Battery Storage in Low-Carbon Energy Systems

Deployment and Data-Driven Operation Strategies

Zur Erlangung des akademischen Grades eines
Doktors der Wirtschaftswissenschaften

(Dr. rer. pol.)

von der KIT-Fakultät für
Wirtschaftswissenschaften
des Karlsruher Instituts für Technologie (KIT)

genehmigte

DISSERTATION

von

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Tag der mündlichen Prüfung: 08.09.2022
Referent: Prof. Dr. Christof Weinhardt
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Karlsruhe, 2022

ACKNOWLEDGEMENTS

This dissertation was made possible by many wonderful people who supported and encouraged me. First, I want to thank Prof. Dr. Christof Weinhardt for the supportive guidance, inspiring ideas, and the opportunity to pursue my doctorate with such creative freedom. Further, I would like to thank my committee members Prof. Dr. Dirk Neumann, Prof. Dr. Orestis Terzidis and Prof. Dr. Melanie Schienle for constructive comments, lively discussions and a fair examination.

I would like to thank the entire chair team for the open arms and ears, the pleasant atmosphere and the cooperative mindset. In particular, I want to thank Team Energy for three amazing years: Armin for athletic support at the walk-in and the first joint publication, Bent and Marc for outstanding IT support and for brightening up dull office days with gossip and Fifa, Frederik for excellent teamwork on Team Lehre and Deep Learning challenges, Patrick for his enthusiasm for Princess Charming and the joint final sprint to the finish line of the dissertation and Jingyi, Saskia, Leo and Malin for bringing fresh spirits to the team, their enthusiasm for Team Energy excursions and great proofreading support. My heartfelt gratitude goes to my PostDoc and mentor Philipp for his inspiring guidance, tireless support, unfailing advice and for placing his trust in me.

I would also like to thank my co-author Dr. Christian Peukert as well as my students for great team work and fruitful collaborations.

Thanks are also due to my master thesis supervisor Dr. Balendra Kandiah and my Network^2-mentor Dr. Nicole Oeter, who laid the foundation for this dissertation by giving me the opportunity to write my thesis at Netze BW and encouraged me to pursue my PhD.

I am grateful to Dharik Mallapragada for hosting me at MIT Energy Initiative, making a great research stay in Boston possible after a long period of pandemic-related (academic) isolation.

To my friends, I am very grateful for diversions in the form of Europapark, cabin weekends and other ventures. I would especially like to thank Desi, Timo, Tabea and Nico for enriching life in Karlsruhe with brunches, long walks, home office adventures and more. To my family, I am immensely grateful for your unconditional support, your down-to-earth approach to life and for the ideals you have taught me. Lastly, to Chris, thank you for everything - words cannot describe the immense support and love you give me every day.

CONTENTS

LIST OF FIGURES

LIST OF TABLES

LIST OF ABBREVIATIONS

A2C	Actor Critic
AQS	Average Quantile Score
AVE	Average Variance Extracted
BA	Balancing Algorithm
BESS	Battery Energy Storage System
BTM	Behind-the-Meter
BW	Baden-Wuerttemberg
CHP	Combined Heat and Power
CVaR	Conditional Value at Risk
CR	Composite Reliability
DDPG	Deep Deterministic Policy Gradient
DDQN	Double Deep Q-Network
DRL	Deep Reinforcement Learning
DSM	Demand Side Management
EEG	Renewable Energy Act
EIW	Energy Information Website
EL	Electrification Scenario
FCR	Frequency Containment Reserve
FTM	Front-of-the-Meter
HTMT	Heterotrait-Monotrait Ratio
LCES	Levelized Cost of Energy Storage
LCOE	Levelized Cost of Electricity
LiB	Lithium-ion Battery
LSTM	Long Short-Term Memory
MDP	Markov Decision Process
MOP	Mobility Panel
MSE	Mean Squared Error
NPV	Net Present Value
P2P	Peer-to-Peer
PI	Profitability Index
PLS-SEM	Partial Least Squares Structural Equation Modeling
PPO	Proximal Policy Optimization
PtX	Power-to-X
PV	Photovoltaic

Q-GRU	Quantile Gated Recurrent Unit
Q-LSTM	Quantile Long Short-Term Memory
Q-REGNN	Quantile Regression Neural Network
RES	Renewable Energy Source
RFB	Redox Flow Battery
RL	Reinforcement Learning
SCA	Safety Control Algorithm
SD	Standard Deviation
SHAP	Shapley Additive Explanation
SoC	State of Charge
StaaS	Storage as a Service
TM	Technology Mix Scenario
UTAUT	Unified Theory of Acceptance and Use of Technology

Part I.

Fundamentals

CHAPTER 1

INTRODUCTION

The reduction of global emissions by at least 80% until 2050 requires a large-scale transformation of current energy systems as generation is shifting from large fossil power plants to intermittent renewable energy sources (RESs). On the consumer side, new electric loads such as heat pumps and electric vehicles can help to decarbonize the previously fossil-fueled heat and transportation sectors (van Nuffel et al., 2018). In future sector-coupled energy systems, electricity will therefore be the most important energy carrier. Therefore, power systems are more and more moving to the center of attention in low-carbon energy systems. In these energy systems that mostly rely on renewable power systems, battery energy storage systems (BESSs) play a vital role to bridge the resulting temporal gap between electricity consumption and intermittent generation (Weitemeyer et al., 2015).

A power system is a hierarchical system consisting of several aggregation levels as shown in Figure 1.1. There are two critical aspects for BESSs on these levels: deployment and operation. When planning the deployment and operation of BESSs, the different stakeholders and requirements on these levels, regarding, for example, application areas or suitable technologies, need to be taken into account. The smallest unit is a single generator or consumer, e.g., a residential household or a photovoltaic (PV) panel. On this level, BESSs can store excess generation from local small-scale RESs or supply consumer loads. On the second level, consumers and generators are connected within the low and medium voltage distribution grid, e.g., forming a community, city or industrial zone. Throughout this thesis, I refer to this level as the connected individual level. Here, BESSs can be deployed to increase local autarky, to supply loads from RESs cheaper than the wholesale market or to prevent congestion in sections of the distribution grid. On the high voltage level, power systems need to ensure the balance of supply and demand and secure grid stability. On this level, transmission system operators (TSOs) can strategically deploy BESSs to relieve network sections of congestion or to ensure resource adequacy in times of unfavourable weather conditions. This may require longer storage durations and consequently other BESS technologies than short-term storage of RES generation on the individual level. To increase utilization of these BESSs on all levels, their capacity can additionally be marketed on wholesale markets.

The differing requirements and operator perspectives on these system levels need to be taken into account when planning BESS expansion in power systems. Consequently, in addition to planning the deployment of BESSs, operation strategies have to be designed for BESSs at all levels of the power grid, according to the requirements of the respective stakeholders. Depending on the location in the grid and the role of the storage operator, operational goals may, for example, include the maximization of revenues, minimization of financial risks, or to ensure grid stability. Since generation, consumption and price developments are subject to uncertainty (Hain et al., 2018), storage operators need intelligent, online operation strategies to achieve these goals. Therefore, well designed strategies and approaches for the deployment and operation of BESSs on all levels of power systems are crucial for a successful path towards low-carbon energy systems.

This thesis presents a holistic perspective on BESS deployment on all levels of (future) low-carbon energy systems. In the first part of the thesis, BESS deployment is analysed across these different levels and in the second part, corresponding data-driven operation are designed and evaluated.

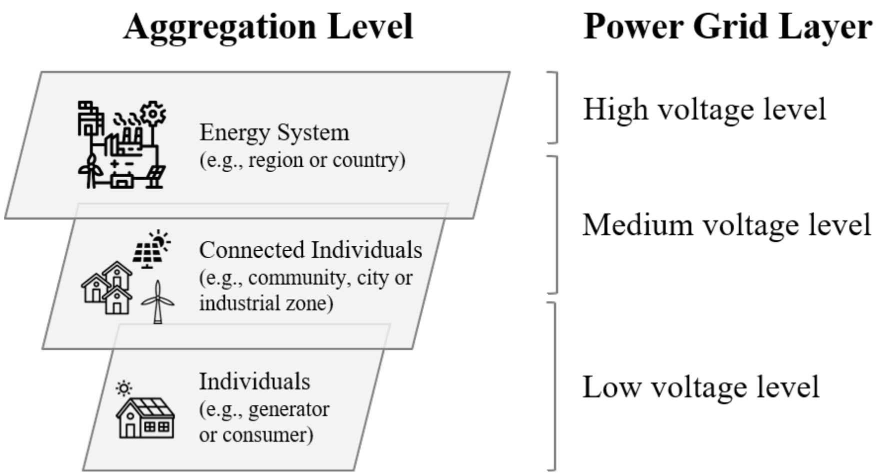

Figure 1.1.: Aggregation levels of power systems

1.1 Motivation

As of 2020, 36.6% or 2.8 TW of globally installed electricity generation capacity was renewable, consisting of around 46% hydropower, 27% wind power and 25% solar power (IRENA, 2021). However, only 11.2% of final energy consumption was covered by renewable generation (REN21, 2021). In the European Union, the "Fit for 55" plan by the European Commission sets a target of 40% renewable energy share of gross energy consumption by 2030, almost doubling the current ratio within 8 years (European Commission, 2022). This illustrates the challenge that still lies ahead regarding the integration of renewable energy generation in currently fossil-fuel based sectors worldwide. This particularly concerns the electrification of the heat and transportation sectors, which will result in a steep increase in electricity demand and will require a large-scale expansion of RESs (van Nuffel et al., 2018). For Germany, the study "Integrated Energy Transition" by the German Energy Agency (dena) predicts an annual electricity demand in the range of 837 to 1,156 TWh in 2050 to reach a 95% reduction in CO_2, depending on the degree of electrification (Bründlinger et al., 2018). This corresponds to an increase in electricity consumption by 48% to 105% compared to 2021 (Umweltbundesamt, 2022). In this context, the term "integrated" refers to a holistic consideration of energy systems and the (partial) integration of the predominantly fossil-fuelled transportation, heat and industrial sectors into the power system through means of electrification (Bründlinger et al., 2018). Therefore, in this thesis, the term integrated energy system refers to a largely electrified energy system powered by RESs.

The integration of these large amounts of intermittent RES generation will require substantial flexibility resources, predominantly (battery) energy storage capacity (Cebulla et al., 2018; Zerrahn and Schill, 2017). Taking the development of rising electricity demand into account, Ruhnau and Qvist (2021) determine BESS energy capacity requirements of 59 GWh to achieve a fully renewable power system by 2050 in Germany. In contrast, around 4.5 GWh of BESS capacity were installed in Germany at the end of 2021, consisting of around 3.2 GWh of residential, 0.2 GWh of medium-sized and 1.1 GWh of grid-scale BESS capacity (Figure 1.2). These figures give an idea of the extent of the efforts that still need to be undertaken to drive the expansion of BESSs to the level needed to support a decarbonized energy system. The expansion of BESS capacity will be needed on all aggregation levels of power systems, including small-scale BESSs for households, medium-scale BESSs for neighborhoods and industry and grid-scale BESSs to support balancing and to reduce congestion in the distribution grid.

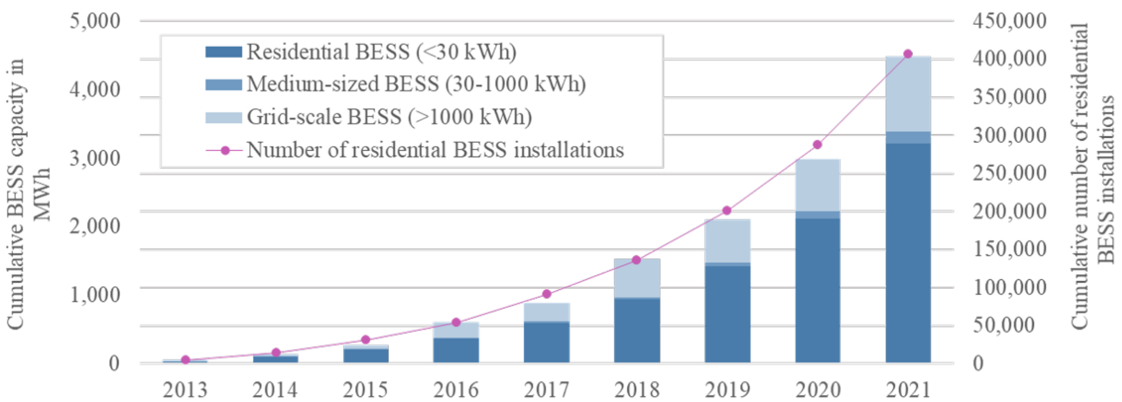

Figure 1.2.: Cumulative installed BESS capacity by storage size and cumulative number of residential BESS installations in Germany. Own representation based on data from Tepe et al. (2021), Weniger et al. (2018), Weniger et al. (2021), Ort et al. (2022), Bundesnetzagentur (2022), ISEA (2019) and EuPD Research 2020 (2020)

Up to date, the expansion of BESSs in Germany has been mainly driven by the rising number of residential BESS installations on the individual level, as shown in Figure 1.2. These residential BESSs are usually in the range of 5 to 14 kWh of usable energy capacity and connected to the low voltage power grid (Weniger et al., 2021). Through a regulatory feed-in tariff for PV generation combined with quickly declining investment costs (Figure 1.3), residential BESSs have become profitable for homeowners. As a result, at the end of 2021, over 400,000 BESSs had been installed in German households, constituting over 70% of installed BESS energy capacity in Germany. Individual, non-expert decision-makers therefore play a central role in the expansion of BESS capacity, a development that will likely continue. Weniger et al. (2018) even state that for an "ambitous" climate protection, 8 million residential PV-coupled BESSs need to be installed by 2050, which would require every second single family home in Germany to be equipped with a BESS. This requires policy that engages households and motivates them to install PV panels and BESS capacity. Energy literacy however, the knowledge of energy consumption and alternatives, is extremely low amongst residential households (Brounen et al., 2013). Therefore, tools and methods are needed to increase awareness of residential decision-makers and facilitate individual household decision processes.

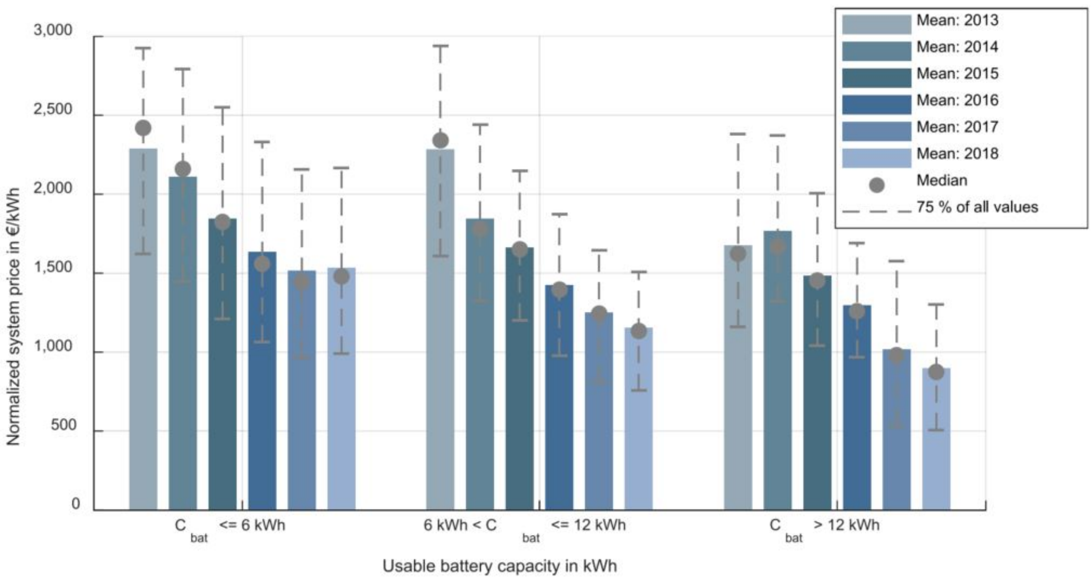

Figure 1.3.: Cost developments for small-scale BESS by Figgener et al. (2020)

On the level of connected individuals, medium-sized BESSs (i.e., community and industrial energy storage) can be deployed to integrate decentralized, intermittent generation to supply decentral energy communities or to shave demand peaks of industrial plants. In the research project "Esquire", for example, two BESSs with 84 and 115 kWh, respectively, have been installed to supply communities with several multi- and single-family buildings (Knoefel and Herrmann, 2021). On the European level, the importance of such "citizen energy communities" that engage in energy generation, distribution, storage or efficiency services has been recognized and emphasized in the *2019 Directive on Common Rules for the Internal Market for Electricity* (European Parliament and Council of the European Union, 2019). However, the very low installed capacity of medium-sized BESSs (see Figure 1.2) demonstrates that these concepts have not yet emerged beyond pilot project implementations in Germany. On the same level of the power grid, residential BESSs within a neighborhood that is connected to the distribution grid can be pooled together to form a (virtual) community BESS. By sharing idle storage capacity within a residential neighborhood, the utilization of existing residential BESSs can be increased, which increases the profitability of BESS investments. This approach is however currently still hindered by regulatory barriers, as increasing self-consumption from PV generation is only exempt from taxes and levies behind the meter, i.e., within one household.

On a system level, grid-scale BESSs can be deployed to prevent grid congestion at strategic locations in the electricity grid. Examples of grid-scale storage projects in Germany include the "Grid Booster" in Kupferzell, where a lithium-ion-based BESS with an energy capacity of 250 MWh and a power capacity of 250 MW is being planned by the regional TSO TransnetBW (Götz, 2021). Similarly, RWE is planning a 117 MW lithium-ion BESS in Lingen and Werne (RWE, 2020).

Figure 1.4 shows that currently, the vast majority of realized BESS projects relies on lithium-ion batteries (LiBs). LiBs are characterized by their high energy density and are currently the most commercially available BESS technology (Sterner and Stadler, 2017). They are especially suitable for short-term storage durations up to six hours (Figgener et al., 2020; Nitta et al., 2015). For longer storage durations, other technologies, such as redox flow batteries (RFBs), are promising alternatives, as they allow for an independent sizing of energy and power capacity (Vanitec, 2022). The world's largest RFB is being constructed in Dalian, China with a total nominal power of 200 MW and 800 MWh of energy capacity (U.S. Department of Energy/National Nuclear Security Administration, 2022). RFBs are not yet cost competitive with LiBs and they are not as commercially available. As this is expected to change (Schmidt et al., 2019), RFBs could become a viable alternative to LiBs, especially for stationary applications with medium-term storage durations. In this thesis, therefore, both LiBs and RFBs are considered.

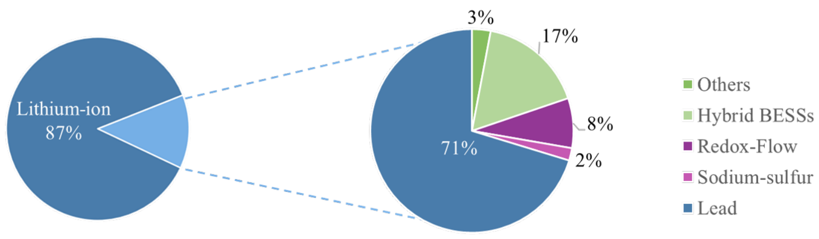

Figure 1.4.: Share of BESS technologies installed in 2019 (Tepe et al., 2021)

As grid-scale projects are increasing in number, they contribute to the BESS capacity requirements in integrated energy systems. For an ambitious energy transition, BESSs of all sized and on all levels of the power grid are needed. The exact requirements in terms of installed energy and power capacity are debated within the literature, which is described in detail in Section 2.1. A common feature is that studies assume the role of a central planner, which results in a cost-efficient estimation of RES and BESS expansion targets. This can lead to an extreme spatial concentration of capacity within a system, an effect that is often not explicitly addressed. Central planning ignores the fact that local acceptance can vary significantly between sites and that even sites with smaller physical potential for RESs can be valuable if local acceptance is greater (Segreto et al., 2020; Smith and Klick, 2008). Alternative, decentral planning approaches are therefore needed to determine storage requirements for integrated energy systems, while considering the lower aggregation levels of these systems as well.

On all aggregation levels of energy systems, BESSs can be deployed for a number of applications that help to integrate intermittent renewable generation, to avoid congestion, to smooth demand peaks or to secure grid stability, just to name a few examples (Baumgarte et al., 2019). While different services may be needed on different levels of power systems, a BESS can also manage several of these applications in parallel (Baumgarte et al., 2019; Parra et al., 2016). In the literature, the combination of several use cases is referred to under varying terms such as *multi-tasking*, *stacking* of services or *multi-use*. In the remainder of this thesis, I refer to this concept as *multi-use*, as this is the term used in German legislation (BVES, 2021).

In general, application areas can be categorized into "behind-the-meter" (BTM) and "front-of-the-meter" (FTM) applications (Englberger et al., 2020). Behind the meter, increasing PV self-consumption through residential BESSs has been heavily incentivized in Germany by the difference between the regulatory feed-in-tariff for PV generation and the considerably higher flat electricity tariffs for households (Figgener et al., 2020). At a larger scale, industrial plant owners can deploy BESSs to shave demand peaks, as their electricity rate often includes a "peak charge" for the highest annual load. In front of the meter, BESSs can become active in wholesale markets. Here, they can exploit temporal price differences in the day-ahead and intraday spot markets and participate in the auctions for ancillary services where they are especially well suited for providing frequency regulation. As wholesale price developments are subject to uncertainties, BESSs participating in these markets need strategies to handle the associated risks (Hain et al., 2018). Further uncertainties arise from the intermittent nature of RES generation and the only somewhat predictable consumption on all levels of power systems. Storage operators therefore need intelligent operation strategies to maximize their revenues or minimize their risks. To this end, data-driven methods can be deployed to assess risks or to design operation strategies based on price, generation or consumption forecasts (Hong et al., 2020; vom Scheidt et al., 2020). For multi-use BESS deployment, intelligent operation strategies are even more important in order to coordinate several tasks and to operate in different markets in parallel, especially considering the interplay of various uncertainties.

In summary, the deployment and operation of BESSs needs to be holistically considered on all aggregation levels of integrated energy systems. This thesis presents, evaluates and discusses solutions to this challenge. The thesis is oriented along the energy market design and regulatory framework of Germany, but many findings and especially the developed data-driven operational strategies can be transferred to energy systems worldwide. The thesis is logically structured into two main parts.

First, Part II addresses the deployment of BESSs on different aggregation levels of integrated energy systems. On an individual level, I evaluate how energy literacy of home owners or building managers can be increased through an information system with interactive and vivid features in Chapter 3. Individual decision-making plays an important part in the decarbonization of buildings, which were responsible for 39% of CO_2 emissions worldwide in 2017 (International Energy Agency and the United Nations Environment Programme, 2018). The low energy literacy amongst households results in an uninformed and insufficient evaluation of efficiency measures and investments in energy-related technologies, such as PV-coupled BESSs (Brounen et al., 2013). In a behavioral experiment, I show that vivid design elements increase the users' intention to use an informative website on energy-related technologies and their willingness to recommend it to others, thus supporting the adoption of BESSs.

On the level of connected individuals, I investigate how a sharing economy can enhance the utilization of (existing) PV-coupled BESSs in residential neighborhoods and how the shared goods can be priced to ensure a fair distribution of profits (Chapter 4). In this setting, two shared goods are considered: (i) electricity generation from PV installations which is directly consumed and (ii) storage capacity needed for charging and discharging the BESS. A simulation of 520 sharing communities consisting of five households each shows substantial annual cost savings and increases in BESS utilization. In addition, I use a data-driven classification approach to predict which household's load profile properties are especially suitable for participation in a sharing community.

Moving to the system level, I determine storage requirements for the German state of Baden-Wuerttemberg (BW) under different planning paradigms. Central planning, as done in existing literature, for example, by Ruhnau and Qvist (2021), ensures a cost-efficient expansion and spatial distribution of RES and BESS capacity. However, potential for RESs may vary both from a physical and a societal perspective within a larger geographical area. While general acceptance of RESs is usually high in Germany and Europe, local acceptance issues have often prevented concrete projects, e.g., in the case of wind park projects or storage facilities (Smith and Klick, 2008; Segreto et al., 2020). Alternative paths to central planning must therefore also be identified and assessed in order to incorporate local peculiarities in the planning process. Furthermore, the differing technology requirements within an integrated energy system are often disregarded in previous literature. In Chapter

5, I compare a central, decentral and in-between planning approach in terms of RES and BESS expansion needs, spatial capacity distribution and overall system costs. In addition, I differentiate between the requirements of short-term (LiBs) and medium-term (RFBs) BESSs. The results show that central planning leads to lower levelized cost of electricity (LCOE) but results in an extreme spatial concentration of the required RES and BESS capacity. The findings offer important insights for local and global policy-makers, who need to factor local acceptance into their decisions and communication strategies for RES and BESS expansion.

Second, in Part III of this thesis, I design, evaluate and discuss data-driven operation strategies for BTM, FTM and multi-use applications. These strategies enable a real-time operation of BESSs while considering the different requirements of stakeholders at different levels of energy systems. In Germany, the Renewable Energy Act (EEG) has enabled and driven the expansion of RESs through a guaranteed fixed feed-in remuneration for generation from PV and wind power plant installations (Bundesnetzagentur, 2020a). In the future, however, the expiration of subsidy programs and decreasing investment costs will mean that operators will have to market their generation directly on wholesale markets. Due to the intermittent nature of weather and fluctuating wholesale prices, operators will then be subject to considerable quantity and price risks. As a consequence, risk hedging will soon take a center stage for renewable generation (May et al., 2017). In Chapter 6, I develop and evaluate a heuristic operation strategy to deploy a BESS to mitigate these risks by shifting generation to hours with higher prices. Decisions on when to rely on the BESS are made based on a data-driven classification approach. The results show that by using this strategy, the conditional value at risk of a renewable generation capacity operator can be reduced substantially in the considered months of the case study.

Risk attitude also plays an important role when deploying BESSs for shaving peak demand in industrial plants. Due to high investment costs and low utilization rates if solely used for peak-shaving, a combination with Frequency Containment Reserve (FCR) provision might be beneficial from a technical and economic point of view (Braeuer et al., 2019). Since bids on FCR auctions have to be made one day in advance, when demand peaks are not yet known, the plant operator risks not being able to shave a peak when bidding too much BESS capacity. In this setting, I introduce the notion of risk-averse operation attitude by planning the BESS's operation based on a probabilistic forecast of industrial demand in Chapter 7. Probabilistic forecasts are a data-driven approach from the domain of machine learning that in this context enable the incorporation of risk attitude in an operation strategy by predicting a confidence interval instead of making a point forecast. The results show that risk-averse planning has little to no negative effects on the profitability of a BESS investment in the conducted case study. Moderate risk-averse planning attitude may even improve profitability in some cases, as demand peaks can be better anticipated.

Finally, I investigate the combination of several BTM and FTM applications in a multi-use "Storage as a Service" (StaaS) model in Chapter 8. StaaS describes the idea that a (battery) storage is operated as a service provider for various applications. For multi-use BESS deployment, the vast majority of previous research relies on deterministic or stochastic optimization approaches which are limited during real-time operation. Incorporating uncertainty into optimization requires careful modeling and complicates the adjustment to a changing underlying environment. In past years, deep reinforcement learning (DRL) has emerged as alternative to model sequential decision-making without the necessity to explicitly model uncertainties (Huang and Wang, 2021). I design and evaluate a DRL-based StaaS agent that handles simultaneous service requests from residential prosumers, an industrial plant and wholesale markets. The results show that the designed DRL agent can achieve higher revenues than a comparable rule-based heuristic operation strategy.

In summary, this thesis contributes to the understanding of a more wide-spread and effective deployment of BESSs at all levels of energy systems, resulting in a holistic consideration of BESS deployment. A particular focus of the thesis lies on the utilization of data-driven analyses and the use of state-of-the-art approaches from machine learning in order to enhance existing operation strategies. The specific research questions are outlined in the following section.

1.2 Research Questions and Outline

The expansion of residential BESS has been the key driver of storage expansion in Germany. This could be even further improved. Weniger et al. (2018) argue that a total of 8 million PV-coupled residential BESSs are needed in Germany to ensure an "ambitious climate protection". This requires the financial engagement of private households, which are often not well aware of their energy consumption and alternatives. To support the decarbonization of the building sector, knowledge must be provided on how BESSs and other energy-related technologies can be optimally combined in residential and office buildings. The first research question therefore addresses the design of a user interface on a website that provides this information in a way that increases energy literacy and leads to further dissemination of the tool. To evaluate this question, an animated website containing vivid and interactive design elements is compared to a static website with purely textual information in an online experiment.

Research Question 1 *What are the effects of interactive and vivid features on a simulative energy information website in the context of increasing citizens' energy literacy on sustainable energy-related technologies in buildings?*

Energy communities consisting of several connected homes and buildings within a residential neighborhood are an important component of the energy transition as they can integrate locally generated electricity from RESs and contribute to more effective use of residential BESSs. Research question 2 therefore investigates the financial benefits of a residential community that shares PV-coupled BESS resources. Because a fair distribution of profits is essential for the participation of local prosumers and consumers in such a sharing community, research question 3 refers to the pricing of the shared goods, i.e., the directly consumed PV generation and (dis-)charged electricity.

Research Question 2 *What are the average financial benefits for a residential sharing community that engages in sharing of local electricity generation and storage capacity?*

Research Question 3 *How does the pricing of the shared goods impact the distribution of profit shares within an energy sharing community?*

At a larger system scale, the necessary expansion of RESs and BESSs in low-carbon, integrated energy systems is a frequently investigated topic. However, while central planning determines a theoretically cost-efficient solution, the spatial distribution of capacities and the resulting local acceptance are often disregarded. I therefore compare a central, a decentral and an in-between planning approach to determine RES and BESS capacity needs for different decarbonization targets. Research question 4 addresses the resulting trade-offs in terms of costs and expansion requirements on the example of the German state of BW.

Research Question 4 *What are the trade-offs in terms of levelized cost of electricity and storage requirements in an energy system using decentral planning compared to central planning?*

In order to achieve the required installation of BESS capacity to integrate large-scale generation from RESs, the expansion of BESSs across all levels of energy systems must be accelerated. BESSs of all sizes and on all aggregation levels of energy systems must be given access to wholesale markets in addition to be able to provide other services on lower aggregation levels. Innovative business models and intelligent operation strategies can then enable profitable BESS investments. This is especially relevant when dealing with the uncertainties faced by operators of BESSs or renewable plants caused by intermittent generation and volatile prices. In this context, the fifth research question addresses the utilization of a BESS service agent to hedge the risk of a renewable plant operator who directly sells her electricity generation on the day-ahead market. The risk is measured with the conditional value at risk, a frequently used risk indicator.

Research Question 5 *How much can the conditional value at risk of a renewable operator be reduced through the deployment of a battery storage service using a developed heuristic operation strategy?*

In the context of an industrial plant owner, BESSs can be deployed to simultaneously provide FCR and shave peak demand. In the past, this combination has been researched. However, the inherent risk assessment of the industrial operator has not been considered. The operator has to decide how much capacity to bid on the FCR auction before knowing the exact industrial load profile of the next day. I include the notion of risk averse operation attitude by planning the joint usage of a BESS for FCR provision and peak-shaving based on a probabilistic forecast.

Research question 6 refers to the effect of this risk-averse planning strategy on the profitability of an industrial BESS investment.

Research Question 6 *What is the financial effect of an industrial consumer's risk aversion on the profit of a battery storage system that is deployed for joint peak-shaving and frequency containment reserve provision?*

Given an appropriate regulatory framework, combining multiple BTM and FTM applications can further increase the profitability of BESS investments. In addition, it has the potential to ensure the most effective deployment of existing BESS capacity for the integration of RESs in energy systems. Traditional optimization approaches have limitations when it comes to dealing with uncertainties in a very high-dimensional state setting and during real-time operation, as they are engineered for specific use cases. I therefore investigate DRL as an alternative data-driven approach to schedule multiple use cases within a StaaS setup. Research question 7 addresses the performance of a DRL-based approach in comparison to an optimal solution and a rule-based benchmark.

Research Question 7 *What is the quantitative performance of a DRL-based algorithm in comparison to theoretically optimal and rule-based operation strategies in terms of financial revenues?*

1.3 Thesis Structure

The structure of this thesis is organized along the research questions and is depicted in Figure 1.5. In Chapter 2, following this chapter, I describe the role of BESSs in the energy system. To provide the necessary background for this thesis, in Part I of this thesis, previous studies on storage requirements are reviewed, storage technologies and application areas are described and an overview of the regulatory framework for BESS deployment is given. Finally, the StaaS concept is outlined along the Market Engineering framework by Weinhardt and Gimpel (2006).

The introductory chapters are followed by the two main parts of this thesis. Part II addresses the deployment of BESSs on different aggregation levels of integrated energy systems. In Chapter 3, I evaluate an information system aimed at increasing energy literacy in buildings to increase the installation of residential BESSs. The concept of a sharing economy for energy communities with PV-coupled BESSs is introduced and evaluated in Chapter 4. BESS requirements in an integrated energy system are determined in Chapter 5 through a bottom-up modeling approach that allows to compare central vs. decentral planning of RES and BESS expansion.

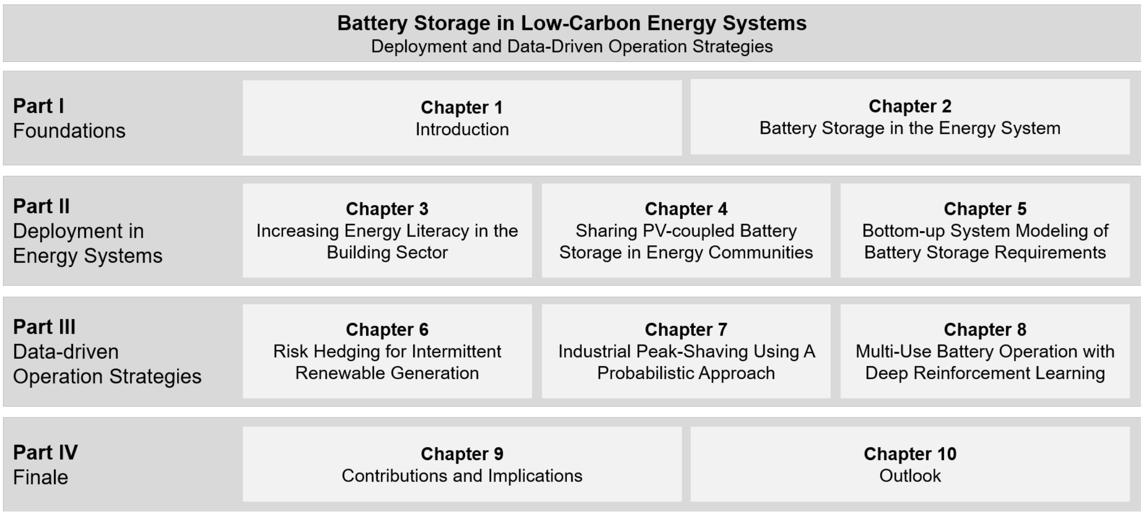

Figure 1.5.: Thesis Structure

In Part III, data-driven operation strategies for BTM, FTM and multi-use applications of BESSs are presented. First, a heuristic risk hedging strategy based on decision tree classification is presented for renewable generators in Chapter 6. For industrial plant owners, I investigate the joint utilization of a BESS for FCR provision and industrial peak-shaving using a probabilistic forecast to incorporate risk-averse planning behavior (Chapter 7). The design of a DRL-based multi-use StaaS agent is presented and evaluated in Chapter 8.

Finally, Part IV summarizes the key findings of this thesis along the proposed research questions and discusses the implications for stakeholders and policy-makers (Chapter 9). In Chapter 10, I outline promising future research paths along the topics discussed in this thesis.

Chapters 3 to 8 are based on published articles or working papers. In all cases, I disclaim this clearly at the beginning of the respective chapters. Within those chapters, I consistently refer to the authors as “we”, since I collaborated with fellow researchers for these articles.

CHAPTER 2

BATTERY STORAGE IN THE ENERGY SYSTEM

On the path to a more sustainable future, efforts are made worldwide to decarbonize the electricity supply through a transition from large centralized power plants towards many smaller renewable generation units. The German energy transition is an example for this transformation: In 2021, 41.1% of Germany's electricity consumption came from renewable sources such as wind and solar generation (Umweltbundesamt, 2022). Globally, almost 30% of electricity generation came from RESs in 2021, of which hydropower accounts for the largest share (IEA, 2022). As hydropower potentials are limited and wind and PV generation are the fastest growing RESs, they are expected to account for the largest shares of generation in future integrated energy systems.

With increasing shares of intermittent RES, large amounts of energy storage will be needed to bridge the temporal gap between intermittent supply and inflexible demand. In past years, global energy storage installations have increased rapidly. While currently, over 97% of installed energy storage capacity are pumped hydropower storage facilities (Stocks et al., 2019), their potential is limited as they require large areas and suitable landscapes. Due to their size, they are also unsuitable for deployment within the distribution grid. In Germany, the potential for pumped hydro storage is almost exhausted (Sterner and Stadler, 2017) and therefore, BESSs will play a more prominent role in future developments.

Historically the BESS market has been dominated by lead-acid batteries (Pillot, 2018), which are, for example, deployed in conventional vehicles. However, in recent years, the relevance of LiBs has increased significantly. Due to their deployment in electric vehicles and stationary storage applications, a further acceleration of this development is expected in the coming years. As it is yet unknown what the generation landscape will look like exactly in the future, storage requirements are a frequently studied topic in the literature. It is also unclear to what extent other flexibility options, such as demand side management or vehicle-to-grid approaches, can be exploited to reduce (battery) storage needs.

In this chapter, I first give an overview on previous analyses of storage requirements in Europe and Germany. Then, I describe the different technologies for electrical energy storage with a particular focus on LiBs and RFBs. Both technologies have been among the fastest growing BESS technologies in terms of worldwide installed capacity and are therefore the focus of this thesis (Vanitec, 2022; U.S. Department of Energy/National Nuclear Security Administration, 2022). In the subsequent section, economic application areas for BESSs within the current German regulatory framework are described. This is followed by the descriptive analysis of a literature review on multi-use BESS deployment and an overview of the regulatory framework of BESS deployment.

To meet the requirements for BESSs in energy systems with high shares of RESs, innovative business models which can incentivize future BESS investments are needed. StaaS refers to the idea that many distributed BESS facilities can be pooled together to offer their free capacity through a service platform. For small BESSs owned by residential prosumers, this concept opens up the possibility of realizing their full potential by providing both (local) flexibility services and by participating in wholesale markets. In the final section of this chapter, I describe the StaaS concept along the Market Engineering framework by Weinhardt and Gimpel (2006).

2.1 Storage Requirements in Low-Carbon Energy Systems

Storage requirements until 2050 have been analysed in numerous studies for energy systems worldwide (e.g., Cebulla et al. (2018); Zerrahn and Schill (2017); Solomon et al. (2017)). Cebulla et al. (2018) provide a comprehensive overview on previous studies on storage requirements in the U.S., Europe and Germany with different levels of RES shares. The results for Germany are shown in Figure 2.1.

The needed storage capacity varies significantly throughout all considered studies. The authors observe the trend that higher levels of RES shares require linearly more storage energy capacity and exponentially more storage power capacity. Another observation is that PV-dominated (as opposed to wind-dominated) systems require higher levels of storage power and to some extent also more storage energy capacity. Wind-dominated systems in turn rely more on transmission expansion. Cebulla et al. (2018) however note that there seems to be a bias towards transmission expansion in previous studies, as the reality of very long planning periods, bureaucratic hurdles and societal opposition is often not considered in modeling approaches. On the other hand, neglecting grid constraints ("copper plate" modeling) may lead to an underestimation of storage requirements.

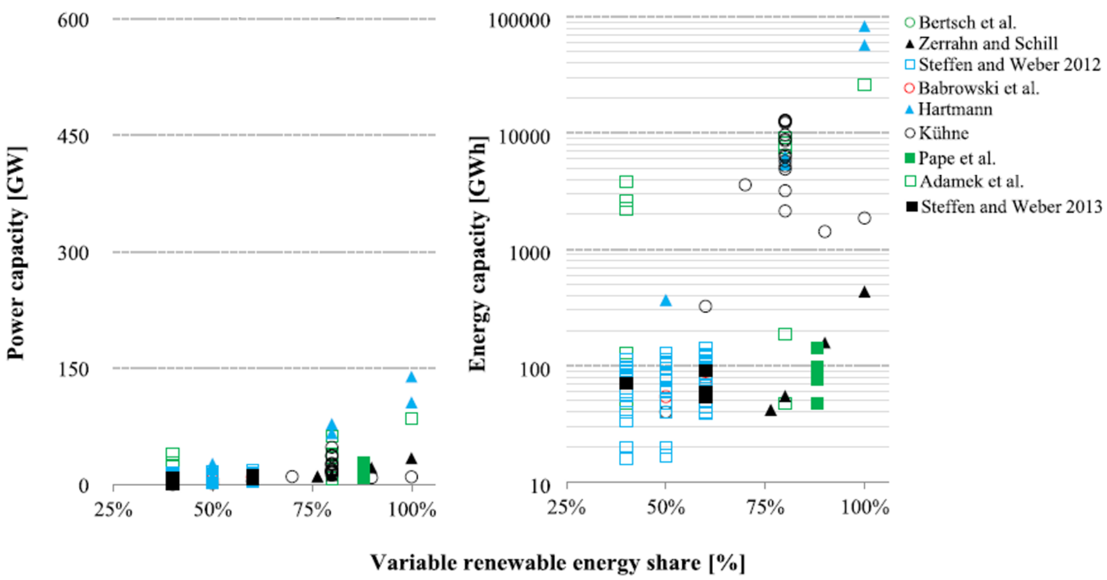

Figure 2.1.: Requirements in terms of electrical storage power capacity [GW] and energy capacity [GWh] for the German energy system by Cebulla et al. (2018)

In general, studies differ, for example, with regard to the (mostly exogenously specified) RES expansion or emission reduction targets (e.g., 80% vs. 95% reduction of CO_2 emissions), the inclusion of grid restrictions, the considered storage technologies and the underlying assumptions regarding the energy supply in 2050. For example, most earlier studies for storage requirements in Germany (e.g., Weiss and Schulz (2013); Schill (2014); Höfling et al. (2014); Agora (2014)) assume that electricity demand remains the same or even decreases until 2050 compared to 2020 due to efficiency improvements. However, recent studies on pathways to decarbonized integrated energy systems unanimously find that electrifying large parts of the energy previously provided through fossil fuels in the heat, transport and industrial sectors is needed to achieve the climate targets in a cost- and energy-efficient manner (van Nuffel et al., 2018; Bründlinger et al., 2018; Gerbert et al., 2018). Consequently, the electricity consumption of Germany is assumed to increase by between 48% and 105% until 2050, depending on the degree of electrification (Bründlinger et al., 2018).

More recent studies on storage requirements take the changing structures of electricity demand into account. For example, EuPD Research (2019) assume an increase in electricity demand of about 60% and predict a storage expansion of 59 GWh by 2040. Their calculation however refers to the economic potential rather than the technical demand for storage. Assuming a 100% renewable electricity supply, Child et al. (2019) calculate Europe-wide grid-scale BESS energy capacity requirements of 1.0 to 1.5 TWh in addition to 1.85 TWh of residential prosumer BESSs. Furthermore, 390 GWh of pumped hydro and around 200 TWh of seasonal gas storage are needed. For the same RES share, Ruhnau and Qvist (2021) calculate BESS requirements of 59 GWh for Germany, in addition to 54.8 TWh hydrogen and 1.3 TWh pumped hydro storage.

Another important factor that distinguishes modeling approaches is the differentiation of storage technologies that are considered. A common finding of previous studies is that up until 50% to 70% of RES penetration, little to no energy storage is needed. For higher RES shares, short- and medium-term storage types (several hours up to one day) are economically efficient, while long-term storage is only needed for very high RES shares close to 100% (Zerrahn and Schill, 2017). BESSs are predestined for short- and medium storage durations. By far the most frequently considered technology are LiBs, which are often the most economically advantageous option (Cebulla et al., 2018; Zerrahn and Schill, 2017). Medium-term duration BESSs, such as RFBs, have been mostly neglected in previous studies (Cebulla et al., 2018; Zerrahn and Schill, 2017). The properties of different BESS technologies and their characteristics compared to other energy storage systems are described in the following section.

All considered studies analyse storage needs in energy systems on a high aggregation level, usually on country level. Regional distribution effects are rarely considered. In one earlier study, Beier and Bretschneider (2013) divide Germany into 146 regions to draw conclusions about regional differences in terms of power balancing requirements. In a system with a 75% renewable electricity supply until 2040, Babrowski et al. (2016) use the PERSEUS-NET-ESS model to determine the spatial distribution of a total of 3.2 GW of BESS over transmission grid nodes in Germany. Neither of the two studies considers increasing electricity demand due to the integration of energy sectors. A holistic analysis of BESS requirements that considers increasing electricity demand, the spatial distribution of needed BESS capacity as well as short- and medium-term BESS technologies is currently missing in the literature.

2.2 Technologies

From a technical perspective, energy storage is a technology which allows three processes: Charging, storing and discharging of different forms of energy (Sterner and Stadler, 2017). Storage technology is typically classified based on technical characteristics, including the power and energy capacity, power and energy density, efficiency, self-discharge rate and duration of charging and discharging processes. The latter is often also referred to as C-rate and can be expressed as ratio of energy capacity to power capacity (Sterner and Stadler, 2017).

Electrical energy storage refers to storage technologies that charge electrical energy and discharge it at a later point in time. The storage process itself can take place in a different form of energy, for example in a thermal or chemical energy carrier. The electrical energy then needs to be converted to a thermal or chemical form of energy during charging and reconverted during discharging (Sterner and Stadler, 2017). The different types of electrical energy storage are depicted in Figure 2.2. BESS technologies belong to the category of electrochemical storage. From both a technical and economic perspective, they are designated to be used for short-term storage durations between 30 minutes and several hours, but usually not for much longer than one day.

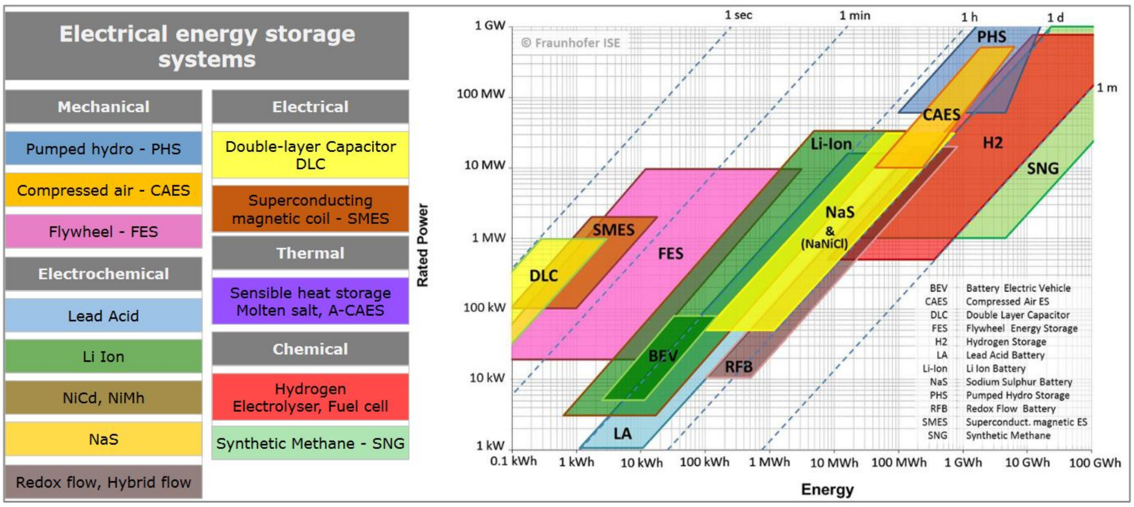

Figure 2.2.: Electrical energy storage technologies by (Shivakumar et al., 2015)

Sterner and Stadler (2017) define technologies with storage durations in between several seconds and one day as *short-term* storage and storage durations between a week and several months as *long-term* storage technologies. In this classification, BESS technologies are predominantly among the short-term storage technologies. As this thesis focuses on BESS technologies, I introduce an additional category and define storage durations in between 6 and 24 hours as *medium-term* storage. This allows a better differentiation between short-term LiBs and medium-term RFBs.

On the one hand, LiBs are well known for their versatility, powering all kinds of applications, from handheld devices and power tools to electric vehicles and stationary storage. As a result, their cost has dropped sharply since they first became commercially viable during the 1980s (Zhang et al., 2020; Nitta et al., 2015). In general, the technology has the advantage of high power density as well as higher energy density compared to other batteries. However, the cycle life of LiBs is limited and ranges from 3,000 to 10,000 cycles, depending on the application, operational strategy and storage duration (Purvins and Sumner, 2013; PowerTech Systems, 2022). A wide range of material combinations exists for LiBs, the most common being lithium nickel manganese cobalt oxide (NMC), lithium ion titanate (LTO) and lithium iron phosphate (LFP). The latter are predominantly chosen for stationary applications due to their higher cycle life (U.S. Department of Energy/National Nuclear Security Administration, 2022; Crawford et al., 2018).

On the other hand, RFBs have been gaining attention during the last years. Unlike in conventional rechargeable batteries, power and energy capacity is spatially separated in RFBs. The energy is stored in a liquid solution often referred to as "electrolyte (solution)". The liquid is pumped through a fuel-cell-like battery cell (stack), which determines the power capacity of the storage plant. This allows greater flexibility in the BESS's design, as power and energy storage capacity can be sized independently. In an RFB, the energy capacity can simply be scaled up by increasing the amount of storage liquid. In LiBs, one also has to increase the power capacity when the system is scaled up by increasing the cell count. Typically, the storage liquid of RFBs is cheap compared to the power unit, i.e., cells (stacks). That is, the BESS becomes more cost-effective for longer (i.e., medium-term) storage duration (Noack et al., 2016; Minke et al., 2017). The efficiency is however lower in RFBs, mostly due to losses from auxiliary consumers, predominantly pumps. Due to the relatively low power and energy density of flow battery systems, their use is mostly limited to stationary storage. The cycle life is higher compared to other batteries as the electrodes are typically not taking part in the charge and discharge reactions directly and the electrolyte solution is not wearing off either. 10,000 cycles and more have been demonstrated, while calendaric lifetime is often stated to reach 20 years (Noack et al., 2015; Sánchez-Díez et al., 2021). The system design is more complex compared to other BESS solutions. Because RFBs require pumps, tanks, valves and other equipment, the BESS is more like a chemical plant than a battery, making the technology more costly as of today. Nevertheless, the cost is expected to drop as more and larger systems are being deployed (Minke et al., 2017; Lüth et al., 2018). Multiple different material combinations are proposed for RFBs. The most dominant type until today is the vanadium-based flow battery (VRFB), which offers additional advantages like simplified maintenance and particularly good stability, i.e., long cycle life (Doetsch and Burfeind, 2016). In a comparison between LiBs and VRFBs for residential BESSs, Uhrig et al. (2016) argue that for the currently assumed specific costs, the scalability advantage in RFBs cannot make up for the higher power losses. For VRFBs, it is mostly power related cost that must be reduced to become competitive (Uhrig et al., 2016).

2.3 Application Areas

From a technical perspective, BESSs can bridge the temporal gap between consumption and intermittent generation from RESs as well as help in ensuring grid stability by providing backup power and blackstart capabilities (Baumgarte et al., 2019). A commercial storage operator is however primarily concerned with the economics of the BESS. In the current German regulatory framework, there are several economic areas of application which can be divided into BTM and FTM use cases as depicted in Figure 2.3. Note that this framework comprises applications that are possible under the current German regulation and is by no means exhaustive. In the future, additional applications, such as a remuneration for avoided grid investments or redispatch costs, are possible.

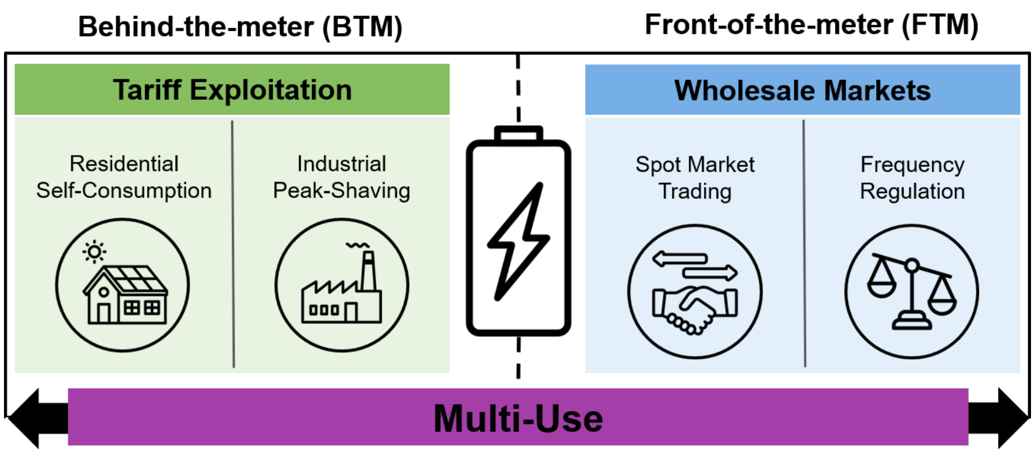

Figure 2.3.: Behind-the-meter and front-of-the-meter applications of battery storage. Own representation based on (Englberger et al., 2020)

Increasing self-consumption from PV generation. Under the current regulation in Germany, a household with a PV-coupled BESS can use its storage system to increase self-consumption from solar generation without additional charges. In doing so, the difference between the EEG feed-in-tariff and the retail household electricity price rate is exploited. It can be seen in Figure 2.4 that this is an economic option since the break-even point between feed-in-tariff and electricity retail price has been reached in 2012.

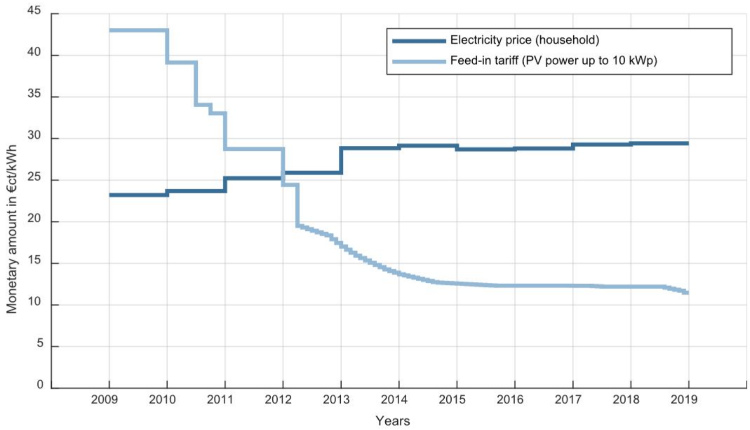

Figure 2.4.: Development of EEG feed-in-tariff and electricity price in Germany by Figgener et al. (2020)

Industrial peak-shaving. In Germany and other countries, another BTM application for BESS exists in the commercial context, due to a special tariff structure. In addition to the (flat) energy retail price that is paid for every consumed kWh of electricity, industrial consumers often pay a capacity-based “peak load price” that is determined by the maximum load that is drawn from the grid within a year (Shi et al., 2018). Since the peak load costs can constitute up to 34% of the annual electricity costs (Shi et al., 2018), industrial consumers have an incentive to reduce this peak, which can be done using a BESS. This application is referred to as “industrial peak-shaving”. Due to high investment costs of BESS in general and relatively low utilization rates if solely used for peak-shaving, it is economically reasonable to combine industrial peak-shaving with one or more other applications.

Spot market trading. On the German electricity spot markets, hourly products are traded on the day-ahead market and quarter-hourly products on the intraday market. BESS can participate in these markets and generate revenues through the exploitation of temporal price differences within one market or price differences across markets. This business model is often referred to as “arbitrage” in the literature (Baumgarte et al., 2019). However, since this is not a case of risk-free trading, and therefore not technically arbitrage, I use the term “(spot market) trading” in this thesis. In previous years, price spreads on spot markets were not sufficient to recover BESS cyclic costs, i.e., the costs that are incurred by the degradation of the BESS when completing one physical charging-discharging cycle (Perez et al., 2016). As renewable generators have marginal costs of zero, volatile RES generation is inversely correlated with the electricity spot price (Hirth, 2012). Higher levels of intermittent RES generation will therefore lead to larger price spreads on the spot markets. It must also be noted that due to the energy and gas crisis that emerged in the spring of 2022, both price level and price spreads for electricity on the spot markets have reached unprecedented levels (Bundesnetzagentur, 2021). Although an immediate alleviation of the current energy crisis and high spot market price levels cannot be expected, it is unclear how this situation will develop in the foreseeable future. This results in a situation of immense uncertainty for participants on the spot markets as well as all stakeholders along the value chain of electricity.

To illustrate current developments, mean spot market prices and maximum daily spreads of the past two years are shown in Figure 2.5. The average daily price spreads are an indicator of whether the levelized cost of energy storage (LCES), i.e, the BESS investment costs per kWh divided by the achievable cycles during its lifetime, can be recovered through spot market trading.

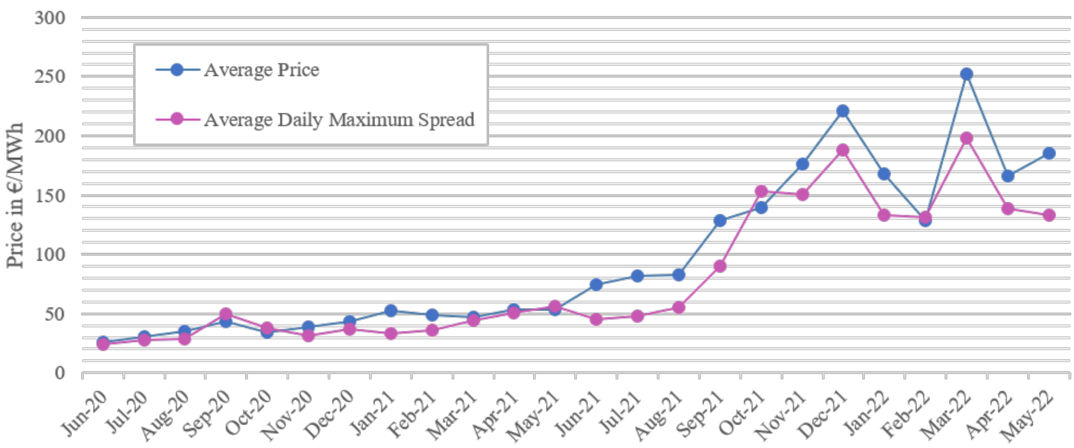

Figure 2.5.: Average price and average daily maximum price spread development on the German day-ahead market. Own representation based on data by Bundesnetzagentur (2021)

Schmidt et al. (2019) report these costs at currently 0.2 to 0.6 \$ kWh^{-1} for LiBs and expect them to drop to 0.1 \$ kWh^{-1} for both LiBs and RFBs by 2030. According to the technical parameters provided by household BESS manufacturers, costs as low as 0.15 € kWh^{-1} can already be theoretically realized today (Kloth, 2022). Taking these figures into account, price spreads on the day-ahead market were not sufficiently high for BESS spot market trading before the end of 2021. Since then however, an economic operation is perceivable, as daily spreads have been almost consistently above 0.15 € kWh^{-1}.

