec{x},p,i) &= el_{p,t}^{i,g(c)} \cdot \hat{e}_c^{el} && \forall\,(i,p) \in I \times P \\ e^{i,th}(\vec{x},p,i) &= th_{p,t}^{i,g} \cdot \hat{e}_g^{th} && \forall\,(i,p) \in I \times P \end{aligned} \tag{7.13}$$

$e^{i,g}$, $e^{i,g(c)}$ and $e^{i,th}$ are the emissions of grid electricity, community electricity and centralized heat for household i, $\hat{e}_g^{el}$, $\hat{e}_c^{el}$ and $\hat{e}_g^{th}$ are the specific emission factors of grid, community electricity and centralized heat.

Application of the Borg MOEA: Having defined the variables and objectives, the mathematical form for the multi-objective investment problem to minimize costs and emissions of household i in a period p has the following form:

$$\begin{aligned} &\min_{\vec{x},p,i} F(O^c(\vec{x},p,i), O^e(\vec{x},p,i)) \\ &\qquad \textit{subject to the constraints stated in Equations 7.1 to 7.13} \\ &\qquad \textit{with } x_p^{i,\theta} \leq x_{max}^{i,\theta}\, \forall\, (i,p,\theta) \in I \times P \end{aligned} \tag{7.14}$$

In the problem formulation, $O^c(\vec{x},p,i)$ and $O^e(\vec{x},p,i)$ are the objective functions providing the mapping mechanism between a variable set and the objective values. $x_{max}^{i,\theta}$ is the maximum application size for each household i. Using this two-dimensional objective function and the simulation described above, the Borg MOEA returns a set of non-dominated investment policies. Non-dominated implies that no solution within the solution space performs worse than any other solution in the solution space in both objectives at the same time. This gives us an approximated pareto front.

Modeling the inertia of energy investment decisions: The gap between the environmental intentions and environmental actions of an individual has been first introduced in (Blake, 1999). This gap can also be described as a delay in action. Even though one feels that a specific problem should be addressed, it is not done right away. Such delay or inertia in decision making especially occurs in the context of investment decisions (Morwitz and Schmittlein, 1992). Greenleaf and Lehmann (1995) propose eight main reasons for individuals to delay consumption decisions: Lack of time, lack of enjoyment, risk exposure, the requirement to obtain third-party advice, procedural uncertainty, lack of information, the expectation of falling prices and expected improvements of product quality. For an overview of existing experimental evaluations of decision-making in the context of household energy investments, we refer to (Kastner and Stern, 2015).

As the policy model proposed in this chapter aims to reflect individual preference-based decision-making over a time horizon of several years, we must account for the possibility of a time delay between intention and actual decision. We argue that customers with clear preferences for one dimension (for instance, preferring the ecological dimension clearly over the economic dimension) are more likely to invest as their investment goals are less ambivalent. Secondly, customers also evaluate whether a specific option among all available non-dominated options reflects their preference. An option that more strongly reflects their preferences is chosen with a higher likelihood than if an option was presented that is far away from their preferences. The likelihood for investment is correspondingly calculated in Equation 7.15.

$$\begin{aligned}
\mu_p^i &= \alpha \cdot (O^{e,n}(\vec{x},p,i)\rho^{i,e} + O^{c,n}(\vec{x},p,i)\rho^{i,c}) && \forall\,(i,p) \in I \times P \\
O^{e,n}(\vec{x},p,i) &= \frac{O^{e,hi}(\vec{x},p,i) - O^{e}(\vec{x},p,i)}{O^{e,hi}(\vec{x},p,i) - O^{e,lo}(\vec{x},p,i)} && \forall\,(i,p) \in I \times P \\
O^{c,n}(\vec{x},p,i) &= \frac{O^{c,hi}(\vec{x},p,i) - O^{c}(\vec{x},p,i)}{O^{c,hi}(\vec{x},p,i) - O^{c,lo}(\vec{x},p,i)} && \forall\,(i,p) \in I \times P
\end{aligned} \tag{7.15}$$

Here, $\rho^{i,c}$ and $\rho^{i,e}$ are the cost and emission preferences of household i. $O^{c,n}$ and $O^{e,n}$ are the normalized cost and emission objectives, $O^{c,hi}$ and $O^{e,hi}$ are the highest possible costs and emissions and $O^{c,lo}$ and $O^{e,lo}$ are the lowest possible costs and emissions with regard to the application of investment decisions for household i in period p. The factor α is a fixed value representing the decision inertia.

According to the equation above, the intention to invest in a combination of energy technologies is higher for an individual with either strong or weak sustainability preferences and lower for an individual with balanced preferences for cost and sustainability. Furthermore, investment intentions are reduced based on the deviation from the best possible outcome for an individual given his or her preference settings and the available investment alternatives. This intent is then subject to the decision inertia α. Previous studies on decision inertia in investment situations state a gap between intention and action of 0.25 (Morwitz and Schmittlein, 1992), meaning that only 25% of the study participants with the intent to buy an application did so within the next 12 months. Following this line of argument, α is set to 0.25 for the case study presented in Section 7.4. For each household, the investment decision $\Delta\vec{x}_p^i$ in p is implemented with probability μ_p^i.

Derivation of the investment proposition: For each household within the community, an investment decision problem is solved in each period based on the possible decision alternatives derived above. Each private household i improves its energy infrastructure during a multi-periodic simulation run by repeatedly evaluating different investment options and deciding whether to make an investment. The best investment from the approximated pareto front is determined at the end of each period p. The application vector for the next period is given by:

$$\vec{x}_{p+1}^i = \begin{cases} \vec{x}_p^i + \Delta\vec{x}_p^i & \textit{with probability } \mu_p^i \\ \vec{x}_p^i & \textit{with probability } 1 - \mu_p^i \end{cases} \quad \forall\,(i,p) \in I \times P \tag{7.16}$$

The decision of a household represented by $\Delta\vec{x}_p^i$ is determined based on the respective individual cost and emission preferences. The set of non-dominated decision alternatives returned by the Borg MOEA contains both cost and emission values for all decision alternatives available to the household. The objective function values for all decision alternatives are normalized from zero to one as displayed in Figure 7.3 to form a decision. The household preferences are modeled by drawing a line with the starting point (0,0) and a slope of $\rho^{i,e}/\rho^{i,c}$. Investment decisions along this line represent a balanced consideration of a household's cost and emission preferences. The decision alternative with the closest distance to the line is selected as $\Delta\vec{x}_p^i$. Using this method, households with a high ecologic preference will settle for an investment decision with low overall emissions compared to the other alternatives and vice versa. We argue that this method can be used to effectively determine the household investment decision that best reflects the household preference trade-off between costs and emissions.

7.4 Case Study

As argued above, individual preferences can greatly influence household decisions regarding the investment in sustainable energy generation, conversion and storage applications. Furthermore, the implementation of CECs influences the development of a community as it changes its economics. To demonstrate the functionality of the model described in Section 7.3, to evaluate the effects of individual preferences and to compare CEC regulation to a residential microgrid, we introduce six different scenar-

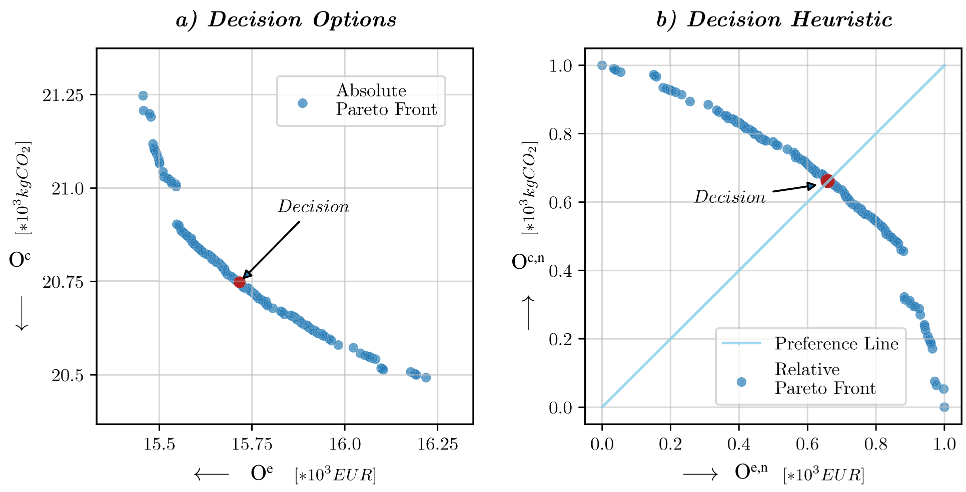


Figure 7.3.: Derivation of a household decision.

ios for a community with 30 households located in Germany. As displayed in Table 7.2, three preference scenarios are used: A strong sustainability preference scenario, where the sustainability preferences of each household are randomly drawn from the interval between 50% and 100%, a weak sustainability preference scenario, where the sustainability preferences are drawn from the interval between 0% and 50% and a heterogeneous scenario, where the ecologic sustainability preferences are drawn from the entire preferences space between 0% and 100%. A sustainability preference of 100% means that a household considers only emission reductions when making an investment decision. The economic preference of each household are relative to the sustainability preferences and are given by $\rho^{i,c} = 100\% - \rho^{i,e}$. Correspondingly, a

Parameter	**Dimensions**		
Regulation:	CEC	Residential Microgrid	
Sustainablity preferences:	Strong 50%-100%	Weak 0%-50%	Heterogeneous 0%-100%

Table 7.2.: Dimensions of the case study.

household with 0% sustainability preference and therefore 100% economic preference considers only cost reductions when making an investment decision. The three preference scenarios are calculated in two settings each, first with an implemented CEC regulation and in the setting of a residential microgrid. As a result, six scenarios are examined. To evaluate the effects of the decision inertia parameter modeled in this chapter, we conduct a second simulation without decision inertia that has otherwise the same parameters.

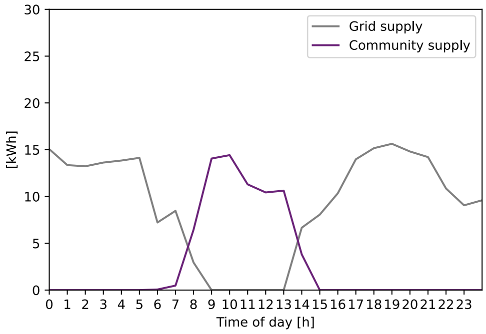
7.4.1 Implementation

The simulated community investigated in this section is located in Germany. This is important, as weather patterns are considered for solar PV generation and the heat demand. The electricity load profiles of the 30 households used in this chapter are derived from a data set containing actual load profiles from single-family buildings located in Germany in close proximity to each other (Tjaden et al., 2015). The community size is chosen within range of existing energy community projects in Germany, Austria and Switzerland that include between 7 and 41 households (Weinhardt et al., 2019). The annual electricity consumption of the considered households lies between 1,289 kWh and 7,374 kWh, with an average of 4,095 kWh and a standard deviation of 1,408 kWh. The electricity consumption profiles are repeated every year during the simulation period. The households' heat demand profiles are calculated based on the heating degree days method. As a reference, we use weather data and solar radiation profiles from 2009 to 2019 from the renewables.ninja tool (Pfenninger and Staffell, 2016). For the simulation, the time resolution is 15 minutes. The building size is set to 130m^2 for each building, which is the average household size in Germany (Gude, 2019). The roof tilt angle is set to 35° and the roof azimuth is set to 180° so that one side of the household roof faces south. A roof size of 32m^2 is available for building PV and PVT panels on each household (Mainzer et al., 2014). The appliances' lifetime, investment and maintenance costs and manufacturing emissions are provided in Table 7.3. The values for the expected lifetimes of the energy infrastructure are taken from (Mayer et al., 2015) and (Popovski et al., 2018). The investment cost parameters are based on (Krampe et al., 2016), (Herrando and Markides, 2016) and (Weidner et al., 2014). The values for maintenance cost are

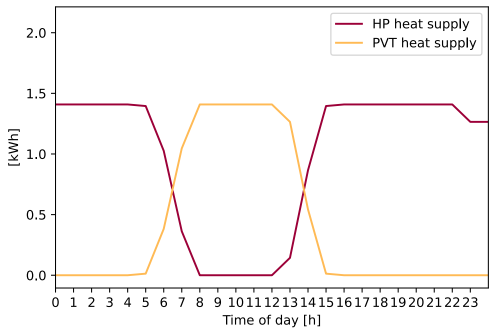
Parameter		**PV**	**PVT**	**BSS**	**HP**
Lifetime	l^{θ}	25 years	20 years	10 years	20 years
Investment costs	$\hat{c}^{I}_{p=0}$	$1052\ \frac{€}{kWp}$	$2144\ \frac{€}{kWp}$	$452\ \frac{€}{kWh}$	$800\ \frac{€}{kW}$
Operating costs	e^{O}	$500\ \frac{kgCO_2}{m^2}$	$500\ \frac{kgCO_2}{m^2}$	$190\ \frac{kgCO_2}{kWh}$	$193\ \frac{kgCO_2}{kW}$
Maintenance costs	$\hat{c}^{M}$	$0.01 * \hat{c}^{I,pv}$	$0.01 * \hat{c}^{I,pvt}$	$0.015 * \hat{c}^{I,bss}$	$0.01 * \hat{c}^{I,hp}$

Table 7.3.: Community energy technology cost and emission parameters.