Frequency regulation. As part of the ancillary services, frequency control is needed to stabilize the grid. In the event of deviations from the grid frequency of 50 Hertz, FCR is activated within seconds, which is followed by the activation of automatic Frequency Restoration Reserve after 5 minutes and manual Frequency Restoration Reserve after 15 minutes. In this thesis, I focus on the provision of FCR. BESS are especially well suited to provide FCR as they have fast response times and power is only provided for a short duration (Zhang et al., 2016). In Germany and most other EU countries, FCR is tendered using an auction mechanism the day before its delivery, which means that bids have to be placed one day in advance (Thien et al., 2017; Bundesnetzagentur, 2020b). Between August 2019 and July 2020, FCR was tendered in a daily bidding block, whereas it was tendered in weekly blocks before (50 Hertz et al., 2022). Since August 2020, each day is divided into six 4-hour bidding blocks and individual prices are determined for each of these blocks (50 Hertz et al., 2020a). FCR is tendered symmetrically and must then be available over the entire period of a bidding block. The FCR auction is cleared with a uniform price.

In order to participate in frequency regulation, operators must fulfill several technical and bureaucratic requirements listed in the so-called "prequalification criteria" (50 Hertz et al., 2020b). Among them is a minimum bidding power capacity of 1 MW which is more than a residential or community BESS can provide. However, several smaller BESS can be connected into a virtual power plant and jointly provide ancillary services. This concept has already been successfully implemented by the German BESS manufacturer sonnenGmbH who participates in the FCR auction with a network of residential BESS (Tietze et al., 2019). In this thesis, I therefore assume that smaller BESS can participate in the ancillary services auctions under the current regulatory framework.

2.4 Multi-Use BESS Deployment

A simultaneous use of BESS capacity for several of the above introduced applications can be desirable from both a technical and economic perspective (Baumgarte et al., 2019). Since some applications are more energy-intensive (e.g., self-consumption and spot market trading) and others are more power-intensive (e.g., FCR provision), a combination of applications can effectively utilize both the power and energy capacity of BESSs, while a single use case may result in an underutilization of existing resources. In the case of residential BESSs, for example, during a typical sunny day, the storage is charged while the sun is shining and discharged in the evening. During these times, as well as on cloudy days, idle storage capacity could be used, for example, to provide ancillary services or trade on the wholesale markets to increase the BESSs' utilization and profitability. The combination of BTM with FTM applications however poses some technical and regulatory hurdles. For example, spot market trading is theoretically possible (even though not economically feasible under current regulation, as taxes and levies have to be paid) for residential BESSs, but the traded electricity should not be confused with stored PV generation (Englberger et al., 2020). Since different levies and taxes apply, the energy quantities of these two applications have to be strictly separated. Another challenge is the operation of a multi-use BESSs, as each of the introduced applications contains uncertainties. For example, the prices on the spot market, the quantities of RES generation and household and industrial loads are not precisely known to the storage operator in advance.

To gain an overview of the existing literature on multi-use BESS deployment as well as the state-of-the-art regarding operational strategies, I provide a structured literature review in the following. An initial paper pool of 37 papers is selected by subject matter experts as a starting point to construct a search string that would retrieve this paper pool (see Appendix 1.1). Scopus and IEEE Library are selected as search databases, which in combination contain 32 out of the 37 papers in the initial pool. In total, 223 papers were found in the databases[1]. All results were then manually filtered by reading the abstract to verify that they fit the scope of the literature review. Only studies handling BESSs are considered (e.g., removing

[1]The search was conducted in June 2021

papers that investigate thermal storage). Studies on BESSs from electric vehicles are removed as well as studies that do not actually consider more than one of the application areas defined in Figure 2.3. Two tasks within one area (e.g., intraday and day-ahead trading, which are both classified as trading) are not considered multi-use. After manual filtering, as well as adding those studies from the initial paper pool which are not found through the search string, 94 papers remain in the final paper pool to be analysed.

All remaining papers are categorized along four dimensions: BESS size (i.e., residential, community, industrial or grid-scale), connected RESs (i.e., wind, PV and hydropower), application area and method. The dimension application area includes the four categories from Figure 2.3 (increasing self-consumption, industrial peak-shaving, spot market trading and providing ancillary services) in addition to "balancing". This application refers to the balancing of demand and supply within a network section of the distribution or transmission grid, e.g., through load leveling or peak-shaving. This application area is often considered in the literature, for example, when the operation of the BESS is planned from the perspective of a distribution network operator. There is however no explicit revenue model for this application, as grid operation is a regulated market area. Therefore, it is not included in the four application areas for BESS revenue generation under the current German regulation. The dimension method refers to the type of algorithm that is deployed for the BESS operation in the case study of the considered papers. It includes "optimization", "simulation", "reinforcement learning", "game theory" and "conceptual". The latter is chosen, for example, when the paper merely describes an auction-mechanism for the sharing of physical storage rights instead of designing an actual operation strategy. "Simulation" refers to all algorithms that do not belong in any of the other categories, e.g., when a rule-based heuristic is proposed. A table containing all analysed papers and their categorizations can be found in Appendix 1.1.

The results of the categorization are shown in Figure 2.6. Grid-scale BESSs are amongst the most researched BESS types. More often than not, the BESSs are connected to an RES, mostly a PV system. Optimization is by far the most frequently used operation strategy method, followed by (and often in combination with) other types of simulations. Only one paper designs a reinforcement learning-based algorithm (Huang and Wang, 2021).

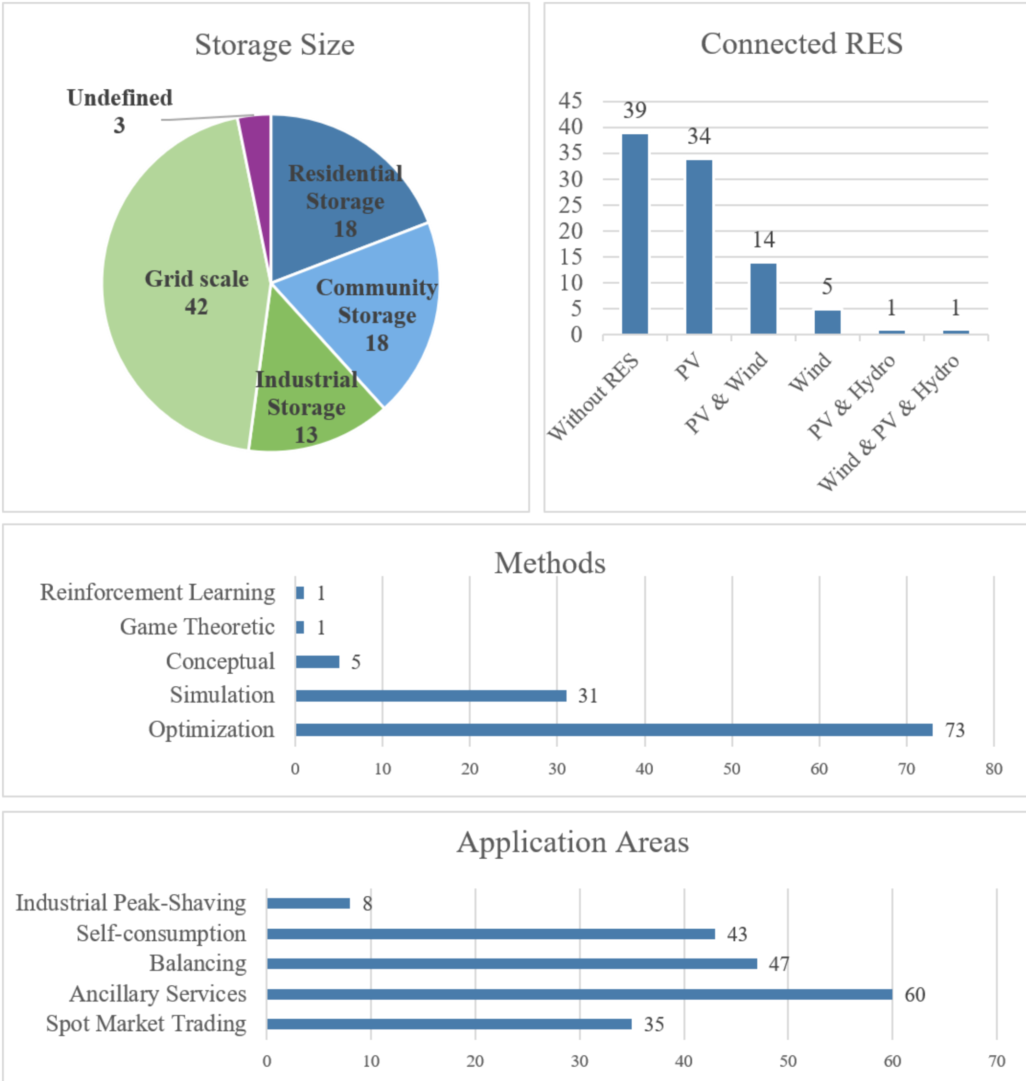

Figure 2.6.: Literature Review descriptive results showing the number of papers found in each (sub-)category

The provision of ancillary services, in particular FCR, is the most frequent application area, followed by balancing and increasing self-consumption. Since the focus of the literature review is on multi-use BESS deployment, the combination of application areas is of particular interest. Here, each storage size category is considered individually, as the location within the power system influences the requirements and goals of BESS deployment. In the category of grid-scale BESSs, the most frequent combination of application areas is spot market trading and ancillary services (e.g., Bera et al. (2019); Cheng and Powell (2016); Kazemi et al. (2017)). This is to be expected since grid-scale BESSs are located in front of the meter and large enough to fulfill the prequalification criteria of wholesale markets. In most papers, community BESSs are deployed for self-consumption in combination with balancing (e.g., A. Zeh et al. (2015); Arghandeh et al. (2014); Homan et al. (2021)). Here, case studies are often constructed from the point of view of a distribution system operator who needs to prevent congestion in network sections. BESSs in industrial plants are most frequently deployed for ancillary services, either in combination with spot market trading or industrial peak-shaving (e.g., Braeuer et al. (2019); Shi et al. (2018); Engels et al. (2020a)). Almost all case studies on residential BESSs include PV as RES and have the goal of increasing self-consumption of residential prosumers (e.g., Hernández et al. (2021); Tant et al. (2013); Engels et al. (2019)). This is frequently done together with the provision of ancillary services, a combination of application areas that is already deployed in practice by sonnen GmbH using a virtual power plant consisting of many residential BESSs (Tietze et al., 2019).

Overall, the literature review reveals the multi-faceted landscape of multi-use BESS deployment and operation strategies, ranging from very technical considerations with high time resolutions in the range of seconds (e.g., Shi et al. (2018) and Cheng and Powell (2016)) to rather economic analyses with a time resolution of 15 minutes to 1 hour (e.g., Braeuer et al. (2019) and Engels et al. (2019)). The comparability between studies is generally quite low, as, for example, the reimbursement of application areas differ depending on a country's energy market design. Moreover, operation strategies are often very specifically designed to the needs of a certain use case, e.g., by considering particular network sections or community configurations in the distribution grid. It is however fairly clear that optimization is the state-of-the-art approach to design operation strategies for multi-use BESS deployment. Only one recent publication proposes DRL for this task (Huang and Wang, 2021). Oftentimes, dynamic and stochastic optimization approaches are deployed to handle uncertainties during operation. These approaches are quite time- and resource-intensive, which poses limitations on real-time operation. Random variables have to be explicitly modeled, which limits these algorithms to specific use cases and price structures and prevents a generalization to other use cases. From the literature review, the need for online operational strategies that can be deployed in real-time applications becomes evident.

In practice, for an ideal BESS deployment in energy systems, decentral BESS resources need to be allocated efficiently and given access to local applications as well as wholesale markets. Multi-use BESS deployment could therefore be realized through a StaaS platform, a concept which is explained in Section 2.6.

2.5 Regulation

In Germany, the Energy Industry Act (EnWG) and the EEG are the two fundamental bodies of law that are concerned with the deployment of BESSs and all surrounding activities such as the feed-in of generation from RESs. The EnWG defines generation, consumption and transport of energy as the three pillars of the German electricity system (Deutscher Bundestag, 2005). As of June 2022, storage has been added to the EnWG as an asset where "the final use of electrical energy is postponed to a later point in time than when it was generated" (Murray, 2022). This ends the unclear regulatory classification of storage systems, which previously had been classified as both generators and end-consumers. This newly implemented regulatory change is expected to provide more clarity and transparency for stakeholders (Reiner Lemoine Stiftung, 2021).

In practice, regulatory barriers are among the main challenges for the expansion of (battery) storage, hindering some possible use cases and especially complicating multi-use deployment. During an expert interview on storage regulation, one expert calls Germany the "country of bureaucratic hurdles" and laments the (seemingly) "thousands of different permits" that are needed for the realization of a BESS project on the scale of the Grid Booster in Kupferzell. This was confirmed by a survey among experts in the course of the "Battery Storage Forum" by the German Energy Storage Systems Association (BVES) (Tepe et al., 2021). A total of 50 experts were asked to distribute 100 percentage points among the regulatory barriers addressed in Figure 2.7. Specific regulatory disincentives include the double burdening with levies and charges of some use cases and the loss of subsidies from the "Renewable Energy Act" (EEG) if business models are combined. The most prominent issues are however of structural nature due to high bureaucratic barriers for measurement and billing concepts and the general lack of legal and investment security. Multi-use applications are further complicated by the technical challenge to account for FTM and BTM applications separately, as different levies and charges may apply to the respective applications (Englberger et al., 2020).

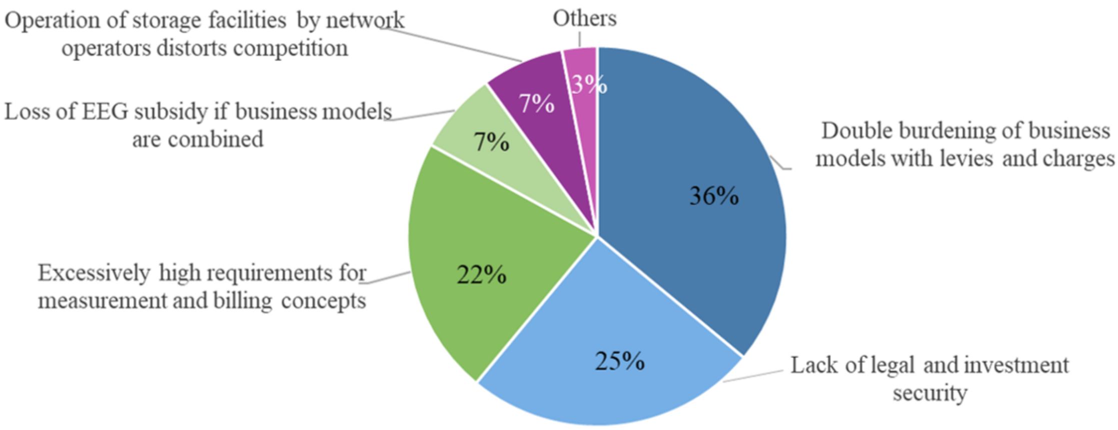

Figure 2.7.: Main regulatory barriers for stationary battery storage in Germany according to the BVES (Tepe et al., 2021)

Currently, some changes in the regulatory framework are underway. In an amendment to the EEG, the German parliament decided in 2021 that both large-scale and residential BESSs may pursue several use cases in parallel and may actively participate in wholesale markets. The suggestions also puts an almost complete end to the double burdening of storage capacity with levies and charges (BVES, 2021). Furthermore, in 2021, the newly elected German government included several planned changes in its coalition agreement for the 2021 to 2025 legislative period. In an evaluation of the proposed changes by the Reiner Lemoine Institute, the "clear commitment to the ambitious expansion of various storage technologies" is praised (Reiner Lemoine Stiftung, 2021, p. 11). However, it is also criticized that solutions are not yet specific enough and are limited to certain storage technologies. Another issue that remains is the sheer complexity and intransparency of the regulatory framework for BESSs, which especially hinders non-commercial BESS owners from participating in multi-use storage deployment.

In the following, I present the results of nine expert interviews on regulation that would support storage expansion, which were conducted to identify barriers and derive suggestions for an improved regulatory framework. All interviews except one

(Expert 9)[2] are structured along a predefined list of questions (see Appendix 1.2 for questionnaire). In order to capture diverse perspectives, a broad spectrum of stakeholders in the energy industry is covered with the interviews.

- Expert 1: Transmission Network Operator
- Expert 2: Distribution Network Operator
- Expert 3: Federal Agency
- Expert 4: Medium-Sized Utility
- Expert 5: Research Associate in the Field of Energy Economics
- Expert 6: RES Interest Group (*Förderverband*)
- Expert 7: BESS Interest Group (*Förderverband*)
- Expert 8: Battery Manufacturer
- Expert 9: Attorney for Energy Law

One expert calls a separate and explicit definition of storage as fourth pillar of the electricity system the "foundation" on which "an appropriate regulation [can be] built" since it introduces the element of temporal shifting of power consumption into regulation. In addition, current regulation does not clearly define the role of storage operators and aggregators. From an aggregator's perspective, another expert further calls for the implementation of the principle of "mutual recognition" (*Gegenseitige Anerkennung*). This means that if the BESS deployment is approved by one distribution system operator, this also automatically applies to all other distribution system operators in Germany. According to the expert, this would facilitate market access for BESSs enormously.

Figure 2.8 shows that the costs for electricity generation only constitute about one quarter of the final electricity price for households in Germany. Another quarter stems from network charges and the remaining 50% are different taxes,

[2] For this interview, the available time frame was too short to follow the entire questionnaire. It was therefore conducted unstructured along the general guideline of interview questions, but some questions remained unanswered due to the time constraints.

levies and fees.[3]. This illustrates the economic limitations for storage operators and aggregators caused by the (double) burdening with some of these components. The removal of the double burden of taxes and levies, which 7 out of the 9 interviewed experts support, is therefore needed to set the groundwork for a leveled economic playing field for BESS participating in power markets. In addition, 6 out of 9 experts are in favor of a removal of the EEG-levy and network charges for BESSs that engage in trading on the spot markets.

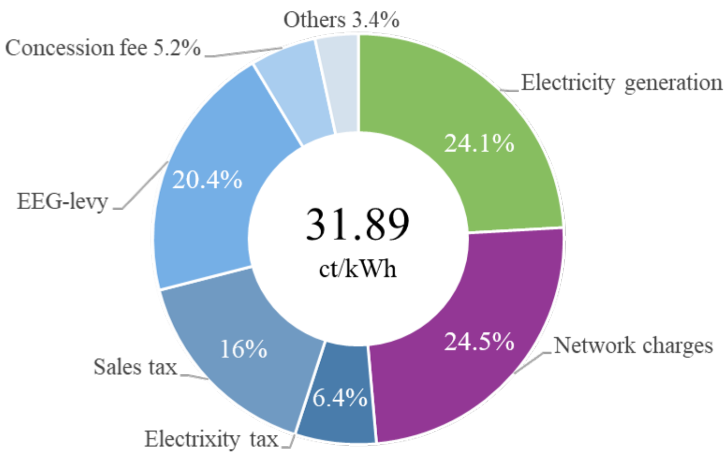

Figure 2.8.: Electricity price components for household customers in Germany in 2021. Own representation based on (BDEW, 2021)

Multi-use BESS deployment could be facilitated by transparent and low-threshold guidelines for the measurement and billing of parallel revenues streams, as previously highlighted by the other expert panel interviewed by the BVES illustrated in Figure 2.7 (Tepe et al., 2021). In addition, experts 2, 7 and 8 plead for a "guarantee of origin" for green electricity (generated by a renewable source) so that it does not become "grey" (i.e., indivisible from conventionally generated electricity) when it comes into contact with the grid and is then stored in a BESS.

In the future, experts 1 and 6 also see great potential for storage facilities to become active in the event of network congestion, thus saving redispatch costs. Here, but also in the case of other applications such as the storage of local PV

[3]It should be noted that the EEG-levy has been removed as of July 1st, 2022 (Bundesregierung, 2022). At the same time, the costs of electricity generation are expected to increase, which may overall increase the price paid by households (BDEW, 2022).

generation, the geographical component plays an important role, i.e., the physical location of the providing BESS. In this case, the regulatory framework would have to specify the spatial situation in the electricity grid between BESSs and RES power plants in order to still be exempt from levies. Currently, increasing self-consumption is only freed from surcharges as long as the PV-coupled BESS is deployed behind the meter. As soon as the electricity is fed into the public grid, i.e., even in a local energy community or in a multi-apartment building, surcharges apply.

Appendix 1.3 contains a list of concrete recommendations for actions on regulatory changes to facilitate storage expansion, which was derived from the conducted expert interviews. Each recommendation is complemented with a legal assessment regarding (i) the compatibility with higher-ranking law (i.e., European law) and (ii) of the complexity (in terms of legal barriers) of implementing the recommendation within the German regulatory framework. An overhaul of regulatory aspects can be the foundation for innovative storage deployment. Such an innovative concept for the pooling and allocation of BESS capacity on all levels of energy systems is presented in the following section.

2.6 Storage as a Service

In order for existing BESS capacity to be used effectively and to stimulate investment in new capacity, it would be helpful if BESSs of all sizes had access to different markets and applications. The current regulatory particularities and prequalification criteria for applications pose a significant barrier especially for individual BESS owners. The capacities of many small residential and community BESSs could otherwise be pooled together through a central platform, possibly with the help of aggregators. In this section, I describe this idea as a hypothetical StaaS platform that coordinates the provision of BESS capacity as a service product for various applications. The StaaS concept is illustrated in Figure 2.9. Participants include (local) residential and industrial consumers who are interested in accessing stored electricity to supply their loads or to shave their peak loads, for example. In order to do so, the consumers can submit service requests on the platform. Other service requests could come from renewable plant operators who want to store excess electricity or network operators who want to prevent grid congestion.

Storage operators on the other hand receive these requests through the platform and can decide to accept or reject them. They can also offer their energy and power capacity on wholesale markets through the platform. Both consumers and storage owners can be pooled together by aggregators in order to facilitate the participation on the platform for all end-users.

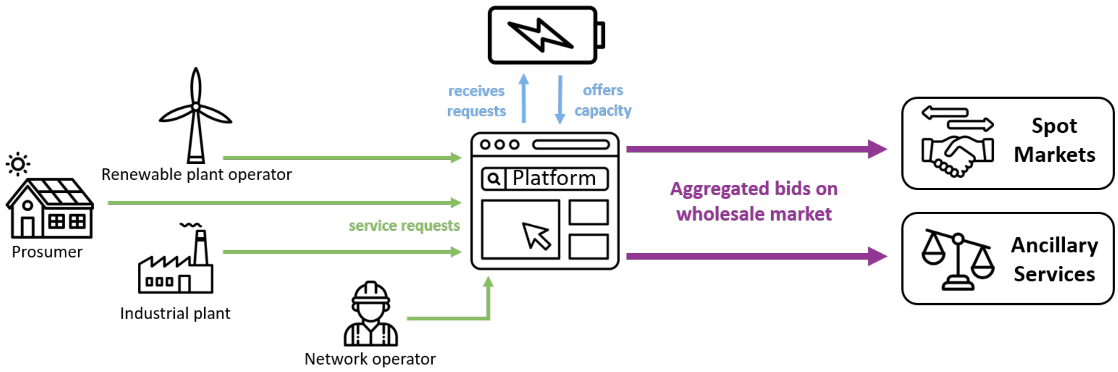

Figure 2.9.: StaaS platform concept

Within the StaaS platform, a distinction can be made between direct and indirect markets. Storage operators can indicate available energy and power capacity in combination with a minimum price for their service provision. On the *indirect* markets, customers submit bids for charging or discharging services to the platform. The storage operator then receives requests for suitable offers (e.g., for storing excess generation or serving local household load if the offer is above the price minimum) and can accept or reject the requests. On the *direct* markets, available storage capacity is automatically pooled together by the platform provider and offered directly on the spot market and frequency regulation auctions. Therefore, no further action on the part of the storage operators is necessary on the direct markets. On the indirect markets, storage operators must actively respond to the service requests, which they receive.

The task of the storage operator is therefore to coordinate the available power and energy capacity on direct and indirect markets in parallel. The main challenge that arises here is the time lag in the decision-making process. For example, the auction for FCR takes place at 8 am day-ahead and therefore up to 36 hours before the actual delivery. If the operator wants to offer power capacity on this auction, she has to decide how much she wants to withhold for other requests that may arise during this time. A similar decision has to be made when participating on the day-ahead auction at 12 pm and the intraday auction at 3 pm. This highlights the complexity of operating a multi-use storage. Commercial aggregators could therefore offer their services to handle this task for residential prosumers with BESSs. Such aggregators can then specialize in the development of accurate forecasts and intelligent operational algorithms that maximize the obtainable revenues from multi-use storage deployment. In Chapter 8 of this thesis, I introduce, design and evaluate a DRL-based agent to provide a solution for this challenge.

In the following, I describe the concept of the StaaS platform along the Market Engineering framework by Weinhardt and Gimpel (2006), consisting of five main components: The economic and legal environment, transaction object, market structure (consisting of the micro structure, IT infrastructure and business structure), agent behavior and market outcome. The components are illustrated in Figure 2.10 and individually described in detail in the following sections.

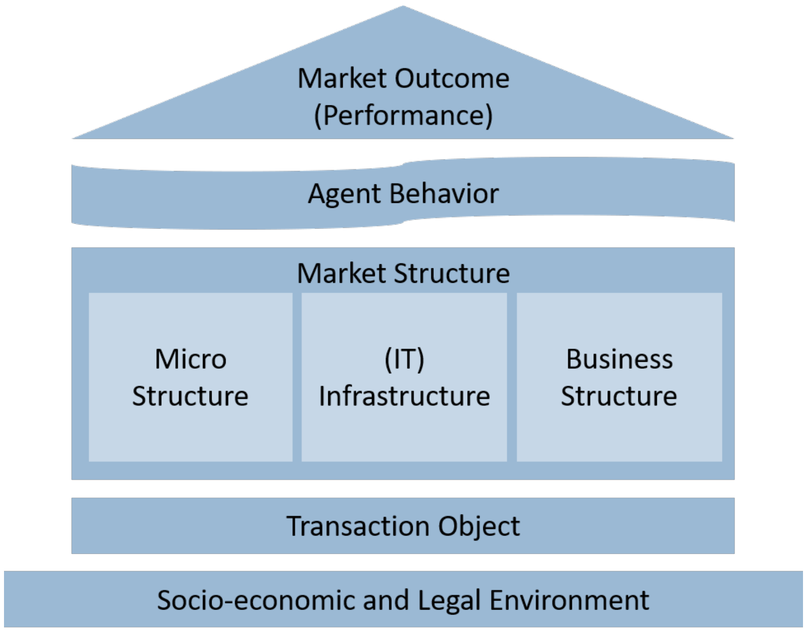

Figure 2.10.: House of Market Engineering by Weinhardt and Gimpel (2006)

2.6.1 Socio-economic and Legal Environment

The socio-economic and legal environment refers to the pre-defined environment that affects the market outcomes, but cannot be directly influenced by the platform participants (Weinhardt and Gimpel, 2006). In the case of the StaaS platform, this particularly concerns the regulation regarding the (multi-use) operation of storage. Within the current regulatory framework, some economic applications for BESSs are not profitable due to taxes and levies. In addition, multi-use deployment and sharing of BESS capacities (e.g., through a platform) are not explicitly supported or uneconomic due to regulatory restrictions. A number of regulatory adjustments, as outlined in the previous section on regulation and in Appendix 1.3, are therefore needed to enable the proposed StaaS platform concept and to facilitate the innovative and effective deployment of BESS as service providers.

In general, the facilitation of multi-use storage deployment is needed to allow operators to offer idle capacity as service products on a StaaS platform. Furthermore, the roles of storage operators or aggregators of storage capacity must be clearly defined. New services, e.g., providing local flexibility in the case of network congestion could also be integrated into a StaaS platform, provided the legal framework allows it (e.g., by specifying exemptions from taxes and levies depending on the spatial situation of the BESS within the power grid).

In order for surplus PV generation to be offered via a StaaS platform, regulation would also have to allow more degrees of freedom in the respect of privileged self-consumption. For example, it could be specified that within a neighborhood or network section in the distribution network, no network charges per kWh apply. This would also facilitate the deployment of BESSs to reduce of local network congestion. In Chapter 4, I show how the sharing of PV surplus generation and BESS capacity in a local energy community can contribute to a significantly higher utilization of storage assets if electricity sharing is exempt from taxes and levies within a residential community.

In the following, I describe the remaining components of the Market Engineering framework under the assumption that an appropriate regulatory framework is in place that enables the described StaaS platform.

2.6.2 Transaction Object

The transaction object describes the good that is traded on the market. In the case of the StaaS platform, this can be electricity which is either sold to or bought from the storage provider as well as storage power capacity (e.g., when submitting bids on the FCR auction). In general, it should be specified over which time duration the electricity has to be delivered or stored, i.e., at which power rate. Customers of storage capacity, e.g., prosumers or industrial plants, therefore have to submit service requests for charging or discharging services. These requests should be entered in standardized form, containing the following relevant information, which all belong to the transaction object:

- charging or discharging request (binary)
- amount to be charged or dicharged in [kWh]
- starting time of charging or discharging process
- storage duration in [h]
- minimum quantity in [kWh]
- use case label (e.g., “peak-shaving” or “self-consumption”)
- geographic information (if applicable)

On the StaaS platform, both customers and suppliers of storage services have to indicate their service requests or availabilities to participate in the trading of (stored) electricity or storage power capacity. Storage operators (or aggregators of storage capacities) should be able to enter available energy and power capacity for any time slot they wish. Similarly to stock trading, storage operators could indicate threshold prices, for which they are willing to buy or sell electricity. Once a request is below this threshold, it could be automatically matched with the available storage capacity. The platform provider could also act as aggregator and pool remaining energy and power capacity and place bids on wholesale markets, provided the realized prices are within the limits of the indicated threshold prices.

In the case of an industrial consumer who wants to use a BESS's capacity for peak-shaving, an exemplary request could therefore be to *discharge* an amount of 20 kWh starting at 11 am of the following day. Since peak load is measured and billed in 15 minute intervals, the consumer might request that the total amount of energy is delivered over the duration of a quarter hour. The consumer might not be willing to purchase any less than 20 kWh (i.e., minimum quantity = 20 kWh), since she would then have to pay higher peak charges anyway. The use case label "peak-shaving" should be included in the request because different levies or technical criteria might apply to different applications. Lastly, for some use cases, the geographical location of the consumer is important for regulatory or technical reasons, e.g., if self-consumption within citizen energy communities is exempt from taxes and levies or if the use case is congestion management. In Chapter 8, I describe the design and implementation of a storage service agent that receives service requests for various BTM and FTM applications, similarly to what is described in this section.

On the StaaS platform, service requests can be matched with suitable capacity offers. Storage providers who are eligible for certain requests (e.g., in the case of household load, the storage system might have to be located within the same distribution network section) will then receive a service request which they can accept or reject.

2.6.3 Micro Structure

The micro structure refers to the market mechanism that is responsible for resource allocation and pricing in the market. On the indirect markets, different pricing and coordination mechanisms for the transaction object are conceivable depending on the application. For example, fixed tariffs could be implemented for the sharing of locally generated PV generation through a community storage in a residential neighborhood, as suggested in Chapter 4. In this case, long-term contracts could be established between household prosumers, consumers and BESS owners, minimizing the associated risk and overhead costs of the involved parties. A fixed tariff further ensures a transparent allocation of cost savings that is easy to understand even for non-experts, which can be advantageous due to the generally low energy literacy amongst residential households. However, if commercial aggregators take over the responsibility for bidding, more complex bidding mechanisms are also conceivable. In this case, the service requests described in the last section are submitted frequently by the storage operators or aggregators and different matching mechanisms are possible. In this regard, the StaaS platform can be seen as an auction platform without periodic market clearing, where buyers and sellers can be matched continuously, similarly to the (continuous) Intraday market.

2.6.4 (IT) Infrastructure

Several hardware and software components are needed to enable the described StaaS platform and the associated business models for BESS operators. First, the platform itself is a software component that needs to be implemented and managed by a platform provider. Participants need to be able to enter their requests or availabilities, which then have to be matched by an algorithm so that, for example, a storage service provider only receives service requests for applications that are within her price thresholds or applicable in terms of location in the power grid. Another algorithm is needed for the pooling of remaining power and energy capacity which can be offered as aggregated bid on wholesale markets.

BESSs who participate on the platform have to manage several (economic) applications in parallel. Commercial BESSs are usually equipped with a BESS management system, which ensures compliance with physical restrictions of the BESS during operation (Sterner and Stadler, 2017). In case of a multi-use deployment, these systems are particularly challenged to ensure an optimal control and to prevent premature aging of the battery cells. The BESSs also need to be equipped with infrastructure that enables the separate measurement of different applications. In particular, a distinction needs to be made between BTM and FTM applications. Since electricity is a homogeneous good, the German Storage Association suggests a “2-meter-approach” that allows the separate measurement and billing of BTM and FTM applications (BVES, 2021). This would require the installation of two smart meters which poses a challenge amidst the already slowly advancing smart meter rollout. An alternative technical solution approach that has been suggested is the accounting of separate applications through a blockchain, which has the advantage that manipulations are not possible (Richard et al., 2019). In addition, guarantees of origin for the various applications could be issued via tokens. This concept is however not very well tested and accompanied by significant regulatory requirements to ensure compliant billing processes. Another drawback that is pointed out by expert 6 in our interviews is the computational effort required to operate the blockchain.

2.6.5 Business Structure

The business structure refers to the business model of the market operator, which in the case of the StaaS platform is the platform provider. It includes the pricing model as well as transaction costs. Several pricing models are conceivable in the case of the StaaS platform. In the case of flexibility markets in distribution grids, one-time sale, subscription and shared revenue models have been suggested or implemented (Dauer et al., 2017). On the StaaS platform, the provider can for example charge a service fee as a share of the profits or in the form of a fixed service fee per trade or traded kWh of storage service.

On the other hand, the business model of the platform participants is also relevant to ensure a high market liquidity. From the storage operator's or aggregator's perspective, any economic application for BESS has to cover the LCES, i.e., the costs for storing a kWh of energy which are determined by the investment costs for the BESS and the total number of cycles per lifetime. Estimates for these cyclic costs vary substantially in the literature. For lithium-based BESSs, they currently range between 0.16 and 0.6 $ kWh^{-1} but are expected to drop to as low as 0.1 $ kWh^{-1} by 2030 for both LiBs and VRFBs (Schmidt et al., 2019; Kloth, 2022). Storage capacity from residential or community BESS should therefore recover at least these costs plus a service margin or revenue share when offered through the StaaS platform. Furthermore, efficiency losses occur during charging and discharging. These losses must be taken into account in the economic evaluation of the BESS service provider.

2.6.6 Agent Behavior

The agent behavior is a critical component of the market engineering framework, as it is difficult to predict but significantly affects the final market outcome. The bidding behavior of participants who submit service requests through the platform, as well as the behavior of the BESS agents who respond to these requests, i.e., storage operators, are of particular interest on the StaaS platform.

Service requests for charging or discharging can come from a number of different stakeholders as seen in Figure 2.9. Residential prosumers may want to sell their excess PV generation to a BESS and buy stored electricity to supply their loads. Industrial consumers could request stored electricity to shave their load peaks. Operators of (larger) renewable plants could also store their generation in the storage, for example, at times when spot market prices are low, in case they have to directly market their generation. In the future, (distribution) network operators could also request storage services in case of network congestion. However, under the current regulation in Germany there is no suitable reimbursement model for this service.

Storage operators on the StaaS platform will face the challenge to decide whether to accept service requests without knowledge on future requests that may be more profitable. Their performance will therefore highly depend on their ability to forecast demand for storage services and thus on the availability of algorithms that can process a lot of information and react quickly in real-time. As suggested before, for small, non-commercial storage owners, such as residential prosumers, it might make sense to leave the decision-making on the StaaS platform to a commercial aggregator. One interesting question raised by expert 6 in our interviews is who could take on the role of these aggregators. He suggests that regional cooperatives ("Genossenschaften") should operate community BESS and also serve as aggregators for distributed BESS within local energy neighborhoods. This would ensure that the created value remains local and that profits could be invested in additional local infrastructure.

The potential behavior of both a service request agent as well as a storage operator are partially investigated in this thesis through case studies. In Chapter 6, I determine a renewable generator's bidding strategy who wants to hedge her generation revenues against price and quantity risks on the spot markets. What remains unclear is whether there are enough suppliers of BESS capacity on the counter side to meet these requests. In a first effort to illustrate the possible behavior of BESS operators, I model a BESS service agent in Chapter 8. Using a DRL algorithm, the BESS agent's decisions between several BTM and FTM service requests during real time operation are demonstrated and evaluated.

2.6.7 Market Outcome

The market outcome describes the result of the designed market structure, which operates within a certain socio-economic and legal environment and is influenced by the behavior of the participating agents. The explicit goal of the market engineer is to design the market structure in such a way that a desirable market outcome is achieved (Weinhardt et al., 2003). As the described StaaS platform does not yet exist, it can be discussed which criteria could be used to measure the quality of the outcome. In the case of markets in the distribution grid, Dauer et al. (2017) name market efficiency as well as incentives that prevent a market failure as crucial outcomes. In addition, consumer data should be protected as the suggested interactions potentially may reveal sensitive data. Market efficiency and competitiveness in general can be compared using the number of market participants, degree of market concentration and the rate of transactions. In this regard, the decentralized nature of renewable generation and BESS might work in favor of a high market efficiency of the described StaaS platform. As of June 2022, around 2.4 million PV plants and more than 400,000 BESS have been installed in Germany, the majority of which belongs to private owners (Bundesnetzagentur, 2022; BMWK, 2021). The 8 million PV-coupled BESSs that are required according to Weniger et al. (2018) would result in a large number of potential participants and a low market concentration. This would further increase the competition and market liquidity of the StaaS platform. The widespread use of aggregators would weaken these indicators, but a certain competitiveness among aggregators could still be expected. In this regard, the regulatory framework is important, in which the role and operating environment of aggregators would need to be defined, as described in section 2.6.1. To further increase market competitiveness, end-users (e.g., residential BESS owners) should be able to switch their aggregator without much effort. From an aggregator's perspective, an important market outcome is the efficient control of her pool of small BESSs. Since the StaaS platform operates within and affects a critical infrastructure, i.e., the electricity grid, incentives on the platform should be in line with the security of supply and grid stability (Dauer et al., 2017). One main market outcome for both aggregators and platform provider is therefore the allocation of service requests in such a way that prevents a market failure.

In general, it is advisable to test the influence of the market structure on the outcomes in advance, e.g., through simulations or experiments (Weinhardt et al., 2003). For the StaaS platform, this could be done through agent-based simulations supported by various learning algorithms. Individual aspects of agent behavior, e.g., bidding behavior, can also be tested and validated in laboratory experiments.

2.7 Summary

In summary, it becomes evident that BESSs are vital for future integrated energy systems and need to be deployed on all aggregation levels of power systems. On the lower aggregation levels, individual homeowners have contributed significantly to BESS expansion in the past and hold the potential to further contribute to closing the gap between currently installed capacity and the requirements in low-carbon integrated energy systems. Although many studies have already examined BESS requirements, the impact of increasing electricity demand in integrated power systems has not always been taken into account. In addition, most studies take the role of a central planner without considering the lower aggregation levels of a system. This gap in previous research is addressed in Part II of this thesis, where a holistic view of BESS deployment across all aggregation levels is presented.

In addition to the planning of optimal BESS deployment, operation strategies must also be designed so that the installed BESSs can be deployed effectively. Depending on the level of the power system that the BESS is deployed on, feasible application areas and operator goals may differ. Multi-use BESS deployment is promising since higher profits can be generated for operators and BESSs are deployed more effectively in power systems by increasing their utilization rate. In this regard, a StaaS platform could facilitate multi-use deployment of BESS resources for all end-users. Since multiple uncertainties have to be addressed, storage operators need online operational strategies that can be deployed in real-time scenarios. This will be addressed in Part III of this thesis through the implementation and evaluation of data-driven, online operation strategies for different stakeholders on different levels of power systems.

Part II.

Deployment in Integrated Energy Systems

INTRODUCTION TO PART II

As outlined in Part I, when planning the deployment of BESSs in low-carbon integrated energy systems, all aggregation levels of power systems have to be considered. On the lowest level, individual decision-makers, such as homeowners and office managers, are key players in the decarbonization of the building sector and therefore need to be informed about sustainable technology alternatives and efficiency measures. On the second level, prosumers and consumers can increase the utilization and profitability of local RES generation and BESS capacity in energy communities, a concept which is currently still hindered by regulatory barriers (Section 2.5). The adjustment of regulatory barriers depends on the objectives of decision-makers regarding pathways towards low-carbon energy systems and the corresponding BESS requirements. These requirements are usually determined on the system level using a central perspective, which disregards lower aggregation levels of a system and questions of public acceptance (Section 2.1).

In Part II, BESS deployment is analysed across these different levels. In Chapter 3, I evaluate how an informative website with vivid and interactive features can contribute to increase (non-expert) individuals' energy literacy. In Chapter 4, I investigate an energy community that engages in the sharing of local PV generation and BESS capacity. In Chapter 5, I introduce a bottom-up system modeling methodology that allows the comparison of central and decentral planning approaches.

CHAPTER 3

INCREASING ENERGY LITERACY IN THE BUILDING SECTOR

On all levels of power systems, the installation of BESSs should not be considered in isolation, but in conjunction with other technologies, such as decentral RESs or flexible consumers. On the individual level, low energy literacy prevents homeowners and office building managers to assess the installation and interplay of sustainable technology alternatives. In order to make an informed decision, individual decision-makers therefore need to be provided with transparent information on energy-related technologies and efficiency measures. In this chapter, an experiment is designed to evaluate the ability of a website with interactive and vivid features to convey information on BESSs and other energy-related technologies in buildings in an engaging way. The aim of the website is to increase the users' enjoyment and their intention to (re-)use and recommend the website and therefore to provide a useful source for information retrieval and technology evaluation that is actively shared. An experiment with two treatments is conducted, in which the participants interact with an animated and a static website, respectively. While participants' self-assessed knowledge improvement is statistically higher in the animated treatment, no difference is found in tested knowledge assessment or technology-specific knowledge. We find that the vividness of the website plays an important role for both the utilitarian and hedonic purpose of the website. However, somewhat contrasting to existing theories, interactivity does not increase enjoyment or diagnosticity.

This chapter comprises large parts of the published article: S. Henni, P. Franz, P. Staudt, C. Peukert, C. Weinhardt, *Evaluation of an Interactive Visualization Tool to Increase Energy Literacy in the Building Sector*, Energy & Buildings, 2022.

3.1 Introduction

As highlighted in Chapter 1, the building sector is of particular importance in achieving the climate targets due to its high emission shares. Residential buildings can contribute to the decarbonization of the power sector, for example, by installing a PV system in combination with a BESS and electrified heating or by taking measures to decrease energy consumption, e.g., through energy efficient equipment and insulation measures. This requires some degree of knowledge on the part of homeowners or office managers, regarding the options and consequences of the installation of energy-related technologies and measures in buildings. Initial investment costs for sustainable technologies such as BESSs, heat pumps, insulation, or PV panels, are high and associated with long payback periods. This is particularly important when considering a BESS installation, whose economic feasibility depends on the installation of additional technologies, for example, PV systems and heat pumps. Furthermore, not all buildings are equally suited for all technologies in question. An essential aspect of the global sustainability movement is thus the involvement and education of (non-expert) citizens by ensuring a high level of information availability and transparency as a basis for individual decision-making and attitude formation. In this study, we concentrate on the design of information distribution tools that are intended to increase energy literacy on an individual level. A low-threshold way to provide transparent information to citizens and therefore to increase their knowledge about possible energy-saving measures are informative websites. The associated challenge is to present information in an engaging way that facilitates the dissemination of the website and the absorption of information. In other research contexts, such as e-commerce, it has already been established that interactive and vivid design elements on a website contribute to the engagement of users and have positive effects on both the hedonic and utilitarian purpose of websites (Jiang and Benbasat, 2007). In the context of the study presented here, the utilitarian purpose of a comparable website is precisely to increase energy literacy. While (interactive) visualizations have been frequently deployed in sustainability contexts (see, for example, Graf et al. (2020); Shevchuk et al. (2019)), the effects of vivid design features on the hedonic and utilitarian means of an informative website have not yet been addressed in the context of the built environment and the related energy literacy of users. Moreover, studies on the effects of interactive mechanisms have delivered inconclusive results (Xexakis and Trutnevyte, 2019; Bishop et al., 2013; Blasch et al., 2017).

To fill this gap, in this study, we evaluate an energy information website (EIW) that allows us to evaluate the effects of vivid and interactive features on the users' (perceived) increase in energy literacy and their intention to (re-)use and recommend an informative website in the context of education on energy-efficient technologies in buildings. The goal of the EIW is not to promote specific technology decisions or recommend certain energy efficiency measures, but rather to provide a comprehensive and transparent information platform for sustainable technologies in the built environment that increases the related energy literacy. To this end, we want to assess whether the interactive and vivid representation of information by means of visual demonstration and interactive feedback (i) enhances the users' enjoyment, (ii) is perceived as useful for retrieving the required information, (iii) affects the level of acquired information and knowledge (energy literacy), and (iv) increases the willingness to (re-)use and recommend the system. Together, these factors can lead to a higher energy literacy in the context of the built environment (Brounen et al., 2013; Martins et al., 2020; Cotton et al., 2015). The resulting research question that summarizes these aspects is therefore the following:

Research Question 1: *What are the effects of interactive and vivid features on a simulative energy information website in the context of increasing citizens' energy literacy in regards to sustainable energy-related technologies in buildings?*

To answer this question, we transfer previous findings from information system research to the context of the simulation of energy-related technologies in buildings. Drawing from these previous results, we develop a research model representing the hedonic and utilitarian purpose of users' interaction with a website. Overall, the model consists of nine hypotheses, which will be detailed in Section 3.3. The evaluation of the research model ultimately allows us to answer the overarching research question on the effects of interactive and vivid design features on users' interaction with the website. The contribution of this chapter is therefore the generalizable effect of animated informative features on the success of information systems intended to increase energy literacy of private households in regards to sustainable technologies in buildings. This includes, among others, the deployment of energy efficiency measures through refurbishment, the installation of BESSs, PV plants or heat pumps, and the evaluation of indoor thermal and lighting systems.

The remainder of the chapter is structured as follows: First, we review related literature on the equipment of buildings with energy-related technologies, the communication of environmental information through visualization and interactive tools as well as previous research in the field of information systems regarding sustainability beliefs and promotion of sustainable behavior. We then introduce the developed EIW, the research model and associated hypotheses for studying the effects of interactive and vivid features on users in the context of energy-related technologies in buildings. Afterwards, we present the research model validation through a behavioral experiment with 107 participants, which is then repeated to ensure reproducibility using a sample from a different participant pool with 101 participants. Finally, we derive suggestions for the improvement of information systems and specifically building simulation tools targeted at increasing citizen involvement and providing information in sustainability transformations.

3.2 Related Work

Homeowners and building managers can take a more active role in the energy supply system by installing smart management systems that allow the active control of flexibilities and the participation in demand response activities (Chen et al., 2018). The equipment of buildings with energy-related technologies and management systems is thus studied extensively. For example, Chellaswamy et al. (2021) propose a smart energy management system to coordinate a PV-coupled BESS in residential buildings. Jin et al. (2021) develop a data-driven control mechanism of commercial building lighting to achieve energy savings and increase human comfort in commercial buildings. Ye et al. (2021) evaluate the impact of different energy efficiency measures in prototype office buildings to provide baselines for decision making. Chen et al. (2021b) address the issue of lacking skills and knowledge of building operators in the context of heating and air conditioning devices and control mechanisms and propose a data-driven approach to identify suitable automated control mechanisms in commercial buildings. While such approaches provide valuable solutions for energy efficiency measures, they often apply to certain, specific types of buildings and technologies or are targeted at expert decision-makers. Studies concerned with non-experts usually analyse or try to simulate building occupants' behavior, such as window opening (Zhong and Ridley, 2020), heat pump usage (Chen et al., 2020), or appliance use patterns and overall energy demand behavior (Jin et al., 2020; Flett and Kelly, 2021). In contrast to these streams of literature, we approach the equipment of buildings in the residential and commercial sector with energy-related technologies on a more general level. We evaluate an interactive building simulation tool that provides entry-level information to all interested parties and particularly non-experts, thus boosting the potential for decarbonization in the building sector by increasing overall literacy on energy-related technology.

3.2.1 Increasing Resident Involvement through Interactive Information Visualization

Improving the energy literacy of (non-expert) citizens by providing information is an important pillar for the transformation towards sustainable societies. For one, transparent communication of knowledge can increase the acceptance of sustainable technologies, both individually and collectively (Huijts et al., 2012; Deckert et al., 2020). Furthermore, individuals often face decisions that can lead to sustainable transformations, such as the refurbishment and equipment of residential or office buildings with sustainable technologies. In the context of the German Energy Transition, visualizations have been frequently used to involve and inform citizens (Billger et al., 2017; Deckert et al., 2020). Deckert et al. (2020) evaluate the effectiveness of a "digital twin", a digital representation of infrastructure projects, to inform and enhance understanding amongst citizens in the case of a pumped-storage power plant and a novel integrated mobility concept. The authors report positive effects of the entertaining and comprehensible design of the digital twin on the participants' assessment of the usefulness for local planning and participation processes, therefore linking the aspects of a stimulating system design and citizen involvement. In a qualitative study on the participatory empowerment of simulation tools in the course of the energy transition, Fiukowski et al. (2017) identify several challenges that need to be addressed. Among them are the different levels of knowledge across stakeholders, missing incentives to use these tools and the risk of misinterpretation of results.

To increase the level of information and to engage users, the knowledge presentation within the information system plays an important role. McInerny et al. (2014) emphasize the importance of interactive visualizations to make scientific findings available to a novice audience and to present unbiased information. They argue that a visually engaging web interface can contribute immensely to reaching a variety of users. Moreover, they state that "success in both science and policy are predicated on reliable unbiased understanding" and suggest making visualization a standard when communicating knowledge in science-policy processes (McInerny et al., 2014, p.155). Lorenz et al. (2015) find that the reaction of users to different visual representations of environmental information, such as histograms, scatter plots, or pictographs, differs even among homogeneous groups. Visualizations have already been frequently used in urban planning processes. However, experimental studies beyond usability evaluations are scarce (Billger et al., 2017). In a survey on different visualizations for informing and transferring environmental knowledge in the context of land-use policy by Bishop et al. (2013), participants and especially non-scientific users find the tools helpful and report higher (self-assessed) knowledge. While many studies highlight the wide-ranged opportunities of visualizations, problems can arise when data is misrepresented or misinterpreted. A high level of visual detail representation in an early planning state can lead to a false impression and create distrust if elements of environmental projects are designed differently at a later stage (Billger et al., 2017). In an evaluation of current visualizations of environmental information for non-scientific audiences, Grainger et al. (2016) develop a design framework spanning the preparation, development, visual encoding, and evaluation phase of visual tools. The authors highlight the necessity of functional visualizations that are tailored to the needs and preferences of the user group and the intended information task.

While there are numerous studies and design frameworks on information visualizations in environmental contexts and many examples of real-life usage of visualization for concrete infrastructure projects, the effects of interactive design elements are less frequently studied and applied. Incorporating interactive functionalities can shift the information process from a passive to an active task, allowing users to specifically explore information of particular relevance to them (Grainger et al., 2016).

However, the influence of interactive elements on learning and increasing the users' level of information is disputed. In a recent publication, Xexakis and Trutnevyte (2019) conduct an experimental study between two groups that are either given an interactive or a static website to explore four scenarios for the Swiss energy system in 2035. The authors find that the provision of interactive features alone seems to have no significant influence on users' self-reported understanding and engagement during website use. On the contrary, users of the static website actually achieved better results in the tested understanding of the presented information. The authors of the referenced study attribute this to the additional cognitive effort that comes with the necessity for active information retrieval as well as the many possible technology combinations that participants need to explore. However, other studies come to different conclusions. For example, Bishop et al. (2013) find that participants prefer the interactive tools when being presented with visualizations on land-use policy. In an experimental study, Blasch et al. (2017) report positive effects of the usage of an interactive decision-support tool on energy-related investment literacy. The diverging findings regarding the effects of interactive tools on understanding and user experience might be the result of task complexity and the amount of time spent with familiarizing and using the tools (Xexakis and Trutnevyte, 2019).

3.2.2 Information Systems Research on Shaping Sustainability Beliefs and Behavior

Information systems, which include websites but also, for example, apps, visualizations, and other simulation tools, as presented in this study, play an important role in shaping beliefs, forming attitudes, and increasing the availability of information for stakeholders, decision-makers, and citizens in general. A large stream of literature has demonstrated the great potential of information systems to influence environmental beliefs and promote sustainable behavior on both individual and organizational level (Henkel and Kranz, 2018; Shevchuk and Oinas-Kukkonen, 2016; Paulsson et al., 2019). The studies in this area can be roughly classified according to whether they investigate the adoption of information systems (i.e., which design features or personality traits influence the willingness to use a system) or the ability of a system to fulfill its task (i.e., how can a system promote sustainable behavior or shape sustainability beliefs, see Table **??**). Normative beliefs and general attitudes are decisive factors for the adoption of new information systems and technologies and persuasive design elements are linked to increased acceptance in the context of user-centric systems (Kranz and Picot, 2011; Brauer et al., 2016). For private households' decisions on efficient energy consumption, an intermediate level of information granularity may yield the same result accuracy as a more detailed information level (Dalén et al., 2013). The elements of information system adoption and task support have been combined in a holistic analysis of motivating factors for the adoption of systems and its effects on environmental orientation in organizations by Jenkin et al. (2011) and a set of comprehensive design principles for sensemaking in sustainability contexts by Seidel et al. (2018).

Table 3.1.: Comparison of related studies in information systems literature (non-exhaustive selection)

<table>
<tr><th></th><th>Adoption of Information Systems</th><th>Task Support</th></tr>
<tr><td rowspan="2">Based on survey, literature synthesis, or evaluation of prototype</td><td>Brauer et al. (2016); Kranz and Picot (2011)</td><td>Loock et al. (2013); Dalén et al. (2013)</td></tr>
<tr><td colspan="2">Seidel et al. (2018); Jenkin et al. (2011); Henkel and Kranz (2018)</td></tr>
<tr><td rowspan="2">Evaluation of ready-to-use system</td><td>Shevchuk et al. (2019); Fiukowski et al. (2017)</td><td>Graf et al. (2020); Diederich et al. (2019); Loock et al. (2013)</td></tr>
<tr><td colspan="2">This study</td></tr>
</table>

While many of these studies have contributed to the theory on design principles and effects of information systems on sustainability beliefs and behavior through surveys and through forming hypotheses, evaluations of ready-to-use systems are scarce. First insights are provided by Graf et al. (2020), who find that an interactive visualization tool for wind power plant planning decreases citizens' preferred share of renewable energy in a system. This demonstrates the potential risks of visualizations, especially when it comes to controversial topics. Diederich et al. (2019) find that the anthropomorphic design of a chatbot positively affects normative and control beliefs in the context of sustainable mobility. In private households, a goal-setting functionality can result in higher energy savings if households can set their own goals (Loock et al., 2013). Whereas the former studies investigate sustainability behaviors and beliefs, Shevchuk et al. (2019) conduct an experiment on the intention to use an app that includes gamified components as persuasive design elements in the context of sustainable behavior. The authors find that both dialogue and credibility support positively influence the adoption of a gamified persuasive system, whereas no significant effects are found for the primary task support and social support.

The information systems that have been evaluated in the context of sustainable decision-making differ from a transparent, informative website as they aim to promote a specific sustainable action or behavior, such as recycling, reduction of energy consumption, or the use of car-sharing. This sets an EIW apart from existing (interactive) visualizations of specific projects in the context of the Energy Transition. While examples of the use of visualizations are diverse and already frequently deployed when communicating the goals and intentions behind specific projects to citizens, an informative website is not intended to promote specific projects, technologies, or attitudes. On the contrary, the aim is to familiarize users with the technology alternatives that are available for buildings and the potential effects on energy supply, costs, and emissions, and thus to generally increase the users' energy literacy. However, this information is conveyed on an abstract level as buildings differ significantly in terms of the effects of technology installations. An informative website thus addresses the previously often overlooked necessity of making citizens aware of the various technologies available on a high information level. To this end, the tool needs to be both engaging and informative, which we aim to achieve by presenting relevant technology-specific information within an interactive and vivid simulated building. In the following, we first describe the instantiation of an EIW that allows us to evaluate the effect of interactive and vivid features within a website in the context of energy-related technologies in buildings. We then introduce a research model for an experimental evaluation of the effects of the animated EIW on hedonic and utilitarian characteristics. Specifically, we conduct an experiment that compares the effect of information presentation on energy-related technologies within a simulated building with and without visual and interactive elements.

3.3 Research Model and Hypotheses

To investigate the proposed research question on the effects of interactive and vivid features on the (perceived) knowledge gain (i.e, increase in energy literacy) and intention to (re-)use and recommend an informative website, an EIW is used (see Figure 3.1)[4]. The EIW contains a simulated office building with various energy-related technologies. The goal is to familiarize citizens with energy-related technologies in buildings and to provide entry-level information about sustainable alternatives.

Figure 3.1.: The developed EIW is an interactive simulation tool that allows users to install various sustainable technology alternatives. Effects of the installations in terms of cost of energy supply, CO_2-emissions, and share of renewables, are shown in the dashboard on the right side. The neutral name is deliberately chosen to avoid a bias of the participants in the studies.

On the website, users can interact with several technologies in a virtual office building by installing heating devices, PV panels, BESSs, refurbish the building's insulation and more. Feedback in terms of annual energy costs, consumption, and carbon emissions is provided on a dashboard and additional information on each technology is available through textual information and forwarding links. Additionally, the website provides technology-specific information and supplementary links for users, who are interested in additional information or need decision support

[4]The Animated EIW is available at https://view-bw-demonstrator.fzi.de:8001/view-bw-demo/present/

for the installation of a specific technology. The website is intended to serve two main purposes: On the one hand, energy literacy should be increased. This means that information should be conveyed neutrally and transparently, giving interested parties an understanding of the technologies described and serving as a basis for individual awareness and sensemaking regarding the equipment of buildings with sustainable technology alternatives. In addition to this utilitarian purpose, the website is also intended to fulfill the hedonic function of bringing enjoyment and of engaging users through interactive, vivid, and visual representations of the presented information. This is intended to increase the willingness to (re-)use and recommend the website and to appeal to a broad group of users and to optimally disperse sustainable building information. In other words, the utilitarian path is intended to increase the individual user's energy literacy, while the hedonic path is intended to ensure an increase in the energy literacy of the broader public. During the experiment, we referred to both websites as "energy information website", a deliberately neutral term in order not to bias participants of either treatment, since there are no visualizations or animations in the static treatment. Drawing from existing literature, we construct a research model of rather exploratory nature that is loosely based on the analysis of the effects of interactive and vivid design elements on online product demonstration by Jiang and Benbasat (2007), shown in Figure 3.2.

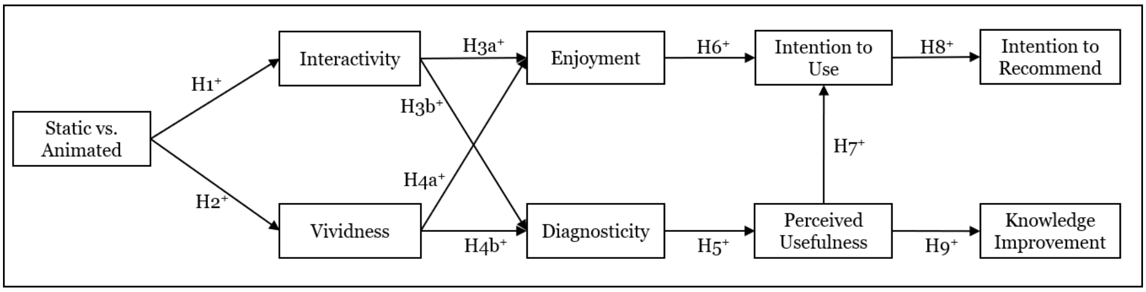

Figure 3.2.: Research model for studying the effects of animated website features on the hedonic and utilitarian path along nine hypotheses

In the context of this study, we call a system animated if it uses interactive elements and visual cues that create a lively perception and information visualization. In the specific context of the experiment, this is realized through a simulated and visualized building containing a range of energy-related technologies. Interactive (INT) design elements allow the user of a system to actively and autonomously retrieve information instead of being (passively) presented with it (Grainger et al., 2016; Jiang and Benbasat, 2007). Therefore, we hypothesize that the ability to install technologies and receive feedback on an EIW should increase the perceived interactivity.

H1: Using an animated EIW enhances the perceived interactivity of the website.

Animations through visual and interactive design elements are often used in gamification contexts to stimulate more senses, inspire imagination, and evoke associations (Liu et al., 2017). For the communication of knowledge, visualization can simplify pattern recognition, stimulate perceptual inference, and reduce information complexity (Card, 2009). In information systems research, the notion of vividness (VIV) refers to the ability of a system to "hold our attention and to excite the imagination to the extent that it is (a) emotionally interesting, (b) concrete and imagery-provoking, and (c) proximate in a sensory, temporal, or spatial way" (Nisbett and Ross, 1980, p. 45). We therefore stipulate that the embedding of information in an animated website, e.g., by illustrating energy-related technologies instead of merely providing textual information, increases the vividness of a system.

H2: Using an animated EIW enhances the perceived vividness of the website.

The ability to interact with objects can enhance the users' attitude towards a system (Schlosser, 2003). In the case of visualizations for land-use policy, users preferred interactive tools over non-interactive ones and showed generally positive attitudes towards visualized and lively communication of information (Bishop et al., 2013). Interactive design elements have also been shown to increase energy literacy (Blasch et al., 2017). In the context of e-commerce shopping experiences, both vividness and interactivity are linked to increased perceived enjoyment (ENJ) while navigating through a shopping website as well as increased diagnosticity, i.e., the ability to evaluate products (Jiang and Benbasat, 2007). In the context of this study, we refer to diagnosticity (DIAG) as the ability to evaluate energy-related technologies. In line with previous literature (Jiang and Benbasat, 2007; Bishop et al., 2013; Schlosser, 2003), we expect a positive influence of an increased interactivity on the hedonic path (ENJ) of the research model and derive the following hypothesis:

H3a: A higher interactivity of an EIW leads to a higher perceived enjoyment while retrieving information about energy-related technologies.

Furthermore, we also expect a positive influence of interactivity on the utilitarian path (DIAG) as suggested by Blasch et al. (2017).

H3b: A higher interactivity of an EIW leads to a higher diagnosticity.

Likewise, we stipulate that an increased vividness leads to a higher enjoyment in accordance with Jiang and Benbasat (2007).

H4a: A higher vividness of an EIW leads to a higher perceived enjoyment while retrieving information about energy-related technologies.

We further expect a positive link between increased vividness and diagnosticity as reported by Jiang and Benbasat (2007).

H4b: A higher vividness of an EIW leads to a higher diagnosticity.

In literature on technology acceptance, the perceived usefulness (PU) is a well-established construct for evaluating the utilitarian characteristics of a system (Davis, 1989; Venkatesh et al., 2003). An information website on energy-related technologies is useful if citizens are able to retrieve the information they seek. The notion of PU is therefore closely related to the ability to retrieve information about the presented energy-related technologies, i.e., the diagnosticity (Peukert et al., 2019). Since the overall PU of an information website on energy-related technologies in buildings strongly depends on the ability to evaluate the presented technologies, we propose the following hypothesis:

H5: Diagnosticity enhances the perceived usefulness of an EIW.

We expect that whether participants would be willing to use an information website on energy-related technologies again depends on whether they found it useful for retrieving information as well as whether they enjoyed their interaction with it. The relation of PU and ENJ with intention to use (IU) has been shown in numerous studies based on the "Technology Acceptance Model" and the related "Unified Theory of Acceptance and Use of Technology" (UTAUT) (Davis, 1989; Venkatesh et al., 2003, 2012). It has been applied to various contexts and is well-established for digital and virtual online shopping experiences (Koufaris, 2002; Jiang and Benbasat, 2007; Peukert et al., 2019). More closely related to the informative purpose of an EIW is the literature on acceptance of internet-based learning systems, which confirms the paths of PU and ENJ to the behavioral IU (Lee et al., 2005; Balog and Pribeanu, 2010). We therefore expect a positive influence of the perceived enjoyment on the intention to use:

H6: Perceived enjoyment has a positive impact on the intention to use an EIW.

Likewise, we stipulate that a higher perceived usefulness also increases the intention to use (Lee et al., 2005; Balog and Pribeanu, 2010):

H7: Perceived usefulness has a positive impact on the intention to use an EIW.

The utilization of an EIW for sustainable technologies differs from the traditional interpretation of the intention to use an information system. Whereas traditional systems are designed to be used on a frequent basis, systems for information retrieval in environmental contexts require only sporadic use but are dependent on their recommendation to others to make use of their full potential. To this end, Naranjo-Zolotov et al. (2019) extend the UTAUT with the intention to recommend (IR) a system in the context of citizen empowerment through e-participation and show that the intention to use significantly affects the intention to recommend. We formulate the following corresponding hypothesis:

H8: Intention to use increases the intention to recommend an EIW.

As energy literacy is generally low among non-experts, we assume that even a short interaction with an informative website can enhance the users' knowledge on energy-related technologies (Brounen et al., 2013). We therefore extend the traditional models on technology acceptance with the construct of (perceived) knowledge improvement that we retrieve from the gaming context (Fu et al., 2009). We argue that improved knowledge (i.e., increased perceived energy literacy) is a result of the utilitarian path in our model and state the following:

H9: A higher perceived usefulness of an EIW leads to a higher perceived knowledge improvement.

The resulting research model that is tested in the experiment is depicted in Figure 3.2.

3.4 Experimental Study

In order to evaluate our research model, we conducted a between-subjects online experiment with two treatments, the animated and the static EIW (Figure 3.4). Further, we demonstrated reproducibility with a second experiment that relied on participants from a different participant pool. The participants were randomly assigned to one of the treatments. They were sampled from two participant pools. The first was the KD^2Lab pool, a proprietary pool in a behavioral lab of the Karlsruhe Institute of Technology that mostly consists of student participants. The participants were randomly sampled and recruited using HROOT (Bock et al., 2014). In the invitation it was stated that participation in the experiment required very good command of the German language. The second sample was recruited via the online survey service provider Prolific, again randomly sampled from all German-speaking participants. After the instructions, participants had to answer questions ensuring that they understood the instructions. We included attention checks that ensure that participants carefully read the instructions and answered thoroughly. The time limit was set to 1:15 hours in total and to one hour that could be spent on a single page of the experiment. Both experiments were conducted as an online survey within a single day. Participants completed the surveys from remote. The experiment was implemented using the experimental framework oTree (Chen et al., 2016). The participants were payed a fixed amount of 10 € for their participation in the first experiment and 6.65 € in the second experiment. Both the amount and the unconditional nature of the payment were communicated before the experiments.

Measures. *Research model constructs:* We measured the constructs of our research model described in Figure 3.2 by adapting established scales from literature (see Appendix 3.1). The items were measured on a 7-point Likert scale ranging from 1: "I totally disagree" to 7: "I totally agree."

General sustainability attitudes: We used two constructs ("Energy Awareness" and "Acceptance of Renewable Energy") in order to control for the personal attitude among the participants, assessing their overall attitude towards sustainability and energy efficient behavior. Both were measured on a 5-point Likert scale and developed by Petra Schweizer-Ries et al. (2010). For the purpose of communicating the results of this study, the items were translated from German to English and can be found in Appendix 3.1.

Technology-specific knowledge: In addition to the self-assessed knowledge improvement from the research model constructs, we also captured the technology-specific knowledge before and after the treatments. Before the interaction with the static or animated EIW (t(0)), we asked the participants to rate their technology-specific knowledge on energy-related technologies. One question addressed the level of knowledge on energy-related technologies overall and four questions addressed specific technologies (heat pumps, PV systems, BESSs, and building insulation), on which the website presents information, e.g., "How well informed are you about heat pumps?" (Appendix 3.2). These five questions were also asked after the use of the websites (t(1)). The answers were ranked on a 4-point Likert scale from 1 ("not informed at all") to 4 ("very informed").

Knowledge assessment: We additionally tested the (objective) knowledge gain (i.e., the increase in energy literacy) by including three multiple-choice questions about cost, emissions, and energy savings associated with installing energy related technologies. The questions were asked before (t(0)) and after (t(1)) the interaction with the static or animated EIW. The participants were asked to assume the role of a building manager and then select the technology that they think would reduce the building's annual (i) energy costs, (ii) CO^2 emissions, and (iii) energy consumption, the most (see Appendix 3.3). They were given four technologies to select from, of which one was the correct answer. The possible choices were not the same for t(0) and t(1), so that participants could not have an advantage at t(1) by specifically searching for the technologies that have already been an answer possibility at t(0). Immediately after answering these questions, the participants were asked how confident they felt about their answers. This "decision confidence" was measured with three items on a 5-point Likert scale adapted from Phillips et al. (2014) and Aldag and Power (1986) (Appendix 3.2).

Technology-specific attitudes: Another measured dimension was the technology-specific attitude towards the same technologies that we evaluated for the technology-specific knowledge, e.g., "using energy related technologies, such as heat pumps is a good idea."

Participation ratings: We measured the participants' attitude towards citizen participation in renewable energy projects before and after using the EIW. We therefore asked for the participants' participation preferences (i.e., the requirement to be informed about renewable energy projects) as well as the evaluation of the existing participation (i.e., whether the participants currently feel well informed and have possibilities to participate). To measure this dimension, we used 5-point Likert scales developed by Petra Schweizer-Ries et al. (2010) (see Appendix 3.2 for translated items).

Qualitative feedback: At the end of the experiment, participants were asked to (voluntarily) comment on (i) the aspects they liked most about the EIW and (ii) possible improvements. For this they were provided a text field with no character limits to express their qualitative feedback.

Procedure. The experimental procedure is depicted in Figure 3.3. The experiment consists of five parts, which were completed by the participants in one session of approximately 30-45 minutes. In Part I, the participants were given information on the procedure and structure of the experiment. They were unaware of the other treatment. In Part II, we conducted a pre-experimental survey. We captured the demographics of the participants and assessed their general attitude towards the energy transition, sustainable energy technology, and participation possibilities for citizens (see Appendix 3.2). Additionally, we tested their energy literacy objectively using multiple-choice questions (see Appendix 3.3). Part II also included a first attention check. In Part III, the participants were free to explore the tool and were instructed to click "Continue" whenever they were done with the exploration. No specific instructions or tasks were provided. We measured the time spent in Part III. In Part IV, the participants were guided through the EIW with an exercise consisting of five multiple choice tasks that needed to be solved (e.g., "Please install a heat pump and select whether the following statement is true: Both the energy consumption and the energy costs are reduced."). They could only proceed with the experiment once the tasks were correctly solved. If a question was incorrectly answered, the participants were informed about that fact but they were not told which question was answered wrong to prevent simple trial and error strategies. This part ensured that participants experienced all the features the EIW can offer. In the final Part V, a post-experimental survey was conducted that included the model constructs (see Appendix 3.1), another assessment of the attitude and knowledge towards some presented technologies, and the basic attitudes towards the energy transition and overall participation possibilities. We also reassessed the objective knowledge of the presented technologies (energy literacy). The latter was achieved using the same questions as in Part II but with different response options. Finally, participants were asked to give their qualitative feedback on the presented EIW.

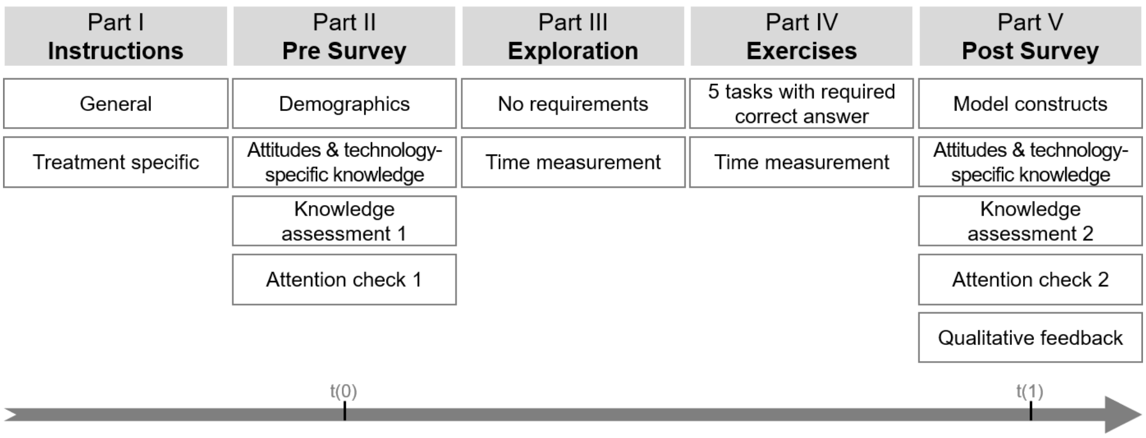

Figure 3.3.: Chronological procedure of the conducted experiment consisting of five parts to be completed within one experimental session

Treatments. We used two different treatments, in which participants either used the animated or the static EIW (Figure 3.4). Other than the presentation of the information, the two experimental procedures were the same. The same information was conveyed and we asked the same questions. Only the formulation during the guidance in Part IV was treatment-specific, as users could not install or de-install technologies in the static EIW treatment. The users of the static EIW were equally able to explore the website freely during Part III, which in their case meant that they could read the provided information on different residential energy technologies.

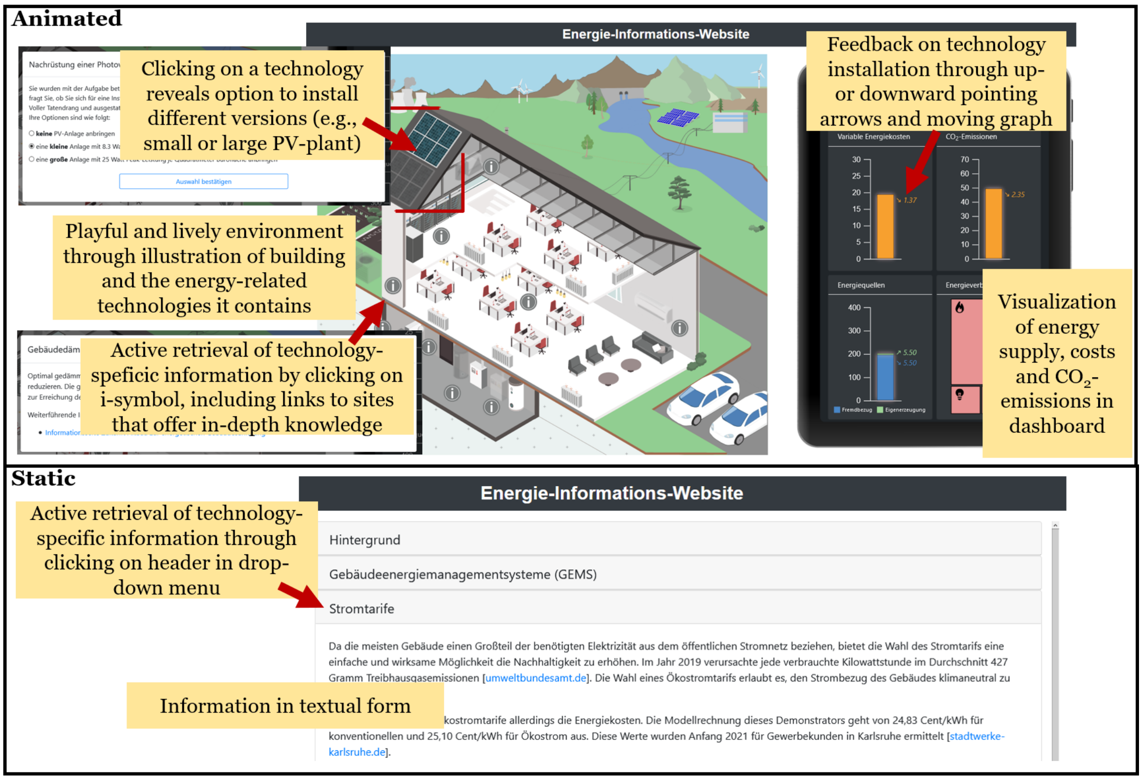

Figure 3.4.: Design elements of the animated and static EIW

In Part IV, for the guided tasks and multiple-choice answers, the participants of the static treatment were able to obtain the same information as in the animated treatment. For example, in the animated treatment, when participants fulfilled the task of “installing a heat pump,” they saw the energy cost increase and the energy consumption decrease on the dashboard on the right-hand side. In the static treatment, participants were instructed to read the information on heat pumps, which included the information that installing a heat pump leads to rising energy costs and reduced energy consumption in the case of the presented building. In order to ensure replicability, the code for the experiment with the animated EIW is published along this article.

3.5 Data Analysis

Descriptive statistics. To obtain the final samples from all participants of an experimental study, participants who do not meet certain criteria during the survey have to be filtered out. If participants exceed a time limit of one hour on a single survey page, we consider them distracted. Likewise, participants were removed if they failed to answer one of the attention checks correctly. With the remaining data, descriptive information in terms of mean age, gender, and occupation is generated. To further characterize participants, the time that is spent during the exploratory part is monitored and reported in this step.

Pure treatment effect. Before analyzing relationships between the variables, the pure effect of the treatment on the dependent variables has to be evaluated to explore the different experiences participants had while using the static and the animated EIW. To compare the treatments, the internal consistency reliability of the applied scales has to be confirmed using Cronbach's alpha, where all values should exceed a threshold of 0.7 (Hair, 2016). Then, item scores for a construct should be merged by calculating the mean value. The data is then analysed for normal distribution using a Shapiro-Wilk test and subsequently compared using an appropriate test for group comparison.

Measurement model assessment. Partial least squares structural equation modeling (PLS-SEM) is then used to test the hypotheses. The PLS-SEM approach focuses on optimizing the predication of endogenous constructs, rather than the model fit (Hair, 2016). It can also be used for exploratory research objectives (Gefen et al., 2011) and is therefore suitable for our research objectives. All analyses are carried out using Smart PLS3 software (Ringle et al., 2015). To obtain valid and reliable results for the structural model, the measurement model has to be evaluated first. The composite reliability (CR) should be above a threshold of 0.7 (Hair, 2016). The average variance extracted (AVE) and the indicator's outer loading are used to evaluate the convergent validity and should be above a threshold of 0.5 and 0.7, respectively (Hair, 2016). Outer loadings between 0.4 and 0.7 should be closely examined and should only be removed if the removal increases the AVE or CR above the recommended threshold (Hair, 2016). To assess the discriminant validity, we use the Heterotrait-Monotrait Ratio (HTMT). The threshold value (< 0.9) should be met for all constructs (Hair, 2016). Furthermore, the results of the consideration of the HTMT confidence interval, obtained through bootstrapping with a resampling method with 5,000 samples, should be obtained to confirm the discriminant validity of the measurement model (Hair, 2016).

Structural model and hypotheses testing. After completing the steps above, the structural model can be evaluated. First, the Inner Variance Inflation factor values should be examined for all predicting constructs to rule out collinearity issues in the structural model. All values should be below the established cutoff value of 5 (Hair, 2016). The significance values for the path coefficients are obtained by means of bootstrapping (5,000 samples).

Further analyses. To compare the treatments, it should further be tested whether they differ in participants' sustainability attitudes and the tested objective knowledge assessment. A Shapiro-Wilk test is thus conducted for the acceptance of renewable energy technologies and the energy-awareness of the participants, and then, depending on the results, the corresponding test for group differences is performed. Similarly, all further measures that are conducted before and after interaction are compared for differences within the treatments (differences between t(0) and t(1)) and between treatments (differences between static and animated treatments). These measures include technology-specific knowledge, objective knowledge assessment and decision confidence, technology-specific attitudes and participation ratings. For all measures, mean value and standard deviation (SD) are calculated and reported. Finally, the qualitative feedback has to be evaluated manually to obtain qualitative insights on participant's experience while using the EIW in both treatments.

3.6 Results

Descriptive statistics. Overall, 107 participants took part in the first study. After data cleansing, this number decreased by 12. Eight participants exceeded the limit of one hour on a single survey page, being considered as distracted during their participation and therefore not able to provide reliable and valid answers. Four participants did not correctly answer the second of two attention checks. The adjusted sample consists of 49 participants for the animated and 46 participants for the static

EIW. The average age of participants of the animated treatment was 24.4 (SD = 5.2), the average age of the participants of the static treatment was 22.4 (SD = 7.6). 45% of the participants of the animated treatment were female and 84% were university students as compared to 30% and 87% for the static treatment, respectively. The sample is thus rather young and predominantly consists of university students. To evaluate for how long participants were exposed to the EIWs to later evaluate their experience, we monitored the time during exploration and guided exercise. The participants of the animated treatment spent 6.88 minutes (SD = 4.47) in the exploration phase on average and 8.95 minutes (SD = 3.55) in the exercise phase. The participants of the static treatment spent 6.27 minutes (SD = 4.33) on average in the exploration phase and 9.17 minutes (SD = 6.18) in the exercise phase.

Pure treatment effect. All Cronbach's alpha values in our experiment are above the threshold of 0.7 (see Appendix 3.1). Table 3.2 provides an overview of the obtained results. As the data is not normally distributed in our case, a one-sided Mann-Whitney U-Test is used to compare the treatment groups. All variables receive significantly higher mean values for the animated treatment than for the static treatment (see Table 3.2). This is also depicted in Figure 3.5. Especially interesting are the significantly higher values for diagnosticity and (self-assessed) knowledge improvement, as both websites differ only in the information presentation, but not in the content of the information itself. It seems that an animated EIW enhances its users' felt ability to evaluate energy-related technologies and increases their perceived knowledge improvement. For the adaption of the proposed informative website in real life, the significantly higher values in the perceived usefulness, enjoyment, and intention to recommend the animated EIW are of particular interest.

Table 3.2.: Test for group differences for dependent variables

	Static				Animated			MWU
Construct	Mean	SD	SW		Mean	SD	SW	**p-value**
INT	4.67	1.65	0.03*		6.33	0.84	<.001***	<.001***
VIV	2.17	0.96	<.001***		4.82	1.09	.164	<.001***
PU	4.49	1.35	.309		5.59	1.00	<.001***	<.001***
ENJ	3.23	1.30	.024*		5.24	1.05	.001***	<.001***
DI	5.09	1.19	.02*		5.59	0.83	.055	.013**
IU	4.26	1.63	.071		5.12	1.38	<.001***	.003**
IR	3.64	1.50	.016*		4.8	1.28	<.001***	<.001***
KI	4.72	0.98	.319		5.45	0.88	.009**	<.001***
*p < .05; **p < .01; ***p < .001								
SW = p-values from Shapiro-Wilk test, MWU = Mann-Whitney U-Test results								

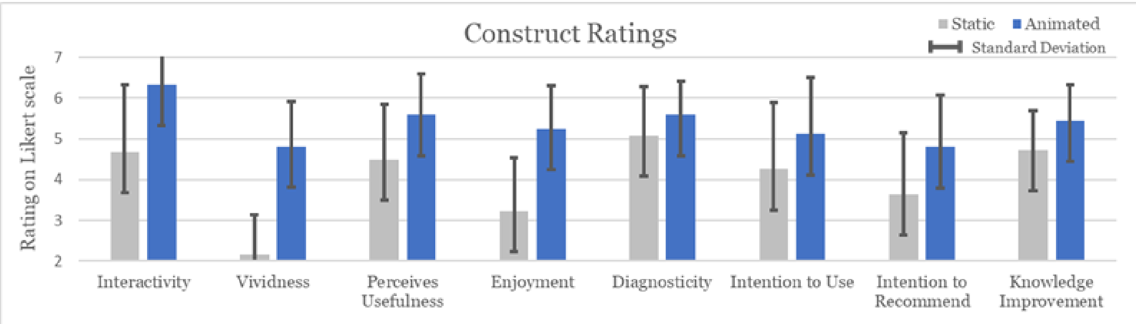

Figure 3.5.: Treatment comparison for dependent variables. Higher ratings can be observed for all constructs in the animated EIW treatment compared to the static treatment

3.6.1 Results for the Research Model

Measurement model assessment. To obtain valid and reliable results for the structural model, we first evaluate the measurement model. See Appendix 3.1 for an overview of the constructs, items, and factor loadings as well as Cronbach's alpha values, CR, and AVE. All CR values are above the threshold value of 0.7 and all AVE values are above the threshold of 0.5 (Hair, 2016). For the outer loadings, one indicator, K5 (.672), had to be further examined. Since all constructs have already fulfilled the recommended thresholds, we decided to retain the item. The threshold value of < 0.9 is met for all constructs for the HTMT. Furthermore, the results of the consideration of the HTMT confidence interval, obtained through bootstrapping, confirm the discriminant validity of our measurement model.

Structural model and hypotheses testing. All Inner Variance Inflation factor values are below the cutoff value of 5. Regarding H1 and H2, we predict a positive impact of the usage of an animated EIW on vividness and interactivity. Both paths are significant at a .001 level. Surprisingly, the paths leading from interactivity to enjoyment and diagnosticity are not significant. H3a and H3b are therefore not supported. With all other paths being significant, we find empirical support for hypotheses H4 to H9. The adjusted R^2 values as well as the path coefficient values can be found in Figure 3.6. The exact p-values are shown in Appendix 3.4.

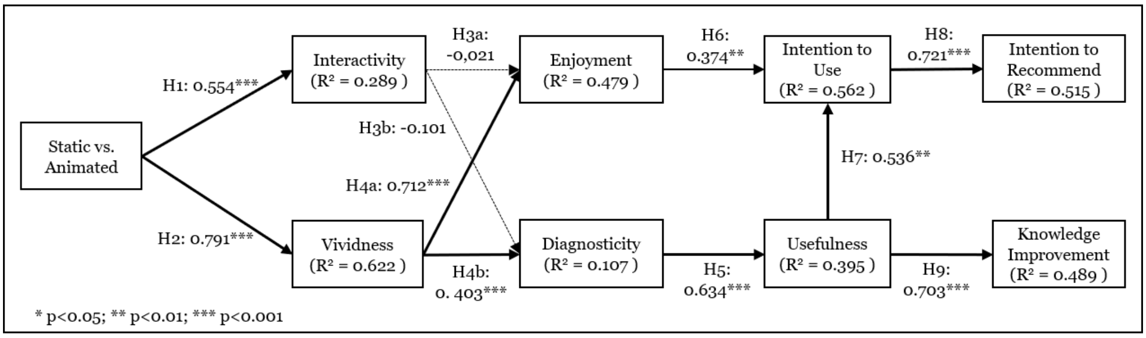

Figure 3.6.: Results for the PLS structural model with adjusted R^2-values. The numbers indicate the path coefficients and significance for the hypothesized relationships. Statistical significance is indicated using the depicted p-value scale

3.6.2 Further Results

General sustainability attitudes. The acceptance of renewable energy technology in general and the energy awareness do not statistically differ between the treatments. Therefore, both samples have equivalent baseline conditions. Especially the acceptance of renewable energy is high in both treatments. Table 3.3 shows the result of the comparison.

Table 3.3.: Test for group differences for general sustainability attitudes variables

	Static			Animated			
Construct	Mean	SD	Shapiro-Wilk	Mean	SD	Shapiro-Wilk	**p-value**
Acceptance RE	4.69	0.47	<.001***	4.71	0.43	<.001***	$.92^b$
Energy Awareness	3.24	0.61	.211	3.48	0.6	.699	$.592^a$
*p < .05; **p < .01; ***p < .001							
SD = Standard deviation, Shapiro Wilk = p-value from Shapiro Wilk test depending on whether the data is normally distributed. a. Two-Sided Welch Two Sample T-test, b. Two-Sided Mann-Whitney U Test							

Technology-specific knowledge. A statistically significant increase in the technology-specific knowledge can be measured both for users of the static (t = -4.393, p-value = <.001)^c, as well as for users of the animated website (V = 141, p-value = <.001)^d. No different level of technology-specific knowledge could be found between the treatments groups at either t(0) or t(1). Two-sided Mann-Whitney-U-Tests or t-Tests, depending on the distribution of the data, are executed to compare data at t(0) and t(1) for both treatments. For the analysed dimensions in this section, no statistical difference can be found between the treatment groups. All mean and SD values are reported in Table 3.4.

Knowledge assessment. Table 3.4 provides an overview of the share of correct answers regarding the tasks measuring energy literacy before and after the interaction with the EIW. A significantly higher correct answer share (at .001 level) is measured for results at t(1) in comparison to t(0) for both treatment groups. Similarly, a significantly higher rating for the decision confidence can be observed for both the static EIW treatment (t = - 8.044, p-value = <.001)^a and the animated EIW treatment (t = - 3.584, p-value = <.001)^a. This underlines the higher correct answer rate both groups achieved after being exposed to the EIW and it shows that the participants felt confident in applying the newly gained knowledge.

Table 3.4.: Additional measures before (t(0)) and after (t(1)) interaction with the EIW

	Technology-specific knowledge		Correct answer share per participant (objective knowledge assessment)		Decision confidence		Technology-specific attitudes		Participation rating	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Static EIW t(0)	2.36	0.66	0.2	0.22	3.27	1.34	4.4	0.51	2.96	0.6
Static EIW t(1)	2.72	0.55	0.63	0.26	4.69	1.39	4.33	0.37	3.05	0.63
Animated EIW t(0)	2.42	0.63	0.12	0.16	3.74	1.27	4.38	0.48	3.03	0.56
Animated EIW t(1)	2.72	0.56	0.57	0.3	4.44	1.05	4.41	0.55	3.5	0.61

SD = Standard deviation. c. Paired, one-sided t-Test, d. Paired, one-sided Wilcoxon signed ranking test with continuity correction

Technology-specific attitudes. While the knowledge was improved through the interaction with the EIW, the attitude towards the technologies was not significantly different between t(0) and t(1) (Table 3.4).

Participation ratings. The results show that while using the animated EIW, users gave significantly higher ratings for both participation ($V = 75.5$, p-value = $<.001)^d$ and the evaluation of participation ($V = 119$, p-value = $<.01)^d$ at t(1) in comparison to t(0) (see Table 3.4). For the static EIW, no such evidence could be found. These results show that an animated EIW can increase the willingness to be informed on renewable energy projects and increases the willingness to participate.

Qualitative feedback. The most common positive feedback was the overall design of the website, either mentioned on its own (eleven participants) or in combination with the interactivity and playfulness of the animation (seven participants). The feedback on technology installations as well as the overall information content of the EIW and, interestingly, the forwarding links to other webpages were each mentioned eight times. Two participants explicitly mentioned that they found the EIW useful to get a general overview over the technologies in buildings, and two other participants praised the understandability of the information for users, who are not familiar with the technologies. Some usability issues were reported in the suggestions for improvement, for example, that clickable objects could be highlighted (seven times) or that feedback on technology installation (upward and downward arrows with numeric display of change in target values) vanished too quickly (five times). In terms of content, more detailed information on technologies was requested (seven times) as well as information on other types of buildings (five times) and specific decision support for sustainability measures (two times). In addition, two participants would have liked video material for a more stimulating experience.

3.6.3 Replicability of Results

In order to show the replicability of the results, the study was repeated using an online sample of participants from the online platform Prolific. The average payout on this platform is lower than for the participant pool of the KD^{2}Lab and therefore, participants were paid 6.65 Euros. The study was conducted in one day and participants were randomly assigned to each of the treatments. The study was completed by 51 participants in the animated EIW treatment and 50 participants in the static EIW treatment. In both cases, two participants failed the attention checks leading to 49 usable responses for the animated EIW and 48 for the static EIW. The average age of all participants was 30 years. The share of female participants was considerably higher than in the first experiment with roughly 58%. The share of students was lower with only about 45%. A total of 21 participants were homeowners and seven owned PV panels. We do not repeat the statistical as for the first study, but all the necessary statistical tests were performed as outlined in the previous sections. The results are depicted in Figure 3.7. The exact p-values are shown in Appendix 3.4 and values for outer loadings, CR, Cronbach's alpha and AVE are reported in Appendix 3.1. Furthermore, the tests for group difference are included in Appendix 3.4 to allow for comparison between both experiments.

The previous model is mostly confirmed with the only notable difference that the path between interactivity and enjoyment is now significant. The results therefore confirm and strengthen the results from the first experiment. This is especially important as the second sample had widely different demographics compared to the first sample.

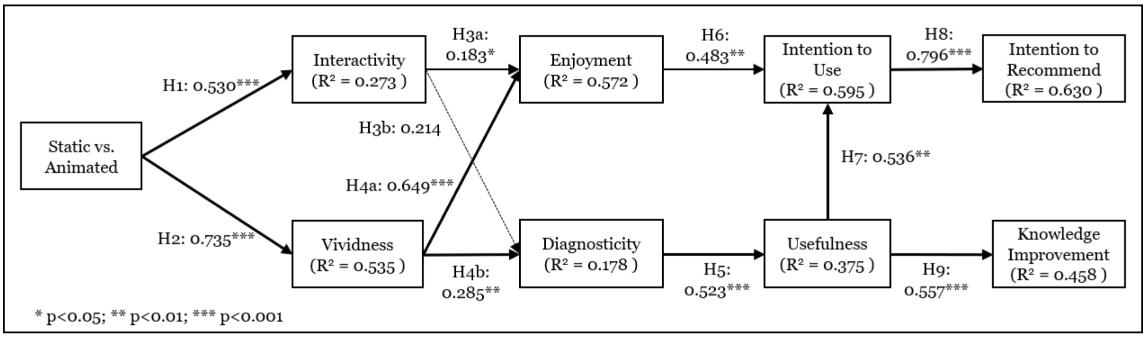

Figure 3.7.: Results for the PLS structural model with adjusted R^2-values for the second experiment tested with a sample recruited via the prolific platform. The numbers indicate the path coefficients and significance for the hypothesized relationships. Statistical significance is indicated using the depicted p-value scale.

3.7 Discussion

The hedonic and utilitarian paths of our research model that are well-established within research on information systems can be largely confirmed in the context of an information website intended to increase building related energy literacy. The results contribute to the understanding of how information should be presented in order to engage citizens, to provide entry-level information, and, thus, to increase energy literacy. The results suggest that both the hedonic (ENJ) and utalitarian (DIAG and PU) paths of the model have a positive effect on the intention to use the EIW (and therefore, the intention to recommend). In the first experiment, the vividness of the animated EIW is the driver for these effects while no significant paths were found in the case of interactivity. This confirms the findings of studies such as Bishop et al. (2013) and Deckert et al. (2020), which report positive effects of stimulating and animated design on the usefulness of digital tools in the context of sustainable, energy-related technologies. The second experiment however suggests that interactivity might also have a (significant) positive influence.

Interactivity. Unlike previous literature in the e-commerce context, we find no conclusive results regarding the influence of the interactivity on perceived enjoyment and diagnosticity. Contrary to these established influences, Xexakis and Trutnevyte (2019) find that interactivity can be an additional cognitive burden during complex information retrieval in the context of presenting energy scenarios. The qualitative feedback of the users in our first experiment provides some further insights into the ambivalent effects of interactive elements. Interestingly, 14 out of 34 participants who comment on positive aspects of the animated EIW explicitly mentioned the interactivity. However, seven out of these referred to it together with the overall animation of the EIW, mentioning, for example, the "playful interactivity" or the "interactivity and (...) design." This shows that the interactive functionality is hard to distinguish from the overall animation of the website. Furthermore, three participants explicitly said that they were annoyed by the interactive functionalities, stating that the necessity to actively retrieve information is perceived as an obstacle. Another possible explanation for why interactivity did not significantly influence the ability to evaluate technologies is the lack of participants' concrete objectives during the experimental study. It is conceivable that, for example, a homeowner who is specifically interested in the effect of a PV system in combination with a heat pump will find the interactive possibilities with the tool more useful.

Knowledge. We included the construct knowledge improvement by Fu et al. (2009). The items (see Appendix 3.2) evaluate both how well the website conveys knowledge as well as how well the users think the EIW is suited to obtain knowledge (i.e., "The EIW motivates the user to integrate the knowledge taught.", "The EIW increases my knowledge."). We therefore included the technology-specific knowledge as well as the tested knowledge assessment to control for previous knowledge of the participants and to obtain an objective measure of the participants' learning. Both, participants in the static and animated treatment, achieved significantly better results regarding their objective knowledge (i.e., an increase in their energy literacy) after the treatment, which is not surprising as they had to engage with and read about some of the technologies during the guided exercise. There were no significant differences in performance in the multiple-choice test between the two groups, which somewhat confirms the equivalent information content of the two treatments. Similarly, participants of both treatments rated their technology-specific knowledge higher after using the EIW, with no significant difference in the gains of the two groups. Yet, participants of the animated treatment rated their knowledge improvement significantly higher and seemed to find the EIW better suited overall for knowledge improvement. This is an important finding because it suggests that even though the static treatment succeeds in conveying the same information as the animated version, potential users might still be under the impression that it is less informative. Hence, they might refrain from using or recommending a less appealing website at all, which limits the potential societal increase in energy literacy.

Participants. Our first sample consisted largely of university students, who have very positive attitudes towards renewable energy and high levels of energy awareness which could limit their potential knowledge gain on an EIW. Since most of them are not homeowners, one could also debate their relevance for the equipment of buildings with sustainable technologies. However, we would like to emphasize that even among an environmentally aware group with a high level of education, an entry-level informative website on sustainable technologies is perceived as useful and leads to significant increases in perceived and tested knowledge. What is more, young, environmentally aware students have been the drivers of sustainability movements in the last few years, e.g., as seen in the “Fridays for Future” movement (Wahlström et al., 2019). Since young and technology-savvy users are generally often amongst the first adopters of digital technologies, their high intention to recommend could prove a decisive factor for the diffusion of the website amongst citizens in general because they could recommend the EIW to their parents, relatives, or friends, that might benefit from the provided information (Czaja et al., 2006).

Replicability and future research. We were able to address some of the limitations mentioned in the previous paragraphs in our second experiment. The findings from the first experiment could be largely confirmed with a more diverse group of participants both in terms of age and occupation whose attitudes were not as in favor of renewable energy technologies in general. The most relevant difference between the two experiments is the significant path from interactivity to enjoyment in the second experiment, while all paths from interactivity were insignificant and even slightly negative in the first experiment. Therefore, we cannot conclusively determine the actual effect of interactivity on users' hedonic and utilitarian path. Notably, in the second experiment, interactivity and the ability to obtain feedback on installations were explicitly mentioned positively in the qualitative feedback by 22 participants. Some participants lamented an overload of information, but, in contrast to the first experiment, none complained about the interactive elements being distracting or annoying. At this point, we can only speculate about why the perception of the interactive elements is so different. In addition to demographic differences, we notice that participants in the second experiment have a significantly lower general acceptance of renewable energy and a slightly lower self-reported knowledge on energy-related technologies but a slightly higher energy awareness compared to the participants of the first experiment (see Appendix 3.4). Future research should therefore further address the needs of different target groups for obtaining information on energy-related technologies. Indeed, as suggested by Lorenz et al. (2015), even amongst homogeneous groups, preferences can differ in regards to visual information display. From this follows a need to investigate whether it is possible to design informative websites along the needs of specific target audiences. One relevant target group are homeowners with specific goals (e.g., energy efficiency measures or equipment of their home with sustainable technologies). However, the qualitative feedback in the second experiment revealed that some participants found the tool useful for general education on sustainable technologies as well ("[One] could also create a kind of game for children in order to inspire and sensitize younger people for this important topic at an early stage"). This is in line with the arguments brought forward by McInerny et al. (2014) who demand that visualization should be a standard when communicating science-policy processes and unbiased information to novice audiences. Therefore, future research should not be limited to homeowners and could address the different needs of different stakeholders.

3.8 Conclusion

In this chapter, we contribute to hands-on solutions to increase energy literacy. The experimental evaluation of the EIW is unique in research on information systems as the website provides information on an abstract, non-project- or task-specific level. This is intended to bridge the gap between uninformed citizens, in particular homeowners and building managers, and the decarbonization of the (residential) building sector through awareness-building and increasing energy literacy. For BESSs, this information provision is of particular relevance, as they are ideally deployed in combination with other energy-related technologies, such as PV systems or heat pumps. We can thus research question 1 with the following main findings:

First, an animated website has a positive effect on the perceived vividness and subsequently the hedonic and utilitarian purpose of an EIW. This is demonstrated with a between-subjects experimental study. The positive effects of vividness are of relevance for the practical implementation and design of informative websites. Interestingly, while the participants' self-assessed knowledge improvement is significantly higher in the animated treatment, no difference can be found in the objective knowledge improvement or the technology-specific knowledge. This indicates that participants feel like the animated EIW is better suited for improving knowledge while the objective information content and retrieval is actually the same for both the animated and the static website. Second, the results regarding the interactive mechanisms are inconclusive. This deviates from previous literature but could be attributed to the different context and purpose of the introduced website than what is commonly researched. Furthermore, participants' qualitative feedback shows that it is difficult to distinguish between the interactive and vivid design elements and some of the interactive elements may have an impact on perceived vividness as well. Third, the experiment shows that the animated EIW engages users for the energy transition. It increased the curiosity regarding the energy transition as well as the will to engage in participatory processes of the energy transition. Therefore, it might contribute to an increased acceptance of the process of powering a still fossil fuel-based economy with renewable energy sources.

We conclude that when designing an informative website on BESSs and other energy-related technologies in buildings, the focus should be on an appealing and stimulating design that invites users to explore technologies and sustainability effects playfully. The higher perceived vividness influences the hedonic and utilitarian path of users' enjoyment, diagnosticity and usefulness, their intention to use the website, and, ultimately, their willingness to recommend it to others. Furthermore, it increases their perceived and objective energy literacy. Interactive elements should be designed with caution so that they do not get in the way of information gathering.

In this chapter, it is analysed how individual decision-makers in buildings can be informed about BESSs in combination with other sustainable technology alternatives with the help of an engaging EIW design. Information provision is the basis for further BESS expansion on the individual level. Once these systems are installed in a neighborhood, several individuals in buildings with PV-coupled BESSs can be connected to deploy their local RES and BESS resources more effectively and profitably. One example of these connected individuals are so-called (citizen) energy communities, which will be the focus of the following chapter.

CHAPTER 4

SHARING PV-COUPLED BATTERY STORAGE IN ENERGY COMMUNITIES

The high expansion potential of PV-coupled BESSs and other energy-related technologies on the individual level should be further exploited. One way of making these deployments more attractive is to connect several individual local residents into energy communities as promoted by the European Union and thus to leverage the potential of peer-to-peer energy sharing. In a setting with privileged self-consumption, connected individuals within an energy community could economically share local PV generation and BESS capacity to increase the profitability and utilization of local resources. In this chapter, a sharing economy model in the context of energy communities is investigated and 520 sharing communities of five households each with differing load profile configurations are simulated. The communities achieve average annual savings of 615 € as compared to individual operation without being connected. Using the gathered data on electricity consumption in a sharing community, a fixed pricing approach is discussed, which allows a fair distribution of the profits generated through the sharing economy. Furthermore, the impact of prosumers' and consumers' load profile patterns on the profitability of the sharing communities is investigated. Based on these findings, the potential to match and coordinate suitable energy communities through a platform-based sharing economy model is explored.

This chapter comprises large parts of the published article: S. Henni, P. Staudt, C. Weinhardt, *A sharing economy for residential communities with PV-coupled battery storage: Benefits, pricing and participant matching*, Applied Energy, 2021.

4.1 Introduction

In recent years, energy communities have been an integral part in the efforts to actively involve citizens in the transition towards a low-carbon energy supply (Weinhardt et al., 2019). The European Union defines the concept of citizen energy communities as a "cooperation of citizens or local actors" within a residential neighborhood that participates in the generation, distribution and storage of energy in order to provide "environmental, economic or social community benefits to its members" (European Parliament and Council of the European Union, 2019). The sharing of BESSs on the individual level allows a higher local consumption of electricity generated by RESs. In addition, BESS investments can become more economic in a setting of privileged self-consumption that exempts joint utilization of BESS and RES resources within an energy community from network fees and taxes. However, it is unclear how different households with different load patterns can contribute to such an energy sharing community and what benefit can be expected. This makes it more difficult to establish such communities as both prosumers with or without BESSs as well as consumers are unaware of the corresponding opportunities. In this chapter, we expand the extant literature with an in-depth analysis of the benefits of local energy sharing communities, in particular regarding the potentials for a higher utilization of existing BESSs within these communities.

Due to current regulation, increasing self-consumption is often the only feasible option for residential users to profit from a BESS. This causes a limited number of operating hours of PV-coupled BESSs. Losses with regards to utilization arise when a household's load during the hours without PV generation is not sufficient to fully discharge the storage unit until the generation of the PV system starts again the next day. Similarly, when the electricity generation throughout the day is not sufficient to charge the BESS to its maximum, its capacity is not fully utilized. The profitability of a BESS is thus not only dependent on a household's overall electricity consumption but also on the distribution of the load throughout the day. To enhance the utilization rate and to subsequently further incentivize local investments in BESSs, we propose a sharing economy model that allows a residential community to share excess PV generation, stored electricity and

BESS capacity. In this chapter, we furthermore contribute to the understanding of a sharing economy in energy markets and explain how under-utilization in residential energy communities can be overcome through a sharing economy model. Aside from the possible financial savings of the community, this approach also allows consumers to participate in the sharing of locally generated electricity without having to invest in the capital-intensive infrastructure themselves. This development can be desirable from a system's perspective as well, since increased local consumption may reduce peak loads and thus relieve the distribution grids (Müller and Welpe, 2018). Correspondingly, sharing approaches in the electricity sector have the potential to promote decentralized structures and to subsequently assist the transition towards a more sustainable energy system (Tietze et al., 2019). To accelerate this development and to increase utilization of BESSs on the individual level, we propose a platform-based sharing economy model to identify and match suitable communities and investigate financial benefits, fair revenue distribution as well as matching between prosumers and consumers. In the course of this study, we answer the two research questions proposed in Chapter 1:

Research Question 2: *What are the average financial benefits for a residential sharing community that engages in sharing of local electricity generation and storage capacity?*

Research Question 3: *How does the pricing of the shared goods impact the distribution of profit shares within an energy sharing community?*

In addition, within this chapter, a focus lies on matching suitable participants for such a community based on households' load properties. We therefore answer the following additional research question:

How can suitable participants for a sharing economy be described and matched into a community based on electricity consumption profile characteristics?

To answer these questions, we first transfer the sharing economy theory into the context of the energy sector regarding the application of sharing solar generation and BESS capacity. We investigate the potential profits of a sharing community depending on load profile patterns of different participants by simulating 520 sharing communities based on empirical demand profiles. Based on the results of the simulation, we discuss a fair pricing approach for the shared goods and propose a solution for the coordination of communities. Finally, we analyse how communities can be set up most profitably.

4.2 Related Work

In this section, we provide an introduction into the literature on the theory of the sharing economy and its application to the energy sector. In the first section of the literature review, we elaborate on the relevance of sharing economy approaches in the energy sector, shedding light on potential business models and current use cases. In the second part, we review similar previous research and address the current regulation on sharing electricity and storage in residential neighborhoods. From this overview, we subsequently derive the research gap that we aim to fill with this chapter.

4.2.1 The Sharing Economy in the Electricity Sector

Platform-based sharing economy companies such as Airbnb and Uber have gained significant attention in recent years by challenging traditional business models. Through these platforms, existing but under-utilized assets are deployed much more efficiently, while end-users gain direct control of services and products which they previously had no access to (Crosby, 2014). On the other hand, the unprecedented changes in the energy sector require ground-breaking innovative business models and hands-on solutions that further drive the transition from large power plants towards decentral and renewable generation (Gholami et al., 2016). Whereas traditionally, consumers would get their electricity from a large supplier, nowadays, an increasing number generates part of their consumption autonomously through RESs. These so-called prosumers are able to partially supply themselves with self-generated local electricity, making them less dependent on large utilities (Butenko, 2016). Combined with an increasing availability of technology such as smart meters, new digital solutions can emerge in this setting. Thus, platform-based sharing economies are expected to have a significant impact on the energy sector by increasing utilization rates of assets and by enabling peer-to-peer (P2P) access to energy related products and services (Crosby, 2014).

A sharing economy can be categorized along the four dimensions shared good, market orientation (e.g., profit or nonprofit, global or local, online or offline), market structure (e.g., consumer-to-consumer or business-to-consumer) and industry sector (e.g., mobility, energy supply) (Plewnia, 2019). In the setting of this chapter this translates to, (1) the shared good is BESS capacity that is shared (2) for profit (3) between residential neighbors (4) in the energy sector. The emergence of sharing economy activities in the context of the energy sector has previously been investigated by Plewnia (2019) who finds that sharing economy business models offer the opportunity to accelerate the energy transition as they share the key properties of decentralization, digitalization and increased P2P interaction. The author derives six key characteristics of a sharing economy and transfers them to the energy domain. In line with Crosby (2014), the relevance of digital energy platforms to increase P2P interaction is highlighted. The leverage of digital technologies allows a more efficient coordination of the increasingly fluctuating and volatile energy supply through RESs. The aspect of shared values, in particular, is seen as an important driver for developments in the energy sector that in some cases may even outweigh cost advantages. Another feature is the better use of under-utilized capacities, often through granting access to capital-intensive resources that previously had to be owned in order to be utilized. Plewnia (2019) further points out the similarity to prominent sharing economy platforms like Uber and Airbnb with high private capital investment. This aspect is supported by the findings in Tietze et al. (2019), where the authors apply the characteristics and dimensions provided by Plewnia (2019) to three case studies and find that one of the main drivers for sharing economy models in the energy sector is the investment of private capital in other assets than real estate, especially in RESs and BESSs, combined with the increasing independence from utilities. One barrier to these developments, which is identified both by Crosby (2014) and Tietze et al. (2019), is missing financial incentives for local energy generation, partially caused by regulatory and bureaucratic hurdles for sharing approaches. One distinctive feature of the sharing economy in the energy sector is the reversal of the principle *Access instead of ownership* in the case of RESs for the prosumers. Whereas in the past, most households were pure consumers who obtained their electricity from large central power plants (and thus without ownership), nowadays many participate in electricity generation themselves through owning PV generation systems.

In contrast to other sharing economies, sharing in the energy sector poses some unique challenges. Since electricity is a homogeneous good and its flows cannot be physically traced from point A to B, electricity sales need to be coordinated through balancing software that coordinates transfers and hardware that can realize the related physical flows (Kalathil et al., 2019). This is especially important when introducing a sharing economy business model between households as granular balances of generation and load have to be documented and billed. Further, electricity supply and demand need to be balanced at all times, i.e., any generation at any given time must be either consumed directly or stored in a BESS. Nevertheless, renewable electricity generation from RESs is not considered an under-utilized resource since it can also be fed into the electricity grid in order to be transmitted and consumed elsewhere (Plewnia, 2019; Tietze et al., 2019).

4.2.2 Residential Sharing of Solar Generation and Battery Storage

With high electricity prices and comparably low feed-in-tariffs, increasing self-consumption is the most profitable way to benefit from residential solar generation. As PV system adoption rates rise, the idea of sharing excess electricity generation with neighbors to increase self-consumption is investigated by a number of authors. Due to the fluctuating nature of solar generation with large peaks during the day, storage technologies can help in further aligning the electricity generation with a household's load. However, residential BESSs such as lithium-ion batteries are still costly and therefore only barely profitable for individual usage (Kaschub et al., 2016). Thus, larger central BESS capacity is seen as an opportunity to supply entire communities more independently while benefiting from economies of scale (Barbour et al., 2018; van der Stelt et al., 2018). However, community storage is not yet widely applied due to a number of regulatory and bureaucratic barriers (Müller and Welpe, 2018). Meanwhile, about 400,000 PV-coupled BESSs are already installed in Germany, with rapidly increasing numbers. We therefore explore the opportunity of connecting these existing assets by investigating a sharing economy model for individual residential PV installations and BESSs.

The implementation of a sharing economy model for residential BESSs is interpreted differently. Lombardi and Schwabe (2017) investigate the utilization of BESSs for several business models such as peak-shaving of industrial load and self-consumption for buildings. Thus, sharing in this context means distributing a BESS's capacity amongst different purposes, not users. In contrast to that, in this study, we investigate the P2P sharing of solar generation and BESS capacity amongst residential households within a neighborhood in spatial proximity as suggested by Chau et al. (2019). An extensive overview of trends and challenges in P2P sharing literature is provided in Tushar et al. (2021), identifying the regulatory framework as key enabler but also barrier of real-world P2P implementations. The main motivational factors for the participants in a P2P network are cost savings and emission reductions (Tushar et al., 2019). However, grid operators may also benefit from such a scheme due to the possibility of balancing electricity supply and demand, e.g., by reducing peak demand in a grid section and thus avoiding infrastructure investments (Tushar et al., 2021, 2020b). Network losses due to flexible power dispatch of prosumers participating in a P2P network can be neglected (Azim et al., 2020). A number of authors investigate possible operating models as well as the financial benefits of sharing PV generation, stored electricity and BESS capacity in a residential neighborhood. Celik et al. (2016) compare four operation paradigms for a community of five households with a PV installation and BESS each, ranging from a central coordination through the utility to a distributed operation by the end-users to a naïve charge-discharge strategy and selfish control with no coordination between the households. While the centralized approach yields the best results in terms of financial gains, it is by far the most computationally expensive. Velik (2013) investigate the maximization of PV self-consumption in a neighborhood with six households through electricity sharing with and without a BESS being installed in each household. The simulation is carried out with demand data from Austrian households over four weeks in winter and summer each. Biech et al. (2016) introduce a tool for a smart neighborhood simulation and illustrate the benefits of BESS sharing in terms of reduced amortization times over the system's lifetime. Schlund et al. (2018) simulate different community sizes within a distribution grid area consisting of 500 households using synthetic load profiles in order to improve grid stability and to investigate the ideal community size for BESS sharing in terms of additional self-consumption. What is missing in the existing literature, is an investigation of the impact of different configurations of household load profiles on the profitability and the simulation of sharing communities over a longer period of time than just a few weeks.

Another aspect that is insufficiently addressed in the previously presented publications, is the distribution of the profits that are generated through the sharing of electricity amongst neighbors. This could be resolved through either a trading or a cost sharing mechanism (Chau et al., 2019). The former requires participants to constantly make decisions to adapt to the market conditions. These can also be determined by an intelligent agent and be based on a participant's preferences and forecasts on consumption and generation patterns. In further research, the analysis of prosumers' decision making is often approached with game theoretic models (Tushar et al., 2018). In the context of sharing PV generation and BESSs on a household level, they have been applied to demonstrate (theoretical) financial and ecological benefits, to design pricing and profit distribution schemes and to show equilibria of different trading mechanisms (Tushar et al., 2019, 2020b, 2017, 2020a; Mengelkamp et al., 2017). There are several pilot projects on local energy markets with P2P trading in place today (Weinhardt et al., 2019), but they mostly do not include BESSs. Instead, projects with BESS sharing at community level are often designed around a large BESS and handle the sharing by assigning fractions of the BESS to the community members (Müller and Welpe, 2018). However, (game-theoretic) P2P trading approaches as described by Tushar et al. (2018) and Weinhardt et al. (2019) have some limitations. They assume that prosumers are willing to participate in the trading of energy at least to some extent in order to make profits or increase a community's independence from the grid. Even if the decisions are made by an intelligent agent, information about the participants' preferences and forecasts on load and generation might be needed. Given that electricity is a low-involvement product that most people have no or little experience with (compare Chapter 3) and given that financial margins for trading electricity are small, this could pose a high entrance barrier for local energy sharing communities. In fact, studies on end-users' participation in energy efficiency measures have shown that only for a vanishingly small proportion of the participants, behavioral efforts could be observed and even this group is significantly less motivated beyond the initial euphoria of the first weeks (Metzler and Jacquemart, 2014; Tiefenbeck, 2017). It has also been shown that the understanding of electricity consumption is very low in residential households in general (Brounen et al., 2013). It is therefore questionable whether inexperienced participants would understand the consequences of their participation and their actions in an energy trading mechanism. At the very least, it has to be assumed that the participation in a complex trading scheme could pose an entrance barrier for many residents. Based on these premises, we design a sharing economy model that requires no active participation in trading. Instead of a trading mechanism, we propose the deployment of an "agreed cost-sharing mechanism" as previously suggested by Chau et al. (2019). Profits are generated by maximizing a community's overall self-consumption through an automatic energy management system. The prices for the shared goods are set through a platform so that the mechanism results in a subjectively fair revenue distribution.