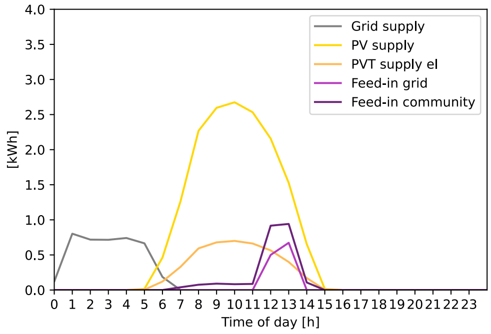
taken from (Fürstenwerth, 2013), (Mailach and Oschatz, 2021) and (Naumann et al., 2015). The values for manufacturing emissions are based on (Ekins-Daukes, 2009) and (Romare and Dahlhöf, 2017). Beyond the values listed in Table 7.3, we need to define the nominal power values for PV and PVT. These are set to 0.18 kWp/m^2 for PV, 0.15 kWp/m^2 for PVT electricity and 0.475 kWp/m^2 for PVT heat. They are based on (Wirth, 2021) and (Abdul-Ganiyu et al., 2020). The HP COP depends on the ambient temperature in the community with a coefficient of 3.5 for 0°C. For very low temperatures, a heater is integrated into the HP (Megan Quentin-Baxter et al., 2011). The price for electricity from the public grid is set to $\hat{c}^{g} = 0.30€/kWh$ (Schwencke and Bantle, 2021), the feed-in tariff is set to $\hat{r}^{f} = 0.094€/kWh$, which corresponds to German feed-in regulation in 2020. The price for community electricity is set to the mid-value between $\hat{c}^{g}$ and $\hat{r}^{f}$ which is $\hat{c}^{c} = 0,197€/kWh$. The community feed-in revenue is set to $\hat{r}^{c} = 0,152€/kWh$ as a compromise between all possible values that profits from the German tax regulation for local energy sharing (German Federal Ministry of Finance, 2019). Emissions for grid electricity are set to $\hat{e}^{g} = 0.401 kgCO_2/kWh$ (Icha and Kuhs, 2019). External heat is supplied through a natural gas distribution grid. The price for external heat is set to $\hat{c}^{th} = 0.1€/kWh$, which is within range of European gas prices in early 2021 (Eurostat, 2021), emissions for natural gas are set to $\hat{e}^{th} = 0.215 kgCO_2/kWh$ (Giegrich et al., 2015). Additional costs that might arise if a municipal utility decides to implement a CEC are not considered. Such costs could, for instance, include the installation of smart meters or intelligent communication gateways. We consider the community development over a time span of 10 years from 2020 to 2030.



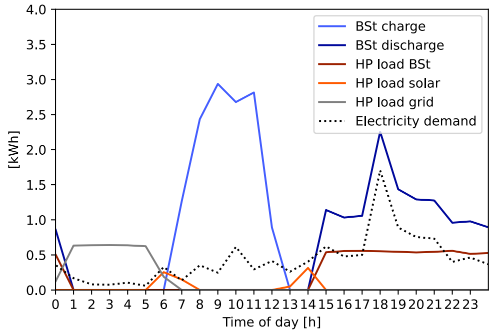
(a) Community load in the CEC.



(b) Household 5: Heat load.



(c) Household 5: Electricity loads and generation for PV, PVT, grid and feed-in.



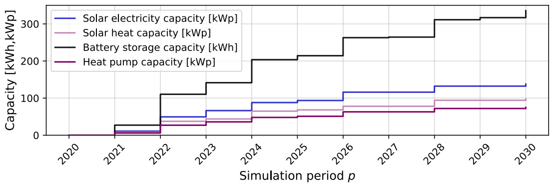
(d) Household 5: Electricity loads for BSS and HP.

Figure 7.4.: Exemplary results of the simulation of a single day in February 2025. The figures show the community electricity generation and loads and the energy generation and load of an exemplary household in the heterogeneous preference scenario with CEC regulation.

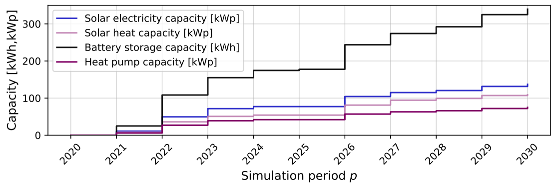
7.4.2 Results

In each period, the energy consumption of all 30 households and the community electricity consumption are simulated in an hourly resolution based on the installed appliances. To give an impression, Figure 7.4 shows the electricity loads and generation within the community and the electricity and heat load for an exemplary household in the heterogeneous preference scenario with CEC regulation. As the household has invested in PV generation capacity, it does not require any electricity from the community but instead uses the battery and HP to cover most of its energy demand. It also feeds electricity to the community and the grid.

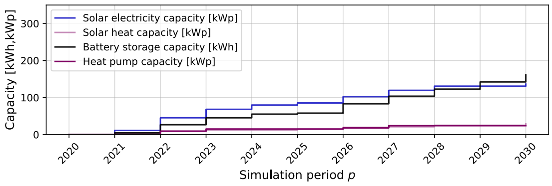
In the first year of the simulation (2020), households in all scenarios start with-



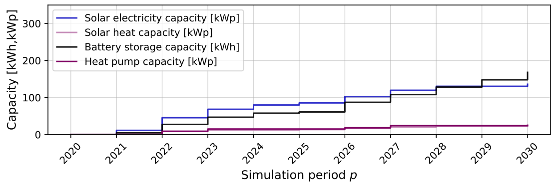
(a) Strong sustainability preferences with CEC.



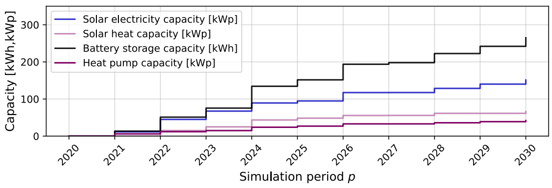
(b) Strong sustainability preferences with RM.



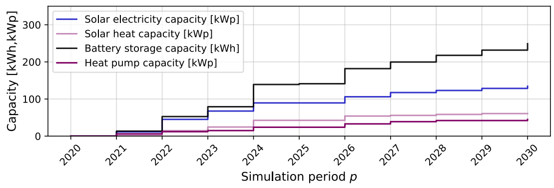
(c) Weak sustainability preferences with CEC.



(d) Weak sustainability preferences with RM.



(e) Heterogeneous preferences with CEC.

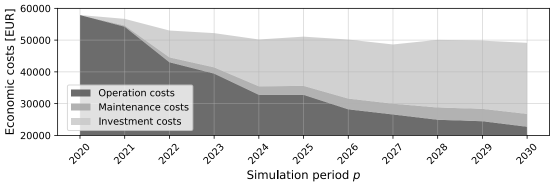


(f) Heterogeneous preferences with RM.

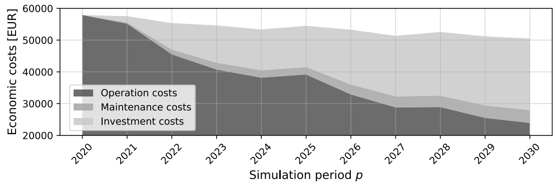
Figure 7.5.: Community infrastructure development of CEC and residential microgrid (RM) in the different scenarios.

out any of the considered residential energy technologies installed. All costs are operational costs from buying electricity from the grid and natural gas to cover the thermal heat demand. In the starting period, the total annual costs within the community amount to around 57,900€. Likewise, the total annual community emissions of 92,400 kg CO_2 originate from energy consumption and are not attributed to the manufacturing of appliances. A comparison of the community infrastructure development is presented in Figure 7.5. Figure 7.6 shows the cost development and Figure 7.7 shows the emission development for all scenarios. Before describing the results in detail, we highlight the most important findings:

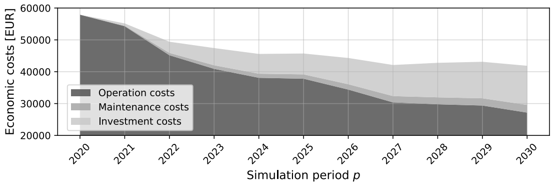
- CEC regulation has a positive influence on community cost and emission reduction in all analyzed scenarios.
- CEC regulation shows the largest impact on community costs and emissions when households have heterogeneous economic and ecologic preferences. Therefore, heterogeneous neighborhoods should be targeted by specific regulation on CECs, for instance, by targeting urban areas with more heterogeneous



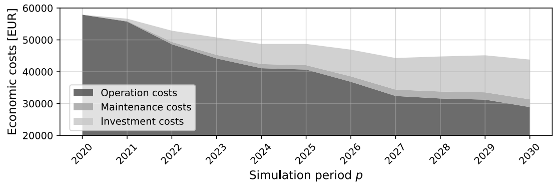
(a) Strong sustainability preferences with CEC.



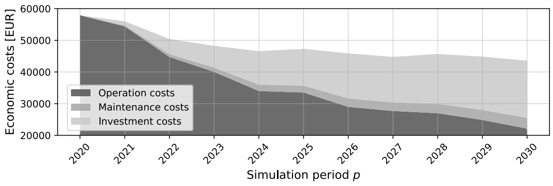
(b) Strong sustainability preferences with RM.



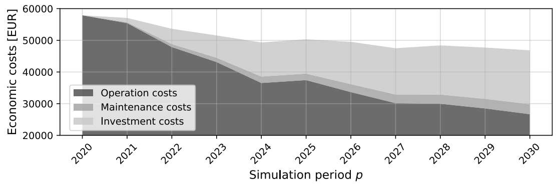
(c) Weak sustainability preferences with CEC.



(d) Weak sustainability preferences with RM.



(e) Heterogeneous preferences with CEC.



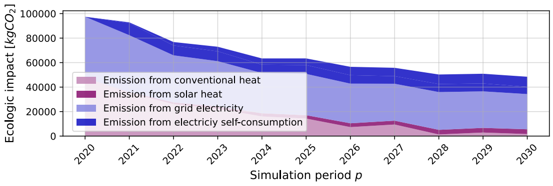
(f) Heterogeneous preferences with RM.

Figure 7.6.: Community cost development of CEC and residential microgrid (RM) in the different scenarios.

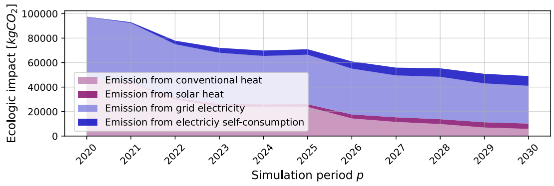
population.

- Decision inertia leads to a slower reduction of community costs and emissions. Due to its impact on household investment decisions, decision inertia should be considered by policymakers in the context of private energy infrastructure development and specifically addressed through policy instruments such as temporally decreasing subsidies.

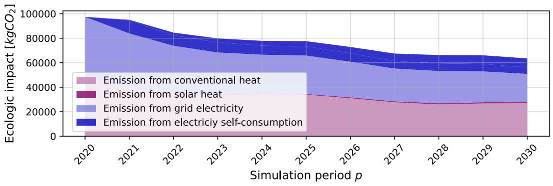
In the strong sustainability preference scenario, the gap between CEC and residential microgrid is the smallest over all three preference scenarios and originates mainly from a slightly higher self-consumption in the CEC. In both scenarios, BSSs are installed from 2022 onwards to more than two-thirds of its maximum capacity. Households invest in HPs, leading to low emissions caused by the centralized gas system. The local emissions, both in the CEC and the residential microgrid scenario are reduced by around 50% in 2030 with an additional small benefit of 584kg CO_2 through the implementation of a CEC. With a 15.12% cost reduction in the CEC scenario compared to only 12.78% cost reduction in the residential microgrid



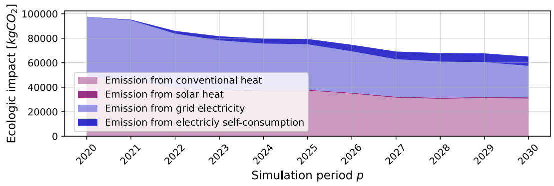
(a) Strong sustainability preferences with CEC.



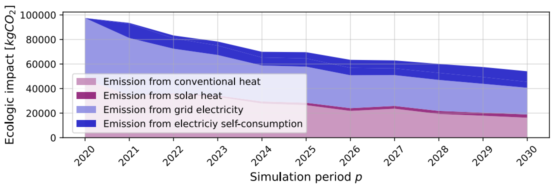
(b) Strong sustainability preferences with RM.



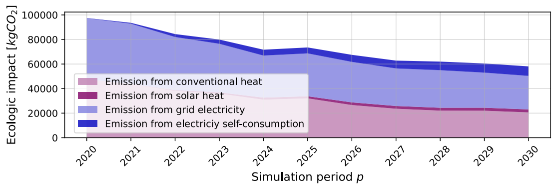
(c) Weak sustainability preferences with CEC.



(d) Weak sustainability preferences with RM.



(e) Heterogeneous preferences with CEC.



(f) Heterogeneous preferences with RM.

Figure 7.7.: Community emission development of CEC and residential microgrid (RM) in the different scenarios.

scenario, the gap is slightly larger when looking at the community costs. The difference translates to 45€ of additional savings per household and year. However, these savings are caused by subsidies which in this case do not lead to significantly increasing ecological sustainability.

In the scenario with weak sustainability preferences, where households focus more on financial benefits, the installed BSS capacity is less than half of the capacity from the previous strong sustainability scenario. PVT investments also decrease, while the overall solar PV electricity capacity is similar to the first scenario. This indicates a larger tendency to use PV systems instead of PVT and to utilize the slightly higher electrical efficiency to increase feed-in revenues. In the CEC scenario, the overall local emissions are reduced by 34.82% in 2030 compared to 2020 and by 33.27% in the residential microgrid scenario. The largest overall cost reduction is achieved in the CEC scenario, with a total annual reduction of 27.70% by 2030, compared to a 24.34% reduction in the residential microgrid scenario in 2030.

Sustainability preferences:		**Strong**	**Weak**	**Heterogeneous**
With CEC:	**Costs 2030**	49,147€	**41,865€**	43,572€
	Emissions 2030	**48.5 tCO_2**	63.5 tCO_2	54.1 tCO_2
With RM:	**Costs 2030**	50,499€	43,811€	46,844€
	Emissions 2030	49.0 tCO_2	65.0 tCO_2	58.1 tCO_2
		Costs 2020: 57,902€		Emissions 2020: 97.5 tCO_2

Table 7.4.: Results of the case study scenarios with a CEC implementation and a residential microgrid (RM).