From the findings above, we derive the necessity of a comprehensive analysis of the theoretical and practical potentials of a sharing economy model for residential PV generation and BESS capacity. We transfer the existing theory to this use case, demonstrate the concept and investigate financial benefits through the simulation of a sharing economy model for 520 different communities, using empirical load profiles from Chicago households. We then discuss a fair revenue distribution based on the gathered data and shed light on the contribution of the individual participants in the sharing economy based on their load profile properties. Previous work has either only investigated operation modes and financial benefits or trading and sharing mechanisms, often with little empirical data on residential load profiles and only over short periods of time. Additionally, we investigate the possibility of matching and coordinating profitable energy sharing communities based on their load profile characteristics.

4.2.3 Regulation of Local Energy Communities

Regarding the use case of sharing local PV generation and BESS capacity, the general findings on possible barriers in the energy sector are confirmed by an overview on current pilot projects and the corresponding business models conducted by Müller and Welpe (2018). The authors find that many pilot projects face regulatory barriers, especially if they rely on the public grid instead of an isolated microgrid setup. They conclude that sharing BESSs may remain a niche phenomenon if no regulatory adjustments are made. As of today, in many countries, the regulation poses great obstacles for residential PV system and BESS sharing. In Germany, for instance, self-consumption of PV generation is free of taxes and levies for all PV systems up to 10 kWp while selling excess generation to a neighbor through the public grid is fully burdened with fees of around 0.18 € kWh^{-1} (BDEW, 2021). With the current electricity price being close to 0.32 € kWh^{-1} and with a fixed feed-in-tariff for electricity from PV systems up to 10 kWp of around 0.10 € kWh^{-1} (Figgener et al., 2018), this renders electricity sharing amongst neighbors unprofitable. It is possible to avoid part of the charges by registering a so-called "customer installation", in which case fees related to grid usage of up to 0.12 € kWh^{-1} does not have to be paid (Sahle, 2019), rendering a profit window for energy sharing of about 0.1 € kWh^{-1}. It is thus important to carefully choose the regulatory framework when investigating the potential benefits of a sharing economy model. Kalathil et al. (2019), for example, employ a time-of-use tariff as it already exists in many areas of the United States. Some studies are based on the current regulation but allow for somewhat more freedom when it comes to sharing, assuming free-of-charge self-consumption and including feed-in-tariffs for excess generation that is fed into the grid (Biech et al., 2016; Schlund et al., 2018; Velik, 2013). Instead of fixed feed-in-tariffs, some authors employ real-time pricing schemes that reflect fluctuations in spot market prices (van der Stelt et al., 2018) or incentive prices to enhance self-consumption during hours of high generation (Celik et al., 2016). In the following, we present a sharing economy model for the described setup with preferential treatment of self-consumption within a community.

4.3 A Sharing Economy Model for PV-coupled BESSs in Energy Communities

Applying the principles derived by Plewnia (2019), we specify the unique features of a sharing economy model for locally generated and stored electricity and BESS capacity. Figure 4.1 shows an exemplary configuration of a local sharing community. Participants can be owners of a PV system (prosumers) and a BESS (battery-prosumers) or merely participate with their electricity load as consumers who do not own assets but instead participate by buying excess electricity from the prosumers and battery-prosumers. All participants are connected to each other through the public grid.

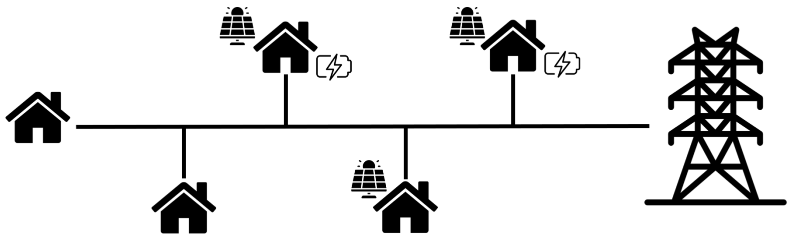

Figure 4.1.: Sharing community setup: Two battery-prosumers (PV + BESS), one prosumer (PV) and two consumers are locally connected through the distribution grid and jointly connected to the national grid.

In Table 4.1 and 4.2, we transfer the dimensions and characteristics of a sharing economy as described by Plewnia (2019) to a residential sharing economy for solar generation and BESS capacity. Two aspects are especially worth noting regarding the use case at hand. In the context of local electricity generation, *access instead of ownership* and *under-utilized resources* can be interpreted differently, depending on the value that is ascribed to the (geographical) origin of electricity. If a value is ascribed to a local origin, then both of the mentioned principles apply to a sharing economy model in a local community. Local electricity can indeed be under-utilized and *access instead of ownership* applies for consumers who can buy locally generated electricity from a neighbor instead of investing in a PV system of their own. In research, it is debated whether consumers are willing to pay a surplus on local electricity (Kaenzig et al., 2013; Löbbe et al., 2020; Mengelkamp et al., 2019). Of course, in this context, local electricity also contains the notion of renewable generation. It can thus be difficult to differentiate whether consumers actually value the geographical origin of the electricity (and the independence that comes with it) or simply the underlying generation technology. Therefore, in our model, we do not assume that participants in a sharing economy are willing to pay more for local electricity than the current electricity price. In this setting, while *access instead of ownership* is reversed in the case of RESs, it applies for BESSs if the regulatory framework allows it. For consumers, on the other hand, it then applies for both RESs and BESSs.

Table 4.1.: Dimensions of a sharing economy model for local solar generation and BESS capacity as described by Plewnia (2019)

Shared good	Market orientation
(Local) Electricity from solar generation: A (battery-)prosumer may share excess PV generation with neighbors that have excess demand at the same time. *BESS capacity*: A BESS can be shared in two ways: A neighbor can buy stored electricity from a battery-prosumer and she can store her own excess solar generation in a battery-prosumer's storage if there is capacity available.	*Profit-oriented*: Participants in the community share electricity at lower costs than what they would have to pay for electricity from the grid. We assume that no fees have to be paid for self-consumption of locally generated electricity. The shared electricity has to be priced so that no participant suffers economic disadvantages. A small annual fee could be charged by the service provider.
Market structure	Industry sector
Consumer-to-Consumer Other settings are perceivable, e.g, Business-to-Consumer if, for example, the platform provider offers additional services or owns BESS capacities.	*Energy supply* Within the sector of energy supply, the provision of energy (i.e., electricity) and capacity (i.e., BESS capacity) has to be distinguished.

For the deployment of a sharing economy model, we propose a platform solution to match and coordinate communities in the spirit of Golla et al. (2020). The benefits of a well-matched community are shown in the results of the case study in Section 4.5. The platform could be operated by producers and distributors of BESSs as an additional service to their customers who can provide information and the possibility

Table 4.2.: Transferring the principles of the sharing economy derived by Plewnia (2019) to the case study of a local energy sharing community

Aspect	Application in Case Study
Platform-based	A platform is needed for the matching and coordination of communities and for the provision of information. The platform operators are service providers and do not need to own any assets.
Leverage of digital technologies	Digital coordination mechanisms are key to manage the interaction of electricity supply and demand as well as storage operation within a sharing community. Digital technologies such as smart meters are necessary for the measurement of the electricity flows that are provided to the coordination algorithm.
C2C/P2P-interaction	The sharing economy is made possible through P2P interaction. Local (battery-) prosumers share their decentral electricity generation and storage capacities with other (battery-)prosumers or consumers. Information, energy and money are exchanged through the digital platform.
Access instead of ownership	*(Battery-)Prosumers* : Ownership (of RESs, BESSs) instead of access (to electricity supply from central power plants) *Prosumers*: Access (to BESS capacity) instead of ownership (of a BESS) *Consumers*: Access (to local electricity and BESS capacity) instead of ownership (of RES, BESS).
Under-utilized resources	Shared good *electricity* : Not applicable for renewable electricity generation per se. (Locally) Unused electricity is fed into the grid and utilized elsewhere. Exception: Sharing can prevent losses of electricity if PV generation would have to be curtailed during peak hours due to insufficient grid capacities. Shared good *local electricity*: Principle is applicable when a value is attributed to the use of local energy, for example to increase independence from utilities. Shared good *BESS capacity* : Higher utilization rate if shared in energy communities.
Shared values	The energy transition is widely supported in the public (Renn et al., 2020). "Green" energy supply and self-sufficiency have non-monetary value (Mengelkamp et al., 2019).

to simulate the sharing mechanism for community members. A comparable approach can be observed in the business model of the sonnenCommunity implemented by the German BESS manufacturer SonnenGmbH (Tietze et al., 2019). This community is a virtual P2P platform, which allows its participants to share excess PV generation with other members. Through the intelligent connection of RESs and BESSs, electricity can be exchanged between community members during peak generation times. In contrast to the sharing economy model proposed in this chapter, community members do not have to live in spatial proximity and can therefore not benefit from regulatory schemes implemented for local energy communities.

4.4 Simulating a Sharing Economy for an Energy Community

To demonstrate the theoretical concept explained in the last section, we simulate a sharing economy model for PV generation and BESS capacity within a residential community. For the simulation, we choose the setting of five households as shown in Figure 4.1 consisting of two battery-prosumers, one prosumer and two consumers. A similar setting is implemented by Celik et al. (2016) to compare operation strategies and Schlund et al. (2018) show that 98% of the efficiency of a large energy sharing community is already achieved with five participating households. While previous studies often perform these simulations on limited empirical data and over short periods of time, we compare the results of 520 different sharing communities over one year with a 30-minute time resolution. Since the utilization rate of a BESS largely depends not only on a household's overall consumption but also on the load pattern throughout the day, we use different combinations of household load patterns for each community. We then simulate the 520 sharing communities twice: During the first simulation, we keep all other parameters constant to explore the effects of different load patterns on the utilization rate of a PV-coupled BESS for different household configurations. We use real load profiles from a Chicago dataset containing 100,000 household load profiles in 30-minute intervals and scale them to the average annual consumption of a single-family home in Germany, which is 4,000 kWh. The sizes of the PV modules and BESSs for each household are chosen to correspond to typically installed systems in German households so that the resulting community represents today's reality as closely as possible (Table 4.3). We use PV generation data from a research campus in southern Germany and scale the data so that it corresponds to the generation of an 8 kWp solar installation with 950 full load hours, which is a typical output for a residential PV system in Germany (AEE, 2013). Losses in battery components are chosen to correspond to the performance of current household BESSs (Weniger et al., 2020). In the second simulation, we keep the original absolute loads of the households in our datasets. Instead, we scale the size of the PV system and BESS capacity and power so that the ratio of load to capacity and power remains the same as in the first simulation. So, for example, a household with an annual load of 5,000 kWh would have a 10 kWp PV system and a 7.5 kWh / 4.375 kW BESS installed. This approach may result in BESS and PV configurations that are not realistic (as sizes come in discrete rather than continuous steps), but it allows us to specifically investigate and compare the effect of the absolute load vs. the load pattern on the profitability of the energy sharing community.

Table 4.3.: Assumptions for the sharing community with all parameters kept constant

	Assumption	Corresponds to
Annual household load	4,000 kWh	Single family home with 3-4 residents (BDEW et al., 2019)
PV generation capacity	8 kWp	Commonly installed residential PV plant in Germany (Bundesnetzagentur, 2020a)
Usable (not nominal) BESS capacity	6 kWh	Commonly installed size and corresponding to assumed annual load (Weniger et al., 2020; Klein et al., 2019)
BESS charging capacity	3.5 kW	Current systems in the market, which predominantly range between 0.4 and 0.6 kW/kWh (Weniger et al., 2020)
Efficiency	95%	Charging/discharging performance of current systems (Weniger et al., 2020)

The five households for each of the 520 communities are randomly drawn from the original dataset. We design two operating strategies for each community: One, where the households operate individually to maximize self-consumption without sharing electricity or BESS capacity and one coordinated strategy that maximizes the community's self-consumption overall. For both strategies, the sum of the households' resulting electricity bills is calculated and compared to investigate a community's combined profit. The distribution of the revenues among the residents is addressed separately in Section 4.5.1. We choose a regulatory framework similar to the German regulation as of today, with an electricity price of 0.3 € kWh^{-1}, and a feed-in-tariff of 0.1 € kWh^{-1}, for solar generation (Figgener et al., 2018). We assume that all electricity generated within the community can be shared without additional costs. This means that every additional self-consumed kWh yields savings of 20 cents. The simulation is carried out over one year of household consumption and PV generation data. In the individual operation strategy, each household follows a greedy strategy as described in Figure 4.2. (Battery-)Prosumers will first directly consume as much PV generation as possible, then use the BESS (if existent) to store excess electricity or supply remaining loads and then resort to the public grid as a last option for remaining load or excess generation. The annual electricity cost of a household is then determined according to Equation 4.1 where buy_t^h and $sell_t^h$ is the electricity that a household h from the set of all households in a community C buys from or sells to the grid at time step t for the fixed electricity price p^{el} and the fixed feed-in-tariff p^{fit}. The overall electricity costs of the community $Cost^c$ are determined by adding the costs of all households in the community according to Equation 4.1. Note that the upper limit for annual electricity costs for a single household is 1,200 € if the entire consumption of 4,000 kWh is supplied by the grid at 0.3 € kWh^{-1}, which applies to all consumers in the individual operating strategy. For (battery-)prosumers, the annual costs can be negative if more money is earned through feed-in than spent on electricity supply from the public grid, i.e., instead of paying a bill they may receive a payment at the end of the year.

$$Cost^c = \sum_{h \in C} Cost^h \qquad Cost^h = \sum_{t \in T} buy_t^h * p^{el} - \sum_{t \in T} sell_t^h * p^{fit} \tag{4.1}$$

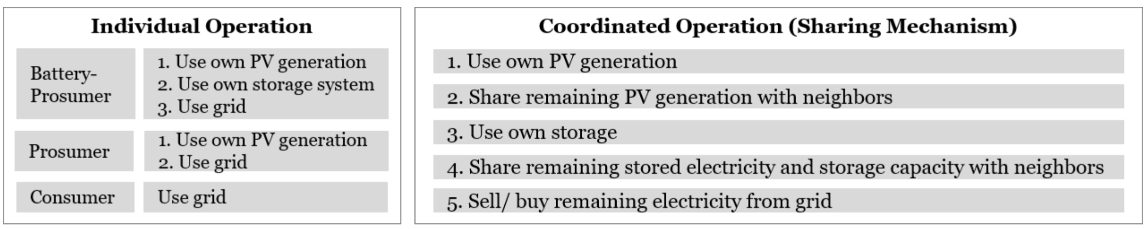

Figure 4.2.: Principles of community electricity supply during individual operation (no sharing between neighbors) and coordinated operation (sharing of PV system and BESS with neighbors)

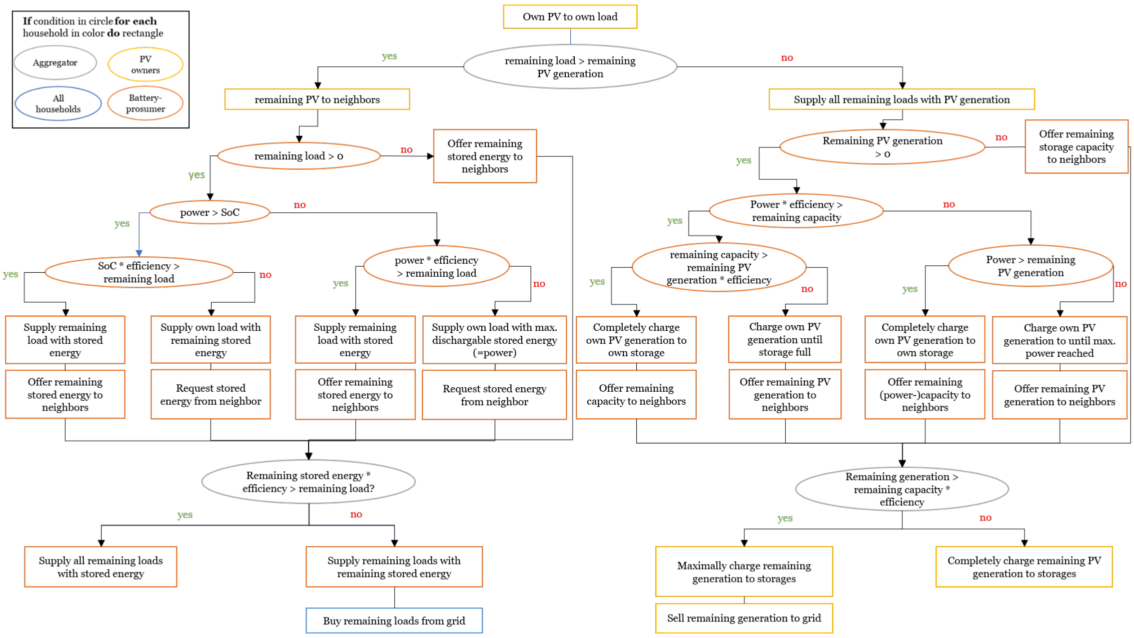

Figure 4.3.: Sharing algorithm of the coordinated community operation at each time step

The coordinated operation strategy for the sharing community as depicted in Figure 4.3 schedules all electricity flows so that a maximum overall self-consumption is ensured. The color scheme illustrates which actions apply to the respective types of households. Similar algorithms have been previously presented in Velik (2013) and Biech et al. (2016) with only battery-prosumers as participants. For this control strategy, no forecast is needed as it is beneficial under a uniform electricity tariff to immediately maximize self-consumption at any given time step. At each time step, (battery)-prosumers first supply their own load with as much PV self-generation as possible. Then, the sharing economy operator (which can be implemented as a simple information system) compares the community's overall remaining load and excess PV generation. At any timestep, each household sends information about remaining load, excess PV generation and remaining BESS capacity to the operator. After the operator compares the overall remaining load and solar generation, any remaining generation is shared with neighbors that have remaining loads. In case there is more remaining load than PV generation in the community, the PV generation is distributed proportionally according to the remaining load of the respective neighbors, and vice versa (this is important with regards to payments in the sharing economy model). The community charges its BESS capacity only after as much PV generation as possible is consumed directly. This is advantageous because the usage of storage is associated with costs due to cyclic degradation. Thus, it would be cost-inefficient for the community as a whole to store electricity instead of sharing it with a neighbor that has immediate load to supply. Each battery-prosumer will first make use of personal BESS capacity before remaining capacity or stored electricity is offered to neighbors. The community buys from the public electricity grid in order to supply remaining load or feed in excess PV generation after as much PV generation as possible has been consumed or stored directly. At any time step, the algorithm ensures that the utilization of storage is within the restrictions of the maximum power capacity of the BESS and that no more electricity is charged or discharged than the current State of Charge (SoC) allows. The resulting electricity costs are calculated for the community as a whole according to Equation 4.1. The overall community profit from the sharing mechanism is then determined as the difference between the community's electricity costs during individual and coordinated operation. For the comparison of overall profits from an energy sharing economy model, the electricity flows between the individual members of the community are not relevant and therefore handled as a "blackbox" for now. The flows and the resulting consequences for the pricing and payment of the shared goods are addressed in Section 4.5.1.

4.4.1 Characterising Participants based on Load Profile Properties

In this study, we aim to not only assess the possible profits of a sharing economy for PV generation and BESSs, but we also determine the impact of the individual participants of the energy sharing community and their characteristics on said profitability. This has not yet been explored in the literature: On the one hand, there is a range of literature dealing with the characterization and classification of electricity load profiles by means of describing parameters (i.e., maximum daily load, summer-winter ratio), clustering or pattern mining (see for example S. S. Cembranel et al. (2019); Chicco et al. (2003); Milton et al. (2018); Rajabi et al. (2017); Ramos and Vale (2008); McLoughlin et al. (2013); Bicego et al. (2018); Luo et al. (2017); A. K. Tanwar et al. (2015); McLoughlin et al. (2012)). But these findings have not yet been applied to the literature on the economics of local energy sharing communities described at the beginning of this chapter. Therefore, in this study, we apply the findings of the research on load profile characterization to find out which characteristics of participants' load profiles are beneficial for the proposed sharing community. To this end, Table 4.4 shows a collection of describing parameters that we calculate for each load profile in our simulations where l corresponds to half an hour during the day (i.e., l=22 refers to 11 am).

Table 4.4.: Parameters for the characterisation of load pattern (S. S. Cembranel et al. (2019); Chicco et al. (2003); Milton et al. (2018); Rajabi et al. (2017); Ramos and Vale (2008); McLoughlin et al. (2012); Bicego et al. (2018); Luo et al. (2017); A. K. Tanwar et al. (2015); McLoughlin et al. (2013) and own extensions)

Parameter	Equation	Explanation
Night impact	$P^i_{night} = \frac{1}{3} * \frac{\frac{1}{N} * \sum_{n \in N} E^i_{d,n}}{\frac{1}{T} * \sum_{t \in T} E^i_{d,t}}$ $N = \{1, ..., 12\} \cup \{46, 47\}$	The share of the consumption during night hours n in N of the total daily consumption.
Lunch impact	$P^i_{lunch} = \frac{1}{8} * \frac{\frac{1}{L} * \sum_{l \in L} E^i_{d,l}}{\frac{1}{T} * \sum_{t \in T} E^i_{d,t}}$ $L = \{22, ..., 26\}$	The share of the consumption during lunch hours l in L of the total daily consumption.
End of work impact	$P^i_{EoW} = \frac{1}{6} * \frac{\frac{1}{EoW} * \sum_{e \in EoW} E^i_{d,e}}{\frac{1}{T} * \sum_{t \in T} E^i_{d,t}}$ $EoW = \{32, ..., 38\}$	The share of the consumption during end of work hours e in EoW of the total daily consumption.
Daily minimum demand	$P^i_{min} = \min_{t \in T} E^i_{d,t}$	Minimum of the daily load profile.
Summer/ winter ratio	$P^i_{SWR} = \frac{\sum_{s \in SM} \sum_{t \in T} E^i_{s,t}}{\sum_{w \in WM} \sum_{t \in T} E^i_{w,t}}$	The ratio of the total demand in summer months SM to the total demand in winter months WM.
Daily non-uniformity coefficient	$P^i_{NUC} = (\frac{\frac{1}{T} * \sum_{t \in T} E^i_{d,t}}{\max_{t \in T} E^i_{d,t}})$	Describes the maximal variation in regards to the average load
PV correlation	$P^i_{PV} = \frac{cov(E^i_d, PV_d)}{\sigma_{E^i_d} * \sigma_{PV_d}}$	The Pearson correlation coefficient of the load profile with a generation profile of a PV system PV_d

In Section 4.5.2, we derive statements about the suitability of various participants for a sharing community. Since we keep the overall electricity consumption constant during the first simulation, the discovered relationships can be fully attributed to the pattern of the respective household's load profile. In the second simulation, we compare the effects of the load patterns to the effect of changes in absolute load. In total, we identified 15 parameters during our investigations, but for the sake of comprehensibility, we present only those for which an impact on the community's performance could be found. Each of the parameters in Table 4.4 is calculated for every day of the load profile. Then, the median of all resulting values is used to describe a "median" day of the load profile. This approach compresses the annual load profile to a few values, thus a lot of information is lost in the process. In order to keep some information, we distinguish between six different "median" days: First, we differentiate between *workdays* (Mo-Fr) and *weekends* (Sa,Su). Second, we account for seasonal effects by distinguishing between *summer* (June - September), *winter* (December - March) and *spring/autumn* (April, May, October and November). For each household, we thus obtain 90 parameters that are then used to build a random forest regression to determine the interaction of load profile properties and community profits. The used method and our results are described in Section 4.5.2.

4.5 Results: Community Profit, Revenue Distribution and Participant Matching

For 520 communities consisting of five households each, we simulate a sharing economy model and compare the annual electricity costs with the case of individual operation of the assets. Figure 4.4 (left) shows the distribution of profits over the 520 simulations. The community that profits least from the sharing of electricity and BESS capacity has annual savings of 445 €, the most profitable sharing economy community yields annual savings of 813 €. On average, 615 € are saved through the sharing of electricity and BESS capacity amongst five households. By keeping all other system parameters constant, the results show the effect of different load pattern configurations on the profitability of a sharing community. The results show the financial potential of a sharing economy model in residential communities. A further finding is the effect of a sharing mechanism on the utilization rates of the assets in the community. Figure 4.4 (right) shows the proportional origin of the annual electricity consumption, averaged over all 520 communities. Since annual household consumption is scaled to 4,000 kWh each, the communities consisting of five households have an annual electricity consumption of 20,000 kWh. During individual operation, almost two thirds of the electricity are supplied from the grid. On average, an additional 3,208 kWh are self-consumed in a sharing community. The largest effect between individual and coordinated operation can be observed in the electricity that is directly consumed from solar generation. The sharing of the BESSs accounts for only 430 kWh out of the additional self-consumption. While this might not seem much, it can be explained by a number of factors. First, we assume that the BESSs are dimensioned to match the annual consumption of a single household, since we want to explore the sharing potential for existing household PV systems and BESSs. Larger community BESSs might lead to higher savings. Second, as previously explained, the joint operation of a solar installation and a BESS has an upper limit of approximately one cycle per day meaning 365 cycles per year. When comparing the utilization rates of the BESS in individual and coordinated operation, we thus have to consider the additional cycles per year that are achieved through means of the sharing economy model. This number increases from approximately 280 cycles per year in the individual scheme to around 320 cycles per year in the coordinated operation for each of the two BESSs employed in the communities. Given that the solar generation is limited on many days during the year, this number suggests that in a sharing community as configured in this simulation, a nearly maximal utilization rate of BESSs for self-consumption is achieved. The increased rate of utilization is thus an incentive for storage owners to participate in a sharing scheme as proposed here. Nevertheless, the bulk of the profits is generated through the additional direct self-consumption, a result that is partly attributable to the addition of the pure consumers to the sharing community. Although these consumers do not bring private capital in the form of technology into the community, they are presumably an important factor in the economics of the sharing economy business model and should therefore be encouraged to participate through financial incentives. Nonetheless, it can be argued that higher initial investments justify higher profit shares for (battery)-prosumers. In the next section, we examine different price configurations and discuss how they encourage the respective types of households to participate in the sharing community.

4.5.1 Distributional Fairness through a Fixed Pricing Approach

During the simulation, all shared electricity flows at each time step are recorded to track the amount of electricity that is shared between the respective households in the community. Figure 4.6 (left) shows this for the average community over one

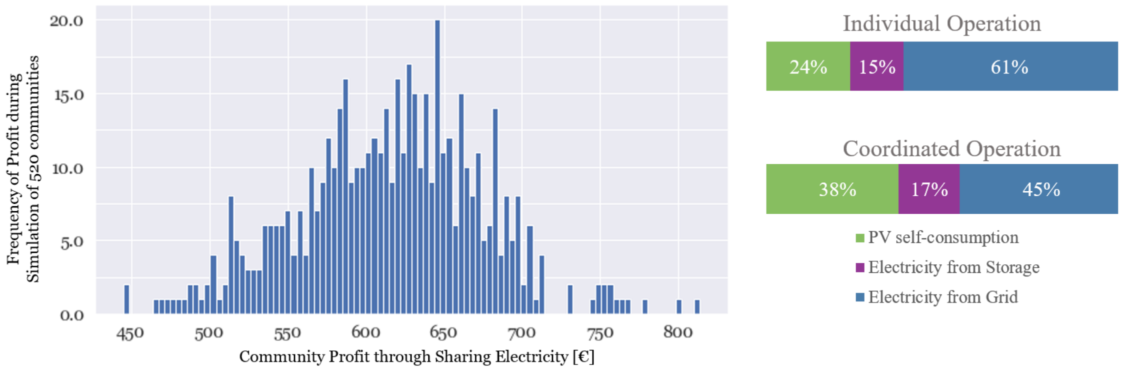

Figure 4.4.: Community profit distribution for 520 sharing communities (left), sources of electricity supply in average community (right)

year. There are three flows that have to be reimbursed differently: First, electricity from a (battery-)prosumer's solar panels can be directly consumed by a neighbor at the price p_{PV}. Second, stored electricity from a battery-prosumer's BESS can be consumed by another customer ($p_{storage}$) and third, electricity from solar generation can be sold to a battery-prosumer to be stored in her BESS. Note that for the latter, the BESS owner pays p_{charge} to the (battery-)prosumer who provides the electricity. We propose to choose fixed values for each of these prices. This is a contrasting approach to a trading mechanism, but, as previously argued, it offers decisive advantages. A fixed pricing mechanism is de facto "business as usual" for the majority of electricity consumers. However, the fixed prices of the shared goods have to be chosen carefully and thus we demonstrate the effects of different pricing configurations in this setting. We argue that some conditions have to be met to result in a "fair" profit sharing outcome. The concept of fairness is quite ambiguous in research and for more differentiation on fairness consider (Joshi, 1989). We stipulate that distributional fairness is achieved if (i) larger investments result in larger profit shares, (ii) additional consumption of locally generated electricity is rewarded (i.e., profit share of consumers > 0), and (iii) no household is penalized for participating in the sharing economy community (i.e., the profit from participating in the community has to be larger than during individual operation). To ensure that no household suffers economic disadvantages from participating, certain limits apply to the three previously described prices (compare Figure 4.5). All have to be above the feed-in-tariff so that there is no incentive to feed electricity into the public grid instead of sharing it. Similarly, consuming local electricity should always be advantageous and thus $p_{storage}$ and p_{PV} should be less than the grid electricity price. The price that is paid for stored electricity $p_{storage}$ has to be at least as high as the price that the owner pays for storing electricity (p_{charge}) plus the (marginal) costs of storing an extra kWh in the BESS c_{kWh}. The marginal costs c_{kWh} are difficult to determine. In general, the LCES can be calculated using the overall system costs and dividing it by the capacity and the achievable cycles during a lifetime. For lithium-ion batteries, Lai and McCulloch (2017) find this value to be between 0.36 and 0.69 \$ kWh^{-1}. As system costs have decreased significantly in the last years, one German online information portal claims that the LCES can be as low as 0.15 € kWh^{-1} for small-sized BESSs currently in the market, even without considering subsidies (Kloth, 2022). However, it could also be argued that in the case of under-utilized BESS capacity, the marginal costs are zero because without the sharing economy model, the BESS would never reach full cycle life before reaching its calendaric end of life of up to 20 years (sonnen GmbH, 2020). Either way, considering the initial investment costs, for the revenue distribution, we stipulate that a battery-prosumer receives a larger profit share than a prosumer, and that a prosumer in turn receives a larger share than a consumer. Subsequently, in the investigated pricing schemes for a sharing economy model, c_{kWh} is set sufficiently high to ensure these conditions. The configuration of the prices can then be reduced to two decisions: *How much is storage worth* (setting c_{kWh})? and *How much is local consumption being rewarded* (setting p_{PV})?

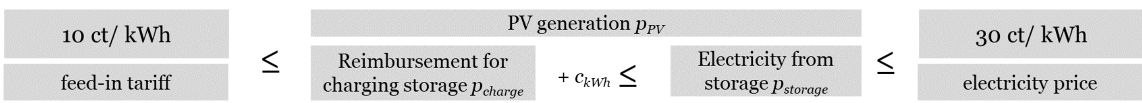

Figure 4.5.: Upper and lower bounds for fair pricing of PV generation (p_{PV}), charging storage (p_{charge}) and buying electricity from storage ($p_{storage}$) when considering the marginal costs of storage c_{kWh}

The flows from the PV system and BESS owners to the consumers in Figure 4.6 (left) show that consumers are responsible for requesting the majority of shared direct self-consumption and stored electricity, again underlining the importance of consumers for the overall profitability. Interestingly, roughly one third of stored electricity is consumed by the respective BESS owner and two thirds are shared with neighbors. This is due to the implementation of the algorithm without forecasts that enables the provision of stored electricity to supply a neighbor's load at time step t without considering whether the storage owner might need it for personal demand in time step $t + x$. However, it is also beneficial for the storage owner to sell this electricity rather than consuming it later.

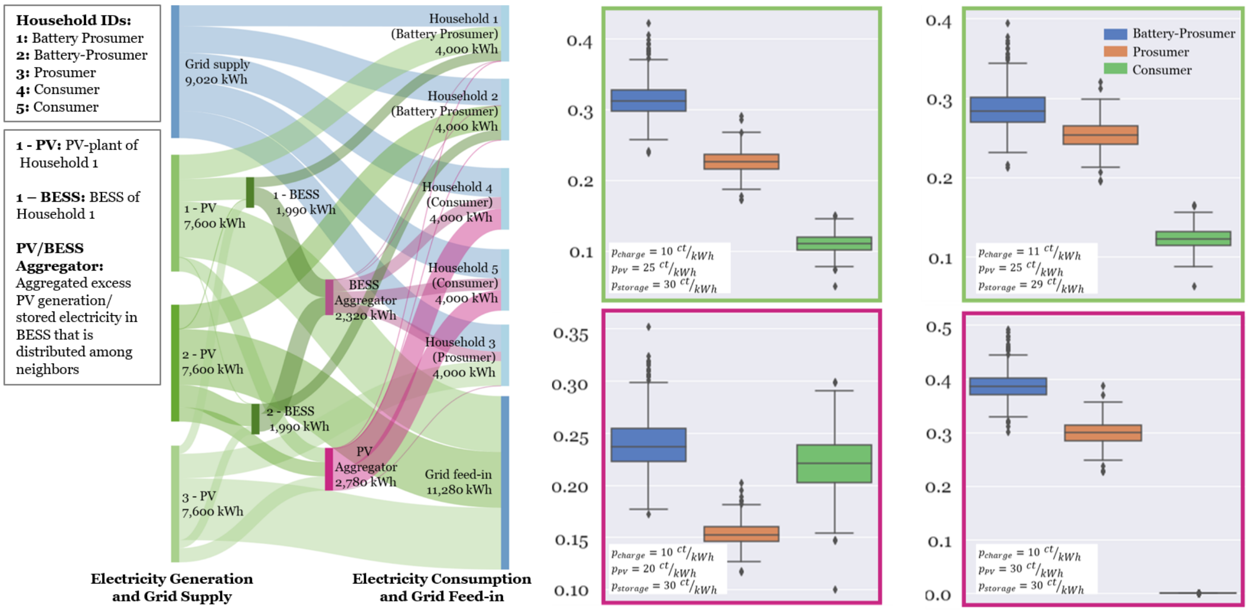

Figure 4.6.: Electricity flows in the average sharing community (left). Distribution of community profits amongst household types in percentages considering different pricing schemes for shared electricity (right)

The four exemplary pricing configurations in Figure 4.6 (right) illustrate the effects of setting p_{PV} and c_{kWh}. Green borders indicate a fair profit distribution for the median community, purple borders highlight unfair distributions. When the two parameters are set to their respective upper limits (bottom right), (battery)-prosumers receive the maximally possible profits at the expense of the consumers. This scheme is not feasible under our fairness principles as it provides no incentive for a consumer to participate in the sharing economy model. A contrary effect is created if the p_{PV} is set significantly lower at 0.20 € kWh^{-1} (bottom left). In this setting, a consumer is rewarded more than the prosumer, which contradicts the guideline that we previously set that higher investments should yield higher profit shares. We therefore conclude that the price for PV generation has to be somewhere in between 0.2 and 0.3 € kWh^{-1} in our setup to reward consumption without marginalizing initial investments in technology. A possible fair revenue distribution scheme is thus illustrated in the top left graph where p_{PV} is set at 0.25 € kWh^{-1}. With an average of around 615 € annual profits for a sharing community, each of the two battery-prosumers receives around 185 €, the prosumer receives around 120 € and each of the consumers 60 €. In this initial feasible revenue distribution scheme, we set the reward for an investment in a BESS as high as possible with $c_{kWh} = 0.2$ € kWh^{-1} since we argue that a battery-prosumer should receive a larger share of the profit than a prosumer. The effect of a slight reduction in c_{kWh} on this ratio is shown in the graph in the upper right corner. While the profit share of the consumers does not change substantially, in the average sharing community, the gap between battery-prosumers and prosumers is gradually closing. This could be justified by the observation that the majority of profits comes from additional PV self-consumption rather than stored electricity as seen in Figure 4.4. As shown with the examples in Figure 4.6 (right), there is more than one set of fixed prices that would ensure distributional fairness as previously defined. Note that while we always refer to the outcome of the pricing configurations on the average sharing community, the box-plots show that the distribution of profits can differ significantly in individual cases. However, the choice of prices can also serve to incentivize individual participants to shift their electricity load in benefit of the sharing community. In a platform-based sharing economy model, the pricing configuration should be considered individually for each sharing community as it is a crucial design element of the initial setup. In general, fair pricing and revenue distribution needs to be further investigated, possibly by undertaking field studies on residential preferences and willingness to participate in a sharing economy model as proposed here.

4.5.2 Matching Communities: Suitability of Participants based on Load Profile Properties

In this section, we want to investigate how to predict the profitability of a sharing community based on the participants' load profile properties. We find that there is a dependency between the performance of battery-prosumers during individual operation and the community profits in a sharing economy (Figure 4.7, left). As previously mentioned, (battery-)prosumers can have negative electricity costs and during our simulation, this was always the case for the battery-prosumers. The figure shows that when the two battery-prosumers in the community perform poorly in individual operation, i.e., their positive cashflow is small when they operate by themselves, the sharing community's profit tends to be larger. No such relationship could be found for the one prosumer (without BESS) in the community. It is an interesting finding that battery-prosumers with poorer individual performance would have a greater incentive to participate in a sharing economy. Since they contribute the largest investments to the community, their willingness to participate is crucial for the formation of sharing communities.

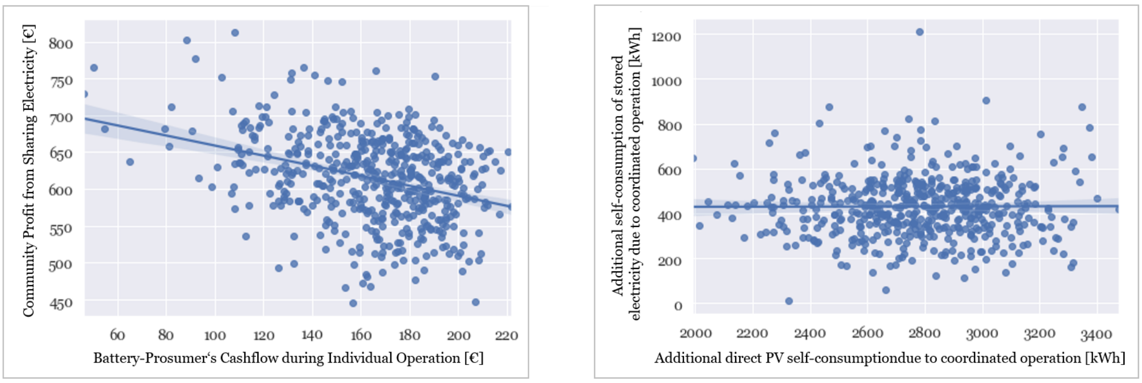

Figure 4.7.: The two battery prosumer's (average) cashflow during individual operation compared to the community profit from sharing electricity (coordinated operation) (left). Relationship of a community's additional self-consumption from PV generation and stored electricity (right)

The overall profits of a sharing community can be attributed to the additional self-consumption from (a) PV generation (direct self-consumption) and (b) stored energy. We therefore split the overall additional self-consumption of each sharing community into these two parts. We find that there seems to be no dependency between additional self-consumption from PV-coupled BESSs (Figure 4.7 right), and we will investigate if we can predict either of these values from participants' properties. Therefore, we want to investigate how we can predict the three target variables (1) additional (direct) PV self-consumption, (2) additional self-consumption of stored energy and (3) overall community profit in a sharing economy, using only the attributes of participants' load patterns. We use the load profile properties described in Section 4.4.1 and obtained 90 descriptive parameters for each household. We train a random forest regression using the

RandomForestRegressor method of the Python package sckit-learn. We average each of the 90 parameters for three sets of participants: (i) the two battery-prosumers, (ii) the two consumers and (iii) all community participants. We then use them as input to predict our three target values. In addition, we train one more tree with the input parameters of battery-prosumers and consumers combined, resulting in 180 input parameters. The maximum depth of the regression tree is set to 12. To evaluate the overall performance of the regression, we split the 520 households in a training (n = 450) and test (n = 70) set. We then calculate the mean squared error (MSE) for the predictions on the test set and compare it to a naive benchmark (Dekking, 2007). As naive benchmark prediction, we use the average of the respective target value for each community (e.g., 615€ for the community profit).

The resulting improvements of the MSE when compared to our naive benchmark are shown in Table 4.5. We find that we can improve the MSE for all target values significantly when using the participants' load profile pattern parameters as input. Interestingly, we can improve our prediction of additional self-consumption from storage by over 40% using the battery-prosumers' parameters as input, but achieve virtually no improvement when using the consumers' parameters. For additional direct PV self-consumption, it is the other way around: Our prediction improves by almost 80% with the consumers' parameters as input and only 9% using the battery-prosumers' parameters. The average over all households taken together yields the worst results which shows that too much information is lost by averaging over all households. We achieve the best results for additional PV self-generation and community profit when combining the battery-prosumers' and consumers' parameters, however the improvements are marginal. From the results we derive that one has to take a closer look at different participants depending on the target of a sharing economy. If the aim is to increase the utilization of PV-coupled BESSs, then it is best to include suitable battery-prosumers while the properties of the other participants are less important. On the other hand, if the main goal is to increase direct PV self-consumption and overall profitability, the properties of the consumers that are added to the sharing economy are decisive. It should be noted that we also performed all of the predictions with the load pattern parameters of the prosumer (both individually and in combination with the other participants) but no improvements could be achieved in any scenario. We conclude that the properties of the single prosumer are of very little importance compared to the other participants in our scenario.

Table 4.5.: Improvement in MSE when using participants' load profile properties to predict the performance of the sharing community

Target value / **Input property**	Additional (direct) PV self-consumption	Additional self-consumption from storage	Community profit
Benchmark (average)	100% (MSE=74283)	100% (MSE=13165)	100% (MSE=3710)
Battery prosumers	91.1 %	56.9%	98.8%
Consumers	22.9%	98.4%	30.6%
All households	82.9%	86.7%	79.5%
Consumers + Battery prosumers	22.3%	60.7%	25.5%

Based on our results in Figure 4.7 and Table 4.5, it seems that battery-prosumers that perform relatively worse on their own, i.e., their load profile leads to a low BESS utilization, profit from joining or establishing a sharing community. To better understand the results and the importance of individual features in predicting the target values, we use the Shapley Additive Explanation (SHAP) introduced by Lundberg and Lee (2017). The SHAP value is more robust than classic feature importance measures as it avoids inconsistencies such as giving higher importance to features that are used earlier in a tree split. For each observation, the SHAP value calculates the marginal contribution of each feature to the target variable. This impact can be calculated both globally (i.e., the overall average impact of the parameter on the model output) and locally (i.e., the impact of the parameter on the output for each observation in the data set), which increases the transparency for the interpretation of the features' impact. Figure 4.8 shows the ten highest global and local SHAP values in the case of predicting additional self-consumption from storage with the battery-prosumer's load profile parameters. We can see that the *daily minimum demand* in summer and spring/autumn on weekends has a strong negative effect on the target value. This means that battery-prosumers with high minimum daily demands on weekends perform better on their own. Our explanation of this observation is as follows: A high daily minimum demand speaks for a relatively less "peaky" load profile. Households with a more even consumption spread throughout the day might make better use of the surplus generation that is stored in the BESS during the day. Notably, both of the two most important features are on the weekend. We suspect that this is the case because most households exhibit a "beneficial" pattern for BESS utilization during the workdays anyway: Standard load profiles typically have high demand in the evening hours. Therefore, the behavior on weekends makes the difference between overall better or worse BESS utilization.

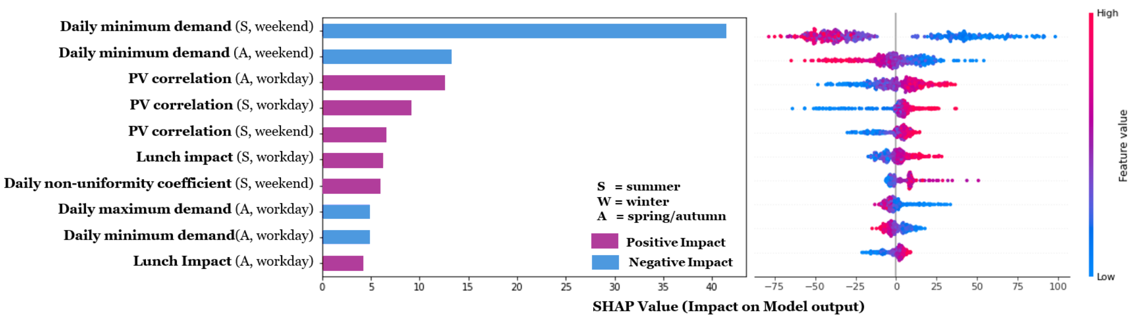

Figure 4.8.: Global (left) and local (right) SHAP values of the ten highest battery-prosumer feature impacts on additional self-consumption from storage in a sharing community

Interestingly, the *PV correlation* of battery-prosumers load profile during summer and on workdays in spring/autumns has a positive effect on additional self-consumption from storage. This is surprising because higher demand during PV generation hours should lead to less available surplus generation to be stored in the BESS. This apparent contradiction can be partially explained by looking at the right side of the diagram. The local SHAP values on the right show the impact of the input parameters on each observation in the dataset, i.e., the individual communities. The impact of the *PV correlation* for example is left-skewed: While low values have a high (negative) impact on the target value, high values have a less pronounced positive impact. From this we can deduce that especially low *PV correlation* leads to less additional self-consumption from BESSs in a sharing community. This could be explained by the fact that households that exhibit a contradicting pattern to PV generation have high BESS utilization rates anyway, meaning that there is not much room for improvement by means of a sharing economy.

The participation of consumers in a sharing economy community has not been the focus in previous research, as they do not own any energy-related technologies that would justify their participation in the community. Therefore, the contribution of their electricity demand and load pattern to the profitability of a sharing community has not yet been extensively analysed. This might immensely influence the profitability of the sharing economy model and utilization rates of BESSs. Biech et al. (2016) find that in a community consisting of only battery-prosumers, internal trading is very low and could be increased by adding consumers. This relationship is also evident in the flow diagram in Figure 4.6 (left), where it can be seen that consumers are responsible for most of the energy exchange within the P2P network. The results of our prediction further emphasise the importance of consumers in a sharing economy for PV-coupled BESSs. The load profile properties of the consumers explain the majority of additional self-consumption from PV and ultimately community profit in our simulation. Figure 4.9 shows the top ten most important features for the identification of suitable consumers. Unsurprisingly, the *PV correlation* in summer on workdays is the most important feature. Yet, the *PV correlation* in summer on weekends is *not* among the top ten parameters. We suspect that this is the case because it is more unusual for a household to correlate with PV generation during the week than on the weekend.

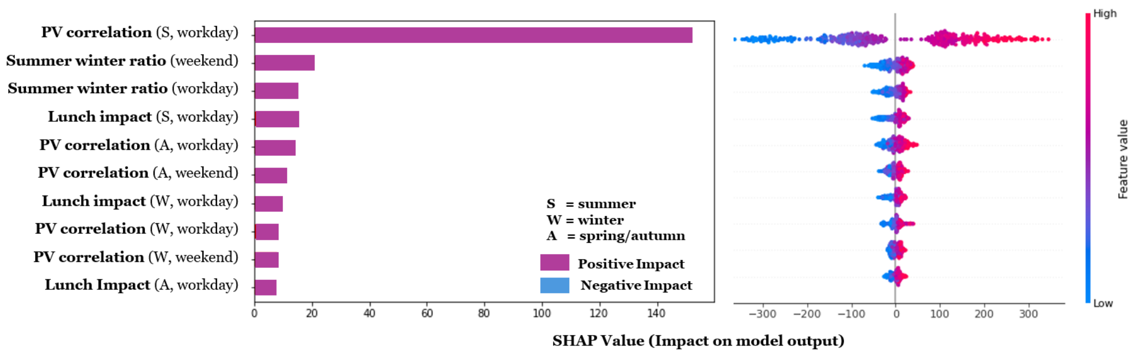

Figure 4.9.: Global (left) and local (right) SHAP values of the ten highest consumer feature impacts on community profit from sharing electricity

On workdays, standard load profiles usually have relatively low demand during the day. Both *PV correlation* and the closely related parameter *lunch impact* appear for all seasons on workday in the ten most important parameters. Twice among the top three is the *summer-winter ratio*. Here, a high value corresponds to higher additional PV self-consumption. Since our dataset consists of households from the USA, there are many load profiles with high demand in summer, indicating an air-conditioning system which is likely reflected in this parameter.

When adding the parameters of battery-prosumers to the input features, we achieve a 5% improvement of community profit prediction. However, the ten most important parameters (compare Figure 4.10) are congruent with Figure 4.9, only slightly differing in the importance order. Only the sixteenth parameter, *end of work impact* in summer on weekends, belongs to the battery-prosumers. A high value indicates a relatively high demand in the late afternoon and evening hours. These households might have a better performance on their own due to high BESS utilization rates and thus profit less from entering a sharing community.

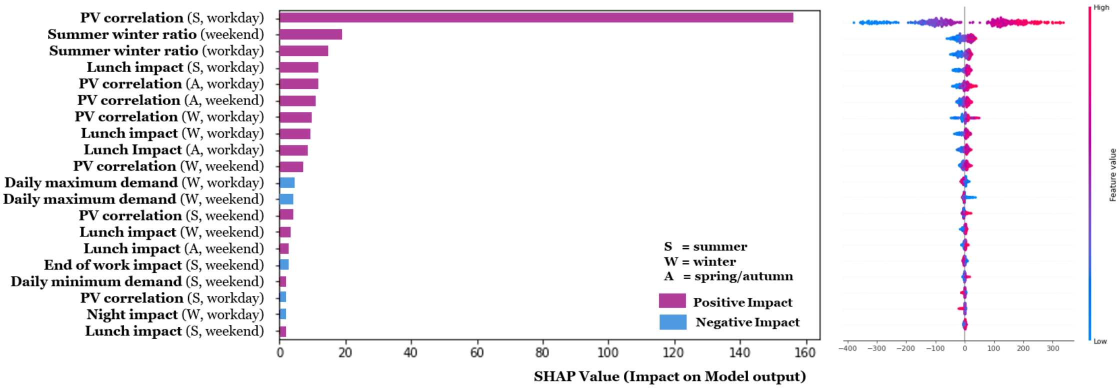

Figure 4.10.: Global (left) and local (right) SHAP values of combined consumer and battery-prosumer feature impact on community profit from sharing electricity

In summary, we can conclude that the choice of suitable participants impacts a sharing community's profit immensely and should therefore be considered when matching a community. Different properties are relevant for the respective choice of battery-prosumers and consumers, for them and others to profit most from an energy sharing economy. Since all other parameters of the community's configuration are kept constant in our simulation, a causal relationship between the identified load profile properties and target values can be concluded. These features can therefore be utilized to match sharing communities with high profit potentials. The identification of relevant parameters is of high practical relevance as well: Since the load profile pattern parameters that are used in this study can be intuitively explained by certain behavior known to the household, they can be approximated even without data of load profile measurements. A promising next research topic would be to link specific behavior or work patterns to the relevant load profile parameters that are identified in this study.

4.5.3 Impact of Changes in Absolute Load

During the simulation, we deliberately set all community and household parameters to the same values to explore causal relationships between the load profile patterns and the performances of sharing communities. However, in practice, this will likely not be the case for households that could potentially be connected in a sharing economy. We thus ran the simulation of the 520 sharing communities a second time, this time with the original absolute annual loads of the households in the dataset. Our objective with this is to quantify the impact of absolute loads, compared to the effect of load patterns, on the target values of the performance of a sharing economy. In order to retrieve comparable results to our first simulation, we scaled the PV system and BESS so that the relation between absolute load of a (battery-)prosumer and installed technology is the same as in the first simulation. This means that for example a battery-prosumer with an annual load of 6,000 kWh would operate a 9 kWh BESS and a 12 kWp solar installation. Obviously, there is a dependency between absolute loads of (battery)-prosumers and resulting community profit and self-consumption from PV generation and BESS. For this reason, we look at relative instead of absolute changes in community profits during the evaluation. Furthermore, instead of predicting absolute additional self consumption, we now define our target values as (1) additional self-consumption from storage per installed kWh and (2) additional (direct) PV self-consumption per installed kWp. This is plausible because larger PV systems and BESSs cause larger investments and thus more self-consumption does not automatically result in a more profitable investment. However, in this simulation, the annual loads of the households relative to each other vary substantially. Furthermore, the load of the consumers is not considered during the sizing of PV systems and BESSs and is therefore expected to have a large effect on the simulation outcomes.

For the prediction of our three target values, we again use the 90 load pattern parameters and add the absolute load as additional input parameter. Figure 4.11 shows a selection of SHAP values for the prediction of our target values. We find that additional self-consumption from storage per kWh can again be best explained using the battery-prosumers parameters, achieving a 23% improvement compared to the benchmark MSE. Figure 4.11 (right) shows the corresponding SHAP values which indicate that the absolute load is not among the parameters that are decisive for increasing BESS utilization. Similar to the previous results, the most important parameters are *daily minimum demand* and *PV correlation*. On the other hand, for the prediction of the relative community profit, the absolute load is by far the household feature with the most impact. Here, we achieve the best results when using both the consumers' and battery-prosumers' parameters as input, resulting in an 84% improvement compared to the benchmark prediction. The annual load of the consumers has the largest impact on the relative gain, closely followed by the annual loads of the battery-prosumers. Notably, the latter effect is negative, indicating that battery-prosumers with low annual load profited more from joining a sharing community, possibly because they are matched with (relatively) larger consumers that increased self-consumption.

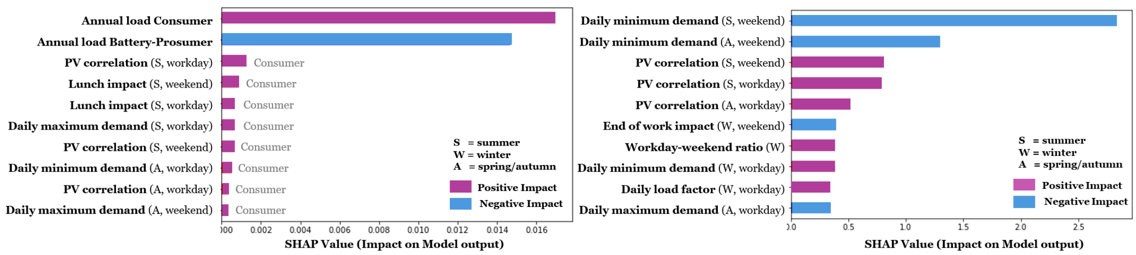

Figure 4.11.: Left: Ten highest SHAP values for the prediction of relative community profit using consumer and battery-prosumer parameters. Right: Ten highest SHAP values for the prediction of additional self-consumption from storage per kWh using battery-prosumer parameters.

In summary, we see large effects of absolute changes in annual loads on the profitability of a sharing community. It is worth noting that the households in our dataset exhibit quite high annual demand in general. Even though we only use single family households without electric heating, the average annual electricity consumption in our data subset is around 7,500 kWh, ranging from around 2,000 kWh to more than

1,2000 kWh. We suspect that this is related to the origin of the data that stems from American households, which evidently have higher electricity consumption than average European households possibly caused by an higher market penetration of air conditioning devices. It is therefore plausible that in many residential neighborhoods in Europe, the spread in annual electricity consumption is not as pronounced and therefore effects of load pattern changes have arelatively greater impact.

4.6 Discussion

For the first simulation, we set all technological parameters as well as overall consumption to fixed values in order to explore the effects of differing load patterns. The storage units are sized to resemble a BESS that is commonly installed in a residential household as of today. It is however also conceivable that with the appropriate regulatory framework, a sharing economy model as proposed incentivizes the installation of larger community storage units. To get a first idea of the impact of larger BESSs, we repeat the first simulation with larger storage units with a capacity of 8 kWh and a power output capacity of 4.6 kW each while all other parameters and load profiles remain the same as before. Figure 4.12 shows the origin of annual community electricity consumption in a direct comparison of the two BESS sizes and averaged over all 520 communities.

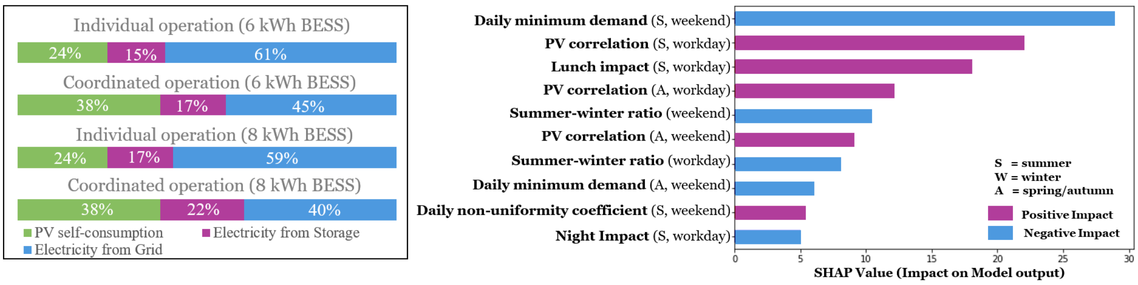

Figure 4.12.: Left: Comparison of sources of community electricity supply in average community for 6kWh and 8 kWh BESSs. Right: Ten highest SHAP values for the prediction of additional self-consumption from storage with battery-prosumers parameters.

The direct PV self-consumption remains the same in both cases as no adjustments are made to the size of the PV installations. During the individual operation, the share of the consumption of stored electricity is slightly larger than with smaller BESSs. A more significant difference can be observed in the additional self-consumption from BESSs in the coordinated sharing community where 22% instead of 17% of stored electricity are now consumed. However, the utilization rate of the larger BESSs in the coordinated operation decreases from 320 to 307 annual cycles. This could still be sufficient to justify the installation of the larger BESSs as it might benefit from smaller specific system costs (Luo et al., 2015). To find out which of the load profile properties affect BESS utilization with a larger storage, we repeat the prediction of the additional self-consumption from storage. We again achieve the best results when using only the battery-prosumers' load pattern parameters, improving the naive benchmark by 54% (compared to only a 43% improvement with smaller BESSs). The most important features for determining battery-prosumers that profit from entering a sharing community (shown in Figure 4.12, right) are similar as with the smaller BESSs (compare with Figure 4.8), except that for larger BESSs, the summer-winter ratio appears among the most important features. As we argued before, a high summer-winter ratio might indicate the presence of an air-conditioning system. The impact of this attribute is right-skewed and has a negative impact on the target value, indicating that the absence of an air-conditioning system leads to higher additional self-consumption from storage in a sharing community, but not the other way around. This observation could be easily used in practice to identify suitable candidates for a sharing community.

We assume a fixed electricity price and feed-in tariff as is they are common in many countries today. However, as we argued before, from a system's view, BESSs are a flexibility measure that could complement grid capacities, and other tariffs might incentivize consumption at certain times. Investigating other regulatory frameworks such as time-of-use tariffs or real-time-pricing of electricity could thus yield interesting additional insights.

4.7 Conclusion

In this chapter, we provide a comprehensive examination of the theoretical and practical potentials of a sharing economy business model for a residential energy community that engages in the sharing of solar generation and BESS capacity. First, the theory on sharing economy is addressed, highlighting the potential that is attributed to its application in the energy sector. The simulation of 520 communities shows that a sharing energy community with five households as configured in the case study yields average annual profits of 615 € that vary individually with the load patterns of the participating households. A fixed pricing approach is suggested, which considers fairness aspects to distribute the generated revenues amongst the participants within the sharing economy. Finally, it is demonstrated that the selection of suitable participants, based on load profile properties, can enhance the potential revenues and also incentivize the participation in sharing local RES and BESS resources.

This chapter shows the potential of connecting several individuals in the residential sector through a platform-based sharing economy model. The resulting energy communities can help to ensure that BESSs on the connected individual level are effectively deployed by integrating generation from RESs locally and thus increasing the utilization of existing BESS resources. In this chapter, we make several assumptions regarding regulatory adjustments that allow energy communities to profitably share their resources and creates additional investment incentives for individuals to install BESSs. Whether these regulatory barriers actually are removed, however, depends on the objectives of policy-makers at the higher system level. This level is the focus of the next chapter.

CHAPTER 5

BOTTOM-UP SYSTEM MODELING OF BATTERY STORAGE REQUIREMENTS

From a system planner's perspective who aims at reducing emissions, it is important to analyse pathways towards low-carbon, integrated energy systems in order to determine the corresponding requirements in terms of RES and BESS capacities. In this regard, the literature overview in Chapter 2 revealed that the central planning of storage requirements on the system level often neglects the underlying decentral structures, such as changing local consumption and the distribution network, as well as the resulting spatial distribution of generation capacities and BESS technologies. Central planning further disregards regions with lower generation potentials and thus ignores large parts of the immense potential of distributed RES and BESS installations on the lower aggregation levels of a system, which was investigated in the two previous chapters. To provide alternative perspectives, in this chapter, a bottom-up modeling framework is introduced for the decentral and central planning of an integrated energy system with high shares of RES generation. Both the distribution network structure and changing local consumption due to electrification are incorporated in the modeling approach. The framework allows the analysis of pathways in between a cost-optimal system design and an equitable spatial distribution of RES and BESS capacity within a supply system. In addition, the optimal combination of short- and medium-term storage technologies, namely LiBs and RFBs, is investigated. The results for the case of the German state BW show that a central planning of renewable generation and storage capacity requirements results in a significant lower LCOE than a decentral design. However, pathways in between the two alternatives can lead to a more equitable inclusion of communities in the energy transition at reasonable cost increases and thus leverage the potential of the lower aggregation levels of an integrated energy system.

This chapter comprises large parts of the unpublished article under review: S. Henni, M. Schäffer, P. Staudt, C. Weinhardt, P. Fischer, *Bottom-up System Modeling of Battery Storage Requirements for Integrated Renewable Energy Systems*, Working Paper, 2022.

5.1 Introduction

As outlined in Chapter 2.1, one key insight of previous studies on BESS requirements has been that short- and medium-term BESSs (up to 24 hours of storage duration) suffice for the integration of large RES shares up to close to 100% (Zerrahn and Schill, 2017). Studies often model these requirements with generic storage models or limit themselves to one technology, such as LiBs, while disregarding other technology options. Moreover, the focus of previous studies has been to model centrally planned, theoretically cost-optimal energy systems. These central approaches may not reflect actual total costs, as local acceptance issues can lead to delays and thus, cost increases. The question of RES and BESS capacity distribution is therefore essential for policy-makers and local stakeholders and needs to be addressed. Furthermore, as the expansion of renewable generation occurs decentrally and involves many local actors and decision-makers, it is necessary to not only consider system-wide requirements but to also take local and regional structures of an integrated energy system into account. An (extreme) alternative approach to a central, cost-optimal design of an integrated energy system is a decentralized organisation with a focus on local power supply and demand. This would result in a more even distribution of RES and BESS capacity expansion and the inclusion of more geographic regions in the design of the energy supply system. Moreover, through opportunities for citizen-financed community RESs, broad sections of the population can be involved, which on the one hand provides financial leverage for the energy transition and on the other hand has been proven to increase acceptance among the population (Pons-Seres de Brauwer and Cohen, 2020). Modeling a decentrally organised system requires the incorporation of local electricity consumption structures and the distribution network topology. In previous literature on system-wide BESS requirements, distribution network structures have been mostly neglected, even though they are becoming increasingly important with the mass installation of RESs at lower voltage levels. Moreover, to address the challenges of an integrated energy system, future developments regarding the electrification of demand for heat and transportation, also referred to as sector coupling, need to be included and assumptions about local energy supply need to be made to model and analyse regional differences.

Contrary to existing literature, we therefore propose a bottom-up approach that allows both the decentral and central planning of an integrated system, taking into account future increased local consumption in an integrated energy system as well as the (simplified) consideration of distribution grid structures. First, we divide the considered system into smaller, self-contained regions based on power substations in the distribution grid. In a second step, we group the isolated regions into larger distribution network groups, again based on the grid topology. Lastly, we model an integrated energy system, in which the distribution network groups can exchange electricity with each other through the existing and planned transmission network infrastructure. In order to be able to take local consumption structures into account, we propose a novel method for the regionalisation of national development paths regarding electricity consumption until 2050. Generation is modeled endogenously using weather data and information on available areas for RESs.

We demonstrate our approach using the case of the south-western German state of BW. We model the requirements in terms of generation and BESS capacity expansion to achieve at least 90% renewable electricity supply in the three scenarios described above. The results of this study are of interest for policy-makers and local stakeholders, as they must address the conflicts that arise on a local level when expansion targets are planned centrally. We therefore answer the following central research question:

Research Question 4: *What are the trade-offs in terms of levelized cost of electricity and storage requirements in an energy system using decentral planning compared to central planning?*

A particular focus of this chapter lies on the explicit consideration and modelling of short- and medium-term BESS technologies, i.e., LiBs and RFBs (see Section 2.2 for a detailed assessment of the two technologies). In addition to answering the central research question, we thus also address the following research question in the course of this chapter:

What is the optimal combination of short- and medium-term storage technologies in an integrated energy system considering the electrification of heat and transportation demand?

The remainder of this chapter is structured as follows: First, we address related work on acceptance issues in the context of RES expansion, which motivates the identification of alternative pathways to central planning. Then, we introduce a methodology to model local energy consumption and generation until 2050. Based on this, RES and short- and medium-term BESS requirements can be determined for any level of spatial aggregation. Finally, we determine the renewable generation and BESS requirements until 2050 for south-west Germany in a case study and quantify the trade-offs in terms of needed BESS and RES capacity and LCOE when planning renewable expansion decentrally or centrally.

5.2 Related Work

The overview on storage requirements in Section 2.1 reveals that most previous studies rely on central planning. This approach disregards local structures of integrated energy systems and the distributional realities of cost-efficient RES and BESS expansion. As the urgency of the climate crisis is increasingly being recognized by the public, general acceptance and support of the public for the expansion of RESs is high (Segreto et al., 2020). In a recent survey in Germany, 83% of all respondents were in (strong) support of RES expansion (AEE, 2021). However, there remains a large gap between general acceptance and ongoing support when a local community is directly impacted by a specific project involving RESs (Segreto et al., 2020). Particularly, in connection with wind turbines, but also transmission lines and other large projects, the so-called NIMBY-phenomenon (*Not-In-My-Backyard*) can often be observed: While there is a consensus among the population that measures must be taken somewhere, projects in the immediate vicinity are sometimes strongly opposed by the local population (Smith and Klick, 2008; Segreto et al., 2020). Some of these concerns can be addressed through targeted and well-designed measures.

According to Emmerich et al. (2020), local acceptance of BESSs can be solely explained by the trust placed in the responsible local actors from municipalities or industry. In the case of wind power projects, the local integration of the developers, the creation of a local network of supporters for the project and the possibility for citizens to participate financially in the installations are decisive for a realisation without resistance (Jobert et al., 2007). A positive correlation has also been found between self-managed wind turbines in a community and local acceptance (Musall and Kuik, 2011).

By the nature of renewable generation technologies, there are usually geographically limited regions within an energy supply system that are particularly well suited for the expansion of RESs (e.g., rural regions with high wind speeds and large non-residential geographic areas available). It can therefore be assumed that a cost-optimal solution for designing a low-carbon energy system, as presented in previous studies, would result in the over-proportional expansion of RESs in certain areas. This approach fails to consider varying local acceptance and thus may be undesirable in two respects. On the one hand, the disproportionate use of land in communities with high potential can lead to resentment and a lack of acceptance in these regions. On the other hand, communities that have lower potentials but could make an important contribution due to committed local stakeholders are ignored. In consequence, potentials to actively involve the population in the energy transition, including substantial financial potential, are neglected (Pons-Seres de Brauwer and Cohen, 2020). The path towards a low-carbon, integrated energy system therefore requires the assessment of alternatives to a central planning transition path that lead to more equitable capacity distribution and inclusion of communities.

5.3 Methodology: Modeling Battery Storage Requirements

Our method to model an integrated energy system consists of several steps as shown in Figure 5.1. Prior to determining RES and BESS expansion needs on different levels of spatial resolution, we need to make assumptions on the regional structure and magnitude of electricity demand and generation. For an integrated energy system, it is important to consider structural changes, such as the electrification of individual transport and heat demand. For the consumption input data, we therefore rely on elaborate studies on pathways to decarbonizing energy systems that consider these developments. These studies have proposed values for nation-wide energy consumption until 2050, provided that a certain level of decarbonization (usually a CO_2 reduction of 80-95%) is achieved. Since these analyses usually only exist for large energy systems, i.e., on a national level, values for electricity demand must be spatially and temporally resolved to model local consumption within these energy systems. Subsequently, the resolved energy consumption values serve as input to model local and regional RES expansion and BESS requirements in three scenarios overall while considering the structure of the distribution network. First, municipalities that are connected to the same substations in the distribution grid are grouped together. Second, larger (distribution) network groups are determined, i.e., geographic regions beyond whose borders electricity is only exchanged via the transmission grid. In both described scenarios, the respective regions are modeled as self-contained energy systems without electricity exchange across borders. This ensures a local or regional supply from RES. Finally, in the third scenario, the existing and planned transmission grid is included to allow power exchange between distribution network groups. In the following, we describe the steps displayed in Figure 5.1 in more detail.

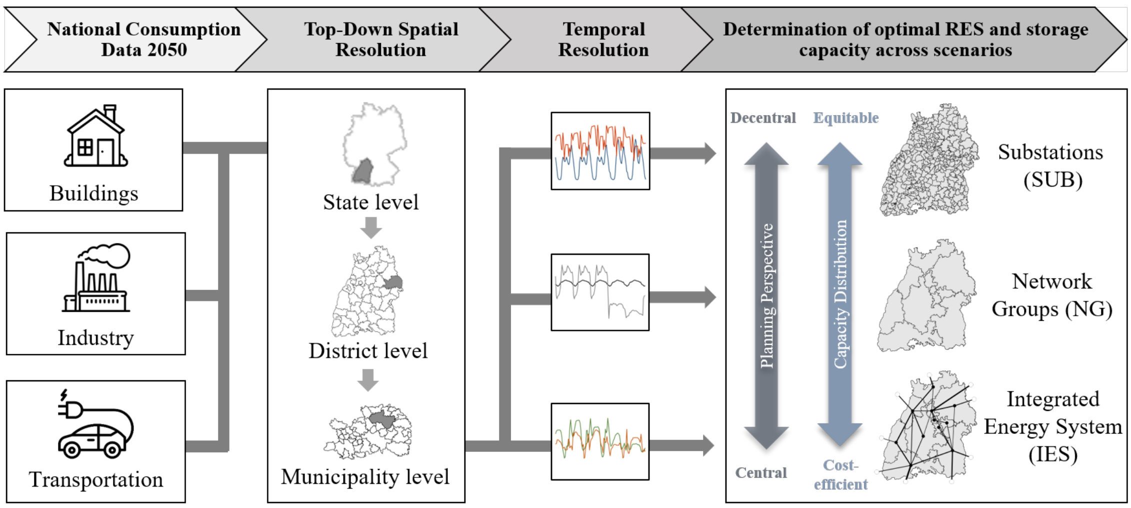

Figure 5.1.: Methodological Framework

5.3.1 Modelling Local Energy Consumption in 2050

Based on two studies on decarbonization pathways for Germany, namely the “Integrated Energy Transition” (dena, Bründlinger et al. (2018)) and “Climate Pathways for Germany” (BDI, Gerbert et al. (2018)), we identify three main (future) consumption sectors for electricity: Buildings, Industry, and Transportation. Buildings include both electricity needed for household appliances as well as the increasing demand for electrified heating in buildings through heat pumps. Industry contains the manufacturing sector as well as demand in the trading, commerce and services sectors. In the Transportation sector, rising numbers of electric vehicles are responsible for a sharp increase in demand for electricity.

In order to enable a comparison of different studies and scenarios, we design a generalizable modeling method for determining local consumption values based on the national values for electricity consumption in 2050 that are reported in various studies. We apply a three-stage top-down methodology using socio-economic parameters to regionalize the national consumption values to the municipality level, the smallest political unit for which socio-economic data is available in Germany. This has to be adapted for other countries. The indirect route via state and district level is chosen because of the decreasing data quality and increasing heterogeneity of electricity demand at more granular levels. Table 5.1 shows the selected socio-economic data for each consumption sector and aggregation level.

Table 5.1.: Socio-economic parameters for the top-down distribution of national consumption values for 2050

Spatial Level	Buildings	Industry and commerce	Transportation
State	(Future) Population	(Future) Population and rate of employment	(Future) Population, rate of registered vehicles and e-mobility penetration
District	Appliances: Population Heat: Population and living space	Industry: Energy consumption Commerce: Electricity consumption	Number of registered vehicles weighted with structural region type
Municipality	Appliances: Population Heat: Population and living space	Number of employees	Number of registered vehicles weighted with structural region type

At the state level, local differences in the magnitude of electricity consumption still largely balance each other out. This can be seen, for example, in the fact that the share of current household electricity consumption roughly corresponds to the share of the population for the state of BW as described in Section 5.4.1. Population is therefore a good estimator at this level which can be further specified through slightly higher or lower rates of employment or registered vehicles in the case of the Industry and Transportation sectors. In addition, on state level, estimations on the population development until 2050 might be available, which allows to take future developments into account. In the Buildings sector, the population is used as parameter to regionalize electricity demand for household appliances onto lower spatial levels. In the case of (electrified) heat demand of buildings, we multiply the population by the respective average per capita living space to account for structural differences, e.g., between rural and urban areas. Since there are considerable differences between districts when it comes to industrial activity, we select the district's overall energy consumption as factor to dissolve the future electricity demand of the (manufacturing) industry. In the case of the commerce sector, we use the district's electricity consumption. This selection is based on the assumption that businesses in trading and commerce already rely more on electrical energy and also impact overall energy consumption less than the manufacturing industry as of today (Umweltbundesamt, 2021). When no data on energy consumption is available, as is the case for municipalities in Germany, the number of employees is selected as parameter to further resolve electricity consumption in the Industry sector. In the Transportation sector, electricity demand will largely come from electric vehicles. The number of registered vehicles is therefore a good estimator to spatially resolve demand to district and municipality level. Since driving behavior may differ, data on the average mileage in the respective "structural region type" (e.g., urban or rural) is used to further specify the weighting of this factor.

For the temporal resolution of the obtained spatially distributed values, representative load profiles are needed for each consumption sector. In most cases, historic data can be used, as for example in the case of standard load profiles to depict household consumption. In other cases, synthetic load profiles have to be generated when no representative historic data is available, as in the case of charging behavior of electric vehicles.

Selection criteria for the socio-economic parameters as well as the modeling of load profiles is described in more detail in Section 5.4.1 for the case of BW, a state in south-west Germany. The methodology can be transferred to any other geographic region but might require adaptions to the chosen socio-economic parameters based on data availability and representativity. The obtained data serves as input for the modeling of an integrated energy system as described in the next section.

5.3.2 Determination of Battery Storage Requirements in an Integrated Energy System

One aim of this study is to demonstrate the differences between the centralized and decentralized planning of an integrated energy system and the implications thereof. RES and BESS requirements are therefore determined for three scenarios that consider both distribution and transmission network structures:

1. **Power substations (SUB):** Each municipality is assigned to a power substation in the distribution grid. Each region is modeled as a self-contained grid without exchange between regions. This scenario depicts a decentral planning approach that leads to an equitable participation of all regions in the energy transition relative to their consumption.

2. **Network groups (NG):** Each municipality is assigned to a distribution network area ("network group") based on the distribution grid infrastructure: Network groups are regions with no connections to other regions on the distribution grid level. In this scenario, each region is modeled as a self-contained grid without exchange between regions to illustrate a midway between central and decentral planning.

3. **Integrated energy system (IES):** Municipalities are aggregated like in NG, but energy exchange between NGs and neighboring states is allowed over the transmission grid, limited by the respective transmission capacities. This scenario represents a physically realistic, central system planning.

In each scenario, the investigated network consists of n regions (nodes) in total, of which n_{in} are internal nodes, i.e., nodes for which production capacity and storage are optimized. External nodes are those that represent other external states or regions and are not optimized as part of the model. In scenarios 1 and 2, only one internal node (i.e., substations or network groups) and one external node (i.e., the public grid) are considered. In scenario 3, to accurately model a holistic system including all existing transmission capacity, electricity can be procured (i.e., imported) from several external nodes (i.e., through all existing transmission lines from network groups to outside regions). Each internal node or region i (i.e., a substation or network group) consists of a set of municipalities denoted by j. For each region, load data in hourly resolution of the associated municipalities is aggregated and serves as input for the determination of optimal RES and BESS expansion as described in the next paragraphs.

Modeling renewable generation

In our model, optimal electricity generation, consisting of PV, wind, and CHP generation with renewable gas, is determined endogenously. The expansion of RESs in a municipality is limited by its respective maximum potential.

The maximum potential of solar power capacity $\hat{P}_{j,t}^{(\mathrm{S})}$ in kW in a municipality j at time step t is calculated as follows (5.1).

$$\hat{P}_{j,t}^{(\mathrm{S})} = A_{\mathrm{PV},j} \cdot a_{\mathrm{PV}} \cdot \eta_{\mathrm{PV}} \cdot G_{j,t} \tag{5.1}$$

where $A_{\mathrm{PV},j}$ is the total available area for PV installations in m^2, a_{PV} a PV area utilization factor, η_{PV} the panel efficiency and $G_{j,t}$ the solar irradiance at time step t in kW per m^2. Peak rated capacity is used for the cost calculation. It is estimated using a peak power factor s_{PV} in $\mathrm{m}^2\ \mathrm{kW}^{-1}$ (5.2).

$$\hat{P}_{\mathrm{PV},j} = \frac{A_{\mathrm{PV},j}}{s_{\mathrm{PV}}} \tag{5.2}$$

Likewise, wind potential $\hat{P}_{j,t}^{(\mathrm{W})}$ in kW is estimated using the region's maximum number of wind turbines $N_{\mathrm{WT},j}$ and the wind turbine power $P_{\mathrm{WT}}(v_t)$ in kW, which is dependent on the wind speed v_t (5.3). The wind turbine power is determined from a lookup table, i.e., the wind turbines' model-specific power curves (e.g., Table 5.2).

Table 5.2.: Assumed power curve for simulation of wind turbine power generation. Values in-between the given steps are linearly interpolated.

Wind speed (m/s)	≤ 3	4	5	6	7	8	9	10	11	12	13	14	15...25	≥ 25
Power (kW)	0	3	25	82	174	321	532	815	1180	1580	1810	1980	2050	0

Power values in-between the given values are linearly interpolated.

$$\hat{P}^{(\mathrm{W})}_{j,t} = N_{\mathrm{WT,j}} \cdot P_{\mathrm{WT,t}}(v_t) \tag{5.3}$$

Peak wind power for a region is calculated with the wind turbine's rated power $P_{\mathrm{WT,rated}}$ (5.4).

$$\hat{P}_{\mathrm{WT},j} = N_{\mathrm{WT,j}} \cdot P_{\mathrm{WT,rated}} \tag{5.4}$$

Wind speed is adjusted for height using the log wind profile equation (5.5) where v_{ref} is the wind speed at reference height z_{r} (=10 m) and z_0 the surface roughness.

$$v_t(z) = v_{\mathrm{ref}} \cdot \frac{\log(\frac{z}{z_0})}{\log(\frac{z_{\mathrm{r}}}{z_0})} \tag{5.5}$$

Bio-gas potential $\hat{P}^{(\mathrm{G})}_{i,t}$ of each investigated *region* i in kW is estimated using a fixed area power factor s_{BG} in m^2 kW^{-1} (5.6) based on estimations provided by Hartmann (2008). For the cost calculation, the rated power $\hat{P}_{\mathrm{BG},j}$ of the CHP in kW is needed. It is equal to the potential power in every time step.

$$\hat{P}^{(G)}_{i,t} = \frac{f_{Agri} \cdot A_{Agri,i}}{s_{BG}} = \hat{P}_{BG,i} \tag{5.6}$$

where $A_{Agri,i}$ refers to the total available arable land in m^2 and its share f_{Agri}, which is usable for bio-gas crop. Unlike PV generation and wind turbines, bio-gas CHPs are modeled as dispatchable generators, i.e., their capacity is available at all times.

The batteries are modeled analogously to the simplified empirical model described by Moncecchi et al. (2018). Charge and discharge efficiencies are assumed to be constant at each time step. Energy charged into and discharged from a BESS in region i at any given time step in kWh, $E_{\mathrm{c/d},i,t}$, can therefore be described as follows (5.7, 5.8).

$$E_{\mathrm{c},i,t} = \eta_{\mathrm{Ch}} \cdot P^{(\mathrm{B})}_{i,t} \cdot \Delta t \tag{5.7}$$

$$E_{\mathrm{d},i,t} = \frac{P_{i,t}^{(\mathrm{B})}}{\eta_{\mathrm{Dis}}} \tag{5.8}$$

where $P_{i,t}^{(\mathrm{B})}$ refers to the BESS's charge or discharge power in kW, Δt denotes the duration of a time step in h and η_{Ch} and η_{Dis} denote the charge and discharge efficiency, respectively. It is derived from the round-trip efficiency η_{Bat} as follows (5.9):

$$\eta_{\mathrm{Ch}} = \eta_{\mathrm{Dis}} = \sqrt{\eta_{\mathrm{Bat}}} \tag{5.9}$$

Charging or discharging above the rated power capacity is not allowed. Any other losses are neglected. Degradation is only represented in the cost.

Modeling load and the transmission grid

For each level of spatial resolution, load data is aggregated from municipality load data to estimate a load profile for the respective regions. We assume that a share of the load profile can be considered "flexible", i.e., that share can be used for demand side management (DSM). A flexible load curve is determined by assuming a "flexibility factor" for every load component (households, industrial, commerce, transport and heat). Total available flexible load $\overline{P}_{\mathrm{flex},i,t}$ is described in Equation 5.10, where $f_{\mathrm{flex,x}}$ are flexibility factors between 0 and 1.

$$\begin{aligned}\overline{P}_{\mathrm{flex},i,t}^{(L)} = f_{\mathrm{flex,house}}\overline{P}_{\mathrm{house},i,t}^{(L)} + f_{\mathrm{flex,ind}}\overline{P}_{\mathrm{ind},i,t}^{(L)} + f_{\mathrm{flex,com}} \\ \overline{P}_{\mathrm{com},i,t}^{(L)} + f_{\mathrm{flex,trans}}\overline{P}_{\mathrm{trans},i,t}^{(L)} + f_{\mathrm{flex,heat}}\overline{P}_{\mathrm{heat},i,t}^{(L)}\end{aligned} \tag{5.10}$$

Assuming a lossless DC model for the nodes n and power lines l, the $N_l \times 1$ vector of power flows z can be calculated using Equation 5.11 (Staudt and Oren, 2021):

$$z = H \cdot y \tag{5.11}$$

where y refers to the $(N_n - 1) \times 1$ vector of power injection (generation or consumption) at each region (node), except a slack node. H is the $N_l \times (N_n - 1)$ matrix of power distribution factors according to Equation 5.12.

$$H = \Omega B(B^T \Omega B)^{-1} \tag{5.12}$$

where B is the $N_l \times (N_n - 1)$ incidence matrix of the network (reduced by the slack node) and Ω a $N_l \times N_l$ diagonal matrix of line impedance. For simplicity, it is assumed that impedance is equal across all lines, i.e., Ω is an identity matrix.

Optimal generation and storage infrastructure

To determine the cost-optimized configuration of RES and BESS expansion for any single region in scenarios 1 and 2 and an integrated energy-system in scenario 3, a linear programming (LP) problem is formulated. The goal is to optimize for a minimum required share of renewable energy (80% and above), which represents the main constraint to the LP model. The set of equations is presented in the following.

Equation 5.13 describes the objective function, that is the cost function to be minimized. $\alpha_{i/j}$ are decision variables. They describe expansion rates or "utilization factors" of RESs and BESSs, expressed as a share of the maximum production capacity within the modeled region or municipality. $\hat{c}_{\mathrm{X},i/j} = \hat{P}_{\mathrm{X},i,j} \cdot c_{\mathrm{X}}/\ L_{\mathrm{X}}$ are the discounted costs of the maximum capacities of RESs or BESSs, where c_{X} and L_{X} are specific cost and lifetimes of system (X) respectively. Due to local climatic differences, the capacities of solar (S) and wind (W) generation are of interest in a spatial resolution down to the municipality level. For renewable gas (G) and BESSs, it is assumed that they are spatially evenly distributed within the region. RFB cost is separated in cost per unit of power (RP) and cost per unit of energy (RE). Storage duration (i.e., the storage's energy to power ratio) for LiB is assumed to be constant, therefore only cost per energy capacity (LE) is considered. The third term models the cost of renewable gas. The product of fuel cost c_{fuel} and corresponding electricity generation is summed up over every time step t. Likewise, the last sum describes the cost of imported energy with $c_t^{(\mathrm{I})}$ as its cost.

Unless otherwise specified, the following applies for the objective function and constraints: $i \in n_{\mathrm{in}}$, $j \in m$, $t \in T$. For the SUB and NG scenarios, each region is modeled as self-contained unit, i.e., $n = 2$ and $n_{\mathrm{in}} = 1$ (one internal and one external node).

$$
\begin{aligned}
\min\, C = &\sum_{j}^{m} \left(\alpha_j^{(\mathrm{S})} \hat{c}_{\mathrm{PV},j} + \alpha_j^{(\mathrm{W})} \hat{c}_{\mathrm{WT},j} \right) \\
&+ \sum_{i}^{n_{\mathrm{in}}} \left(\alpha_i^{(\mathrm{G})} \hat{c}_{\mathrm{BG},i} + \alpha_i^{(\mathrm{RP})} \hat{c}_{\mathrm{RFB,P},i} + \alpha_i^{(\mathrm{RE})} \hat{c}_{\mathrm{RFB,E},i} + \alpha_i^{(\mathrm{LE})} \hat{c}_{\mathrm{LiB},i} \right) \\
&+ \sum_{i}^{n_{\mathrm{in}}} \sum_{t} c_{\mathrm{fuel}} P_{i,t}^{(\mathrm{G})} \Delta t + \sum_{i=n_{\mathrm{in}}}^{n} \sum_{t} c_t^{(\mathrm{I})} (-P_{i,t}^{(\mathrm{D})}) \Delta t
\end{aligned}
\tag{5.13}
$$

The cost function is subject to the following constraints. Renewable production $P_{i,t}$ is variable for every step and every generator but is limited to the maximum generation in every time step (5.14-5.16). The maximum solar $\hat{P}_{i,t}^{(\mathrm{S})}$ and wind power $\hat{P}_{i,t}^{(\mathrm{W})}$ for every region and time step are calculated from the sum of the maximum generation $\hat{P}_{j,t}$ in the respective municipalities j, where m_i is the number of municipalities of region i.

$$P_{i,t}^{(\mathrm{S})} \leq \sum_{j}^{m_i} \alpha_j^{(\mathrm{S})} \hat{P}_{j,t}^{(\mathrm{S})} \tag{5.14}$$

$$P_{i,t}^{(\mathrm{W})} \leq \sum_{j}^{m_i} \alpha_j^{(\mathrm{W})} \hat{P}_{j,t}^{(\mathrm{W})} \tag{5.15}$$

$$P_{i,t}^{(\mathrm{G})} \leq \alpha_i^{(\mathrm{G})} \hat{P}_i^{(\mathrm{G})} \tag{5.16}$$

Battery constraints in equations 5.17-5.22 apply for both, RFB and LiB. However, in the case of LiB, the maximum power capacity is fixed to a fraction of maximum energy capacity: $\alpha_i^{(\mathrm{BP})} = 1$ and $\hat{P}_i^{(\mathrm{BP})} = \alpha_i^{(\mathrm{BE})} \hat{E}_i^{(\mathrm{BE})} / d_{\mathrm{LiB}}$, with the storage duration d_{LiB}. In both cases, battery power $\hat{P}_{i,t}^{(\mathrm{B})}$ is defined as the sum of charging power $P_{\mathrm{c},i,t}^{(\mathrm{B})}$ and discharging power $P_{\mathrm{d},i,t}^{(\mathrm{B})}$ (5.17), where charging power must be positive and discharging power negative. Their absolute values must be smaller than the maximum power capacity (5.18, 5.19)

$$P_{i,t}^{(\mathrm{B})} = P_{\mathrm{c},i,t}^{(\mathrm{B})} + P_{\mathrm{d},i,t}^{(\mathrm{B})} \tag{5.17}$$

$$0 \leq P_{c,i,t}^{(\mathrm{B})} \leq \alpha_i^{(\mathrm{BP})} \hat{P}_i^{(\mathrm{B})} \tag{5.18}$$

$$-\alpha_i^{(\mathrm{BP})} \hat{P}_i^{(\mathrm{B})} \leq P_{d,i,t}^{(\mathrm{B})} \leq 0 \tag{5.19}$$

In every time step the SoC $E_{i,t}^{(\mathrm{B})}$ is updated with the sum of the SoC in the previous time step and the charged or discharged energy (5.21).

$$E_{i,t}^{(\mathrm{B})} = E_{i,t-1}^{(\mathrm{B})} + \eta_\mathrm{c} P_{\mathrm{c},i,t}^{(\mathrm{B})} \Delta t + \frac{1}{\eta_\mathrm{d}} P_{\mathrm{d},i,t}^{(\mathrm{B})} \Delta t \tag{5.20}$$

The BESS cannot discharge below an SoC of 0 and is limited by the maximum energy capacity $\hat{E}_i^{(\mathrm{B})}$ (5.21). The SoC at $t = 0$ is set to 50% (5.22).

$$0 \leq E_{i,t}^{(\mathrm{B})} \leq \alpha_i^{(\mathrm{BE})} \hat{E}_i^{(\mathrm{B})} \tag{5.21}$$

$$E_{i,t=0}^{(\mathrm{B})} = \frac{\alpha_i^{(\mathrm{BE})} \hat{E}_i^{(\mathrm{B})}}{2} \tag{5.22}$$

The net power injection (D) on every internal node is defined by the difference between the load (L) and the renewable power generation (5.23).

$$P_{i,t}^{(\mathrm{D})} = P_{i,t}^{(\mathrm{L})} - (P_{i,t}^{(\mathrm{S})} + P_{i,t}^{(\mathrm{W})} + P_{i,t}^{(\mathrm{G})} - P_{i,t}^{(\mathrm{B})}) \tag{5.23}$$

The power demand at all internal nodes must cover the imported power (i.e., "negative demand" at external nodes) in every time step (5.24). Furthermore, export is not considered, i.e., net injection on external nodes must always be negative (5.25).

$$\sum_i^{n_\mathrm{in}} P_{i,t}^{(\mathrm{D})} = - \sum_{i=n_\mathrm{in}}^{n} P_{i,t}^{(\mathrm{D})} \qquad \forall\ i \in n \tag{5.24}$$

$$P_{i,t}^{(\mathrm{D})} \leq 0 \qquad \forall\ i \in [(n_\mathrm{in}+1)..n] \tag{5.25}$$

Equation 5.26 describes the constraint that ensures that a certain share of renewable generation f_Ren (e.g., 90%) is satisfied for the energy supply throughout the entire considered period. The numerator of the fraction contains the total non-renewable energy (related to imports, i.e., negative demand on external nodes), where $f_{\mathrm{Ren},t}^{(\mathrm{I})}$ is the renewable share of imported energy for every time step. The denominator contains the total load.

$$1 - \frac{\sum_{i=n_\mathrm{in}+1}^{n} \sum_t (1 - f_{\mathrm{Ren},t}^{(\mathrm{I})})\ (-P_{i,t}^{(\mathrm{D})})}{\sum_i^{n_\mathrm{in}} \sum_t P_{i,t}^{(\mathrm{L})}} \geq f_\mathrm{Ren} \tag{5.26}$$

Equations 5.27 and 5.28 describe the deployment of DSM. The load in every time step consists of a fixed amount $\overline{P}_{\text{fix},i,t}$ and a (variable) flexible amount $P_{\text{flex},i,t}$. The sum over the flexible energy must be equal to the sum of theoretically available flexible energy $\sum \overline{P}_{\text{flex}}$ over every time window of length 2τ. It must be noted that this neglects the time windows smaller than τ at the very beginning and the end of the time series, otherwise $P_{\text{flex},i,t}$ would be fully defined for every time step. The deviation caused by this effect is neglected.

$$P^{(\text{L})}_{i,t} = \overline{P}^{(L)}_{\text{fix},i,t} + P^{(L)}_{\text{flex},i,t} \tag{5.27}$$

$$\sum_{t-\tau}^{t+\tau} P^{(L)}_{\text{flex},i,t} = \sum_{t-\tau}^{t+\tau} \overline{P}^{(L)}_{\text{flex},i,t} \quad \forall\ t \in [\tau..(T-\tau)] \tag{5.28}$$

Lastly, only for scenario 3 (IES), the transmission system constraints apply: Power distributed between nodes is limited by the respective transmission capacities according to Equation 5.11. The $\hat{P}^{(\text{T})}$ vectors contain transmission capacities of all lines up to line l. H is the distribution matrix (5.29).

$$-\begin{pmatrix} \hat{P}^{(\text{T})}_1 \\ ... \\ \hat{P}^{(\text{T})}_l \end{pmatrix} \leq H \cdot \begin{pmatrix} P^{(\text{D})}_1 \\ ... \\ P^{(\text{D})}_n \end{pmatrix} \leq \begin{pmatrix} \hat{P}^{(\text{T})}_1 \\ ... \\ \hat{P}^{(\text{T})}_l \end{pmatrix} \tag{5.29}$$

5.4 Case Study: Battery Storage Requirements in Baden-Wuerttemberg until 2050

We demonstrate the described methodology on the case of BW, a state in southwest Germany. First, we model local consumption in 2050 for two different development paths towards a low-carbon energy system. The spatially and temporally resolved values serve as input for the determination of optimal RES and BSS expansion in three scenarios of varying degrees of decentral and central planning.

A common feature of recent studies on pathways to low-carbon energy systems is the increased demand for electricity, especially due to the electrification of parts of the transportation and heating energy demand. The reported consumption values still vary significantly depending on the chosen degree of electrification in the scenarios. As input for our analysis, we therefore choose two scenarios from the dena study “integrated energy transition” (Bründlinger et al., 2018), namely “electrification” (EL) and “technology mix” (TM) with an 80% CO_2 reduction target, depicted in Figure 5.2 (right). Note that Bründlinger et al. (2018) also depict scenarios for higher renewable shares (i.e., TM and EL scenarios for 95% emission reductions). However, the differences are not apparent in electricity consumption, but rather the structure and sources of energy supply and generation.

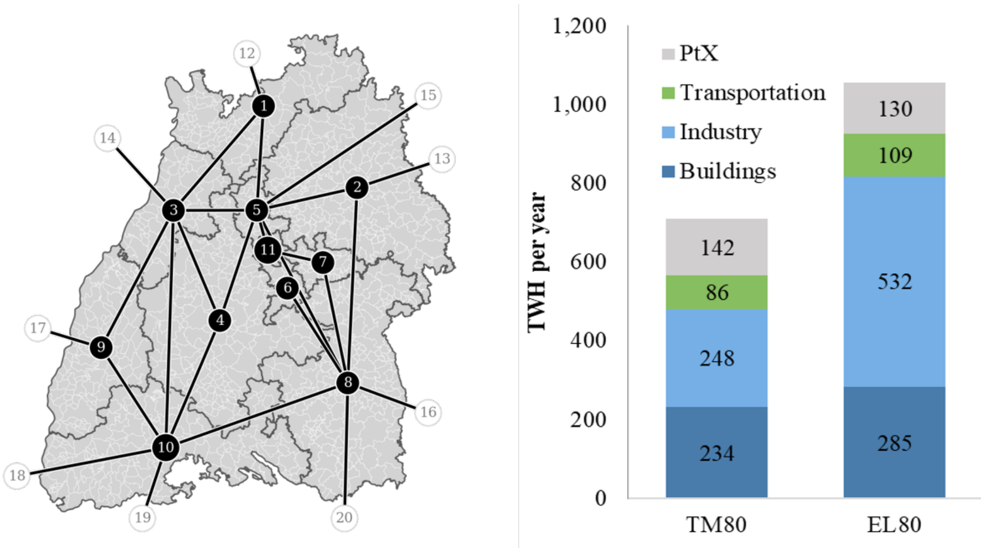

Figure 5.2.: Map of “network groups” (NG, IES scenario) with assumed network structure of transmission grid (left). Electricity consumption 2050 in Germany in the scenarios “technology mix” and “electrification” with a CO_2 emission reduction target of 80% based on Bründlinger et al. (2018) (right)

Overall electricity consumption ranges between 700 and 1,100 TWh, a steep increase of 40 - 120% compared to the baseline in 2018. The national electricity consumption values in the sectors Buildings, Industry and Transportation serve as input for the spatial and temporal resolution described in the following section. We refrain from explicitly modelling the accruing generation for Power-to-X (PtX) applications, as BW is not expected to play a significant role due to its low potentials for RESs compared to the rest of Germany (vom Scheidt et al., 2021). In Section 5.5, we do however address the resulting amounts of surplus electricity generation in our models, which could be used for PtX applications.

5.4.1 Modeling Local Electricity Consumption in 2050

As outlined in Section 5.3.2, national consumption values need to be spatially resolved using representative socio-economic parameters before load profiles can be generated for each consumption sector. We describe the obtained data used for consumption modeling in the following.

Spatial resolution

Buildings. In 2018, BW's share of household electricity consumption approximately corresponded to its population share within Germany of roughly 13% (Statistische Ämter des Bundes und der Länder; Bundesinstitut für Bevölkerungsforschung, 2018; Statistisches Landesamt Baden-Württemberg, Ministerium für Umwelt, Klima und Energiewirtschaft Baden-Württemberg, 2019; Umweltbundesamt, 2018). According to forecasts by the Federal Statistical Offices and the Federal Institute for Population Research, BW's population share will grow to 14.04% by 2050 (Statistische Ämter des Bundes und der Länder; Bundesinstitut für Bevölkerungsforschung, 2018). We choose the expected population share of BW in 2050 as parameter to determine the electricity consumption of the household sector in 2050. For the subsequent distribution of electricity demand onto district and municipality-level, we use the respective regions' current population (Statistische Ämter des Bundes und der Länder, 2018a). For the distribution of heat demand, the population is weighted with the average per capita living space in the region obtained from (Statistische Ämter des Bundes und der Länder, 2018a,b). As a result, rural regions, for example, are ascribed a higher per capita heat consumption than urban regions.

Industry and commerce. In 2018, BW's share of all employees in Germany was 14.13%, which is slightly higher than its share of the total German population (13.3%) (Ministerium für Umwelt, Klima und Energiewirtschaft des Landes Baden-Württemberg, 2014; Umweltbundesamt, 2018). Electricity consumption in the commerce sector was relatively high (14.9%) while the industrial sector consumed relatively little (12.65%) in reference to the share of employees. Assuming these relations will persist, we multiply the increased population share of 14.04% until 2050 with the higher electricity consumption per employee in the commerce, and the lower electricity consumption per employee in the industrial sector, respectively. BW's derived shares of electricity consumed in Germany by the industry and commerce sectors are thus 13.58% and 16.00%, respectively. On district level, we use each district's current share of BW's total energy and electricity consumption, respectively (Statistische Ämter des Bundes und der Länder, 2021). On municipality level, the number of employees is used as parameter for both industry and commerce, as no other related data is available (Statistische Ämter des Bundes und der Länder, 2018a).

Transportation. In recent years, BW's share of registered vehicles (passenger cars, light- and heavy-duty-vehicles) has been 5% higher than its population share, at 13.93% (Statistisches Landesamt Baden-Württemberg, 2020; Kraftfahrt-Bundesamt, 2020). In addition, the share of electric vehicles was about 33% higher than in the nationwide comparison (Landesagentur für neue Mobilitätslösungen und Automotive Baden-Württemberg, 2019). We assume that the higher rate of registered vehicles will persist until 2050, but that the higher penetration of electric vehicles will decrease significantly. Current registration numbers show that today's electric vehicle users are among the early adopters according to the innovation cycle by Rogers (2003) (Kraftfahrt-Bundesamt, 2022). With a 70-85% registration rate (Gerbert et al., 2018) expected by 2050, electric cars will by then have been adopted by the large majority of users. Therefore, it cannot be assumed that the large differences in e-mobility utilization between states will persist. In summary, we multiply the expected population share in 2050 with a 5% higher registration rate and a diminished 3% higher electric vehicle penetration. BW is thus attributed 15.22% of the national electricity consumption in the transportation sector. To further distribute consumption onto district and municipality level, we use the number of registered vehicles, weighted with the average mileage per vehicle in the respective structural region type (Kraftfahrt-Bundesamt, 2020; Statistisches Landesamt Baden-Württemberg, 2020). To obtain the mileage (i.e., driven km per vehicle), we rely on the "German Mobility Panel" (MOP) (Bundesministerium für Digitales und Verkehr, 2018), a regularly conducted assessment of driving behaviour, classified by type of settlement structure according to the Federal Institute for Research on Building, Urban Affairs and Spatial Development (i.e., urban, rural etc.) (Bundesamt für Bau-, Stadt- und Raumforschung, 2022). Each municipality in BW is assigned to a structural type and weighted with the average mileage of vehicles in the respective type as reported in the MOP. For each structural region type, the 20% longest rides are omitted and not included in the average mileage. This is justified because in the scenarios TM and EL, only 66% to 85% of passenger vehicles are electrified, and we assume that the longest rides are least suitable for electrification (Bründlinger et al., 2018).

Temporal resolution

In addition to the spatial resolution of electricity consumption, we need load profiles in sufficient temporal resolution that are representative of each consumption sector and thus allow us to adequately determine BESS requirements. We derive profiles in an hourly resolution for each sector.

Buildings. In the Buildings sector, we distinguish between electricity consumption for household appliances, which is modeled using a standard load profile obtained from Energienetz Mitte GmbH (2018), and consumption of heat pumps, for which we use a synthetic heat pump profile, averaged from three different sources (bonn-Netz GmbH, 2018; ED Netze GmbH, 2017; Stadtwerke Gustrow GmbH, 2017).

Industry and commerce. Load profiles for both the (manufacturing) industry and commerce are obtained from Beier and Bretschneider (2013). In the case of (manufacturing) industries, we further distinguish between load profiles for workdays only and continuous production. We derive an average load profile for industrial electricity consumption for each district in BW based on information from Beier and Bretschneider (2013) and Statistisches Landesamt Baden-Württemberg (2019) on industry branches with operation only on workdays or a continuous operation combined with numbers on employees in the respective branches from Statistisches Landesamt Baden-Württemberg (2019).

Transportation. Due to the current low penetration of electric vehicles, empirical data for load profiles is not available, especially for the large-scale use of electric vehicles in municipalities or districts. We therefore rely again on the MOP to create synthetic charging profiles for the structural region types “metropolitan”,“urban”, “suburban” and “rural” based on the measured driving behaviour in these regions. To simulate a somewhat “smooth” charging behavior, we assume that whenever a vehicle returns home from a trip, the driven mileage is charged evenly in the hours until the subsequent trip. We assume a maximum charging power of 11 kW, corresponding to a typical wallbox installed in private homes and a baseline electricity consumption of 16 kWh per 100km (Agora Verkehrswende, 2019). We further incorporate additional consumption of vehicles caused by low temperatures as specified by Forschungsstelle für Energiewirtschaft e.V. (2016) based on monthly average temperatures. As a result, in January, for example, electricity consumption is 1.4 times higher per 100 km than in June.

5.4.2 Modeling Cost and Renewable Share of Imported Electricity

In all scenarios, regions are allowed to import electricity from the public grid to simulate a realistic system. To incorporate imports, we need to make assumptions regarding the cost as well as the associated renewable share of the imported electricity at each time step. BW has connections to the remainder of Germany as well as the neighboring countries Switzerland and France. For simplicity, we assume the structure of the anticipated German electricity mix in 2050 for all imported electricity through the public grid. We derive the electricity mix for Germany as follows: To get an estimation of overall RES generation, we use the estimated RES capacity expansion in the dena TM scenario for PV, wind on- and offshore, biomass and hydropower (Bründlinger et al., 2018). For PV and wind, we scale up the respective national generation profiles in 2020 obtained by Bundesnetzagentur (2021) with the capacity values for 2050 to simulate a renewable power curve for the entire year of 2050 in 1-hour resolution. In the case of biomass and hydropower, flat generation curves are assumed. Similarly, we scale up the German demand curve in 2020 using the total German consumption in 2050 in the TM scenario. By dividing the aggregated generation curve by the demand curve, we obtain an estimate for the renewable share for imported electricity in each time step.

To obtain an estimation of the cost of imported electricity, we train a linear regression model that takes the current hour's renewable generation from wind on- and offshore and PV as well as the system load, CO_2 price, weekday and month as input to predict the hourly price on the day ahead market. Data from January 2019 to May 2021 from Bundesnetzagentur (2021) is used to train the model. The synthetic renewable generation and system load data for 2050 is then used as input to predict hourly costs in 2050. The assumed CO_2 price plays a decisive role for the overall resulting price level (not the price spreads) of the cost estimations. We assume a CO_2 price of 199€ per ton as suggested by Pittel and Cordt (2020). The effects of a lower CO_2 price are included in the sensitivity analysis. This is obviously a proxy that does not represent the actual prices in 2050 since these are impossible to predict as the current energy crisis shows. However, they are best guess estimations that are necessary to model an approximation of the future energy system.

5.4.3 Results: Renewable Capacity and Battery Storage Expansion Requirements Across Scenarios

BESS requirements are determined for BW based on the three scenarios SUB, NG and IES as detailed in section 5.3.2. In the SUB scenario, each of the 1103 municipalities in BW is assigned to the respective closest substation in the distribution network, resulting in 283 substation regions overall. For the investigation of the NG scenario, BW is subdivided into 11 regions according to information from BW's largest distribution network operator (Netze BW, 2020). To estimate transmission capacities between the network groups for the IES scenario, line capacities for each connection are aggregated based on the grid data provided by vom Scheidt et al. (2020). This data set includes not only today's existing transmission capacity, but also planned grid reinforcement measures according to the grid development plan of the four German transmission system operators. Figure 5.2 (left) shows the network group setup and the resulting transmission network along with the connections between the regions. Black nodes (1..11) represent network groups, white nodes represent external connections to other German states (12..16), France (17, 18), Switzerland (19) and Austria (20).

Climate data is retrieved from the database of the German Meteorological Service (Deutscher Wetterdienst, 2020) for 2020 in hourly resolution. Wind speed and solar irradiance profiles are determined for every municipality in hourly resolution by determining the weighted average from the three closest weather stations. Using this assumption, we are of course ignoring changes in weather patterns caused by climate change. But similarly to the argument for prices, we need to make a best guess that allows us to model an approximation of the future system. It would be interesting future work regarding all types of future energy system modeling to work with meteorologists to include the estimated effect of climate change for 2050 in a wind and solar dominated system.

The parameters used for the calculation of RES maximum capacities and the LP model are shown in Table 5.3. Different flexibility factors are assumed for the five sectoral components of the load curve (i.e., households, heat demand in buildings, (manufacturing) industry, commerce and transportation). Heat pumps are assumed to be the most flexible resource in 2050. Indeed, Elsland et al. (2017) assume that all heat pumps can be flexibly controlled until 2050. We therefore assume that 50% of heat demand can be shifted within one day. In the case of households, industry and commerce, 10% of the load are assumed to be subject to flexible dispatch following estimations by Bründlinger et al. (2018). It is unclear how much flexibility electric vehicles will provide. Estimations range between 50% and 100% of vehicles being able to charge intelligently. We therefore assume that 30% of the demand in the transportation sector is flexible. For all flexible demand components, we assume that load can only be shifted within the window of one day, i.e., $\tau = 12$ hours.

The data for renewable potential, i.e., suitable PV and wind areas is retrieved from the open data source "Energieatlas Baden-Württemberg" (LUBW, 2022). Since wind potential is given as mean annual energy yield in kWh, the maximum number of wind turbines per region is estimated by dividing energy generation by the mean full load hours for wind turbines in BW (1,208 hours) and rated wind turbine power. The calculations are based on the *Qreon Q-82* wind turbine that has a rated power of 2.05 MW. The corresponding power curve is presented in Table 5.2. The LCOE is calculated by dividing the annual cost by total annually served load. It is assumed that only 40% of roof area and 60% of available area for open-field PV installations can realistically be used for installations. However, since wind potential is already low in BW, all designated areas are considered. Respective data is again retrieved from LUBW (2022). For the renewable gas potential, it is assumed that arable land is split equally between biomass from silage corn and pasture which results in $s_{\mathrm{BG}} \approx 0.75$ ha kW^{-1}. It is further assumed that 20% of available arable land is used for renewable gas crop as this leads to total bio-gas CHP capacity that approximately corresponds to current values.

Table 5.3.: Input parameters for case study

Symbol	Parameter	Value	Symbol	Parameter	Value
a_{PV}	PV area utilization factor	0.5	L_{BG}	Bio-CHP lifetime (a)	15
f_{Agri}	Bio fuel share of arable land	0.2	L_{LiB}	LiB lifetime (a)	10
$f_{flex,com}$	DSM flexibility factor households	0.05	L_{PV}	PV lifetime (a)	25
$f_{flex,ind}$	DSM flexibility factor industry	0.1	L_{RFB}	RFB lifetime (a)	20
$f_{flex,heat}$	DSM flexibility factor heat	0.5	L_{WT}	Wind turbine lifetime (a)	25
$f_{flex,house}$	DSM flexibility factor trade & commerce	0.1	$P_{WT,rated}$	Wind turbine rated power (MW)	2.05
$f_{flex,trans}$	DSM flexibility factor transport	0.3	s_{BG}	Bio-gas power factor (ha kW^{-1})	0.75
c_{BG}	Bio-CHP specific cost (€ kW^{-1}) (Kost et al., 2018)	2,000	s_{PV}	PV power factor (m^2 kW^{-1})	0.2
c_{fuel}	Bio-gas fuel cost (€ kWh^{-1})	0.05	z	Wind turbine hub height (m)	100
c_{LiB}	LiB specific cost (€ kWh^{-1}) (Baxter, 2018)	400	z_0	Surface roughness ("Forest") (m)	0.8
c_{PV}	PV specific cost (€ kW^{-1}) (Kost et al., 2018)	600	z_r	Reference height (m)	10
$c_{RFB,P}$	RFB specific power cost (€ kW^{-1}) (Minke et al., 2017)	1,080	η_{LiB}	LiB round trip efficiency	0.85
$c_{RFB,E}$	RFB specific energy cost (€ kWh^{-1}) (Minke et al., 2017)	385	η_{PV}	PV panel efficiency	0.2
c_{WT}	Wind turbine specific cost (€ kW^{-1}) (Stehly et al., 2017)	1,200	η_{RFB}	RFB round trip efficiency	0.7
d_{LiB}	LiB storage duration (h)	2	τ	Flexibility time interval (h)	12

5.4.4 Simulation Results

Required RES and BESS capacities for RFBs and LiBs are determined for different levels of required renewable generation shares, i.e., 90%, 95%, 98% and 100%. While

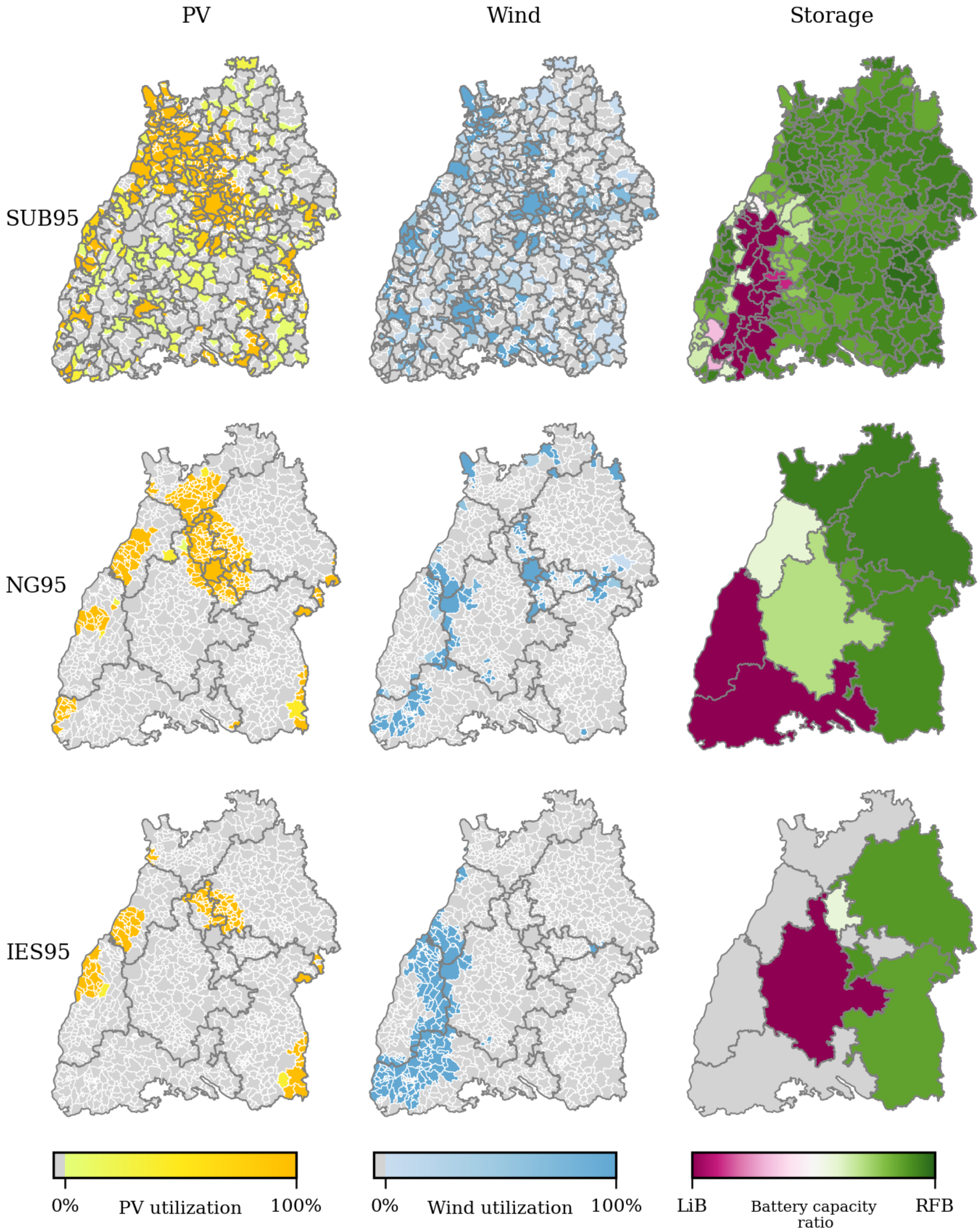

Figure 5.3.: Optimal placement of PV and wind capacity generation and BESSs for the three spatial resolutions (SUB, NG, IES) and a minimum renewable share of 95%, TM consumption scenario. Grey: no placement. Battery capacity ratio refers to RFB capacity ratio: $ratio = \hat{E}_{\mathrm{RFB}}/\hat{E}_{\mathrm{total}}$

the 90% and 95% objectives are calculated for all three scenarios SUB, NG and IES, only the IES scenario is considered for shares of 98% RESs and above. This is necessary because Stuttgart, the capital of BW, is modeled as a self-contained region in scenarios SUB and NG (region 11 in Figure 5.2, left). However, Stuttgart does not have sufficient RES potentials to achieve the corresponding shares of RESs. We further differentiate between the two consumption scenarios TM and EL. The *Gurobi* solver is used to solve the LP model.