This translates to 65€ less energy costs in the CEC scenario per household and year.

The largest differences between CEC and residential microgrid occur in the scenarios with heterogeneous preferences. The community emissions are reduced by 40.41% in the residential microgrid scenario and by 44.50% in the CEC scenario, which is the equivalent of two additional households in comparison. Looking at the costs, a 24.75% reduction is achieved in the CEC scenario, compared to a 19.10% decrease in the residential microgrid scenario, which translates to 109€ less energy costs in the CEC scenario per household and year. One reason for the considerable benefit of CEC regulation for communities with heterogeneous preferences lies in the distribution of energy infrastructure among the households. In both heterogeneous scenarios, almost every household builds PV or PVT panels and most households also build a small BSS. Thereby, it is easier to flexibly share renewable energy within the community than, for example, in the weak sustainability scenario, where fewer households build BSSs. Compared to the strong sustainability preference scenario, where BSSs are also built by almost every household, the overall BSS capacity is smaller in the heterogeneous preferences scenario which leads to lower costs. Thereby, households profit more from flexible energy supply and demand within the CEC without paying for it excessively.

An overview of the results in all scenarios is presented in Table 7.4. Overall, a notable reduction of community costs and emissions is achieved in all scenarios through the investment in renewable residential energy technologies. The implementation of CECs positively affects the community costs and leads to local emission reductions that are largest in the heterogeneous preference scenario.

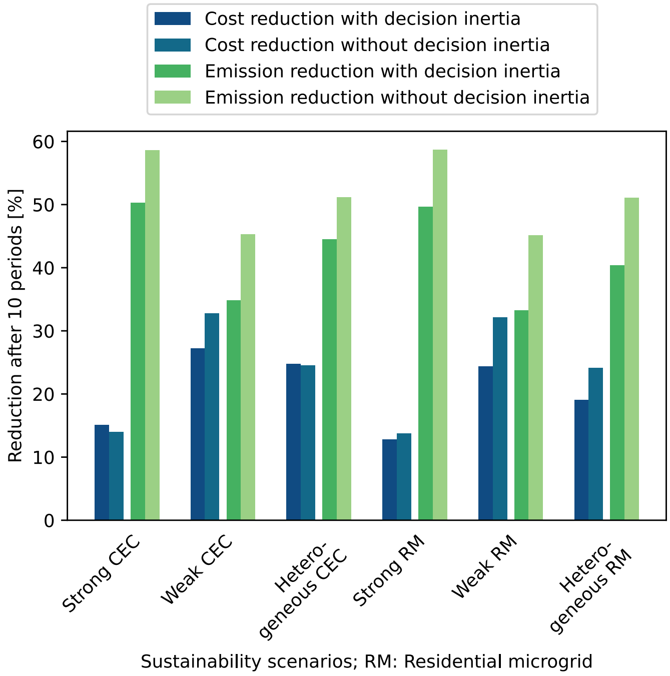


Figure 7.8.: Comparison of community cost and emission reduction after 10 periods with and without decision inertia.

To evaluate the effects of the decision inertia factor proposed in this chapter, we conduct another simulation without an inertia factor. A comparison of the results in Figure 7.8 shows that the decision inertia parameter has a strong influence on the overall results. Without a decision inertia factor, household investment decisions for HP, PV and PVT are made in the first year, the decision to add BSSs is made within the first five years. Compared to the original scenarios with decision inertia, these scenarios result in a greater and faster overall emission reduction. The cost reduction is larger especially in the weak sustainability and heterogeneous preference scenarios with residential microgrid. This suggests that the communities do not realize their entire cost and emission reduction potential in the scenarios with decision inertia due to delayed decision making. If incentives can be created for households to make investment decisions for renewable energy technologies earlier, this could reduce the cumulative household energy costs and carbon emissions, which is especially important in the efforts to limit global warming.

7.5 Discussion and Policy Implications

As demonstrated in the case study, implementing CEC regulation positively affects community costs and emissions. However, these effects need to be balanced against system costs for installing additional hard- and software. When the potential benefits for municipal utilities are not large enough, policymakers need to consider whether additional advantages of CECs justify further regulatory support. Our model shows that the implementation of CECs enables individuals to lower their household carbon footprint and to thereby contribute to the decarbonization of the energy sector.

The preference selection process and the model of investment delay caused by inertia allow for a more realistic assumption on household behavior than pure profitability considerations. According to the German federal environmental agency, an emission reduction of 40.7% between 2020 and 2030 is necessary to reach the emission reduction target set in the German climate protection law (Günther and Gniffke, 2021). Our simulation results for a case study with 30 households show that especially in a community with heterogeneous preferences, CEC regulation can help to achieve these targets. This leads to a recommendation for policymakers and managers in municipal utilities to promote the implementation of CECs in targeted communities. Furthermore, the analysis shows that incentives for individuals with an economic preference setting should be improved to meet the federal emission targets. Additionally, we find that decision inertia might delay the benefits for years. Therefore, policymakers should consider setting high incentives at the beginning that are lowered year by year. This could additionally incentivize private households to overcome decision inertia. While this chapter proposes one possible method of modeling the delay in investment decision-making, further research must focus on evaluating and comparing different decision inertia components. Such research could be further enhanced by going beyond the modeling perspective towards an evaluation of actual investment behavior for renewable energy technologies in the field using the framework proposed in (Staudt et al., 2019).

As the proposed model is applied within the German energy system, the numerical results might be different for other countries and depend on the local consumption patterns and regulation, especially regarding feed-in and network charges. Advancements in technology efficiency or the possibility of disruptive innovations in energy infrastructure are not considered in the simulation. While the per-year electricity consumption of the 30 households is within range of the German average and the average household consumption patterns in the data set are similar to the German standard load profile (Tjaden et al., 2015), the results might be different for other communities. In the face of rising energy prices, especially for natural gas, we expect that the integration of renewable energy systems on a household level and in communities will become even more important. We expect that the emission reduction effects described in this chapter can be achieved in a shorter time, as households might choose to install renewable energy generation and storage applications earlier if conventional energy becomes more expensive. The impact of the neighborhood size on the community infrastructure and the determination of an optimal CEC size is beyond the scope of this chapter, but presents a relevant path for further research. Besides the application on small communities, the methodology presented in this chapter can be scaled to the context of entire cities or even states. In addition, to adapt this chapter to the context of other countries, different energy scenarios, such as those proposed in the Future Energy Scenarios report (National Grid ESO, 2021), can be included.

7.6 Conclusion

In this chapter, we evaluate the impact of Citizen Energy Community (CEC) regulation and individual household preferences on private investment in renewable energy technologies within a community over a multi-year horizon. Individual economic and ecologic preferences shape a community's infrastructure and have an impact on possible community cost and emission reductions. According to our results, the implementation of CECs has a positive influence on community costs and emissions regardless of the households' preference structure. Compared to 2020, the household investments lead to a cost reduction of up to 28% and an emission reduction of up to 50%. However, a community with heterogeneous economic and ecologic preferences benefits most from a CEC implementation. Here, the cost reduction is 30% higher and the emission reduction is 10% higher in the CEC scenario than in the scenario with a residential microgrid. This holds important insights for regulators, as such communities should be specifically targeted with corresponding regulation.

Furthermore, delayed investments in utility-increasing alternatives caused by household decision inertia can considerably slow down the energy transformation process and lead to a smaller reduction of community costs and emissions. This also holds important insights for regulators who need to tailor subsidy schemes that counteract this decision inertia. By showing the potential for investments in individual energy infrastructure, we aim to contribute to a successful energy transition and provide new perspectives on the potential of CECs for policymakers worldwide. For the real-time operation of these CECs with residential energy technologies, efficient operation strategies are necessary to promote the integration of the heat and electricity sector through sector coupling. Such operation strategies must be able to integrate volatile renewable generation and uncertainty regarding individual consumption patterns. These challenges are addressed in Part IV.

Part IV.

Operation Strategies for Sector Coupling

INTRODUCTION TO PART IV

Once residential energy technologies are deployed in a CEC, they should be operated optimally considering the needs of the corresponding stakeholders, i.e., the grid operator or the citizens in the community. Operation strategies for sector coupling technologies in CECs can help to mitigate the effects of volatile renewable generation and uncertain demand (Hansen et al., 2019; Liu et al., 2018) and thereby contribute to a successful decarbonization of CECs.

In Part IV of this thesis, two use cases for sector coupling applications between the heat and electricity sector are presented. The first use case considers the operation of a coupled heat, electricity and cooling system (Chapter 8). In the second use case, an operation strategy for an HP in a DHN with TSS is developed, using a 24 hours rolling horizon online optimization with a heat load forecast (Chapter 9). While the evaluated case studies use data from a research facility and a city in northern Germany, the presented concepts can also be applied in a CEC.

CHAPTER 8

COMBINING PVT GENERATION AND AIR CONDITIONING: A COST ANALYSIS OF SURPLUS HEAT UTILIZATION

The average global temperature in Europe will continue to rise over the next years and extreme weather phenomena such as heat waves are more likely to occur. This will likely create a higher demand for cooling (Larsen et al., 2020; Day et al., 2009).

In this chapter, a cooling system driven by an absorption chiller that uses the heat surplus from PVT panels is compared to a conventional cooling system with PV supply and a base scenario without renewable generation. Hot water from the PVT panels and cold water from the absorption chiller is distributed among participating households via a district heating and cooling network. For the case study on the National Renewable Energy Laboratory in Golden, Colorado, the proposed system can reduce energy costs by 73% compared to a PV -based system.

This chapter comprises the published article: Golla, Armin; Staudt, Philipp; Weinhardt, Christof (2019): *Combining PVT Generation and Air Conditioning: A Cost Analysis of Surplus Heat Utilization.* In: International Conference on Smart Energy Systems and Technologies 2, p. 1–6.

8.1 Introduction

To limit the effects of global climate change, policies are implemented to develop a more sustainable energy system and reach the objective of keeping global warming below 2°C (Council of the European Union, 2005). However, with nonetheless rising temperature, the cooling demand in many European countries will increase (Larsen et al., 2020). With the ongoing trend towards renewable energy generation and the goal of a 100% renewable energy system in 2050, solar generation may play a major role in the future and account for approximately 79% of the worldwide energy generation capacity (Bogdanov et al., 2019). Thus, the utilization of solar energy might become one of the major tasks in future energy systems. With this chapter, we contribute to a more efficient approach in the area of cooling demand in buildings. The following paragraphs introduce the technicalities of PVT technology, different cooling systems, explain the term surplus heat and address the general assumptions of the case study.

a) PVT: PVT systems combine photovoltaic and solar thermal components to produce both electricity and heat at the same time in one integrated system (Chow, 2010). Absorption chillers take heat to produce cold water that can be used for air conditioning. Utilizing the surplus heat of a PVT panel to run the absorption chiller could lead to an increase in the overall efficiency of a household energy system. Moreover, heat surplus from a PVT panel is available particularly in periods of high solar radiation, when cooling demand is high and heat demand is low. This creates useful synergies.

b) Air conditioner (AC): ACs used in public and private buildings are the main technology to provide cooling and the number of installed devices is rising every year(JRAIA, 2019). This counteracts the objective of increased energy efficiency and a reduction in energy use. Due to the high energy consumption of ACs, we are looking for a more efficient method of cooling homes. We evaluate the use of an AC supplied by an absorption chiller and compare it to conventional compression cooling ACs. According to literature, the cooling COP of a compression cooling AC is within the range of 2-5 (Ji et al., 2003; Fahlén et al., 2012). However, fixed-speed centrifugal chillers with a cooling COP of more than 6 and variable-speed centrifugal chillers driven by an inverter that reaches a cooling COP of almost 22 in part-time load are evaluated in (Ueda et al., 2009). Fahlén argues that for a cooling COP greater than 6, compression cooling ACs can be more efficient than absorption chilled ACs from an exergy perspective (Fahlén et al., 2012). Since the proposed model utilizes surplus heat, the absorption-cooled system can nonetheless work both cost- and emission-effective.

c) Surplus heat: The thermal energy supplied by a PVT system is used to cover the heat demand of a system or building. However, the generated heat does not always fit the demand. In times of low heat production and high demand, heat has to be bought from an external supply, e.g., a gas generation plant or a DHN. During low heat demand periods, the heat supply can exceed the demand. Energy that would have been supplied by the PVT cannot be used, thus lowering the potential system efficiency. In the context of this chapter, surplus heat is the thermal energy that would otherwise be released to the environment (Chiu et al., 2016). In a study from 2008 by the U.S. Department of Energy, it is estimated that 20% to 50% of the U.S. energy generation was surplus or waste heat (U.S. Department of Energy, 2008). By connecting the PVT to an absorption chiller, surplus heat can be used to satisfy the demand for cooling.

d) Case study: We conduct a simulative case study that 1) evaluates the use of conventional ACs for a group of households with installed PV generators and 2) analyses the costs for the same group of households with a central, common absorption chiller. The absorption chiller uses the heat surplus from PVT panels. The hot water from the PVT panels and the cold water from the absorption chiller is distributed via a district heating and cooling network. In the third step, we compare the operating costs and benefits of both scenarios to answer the following research question:

RQ 7: What are the financial benefits of a sector-coupled PVT installation in combination with absorption cooling compared to conventional compression cooling with a PV installation?

8.2 Related Work

In this section, the related work on PVT and absorption chillers is presented. An overview on district cooling can be found in Section 2.1 of Chapter 2.

8.2.1 Photovoltaic/Thermal Power

Aside from wind and solar PV or solar thermal power plants, hybrid PVTs are becoming more popular in residential areas, as the overall efficiency of solar power increases. A detailed overview of hybrid PV and thermal solar technology can be found in (Chow, 2010). A classification and evaluation of PVT systems is given in (Joshi and Dhoble, 2018). The authors find that for concentrated and non-concentrated PVT systems, the electrical efficiency is between 8-12% and the thermal efficiency is between 40-70%. The high thermal efficiency is a major argument for the use of PVT systems. In comparison to other solar energy systems, PVT has the advantage of a higher overall efficiency. However, the electrical efficiency of a PVT plant is around 30% lower than a state of the art PV system (Joshi and Dhoble, 2018; Gul et al., 2016). This also illustrates that PVT is especially efficient when the heat utilization is high. Another review on the performance of PVT technology and applications is provided in (Sultan and Ervina Efzan, 2018). In (Othman et al., 2016), a PVT system with water and air heating is proposed, that reaches an electrical efficiency of 17% and a thermal efficiency of 76%. Zaite et al. (2020) assess the potential for night radiative cooling of buildings with a PVT collector. On the example of two Marrocanian cities, their results indicate that PVT helps to reduce energy required for air conditioning and heating.

8.2.2 Absorption Chiller

Absorption chillers can use heat to cool a transportation medium, e.g., water. The cooled fluid can be used in AC systems to satisfy the cooling demand of a household. Florides et al. (2002) investigate a modeling and simulation approach of an absorption solar cooling system. A solar absorption cooling and heating system for building applications is evaluated in (Mateus and Oliveira, 2009). The use of absorption cooling in a district heating driven AC in comparison to conventional compression cooling is investigated in (Fahlén et al., 2012). The authors evaluate potential cost and carbon reductions due to an expansion of such ACs in the city of Göteborg. An example for the use of solar-powered lithium bromide-water absorption chillers is given in (Ali et al., 2008), including a field study in the German city of Oberhausen.

8.3 Methodology

We propose a cooling system that uses surplus heat generated by a PVT to satisfy the cooling demand of households within a district cooling network. The cold water is produced by an absorption chiller that is run with thermal energy provided either

Variable	**Description**	**Unit**
c_el	Electricity grid tariff	$€/W$
c_h	DHN tariff	$€/W$
d_c	Household cooling demand	W
d_{el}	Household electricity demand	W
d_h	Household heating demand	W
P_{DHN}	Power supplied by or fed into the DHN	W
P_{Grid}	Power supplied by or fed into the grid	W
P_{sol}	Solar power	W
r_{PV}	Revenue of the PV system	€
r_{PVT}	Revenue of the PVT system	€
$\eta_{PVT_{el}}$	Electric efficiency of the PVT	%
η_{PVT_h}	Thermal efficiency of the PVT	%

Table 8.1.: Nomenclature.

by the PVT or an external system.

To operate a PVT system on a cost-efficient basis, the capacity utilization of the heat generated by the PVT should be as high as possible. With the additional heat utilization through the absorption chilled AC system, the general energy efficiency can be increased. The additional electric power that is available can be used to satisfy the electricity demand of the household or be fed into the grid. Heat, cooling and electricity demand that is not covered by the PVT need to be satisfied from external sources. Thus, a PVT system is most useful for a household or neighborhood with high heating and cooling demand that occur during times when the PVT system is working. For households that have primarily electricity demand, a PV system remains the best option.

For our model, we assume that all remaining electricity demand is covered by the grid while the heating and cooling demand is supplied by a DHN. Surplus heat from the PVT system that cannot be used for heating or cooling is fed back into the DHN. A schematic overview of the model is given in Figure 8.1. When the PVT system is working, it generates both heat and electricity. The electricity is first used to satisfy the in-house demand and a possible surplus is then fed into the grid. Heat is at first used to satisfy the demand within the building. If the heat supply is higher than the demand, the heat is converted in the absorption chiller to satisfy the cooling demand. Surplus heat is fed into a connected DHN. The DHN can also supply heat demand

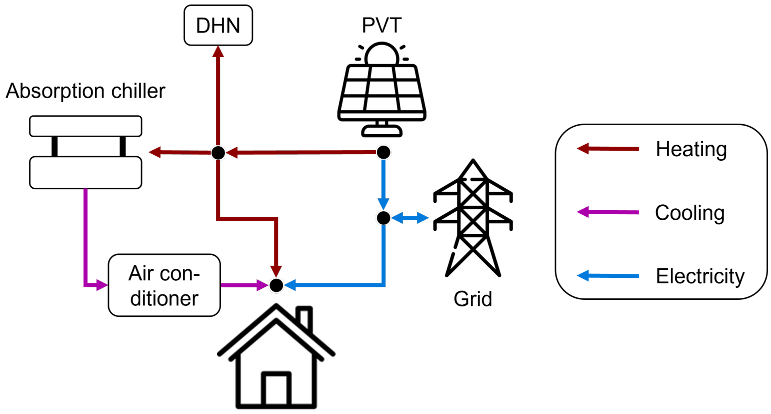


Figure 8.1.: Model structure of a household with PVT generation.

beyond the PVT generation. The energy balance for the electricity generation of the PVT at a specific point in time is described in

$$d_{el} = P_{sol} \cdot \eta_{PVT_{el}} + P_{Grid} \tag{8.1}$$

d_{el} is the household electricity demand in Watt $[W]$, P_{sol} is the solar power, $\eta_{PVT_{el}}$ is the electric efficiency of the PVT and P_{Grid} is the power supplied by or fed into the grid. The energy balance for the heat generation of the PVT at a specific point in time is described in

$$d_h + d_c = P_{sol} \cdot \eta_{PVT_h} + P_{DHN} \tag{8.2}$$

d_h and d_c are the household heating and cooling demands in Watt $[W]$, η_{PVT_h} is the thermal efficiency of the PVT and P_{DHN} is the heat power supplied from or fed into the DHN.

The use of a PVT system may lead to a cost reduction or even an increase in revenue from a prosumer or producer point of view. To evaluate this, Equation (8.1) and (8.2) must be extended to cost functions. For the proposed model, those consist of a feed-in tariff for heat and electricity as well as purchasing tariffs for energy supplied by the grid or the DHN. To compare PV and PVT generation, the monetary results of both systems need to be measured. With a net metering approach, as widely used in the U.S. (Darghouth et al., 2011), the feed-in tariff equals the consumption tariff. For a system with PV generation and an AC with compression cooling and heat supplied by a DHN, the revenue is calculated by

$$r_{PV} = (P_{sol} \cdot \eta_{PV} - (d_c + d_{el}))c_{el} + d_h \cdot c_h \tag{8.3}$$

The revenue of the PV system is given by r_{PV}, η_{PV} is the PV efficiency and c_{el} is the grid electricity tariff. The result is $r_{PV} \geq 0$ when the PV generation is higher or equal to the overall energy demand and $r_{PV} < 0$ when the energy demand of the building is higher than the PV generation.
For a system with PVT generation and an AC with absorption cooling, the revenue is calculated by

$$\begin{aligned} r_{PVT} =& (P_{sol} \cdot \eta_{PVT_h} - (d_h + d_c))c_h \\ &+ (P_{sol} \cdot \eta_{PVT_{el}} - d_{el})c_{el} \end{aligned} \tag{8.4}$$

r_{PVT} is the revenue of the PVT system, c_h is the DHN tariff and c_{el} is the grid electricity tariff.

Note that investment and maintenance costs play a huge role in the decision whether to implement a PVT system or not. According to (Matuska, 2014) the investment costs for PV systems are at 120 €$/m^2$ for polycrystalline models and 350 €$/m^2$ for high-end spectrally selective solar thermal collectors. Investment costs for PVT systems are substantially higher and within the range of 290-500 €$/m^2$ for the selective and nonselective type. Hybrid PVT liquid collectors require even higher investments of 450-950 €$/m^2$. In this chapter, we abstract from these costs and purely concentrate on the operational system costs.

8.4 Case Study

To give a motivating example for the utilization of surplus PVT heat in absorption chilled air conditioners, a case study is performed. The PVT system is compared to a base case without renewable generation and a system using PV generation and conventional compression cooling.

8.4.1 Input Data

The study presented in this section uses generation and consumption data from the research and support facility of the U.S. National Renewable Energy Laboratory (NREL) (U.S. Department of Energy, 2011). The facility is located in Golden, Colorado. With an area of 21,000 square meters, the research and support facility is a large building complex with around 720kW of installed PV generation capacity (U.S Department of Energy, 2012). The dataset provides cooling demand, heat demand, electricity demand and PV generation data in an hourly resolution for the year 2011.

For this chapter, we assume a PVT system with 12% electrical efficiency and 70% thermal efficiency. This is within the range of PVT systems as evaluated in Section 8.3. The electrical efficiency of recent commercially available PV technology is in the range of 13.8%-20.4% (Gul et al., 2016). Since the PVs on the research and support facility were built around 2008, their efficiency must be lower. However, to compare recent PV and PVT technology, we assume an electrical efficiency of 17% for the PV. For the absorption chiller, a lithium-bromide absorption cooler with a cooling COP of 0.8 is assumed as proposed in (Ali et al., 2008), which is slightly higher than in other publications (Fahlén et al., 2012). We assume that a cooling COP of 0.8 is within the technological capabilities of an absorption chiller. The compared compression cooling AC has a cooling COP of 7 which is in line with similar studies (Fahlén et al., 2012; Ueda et al., 2009).

8.4.2 Analysis

The distribution of heating and cooling demand hours as well as the PV generation over the year within the NREL is displayed in Figure 8.2. The peak hours for cooling are between 13:00 and 16:00. This does match the generation times of the PVT, which is mostly providing electricity between 8:00 and 17:00. Between 9:00 and 16:00, the PV is generating electricity in roughly 91% of the year. Contrary to that, heat demand mostly occurs during night hours and in the early morning, when cooling demand is low.

The cooling demand is small in comparison to heat and electricity demand. While the average heat demand is 87kW for the research and support facility in 2011 and

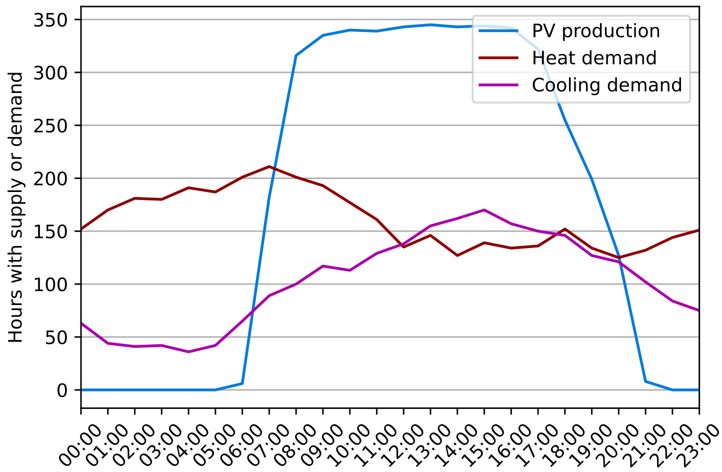


Figure 8.2.: Heat demand, cooling demand and PV generation hours.

Hours with cooling demand: 2468 h	**PV**	**PVT**
Partly covered cooling demand	1018 h	1735 h
Completely covered cooling demand	988 h	1617 h

Table 8.2.: Cooling supply comparison of PV and PVT.

the average electricity demand is 179 kW, the average cooling demand is only 3 kW. More than 50% of the hours when cooling is required have a demand of 10 kW or less and only 5% have a demand of 20 kW or more. Figure 8.3 provides demand duration curves for electricity, cooling and heat demand.

Of the 2468 hours with cooling demand within the sample, 1018 can at least partially be supplied by the PV panel. With a PVT panel, the number of hours that can at least partially be supplied is increased by around 70%. The number of hours where the cooling demand is completely satisfied by the PVT is more than 60% higher than with PV. A comparison of the systems is given in Table 8.2.

As proposed in Section 8.3, we assume a net metering approach where the feed-in tariff equals the purchase price per unit for both the grid and the DHN. The price for heat and electricity is oriented along German energy market prices for customers between 2017 and 2019 (BDEW, 2019; Wolf and Schmitz, 2017). We assume an electricity price of 0.30 € per kWh and a heat price of 0.07 € per kWh.

A revenue comparison of PV, PVT and non-renewable generation is provided in

	No renewables	PV	PVT
Energy cost per year	525 $k€$	249 $k€$	65 $k€$
Electricity demand	1,565 MWh	1,565 MWh	1,565 MWh
Electricity generation	-	919 MWh	648 MWh
Heat and cooling demand	787 MWh	787 MWh	787 MWh
Heat generation	-	-	3,785 MWh

Table 8.3.: Cost Comparison of PV and PVT.

Table 8.3. In the non-renewable generation scenario, all energy is purchased from the grid. To perform a long-term comparison of all three systems, a deeper evaluation of the investment and maintenance costs of each system would be required. The work within this chapter focuses on the operational costs of the three scenarios.

As displayed in Table 8.3, the use of PVT generation is more efficient from a cost operating perspective in this case study. The reason for that lies in the high amount of heat generation by the PVT. In the net metering approach, we assume that the surplus heat that is not used to cover the heat or cooling demand of the building is fed directly into the DHN. The revenue from that feed-in lowers the total energy costs. Over the whole year, the NREL research and support facility with a PVT system has the potential to generate almost as much energy as is used within the building. Thus, the system has the ability to run almost self-sufficient on a cost-term basis. The daily costs and feed-in

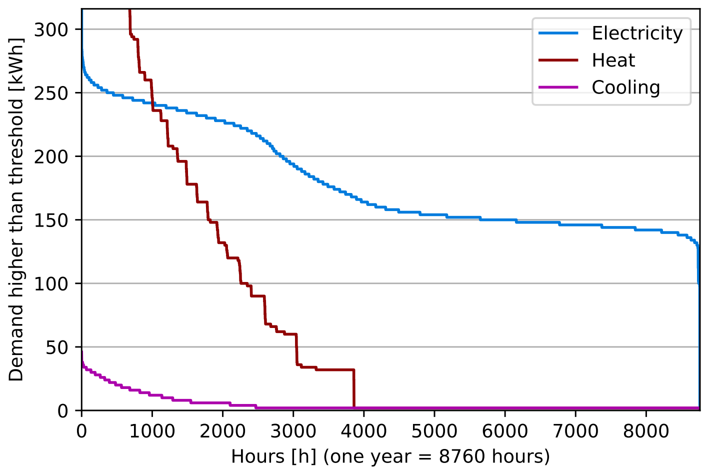


Figure 8.3.: Heat, cooling and electricity demand hours.