Figure 5.3 shows the resulting distribution of PV installations and wind turbines and RFB and LiB storage on the map of BW in the case of a required renewable share of 95%. As expected, the highest production capacities are required for the SUB resolution where approx. 49 GW of PV and 16 GW of wind capacity are needed for the TM scenario. Additionally, 128 GWh of storage capacity and 19 GW of storage power are required (Figure 5.4). Due to the geographically confined regions, densely populated areas have the most difficulty to reach the emission targets. It is those areas (in the center and the north-west), where almost all renewable potential is exhausted. Additionally, the mostly urban regions need longer storage durations to fill the generation gaps due to lower renewable potential. In the SUB scenario, for the majority of BW, RFB storage accounts for a larger share of storage. Only in the south-west ("Black Forest"), LiB seems preferable due to high wind potential and low power demand, which results in shorter renewable gaps. However, due to the constraints in the scenario, those regions cannot share the wind energy with surrounding areas. Therefore, designated wind areas are only sparsely utilized. Consequently, the LCOE for this scenario is relatively high with approximately 94 € MWh^{-1}. However, a relatively equitable inclusion of regions in the energy supply of BW is ensured.

In the NG scenario, self-contained regions are much larger than in the SUB resolution, and thus optimal placement of PV and wind power plants accumulates in favourable areas. For PV capacity, that is in the west ("Rhine valley") and the south-east with longer hours of sunshine. PV potential is comparatively low in the center of BW. However, high demand in the urban regions especially in network groups 5, 6, 7 and 11 (see Figure 5.2, left) requires a large expansion of PV capacity. In contrast to the SUB scenario, a large share of wind turbines is concentrated in the high potential Black Forest area in the south-west of BW. In total, the required capacities are considerably lower compared to the SUB resolution with 37 GW of PV and 20.6 GW of wind power. The necessary storage capacity is more than halved. Only 8.3 GW of power and 52 GWh of energy capacity are required to fill the gaps to reach a renewable share of 95%. Mean storage duration is also lower for the NG resolution. Therefore, a slightly larger share is attributed to LiB compared to RFB. Again, the south-west region is more suitable for LiB storage due to high renewable potential and low demand. Due to the much lower investments required, the LCOE is also expected to be much lower with approximately 64 € MWh^{-1}.

In the IES scenario, power can flow between network groups. Therefore, renewable capacity placement is even more concentrated in high potential areas, with almost all wind production being located in the south-west. The total PV capacity is almost halved compared to the NG resolution. This also implies that under central planning, rural areas in the south-west of the state would have to provide the majority of BW's total electricity supply. In these regions, the existing wind potential would be fully utilized. Given past issues with local acceptance, the question arises as to whether the significant impacts on the region's land use can be communicated to and would be accepted by the local population. Overall, wind capacity remains almost the same with 20.6 GW of nominal power. Required BESS capacity is drastically reduced. For the IES resolution, 1.7 GW of storage power and 6.8 GWh of energy capacity are sufficient for a renewable share of 95%. These values are in the range of the storage needs reported in previous studies, assuming that BW's share of Germany's BESS requirements lies in between 10 to 20%. Again, mean storage duration is slightly reduced compared to the NG scenario. Since network groups can now share power, not all regions require BESSs. In the center and the south-west, LiB storage is preferred, in the east RFB accounts for the majority of BESSs. The LCOE is lowest for this scenario with expected 42 € MWh^{-1}. It must be noted that for the two IES scenarios where a minimum renewable share of 90% is required (IES90), the resulting *optimal* renewable share (i.e., renewable share at optimized cost) is above 93% for both the TM and EL consumption scenario, showing that a small BESS expansion could be a cost-effective solution at the assumed price for emissions even if no minimum renewable share constraints are imposed.

For all scenarios, renewable gas capacity is fully or almost fully utilized even though full load hours of renewable gas fueled CHP goes down when increasing the renewable share. This highlights the importance of dispatchable generation in an otherwise volatile power grid.

When comparing different RES share and consumption scenarios, it can be seen that storage demand increases sharply with the required renewable share (Figure 5.4). To reach a renewable share of 90%, only about 1.4 GWh of storage energy capacity is needed. However, beyond these values, storage demand increases exponentially, again confirming previous findings. To fill the last 2 percentage points between the IES98 and IES100 scenario, required storage capacity increases from 44 GWh to 296 GWh in the TM scenario. Mean storage duration then reaches over 17 hours and the batteries only perform roughly half as many cycles per year compared to the IES98 scenario. Consequently, the LCOE is highest for the 100% scenario with 132 € MWh^{-1} in the IES scenario. We conclude that in a future grid at least some dispatchable power capacity should be provided in order not to oversize the BESSs and waste resources in the process.

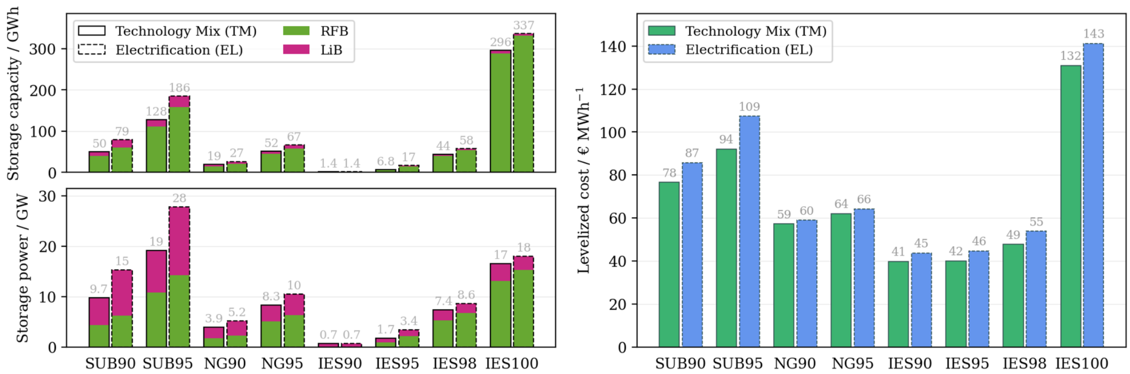

Figure 5.4.: Simulation results for the three spatial resolutions (SUB, NG, IES) and both consumption scenarios (TM, EL) for different shares of renewable energy (90, 95, 98, 100%). Left: Requirements for RFB (green) and LiB (purple). Right: LCOE

For the EL scenario, the load is higher in general. Therefore, needed storage capacity and power are also higher. This effect is especially pronounced for the SUB resolution, where regions are most confined. However, cost only increases slightly compared to the TM scenario since storage is not expanded at the same rate as consumption. This indicates that generated energy can be utilized more effectively (e.g., heat generation, which accounts for a larger share in the EL scenario mostly occurs during the day where renewable energy is more abundant and is somewhat flexible.)

5.4.5 Sensitivity Analyses

Our analysis features several assumptions regarding RES and BESS cost developments, DSM potential, and more. We therefore conduct a sensitivity analysis for the IES95 TM scenario. Figure 5.5 shows the impact of various key parameters on RFB and LiB capacities and costs.

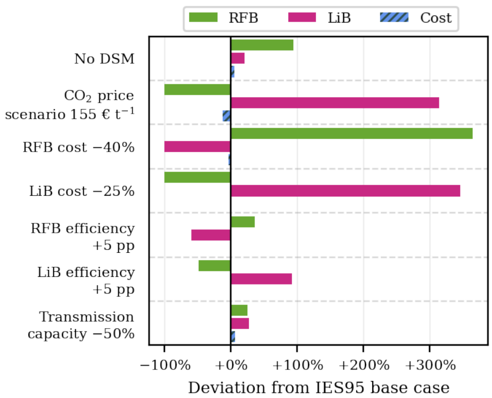

Figure 5.5.: Deviation of RFB (green) and LiB capacity (purple) and cost (blue) from IES95 TM scenario for variation of different parameters

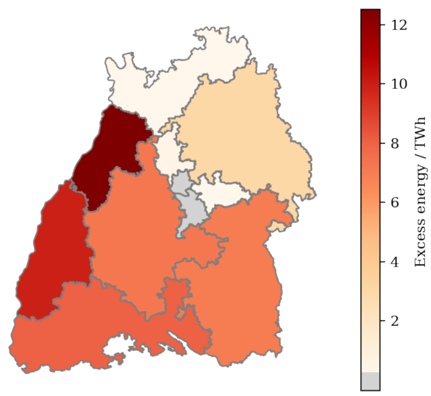

Figure 5.6.: Excess (curtailed) renewable energy per region (network group) for IES95 TM scenario

To simulate DSM potentials, a simple LP constraint is implemented. However, for many sectors it is still largely unclear to what degree load will be flexible. The assumed flexibility factors lead to approximately 15 to 20% of flexibility potential depending on the region. This is in the range of what is stated in literature. It can be shown that if DSM is not performed, the required storage capacity almost doubles. RFB is preferable in this case, as the production gaps can be expected to grow larger and persist for longer periods. However, the impact on cost is relatively low since storage capacity is not very high in the base case scenario. It must be noted that DSM is not assigned with any cost in the model. It could therefore be suggested that to achieve the renewable share of 95%, DSM must not cost more than 50 M€ per year. Otherwise BESS expansion might be preferable.

We can show that a lower CO_2 price and therefore lower import power costs heavily favor LiBs over RFBs. Furthermore, RESs are slightly lower sized, indicating that the lower power cost could make charging the BESS from the grid more viable, specifically when the renewable share in the grid is high. LiB could be better suited for this application if price peaks are short enough.

Altering BESS costs or efficiency mostly impacts the proportion between RFBs and LiBs while the LCOE stays almost the same. According to price projections, LiB storage cost is expected to drop by 25% between 2020 and 2030 (Baxter, 2018). Assuming this cost reduction while maintaining RFB cost, the scenario leads to higher installation of LiBs relative to RFBs. For RFBs, even higher cost reduction can be assumed as the technology is still in an earlier stage of commercialization, likewise resulting in a shift towards RFB storage for the IES95 scenario. It is expected that both prices go down in the future. Depending on the application and—as shown in the results of this study—on the location, we expect both storage technologies to become more important for power grids with high renewable shares. Similarly, an increase of 5 percentage points in round-trip efficiency for either storage technology shifts the RFB to LiB ratio towards the respective BESS. However, the impact is not as severe as with costs. It is thus expected that both technologies will remain relevant even if RFB performance might have more potential for improvement.

Reducing transmission capacity requires an increase of both storage capacities by approximately 25%, while cost is increased by roughly 6.4%, indicating that the transmission lines are a limiting factor for the investigated scenario. However, this effect becomes less severe when the renewable share is increased, as RESs have to be expanded more widespread through the regions moving towards a more decentralized energy system. By comparing the IES scenario with the benchmark of the "copper plate", we further find that the cost is only slightly higher for the transmission constrained scenario, indicating that the transmission grid in BW in its current and planned state should be sufficient for an expansion of RES. Expansion rates of RESs and BESSs are very similar in both scenarios as well. Nevertheless, the grid constrained model provides valuable insights into the optimal placement of generators and storage systems. For the copper plate scenario, PV capacity and wind turbines are placed in regions with the most suitable climatic conditions which would require the expansion of transmission capacities. This could be included as endogenous parameter, which however disregards the reality of long planning periods for transmission lines.

5.5 Discussion

PtX applications and most notably hydrogen electrolysis are not explicitly modeled in our scenarios for the integrated energy system of BW. However, the cost-optimal solution yields significant amounts of excess generation that could be used for the production of synthetic fuels or hydrogen as shown in the case of the IES95 scenario in Figure 5.6. For example, districts 3 and 9 alone (regions with significant wind and PV expansion) generate more than 10 TWh of excess renewable electricity each, which is more than 10% of needed electricity for PtX applications in Germany according to Bründlinger et al. (2018). Of course, in addition to the overall values, the temporal distribution of the surplus generation is important, as some electrolyzers need to achieve a certain amount of full load hours to be economical. In district 3 for example, 1 GW excess capacity is available for more than 4000 hours, therefore maximally 4 TWh of the overall excess generation of 12 TWh could be used for electrolyzer capacity. The numbers thus suggest that to a certain degree, PtX applications are feasible in BW in this scenario, a finding consistent with Henni et al. (2021).

To analyse varying degrees of electrification, we consider the consumption scenarios TM and EL. Unsurprisingly, the higher electricity consumption in the EL scenario leads to a higher LCOE for electricity. It must be noted that in both scenarios, other energy sources are needed in addition to electricity, such as hydrogen or synthetic fuels. In addition to domestic production, imports are necessary, for which costs are incurred. Consequently, lower electricity costs in the TM scenario do not necessarily imply lower overall system costs. In their analysis for Germany, Bründlinger et al. (2018) report that the TM scenario leads to lower overall costs than the EL alternative.

It must be noted that in our model, BESS degradation is only represented in terms of cost. However, specifically LiBs have limited cycle life. From the simulation results, we find that LiBs would often perform close to 1,000 cycles during one year. This frequent utilization could be enabled by coupling the LiB with an RFB, which allows to cover longer gaps and thus allows the LiB to be sized optimally. Assuming a cycle life of 10,000 cycles, the assumed lifetime of 10 years for LiBs should be a good assumption. However, constant operation also slowly reduces energy capacity over time, which is not being represented in the model. The assumptions should produce less errors for RFBs, which are reported to be less prone to cycle degradation.

5.6 Conclusion

In this study, we develop and demonstrate a bottom-up modeling approach to evaluate central and decentral designs for a low-carbon integrated energy system including two different BESS technologies. We can thus answer the research questions as follows.

For a renewable share of power generation of 95% including electrical energy needed for heat and transportation purposes, BESSs with at least 6.8 GWh of energy and 1.7 GW of power capacity are required for the state of BW, resulting in an LCOE of 42 € MWh^{-1}. Of the total BESS capacity, RFB accounts for 0.8 GW/5.0 GWh and LiB for 0.9 GW/1.8 GWh of power and energy, respectively. The values increase drastically when moving the system to 100% of renewable power supply, with storage power capacity of 17 GW and energy capacity of 296 GWh and an LCOE of 132 € MWh^{-1}. When comparing the different BESS technologies, we find that for the assumed cost and performance parameters, both LiBs and RFBs can provide viable solutions depending on the location. While LiBs are preferable in regions with high renewable potential (especially wind) and low consumption, RFBs can be particularly advantageous in regions with higher solar and low wind potential, as they are subject to potentially longer generation gaps. A combination of both can help to utilize the batteries more effectively. However, pricing of storage systems has a major impact on the optimal choice of BESS technology.

In a system subject to central planning, RESs are concentrated in high potential areas as shown in Figure 5.3, leading to a maximum utilization of available areas for wind generation in rural areas in the south-west of BW in our case study. PV generation capacity is concentrated in high potential, mainly urban regions. Under this paradigm, large areas in mid-south and north-east BW would not contribute to the supply of renewable electricity.

Depending on the degree of (de-)central planning and electrification, in the case of a 95% RES share, the LCOE ranges in between 42 and 109 € MWh^{-1}. Overall BESS requirements range in between 1.4 and 186 GWh. This shows the cost-disadvantages that would come from decentral planning approaches with more even distribution of capacity expansion. However, there are paths in between a completely central and decentral design: The NG scenario illustrates one possible solution where more regions are included in the expansion of RES, while keeping the LCOE relatively low at approximately 60 € MWh^{-1} and BESS requirements between 52 and 67 GWh.

The results of this study are of significance for policy-makers at national and regional level, system planners as well as local stakeholders. Considering local acceptance of pathways towards low-carbon energy systems and weighting them against cost considerations will pave the way for targeted measures to increase citizen involvement and accelerate the energy transition to a renewable integrated energy system.

This chapter concludes Part II of this thesis, in which the deployment of BESSs across all different aggregation levels of energy systems has been analysed. Homeowners and office managers need to be provided with transparent and engaging information in order to leverage the potential of BESS deployment on the individual level. This can be achieved through an engaging user interface design, which contains vivid and carefully designed interactive features as shown in Chapter 3. By connecting and matching suitable individual RESs and BESSs within an energy community, the profitability of individual BESS investments can be increased and existing resources can be deployed more effectively (Chapter 4). These distributed BESSs can build the foundation for the required system-level capacity if appropriate regulatory measures are taken by policy-makers. On the system level, BESS requirements need to be analysed to showcase alternative pathways towards low-carbon energy systems to policy-makers. The introduced bottom-up modeling method of BESS requirements in Chapter 5 demonstrates the trade-offs in terms of spatial RES and BESS capacity distribution and LCOE that policy-makers need to consider.

While the considerations in Part II show the potentials of optimal BESS deployment in integrated energy systems, during real-time operation, uncertainties regarding generation, consumption and price developments complicate a profitable and effective deployment of BESSs. In practice, BESSs therefore need to be equipped with online operation strategies in order to deal with uncertainty and to handle simultaneous applications. In this regard, the needs and goals of storage operators and other stakeholders differ depending on the system level a BESS operates on. In the following Part III, these different perspectives and operational goals are addressed through the development of data-driven operation strategies.

Part III.

Data-driven Operation Strategies

INTRODUCTION TO PART III

Once BESSs are deployed, they should be operated optimally considering the needs of the corresponding stakeholders on that system level. Storage operators need to handle different uncertainties during real-time operation, e.g., regarding renewable generation, consumption and price developments on wholesale markets (Chapter 2). Multi-use BESS deployment in particular must deal with several of these uncertainties when coordinating multiple applications in parallel (Section 2.3). In this context, online operation strategies have not been well researched, as optimization is the state-of-the-art method for case studies on BESS operation (Section 2.4).

In Part III, I design and evaluate data-driven online operation strategies to handle these uncertainties for various stakeholders on different levels of energy systems. In front of the meter, renewable operators who are subject to direct marketing of their generation could deploy grid-scale BESSs to hedge again price and quantity risks on the spot markets. For such a renewable plant operator, I design and evaluate a rule-based heuristic strategy to deploy a grid-scale BESS for risk hedging in Chapter 6. Behind the meter, BESSs deployed for peak-shaving in industrial zones can be operated more profitably by simultaneously providing frequency regulation services. In Chapter 7, I therefore investigate the case of a BESS deployed in an industrial plant for the joint participation in industrial peak-shaving and frequency regulation provision and introduce a risk-averse operation strategy based on a probabilistic forecast. Combining BTM and FTM use cases, BESSs can be deployed more profitably if several of these application areas are combined. In Chapter 8, I design a DRL-based BESS service agent that coordinates several BTM and FTM applications during real-time operation and compare the results with rule-based operation strategies and the theoretical optimum.

CHAPTER 6

RISK HEDGING FOR INTERMITTENT RENEWABLE GENERATION

In the future, operators of renewable plants on all levels of power grids may face the challenge of directly marketing their generation on electricity wholesale markets. In the low voltage grid, the EEG subsidies for residential PV systems expire after 20 years of operation. At a higher level, large solar parks in Germany have already been realized without subsidies (Erneuerbare Energien, 2021). Their operators face significant price and quantity risks due to the volatile spot market prices, which are inversely correlated with high generation from RESs. They therefore need strategies to hedge against these risks (Hain et al., 2018; May et al., 2017), for example, through the deployment of a BESS, which can shift the generated electricity to times of higher spot market prices. In this chapter, first steps are taken in modelling BESS options, i.e., a service product similar to financial options that is provided by BESS operators to renewable generation operators. First, a theoretical model is introduced and corresponding hedging strategies are developed. The model is then applied to a fictional solar PV plant. The results show that BESS options can reduce the conditional value at risk for intermittent renewable generators by on average 38% in the considered month of the case study.

This chapter comprises large parts of the published article: S. Henni, P. Staudt, P. Jaquart, C. Weinhardt, *Towards Financial Risk Management for Intermittent Renewable Generation with Battery Storage*, 54th Hawaii International Conference on System Sciences, 2021.

6.1 Introduction

Renewable generators face two types of risk: Quantity and price risk. A similar perspective on price and quantity risk is described in Oum et al. (2006) for load serving entities. The authors also describe some correlation between the two risks. A higher demand in terms of quantity is positively correlated with high prices and vice versa. This is similarly true for renewable generation but with inverse correlation. Higher renewable generation from intermittent resources leads to lower electricity prices as their marginal cost of production is zero. Therefore, higher generation is inversely correlated with the market price. This is a dilemma for renewable generators even though it allows for some natural hedging because lower quantities are supported by higher prices and lower prices are associated with higher generation. However, as the relationship is not strictly linear, renewable generators face considerable market risks, since their generation is not dispatchable Hain et al. (2018).

The intermittency of renewable generation can be complemented with BESS capacity to increase the controllability in regards to the system but also the profit of renewable generators. A BESS can be used to shift the income of excessive generation to times with lower cheap renewable generation and consequently higher prices. This way, renewable generators are less vulnerable to temporarily low market prices. However, BESS capacity is expensive and it is not profitable to keep a BESS charged over several days only to discharge in times of low generation. This way the BESS's capacity is idle for a substantial time and can therefore not turn any profit. Consequently, renewable generators need BESS service providers that agree to charge their batteries at certain times and discharge them for the renewable generator when needed, while simultaneously optimizing their own profits in between. The BESS operators are thus providing a service for renewable generators that needs to be fairly priced. In this chapter, we model this situation and the fair pricing of such an instrument. We then introduce several heuristic strategies for renewable generators which intend to reduce their price and quantity risk. We assess the effect and the pricing for these strategies in a case study. We also discuss whether this service is financially viable given the price of BESS or other storage capacity. We thus provide three contributions with this chapter: We model the use of a BESS for renewable risk hedging as a form of option and provide a fair pricing mechanism. We develop heuristic strategies for renewable generator risk hedging through the use of a BESS and finally we assess the use of these strategies in a case study and determine a fair market price. This results in the following research question:

Research Question 5: *How much can the conditional value at risk of a renewable operator be reduced through the deployment of a battery storage service using a developed heuristic operation strategy?*

The remainder of this chapter is structured as follows: First, we review related literature on risk hedging in energy market research and the joint operation of a BESS with renewable power plants. Then, we introduce a theoretical model for BESS service options that can be contracted by renewable operators to hedge against price and quantity risks. We then demonstrate this concept on the case of a large PV plant, and evaluate both the perspective of the plant operator and the BESS operator. Finally, we discuss promising future research and conclude with the results of this chapter.

6.2 Related Work

Risk hedging strategies have a long tradition in energy market research (e.g., Deng and Oren (2006); Harvey and Hogan (2000); Bessembinder and Lemmon (2002)). Options as a specific hedging instrument and their effects are described in Willems and Morbee (2010), for example. One of the first considerations of combined price and quantity risk is presented in Oum et al. (2006) for load serving entities that need to supply varying demand from a wholesale market with varying prices at fixed retail rates. Pircalabu et al. (2017) use a copula approach to assess joint generation and price risk for a wind turbine in Denmark. They find that an independent consideration of the two risks leads to an underestimation of the total risk for the wind turbine. The case risk hedging for renewable generators has recently attracted more attention. Hain et al. (2018) find that the intermittent generation by growing renewable generation capacities further increases the price and quantity related risks of operators. They conclude that unhedged renewable portfolios carry a significant amount of risk and that plain vanilla forwards provide poor hedging opportunities.

However, they are the only liquid market alternative for risk hedging on the electricity market. Oum et al. (2006) develop a hedging strategy but state themselves that the results are purely hypothetical as options are not actively traded on electricity markets. Gersema and Wozabal (2018) describe a risk reduction strategy for renewable generators through the diversification over different technologies and locations to reduce the dependence on local weather phenomena. Staudt et al. (2019) describe the interplay between forward and spot trading and the effects of different trading strategies for renewable generators.

Another approach is the short-term risk hedging through multi-period trading on the day-ahead and intraday market which has been considered by La Sánchez de Nieta et al. (2020) for solar and by Morales et al. (2010) for wind park operators. Both studies include imbalance prices to model penalties for deviations from production forecasts and thus consider a short-term hedging problem for daily deviations. Pinson et al. (2009) consider the dynamic sizing of storage capacities in order to compensate for wind production forecast deviations, again focusing on short-term deviations from production forecasts in order to avoid imbalance penalties. Radchik et al. (2013) link a solar plant and a natural gas generation unit that do not have to be located in physical proximity into a virtual generator that is able to provide stable electricity generation. Solar and gas swaps are introduced as financial instruments to mitigate the price and quantity related risk of both operating entities.

The joint operation of a renewable power plant and a connected BESS has been addressed in numerous publications, however, often not in regards to risk reduction. For example, Ratnam et al. (2015) investigate the optimal operation of a co-located PV and storage system in order to maintain an energy systems voltage limits. Núñez-Reyes et al. (2017) develop a strategy for a PV system with an integrated storage system to optimally participate in the electricity market. Control strategies to enhance grid integration and to smoothen short-time production deviations from large solar plants using BESSs have been designed by Yang et al. (2018). Kroniger and Madlener (2014) assess hydrogen production as storage option for renewable generation but find that it is not economical to re-convert the hydrogen to power. One closely related study is Hedman and Sheblé (2006). The authors are evaluating the use of options as hedging instruments for renewable generation and compare it to the use of a pumped hydro power plant. However, the authors hedge the deviation from a forecasted generation instead of a deviation from long-term financial expectations of generation. They are also assuming known electricity prices and formulate the use of a forecast as possible future work. We address both limitations in this study.

As shown, previous studies usually focus on an integrated renewable energy and storage system that is jointly installed and operated. This approach significantly increases the investment costs that an operator faces in advance. For the case of risk hedging with a BESS, Pinson et al. (2009) find that the best results can be achieved through dynamic sizing of the storage unit, i.e., the utilization of different storage capacities each day. The authors suggest that the storage should operate "as an independent market entity, where each producer may rent the necessary daily storage capacity for hedging the risk". Following these results, we consider the utilization of a BESS unit as a service provider. We investigate the potential of a solar plant operator to protect herself against quantity and price risk through a service agreement with a storage provider that allows the charging of the BESS at one point in time and the discharging at another freely chosen point in time within the agreed duration period of the contract. In the course of this chapter, we describe the general features of risk hedging strategies for the solar plant operator and demonstrate an exemplary strategy on the example of a simulated solar plant. Besides the description of the storage strategy, the main contribution is the evaluation of the possibility of using BESS capacity as a service for risk hedging purposes for renewable generators in the form of BESS options.

6.3 Theoretical Considerations

In this section, we begin by describing the problem analytically. We model the risk of renewable generators and introduce the use of a BESS for risk management. Assume that q_t is the actual generation of a renewable generator at time t and Q_t is the random variable of the generation at time t. Furthermore, assume that $\tilde{Q}_t$ is the distribution of that generation. We use the same nomenclature for the price at any given time with p_t as the actual market price, P_t is the random variable of the price and $\tilde{P}_t$ is the corresponding distribution. The random profit Π of a renewable generator with marginal generation cost of zero is then given as $\Pi_t = Q_t \cdot P_t$.

From this, we can calculate the expected profit for any given time. This leads to the equation of expected profit as $\mathbb{E}(\Pi_t) = \mathbb{E}(Q_t) \cdot \mathbb{E}(P_t) + Cov(Q_t, P_t)$. As higher renewable infeed leads to lower wholesale electricity prices, the covariance in this equation serves as a natural hedging as it is negative between prices and renewable quantities. However, while this association is true on a global level, it is not necessarily true for individual renewable power plants. To assess the associated risk, we need to consider the variance of the profit. It is described in the following formula.

$$\begin{aligned} Var(\Pi_t) = Var(Q_t \cdot P_t) = Cov(Q_t^2, P_t^2) + \\ (Var(Q_t) \cdot \mathbb{E}^2(Q_t)) \cdot (Var(P_t) \cdot \mathbb{E}^2(P_t)) - \\ (Cov(Q_t, P_t) + \mathbb{E}(Q_t)\mathbb{E}(P_t))^2 \end{aligned} \tag{6.1}$$

The joint variance increases with the individual variances and the expected values. It can be reduced through a negative covariance between the prices and generation quantities but it depends on the individual mechanics.
A renewable generator that wants to reduce the uncertainties of her profits is not necessarily interested in reducing the risk of individual time steps but would rather try to guarantee a stable stream of profits over periods of time, such as days or weeks. Therefore, in this chapter, we consider the differences in profit relative to an average day in the respective month. As renewable generation varies greatly over the seasons, it is reasonable to assume that a renewable generator would have different profit expectations for a day in July and December. However, even in December, a renewable generator might achieve an average, above average or below average day. Being able to hedge against below average days is an argument towards investors for lower interest rate payments and thus an important tool for renewable generators. It is important to define the risk measure that renewable generators are trying to minimize. One obvious choice is the reduction of the variance. A renewable generator has the following objective in regards to the reduction of the variance with m being a particular month, n being the number of considered days for that month and d_m

being a particular day in that month.

$$min(\bar{\pi}^m - \pi^{d_m})^2 = min(\frac{1}{n}\sum_{j=1}^{n}\sum_{t=1}^{24}\pi_t^m - \sum_{t=1}^{24}\pi_t^{d_m})^2 \tag{6.2}$$

Other measures that we consider in this study are the Value at Risk (VaR) and the Conditional Value at Risk (CVaR) (R. Tyrrell Rockafellar, Stanislav Uryasev, 2000). The VaR for a certain confidence level α is the α-quantile of the distribution function of the loss function X for a certain portfolio. The CVaR is the integral over the interval [0,α] of the inverse distribution function of losses. Assume that the losses of a renewable generator for a day in a specific month are distributed according to $F(\pi^m)$. Then the VaR to the level of α is defined as $VaR^m(X) = min(x|F_X(x) \geq \alpha)$ and the CVaR is defined as $CVaR^m = \frac{1}{\alpha} \cdot \int_0^\alpha VaR^m(X)$. The VaR for $\alpha = 0.05$ thus corresponds to the lowest of the 5% largest losses. The CVaR is the average of the 5% largest losses and is therefore always higher than the VaR, but is a more robust measure of risk. The VaR and the CVaR are better measures to model the risk of a renewable generator than the variance as they describe negative deviations from the mean rather than also punishing positive deviations. Consequently, they have been used as risk measures by the authors of the studies presented in La Sánchez de Nieta et al. (2020) and Morales et al. (2010).

We now introduce the BESS as a risk hedging instrument. The action of charging and discharging a BESS can only be described over a time horizon. Therefore, we propose a time period T that is associated to each BESS option equivalent to the life of a regular financial option. The renewable generator has to choose this period when charging the BESS, which influences the option pricing. We can then differentiate between BESS options that can be exercised at any time during the period (American BESS options) or which can only be exercised at the end of the period (European BESS options). We will describe the impact on the option price later in this section. In the case of American BESS options, the renewable generator also needs to decide on when to exercise the option. She can develop a strategy with a specific time to exercise or try to optimize the time to exercise over the lifetime of the BESS option. It is of course important to discuss when such decisions need to be communicated to the storage operator so that she can optimize her load schedule around these decisions of the renewable generator. This detailed definition of the financial product is subject to future work. The profit of the renewable generator with a BESS π^{bst} over a time horizon T with the charging decisions s_t is then given by the following equation.

$$\pi_T^{bst} = \sum_{t=1}^{T} (q_t - s_t) \cdot p_t \tag{6.3}$$

Therefore, a risk neutral renewable generator is willing to pay the difference between the profit with and without the use of a BESS ($\pi_T^{bst} - \pi_T$). However, risk averse renewable generators can use this strategy to reduce their VaR and CVaR and might therefore be willing to pay a premium.

To price the service from a storage operator's perspective, we ignore the cycling costs for the moment and focus on the opportunity costs of the BESS. The renewable generator charges the BESS for free but then reserves the right to sell the charged energy at any moment within the BESS option period (American) or at the end of the period (European). To price the American form of the option, we first define $\hat{p}_{T,t_0} = max_{t \in T}(p_t)$ as the maximum price within the option period T that starts at t_0. This price can also be expressed as a random variable $\hat{P}_T$ that has a distribution $\tilde{\hat{P}}_{t_0,T}$ depending on the time period T and the starting time t_0. This is easier for the European BESS option because we only need to consider the distribution of the price at the end of the option period at t_1 for which we have already defined a probability distribution as $\tilde{P}_{t_1}$. The pricing of the according options then depends on the risk propensity of the BESS. Assuming a risk neutral storage operator and ignoring cyclic aging and fixed costs, then a fair price p^o for the American BESS option is calculated as $p^o = (\mathbb{E}(\hat{P}_T) - p_{t_0}) \cdot s_{t_0}$. It is the difference between the expected maximal price over the option period and the current price multiplied with the charged quantity. The calculation for the European BESS option is equivalent. If a storage operator is more or less risk averse then the pricing changes. However, for a storage operator, providing such a service also reduces risks. By receiving a fixed premium she is less dependent on price volatility and has a secure income. Therefore, the pricing of such BESS options also depends on the preferences of the involved parties. In the following, we describe these theoretical considerations along a case study for a fictional solar PV power plant.

6.4 Data Analysis

In order to investigate the presented theory of risk hedging of the revenues of an operator of a renewable energy generation plant, we implement and evaluate the concept by means of a case study. We select the case of a solar PV plant operator, mainly for one apparent reason: Since the price risk is increased by the feed-in from renewable energy, in the case of a wind park it might be necessary to bridge long periods of time to avoid the price risk, since periods of high wind feed-in can continue over several days or weeks. A negative influence on electricity prices can also be observed during periods of high feed-in from solar generation, but naturally only for a few hours each day. This means that a solar PV plant operator can avoid her price risk by a short-term shift of generation from the midday hours into the evening. In the case of a solar PV plant operator, the results for a delimited period of time are more robust and can be interpreted more generally. For our analysis, we use the German price, load and generation data for the years from 2015 to 2019 which is publicly available (Bundesnetzagentur, 2020a). We use the years 2015 to 2018 as training data to create a risk hedging storage strategy for a solar PV plant operator and subsequently test it for the months from May to September of 2019. We deliberately only take the summer months into account, as this is when the price effects from feed-in of solar PV generation are most pronounced and the most significant results can therefore be expected.

The analysis of the training data set shows the effects of quantity- and price-related risks. Daily revenues of a solar PV plant operator who directly markets her generation on the day-ahead-market fluctuate significantly. This is illustrated for the period of one month in Figure 6.1 using the example of a fictional 1 MW solar plant. Revenues are calculated using $\pi^{d_m} = \sum_{t \in d_m} max(0, p_t) \cdot q_t$, where for each hour t in a day, the respective solar generation q_t and price on the day-ahead-market p_t are multiplied and then added. We assume that in hours with negative prices, generation is curtailed instead of sold, thus the revenue in hours with negative prices is zero. To investigate the influence of prices and daily generation on the daily revenues, we plot these dependencies in in Figure 6.2. The daily generation is calculated as $q^{d_m} = \sum_{t\, in\, d_m} q_t$ and the realized average price for the solar generation as $P^{solar} = \pi^{d_m}/Q^{d_m}$. It can be seen that both the daily production quantity and the price that is realized per MWh have a positive effect on the daily income. The graphs show this dependency for all days in the months May to September of the training data set (2015 - 2018).

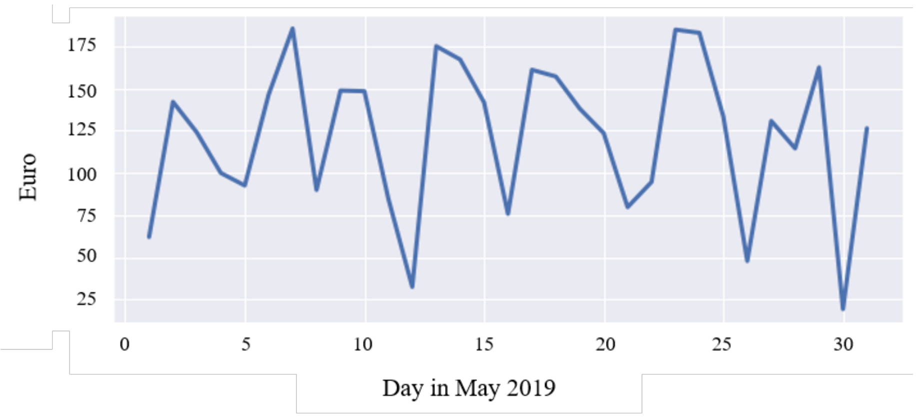

Figure 6.1.: Daily revenues of a 1 MW solar plant

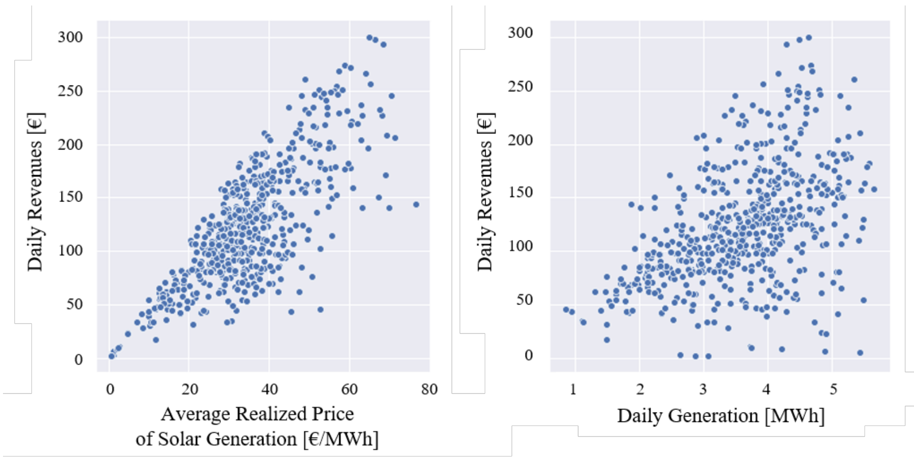

Figure 6.2.: Influence of generation quantity and realized price on daily income

In order to hedge the price and quantity risk of a solar PV plant operator, we therefore create BESS utilization strategies that are specifically targeted to counteract the respective cause of losses in revenues. We assess the risk of the solar PV plant operator using the risk measure CVaR described in the previous section. This measure penalises downward deviations in revenues, i.e., losses compared to the expected daily revenue, while above-average revenues are not considered.The strategies developed, which are presented in the following section, are therefore aimed at specifically preventing downward deviations in profits caused by quantity or price fluctuations.

6.5 Operation Strategies to Mitigate Price and Quantity Risk

On a given day, the storage operator faces the decision of how much of the electricity forecast for the next day to sell directly on the day-ahead-market and how much to charge or discharge at a given time during the next day. We stipulate that the operator must inform the BESS service provider about these charging and discharging decisions in advance, so that the storage operator has enough time to plan her operation schedule accordingly. To address the revenue fluctuations associated with price and quantity uncertainties of a solar PV plant operator, we employ strategies for the BESS service utilization specifically targeted at counteracting each of the two risks of negative deviations of next day's prices and production quantities. For the determination of benchmarks and decision rules, we analyse generation, load and price data from the years 2015 - 2018 and apply the derived rules to the months of May to September 2019 to test and evaluate the storage strategies. As the quantity and price risks differ with regard to the time horizon concerned, we develop two strategies to address each of the risks separately first and then later examine the effects of the individual and combined strategies. Whereas losses due to price drops can be mitigated by shifting generation within one day from low price hours to later occurring high price hours, quantity-related losses can only be compensated by shifting generation from days with above average generation to days with low generation.

6.5.1 Price Risk Strategy

The main risk of price-related losses consists of periods of high feed-in from renewable energy sources, as these have marginal production costs of zero and thus negatively affect prices on the day-ahead market. This is particularly noticeable at times of high wind feed-in, but also during the summer, when solar feed-in is at its peak, prices are systematically lower around midday than in the morning or evening hours. If additional influences, such as a high wind speeds occur simultaneously, periods with negative prices can occur.

A solar PV plant operator can circumvent the price risk through a short-term utilization of the BESS service. If significantly lower prices are expected on the following day, solar generation can be shifted from the hours of high generation into the evening hours, thus avoiding significant price drops even with little and short-term BESS usage. The *price risk* storage strategy for a solar plant operator is intended to reduce downward deviations from the expected revenue that are caused by price drops. It consists of shifting generation from the midday hours, which are high in solar generation, to the evening hours during which higher prices occur due to declining feed-in from solar PV. To this end, we train a decision tree on the data for the years 2015 to 2018, which takes the respective national load as well as wind and solar generation forecasts for the following day as input, as well as the respective month and day of the week. On this basis, the decision tree predicts whether the prices in the five hours of the following day with the highest generation fall below the 25% quantile of a month's historic electricity prices during 2015 to 2018. If the algorithm predicts such a price drop for the next day, the price hedging strategy is triggered. For each of the hours t in the charging period CP, a share $a \,\epsilon\, [0,1]$ of the generation forecast is stored using $charge_t = a \cdot q_t \quad \forall t \in CP$. The entire stored electricity of the midday hours is then discharged in equal parts in the hours of the discharging period DP in the evening using $discharge_t = \frac{\sum_{t \in CP} \; a \cdot q_t}{N_{DP}}$, where N_{DP} is the number of hours in the discharging period. The *price risk* strategy does not postpone the sales of the generator beyond one day.

Figure 6.3.: Implementation of decision tree to trigger the *price risk* strategy

6.5.2 Quantity Risk Strategy

The short-term quantity-related risk is expressed by the fact that the total generation on some days falls short of the average for a month, usually due to weather influences that are only predictable in the short-term future. Shifting production within one day is therefore not sufficient to protect the solar PV plant operator against these quantity associated deviations from the expected revenues. Instead, in order to counteract the quantity risk, the operator can request discharging of stored electricity from the BESS service provider on days of low generation. In order to do so, she must preventively store surplus generation on days with above-average generation in order to build up credit with the BESS service provider. The *quantity risk* strategy thus includes decision rules for such charging and discharging events. Based on the generation data from 2015 to 2018, the average daily generation is calculated for each month. This serves as a benchmark for the expected generation $\mathbb{E}(Q_{d_m})$ on a typical day d in a given month m. Based on her risk aversion, the storage operator then chooses a factor $l \epsilon [0, 1]$ that triggers a discharging event. If the generation forecast for the next day Q_{d+1} falls below this threshold (e.g., $0.8 \cdot \mathbb{E}(Q_{d_m})$), a discharging event is requested in the amount of the forecast deficit, if the operator has enough credit with the BESS service provider. Credit can be built up by charging electricity to the BESS and is treated as described in the previous section in the same way as an American option. When a charging event is commissioned, the solar PV plant operator determines a time horizon T for the option, within which she can retrieve, i.e., discharge, the credit at any time. However, as with all charging and discharging events, she must announce the discharging of electricity in advance. In order to make sure that sufficient credit is available with the BESS service provider to cover a discharge event when it occurs, the solar PV plant operator has to built up credit in advance on days with excess generation. For the *quantity risk* strategy, the operator may decide on a planning horizon T, i.e., how long in advance a shortfall should be planned for. The longer this period is chosen, the more likely it is that all discharge events can be covered but this security may come with a higher price for the BESS service as the BESS service provider faces larger uncertainties. The charging events of the *quantity risk* strategy are triggered as follows: For each month, we calculate the expected generation deficit that is faced by the operator for a given threshold l and a planning horizon T, based on the years 2015 to 2018. On each day, the solar PV plant operator decides whether electricity should be charged to the BESS the next day based on two conditions. (1) A charging event is only requested when the generation forecast for the next day is above a month's expected daily generation and only this excess will be stored and (2) a charging event is only requested if the existing credit with the BESS service provider is below the expected quantity deficits over the planning period T. When electricity is stored, the solar PV plant operator has the option of discharging this credit at any given time within the planning horizon. Note that credit with the BESS service provider may expire if the requested number of days of the option elapses without a discharging event. In that case, the solar PV plant operator will request a discharging event on the last day of validity of the option in any case. In case of a discharging event, the credit with a shorter remaining option lifetime is always requested first. Figure 6.4 shows an exemplary set of consecutive days and the respective daily generation (blue lines) to illustrate the benchmarks for charging and discharging events. The corresponding algorithms that determine the amount of generation to be charged or discharged in each hour t when an event is triggered are displayed in Figure 6.5. For both the *price* and *quantity risk*, the strategy s is then defined as $s_t = charge_t - discharge_t$.

When combining the two strategies, it can make a difference in which order they are employed. If, for example, the *price risk* strategy is commissioned first, it is possible that generation has already been stored, which is then no longer available to use for the *quantity risk* strategy. We therefore deploy and investigate four different storage strategies for the solar PV plant operator: *price risk only*, *quantity risk only*, *price risk first, then quantity* and *quantity risk first, then price*.

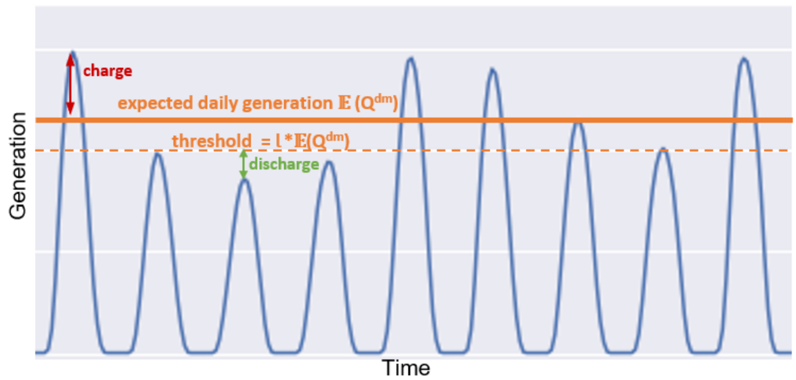

Figure 6.4.: Schematic illustration of a charging and a discharging event in the *quantity risk* strategy

charging event

```
while excessGen > 0:
  for t in CH:
    charge_t = min(generation_t, excessGen)
    excessGen = excessGen – charge_t
```

excessGen = Q_{d+1} - $\mathbb{E}(Q^{dm})$
CH = historically cheap hours in ascending order

discharging event

```
while deficitGen > 0:
  for t in EH:
    discharge_t = min(deficit, remainingCredit)
    deficitGen = deficitGen - discharge_t
```

deficitGen = l * $\mathbb{E}(Q^{dm})$ - Q_{d+1}
EH = historically expensive evening hours in descending order

Figure 6.5.: Algorithms for charging and discharging events

6.6 Evaluation

We apply the strategies presented in the previous section to the price, load and renewable generation data in Germany during the months May to September 2019. For the design and evaluation of a storage strategy for a fictional solar PV plant operator, we scale the generation to 1 MW of installed capacity. Based on the historical training data from 2015 to 2018, we train the decision tree that decides when the price strategy is applied and determine the parameters that are required for each strategy. For the *price risk* strategy, we set the charging period CP to the fixed hours between 11 a.m. and 4 p.m. and the discharging period DP to be between 6 p.m. and 11 p.m. for each day when the *price risk* strategy is triggered. We set the share a that is to be charged during each hour in the charging period to be 1, thus all generation is charged and then later discharged. For the *quantity risk* strategy, we set the parameter l to 0.8, thus a discharging event is commissioned whenever the generation forecast for the next day is below $0.8 \cdot \mathbb{E}(Q^{d_m})$. The planning horizon T and accordingly the time period for the BESS option that is chosen when charging the BESS is set to four days. For the *price risk* strategy, the BESS option is analogous to a European option since the time of discharging is specified to be at the end of a one day period.

Fig. 6.6 shows a section of the resulting storage strategies based on the selected parameters, where positive values are charging events and negative values indicate discharging events. In this section, it can be seen that the two strategies do not overlap and can therefore easily be combined. In general, only very few overlaps

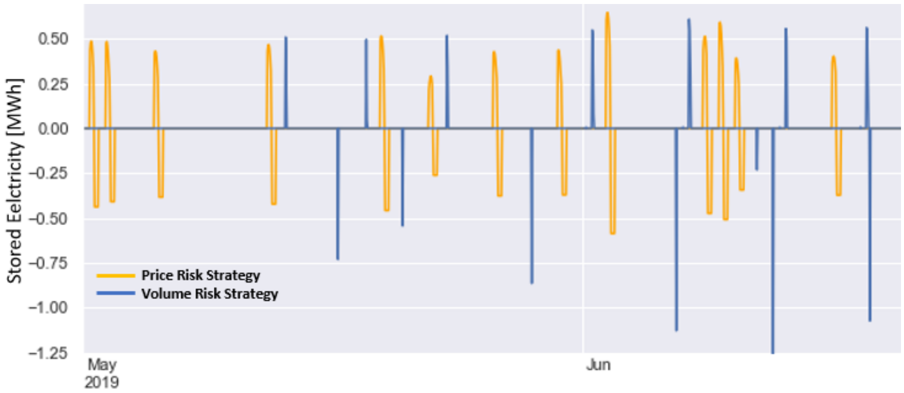

Figure 6.6.: Extract of the resulting storage strategies

occurred throughout the testing period, so that the strategies *quantity risk first, price second* and *price risk first, quantity second* only differ slightly. This indicates that the solar PV plant operator can address both the quantity and price risk through the utilization of a BESS service without the two strategies getting in each others way. In the next paragraphs, we analyse the implications of the resulting strategies for the solar PV plant operator as well as the BESS service provider in terms of revenues and risk hedging.

6.6.1 Solar Photovoltaic Plant Operator

The CVaR serves as risk measure for the revenues of the solar PV plant operator. This measure penalises "losses" in terms of negative deviations from the average daily revenue. In order to obtain comparable values, we use the average revenues without BESS utilization to measure the downward deviations and to determine the CVaR. Our results in Fig. 6.7 show that the CVaR can be reduced substantially through the utilization of the BESS service. The results range within a 28% CVaR reduction in September and a 58% CVaR reduction in May when using the combined strategy. On average, the CVaR can be reduced by 38% in the five months that are considered. In particular, the strategies that involve the *price risk* strategy improve the CVaR in all months under consideration. In fact, only the *quantity risk* strategy by itself is not suitable to reduce the CVaR in all but one month. The combination of the two strategies yields the best CVaR in three out of five months and ties with the *price risk* strategy in the other two months. A closer look at the amount of electricity stored in Fig. 6.8 in the respective strategies could provide an explanation for the findings. The *quantity risk* strategy uses the BESS service for a comparatively small quantity of stored electricity. This could indicate that the parameters for the *quantity risk* strategy have been chosen too conservatively. For example, the threshold l for a discharging event could have been set higher.

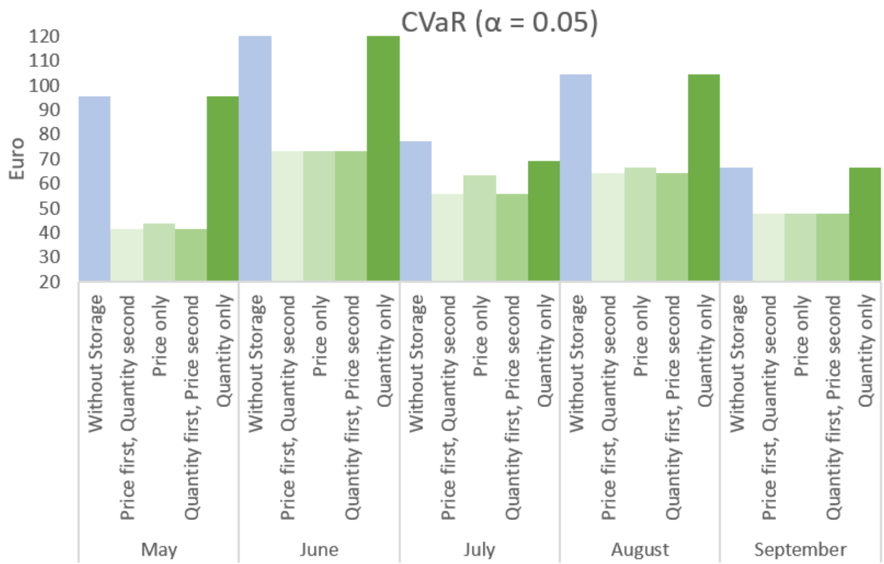

Figure 6.7.: Negative deviations from average daily revenue

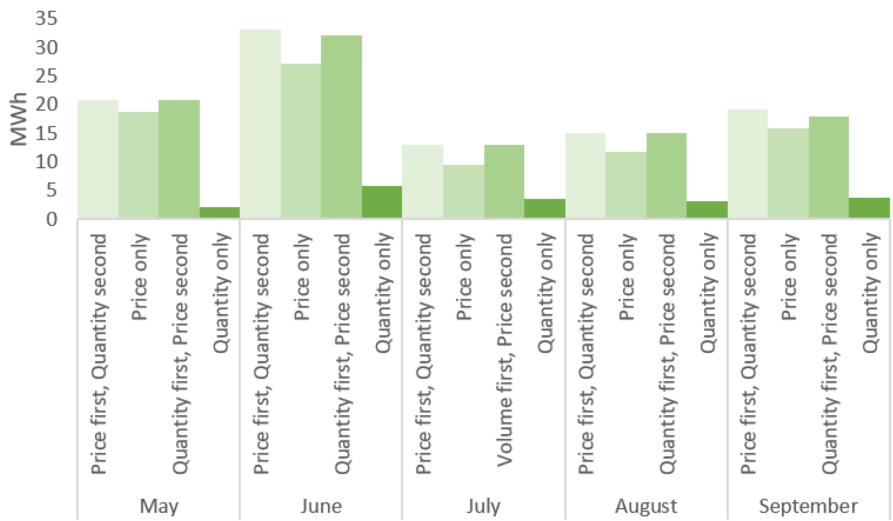

Figure 6.8.: Quantity of stored electricity

However, Fig. 6.9 also suggests that the quantity may not have the same importance as the price for the largest deviations from the average revenues. In

May, the three largest deviations (on days 12, 26 and 30) can be reduced with the *price risk* strategy, which is expressed in the positive effect on the CVaR. The *quantity risk* strategy only affects the fifth largest deviation (day 16), which is not reflected in the CVaR with $\alpha = 0.05$. In summary, we find that the CVaR can be improved substantially with the proposed strategies based on decision heuristics from the four years prior to the testing period. This is a promising finding for future work considering the utilization of a BESS as a service to hedge price and quantity related risks of renewable generation operators. We expect that with more data and a more granular strategy design, even better results can be achieved.

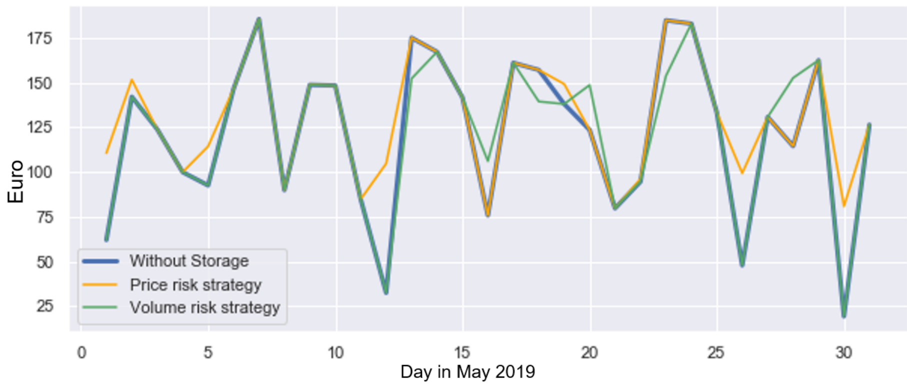

Figure 6.9.: Impact of storage strategies on revenues

6.6.2 Battery Storage Service Provider

In this subsection, we evaluate the necessary payments to the storage operator for him to accept providing the BESS options for the above described strategies. To do so, we are optimizing the storage operation assuming perfect foresight of the price development with and without the storage hedging strategy of the PV solar plant operator interfering with the storage strategy. The difference between the results gives us the opportunity costs for the operator. The BESS operator solves the following optimization problem.

$$\max \quad \sum_{t=1}^{T} -s_t \cdot p_t \tag{6.4}$$

$$\text{s.t.} \quad S_t = S_{t-1} + s_{t-1} + s_{t-1}^{solar} \forall t \in T \backslash \{0\} \tag{6.5}$$

$$|s_t| \leq s \tag{6.6}$$

$$0 \leq S_t \leq S \tag{6.7}$$

$$S_0 = 0 \tag{6.8}$$

S	Storage capacity
S_t	State of charge at time t
s	Storage charging power
s_t	Charging decision of storage at time t
s_t^{solar}	Charging decision of solar PV at time t
p_t	Price at time t

During the considered period and with a parametrization of $s = 2MW$ and $S = 4MWh$ the BESS can achieve a profit of 22,618 € without interference of a strategy. Including the *price risk* strategy, the BESS's profit decreases to 20,486€. For the *quantity risk* strategy, the profit decreases slightly to 22,304 €. Finally, for the combined strategy the profit is 20,270 €. Another important consideration is the throughput. An increasing throughput can lead to more cyclic aging which would lead to more costs for the BESS. The throughput without the provision of BESS options is 1,436 MWh, with the *price risk* strategy it is only 1,429 MWh, with the *quantity risk* strategy it is 1,434 MWh and with the combined strategy it is 1,429 MWh. Therefore, the impact of cyclic aging in regards to BESS option provision is negligible. Finally, to give an indication of the cost per MWh of the BESS option we can divide the lost profit for the BESS by the throughput caused by the renewable generator. Thus, the cost is 25.7 € MWh^{-1} for the *price risk* strategy, 15.2 € MWh^{-1} for the *quantity risk* strategy and 23.2 € MWh^{-1} for the combined strategy. It is therefore potentially in the range of BESS costs but further cost decreases for BESSs or increasing price volatility are necessary to make it profitable.