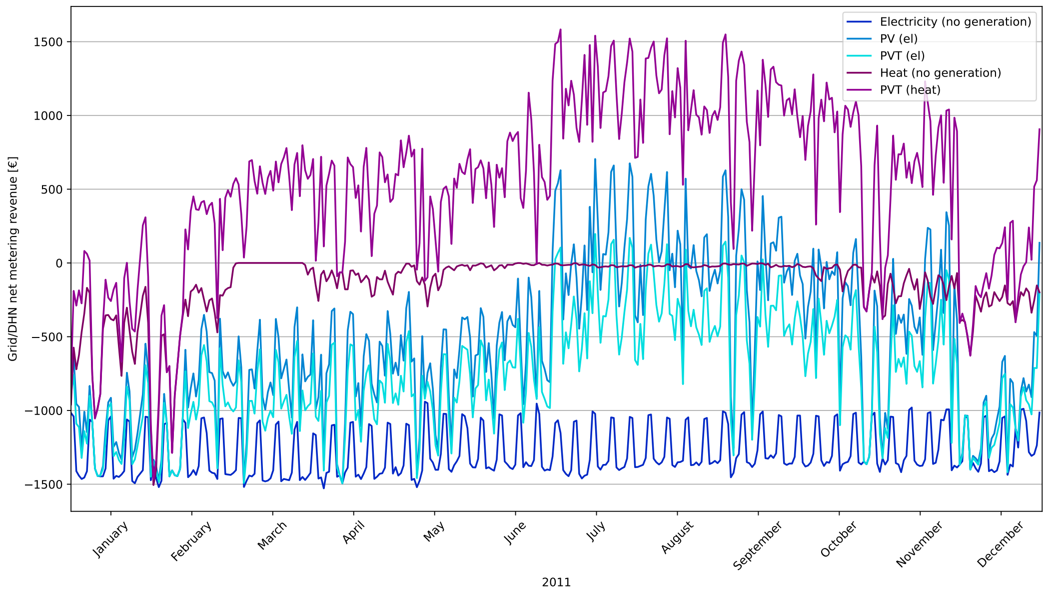


Figure 8.4.: Daily feed-in costs(-) and revenue(+) of PV, PVT and without renewable generation.

revenues of PV, PVT and no renewable energy generation during the whole year are displayed in Figure 8.4. The graph shows that the surplus heat which is responsible for the low energy costs is mainly produced during the summer months.

In summary, the combination of PVT and absorption chilled cooling ACs leads to an overall energy cost reduction and improves the satisfaction of cooling demand from renewable energies in this case study.

8.5 Conclusion

To address the challenges of climate change, new ideas are needed to improve the future energy system. Photovoltaic/thermal (PVT) generation has gained attention from the scientific community in recent years and provides an alternative to common photovoltaic (PV) generation. Absorption chillers can become more important in sector-coupled energy systems and contribute to improved utilization of surplus and waste heat. In this chapter, the surplus heat of a PVT system is used to operate an absorption chiller that satisfies the cooling demand of a building. To answer

Research Question 7, we find that for a group of buildings, the use of absorption chilled air conditioners (ACs) in combination with PVT leads to a cost reduction of 74% compared to a system with PV and conventional cooling. The utilization of heat generated by a PVT system can be improved through the connection of heat and cooling systems, lowering the amount of waste heat released into the environment. The findings of this chapter can contribute to an integrated multi-energy system framework that is optimized for more efficient resource allocation to increase the overall welfare and energy efficiency. We develop the calculations necessary for a comparison between PV and PVT generation and the use of absorption chilled cooling. The necessary circumstances for cost-efficient utilization of surplus heat for absorption cooling are determined. A study using data from the National Renewable Energy Laboratory (NREL) research and support facility shows that the combination of a PVT system and AC supplied by an absorption chiller can deliver more efficient results than a PV generation plant with compression cooling AC.

In future work, the investment costs for PV and PVT systems should be considered. The calculations are made on a very isolated basis and further effects like network restrictions or other forms of satisfying the cooling demand or using the surplus heat of the PVT system are not within the scope of this chapter. Beyond that, the proposed methodology should be applied to other case studies in different geographies. For future projects, this chapter can provide basic calculations and considerations for the operation and evaluation of greater district cooling networks within a city or neighborhood. This chapter provides a method that can help to improve the efficiency of sector-coupled energy systems. It contributes to the progress of a successful energy transition and the efforts to limit global climate change. For an efficient online operation, the model can be further enhanced to integrate uncertainty regarding future supply and demand. This, could for example, include the use of forecasts for electricity, heat and cooling load. Such an application of a heat load forecast for an online operation strategy is presented in Chapter 9.

CHAPTER 9

AN OPERATIONAL STRATEGY FOR DISTRICT HEATING NETWORKS: APPLICATION OF DATA-DRIVEN HEAT LOAD FORECASTS

In this chapter, a sector coupling control strategy for an HP and TSS in a DHN is proposed. The control strategy utilizes hourly heat load forecasts with a 24-hour rolling horizon. First, supervised forecasting techniques are investigated on three different heat load data sets. The application of a CNN on data from the DHN in Flensburg, Germany delivers the most promising outcome. Extending this example, an online control strategy for an HP and TSS is developed using the 24-hour heat load forecast from the CNN. The control strategy is demonstrated on two use cases using different objectives: Improving the utilization of offshore wind generation and reducing energy costs.

This chapter comprises the published article: Golla, Armin; Geis, Julian; Loy, Timon; Staudt, Philipp; Weinhardt, Christof (2020a): An operational strategy for district heating networks: application of data-driven heat load forecasts. In: Energy Inform 3 (S1), p. 1–11.

9.1 Introduction

Due to higher efficiency and the ability to integrate various generation technologies, DHNs are a promising approach to replace individual residential gas and oil heating systems (Lund et al., 2014). Through an efficient operation of generation technologies like HPs, CHP plants or boilers in a DHN, the required generation capacity can be reduced, thus lowering investment costs and capacity-related emissions (Urbanucci and Testi, 2018). In this chapter, we present an online operation strategy for a DHN with an HP and TSS that can be implemented with regards to various objective functions, e.g., with financial or environmental objectives.

The development of DHNs towards lower supply and return flow temperatures is subject to ongoing research. Buffa et al. (2019) introduced the 5^{th} generation of DHNs which incorporates low temperature heating and cooling systems. The authors argue that such systems can utilize renewable energy by using excess heat and enhance sector coupling through the use of hybrid substations. As described in (Lund et al., 2014), an increase in the share of renewable energy and in the overall energy efficiency of DHNs can be achieved through the extension of an integrated thermal network by inclusion of multiple thermal energy producers. To reach this goal, DHNs have to be integrated in smart energy systems (i.e., electric, gas and thermal grids). This can be enabled by the electrification of the heat supply with electric boilers, HPs and TSSs.

The analysis and forecast of heat consumption patterns are important for the general planning of DHNs (Idowu et al., 2016). Heat load forecasts enable the inclusion of volatile renewable energy generation such as solar and wind (Benonysson et al., 1995). By implementing demand-side balancing solutions based on heat forecasts, the share of renewable energy within a DHN can be increased (do Carmo and Christensen, 2016). The thermal energy storage in the DHN is a key component to enable a more efficient use of renewable energy in the system. In contrast to BSSs, TSSs do not typically experience cycle-induced degradation (Alva et al., 2018). For an overview on thermal energy storage systems, please refer to (Zhang et al., 2016).

9.1.1 Related Work

Accurate heat load forecasting has gained momentum within the scientific community over the past few years, with both statistical and machine learning driven methods. Dahl et al. (2017) use an autoregressive forecast model with predicted weather features. The authors introduce ensemble weather forecasts in the operation of district heating systems to create heat load forecasts with dynamic uncertainties. The model is then used to implement an operational strategy for heat exchanger stations. For the applied case study of three area substations, their findings show that systems with smaller capacities benefit most from the use of dynamic uncertainties. In contrast to this chapter, the authors do not consider a TSS in their control strategy, which adds an important component for the integration of intermittent renewable generation. Hietaharju et al. (2019) apply two models to forecast heat demand. The first model presents a dynamic approach that uses past heat demand and heat loss caused by the temperature difference between indoor and outdoor temperature. In the second model, an artificial neural network (ANN) uses the heat load in the previous period, the outdoor temperature, the hour of the day and a weekend dummy to produce a 48 hours forecast. The models are tested on data of the DHN in Jyväskylä, Finland, during the heating months of 2013. Both models achieve similar results on the forecast of the overall heat load for 4061 buildings, with slightly better performance of the dynamic implementation.

Johansson et al. (2017) test a feed-forward neural network (FFN) with one hidden layer against a model with randomized decision trees. Both forecast models are trained with historical heat load data and weather forecasts. The models are implemented as online, real-time predictors on the DHN in Rottne, Sweden. They are run once a day at 2 p.m., using all real-time data that is available until then, to predict the next 24 hours. The results on the evaluation from January to March 2016 indicate that on average the decision tree model slightly outperforms the ANN model.

There are more studies on the use of ANNs in the area of short-term heat load forecasting, which do not consider the city level but are rather developed for individual consumption profiles. For example, see (Ciulla et al., 2019) for short-term load forecasting of non-residential buildings, (Jovanović et al., 2015) for the forecast of heat load of a university campus, (Saloux and Candanedo, 2018) for heat load forecast of 52 residential houses and (Idowu et al., 2016) for the analysis of ten residential and commercial buildings.

9.1.2 Contributions and Organization

As presented in Section 9.1.1, some research has already been conducted on the topic of heat load forecasts. However, only few authors address the challenge of embedding heat load forecasts in an operational strategy. Aside from that, most studies either consider only one forecast model or only test it on the dataset of one case study application. Therefore, we propose an evaluation of multiple forecasting methods and use the best-suited method in our operation strategy. It is an important subject of future work to develop and compare heat demand forecasting methods, which are benchmarked and validated on a broad range of data sets to demonstrate the potential generalizability of the approach and avoid overfitting (vom Scheidt et al., 2020). Thus, we address the following research question in this chapter:

RQ 8: What is the performance of an online operation strategy for a district heating system with an HP and a TSS that uses a 24-hours rolling horizon heat load forecast compared to (i) a naive approach and (ii) benchmarked against the global optimum with respect to the integration of renewables and cost minimization?

9.2 Forecasting Heat Load

To effectively evaluate the effects on the operation of a DHN, this chapter investigates forecasts with different forms of ANNs. The ANNs are trained based on heat load and weather input data from three use cases. For the weather data, outdoor temperature at hourly resolution is considered. The heat load data follows certain patterns that allow for conclusions about consumer behavior. For instance, there is a higher level of load on working days than there is on non-working days and the daily load follows a characteristic pattern (Gao et al., 2018). In a large network with different types of customers, the daily pattern can be observed more clearly due to balancing effects (Fang, 2016).

9.2.1 Artificial Neural Network Forecasts

This chapter employs different ANN structures. The selected models have recently attracted attention in research on load forecasting as presented in Section 9.1.1. CNNs have the ability to process time series data and achieve good performances in studies on pattern recognition and forecasting in the context of electricity systems (vom Scheidt et al., 2020). Beyond that we use an implementation of an FFN for a heat load forecast. We also compare our results to recurrent neural network structures that are used to forecast heat load in other studies, namely gated recurrent units (GRUs) and long-short term memory (LSTM).

Hyperparameter	Tested values
Scaling	{ None, Z-Score, Min-Max Scaling }
Training algorithm	{ SGD, AdaGrad, RMSProp, Adam }
Activation function	{ Sigmoid, ReLU, tanh, linear (in the output layer) }
Hours of input data	$\{24 \times 3, 24 \times 5, 24 \times 7, 24 \times 9\}$
Learning rate	$\{lr_d \times 10^{-1}, lr_d, lr_d \times 10^1, lr_d \times 10^2\}$ with lr_d = default learning rate of the corresponding optimiser as implemented in the python keras api
Hidden layers	$\{1, 2, 3, 4\}$
Decay	$\{0, 0.0001, 0.001, 0.01\}$
Patience of early stopping	$\{10, 20, 30\}$
Test split	$\{0.25, 0.3, 0.35\}$
$L^2 - Regularisation$	$\lambda \in \{0, 0.001, 0.01, 0.1\}$
Dropout	$\{0.1, 0.2, 0.3\}$

Table 9.1.: Hyperparameters and corresponding values that are tested during the random search.

The size of the feature set determines the number of neurons in the input layer. We use a multiple output strategy to predict the next 24 hours, thus there are 24 neurons in the output layer.

The basic structures of the FFN, LSTM and GRU are evaluated by testing all combinations of the number of hidden neurons and hidden layers displayed in Table 9.1. The architecture of the CNN is evaluated by testing the combinations of one to four convolutional layers and pooling layers, with the convolutional layers containing 20, 40, 60 or 80 filters and four, eight and twelve kernels. An overview of the tested hyperparameters is given in Table 9.1. For the hyperparameter optimization, we use random search, which has shown to find better models and to require less computational time than manual or grid search (Bergstra and Bengio, 2012; Larochelle et al., 2007).

9.2.2 Forecast Comparison

To increase the validity of the forecasts, the methods are applied to three different datasets. All ANNs are tested on data of the Flensburg DHN. The two most promising structures, CNN and FFN are then further evaluated on data from the

Forecast Method	Naive Forecast	ARIMAX	FFN	CNN	LSTM	GRU_2
RMSE [MWh]	18.55	12.69	10.44	**10.43**	12.52	12.18
MAPE [%]	12.55	9.25	6.38	**6.34**	6.91	6.98

Table 9.2.: 24h forecast results for the Flensburg DHN.

U.S. National Renewable Energy Laboratory (NREL) and the Sønderborg DHN.[4]

Flensburg is a city in Northern Germany. Its DHN supplies 98% of the households with approximately 600 km of transport pipes. The obtained consumption data is aggregated over all district heating consumers for the years 2014 to 2016 in hourly resolution (Stadtwerke Flensburg GmbH, 2019). The network consists of 20% industrial, 24% trade, commerce and services and 56% household customers. The dataset of the NREL provides heat demand for the research and support facility in Golden, Colorado for 2011 in hourly resolution (U.S. Department of Energy, 2011). The facility is a large building complex with 21,000 square feet. The Sønderborg dataset from Denmark contains data from 32 industrial and residential buildings. Individual missing data points of the features or the heat demand are filled with linear interpolation. In the Flensburg dataset, data from 2014 and 2015 is used as the training set and 2016 as the test set. Table 9.2 gives an overview on the results of the ANN forecasts. To benchmark the results, a naive forecast that uses load data from the previous day as forecast and an ARIMAX model are used. The lowest mean absolute percentage errors (MAPEs) and root-mean-square errors (RMSEs) for the Flensburg DHN are achieved with the FFN and the CNN. Exemplary weekly performances of the ANN forecast algorithms are presented in Figure 9.1 for a week in the heating period. The CNN and the FFN achieve the best results with one hidden layer, whereas the LSTM and the GRU network achieve the best results for network structures with two and three hidden layers.

Table 9.3 shows the 24 hours forecast performances of the NREL research and support facility and the Sønderborg datasets. Again, the CNN and the FFN produce nearly the same results, for the NREL, the FFN performs slightly better. As both datasets contain periods with very small or zero heat demand, the MAPE is not

[4]The data for the Flensburg DHN can be obtained at (Stadtwerke Flensburg GmbH, 2019). The NREL data is available at (U.S. Department of Energy, 2011). For the Sønderborg DHN data, please refer to (Gianniou et al., 2018).

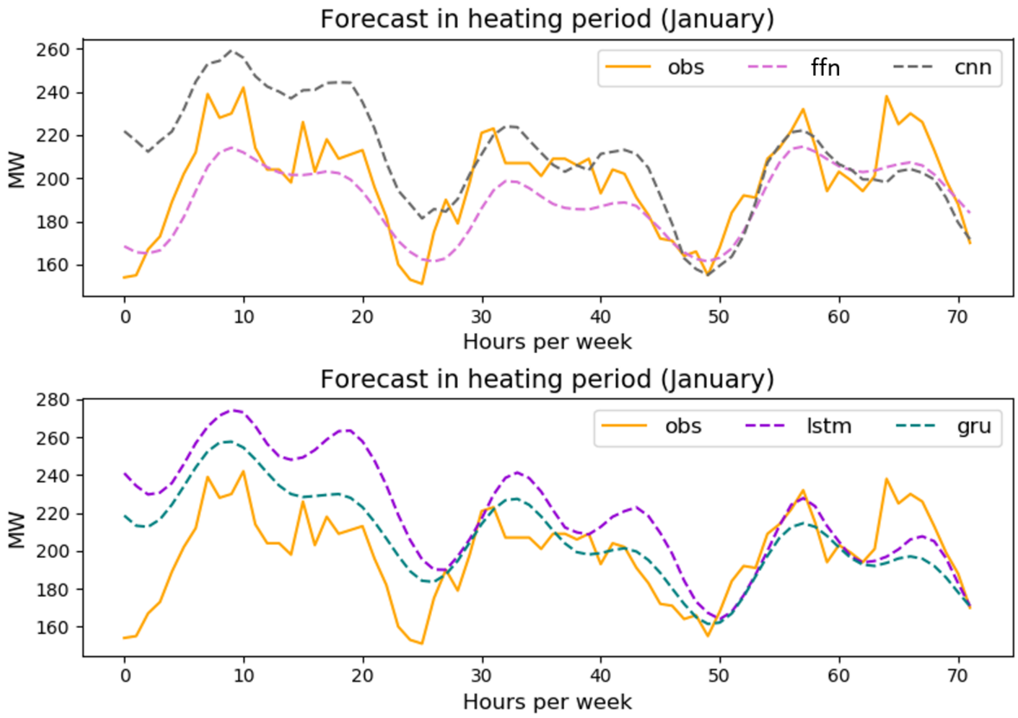


Figure 9.1.: ANN forecast in the heating period for the Flensburg DHN.

Forecast Method	NREL RMSE [MWh]	Sønderborg RMSE [MWh]
FFN	0.079	0.051
CNN	0.095	0.051

Table 9.3.: 24h forecast results for the NREL in Golden, Colorado and the Sønderborg DHN.

suited as a performance measure in this section.

9.3 A Control Strategy for District Heating Networks

As discussed in Section 9.1, the key for an increased share of renewable energy in the heat sector lies in the utilization of renewable electricity generation through sector coupling technologies. Integrating intermittent renewable electricity generation into the heat sector requires accurate forecasting and a corresponding heat system operation strategy. This way, heat generated from electricity in times of low heat demand and excess electricity supply can be stored and consumed when consump-

Variable	**Description**
d^{ht}	Heat demand
F	Utility function
$g^{el,w}$	Amount of electricity generation from offshore wind
l^{s}	Heat storage load
$l^{s,max}$	Maximum TSS charging or discharging load
l^{el}	Amount of electric load
l^{hp}	HP load
$l^{hp,max}$	Maximum load of the HP
p^{el}	Hourly electricity price
t	Current time step
T	Time horizon
s	Heat storage level
s^{max}	Maximum capacity of the TSS
Θ	Share of offshore wind
ϕ	Hourly storage efficiency

Table 9.4.: Nomenclature.

tion of both heat and electricity increases or the availability of renewable electricity generation decreases. This requires the development of operational strategies that exploit forecasting ability and deal with the uncertainty of forecasting errors. In this section, we propose a strategy for the operation of an HP and a connected TSS within a DHN. We use an online algorithm with a rolling horizon that is able to forecast the next 24 hours with the presented algorithms. Subsequently, the optimal operational decisions for these 24 hours are calculated based on the forecasted demand. The decisions for the present hour t are executed and the process is started again for $t + 1$ with an adjusted 24 hours forecast and a changed system state. In every time step, the control strategy is used to satisfy the given heat demand. The required heat is either supplied by an HP or from the TSS. The HP can also be used to charge the TSS. The objective of the control strategy can be adjusted according to individual preferences. We demonstrate the maximization of the integration of renewable energy generation and the minimization of generation costs as two possible objective functions in Section 9.3.1. All variables of the control strategy are explained in Table 9.4. The objective for the control strategy is to maximize (or minimize) the objective function F that is subject to optimization. The demand within the DHN has to be satisfied in any time step. The constraint for demand and supply balance is given by:

$$d_t^{ht} = l_t^s + l_t^{hp} \,\forall\, t \in T \tag{9.1}$$

The TSS level in each time step is determined by:

$$s_t = s_{t-1} \cdot \phi - l_t^s \,\forall\, t \in T \backslash \{0\} \tag{9.2}$$

Further constraints are added regarding the maximum capacities and loads for the HP and TSS. Those capacity restrictions are given by:

$$0 \leq l_t^{hp} \leq l^{hp,max} \qquad \forall\, t \in T \tag{9.3}$$

$$0 \leq s_t \leq s^{max} \qquad \forall\, t \in T \tag{9.4}$$

$$-l^{s,max} \leq l_t^s \leq l^{s,max} \qquad \forall\, t \in T \tag{9.5}$$

The proposed control strategy can be applied on a DHN structure with a given set of HPs and operated with forecast heat demand values as derived in Section 9.2.

9.3.1 Demonstration of the Control Strategy

To achieve our second research objective, the control strategy is evaluated on the example of the Flensburg DHN for the year 2016 with regard to grid integration in Section 9.3.2 and economic benefits in Section 9.3.3.

In the given scenario, the entire heat demand of the Flensburg DHN is covered by an HP and a TSS. The HP is able to cover the entire heat demand, while the TSS has restrictions with regard to size and load capacity. The maximum storage capacity is $1,000 MWh$, the maximum load is $200 MW$ and it is the same for charging and discharging. Thus, it is possible to completely fill or empty the TSS within 5 hours. Larger and smaller ratios of energy to capacity are possible for the TSS. However, a TSS that could store more heat than is required for 24 hours would require larger forecast horizons. The hourly efficiency of the TSS is given by $\Theta = 0.996$ resulting in a 24 hour storage efficiency of around 90%, which is in line with efficiency values for daily TSS (Sarbu and Sebarchievici, 2018). To benchmark the online control strategy, it is compared to a naive algorithm and a global optimization. The naive algorithm does not use the TSS and instead generates the heat that is required in every hour using the HP. The global optimization assumes perfect foresight and optimizes the use of HP and TSS for the entire operation time horizon at once. For the online operation, we use the 24 hour rolling horizon forecasts generated by the CNN as presented in Section 9.2.2.

9.3.2 Offshore Wind Generation

In the first demonstration, the control strategy is used to improve the grid integration of renewable energy. The objective is to maximize the share of offshore wind energy that is used by the HP. In times of peak offshore generation in the German North Sea, the German network is often not able to transmit all generated wind power to the South, where much of the industry is located (Staudt et al., 2018). Thus, encouraging a use of the offshore wind close to its origin can contribute to both an increased share of renewables in the heat system and grid integration of wind power. The objective function that needs to be maximized in this scenario is then given by:

$$F = \sum_{t=1}^{T} (\Theta_t) \tag{9.6}$$

A high Θ_t indicates that a larger portion of the electricity used by the HP is consumed in times when the system is served by offshore wind generation. The wind share is determined by the ratio of offshore wind generation and the electric load of the respective transmission system:

$$\Theta_t = \frac{g_t^{el,w}}{l_t^{el}} \ \forall \, t \in T \tag{9.7}$$

The data for offshore wind electricity generation $g^{el,w}$ and amount of electric load in the system l^{el} is acquired from the German network operator Tennet and represents generation and load within the network area covered by Tennet (TenneT TSO BV, 2020). The results displayed in Table 9.5 show that the online control strategy is able to achieve a share of offshore wind utilization in heat generation of 10.90%, which is nearly 20.5% higher than with a naive approach and only 0.3% worse than the global optimization with perfect foresight. An exemplary three-day operation

	Naive approach	**Forecast**	**Global**
Average offshore wind share Θ_t	9.05%	10.90%	10.93%
Performance w.r.t global optimum	82.76%	99.70%	100%

Table 9.5.: Comparison of results for the operation strategy with regard to grid integration.

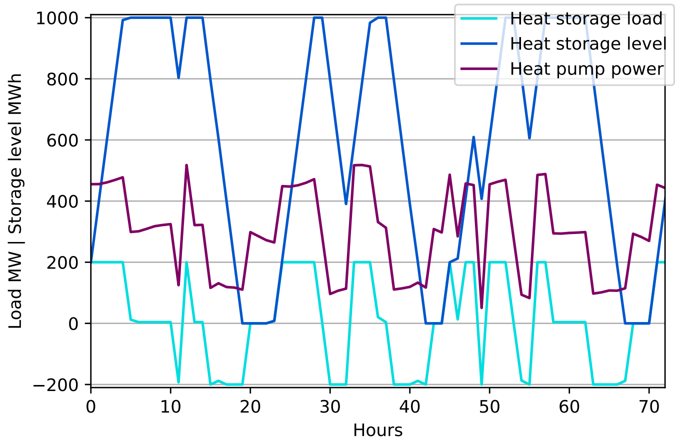


Figure 9.2.: HP operation, TSS load and TSS status for the online control strategy.

period in January 2016 for the control strategy is depicted in Figure 9.2. The TSS is used very regularly to maximize the share of wind generation in the energy mix. A comparison of the HP operation is shown in Figure 9.3 for the same time period. The global optimization shows only slight deviations from the online operation using a 24-hour rolling forecast. It indicates that for such a system, a 24-hour forecast with a reasonably good accuracy as presented in this chapter can achieve nearly optimal operation results.

9.3.3 Cost Minimization

In a second evaluation of the control strategy, we examine the online operation of a DHN with regard to hourly day-ahead prices of the German electricity market (German Federal Network Agency, 2020). The objective function that needs to be minimized in this scenario is then given by:

$$F = \sum_{t=1}^{T} \left(p_t^{el} \cdot l_t^{hp} \right) \tag{9.8}$$

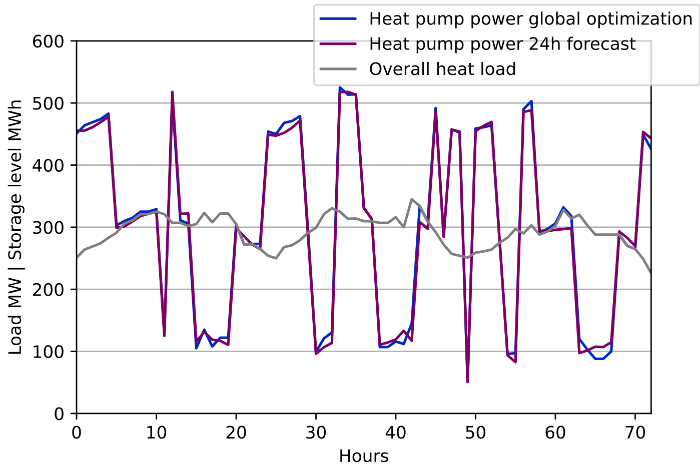


Figure 9.3.: Comparison of the HP operation for the naive approach, 24-hour forecast and global optimization.