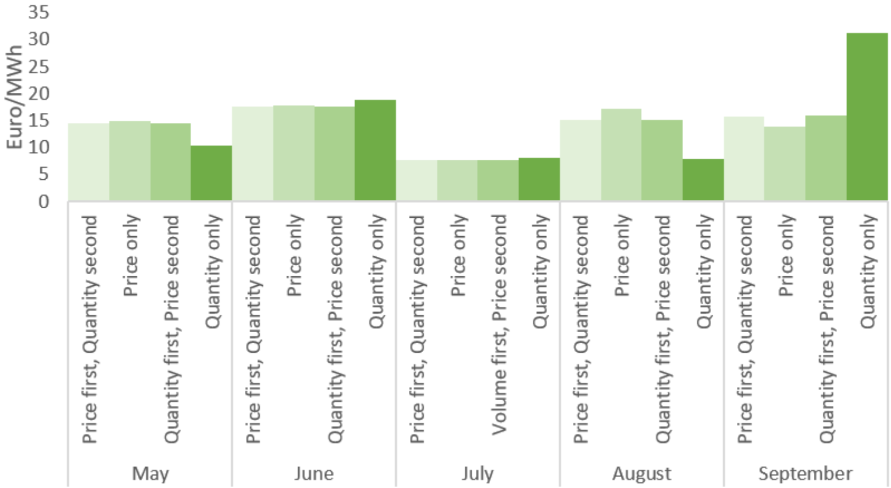

Figure 6.10.: Revenues from storage utilization

6.7 Discussion

In the presented case study, we show that both the solar PV plant operator and the BESS operator can benefit from the proposed constellation. Future BESS costs are difficult to estimate due to the large number of technologies and dynamic price developments. However, the assessment of the opportunity costs of the BESS service provider showed that the optimal strategy of the service provider actually yields less cycles when including the strategy of the solar PV plant operator and therefore marginal cyclic costs of zero could be assumed. Fig. 6.10 shows the revenues that the solar PV plant operator realizes through the utilization of the BESS service. The values are in the range of the compensation that the BESS service provider needs to request for her service as determined in the previous section. As we argued in Section 6.3, the solar PV plant operator might even be willing to pay a premium for the ability to decrease her risks in revenue streams in order to provide a stable investment plan. Likewise, the BESS service provider may have incentives to adjust the demanded compensation according to her risk aversion and operational goals. Future research should further look into the extent to which the revenues of the solar PV plant operator justify the reimbursements for the BESS service provision and the cyclic costs of BESS utilization as well as the pricing of the service provided by the storage operator. However, it should be noted that electricity price spreads are likely to increase in the future as installed renewable capacities increase, thereby increasing the potential revenues from BESS usage as well.

In our model, we assume that a BESS is accessible as a service on demand. This is not a feasible use case for a BESS under current regulation in many countries, mainly because of the fees charged for the charging and discharging processes. However, we assume that, in a system increasingly based on renewable energy sources, more flexibility solutions will be necessary and thus the usage of BESSs will be promoted more strongly in the course of this development. In particular, the deployment of BESSs to balance intermittent generation, as presented in this study, can make a significant contribution to integrating the increasing feed-in from renewable energy into the energy system and is thus an important contribution to the stability of the energy supply.

6.8 Conclusion

In this chapter, we make several contributions towards the financial risk management for intermittent renewable energy generation through the utilization of a BESS service. We provide a theoretical model for the risk assessment of a renewable plant operator and the pricing of the BESS service. We then develop heuristic storage strategies for a solar PV plant operator to mitigate price and quantity related negative deviations in profits. In a case study, we can show first promising results, and answer the research question with an average CVaR reduction of 38% in the five months that are considered. These results indicate that the use of BESSs similarly to an option as a financial instrument can provide a feasible contribution to the risk hedging objectives of the solar PV plant operator. We furthermore determine the pricing of the BESS service and conclude that the proposed constellation can be beneficial for both the solar operator and the BESS service provider.

In this chapter, we analyse the case of a large renewable generator relying on a grid-scale BESS to manage and hedge the risk of her intermittent generation. However, the discontinuation of the EEG-subsidy after 20 years could make this strategy interesting for renewable generators at lower aggregation levels as well, e.g., in the case of a residential prosumer. This chapter further motivates research on the perspective of the BESS service provider, i.e., the storage operator who would receive requests for multiple applications. This perspective is addressed in Chapter 8.

While the focus of this chapter was the perspective of a large renewable operator who deploys a grid-scale BESS in front of the meter to hedge against risks, behind the meter, risk attitude also plays an important role for operators of industrial BESSs. These BESSs can be operated more profitably by providing FCR as second use case. This however comes with a higher risk of missing crucial peaks, which requires operational strategies that incorporate the inherent risk assessment.

CHAPTER 7

INDUSTRIAL PEAK-SHAVING USING A PROBABILISTIC APPROACH

Behind the meter, industrial peak shaving is a broadly discussed application for BESSs in the medium voltage level of the power grid. In previous research, this use case is often combined with FCR provision, which can increase a BESS's utilization and profits, but also adds planning uncertainty to the corresponding operation strategy. An industrial consumer has an incentive to plan conservatively when reserving a BESS's capacities for peak-shaving, as a single missed peak can drive up annual electricity costs steeply in the presence of peak-load charges. In this chapter, the notion of risk attitude is introduced in the context of joint industrial peak-shaving and FCR provision by combining a probabilistic quantile forecast with a rolling-horizon BESS control mechanism. Probabilistic load forecasts incorporate prediction uncertainty by generating a distribution of future load and therefore allow the conservative scheduling of the BESS's capacity. In a novel approach, we therefore combine a probabilistic forecast with the joint scheduling of peak-shaving and FCR provision in the case of an industrial consumer to evaluate the economic effects of risk averse planning. The results of this chapter show that extremely risk averse planning behavior can lead to a decrease of up to 10% in monetary performance of a BESS investment compared to risk neutral planning. This loss might be tolerated in exchange for the significantly reduced risk of missing a critical peak. Moreover, moderate risk averse planning behavior does not lead to financial losses in most cases and can even improve monetary performance by up to 3% in the considered case study. This chapter comprises large parts of the unpublished article under review: S. Henni, J. Becker, P. Staudt, C. Weinhardt, *Industrial Peak-Shaving with Battery Storage us-*

ing a Probabilistic Approach: Monetary Evaluation of Risk Attitude, Working Paper, 2022.

However, this limits the use of BESS energy and power capacity for other financially attractive applications.

7.1 Introduction

Since the peak load costs can constitute up to 34% of the annual electricity costs according to (Shi et al., 2018), industrial consumers have an incentive to reduce this peak, which can be done with a BESS. To increase the utilization of the deployed BESS, the combination of peak-shaving and FCR is a promising approach both technologically and economically, while trading is not yet economically feasible and also increases the risk of premature degradation of the BESS (Braeuer et al., 2019; Perez et al., 2016). This however leads to a situation of uncertainty regarding the scheduling of the parallel applications.

Unlike in many other applications, for an industrial consumer who engages in peak-shaving, risk attitude plays an important role in the simultaneous scheduling of peak-shaving and FCR activities, as a single missed load peak can drive up the annual electricity bill. Therefore, it seems sensible for the operator to plan conservatively, i.e., to reserve more capacity for peak-shaving than likely needed. Traditional point forecasts (i.e., predicting one expected value for the load in every given time step) as used by previous studies (see, for example, Oudalov et al. (2007), Lucas and Chondrogiannis (2016) and Shi et al. (2018)) do not capture this notion of risk averse planning. Such planning would require adjustments for an operations strategy based on point forecasts, for example, with the help of heuristics. However, probabilistic forecasting already inherently incorporates a risk assessment in terms of prediction uncertainty. Instead of only predicting a quantity as in the case of a point forecast, a probabilistic forecast generates a predicted distribution of the future load (vom Scheidt et al., 2021). This makes it possible to reflect the uncertainty of a prediction, which can be crucial for risk aware decision-making (Gneiting and Katzfuss, 2014). In the case of quantile forecasts, a sub-category of probabilistic forecasts, a confidence interval is predicted for a percentile (for example, 90%), i.e., in 90% of the cases the true value is below the predicted value (Hong et al., 2013; Hong and Fan, 2016). In this sense, a point forecast can be thought of as a quantile forecast for the median. Using a percentile lower or higher than the median for the scheduling of BESS capacities thus makes it possible to incorporate the risk affinity or aversion of an operator. In the case of an industrial consumer engaging in simultaneous peak-shaving and FCR provision, the risk aversion can be modeled by planning the BESS's dispatch based on a quantile forecast. However, if more capacity is held back for peak-shaving due to the presence of risk aversion, this can lead to lower revenues on the FCR market. This inherent trade-off between reducing the risk for missed peaks in peak-shaving and (potential) losses in FCR revenues raises the question of the magnitude of monetary losses due to risk averse planning. In this chapter, we therefore compare risk neutral and risk averse planning using a probabilistic forecast for the operation of an industrial BESS for joint peak-shaving and FCR provision. We thus answer the following research question:

Research Question 6: *What is the financial effect of an industrial consumer's risk aversion on the profit of a battery storage system that is deployed for joint peak-shaving and frequency containment reserve provision?*

The remainder of this chapter is structured as follows: We first introduce related research on the combined deployment of BESS for peak-shaving and FCR provision as well as previous work on probabilistic forecasting in the context of energy systems. We then introduce the methodology, consisting of two parts. First, we describe the design of a probabilistic load forecast that is implemented with the help of a quantile long short-term memory (Q-LSTM) network. Then, we introduce a rolling-horizon control algorithm for a BESS operated by an industrial consumer. Finally, we demonstrate the application of the methodology on the case of five empirical industrial load profiles and evaluate the monetary implications of risk attitude during the scheduling of BESS capacities.

7.2 Related Work

In this section, we present literature that deals with the simultaneous BESS deployment for peak-shaving and FCR provision, with a focus on the modelling of uncertainty. We then turn to related work on probabilistic load forecasts using neural networks.

7.2.1 Simultaneous Peak-Shaving and Frequency Containment Reserve Provision

Lucas and Chondrogiannis (2016) develop a smart grid energy storage controller for frequency regulation and peak-shaving, using a VRFB. The study focuses on the technical features of BESS control, i.e., it considers resistance, discharging current and response time. The simulation results, for which perfect foresight is assumed, show that the BESS can regulate frequency effectively due to its fast response time, while still performing peak-shaving services. Engels et al. (2020b) present an approach that divides the BESS into two virtual batteries, which are deployed for peak-shaving and FCR, respectively. Uncertainty is modelled by deploying a stochastic consumption profile and using the inherently stochastic frequency deviation profile. By using a sample average approximation, the model relies on the expected value, indicating risk neutrality. Through the joint deployment of the BESS for both services, net profits are increased by 100% compared to peak-shaving alone and by 10% compared to solely providing FCR.

Superlinear gains are also found for the joint use of a BESS for industrial peak-shaving and frequency control by Shi et al. (2018). The authors use load data from a Microsoft data center and a university building and obtain frequency regulation signals from the PJM fast frequency regulation market. A joint optimization is used to determine day-ahead decisions on capacity bidding and the peak threshold. A multiple linear regression is deployed as a point forecast to predict the load for the next day and the BESS movements are scheduled using a real-time control.

Braeuer et al. (2019) approach the topic from an economic perspective, relying on an hourly resolution of data from 50 small and medium-sized businesses in Germany. In addition to peak-shaving and frequency control, they include trading on the intraday and day-ahead markets as a third application. To ensure the ability to provide FCR, a part of the BESS's capacity is reserved in every time step. Uncertainty is again included by means of a multiple linear regression. In the case-study, the combination of peak-shaving and FCR proved (highly) economically advantageous for about half of the industrial load profiles. Adding trading as a third use case could further enhance profitability by a small margin, but only for a few industrial consumers.

Although these studies provide valuable insights, they do not address the risk attitude of an operator in a scheduling strategy. This can be achieved by using a probabilistic forecast for the joint scheduling of a BESS for peak-shaving and FCR.

7.2.2 Probabilistic Load Forecasting

Instead of only predicting one single value for a future load, a probabilistic forecast generates a distribution over the possible values of the future load (vom Scheidt et al., 2021). This makes it possible to reflect on the uncertainty of a prediction, which can be crucial for decision-making (Gneiting and Katzfuss, 2014). Hong and Fan (2016) suggest that probabilistic load forecasts can be executed as quantile forecasts, interval forecasting and density forecasting. In this chapter, we focus on quantile forecasts, i.e., probabilistic forecasts that generate the estimate of percentiles as output. The estimation $\hat{y_q}$ of a percentile q is the value, for which $q\%$ of all values are expected to be smaller or equal to $\hat{y_q}$, according to the generated distribution. To describe the meaning more illustratively, if we predict a load of 5 kW for the 90^{th} percentile, this means that we expect the load to be smaller than or equal to 5 kW in 90% of cases. Of course, the larger we choose the percentile, the more certain we can be that our real value will indeed not be larger than the predicted value. At the same time, a larger percentile also makes our prediction interval larger, meaning that we might severely overestimate the actual load.

Probabilistic forecasting was first introduced to the field of residential load forecasting by Gan et al. (2017). Their forecasting method is a Q-LSTM, which uses the average quantile score (AQS) as scoring rule. The AQS penalizes the prediction error based on the percentile value itself. For instance, the 80^{th} percentile is penalized less than the 90^{th}, if the prediction is too low in both cases. The AQS then is the average of all percentile errors. The authors work with nine percentiles from 0.1 to 0.9 and a half-hourly resolution, i.e., 48 data points per day. The forecast time horizon turned out to pose a limitation at the time: Only one time step at a time could be predicted by the Q-LSTM. However, it outperformed a fully convolutional neural network and a holistically-nested edge detection.

The finding that LSTM-networks are the superior method for probabilistic load forecasting is underlined by Wang et al. (2019). For residential load forecasting, a

Q-LSTM network with the pinball loss as scoring rule is deployed. The pinball loss is based on the same idea as the AQS, but without computing the average over all observed percentiles. It is explained in more detail in Section 7.3.1. Contrary to the approach of Gan et al. (2017), Wang et al. (2019) deploy multiple and longer prediction horizons. For all quantiles, 0.5 hour, 1 hour, 2 hour and 4 hour intervals are predicted, respectively. For these prediction horizons, the Q-LSTM outperforms the quantile recurrent neural network and quantile gradient boosting regression tree benchmarks. vom Scheidt et al. (2021) present three probabilistic load forecasting methods, namely a quantile gated recurrent unit (Q-GRU), a Q-LSTM and a quantile regression neural network (Q-REGNN). As empirical load data, they use half-hourly data points recorded by residential smart meters. In addition, solar data, weather data and calendar data is acquired. The authors use 0.1, 0.25, 0.5, 0.75 and 0.90 as percentiles. The forecasting methods predict the next hour based on the last 336 hours (i.e., two weeks). For the Q-GRU and Q-LSTM, 20% and 15% lower test losses are observed compared to the Q-REGNN when considering non-solar households. Remarkably, the Q-LSTM further reduces the loss by 26% for the customer group without weather data. Again, the Q-LSTM emerges as the superior method, especially when no weather data is available.

A quantile probabilistic forecast generates the estimation $\hat{y}_q$ for different percentiles q. The estimate $\hat{y}_{q_h}$ of a high percentile q_h is naturally higher than that of a lower percentile q_l. The true value y is therefore more likely to be smaller than $\hat{y}_{q_h}$ than $\hat{y}_{q_l}$. Therefore, with the estimate $\hat{y}_{q_h}$, peak-shaving is more reliably possible. However, in most cases $\hat{y}_{q_h}$ will also be further from the true value y than $\hat{y}_{q_l}$. When combining peak-shaving with FCR, this means that using a lower percentile, and thus the estimate $\hat{y}_{q_l}$ to reserve BESS capacity for peak-shaving, leaves more capacity to provide FCR. This results in a trade-off between (un)certainty for peak-shaving activity and profits on the FCR market. This trade-off has not been taken into account in previous studies on combined peak-shaving and FCR. In the two studies by Shi et al. (2018) and Braeuer et al. (2019), a point estimator is employed, which does not incorporate risk attitude of operators. Engels et al. (2020b) model the uncertainty of the load as a stochastic consumption profile. But it is then used in a stochastic optimization, to find the expected value, which again implies risk neutral behavior. Therefore, with this chapter, we provide first insights into the monetary effects of non-risk neutral risk attitude in the context of industrial peak-shaving and FCR provision.

7.3 Methodological Framework

The method described in this chapter is then demonstrated on two years of load data in the presented case study, as depicted in Figure 7.1. First, we develop and train a probabilistic forecast model using a Q-LSTM. Then, we determine the optimal size in terms of power and energy of a BESS that is used for simultaneous peak-shaving and FCR provision based on the historic load profile of an industrial consumer. Based on these results, we simulate a rolling-horizon BESS control, consisting of day-ahead and real-time decisions regarding the dispatch of BESS capacities.

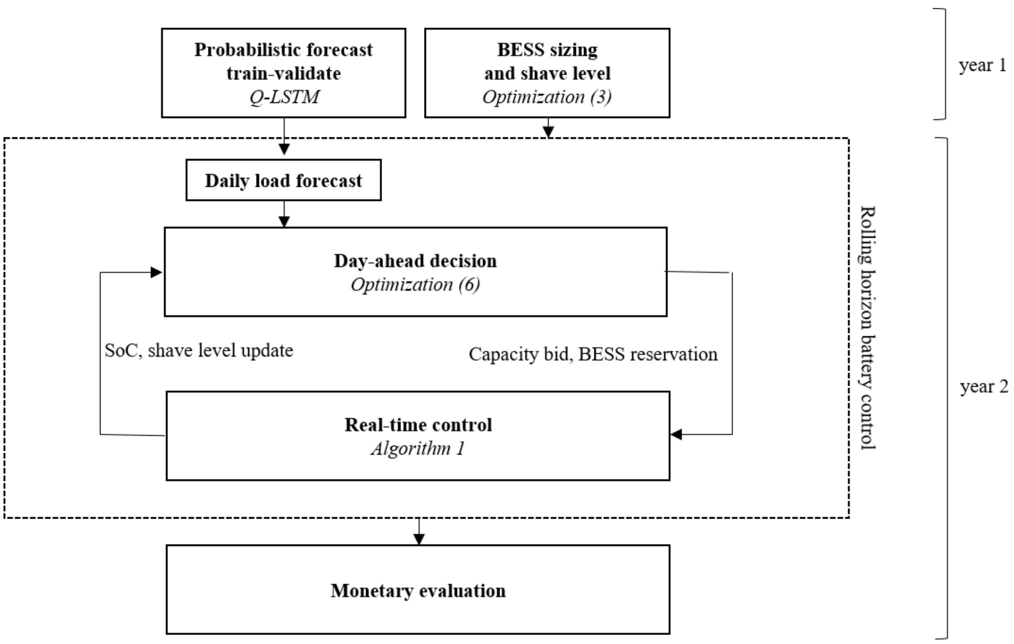

Figure 7.1.: Flow chart of the methodology, carried out on two years of load profile data in the case study

On the day before operation, it is decided how much of the BESS's capacity is offered in the FCR auction and how much is reserved for peak-shaving. During this planning step, we differentiate along the risk attitude of the operator, i.e., the percentile of the probabilistic forecast that is used for reserving capacity for peak-shaving. During real-time operation, the BESS dispatch for peak-shaving has to be adjusted to the actual load using the real-time BESS control. Finally, after simulating a one year operational period on the second year of data, the monetary evaluation is performed and compared for different levels of risk attitudes. In the following, every box in the flow chart in Figure 7.1 is explained in a separate section.

7.3.1 Probabilistic Load Forecasting via Quantile Long Short-Term Memory Networks

As described in the previous chapter, Q-LSTMs have been shown to be particularly well suited for a probabilistic load forecast. The structure of an LSTM is depicted in Figure 7.2. LSTMs are based on recurrent neural networks, which belong to the category of sequence models. In contrast to traditional neural networks, sequence models are able to learn sequential data and are thus especially well suited for time series applications. LSTM networks in particular are able to detect long-term dependencies in sequence data (Gers et al., 2000). This is because each cell in an LSTM network has a cell state C_t that is passed on to the next cell. A forget gate f_t decides how much of the preceding cell state C_{t-1} is forgotten, while the input gate i_t decides how much of the input is used for the calculation of C_t. This input consists of the empirical input data of t, but also of the output data of the previous layer. The latter is stored by each cell in a hidden state h_t. Finally, the output gate o_t determines how much of the input is used for the calculation of h_t.

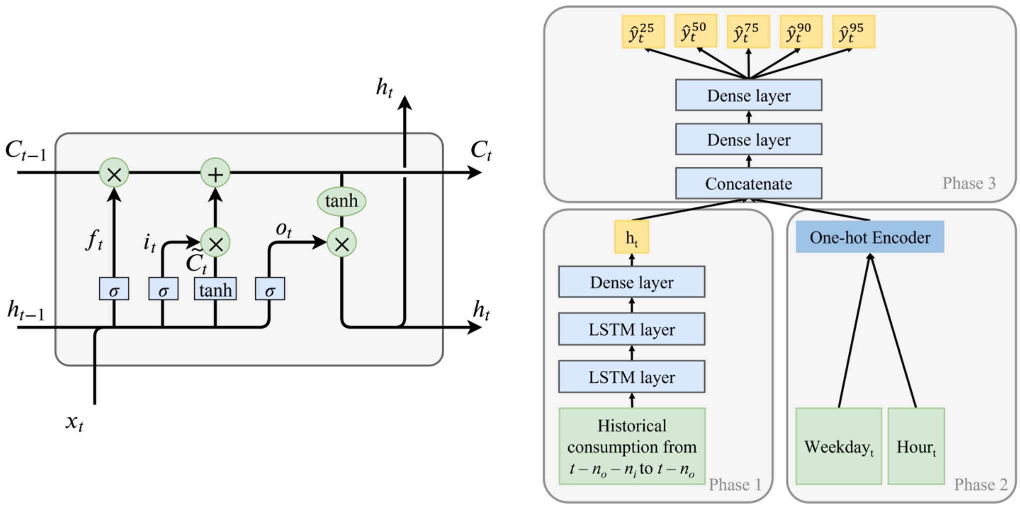

Figure 7.2.: Left: LSTM unit structure. Right: Q-LSTM network structure

Network structure. The network structure in this chapter follows a 3-phase approach as suggested by Wang et al. (2019) and vom Scheidt et al. (2021). A graphical representation of the approach is shown in Figure 7.2. Each input for the LSTM consists of a vector of 105 entries composed of the load (96 observations per day), the company ID and the one-hot-encoded calendaric data. In the first phase, the normalized historical load data is taken as input. Here, t denotes the single time step to be predicted and n_o is the number of output steps, i.e., the prediction horizon, which specifies how many time steps are to be predicted simultaneously. The network uses the last n_i input steps for one prediction. The load data first passes through two LSTM layers with sigmoid activation functions and then a dense layer with a relu activation function, which passes on the hidden state h_t. In the second phase, the nominal calendaric data, consisting of the day of the week and the time of day is converted by a one-hot encoder into a format that can be used by the LSTM. In the third phase, the hidden state h_t and the associated calendaric data are concatenated. They are then run through two fully-connected dense layers with relu activation functions to generate five quantile forecasts.

Loss function and hyperparameter tuning. As evaluation metric, we choose the pinball loss (7.1). It is a loss function that is used frequently for the evaluation of quantile forecasts and is also used by Wang et al. (2019), vom Scheidt et al. (2021) and Elvers et al. (2019), among others.

$$Ls_{q,t(y_t,\hat{y}_t^q)} = \begin{cases} (1-q)(\hat{y}_t^q - y_t), & \hat{y}_t^q \geq y_t \\ q(y_t - \hat{y}_t^q), & \hat{y}_t^q < y_t \end{cases} \tag{7.1}$$

y_t: real observation at time step t

$\hat{y}_t^q$: the qth quantile forecast at time step t

The pinball loss evaluates the predicted value based on its distance from the actual value, but also in relation to the prediction quantile. For an example, looking at the 90^{th} percentile: If the prediction $\hat{y}_t^{90}$ is greater than the actual value y, the pinball loss is 10% of $\hat{y}_t^{90} - y_t$. But if $\hat{y}_t^{90}$, underestimates y, the penalty is nine times higher (90% of $\hat{y}_t^{90} - y_t$). Thus, an underestimation of a quantile is more severely punished as this is to be avoided. This principle is illustrated in Figure 7.3.

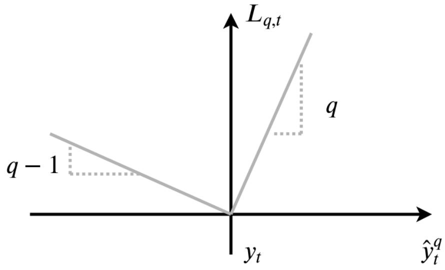

Figure 7.3.: Pinball loss illustration

In this chapter, we use the Q-LSTM to generate predictions for the percentiles $q \in [25\%, 50\%, 75\%, 90\%, 95\%]$. During the training process, the hyperparameter setting with the smallest average pinball loss over all quantiles is chosen as shown in Equation 7.2.

$$minLs = \sum_{q} \sum_{t=1}^{T} Ls_{q,t}, q \in [25\%, 50\%, 75\%, 90\%, 95\%] \tag{7.2}$$

Similar to vom Scheidt et al. (2021), we choose the learning rate, the number of units in the Q-LSTM-layers and the number of units in the dense layers as hyperparameters to tune. The tuning takes place on 50% of the data. Therefore, to predict one year, the resulting train, validation and test split is set to 25%, 25% and 50% of the data, respectively. During the hyperparameter tuning, each possible combination of the hyperparameters reported in Table 7.1 is tested, and then, the combination of hyperparameters that performs best on the validation set is selected.

Table 7.1.: During hyperparameter tuning, each possible combination of hyperparameters listed here is tested

Hyperparameter	Value
Learning rate	$0.001, 0.01, 0.1$
Number of units in Q-LSTM-layers	$4, 8, 12$
Number of units in dense layers	$10, 30, 50$

The resulting probabilistic quantile forecast then serves as the basis for the decision-making in the rolling-horizon BESS control strategy. Based on the chosen percentile, which reflects differing risk attitudes, the industrial consumer decides at the time of the FCR auction how much of the BESS's capacity has to be reserved for peak-shaving for the next day, and as a result, how much remaining capacity can be tendered on the FCR auction. However, before simulating the BESS dispatch, the optimal size of the deployed BESS must be determined.

7.3.2 Determination of the Battery Storage Size and the Initial Grid Capacity Level

An industrial consumer, who wants to engage in peak-shaving, initially has to make a decision regarding the BESS investment, i.e., how large the BESS's capacity needs to be. This might be computed based on past load data. We therefore develop an optimization to determine both the optimal BESS size and grid capacity level, i.e., the level of load that under optimal operational circumstances is the resulting maximum annual peak load after peak-shaving measures (Equation 7.3). Note that while the investment size cannot be changed later (once the operator invested in the BESS, its size is fixed) an operator can adjust the grid capacity level during the lifetime of the BESS, e.g., in response to changing load patterns.

$$\min \quad \left(\lambda_{elec} \sum_{t=1}^{T} l(t)\Delta t\right) + \lambda_{peak} U^* + (c_P P^{max} + c_E E) \tag{7.3a}$$

$$\text{s.t.} \quad l(t) = L(t) - b^{dc}(t) + b^{ch}(t) \qquad \forall\, t \in [1, ..., T] \tag{7.3b}$$

$$l(t) \leq U^* \qquad \forall\, t \in [1, ..., T] \tag{7.3c}$$

$$SoC(t+1) = SoC(t) - \left(\frac{b^{dc}(t)}{\mu} + b^{ch}(t)\mu\right)\Delta t \qquad \forall\, t \in [1, ..., T] \tag{7.3d}$$

$$SoC_{min} \leq SoC(t) \leq SoC_{max} \qquad \forall\, t \in [1, ..., T] \tag{7.3e}$$

$$SoC(0) = \frac{SoC_{max} - SoC_{min}}{2} \tag{7.3f}$$

$$0 \leq b^{dc}(t) \leq P^{max} \qquad \forall\, t \in [1, ..., T] \tag{7.3g}$$

$$0 \leq b^{ch}(t) \leq P^{max} \qquad \forall\, t \in [1, ..., T] \tag{7.3h}$$

The decision variables of the resulting optimization are the optimal BESS power and energy capacity P^{max} and E and the discharging and charging behavior in time step t, $b^{dc}(t)$ and $b^{ch}(t)$ which result in the optimal peak load (after shaving measures) U^*. The objective function (Equation 7.3a) consists of three different cost components. The first cost component are the annual electricity costs $\lambda_{elec} \sum_{t=1}^{T} l(t)\Delta t$, consisting of the electricity price λ_{elec} in € kWh^{-1} multiplied with the consumed load $l(t)$ in each time period t. To convert the load into energy, we multiply it with the factor Δt, which refers to the time resolution in hours. The second part of the objective function are the peak load costs $\lambda_{peak}U^*$, where U^* is the highest load of the observed year in kW and λ_{peak} denotes the peak demand charge in € kW$_\mathrm{p}^{-1}$. The third component are the investment costs $c_P P^{max} + c_E E$ for the BESS's power P^{max} in kW and energy capacity E in kWh. The parameters c_P, c_E denote the annuitized costs in € a^{-1} and are a result of the investment costs p_P in € kW^{-1} and p_E in € kWh^{-1}, multiplied with the annuity factor as detailed in Equations 7.4 and 7.5. Here, i denotes the discount rate and n the number of annuities, i.e., the lifetime of the BESS in years.

$$c_P = p_P \frac{(1+i)^n i}{(1+i)^n - 1} \tag{7.4}$$

$$c_E = p_E \frac{(1+i)^n i}{(1+i)^n - 1} \tag{7.5}$$

Constraint (7.3b) models the load $l(t)$ after shaving, which is a result of the original load $L(t)$ and discharging $b^{dc}(t)$ and charging values $b^{ch}(t)$ in kW. Constraint (7.3c) ensures that the maximum value of $l(t)$ for $t \in [1, ..., T]$ determines the magnitude of the peak load U^*. The SoC update is defined in Constraint (7.3d), where $SoC(t)$ is the SoC in each time period t in kWh. The SoC for the next period $t+1$ depends on the current $SoC(t)$ and the BESS charging and discharging behavior while considering the BESS's efficiency μ. Constraint 7.3e ensures that the SoC does not violate the lower and upper bounds of the BESS. Similarly, the power limits are enforced by Constraints (7.3g) and (7.3h).

The optimization yields the optimal BESS parameters P^{max} and E based on the empirical load data. The optimal peak-grid capacity level U^* can serve as a first indicator for a feasible peak-shaving level in the following years. It could however also be adapted flexibly to changing load patterns. Hence, for the rolling-horizon BESS control in real-time, we use the peak-shaving level U^* that is derived from historic data as a first proxy for a feasible peak-shaving level. We do however also assess alternative scenarios with other peak-shaving levels to evaluate the sensitivity of the model.

7.3.3 Rolling Horizon Battery Control

As previously described, the rolling-horizon BESS control includes two main components: (i) The day-ahead decision during which the operator must decide how much of the BESS's capacity has to be reserved for peak-shaving, and as a result, how much is left to tender on the day-ahead FCR auction, and (ii) the real-time control that manages the BESS's operation once the actual load is known and the BESS charging and discharging behavior has to be adjusted accordingly. Figure 7.4 depicts the rolling-horizon BESS control from Figure 7.1 in more detail. We describe this sequential decision-making and its interdependencies in the following paragraphs.

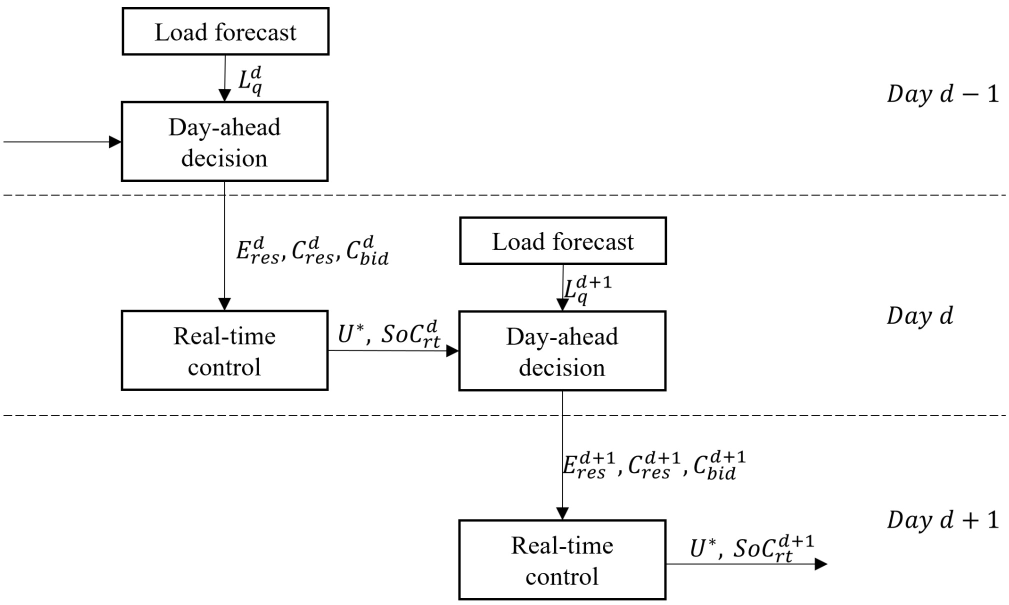

Figure 7.4.: Rolling horizon BESS control. Based on a quantile forecast, the day-ahead decision is made to determine the optimal bid on the FCR auction. Then, the BESS is controlled in real-time to adjust to the actual load.

Day-ahead decision

In Germany, each day of FCR provision is divided into 6 blocks of 4 hours duration each that are tendered separately (Bundesnetzagentur, 2020b). We therefore divide the day into W bidding windows. Every day, the operator must make a capacity bid $Cap_{bid,w}$ for each bidding window $w \in [1, ..., W]$ on the FCR auction for the following day, which we assume is accepted. For each of these windows, Cap_{bid} can differ, but all W bids must be placed at once during the day-ahead FCR auction. At this point, we consider the risk attitude: Since we do not know our actual load on the following day, the bid is made based on a forecast. If we rely on a risk neutral, i.e., point forecast, we do not take into account that the monetary penalty for missing one single peak might be much higher than losses that occur because of conservative bidding behavior on the FCR market. We therefore plan our bids based on a probabilistic quantile forecast that reflects a risk averse attitude if choosing a percentile higher than 50%. Based on a given quantile load forecast L_q, we therefore solve the following optimization to determine the optimal bid $Cap_{bid,w}$ for each bidding window during the day-ahead decision (7.6).

$$
\begin{aligned}
\min \quad & \left(\lambda_{elec}\sum_{t=1}^{D} l(t)\Delta t\right) + \lambda_{peak}\tilde{U} - \left(\lambda_c \sum_{t=1}^{D} Cap_{bid}(t)\Delta t\right) && && (7.6a)\\
\text{s.t.} \quad & l(t) = L_q(t) - b^{dc}(t) + b^{ch}(t), && \forall\, t \in [1, ..., D] && (7.6b)\\
& l(t) \leq \tilde{U'} && \forall\, t \in [1, ..., D]) && (7.6c)\\
& \tilde{U} = \max(\tilde{U'} - U^*, 0) && && (7.6d)\\
& Cap_{bid}(t) = Cap_{bid,w} && \forall\, t \in [1, ..., D], t \in w && (7.6e)\\
& Cap_{res}(t) = Cap_{bid}(t) \cdot r && \forall\, t \in [1, ..., D]) && (7.6f)\\
& E_{res}(t) = Cap_{bid}(t) \cdot \frac{1}{4} hours && \forall\, t \in [1, ..., D] && (7.6g)\\
& SoC_{min} + E_{res}(t) \leq SoC(t) \leq SoC_{max} - E_{res}(t) && \forall\, t \in [1, ..., D] && (7.6h)\\
& SoC(t+1) = SoC(t) - \left(\frac{b^{dc}(t)}{\mu} - b^{ch}(t)\mu\right)\Delta t && \forall\, t \in [1, ..., D] && (7.6i)\\
& SoC(1) = SoC_{rt} && && (7.6j)\\
& SoC(D) = \frac{SoC_{max} - SoC_{min}}{2} && && (7.6k)\\
& 0 \leq b^{dc}(t), b^{ch}(t) \leq P^{max} - Cap_{res}(t), && \forall\, t \in [1, ..., D] && (7.6l)\\
& 0 \leq Cap_{bid,w} \leq P_{max} && \forall\, w \in [1, ..., W] && (7.6m)
\end{aligned}
$$

In the objective function (7.6a) we minimize the cost for the next day where D denotes the number of time intervals per day, i.e., 96 in the case of a 15-minute resolution. The first cost component is the daily electricity cost λ_{elec} in € kWh^{-1} multiplied with the sum of the resulting daily load $\sum_{t=1}^{D} l(t)\Delta t$ in kWh. In each time step, the (shaved) daily load l is a result of the original (forecasted) load L_q and the discharging and charging behavior b^{dc} and b^{ch} in kW (7.6b). The second cost component are the additional peak costs $\lambda_{peak}\tilde{U}$ in € kW^{-1}, which may arise if on the next day, a peak occurs that is larger than any previously occurring peaks. $\tilde{U}$ represents the positive difference between the maximum load of the day $\tilde{U'}$ and the current grid capacity level U^* as specified by Constraints (7.6c) and (7.6d). $\tilde{U}$ is to be interpreted in such a way that only an increase of the global peak U^* leads to further peak costs, but if the maximum load of the day remains below U^*, no costs occur. The last component of the objective function are the FCR market revenues that consist of the compensation λ_c in € kW^{-1} that the operator receives per capacity bid $Cap_{bid}(t)$ per time step t in bidding window w (7.6e).

To incorporate the FCR market bid into our operational strategy, we expand on the idea of Braeuer et al. (2019), where a portion of the BESS's capacity is reserved corresponding to the bid on the FCR auction. Participants on the FCR market must be able to provide the maximum of Cap_{bid} symmetrically for at least 15 minutes, meaning the BESS must be able to charge or discharge at full bid capacity during that time (Thien et al., 2017; Bundesnetzagentur, 2020b). Therefore, we must reserve a certain amount of energy capacity $E_{res}(t)$ in kWh at each time step t to allow for both eventualities (7.6g). Constraint (7.6h) ensures that the SoC cannot exceed the lower and upper BESS energy limits while taking into account the ability to fulfill the requirements for the FCR provision. To be able to provide positive control energy at maximum bid capacity for at least 15 minutes, the SoC at time step t cannot be lower than $E_{res}(t)$. Similarly, the same amount of energy capacity must still be unoccupied to allow for negative control energy.

Braeuer et al. (2019) neglect the actual power signal for FCR provision. In reality, the frequency regulation signal $r(t) \in [-1, 1]$ determines the share of Cap_{bid} that must actually be delivered every 2 to 4 seconds. Over a period of 15 minutes, the frequency signals would balance out to a mean of zero, as positive and negative FCR is considered to be roughly symmetric (Xu et al., 2016). To be able to estimate the share r of the capacity bid Cap_{bid} that we need to reserve, we thus look at frequency signal data from 2019 to 2021 in 1 second resolution by Mumm (2021) and model the FCR provision per tendered MW of FCR. We then only look at one side of the symmetric provision (i.e., only positive FCR provision) and retrieve the 90th percentile, which is $r = +0.135$. This means that from 2019 until 2021, a (hypothetical) participant on the FCR market who would have made a constant bid (that was accepted) of 1 MW on the FCR auction, would have had to actually provide a power (either positive or negative) of $0.135 \cdot 1$ MW $= 135$ kW or less during 90% of time. We therefore block a portion of the BESS's power capacity $Cap_{res}(t) = Cap_{bid}(t) \cdot r$, with $r = 0.135$ so that the expected signal r can be adequately fulfilled at all times (7.6f). This estimate further ensures that the BESS operation meets the prequalification criteria of the German FCR market, which require that at least 80% of the total signals can be responded to (Thien et al., 2017; Bundesnetzagentur, 2020b).

The correct updating of the SoC is ensured in Constraint (7.6i), analogously to Equation 7.3d in Section 7.3.2. Constraints (7.6j) and (7.6k) determine the initial and the final SoC value for the day. The initial value SoC_{rt} represents the last SoC level of the previous day, which is transferred from the real-time BESS control of the previous day. Since we work with a rolling horizon approach, the operator cannot know the optimal SoC for the end of the day one day in advance. We therefore set this constraint for the last period of the day, effectively leaving the BESS half full. This is necessary since we always need to be able to provide FCR symmetrically, i.e., both charging and discharging must be possible. If we allow the BESS to run empty at the end of the day, this would interfere with our ability to provide FCR on the next day. The BESS actions $(b^{dc}(t), b^{ch}(t))$ for peak-shaving can only access the non-blocked power portion $P^{max} - Cap_{res}(t)$ (Constraint (7.6l)). Constraint (7.6m) ensures that $Cap_{bid,w}$ does not exceed the power of the BESS, so that the bid can always be fulfilled technically.

Real-time control

After the assumed optimal FCR auction bids $Cap_{bid,w}$ are determined, and subsequently $E_{res}(t)$ and $Cap_{res}(t)$ are derived, the industrial operator needs to schedule the BESS's capacity to perform peak-shaving in real-time, depending on the true load $l(t)$ that is revealed, i.e., known with certainty at time step t. We therefore adapt and extend a real-time control algorithm proposed by Shi et al. (2018) and

Engels et al. (2020b) (Algorithm (1)).

For the real-time control, we need the actual load $l(t)$, the initial grid capacity level U_0^* and the BESS power and energy capacity sizes P^{max} and E as input. Note that at the beginning of the simulation, i.e., on the first day of any year, an initial grid capacity level has to be chosen. This grid capacity level can be derived based on historic data as described in Section 7.3.2, but can also be set arbitrarily by the operator. During real-time operation, the BESS will try to shave any load above the (initial) grid capacity level. If this is not achieved on a certain day, i.e., a load $l(t) \geq U_0^*$ occurs that cannot be shaved, then $l(t)$ will be set to be the new grid capacity level U^*. Since the peak charges will then have to be paid for the (new) maximum load U^* anyway.

Here, T denotes the total number of time periods t, Δt denotes the length of one time period t in hours and D denotes how many time periods t add up to one day. Lines (1-4) set initial values. The values R_{FCR}, C_{elec} and C_{peak} are annual revenues on the FCR market, electricity costs and peak costs that are needed for the monetary evaluation in the following section. Line (5) begins to iterate through all time steps $t \in [1, ..., T]$. When a new day is started, line (6) becomes true and $Cap_{bid}(t), E_{res}(t), Cap_{res}(t)$ are set for the next day according to the day-ahead decision (Optimization (6)). Line (9) calculates $b(t)$ as the difference between the present load $l(t)$ and the current grid capacity level U^*. If this value is positive (line 10), it means the current load at t is larger than the set grid capacity level, and we therefore have to start to discharge the BESS for peak-shaving. In the following lines (11-13), the discharging magnitude is determined. While the ultimate goal is to shave all of $b(t)$, the BESS's limits such as (remaining) power and SoC have to be taken into account (lines 11 and 12). If $b(t)$ is negative, the BESS is not needed for peak-shaving at this time. This gives the operator time to charge the BESS in preparation for future peaks, which is done in lines (15-16). The BESS control decisions in lines (10-16) are based on Shi et al. (2018) and Engels et al. (2020b) and have been proven to be close to (economically) optimal and computationally efficient. We expand on the approaches of Shi et al. (2018) and Engels et al. (2020b), because we are taking bidding windows into account. Therefore, we add a constraint that also takes $E_{res}(t+1)$ into account (lines 11-12 and 15). This makes sure that no inconsistencies in the transition between bidding windows occur. Note that $E_{res}(t)$

Algorithm 1: Real-time control

input : $l(t)$, U_0^*, P^{max}, E

$D \leftarrow \frac{24}{\Delta t}$

$t \leftarrow 1$

$SoC(1) \leftarrow \frac{E}{2}$

$R_{FCR}, C_{elec}, C_{peak} \leftarrow 0$

for $t = 1 \rightarrow T$ **do**

  if $t == new\ day$ **then**

    for $t = t \rightarrow (t + D)$ **do**

      $E_{res}(t), C(t), Cap_{bid}(t) \leftarrow Optimization(6)$

  $b(t) = l(t) - U^*$

  if $b(t) \geq 0$ **then**

    $b(t) \leftarrow min\{b(t), P^{max} - Cap_{res}(t), \mu(SoC(t) - (SoC_{min} + E_{res}(t))\Delta t,$

    $\mu(SoC(t) - (SoC_{min} + E_{res}(t+1))\Delta t\}$

    $b^{dc}(t) \leftarrow b(t)$, $b^{ch}(t) \leftarrow 0$

  else

    $b(t) \leftarrow max\{b(t), Cap_{res}(t) - P^{max}, \frac{(SoC(t)-(SoC_{max}-E_{res}(t))}{\mu}\Delta t, \frac{(SoC(t)-(SoC_{max}-E_{res}(t+1))}{\mu}\Delta t\}$

    $b^{dc}(t) \leftarrow 0$, $b^{ch}(t) \leftarrow |b(t)|$

  if $t == last\ hour\ of\ day$ **then**

    if $SoC(t) > \frac{SoC_{max}-SoC_{min}}{2}$ **then**

      $b(t) \leftarrow min\left\{P^{max} - Cap_{res}(t), SoC(t) - \frac{\mu(SoC_{max}-SoC_{min})}{2}\Delta t\right\}$

      $b^{dc}(t) \leftarrow b(t)$, $b^{ch}(t) \leftarrow 0$

    else

    $b(t) \leftarrow max\left\{Cap_{res}(t) - P^{max}, SoC(t) - \frac{SoC_{max}-SoC_{min}}{2\mu}\Delta t\right\}$

    $b^{dc}(t) \leftarrow 0$, $b^{ch}(t) \leftarrow |b(t)|$

  $SoC(t+1) \leftarrow SoC(t) - \left(\frac{b^{dc}(t)}{\mu} - b^{ch}(t)\mu\right)\Delta t$

  $S(t) \leftarrow l(t) - b(t)$

  if $S(t) \geq U^*$ **then**

    $U^* \leftarrow S(t)$

  $R_{FCR} \leftarrow R_{FCR} + \lambda_c Cap_{bid}(t)\Delta t$

  $C_{elec} \leftarrow C_{elec} + \lambda_{elec} S(t)\Delta t$

$C_{peak} \leftarrow \lambda_{peak} U^*$

and $Cap_{res}(t)$ are virtually shrinking the BESS so that only the remaining energy and power capacities can be used for peak-shaving. To synchronize with the day-ahead optimization, we reset the SoC to $\frac{SoC_{max}-SoC_{min}}{2}$ in the last period of the day (lines 17-23), given the BESS's physical restrictions. This final SoC is then updated (line 24) and taken as initial value for the next day-ahead optimization as can be seen in Constraint (7.6j). In line (25), $S(t)$ is defined as the result of the load $l(t)$ and BESS activity $b(t)$, i.e., the power that is drawn from the grid. If $S(t)$ is larger than the current grid capacity level U^*, the latter will be updated to $S(t)$ in lines (26-27). Finally, lines (28-30) update the FCR market revenues and electricity costs based on the bid on the FCR auction $Cap_{bid}(t)$ from the day-ahead decision and the electricity consumption $S(t)$. At the end of one year, the resulting annual peak costs are calculated based on the final grid capacity level (i.e., maximum load) U^*. The monetary evaluation is described in more detail in the following section.

Note that since this strategy does not include degradation, while it has been proven to be close to (economically) optimal, it may not be ideal from a technical perspective. Moreover, since at times that require no peak-shaving activity, the BESS may still be charged in preparation for future peaks, unnecessary cycling might occur that would lead to premature degradation. We neglect this issue for now, since we are mainly interested in the economic effects that risk averse planning has on the trade-off between peak-shaving and FCR provision. This is further justified by the low time resolution of 15 minutes that we choose in this chapter, which does not allow for a detailed investigation of degradation and other technical parameters. In practice, a BESS management system would be needed to ensure adequate FCR provision in real-time as well as to prevent unnecessary cycling during peak-shaving activities.

7.3.4 Monetary Evaluation

The final part of the methodology as depicted in Figure 7.1 is the monetary evaluation of the BESS's deployment for simultaneous peak-shaving and FCR provision. For every considered forecast quantile $q \in [25\%, 50\%, 75\%, 90\%, 95\%]$, the electricity costs $C_{elec,q}$, peak costs $C_{peak,q}$ and FCR market revenues $R_{FCR,q}$ are calculated with the corresponding values from the real-time control (Equations 7.7 - 7.9).

$$C_{elec,q} = \lambda_{elec} \sum_{t=1}^{T} S_q(t)\Delta t \tag{7.7}$$

$$C_{peak,q} = \lambda_{peak} U^{*,q} \tag{7.8}$$

$$R_{FCR,q} = \lambda_c \sum_{t=1}^{T} C_{bid,q}(t) \Delta t \tag{7.9}$$

The resulting annual electricity costs C_q of the industrial operator using the qth percentile for the load forecast during operation are then calculated as the sum of the three components in (Equation 7.10).

$$C_q = C_{elec,q} + C_{peak,q} - R_{FCR,q} \tag{7.10}$$

In addition to the variable costs, the (fixed) investment costs that incur for the acquisition of the BESS have to be taken into account. I denotes the initial investment costs, depending on the energy capacity E and power capacity P^{max} of the BESS that are determined based on the approach presented in Section 7.3.2 multiplied with the prices for energy and power capacity p_E and p_P (Equation 7.11).

$$I = p_E \cdot E + p_P \cdot P^{max} \tag{7.11}$$

The net present value (NPV) of an investment determines its profitability while considering that the cash flow CF is spread over time (Fisher and Barber, 1907).

$$NPV(i, N) = -I + \sum_{n=1}^{N} \frac{CF}{(1+i)^n} \tag{7.12}$$

The initial investment costs I are set against the interest-bearing cash flow CF which we assume is constant for all n. We consider the cash flows of the BESS investment to be the cost savings each year compared to not installing a BESS. We therefore first have to calculate the electricity costs that the industrial consumer has to pay if no BESS is installed. In this case, the costs C^{nb} consist of the load $l(t)$ multiplied with the electricity costs per kWh λ_{elec}, as well as the peak costs λ_{peak} multiplied with the maximum annual load (Equation 7.13). The cashflow from the BESS investment CF_q, depending on the used quantile forecast during operation, then is the difference between costs without and with BESS investment (Equation 7.14).

$$C^{nb} = \lambda_{elec} \sum_{t=1}^{T} l(t)\Delta t + \lambda_{peak} \max\left(l(t), t \in [1, ..., T]\right) \tag{7.13}$$

$$CF_q = C^{nb} - C_q \tag{7.14}$$

An NPV greater than zero indicates that an investment I is profitable while an NPV smaller than zero is an unprofitable investment. However, comparability of different NPVs is limited because the indicator depends on the size of the initial investment. To compare the profitability of a BESS investment across different scenarios and companies, we therefore use the profitability index (PI) that calculates the NPV per invested Euro (Braeuer et al. (2019); Brealey et al. (2011), Equation 7.15).

$$PI = \frac{NPV(i, N)}{I} \tag{7.15}$$

In the next step, we apply our introduced methodology to a case study to demonstrate the effects of risk attitudes on the profitability of a BESS investment for simultaneous peak-shaving and FCR provision.

7.4 Case Study

The case study is conducted using two years of empirical power consumption data of five German industrial companies, which operate in the fields of metal processing, wood industry and manufacturing published by Huber et al. (2019). The first year of the empirical data of each company is used to implement (i.e., train and validate) the probabilistic forecast as well as to determine the optimal BESS size and initial optimal grid capacity level individually. The rolling horizon BESS control and monetary evaluation is then performed on the second year of data. We assume that in reality, an industrial consumer would equally decide on a BESS investment based on historical data.

For the Q-LSTM network, the output step size is set to $n_o = 96$ while the input step size is set to $n_i = 1344$ for each prediction. Practically, this means that one day is forecasted on the basis of the last two weeks, which is the conventional cut-off horizon for short-term load forecasting (Hong and Fan, 2016; vom Scheidt et al., 2021). The model is implemented in Python using Keras. The code is published by vom Scheidt et al. (2021) and is publicly available[5]. The results of the hyperparameter tuning and the total pinball loss Ls of the optimal hyperparameter combination is presented in Table 7.2. An exemplary excerpt of the forecast is shown in Figure 7.5.

Table 7.2.: Optimal hyperparameter values for probabilistic forecast of load data of companies 1 - 5

ID	**Learning rate**	**# Units in LSTM layers**	**# Units in dense layers**	**Pinball loss**
1	0.01	4	10	0.006
2	0.1	12	30	0.123
3	0.1	4	10	0.031
4	0.1	4	10	0.048
5	0.1	4	30	0.015

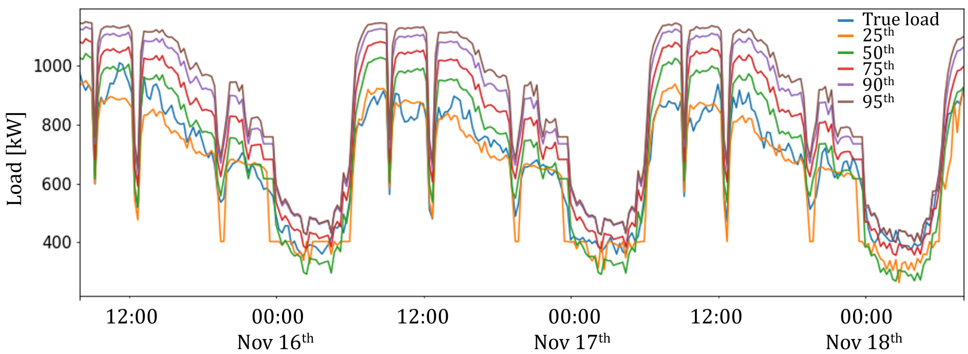

Figure 7.5.: Forecast of Company No. 2 of Nov 15^{th} - 18^{th}

The obtained percentiles of the probabilistic quantile forecast then serve as input for the case study on the monetary effects of risk attitude in the deployment of a BESS for simultaneous peak-shaving and FCR provision. The temporal parameters for the case study are reported in Table 7.3. We simulate one year of operation in a 15-minutes resolution. The number of bidding windows is chosen based on the bidding blocks on the German FCR auction (Bundesnetzagentur, 2020b). We need to make further assumptions regarding BESS investment costs (differentiated by power and energy capacity), lifetime and other technical parameters. All assumptions and corresponding sources are reported in Table 7.4. In line with other publications, we assume the BESS to be lithium-ion batteries (Shi et al., 2018; Braeuer et al., 2019; Simpkins and O'Donnell, 2017).

[5] https://github.com/FVS-energy/prob_forecasting

Table 7.3.: Time-based parameter values for the case study

Parameter	**Value**
Total simulation length	363 days
Length of one period Δt	$\frac{1}{4}h$
Total number of periods T	$34,848$
Number of periods per day D	96
Number of bidding windows per day W	6

Table 7.4.: Technical and economical assumptions for the case study

Assumption	**Unit**	**Value**	**Source**
BESS price, energy capacity portion p_E	€ kWh^{-1}	162	Simpkins and O'Donnell (2017)
BESS price, power capacity portion p_P	€ kW^{-1}	440	Simpkins and O'Donnell (2017)
Discount rate i	%	2	Braeuer et al. (2019)
BESS lifetime N	a	11	Braeuer et al. (2019)
BESS efficiency μ	%	95	Xu et al. (2018b)
Upper limit SoC_{max}	kWh	$0.95 \cdot E$	Xu et al. (2018b)
Lower limit SoC_{min}	kWh	$0.1 \cdot E$	Xu et al. (2018b)
Electricity price λ_{elec}	€ kWh^{-1}	0.175	Bundesnetzagentur and Bundeskartellamt (2021),
Peak price λ_{peak}	€ kW$_\mathrm{p}^{-1}$	86.06	NEW NETZ (2021), Braeuer et al. (2019)
FCR market price λ_c	€ MW^{-1} h^{-1}	12	Engels et al. (2020b),Bundesnetzagentur (2021)

For the industrial consumers' electricity costs, we assume a per-kWh price of $\lambda_{elec} = 0.175$ € kWh^{-1}. This consists of the German electricity price of 0.17 € kWh^{-1} for industrial consumers from 2021 (Bundesnetzagentur and Bundeskartellamt, 2021), plus a per-kWh price component of 0.0056 € kWh^{-1} charged by the grid operator (NEW NETZ, 2021). We assume an exemplary current peak load price of $\lambda_{peak} = 86.08$ € kW$_\mathrm{p}^{-1}$ based on (NEW NETZ, 2021). For the FCR market price, similar to Shi et al. (2018) and Engels et al. (2020b), we assume a fixed price, because the fluctuations of the market price have no direct impact on our model. Moreover, depending on the (random) timing of the industrial load profiles' annual peaks, the results could be less generalizable if by chance the FCR prices work to the (dis-)advantage of a specific industrial load profile. To estimate a fixed FCR revenue, we examine the FCR market prices from July 2019 to December 2021 obtained from (Bundesnetzagentur, 2021). Note that before July 30th 2020, prices were formed based on one daily bidding block. From then on, prices are differentiated into six daily 4-hour bidding blocks. Taking this feature into account, we calculate the average price of around $\lambda_{elec} = 12$ € MW^{-1} per hour, which is in line with the price assumed by Engels et al. (2020b). The BESS efficiency is set to $\mu = 95\%$. To model sustainable BESS usage, we set lower and upper limits for the SoC. These make sure that the SoC cannot go below 10% or exceed 95% of the total energy capacity E, which is advisable to avoid premature aging (Xu et al., 2018b). Bids on the German FCR market must be at least 1 MW, which is more than the BESS's power capacity for all industrial customers in our case study. We therefore assume that the BESSs are part of a virtual power plant that meets this requirement, similar to the model employed by the BESS provider sonnenGmbH with residential BESSs (Tietze et al., 2019). The simulation is implemented in Python. For the optimizations we use the Gurobi solver with an academic license. The simulation is run on a 3.1 GHz Intel Core i5 HP Pavilion with 8 GB memory.

In the following, we present the findings of the effect of risk attitudes on the profitability of BESS deployment for simultaneous peak-shaving and FCR provision.

7.4.1 Simulation Results

For each of the five companies in our data set, we evaluate the monetary potential of the BESS investment, which was made on the basis of the first year of empirical load data. We use the PI that expresses the profit per invested Euro to achieve comparability across all companies and scenarios. We differentiate between five different quantile forecasts as inputs during the rolling-horizon scheduling of BESS capacities in order to incorporate the industrial consumer's risk attitude. The percentiles represent risk neutral (50^{th}) and risk averse attitudes (75^{th}, 90^{th} and 95^{th}). We also include the 25^{th} percentile as comparison for a risk seeking strategy. In addition, we evaluate the scenario "foresight" as an upper benchmark, in which the true load of the next day is known during the day-ahead scheduling of the BESS's capacity.

Note that this does not necessarily depict a global optimum, since the foresight is only for one day at a time.