	Naive approach	**Forecast**	**Global**
Average price (EUR/MWh)	24.01	20.93	20.91
Performance w.r.t optimum	114.8%	100.01%	100%

Table 9.6.: Comparison of results for the operation strategy with regard to cost minimization.

The results show that the proposed online control strategy achieves results similar to the global optimization. An overview is given in Table 9.6. With a 24 hours rolling horizon forecast, our model is able to achieve results that are within 0.1% of the global optimum with perfect foresight and outperforms the naive approach by around 15%.

9.4 Discussion

To evaluate the methodology and discuss the results, we first review the presented heat load forecasts and then discuss the proposed control strategy. Among the ANNs, the FFNs and the CNNs achieve considerably better results within the test set. Compared to the benchmarks, all ANNs achieve good results on the test data with a MAPE in the range of 6.34% to 6.98% for the Flensburg DHN. With an RMSE of 10.43 MW and 10.44 MW, the CNN and FFN outperform the GRU and LSTM models, which show RMSEs of 12.18 MW and 12.52 MW. The similar results between FFN and CNN also carry over to forecasting results for the NREL and the Sønderborg DHN. The slightly worse result of the recurrent neural networks compared to FFN and CNN might originate from several reasons. As the recurrent neural networks obtain a deep structure due to the unfolding in time, overfitting becomes a more problematic issue in general. Especially for the LSTM network, this is also indicated by larger differences between testing and training errors. Gers et al. (2002) investigate the usage of LSTM networks in time series forecast tasks. They conclude that the superiority of LSTMs against FFNs does not carry over to certain simpler time series forecasts. The results are within the range of similar studies (Geysen et al., 2018; Keçebaş and Yabanova, 2012; Dahl et al., 2017), even though the quality and form of the dataset plays an important role for such comparisons. The control strategy can be performed by implementing different objectives of which we focus on costs and renewable integration in this chapter. We do not consider investment and maintenance costs for the DHNs, which are subject to further analysis in the course of implementing the proposed system, for example as part of a local energy network as introduced in Chapter 4. For the given objectives and dataset, the proposed control strategy clearly outperforms the naive strategy and is only slightly inferior to a global optimization with perfect foresight. The offshore wind generation is based on given data to isolate effects of the heat load forecast. For a real-world application, the model would need to be provided with wind forecasts instead of actual generation. However, this is only an issue of setting the right objectives. Beyond the scope of this chapter, the proposed control strategy offers potential for further connection of energy sectors. For example, the model could be used to develop a supply strategy for cooling load as presented in Chapter 8.

9.5 Conclusion

This chapter introduces an online operation strategy for district heating networks (DHNs) that utilizes hourly heat forecasts with a 24 hours rolling horizon, achieving two research objectives: (1) The heat load is forecasted with supervised machine learning algorithms. In a comparison of the results on three different datasets that include one large facility, a community of buildings and one large DHN, convolutional neural networks and feed forward networks return the best results overall. (2) The proposed control strategy for the DHN utilizes heat forecasts for the operation of electric heat coupling devices, i.e., a heat pump and a thermal storage system. The control strategy is applied in two use cases to answer Research Question 8. In the cost minimization use case, the operation strategy outperforms the naive approach by 15% and is within 0.1% of the global optimum. In the grid integration use case, the operation strategy outperforms the naive approach by 20.5% and is within 0.3% of the global optimum. In this chapter, we offer a methodology to include forecasts for the operation of a DHN with a focus on the integration of renewable generation or cost minimization. The application of such strategies can lead to a smart electrification and thereby decarbonization of a DHN. Thus, with our work, we contribute to a sustainable energy system and a successful energy transition.

Part V.

Finale

CHAPTER 10

CONTRIBUTIONS AND IMPLICATIONS

An increase of investments in renewable residential energy technologies and the promotion of coupling between the heat and electricity sectors contribute to the decarbonization of integrated energy systems in residential areas and thus to the limitation of global warming to 1.5°C. In this thesis, I contribute to the development of the citizen energy community (CEC) concept through the determination of preference-based investment recommendations and corresponding operation strategies for sector coupling. To support individuals in their decision process regarding these investments, I design preference-based decision support systems (DSSs) for participants (Chapter 4) and analyze acceptance factors for preference-based recommendations (Chapter 5). For the determination of investment recommendations for these DSSs, I develop a multi-objective optimization that is able to reflect the trade-off between different objectives and integrates sizing and operation in one model (Chapter 6). Furthermore, I investigate the influence of CEC regulation on the investment activity of participants (Chapter 7). Based on two use cases, I show the potential of coupling the heat and electricity sector to integrate the rising amount of volatile renewable generation (Chapter 8 and Chapter 9). This chapter summarizes the answers to the research questions presented in Chapter 1.

Part II focuses on the integration of individual preferences in the design of DSSs for CECs. Regarding Research Question 1 (*"What are the required elements to provide investment recommendations to CECs through a platform-based DSS in order to coordinate financial and ecological interests of participants?"*) the required elements for investment recommendations for CECs comprise a combination of structural elements (geographic location, existing technologies, existing infrastructure), user-centric elements (load profiles, weighting of preferences, preferred degree of self-sufficiency, investment costs, technology preferences, intentions regarding planned technologies) and regulatory elements. The proposed platform has the potential to positively influence the scaling of CECs by facilitating participation and supporting interaction, providing comprehensible information on environmental impact and by presenting different paths of actions and their economic and environmental consequences.

However, the effectiveness of this system depends on the acceptance of the investment decision proposed by the DSS. To investigate the acceptance factors of preference-based recommendations in a DSS for residential energy technology investments, an online experiment with 324 participants was conducted. The participants had to choose between 20 investments for residential energy technologies and were provided with a recommendation based on their preferences regarding costs and emissions that were evaluated using a ranking-based conjoint analysis. To answer Research Question 2 (*"To what extent does providing recommendations that take into account the trade-off between individual cost and emission preferences in a DSS for residential energy technology investments increase the recommendation acceptance compared to recommendations that consider either costs or emissions?"*), the acceptance rates of these recommendations are compared to the acceptance rate of recommendations that indicate either the alternative with the lowest costs or the lowest emissions. The results show that the provision of preference-based recommendations increases the acceptance rate in the given experiment from 47% to 69%. Due to the low external validity of the online experiment, these numbers cannot be translated directly to a real-world application. The findings contribute to the understanding of acceptance factors for preference-based recommendations in DSSs and can be used in the development of application-oriented information systems.

When making investments in residential energy technologies, participants face uncertainty, for example, regarding the development of energy prices, energy consumption, or volatile renewable generation. To evaluate the impact of uncertainty on preference-based recommendations, the online experiment was conducted in treatments with and without uncertainty to answer Research Question 3 (*"What is the effect of uncertainty on recommendation acceptance and the perceived usefulness of* *the DSS?"*). The results show no significant effect of uncertainty on the recommendation acceptance across all treatments. This might also be explained by the low monetary investment value in the experiment compared to real investments in residential energy technology.

However, participants reported a higher usefulness of the recommendation in treatments with uncertainty compared to treatments without uncertainty. The extent to which the effect is related to the fact that participants are told in the experiment that the recommendation is based on their preferences requires further research on that topic.

In summary, the research of Part II addresses the integration of individual preferences in DSSs for private individuals. The proposed DSS design elements and the behavioral analysis in the online experiment contribute to the development of preference-based DSSs for citizen investments in residential energy technologies. According to the results of the online experiment, preference-based energy technology investment recommendations increase the perceived usefulness of the DSS. This should be taken into account by policymakers when considering subsidy programs for residential energy technologies. The findings encourage municipal utilities to solicit customer preferences regarding costs and emissions to potentially increase the acceptance rate of recommendations for investments in residential energy technologies. An application of the proposed DSS enables citizens to take an active role in the energy transition by becoming prosumers.

To provide preference-based investment recommendations to citizens, it is necessary to determine the possible investment alternatives with regard to individual preferences, for example, costs and emissions. This is addressed in Part III. Research Questions 4 to 6 address the generation of investment recommendations with regard to individual preferences. Furthermore, they investigate the effects of individual investment decisions on energy costs and emissions in CECs.

In a CEC, the combination and sizing of different energy technologies have a direct effect on the community operation and should thus be evaluated in an integrated model. Therefore, a multi-objective evolutionary algorithm is combined with an energy system simulation to determine a set of non-dominated energy technology investment recommendations considering the objectives costs and emissions. To answer Research Question 4 (*"What is the financial (cost) and environmental (emission) performance of a multi-objective evolutionary optimization of the integrated sizing and operation of energy technologies in a CEC relative to an upper benchmark optimization with perfect foresight that optimizes the objectives individually?"*), the model results are compared to an upper benchmark optimization with perfect foresight that regards each of the objectives individually. In a case study using residential heat and electricity data from ten households in southern Germany, three scenarios "summer", "winter" and "mid-season" are evaluated based on household load and solar generation data aggregated to average weeks. In all three scenarios, the model achieved good results with regard to emissions. The results are within 0.8% to 4.5% of the linear optimization benchmark. With regard to the cost objective, the results in the winter scenario come within 0.5% of the linear optimization benchmark. However, in the summer and mid-season scenarios, there is a larger gap between the results of the evolutionary algorithm and the linear optimization, indicating that the evolutionary algorithm is less suited to these scenarios. To address this issue, the solution space needs to be searched more thoroughly (i.e., improvement of the evolutionary algorithm or higher number of iterations).

The proposed multi-objective evolutionary algorithm enables the integrated assessment of energy technology sizing and operation with regard to competing objectives. The model considers the sectors heat and electricity on a community level. The set of solutions can be used to provide investment recommendations in a preference-based DSS for local decision-makers in CECs. For the cost objective in the summer and mid-season scenarios, the difference between the evolutionary algorithm and linear optimization indicates that the solution space must be more thoroughly searched than in the other scenarios. The differences between the scenarios further show the need to observe larger time periods for the determination of investment alternatives. This is addressed in the subsequent chapter, where the evaluation period is extended to one year.

While a set of optimal investments provides useful insights for CECs, in reality, investments do not happen all at once but depend on the decisions of individuals over time. To contribute to the understanding of CEC development, Research Questions 5 and 6 address the development of a CEC on the path to decarbonization and coupling of the heat and electricity sector through investments in residential energy technologies over a period of ten years. The energy technologies considered in the chapter are residential heat pumps, battery storage systems, photovoltaic and photovoltaic/thermal panels. To evaluate the long-term influence of CEC regulation in a community, Research Question 5 (*"What are the long-term financial (cost) and environmental (emission) effects of CEC regulation on the development of a community with respect to electrification and the investment in residential energy technologies?"*) addresses the impact of such regulation on decarbonization and energy costs through investments in energy technologies. For a community with 30 households in close proximity to each other, the community development is simulated over a period of 10 years, starting in 2020. The development of the community is simulated with and without CEC regulation, i.e., the possibility to buy and sell excess renewable electricity generation to and from households in the community. The results show that CEC regulation is beneficial with regard to cost and emission reduction in all considered scenarios. In the CEC scenarios, household investments lead to a cost reduction of up to 28% and an emission reduction of up to 50% compared to 2020. Addressing Research Question 6 (*"To what extent does the spread of individual household preferences in a community impact the potential of CEC regulation for a faster decarbonization?"*), the case study results show that CEC regulation is especially beneficial for communities with heterogeneous environmental and economical preferences, as might be the case in urban areas. Here, the cost reduction over the ten-year period is 30% higher in the scenario with CEC regulation than in the scenario without CEC regulation. The emission reduction in this period is also 10% higher in the CEC scenario.

In summary, the research in Part III of this thesis contributes to the derivation of investment recommendations in CECs. One of its main contributions is the analysis of CEC regulation. The results of the analysis demonstrate that German policy-makers can accelerate the decarbonization process in urban areas by implementing a scalable CEC regulation, as required by the European Union (European Parliament and Council of the European Union, 2019). This regulation should allow households to sell excess energy production to their neighbors, thereby increasing the revenue from residential energy generation and supporting investment in residential energy technologies.

Citizen investment in residential energy technologies is necessary to reduce carbon emissions in CECs. However, this creates new challenges for real-time operation, as fluctuating generation must be balanced with uncertain demand. The efficient operation of sector coupling technologies can help to address these challenges and contribute to the decarbonization of the heat sector in residential areas. Part IV presents two use cases to show the potential of sector coupling technologies for CECs during operation.

The first use case focuses on the use of photovoltaic and solar thermal generation to provide electricity, heating and cooling. Hybrid photovoltaic/thermal systems present an alternative to regular photovoltaic power by providing both heat and electricity at the same time. To answer Research Question 7 (*"What are the financial benefits of a sector-coupled photovoltaic/thermal installation in combination with absorption cooling compared to conventional compression cooling with a photovoltaic installation?"*), the potential financial benefits of using a photovoltaic/thermal power plant in combination with absorption cooling to supply both heat and cooling are investigated. In a case study using data from the National Renewable Energy Laboratory (NREL), the combination of absorption cooling with a photovoltaic/thermal system reduces operation costs by 74% compared to a system with a photovoltaic system and conventional cooling. As the approach considers net metering, it cannot be transferred directly to the European landscape, due to regulatory barriers. However, it is a clear indication towards the benefits of photovoltaic/thermal power in integrated energy systems and their potential contributions towards a successful energy transition in CECs.

The second use case addresses the development of an operation strategy for a heat pump and thermal storage system in combination with heat load forecasts. The operation strategy is based on an online optimization using a 24 hours rolling horizon heat load forecast and is designed to consider different objectives, for example, cost minimization or the integration of renewable generation. The efficiency of the operation strategy is compared to a global optimization and a naive lower benchmark to answer Research Question 8 (*" What is the performance of an online operation strategy for a district heating system with a heat pump and a thermal* *storage system that uses a 24-hours rolling horizon heat load forecast compared to (i) a naive approach and (ii) benchmarked against the global optimum with respect to the integration of renewables and cost minimization?"*). To answer the research question, a heat load forecast is implemented using a convolutional neural network architecture. The heat load forecast is used as input for the online optimization of the operation strategy. The designed operation strategy is applied to a large-scale heat pump in combination with a thermal storage system for the Flensburg district heating network. The operation strategy is applied in an economic scenario using day-ahead market prices and in an ecologic scenario using offshore wind generation data. In the economic scenario, where the objective is to minimize electricity prices, the operation strategy outperforms a naive approach by 15% and is within 0.1% of the global optimum. In the ecologic scenario, where the objective is to maximize the share of offshore wind generation in the electricity mix, the operation strategy outperforms the naive approach by 20.5% and is within 0.3% of the global optimum.

The research presented in Part IV comprises operational strategies for a coupling of the heat and electricity sector in integrated energy systems that can support decarbonization in CECs. The developed approaches contribute to a successful energy transition in two ways. First, the proposed operation strategies can help to better utilize available resources and capacities, thereby reducing the system costs. Second, the proposed mechanisms and the integration of the heat and electricity sectors improve the utilization of intermittent renewable generation in CECs, thereby promoting the decarbonization in residential areas. While the case studies in Chapter 8 and Chapter 9 do not explicitly consider a CEC context, the presented methodologies can also be applied in CECs. The presented operation strategies can be applied by municipal utilities and executive decision-makers who are involved in the energy management of a CEC. For policymakers, this part presents concepts for the coupling of energy sectors and showcases the potential of integrated approaches to improve the resilience of an energy system that is based on intermittent renewable generation.

In summary, this dissertation contributes to the decarbonization of integrated energy communities, focusing on supporting residential investments in energy generation, conversion and storage technologies and the coupling of sectors to develop integrated energy systems. The findings contribute to the knowledge of preference-based decision support tools for residential energy technology investments. Furthermore, the dissertation provides a model to determine investment alternatives based on these preferences with regard to technology size and operation in the heat and electricity sector. It provides guidance for policymakers and municipal utilities in their design of incentives and corresponding regulation for energy communities and the development of efficient operation strategies for sector-coupled energy systems in residential neighborhoods.

CHAPTER 11

OUTLOOK

Several avenues for further research emerge from the results of this work.

As stated by Gholami et al. (2016) and Watson et al. (2010), there is a need for further development of information systems that can help to address the challenges of climate change. With respect to DSSs, three main areas of further research can be pursued in this context.

The first area comprises the development of DSSs for group investment decisions in CECs, building on the insights presented in Chapters 4 and 5. As the installation of technologies such as battery storage systems or renewable generation often affects multiple households in a CEC or a multi-family house, consensus mechanisms are necessary to support the decision process. This includes not only the decision for, e.g., a community photovoltaic system, but also the division of future rights of use, possible yields and the responsibility for maintenance and operation.

Second, Chapters 6 and 7 present one possible approach to model the implementation of investment recommendations by individuals. While the proposed approach focuses on the trade-off between economic and environmental preferences, it does not consider the overall strength of these preferences or the general interest in investing in residential energy technologies as a separate measure. The target of 8 million residential solar photovoltaic and battery storage systems proposed by Weniger et al. (2018) will likely require investments from citizens with low interest in residential energy technologies. Designing DSSs for these individuals could help accelerate the energy transition. Such systems would need to focus on minimizing the effort for potential customers and highlighting the monetary benefits while placing less emphasis on the environmental aspect of investing in residential energy technologies.

Third, while this thesis focuses on the design and simulative evaluation of DSSs for residential energy technology investments, the functionality of the proposed systems needs to be evaluated in the field. Ideally, such an experiment would accompany actual investments in residential energy technologies to provide more insights on the acceptance, design and effectiveness of preference-based DSSs. The determination of residential investment recommendations is, for example, part of the ongoing research project "Smart Microgrids as a Service" (SMaaS)[5].

Increasing investments in residential energy technologies and motivating environmentally friendly behavior by citizens can be supported through incentive mechanisms in CECs. In the electricity sector, this includes the implementation of time-varying tariffs, for example (Burger et al., 2020). When the focus is on electricity only, the network restrictions can be neglected in the design of incentive mechanisms in a CEC due to the close proximity of the households. For the design of market mechanisms for integrated energy systems with sector coupling technologies, control power restrictions of the heat network need to be considered. This has already been done in a first study for a static system (Maurer et al., 2021), but can be further extended to be applicable in the operation of integrated CECs.

With regard to the operation of sector coupling technologies, the application of long-term thermal storage systems presents an opportunity to further decrease the dependence on fossil fuels in the residential sector. Large-scale seasonal thermal storage systems have already been implemented in some regions in Germany (Mangold, 2007). As system costs decrease with a larger size of the seasonal storage, households connected to an energy community could benefit from these systems that often use water or gravel as a storage medium. Given the seasonal differences in heat demand that are opposite to solar generation potential, seasonal storage is a key technology to further decarbonize the residential heating sector. As a seasonal thermal storage system is charged over a period of several months, existing operation strategies must be adapted to these periods. In operation strategies using day-ahead forecasts, as proposed in Chapter 9, this could be facilitated by assigning

[5]smaas.iism.kit.edu

a value to the stored heat. A first study evaluating the application of seasonal storage using hydrogen as a storage medium shows the potential to reduce carbon emissions (Katholnigg et al., 2023). However, the use of hydrogen for seasonal thermal storage in CECs is not yet economically viable and further research is necessary to improve the strategies for real-time operation.

Finally, the European energy crisis and the associated increase in energy prices pose new challenges for the energy sector. On one hand, higher energy prices increase the incentive to invest in residential energy technologies. On the other hand, this development may lead to an increased focus on self-sufficient energy systems that are less dependent on external energy supplies, such as natural gas. The influence of this development on the attitude towards residential energy technology investments and the energy consumption behavior of citizens could be measured over a longer period of time by means of a social sentiment study.

As this thesis demonstrates the importance of sector coupling for the decarbonization of CECs, it motivates further research toward a more holistic view of the electricity and heat sector in residential areas.

Appendices

Appendix A. Chapter 5: Items and Instructions, (translated from original German)

Introduction	Thank you for participating in the study by the Institute of Information Systems and Marketing (IISM). This experiment explores private investment decisions in the energy sector. Please read the texts thoroughly, the amount of the payoff depends on your decisions within the experiment. If you are able, preferably go to a place where you will be undisturbed. The experiment will take about 20 minutes and you will receive an allowance of up to 5 € at the end. The amount of CO_2 saved by your decisions within the experiment will be compensated by the IISM through the provider 'atmosfair'. Atmosfair supports projects to mitigate climate change. For example, atmosfair promotes the expansion of renewable energies in developing countries and thus saves CO_2. The Ministry for Climate, Environment and Energy in Baden-Würtemberg and the mobility provider Flixbus cooperate with atmosfair.
Conjoint analysis	Imagine you have to decide on a new electricity tariff. Your old electricity tariff costs 30 cents/kilowatt hour (kWh) and causes CO_2 emissions worth 30 cents/kWh. The value of the CO_2 emissions represents the amount of money it would cost to offset the CO_2 emissions generated (e.g., via atmosfair). In the table at the bottom of this page, different electricity tariffs are presented. Please arrange the electricity tariffs through drag and drop so that the order of the tariffs corresponds to your preferences. The first tariff is the one you would most likely choose and the ninth tariff is the one you would least prefer.

Investment decision	In this part of the experiment, you have the opportunity to make an investment. In principle, the investment is comparable to installing solar panels on the roof or installing a new heating system in a residential building. First, a fixed amount must be paid. Then, over the lifetime of the technology (5 years in this study), costs are incurred as well as CO_2 emissions in each year. On this page, the investment mechanism is explained with an example. On the following page you will then have the opportunity to make a selection. Your budget is 500 monetary units (GE) (100 GE = 1€) and 500 emission units (EE) (100 EE = compensation worth 1€ at atmosfair (43.5 kg CO_2)). The investment is considered over a period of 5 years. If you decide not to invest, you can opt-out and receive a fixed expense allowance of 2,50€.

Table A.1.: Participant instructions.

Construct	**Item**
General importance cost (C1)	What role do costs play in your consumer behavior in general?
General importance emission (E1)	What role do emissions* play in your consumer behavior in general?
Energy context importance cost (C2)	What role do costs play in connection with decisions affecting your energy consumption?
Energy context importance emission (E2)	What role do emissions* play in connection with decisions affecting your energy consumption?
Clarification	*In this experiment we understand emissions as all forms of climate-damaging gases (e.g., CO_2).

Table A.2.: Pre-experimental questionnaire, answers are given on a five-point Likert scale.

Construct	Item
Energy knowledge (P1)	I am very well acquainted with the subject “renewable energy”.
Personal measures (P2)	Personal measures to save CO_2 are very important to me.
Individual CO_2 saving (P3)	I would describe my personal behavior to save CO_2 as very committed.
Perceived recommendation usefulness (P4)	The recommendation on the investment page helped me make my decision.
Truthful investment (P5)	The decisions within the experiment reflect my actual investment behavior.
Recommendation notice (P6)	I consciously noticed the recommendation on the investment page.
Task understanding (P7)	I understood the investment decision task.
Conscious investment (P8)	I made a conscious choice in my investment decision.
Emission compensation trust (P9)	I trust that my emission savings will be sensibly compensated via atmosfair.
Information overload (P10)	The number of choices on the investment page overwhelmed me.
Overload influence (P11)	The number of choices on the investment side influenced my investment decision.

Table A.3.: Post-experimental questionnaire, answers are given on a five-point Likert scale.

Appendix B. Post-experimental Questionnaire

Item	Accept recommendation Mean (SD)	Deny recommendation Mean (SD)	T-test
Energy knowledge (P1)	3.36 (1.02)	3.67 (0.96)	-1.55 (p=0.123)
Individual impact on emission reduction (P2)	3.19 (1.15)	3.79 (0.76)	-2.38 (p=0.019*)
Individual emission reduction behavior (P3)	2.62 (1.14)	3.13 (0.83)	-2.57 (p=0.011*)
Perceived usefulness of recommendation (P4)	4.36 (1.14)	3.03 (1.29)	5.34 (p<0.001***)
Investment behavior (P5)	3.74 (1.10)	3.65 (1.10)	0.40 (p=0.687)
Recommendation notice (P6)	4.87 (0.33)	4.71 (0.66)	1.48 (p=0.139)
Task understanding (P7)	4.76 (0.47)	4.62 (0.84)	1.08 (p=0.284)
Conscious investment decision (P8)	4.68 (0.62)	4.71 (0.53)	-0.26 (p=0.794)
Emission compensation trust (P9)	3.89 (1.22)	4.12 (1.01)	-0.98 (p=0.332)
Information overload (P10)	3.89 (1.22)	4.12 (1.01)	-0.98 (p=0.079)
Overload influence (P11)	2.98 (1.45)	2.83 (1.17)	0.57 (p=0.571)

Table A.4.: Comparison of items in the post-experimental questionnaire in the cost treatments on a five-point Likert scale (1-5). Items P1-P11 can be found in Table A3.

Item	Accept recommendation Mean (SD)	Deny recommendation Mean (SD)	T-test
Energy knowledge (P1)	3.49 (0.99)	3.12 (0.89)	1.96 (p=0.053)
Individual impact on emission reduction (P2)	3.85 (0.94)	3.79 (0.91)	0.33 (p=0.74)
Individual emission reduction behavior (P3)	3.17 (1.08)	3.15 (1.01)	0.08 (p=0.939)
Perceived usefulness of recommendation (P4)	2.89 (1.34)	3.50 (1.32)	0.08 (p=0.027*)
Investment behavior (P5)	3.72 (1.00)	3.63 (0.90)	0.46 (p=0.647)
Recommendation notice (P6)	4.74 (0.76)	4.58 (0.72)	1.12 (p=0.324)
Task understanding (P7)	4.72 (0.57)	4.40 (0.88)	2.09 (p=0.039*)
Conscious investment decision (P8)	4.74 (0.56)	4.56 (0.60)	1.57 (p=0.119)
Emission compensation trust (P9)	3.74 (1.175)	4.10 (1.15)	-1.49 (p=0.139)
Information overload (P10)	2.94 (1.51)	3.31 (1.26)	-1.31 (p=0.190)
Overload influence (P11)	3.02 (1.36)	2.88 (1.14)	0.54 (p=0.592)

Table A.5.: Comparison of items in the post-experimental questionnaire in the emission treatments on a five-point Likert scale (1-5). Items P1-P11 can be found in Table A3.

Item	**Accept remendation** Mean (SD)	**Deny remendation** Mean (SD)	**T-test**
Energy knowledge (P1)	3.40 (0.97)	3.71 (0.80)	-1.10 (p=0.275)
Personal measures (P2)	3.71 (0.89)	3.71 (0.96)	-0.02 (p=0.983)
Individual CO_2 saving (P3)	2.90 (1.16)	2.93 (1.03)	-0.09 (p=0.926)
Perceived usefulness of recommendation (P4)	4.27 (1.09)	2.29 (1.16)	5.79 (p<0.001***)
Investment behavior (P5)	3.92 (1.02)	4.14 (0.83)	-0.75 (p=0.457)
Recommendation notice (P6)	4.73 (0.73)	5.00 (0.00)	-1.37 (p=0.176)
Task understanding (P7)	4.73 (0.49)	4.71 (0.45)	0.10 (p=0.92)
Conscious investment decision (P8)	4.48 (0.79)	4.93 (0.26)	-2.06 (p=0.044*)
Emission compensation trust (P9)	4.13 (1.11)	3.93 (0.88)	0.60 (p=0.55)
Information overload (P10)	3.40 (1.32)	2.86 (1.46)	1.29 (p=0.202)
Overload influence (P111)	3.10 (1.33)	3.43 (1.12)	-0.82 (p=0.416)

Table A.6.: Comparison of items in the post-experimental questionnaire in the preference treatments on a five-point Likert scale (1-5). Items P1-P11 can be found in Table A3.

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