Table 7.5 shows the resulting BESS power and energy capacity parameters for the five companies, along with information on their annual load and maximum peak load. The companies differ significantly in terms of overall electricity consumption. Consequently, the BESS sizes also differ, ranging from small to medium-sized storage systems. The power to energy capacity ratio (also referred to as c-rate) varies between 0.7 and 1.6, as we allow for a flexible dimensioning of power and energy capacities.

Table 7.5.: Annual load and maximum peak of companies 1 - 5 along with the resulting optimal BESS power and energy capacities

ID	BESS capacity E [kWh]	BESS power P^{max} [kW]	Total yearly load $\sum_t L(t)$ [MWh]	Yearly peak load $\max L(t)$ [kW]
1	2	2	26	19
2	68	109	4,002	1109
3	111	75	629	315
4	46	58	1,629	575
5	15	12	169	117

Figure 7.6 shows the achieved PI for the BESS operation under different risk preferences and daily perfect foresight. The comprehensive numeric results of all simulations are reported in Appendix 7.1. In line with Shi et al. (2018), Engels et al. (2020b) and Brealey et al. (2011), we find that the simultaneous application of peak-shaving and FCR is economically advantageous compared to only one application for all companies. In the base case scenario shown in Figure 7.6 and Appendix 7.1, the initial grid capacity level is chosen based on the optimal grid capacity level for the first year of data. Unsurprisingly, the perfect foresight performs a least as well as the operation based on quantile forecasts. One key insight that can be taken from the cases of all companies is that risk averse planning does generally not have a (large) negative effect on the monetary performance of the BESS investment. In the case of company 5, we observe a 10% lower PI compared to the 50^{th} percentile (i.e., the point forecast equivalent) for the 95^{th} percentile. For company 1, utilizing the 75^{th} and 95^{th} percentile results in a slightly decreased

PI by 2% compared to the 50^{th} percentile. It might seem counter-intuitive that the 90^{th} percentile performs better than both the 75^{th} and 95^{th} percentile. This is the result of a rare effect that can take place because we determine BESS size and grid capacity level based on historic data that results in the BESS being not large enough to shave a certain peak in the following year. Depending on the percentile that is used for planning, and the respective reserved capacity for peak-shaving, the operator still tries to shave the original peak as long as possible, until the BESS is empty and has to set a new grid capacity level. In rare cases, this might then occur inconveniently timed and lead to the observed results.

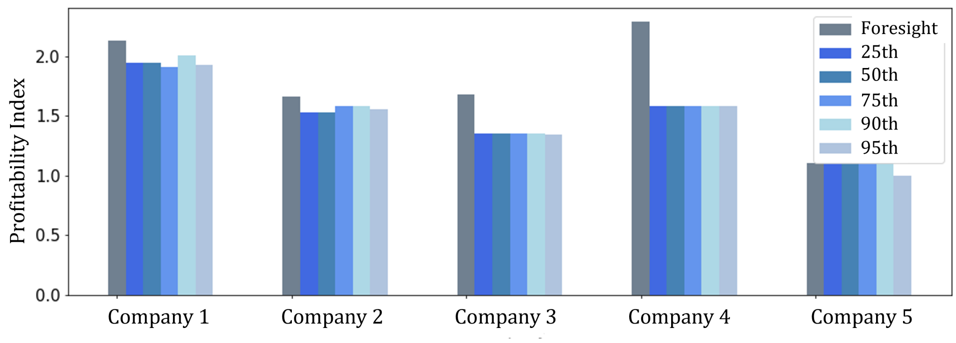

Figure 7.6.: PIs across all percentiles and foresight

In some cases, we can even see positive monetary effects when planning peak-shaving capacity risk aversely. In the case of company 2, planning based on both the 75^{th} and 90^{th} percentile yields a 3 % better monetary performance than planning with the point forecast. When planning extremely risk averse by utilizing the 95^{th} percentile, the PI declines but is still 1% above the point forecast. We further observe that there is no difference in monetary performance between any of the quantile forecasts in the cases of companies 3 and 4, again underlining the finding that risk averse planning has little to no negative effects on the monetary performance of the BESS. Overall, this is an encouraging finding, as it implies that a risk averse attitude, which reduces the risk of missing a high peak load event, is not very costly for an industrial consumer even in the worst case scenario.

Since our results depend on many assumptions, we perform extensive sensitivity analyses to evaluate the effects of changing costs, prices, and technical parameters.

7.4.2 Sensitivity Analyses

We perform sensitivity analyses for the parameters peak price, FCR market price, initial grid capacity level, BESS investment costs and BESS size. The most important findings are described in the following.

The initial grid capacity level is determined based on the first year of data, along with the optimal BESS power and energy capacity. This means that in the second year of data, which we use for our simulation and monetary evaluation, the chosen grid capacity level is not necessarily optimal anymore. Since the grid capacity level can be adjusted flexibly by the industrial consumer during operation (in contrast to the BESS investment which is fixed once the BESS is acquired), it is plausible to test variations of initial grid capacity levels during the simulation. The effect of decreasing the peak-grid capacity level (i.e., trying to shave to a lower load level than in the base case scenario) is illustrated in Figure 7.7 for all companies and forecast scenarios.

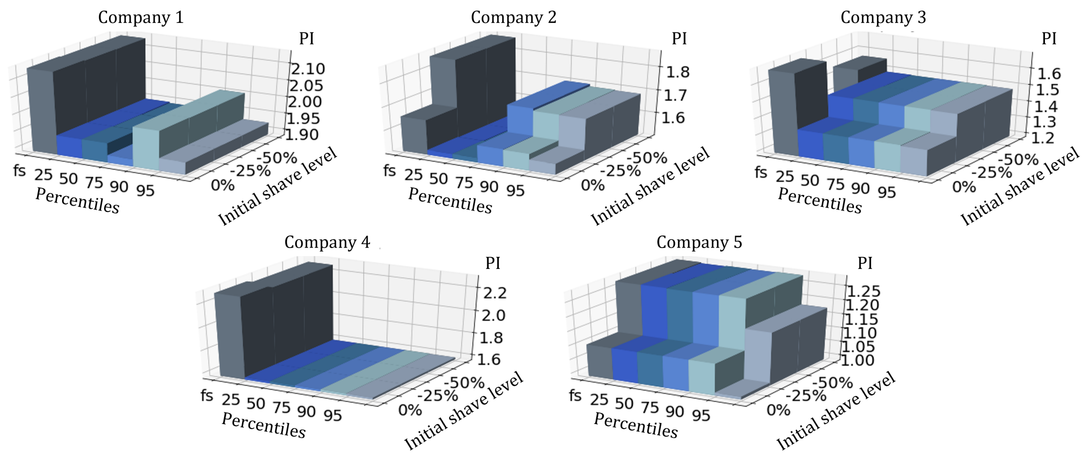

Figure 7.7.: Effects of a reduced initial peak-grid capacity level compared to the initial level that is derived from the optimization on the first year of data

We observe that for companies 1 and 4, a lower initial grid capacity level does not change the monetary performance of the BESS deployment. The most plausible explanation is that when the peak-grid capacity level is set (too) low in the beginning, the BESS fails to shave to this level on some days and therefore readjusts (i.e., increases) the grid capacity level during the course of the year which then yields similar results to the base case scenario. In the case of companies 2, 3 and 5, however, we observe a different (desirable) effect: A lower initial grid capacity level leads to a better monetary performance across all forecast scenarios, most likely because the level that is determined on the previous year did not fully take advantage of the BESS's peak-shaving potential. Overall, this sensitivity analysis reveals a valuable finding: A reduction of the initial grid capacity level might be preferential as the level can simply be reset during operation if it cannot be held. However, as previously discussed, this might not always be beneficial.

We further test the effects of a higher or lower peak load price. The peak price that an industrial consumer has to pay in Germany varies depending on the region and respective grid operators. We use an exemplary peak price that is representative of these charges in general in the base case scenario and test the effects of a 20% increase or decrease in peak prices for all companies and forecasts as sensitivity (Figure 7.8).

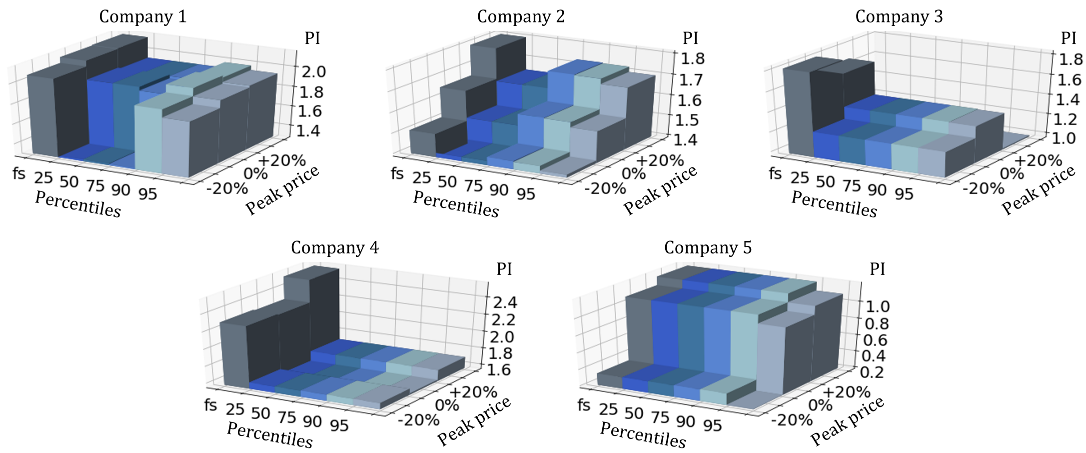

Figure 7.8.: Effects of a higher and lower peak load price on the monetary performance of the BESS investment

For companies 2 - 5, we observe that while the level of the PI changes between the scenarios, the relative performance for the different percentiles remains the same. Generally, higher peak prices lead to a better monetary performance of the BESS as there are more potential savings of shaving peak loads. One exception is company 3, where we observe a different effect. Whereas a reduced peak price also leads to a lower PI, a 20% increase in the peak price suddenly further reduces the PI across all percentiles. Note that in the case of a changed peak load price, the optimal BESS size is also adjusted to the new prices during the optimization, which might explain this unusual effect. Company 1 poses an exception in terms of the relative performance of the quantile forecasts. While the performance is similar among all percentiles in the base case and +20% scenarios, the 25^{th}, 50^{th} and 75^{th} percentile perform notably worse when peak prices are reduced by 20%. This might be caused by a smaller optimal BESS size (and a change in power to energy ratio) in the presence of low peak charges, which makes it more difficult to adequately react to unforeseen peaks. We can thus observe that in this constellation, the improved anticipation of costly peaks through highly risk averse planning increases the monetary performance of the BESS by more than 15%.

Further results of the sensitivity analysis are shown in Figure 7.9. On the left side, we compare the effects of higher or lower FCR price levels and peak prices, averaged over all companies and quantile forecasts. These two parameters illustrate the monetary trade-off between the two considered BESS applications. We find that generally, higher FCR price levels lead to better monetary performance, while the effect of the peak price is not quite as pronounced and straightforward, as also seen in Figure 7.8.

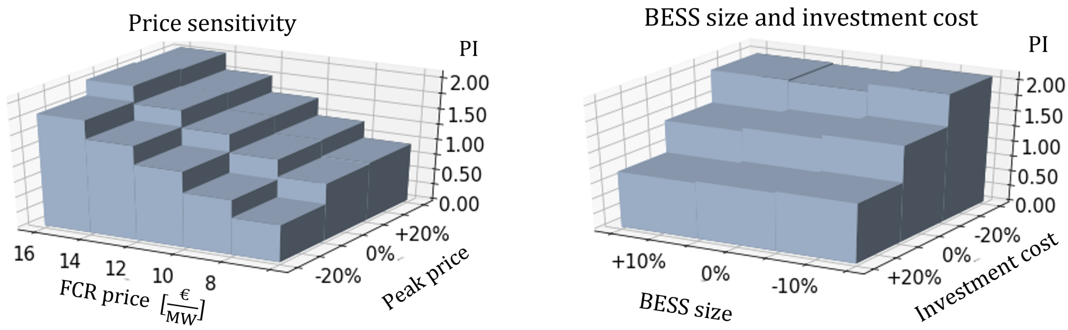

Figure 7.9.: Left: Joint effect of peak load price and FCR price variations. Right: Joint effect of BESS size and investment variations. Both figures depict the average over all quantile forecasts (without foresight scenario).

On the right-hand side, BESS size and investment costs are compared, again averaged over all companies and forecast quantiles. Unsurprisingly, lower investment costs lead to higher PIs. BESS size on the other hand leads to only small effects, but we see a slight increase in monetary performance if the BESS size is reduced by 10% in comparison to the size that was optimal on the first year of data. Due to the limited number of use cases, it is unclear if this finding can be generalized to other industrial consumers.

7.5 Discussion

It should be noted, that the training-validation-test split of 25-25-50 is not ideal for training a Q-LSTM. However, this split is necessary because of the problem context of annual peak load pricing and the two-year data availability. Future research should try to acquire longer time series to improve the model training. Moreover, testing the introduced methodology on more industrial load profiles could reveal more generalizable results.

The BESS sizing and the initial grid capacity level is optimized for peak-shaving only and depends on load data of a single year. Therefore, the optimization problem in Section 7.3.2 may lead to results that are not optimal for the following year. It should be emphasised that this is a deliberate modelling decision. It is realistic that business operators cannot provide optimal BESS sizes and initial grid capacity levels for the next year. Nevertheless, it could have been better to perform the optimization on more than one previous year, since the load profiles of the two years differ considerably in certain cases. Again, longer time series should be acquired for future research in this area.

Furthermore, we want to address the chosen rolling horizon approach presented in Figure 7.4. The focus of this chapter is to enable a synchronised interaction between day-ahead optimization and subsequent real-time BESS control. The latter charges the BESS to grid capacity level whenever possible. Non-optimal BESS movements may occur in our real-time control, which we accept for the purpose of the economic evaluation of this study. In reality, however, a more intelligent real-time control, as presented by Lucas and Chondrogiannis (2016) and Koller et al. (2015) would be advantageous. This would also enable an accurate representation of the BESS's degradation, which depends on charging cycles and is not considered in this study. Lunz et al. (2012) investigate the effects of uncontrolled charging and find that it can reduce the lifetime of a BESS by up to 42%. This would render the investments in our case study unprofitable, but would not change the relative performance of the quantile forecasts, as shown in the sensitivity analysis with reduced investment costs.

In Section 7.3.4, we argue why we assume a fixed average price λ_c for the FCR market. Since the FCR market is a pay-as-bid market (Braeuer et al., 2019), we can assume that the company operator bids for the fixed price λ_c over the course of the whole year. Nevertheless, the prices could be modelled more precisely by taking varying λ_c into account. We investigate the combination of peak-shaving and FCR provision, as previous research suggests that these applications are both economically and technically well compatible. It should be noted, however, that the demand of the FCR market is limited, and a rising numbers of participating BESSs could lead to decreasing prices. Moreover, with the recent rise in spot market electricity prices and expected increase in price spreads due to the expansion of renewable energy sources, including trading as a third application could be subject of future research. A further use case extension could be self-consumption from company-owned, on-site renewable generation from solar or wind power plants. The monetary effects of risk averse planning are quite low in the case of joint peak-shaving and FCR provision, as these applications are complimentary from a technological perspective since peak-shaving is an energy intensive application and FCR provision a more power intensive application. Both of the latter mentioned additional applications could severely change the effects of risk averse planning on financial trade-offs, as they are energy-intensive and thus less complimentary to peak-shaving.

7.6 Conclusion

In this chapter, we evaluate the effects of risk aversion during the joint scheduling and operation of BESS capacities for industrial peak-shaving and FCR provision. To this end, we introduce a probabilistic quantile forecast as means to model risk attitude and describe a rolling horizon BESS control strategy for the (uncertain) scheduling of BESS capacities for the two considered applications. We demonstrate the proposed methodology on the case of five industrial consumers and can thus answer our research question as follows: In most cases, moderate risk averse planning does not affect the monetary potential of a BESS negatively and can even increase the monetary performance in the case of some companies. Highly risk averse planning behavior can lead to a decrease in performance in some cases. While this may not be a desirable effect, the results show that even extreme risk averse attitude leads to relatively low penalties compared to the significantly reduced risk of missing a high peak load event. These results provide valuable insights for operators of BESSs in industrial companies and encourage further investigation of probabilistic forecasting in operational strategies of power technologies.

This chapter presents an online operation strategy for joint peak-shaving and FCR provision,i.e., one BTM and one FTM application, in the context of a BESS deployed by an industrial consumer. Combining a data-driven forecast with a rolling-horizon optimization approach allows us to address and handle the present uncertainties in this case. However, with more use cases, the operational problem becomes more complex due to several uncertainties and technical requirements that need to be considered. In the case of a multi-use BESS serving several BTM and FTM applications, alternative approaches, which do not rely on optimization, are needed for an online operation strategy. In the following chapter, a DRL based approach is investigated to address this problem.

CHAPTER 8

MULTI-USE BATTERY OPERATION WITH DEEP REINFORCEMENT LEARNING

The combination of several BTM and FTM applications is a growing area of research, as multi-use BESS deployment potentially enables a more effective and profitable operation of BESSs on all levels of power systems. However, several uncertainties regarding generation, consumption, price developments and the trade-off between use-cases have to be addressed during real-time multi-use operation. The need for online operation strategies becomes evident from the previous chapters and the literature review in Section 2.4. In this regard, DRL is a promising approach for BESS operators in times of fast changing market conditions due to its ability to adapt to changing conditions. In this chapter, a DRL controlled BESS service agent is therefore designed that handles multiple BTM and FTM use cases in parallel. The results show that the data-driven approach outperforms a rule-based benchmark strategy during real-time operation. Through its ability to coordinate several use cases, the DRL-based approach increases annual profits by up to 28%.

This chapter comprises large parts of the unpublished article: S. Henni, M. Rominger, P. Staudt, *A Deep Reinforcement Learning-Based Storage Service Agent for Coordinating Multiple Use Cases*, Working Paper, 2022.

8.1 Introduction

Conventional approaches for multi-use operational strategies include, for example, stochastic programming (He et al., 2016), robust optimization (Wang et al., 2018) or model predictive control (Kumar et al., 2018). These optimization approaches are limited during real-time operation, as they require either a perfect forecast of uncertain generation, consumption and price developments or strict assumptions regarding random variables. This limits such methods to specific case studies and prevents a flexible adaption to changing conditions of the environment. To enable multi-use BESS deployment in practice, a method is required that makes decisions during real-time operation without explicitly modeling underlying uncertainties. In recent years, DRL, a data-driven method from the area of machine learning, has emerged as alternative method to address this issue for sequential decision making problems (Huang and Wang, 2021; Cao et al., 2020). In principle, DRL algorithms learn through a trial-and-error strategy and do not require an explicit model of their environment, e.g., the random variables that affect its performance. In addition, online DRL algorithms are able to continuously adapt to changing conditions of the environment they operate in (Lapan, 2020). Applications of DRL are however poorly researched in the context of multi-use BESS deployment, with only one publication appearing in the literature review in Section 2.4. Moreover, to the best of our knowledge, no other publication has yet approached the modelling of a multi-use BESS service agent, which receives real-time service requests for multiple use cases. To close this gap, in this chapter, we design, evaluate and discuss a BESS service agent, which answers service requests from multiple applications and markets using an online DRL algorithm. To analyse the algorithm's ability to coordinate multiple use cases under uncertainty, we benchmark it against a rule-based online operation strategy and the theoretically optimal solution. We thus answer the following research question:

Research Question 7: *What is the quantitative performance of a DRL-based algorithm in comparison to theoretically optimal and rule-based operation strategies in terms of financial revenues?*

The remainder of this chapter is structured as follows: First, we introduce related literature on DRL-based operation strategies for single- and multi-use BESS deployment. Then, we describe the theoretical foundations of DRL before applying it to the StaaS concept explained in Section 2.6. In a case study, we demonstrate and evaluate the designed DRL model on a community BESS that operates within a residential neighborhood. Finally, we discuss the limitations and describe possible future steps for the improvement of the introduced DRL model before summarizing the results of this study in the conclusion.

8.2 Related Work

The stacking of services to enhance the profitability of BESSs has been investigated in various settings, as becomes evident from Section 2.4. A common finding is that the provision of ancillary services is a lot more profitable than trading on the spot markets (e.g., Braeuer et al. (2019); Moreno et al. (2015)) but that in general, stacking services is beneficial due to higher utilization rates of the storage capacity. There are downsides as well, mainly the increase in cyclic degradation that depends on factors such as depth of discharge, overall throughput, and temperature (Sterner and Stadler, 2017). Consequently, the additional cyclic degradation differs for certain tasks. The authors of (Perez et al., 2016), for example, find that trading affects cyclic degradation more than the provision of ancillary services due to very high and frequent depths of discharge. Engels et al. (2020a) investigate parallel revenue streams in industrial applications and find that combining peak-shaving and FCR leads to larger profits than either individual task. Again, in an industrial setting, Braeuer et al. (2019) extend these two tasks to include trading on the day-ahead and intraday spot markets and find that some companies may realize a positive net present value by combining all three tasks, although arbitrage trading is found to only add very little to the outcome. Lombardi and Schwabe (2017) compare several technologies for the combined application of peak-shaving, self-consumption, and trading on the day-ahead market in order to adhere to the previously sold energy profile of a wind turbine. They find that the prioritization of some use cases, such as peak-shaving of an industrial user, can lead to additional benefits when sharing the BESS's capacity amongst several users. The combination of increasing self-consumption and providing ancillary services has also been addressed in various residential settings. Litjens et al. (2018) combine self-consumption and the provision of FRR in a residential community in the Netherlands. Engels et al. (2019) analyse the trade-off between the provision of FCR and self-consumption and show that revenues can be increased by 25% in comparison to the most profitable single use case.

In general, optimization approaches account for the majority of methods when designing multi-use operational strategies (Section 2.4). In recent years, however, DRL-based approaches have emerged as alternative solution to model BESS operation. For example, Cao et al. (2020) use a NoisyNet Double Deep Q-Network (NN-DDQN) to implement a storage agent that engages in spot market trading. The actions of the agent are discretized and the model is combined with a convolutional neural network and an LSTM that provides the BESS agent with the necessary price forecasts as input data. A similar task is undertaken by Xu et al. (2018a), who compare a simple Q-learning strategy (without the usage of neural networks) with a proximal policy optimization (PPO) DRL approach. In contrast to DDQN, PPO allows continuous action states and is therefore better suited to model the physical reality of storage operation. Both Cao et al. (2020) and Xu et al. (2018a) compare the performance of their algorithms to other, simpler DRL models, which are (unsurprisingly) outperformed by the more complex models. Similarly to these contributions, Lehna et al. (2022) and Yang et al. (2020) also design DRL-based spot market trading strategies. However, they take on the perspective of a wind park operator who wants to sell her generation at times of high prices using a BESS, similar to the approach presented in Chapter 6. This increases the level of uncertainty involved in the use case, as not only spot market prices are unknown but also the exact renewable generation quantity. To tackle this problem, Yang et al. (2020) develop a multi-layer architecture, extending a DDQN algorithm with a prioritized replay buffer, a dueling network, and a dropout layer. The authors report better performance than with comparable stochastic optimizations. Lehna et al. (2022) on the other hand rely on a PPO algorithm for the same task and demonstrate a 45% improvement in revenues compared to baseline approaches. Miao et al. (2021) and Huang and Wang (2021) introduce DRL-based multi-use BESS operation strategies. Miao et al. (2021) combine spot market trading with frequency regulation provision, but reduce the decision of the DRL agent to one charging or discharging action. They demonstrate that a triplet deep deterministic policy gradient (DDPG) with exploration noise decay approach outperforms a comparable deep Q-learning algorithm. Huang and Wang (2021) combine spot market trading with two other use cases, namely increasing PV self-consumption and providing frequency regulation. The authors show that the agent is capable of handling these multiple applications simultaneously. In a comparison of a PPO algorithm with DDQN, DDPG and an actor-critic (A2C) approach, they demonstrate the superiority of PPO. Notably, both previous studies on multi-use BESS deployment only consider other DRL algorithms as benchmarks. Furthermore, both models are relatively simple. Huang and Wang (2021) model one action for each of the three use cases at each time step. In reality, this decision process might not be realistic. In Germany, for example, the tendering of frequency regulation and the day-ahead spot market take place through an auction ahead of the actual realization. This means, that for some applications, all actions for the next day have to be chosen at one time step (i.e., at the time of the auction), while other applications might require continuous decisions, closer to the actual real-time execution (e.g., charging excess PV generation or intraday trading).

We conclude that there is a research gap to design and evaluate a multi-use DRL agent that handles several applications in their consecutive order. To provide a solution to this task, we implement a BESS service agent that receives service requests from both an auction, which requires several actions at once, as well as from continuous use cases.

8.3 Methodology

In this section, we first describe the theoretical foundations of DRL and introduce PPO, a state-of-the-art DRL algorithm that allows continuous action spaces (in contrast to discrete actions) and has been shown to outperform other DRL algorithms in the case of multi-use BESS deployment (Huang and Wang, 2021). Then, we apply the concept of a multi-use BESS service agent to a Markov Decision Process (MDP), which allows it to be solved by a DRL algorithm.

8.3.1 (Deep) Reinforcement Learning

Along with supervised and unsupervised learning, reinforcement learning (RL) is one of the three fundamental pillars of machine learning (Sutton and Barto, 2018). The central component of the RL is an *agent* who interacts with its *environment* in several consecutive time steps (Figure 8.1). In each time step t, the agent receives an *observation* S_t from the environment and then chooses an *action* A_t. It communicates this action to the environment, which then calculates and return a *reward* R_t to the agent. Through many such interactions, the agent eventually learns by trial-and-error, which actions, given certain observations, lead to good results, i.e., high rewards. The goal of the agent is to learn a *policy*, i.e., a strategy, which maximizes the cumulative rewards (Sutton and Barto, 2018). This agent-environment interaction can be modelled as MDP, a discrete time stochastic control process. The most important property of the MDP, the so-called Markov property, is that a future state depends only on the current state, regardless of how it was reached (i.e., regardless of past states). When modeling the environment of an RL algorithm, it is important to maintain this criterion. In practice, this means that the current observation, which the agents receives, contains all relevant information for future decisions.

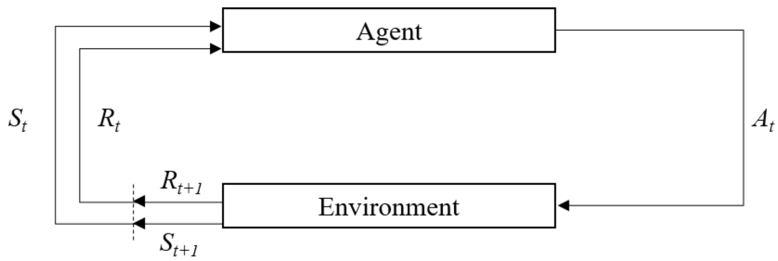

Figure 8.1.: Interaction between agent and the environment in the markov decision process (Sutton and Barto, 2018)

In general, an MDP can be described with a tuple (S, A, P_a, R_a) where S is the set of states (i.e., observations), A the set of actions, $P_{s,a}$ the state transition function and $R_{s,a}$ the set of rewards. The transition probability $P_{s,a,s'} = \{s_{t+1} = s' \mid s_t = s, a_t = a\}$ thereby represents the probability that the agent, which is in state s at time t, will be transferred to state s' at the next time step $t+1$ after choosing action a. The transition probability is often unknown and is approximated by the agent through repeated simulation runs from random initial states (Sutton and Barto, 2018; Lapan, 2020).

The RL agent pursues the goal to learn a policy π that maximizes the expected cumulative rewards $\sum_{t=0}^{\infty} R_t$ it receives through the interaction with the environment. Usually, a discount rate $\gamma \in [0, 1]$ is introduced to give higher weighting to immediate rewards. Thus, the agent can arrive at a solution even with infinite time horizons. To achieve this goal of reward maximization, the RL agent relies on the so-called q-function, which describes the expected reward for performing an action a while in a state s, given a policy π.

$$Q_\pi(s,a) = \mathbb{E}_\pi[\sum_{k=0}^{\infty} \gamma^k R_{t+k+1} \mid S_t = s, A_t = a], \quad \forall s \in S \tag{8.1}$$

Another important notation in RL is the *value* $V_\pi(s,a)$ of a state s, which describes the expected reward if the agent follows the strategy π at every time step t.

$$V_\pi(s,a) = \mathbb{E}_\pi[\sum_{k=0}^{\infty} \gamma^k R_{t+k+1} \mid S_t = s], \quad \forall s \in S \tag{8.2}$$

In the so-called tabular q-learning, the agent tries to maximize the q-function by explicitly iterating over all state-action pairs. However, for complex problems, this RL approach soon becomes infeasible in acceptable computational times. Therefore, DRL uses one or more neural networks consisting of several layers to approximate Q and V or to directly learn an optimal policy π. DRL algorithms can be further categorized into policy-based and value-based approaches. Value-based algorithms try to maximize the q-function in order to find the best policy, whereas policy-based algorithms try to find the best policy $\pi_\eta(a|s)$ directly, without explicitly calculating Q and V.

For continuous action spaces, the policy π_θ parameterized by θ represents the probability distribution of actions given a certain state. Policy-based methods rely on a policy gradient ∇J, which is used to update the policy of the agent without explicitly calculating Q and V.

$$\nabla J = \mathbb{E}[Q(s,a) \nabla log \pi(a|s)] \tag{8.3}$$

The policy gradient indicates the direction, in which the network parameters have to be changed in order to improve the policy. The goal is to increase the probability of actions that yield large rewards and vice versa (Lapan, 2020).

8.3.2 Proximal Policy Optimization

Lately, one of the most prominently deployed DRL algorithms in literature has been PPO, a policy-based algorithm first introduced by Schulman et al. (2017), which allows continuous actions spaces and has been shown to outperform similar algorithms, such as DDPG or A2C (Huang and Wang, 2021; Schulman et al., 2017). PPO is an extension of the A2C. An important notion of the actor-critic concept is that the reward Q can be represented as the value V of a state plus the advantage Adv of an action, i.e., $Q(s,a) = V(s) + Adv(s,a)$. Actor-critic methods deploy two separate neural networks, an *actor*, which learns the policy π and a *critic*, which learns the value $V(s)$, which is used to stabilize the policy updates of the actor network (Lapan, 2020). PPO relies on a clipped policy gradient function (8.4). To prevent unstable updates of the policy, the policy ratio is limited by the clipping parameter ϵ, which ensures that the update is within the interval $[1-\epsilon, 1+\epsilon]$.

$$J_\theta^{clip} = \mathbb{E}_t[ra_t(\theta) \cdot Adv_t, clip(ra_t(\theta), 1-\epsilon, 1+\epsilon) \cdot Adv_t] \tag{8.4}$$

Here, ra is the ratio between the new and old policy.

$$ra_t(\theta) = \frac{\pi_\theta(a_t|s_t)}{\pi_{\theta_{old}}(a_t|s_t)} \tag{8.5}$$

The advantage function is calculated as follows:

$$Adv_t = \sigma_t + (\gamma \cdot \lambda) \cdot \sigma_{t+1} + (\gamma \cdot \lambda)^2 \cdot \sigma_{t+2} + ... + (\gamma \cdot \lambda) < T - t + 1 \cdot \sigma_{t-1} \tag{8.6}$$

where λ is a factor $\in [0,1]$ and σ is defined as follows:

$$\sigma_t = ra_t + \gamma \cdot V(s_{t+1}) - V(s_t)) \tag{8.7}$$

The introduced clipping parameter ϵ, discount rate γ and λ are s that can be adjusted individually and can significantly influence the performance of the DRL algorithm's learning process. Additional hyperparameters include the learning rate α and the entropy loss β. For a detailed description of the PPO algorithm and its implementation using OpenAI Gym see (Schulman et al., 2017) and (Lapan, 2020).

8.3.3 Modeling a Deep Reinforcement Learning-Based Storage Service Agent

In order to be able to solve the real-time operational problem of a BESS service agent with DRL, the problem has to be modelled as an MDP. The BESS service agent is based on the StaaS concept described in Section 2.6. Figure 8.2 shows the MDP principle of agent-environment interaction applied to the concept of a BESS service agent. In each time step, the BESS receives service requests for several differing use cases, e.g, storing excess PV generation (i.e., charging), supplying household loads (i.e., discharging) or trading on the spot markets (either charging or discharging). These service requests need to contain all relevant information that allow the identification of the use case, the required energy and power capacity and the offered or requested price of the service. Another important information to include in the state space is the battery status, i.e., the already planned occupation of energy and power capacity in the form of SoC and power vector P. Any additional helpful information can also be passed to the agent in the state space, in particular forecasts of future generation, loads or (wholesale) prices. In the DRL-based BESS service model, the actions then refer to the acceptance or rejection of the submitted service requests.

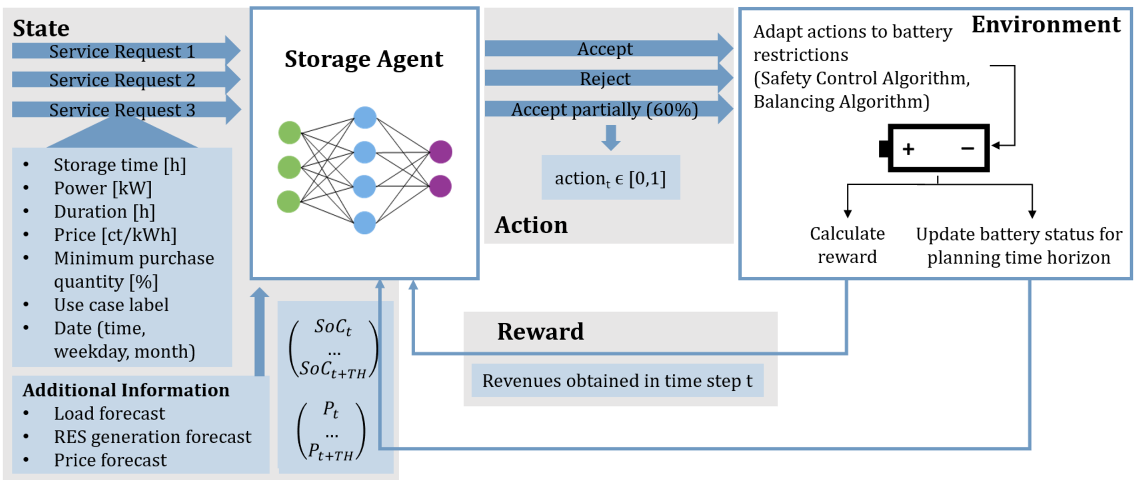

Figure 8.2.: Storage as a Service concept embedded in a Markov Decision Process

A continuous action space allows arbitrary partial acceptance of service requests. In our model, this can be prevented by the submitter of a request by specifying a minimum purchase quantity, which then poses a constraint on the agent's action.

The chosen actions are then processed by the environment that the agent interacts with. Here, a safety control algorithm (SCA), inspired by Huang and Wang (2021), comes into play. The SCA ensures the feasibility of actions with physical constraints of the BESS as well as with the predefined requirements of the service requests. That is, for example, in case a minimum purchase quantity of 100% was indicated and the agent chooses a lower value as action, the action is adjusted to zero by the SCA. Likewise, if the agent tries to charge or discharge more than the current SoC allows, the SCA adjusts the action so that it complies with the constraints. Once all actions have been adjusted to feasible values, the control signal is given to the BESS and the environment updates the SoC and calculates rewards according to the adjusted actions. In our model, a natural reward for the BESS operator is the monetary revenue thath she receives based on accepting service requests. However, other, non-monetary reward components that incentivize specific behavior could also be included. The reward is then returned to the agent, whereas the updated battery status is included in the state space of the subsequent time step. All above mentioned components of the DRL-based BESS service agent are described formally in the following.

Service requests. Each service request needs to be submitted in the form of a standardized vector, which contains the information seen in Figure 8.2 and described in the transaction object of the StaaS concept in Section 2.6. A service request is thus denoted as follows:

$$\begin{aligned} request_n = [&storageTime_n, power_n, duration_n, price_n, \\ &minimumQuantity_n, label_n, weekday_n, time_n, Month_n] \end{aligned} \tag{8.8}$$

Here, we stipulate that the agent receives up to N service requests per time step t. The storage time refers to the starting time of the service requests $\in [0, TH]$ where 0 is a request for the current time step and TH refers to the planning time horizon, i.e., the maximum number of time steps that the agent plans ahead. The price is indicated in € kWh^{-1}. It can be negative if the BESS operator is charged for the service request (e.g., when buying and storing excess PV generation). From the required duration in hours and power in kW, the BESS operator can derive the volume (in kWh) of the service request as $volume_n = duration_n \cdot power_n$ for all use cases except FCR povision. The minimum purchase quantity is indicated as a factor $\in [0, 1]$. The label refers to the use case and has to be decoded in numerical form (e.g., 1 = storing excess PV generation, 2 = industrial peak-shaving etc.). Weekday, time and month of the service request are modelled as cyclical features through a *sin* and *cos* transformation as demonstrated by Haben and Giasemidis (2016). At each time step t, the agent receives the request vector $Request_t = [request_{t,1}, ..., request_{t,N}]$ as part of the observation space.

State space. In each time step, the state space is the information, which the DRL agent observes and on which it bases its decisions on. It therefore needs to contain all relevant information for the decision making. The service requests therefore need to be part of the state space. In addition, the agent needs to know about the current and future status of the BESS, i.e., the BESS's energy and power capacity that has already been scheduled for other services. This information can be conveyed through an SoC and a power vector, respectively.

$$SOC_t = [soc_t, soc_{t+1}, ..., soc_{t+TH}] \tag{8.9}$$

$$P_t = [P_t^{ch}, P_t^{dc}, ..., P_{t+TH}^{ch}, P_{t+TH}^{dc}] \tag{8.10}$$

The SoC vector contains the planned SoC occupation *soc* for each time step between the current time period t and the end of planning time horizon TH. We divide the power vector P_t into discharging power P^{dc} and charging power P^{ch} for a better differentiation between discharging and charging use cases in the following paragraphs.

The SoC information can further be divided into BTM, FTM and FCR shares for regulatory and technical reasons. We assume that BTM (i.e., storing local RES generation, supplying local households or industrial loads) and FTM (i.e., trading on wholesale markets) use cases have to be accounted for separately for regulatory purposes. This means, for example, that electricity bought on the spot market cannot be used to supply household loads, because then charges and levies would apply. For FCR, no actual electricity is charged or discharged, but rather a certain share of the BESS's energy capacity is reserved so in case of a steep frequency deviation, the power that was bid on the FCR auction can be fully activated. This is a requirement of the prequalification criteria for participating in frequency regulation. In order to comply with negative and positive FCR, we reserve both discharged and charged shares of the BESS's capacity for FCR provision, as illustrated in Figure 8.3. We differentiate between SOC_t^{BTM}, SOC_t^{FTM} and SOC_t^{FCR}, which refer to the amount of energy capacity occupied by the respective use case. Furthermore, $SOC_t^{BTM,res}$ and $SOC_t^{FTM,res}$ refer to the electricity that is temporarily reserved for the FCR use case but can be later used again for the respective use case. Each SoC information is thereby passed as a vector of length TH.

Figure 8.3.: SoC of the BESS divided into shares for BTM, FTM and FCR use cases

In addition to the battery status, forecast vectors of length TH are included in the additional information of the state space:

$$Forecast_t = [forecast_t, forecast_{t+1}, ..., forecast_{t+TH}] \tag{8.11}$$

The additional information S' therefore consists of the battery status (SoC and power) as well as forecast information:

$$S'_t = [SOC_t^{BTM}, SOC_t^{FTM}, SOC_t^{BTM,res}, SOC_t^{FTM,res}, SOC_t^{FCR}, \\ P_t, Forecast_{t,1}, ..., Forecast_{t,FC}] \tag{8.12}$$

where FC describes the set of variables for which a forecast is included, which may include, e.g., relevant generation, consumption and price forecast data.

Finally, the state space in time step t consists of the set of service requests and the additional information S'_t:

$$S_t = [Request_t, S_t^{'}] \tag{8.13}$$

Action space. As illustrated in Figure 8.2, the actions of the DRL agent refer to the acceptance or rejection of service requests. The action space is therefore a vector of length N, where $a_{t,1}$ refers to service request 1 at time t, $a_{t,2}$ to service request 2, and so on. Each action $a_{t,request} \in [0, 1]$ refers to the share of the volume of the service request that is accepted by the agent.

$$A_t = [a_{t,1}, ..., a_{t,N}] \tag{8.14}$$

Environment. In the environment, the SCA ensures the physical feasibility of the actions, calculates the resulting rewards and updates the SoC status. Before introducing the SCA, we begin by defining all relevant mathematical operations. The BESS is restricted by its upper and lower SoC limits, soc^{max} and soc^{min}. In each time step t, the SoC of the BESS is determined by the energy capacity that is occupied by BTM, FTM and FCR use cases:

$$soc_t = soc_t^{BTM} + soc_t^{FTM} + soc_t^{FCR} + soc_t^{BTM,res} + soc_t^{FTM,res} \tag{8.15}$$

Since the BESS needs to be able to discharge at maximum FCR bid power capacity for at least 15 minutes, a certain level of SoC always needs to be ensured at times when FCR is provided. This electricity can come from a BTM or FTM use case, will remain reserved for the duration of the FCR provision and is available for usage after the FCR provision period. See Figure 8.3 for a schematic illustration of the SoC and reserved capacity of the BESS. The purple colored SoC share for positive FCR provision is energy that belongs to an FTM or BTM use case, but is temporarily reserved for FCR provision. Therefore, FCR provision limits the available unoccupied capacity of the BESS.

The remaining available upward energy capacity soc_t^{up} as well as the down-ward available capacity soc_t^{down}, which is available for discharging for BTM or FTM use cases, can then be calculated as follows:

$$soc_t^{up} = soc^{max} - soc_t \tag{8.16}$$

$$soc_t^{down,BTM} = soc_t^{BTM} - soc^{min} \tag{8.17}$$

$$soc_t^{down,FTM} = soc_t^{FTM} - soc^{min} \tag{8.18}$$

Similarly, the maximum charging and discharging power $P^{max,ch}$ and $P^{max,dc}$ pose limits on the available charging and discharging power P^{ch} and P^{dc}. We assume that the minimum charging and discharging power is zero. At each time step, the remaining available charging and discharging power can be calculated as:

$$P_t^{ch,rem} = P^{max,ch} - P_t^{ch} \tag{8.19}$$

$$P_t^{dc,rem} = P^{max,dc} - P_t^{dc} \tag{8.20}$$

Once the agent communicates the action vector A_t to the environment, the SCA's task is to ensure that the agent's chosen actions are compatible with the physical restrictions of the BESS at the time of the service provision. The starting time of the service provision st can be determined by the current time step t and the service request information $storageTime$, which indicates how many time steps in the future the service request starts:

$$st = t + storageTime \tag{8.21}$$

Likewise, the end time of the service provision is determined by the duration of the storage requests:

$$et = st + duration - \Delta t \tag{8.22}$$

where Δt is the time resolution in hours, e.g., $\Delta t = 1h$ in the case of an hourly resolution and $\Delta t = \frac{1}{4}h$ in the case of a 15 minute resolution. Given an hourly resolution, a duration of one hour will thus result in $st = et$. From here on, we denote the entire service period of one service request as $SP = [st, et]$.

If an action is not compatible with the physical restrictions, it is adjusted by the SCA. For the adjustment of actions, discharging and FCR use cases need to be differentiated due to the different technical requirements, which will be described in the following.

Charging use cases. Let $N^{ch} \subset N$ be the set of service requests that require charging of the BESS. For every service request $request^n$, $n \in N^{ch}$, the maximum feasible action a^{max} can be calculated as:

$$a^{max}_{t,n} = min(1, \frac{min_{s\in[st,t+TH]}(soc^{up}_s)}{power_{t,n} \cdot \Delta t \cdot \eta}, \frac{min_{s\in SP_{t,n}}(P^{ch,rem}_s)}{power_{t,n}}) \tag{8.23}$$

where η is the efficiency of the BESS and Δt the time resolution in hours. The minimum value of soc^{up} for the remainder of the planning time horizon poses an upper limit on the available feasible action. Likewise, the minimum available charging power $P^{ch,rem}$ during the service period SP^n_t of $request^n_t$ is considered in order to ensure that the service can be fulfilled for the entire service period. To comply with the technical restriction of the BESS, the chosen action a^n of the agent is then clipped to a feasible action $a^{n,adj}$ according to (8.24).

$$a^{adj}_{t,n} = min(a_{t,n}, a^{max}_{t,n}) \tag{8.24}$$

Furthermore, the minimum purchase quantity indicated in the service request needs to be considered. That is, if the resulting adjusted action is smaller than the minimum purchase quantity, the request is rejected alltogether:

$$\textbf{if} \quad a^{adj}_{t,n} < minimumQuantity_{t,n} \quad \textbf{then} \quad a^{adj}_{t,n} = 0 \tag{8.25}$$

For any time step s during the service period SP, the resulting bought energy from service request n can then be calculated as:

$$e^{in}_{s,n} = a^{adj}_{t,n} \cdot power_{t,n} \cdot \Delta t \qquad \forall s \in SP_{t,n} \tag{8.26}$$

The resulting revenue of the BESS for accepting the service request is then:

$$r_{t,n} = \sum_{s\in SP_{t,n}} (e^{in}_{s,n} \cdot price_{t,n}) \tag{8.27}$$

Note that for charging use cases, the price is usually negative because the BESS operator buys the electricity from a RES generator or the spot market.

Now let $N^{ch,BTM} \subset N^{ch}$ be the set of charging service requests for BTM use cases.

For all $n \in N^{ch,BTM}$, the SoC of BTM use cases can then be updated as:

$$soc_s^{BTM} = soc_s^{BTM} + e_{s,n}^{in} \cdot \eta \qquad \forall s \in [st, t+TH] \tag{8.28}$$

Analogously, let $N^{ch,FTM} \subset N^{ch}$ be the set of charging service requests for FTM use cases. For all $n \in N^{ch,FTM}$, the SoC of FTM use cases is updated as follows:

$$soc_s^{FTM} = soc_s^{FTM} + e_{s,n}^{in} \cdot \eta \qquad \forall s \in [st, t+TH] \tag{8.29}$$

For all $n \in N^{ch}$, the charging power P^{ch} is updated as follows:

$$P_s^{ch} = P_s^{ch} + a_{t,n}^{adj} \cdot power_{t,n} \qquad \forall s \in SP_{t,n} \tag{8.30}$$

Discharging use cases. Let $N^{dc} \subset N$ be the set of service requests that require discharging of the BESS. Let further $N^{dc,BTM} \subset N^{dc}$ and $N^{dc,FTM} \subset N^{dc}$ be the set of discharging service requests from BTM and FTM use cases, respectively. For all service requests $n \in N^{dc,BTM}$, the adjusted action is calculated using Equation 8.31 and the clipping function 8.24.

$$a_{t,n}^{max} = min(1, \frac{min_{s\in[st,t+TH]}(soc_t^{down,BTM})}{power_{t,n} \cdot \Delta t \cdot \frac{1}{\eta}}, \frac{min_{s\in SP_{t,n}}(P_s^{dc,rem})}{power_{t,n}}) \tag{8.31}$$

Analogously, for all service requests $n \in N^{dc,FTM}$, the adjusted action is calculated using Equations 8.32 and 8.24.

$$a_{t,n}^{max} = min(1, \frac{min_{s\in[st,t+TH]}(soc_t^{down,FTM})}{power_{t,n} \cdot \Delta t \cdot \frac{1}{\eta}}, \frac{min_{s\in SP_{t,n}}(P_s^{dc,rem})}{power_{t,n}}) \tag{8.32}$$

The available downward SoC of BTM and FTM use cases poses an upper limit on the electricity that is available for discharging. Furthermore, the action is restricted by the remaining available discharging power. For all $n \in N^{dc}$, the resulting sold energy and revenues can then be calculated as follows:

$$e_{s,n}^{out} = a_{t,n}^{adj} \cdot power_{t,n} \cdot \Delta t \tag{8.33}$$

$$r_{s,n} = \sum_{s\in SP_{t,n}} e_{s,n}^{out} \cdot price_{t,n} \tag{8.34}$$

The available remaining discharging power can then be updated as follows:

$$P_s^{dc,rem} = P_s^{dc,rem} + a_{t,n}^{adj} \cdot power_t^n \qquad \forall s \in SP_t^n \tag{8.35}$$

Then, we can update the SoC of all BTM use cases where $n \in N^{dc,BTM}$:

$$soc_s^{BTM} = soc_s^{BTM} - e_{s,n}^{out} \cdot \frac{1}{\eta} \qquad \forall s \in [st, t+TH] \tag{8.36}$$

Analogously, the SoC for FTM use cases, where $n \in N^{dc,FTM}$, is updated as:

$$soc_s^{FTM} = soc_s^{FTM} - e_{s,n}^{out} \cdot \frac{1}{\eta} \qquad \forall s \in [st, t+TH] \tag{8.37}$$

Note that the power vector is only updated for the duration of the service period whereas the SoC needs to be updated until the end of the planning horizon.

FCR use case. The use case FCR, and frequency regulation in general, has to be considered separately due to its differing nature from charging or discharging use cases. Here, we only consider FCR for simplicity, as it is currently the most profitable frequency regulation service for BESSs operating in Germany. Modeling FCR slightly differs from, for example, aFRR, as it has to be provided symmetrically, whereas positive and negative aFRR is tendered separately. In contrast to other use cases, FCR provision does not require explicit charging or discharging of predefined volumes of electricity. Instead, on the FCR auction, BESS power capacity is tendered, which has to be (partially) provided according to frequency deviations in the network. As described in Chapter 7, during 90% of times, for 1MW that is tendered on the FCR auction, less than 0.135 MW have to be actually provided. Furthermore, positive and negative signals balance each other out over longer time periods. For modeling low time resolutions, such as $\Delta t = 1h$, the power provision can therefore be neglected for the sake of simplicity (Braeuer et al., 2019). However, the prequalification criteria of the FCR auction require a provider of FCR to be able to deliver the maximum power capacity at any time for the duration of 15 minutes in case of a severe frequency deviation. We therefore need to reserve a portion of the BESS's SoC for FCR provision. For positive FCR provision, a certain level of energy has to be present in the BESS in order to be able to discharge for 15 minutes. For negative FCR provision, there needs to be enough soc^{up} available to charge the BESS for 15 minutes (see Figure 8.3). In the SCA, we do however not immediately reserve these portions of the SoC, since at the time of the FCR auction, the actual provision is at least 16 hours into the future and this would block the BESS's SoC for other use cases before that time. At the time of the auction, we therefore only note the offered FCR bid power $power^{FCR,bis}$ in a virtual placeholder SoC vector $soc^{placeholder}$ as follows:

$$soc_s^{placeholder} = 0.25h \cdot power_{t,n} \cdot a_{t,n} \cdot \eta \tag{8.38}$$

for all s in SP_t^n, for all n in the set of FCR service requests $N^{FCR} \subset N$ at time step t. The revenue of the FCR use case is then calculated as follows:

$$r_{t,n} = a_{t,n} \cdot power_{t,n} \cdot price_{t,n} \tag{8.39}$$

Note that the FCR provision is payed in € kW^{-1}, whereas charging and discharging service requests are offered in € kWh^{-1}. FCR actions are not clipped, since the occupation of the BESS's SoC is not known at the time of the auction. Instead, we deploy a separate Balancing Algorithm (BA) shortly before the start of FCR provision, which reserves the required capacity. If the SoC is too high or too low for FCR provision, the agent can buy or sell electricity on the intraday market.

Finally, the entire procedure undertaken by the environment at each time step t is shown in Algorithm 2. The environment receives the service requests vector $Request_t$, the action vector A_t and the last SoC and power window SOC_{t-1} and P_{t-1}. In the first step, the SOC and power vectors are updated to show the current time window by removing the first value $t-1$. For the SoC, the last value of the previous vector SOC_{t-1} is copied and appended at the end. The power values of time step $t+TH$ are set to zero. In the second step, the BA is activated if FCR has to be provided in the following hour. Finally, in the third step, the SCA is deployed, which iterates over all chosen actions in A_t to ensure the feasibility with physical constraints and to subsequently update the resulting changes in the BESS's SoC and to calculate the resulting revenues. The BA (Algorithm 3) and the SCA (Algorithm 4) are desrcibed in detail in the following.

Algorithm 2: Environment: steps performed by the environment in each time step t

Input : $Request_t$, A_t, SOC_{t-1}, P_{t-1}
Output: SOC_t, revenue

STEP 1: Update SoC and power vector
$SOC_t = SOC_{t-1}$
$P_t = P_{t-1}$
Remove first value of SOC_t and P_t
Copy and append last value of SoC: $soc_{t+TH} = soc_{(t+TH-1)}$
$P^{ch}_{t+TH} = 0$
$P^{dc}_{t+TH} = 0$
STEP 2: Reserve SoC for FCR blocks
if *FCR is provided in* $t + \frac{1}{\Delta t}$ **then**
    Perform Balancing Algorithm
STEP 3: Ensure physical feasibility of actions
Perform Safety Control Algorithm
STEP 4: Calculate overall revenues
$R_t = R^{ID} + \sum_{n \in N} r_{t,n}$

Balancing Algorithm. The purpose of the BA is to ensure the ability of the BESS to provide positive FCR in case it has been accepted through a service request. As the auction for FCR provision is held at 8 a.m. on the previous day, the service requests for this use case arrive at least 16 hours before the actual provision is due. Therefore, it would not be feasible to reserve the corresponding capacity at the time of the service request, because other use cases might not have been scheduled yet, and therefore, the SoC at 16 or more hours into the future will be subject to changes. We therefore deploy the BA one hour before FCR needs to be provided, i.e., when $soc^{FCR}_{t+\frac{1}{\Delta t}} > 0$. The BA then makes sure the BESS can provide positive and negative FCR for the duration of one hour at a time. In the first step, the BA checks whether enough capacity is free for negative FCR provision (line 7). If this is the case, the corresponding (empty) capacity is reserved (line 8). Then electricity has to be reserved for positive FCR provision. First, the BA reserves as much electricity from FTM use cases as possible (line 10). If this is not sufficient, electricity from BTM use cases is reserved (line 11). If this is still not sufficient, i.e., if the SoC of the BESS is not high enough for positive FCR provision, the remaining needed electricity is bought on the intraday market (line 13).

Algorithm 3: Balancing Algorithm that ensures the reservation of adequate amounts of energy for FCR provision

Input : Intraday prices p^{ID}, SOC_t^{BTM}, $SOC_t^{BTM,res}$,SOC_t^{FTM}, $SOC_t^{FTM,res}$, P_t
Output: SOC_t^{BTM}, $SOC_t^{BTM,res}$,SOC_t^{FTM}, $SOC_t^{FTM,res}$, P_t, r^{ID}

1 $start = t + \frac{1}{\Delta t}$
2 $end = t + \frac{2}{\Delta t} - 1$
3 $e_s^{required,pos} = soc_s^{placeholder,FCR} \quad \forall s \in [start, end]$
4 $e_s^{required,neg} = power_s^{placeholder,FCR} \cdot \eta \quad \forall s \in [start, end]$
5 **for** $s \in [start, end]$ **do**
6 Determine soc_s^{up} according to (8.16)
7 **if** $e_s^{required,neg} < soc_s^{up}$ **then**
8 Reserve empty storage space $soc_s^{FCR} = e_s^{required,neg}$
9 Reserve $min(soc_s^{FTM}, e_s^{required,pos})$, update $e_s^{required,pos}$
10 **if** $e_s^{required,pos} > 0$ **then**
11 Reserve $min(soc_s^{BTM}, e_s^{required,pos})$, update $e_s^{required,pos}$
12 **if** $e_s^{required,pos} > 0$ **then**
13 buy remaining $e_s^{required,pos}$ on intraday market
14 **if** $e_s^{required,neg} > soc_s^{up}$ **then**
15 sell $min(soc_s^{FTM}, e_s^{required,neg} - soc_s^{up})$ on intraday market **if** *still not enough* soc_s^{up} **then**
16 Feed PV generation in the amount of $e_s^{required,neg} - soc_s^{up}$ into the grid
17 Reserve empty storage space $soc_s^{FCR} = e_s^{required,neg}$
18 Execute lines (9-11) to reserve SoC for positive FCR provision

In the second case, if the SoC is too high for negative FCR provision, some electricity needs to be discharged. The BA first tries to sell the excess electricity on the intraday market (line 15), and then discharges further excess electricity from BTM use cases (line 16). The free capacity is then reserved for FCR. For positive FCR provision, the same steps as in lines 9-11 are undertaken, first reserving electricity from FTM use cases and then from BTM use cases. We assume that electricity can be bought or sold on the intraday market for the current intraday price p^{ID} while electricity from BTM use cases (i.e., generation from RESs) can be fed into the grid for the current feed-in tariff.

Safety Control Algorithm. The SCA (Algorithm 4) is responsible for ensuring the compatibility of the actions with the physical constraints of the BESS, e.g., preventing overcharging. Furthermore, it keeps track of the SoCs of FTM and BTM use cases and makes sure the two application areas are accounted for separately and are not mixed with each other. As input information, the SCA requires the vector of service requests, $Request_t$, the action vector A_t, the current state of charge vector SOC_t and the power vector P_t that contain all already scheduled services from time step t until the end of the observed time horizon $t + TH$.

Algorithm 4: Safety Control Algorithm that is deployed by the environment to ensure the feasibility of actions with physical constraints

Input : $Request_t$, A_t, SOC_t, P_t
Output: SOC_t, A_t^{adj},$R_n \forall n \in N, P_t$

for $a_{t,n} \in a_t$ **do**
  $SP_{t,n} = [st, et]$ according to (8.21) and (8.22)
  if $n \in N^{ch,BTM}$ **then**
    Adjust $a_{t,n}$ according to (8.23), (8.24) and (8.25), obtain $a_{t,n}^{adj}$
    Determine $e_s^{n,in}$ using (8.26), update P_s^{ch} using (8.30) $\forall s \in [SP_{t,n}]$
    Update soc_s^{BTM} using (8.28) $\forall s \in [st, t + TH]$
    Calculate R^n using (8.27
  if $n \in N^{dc,BTM}$ **then**
    adjust $a_{t,n}$ according to (8.31), (8.24) and (8.25), obtain $a_{t,n}^{adj}$.
    Determine $e_{s,n}^{out}$ using (8.33), update P_s^{dc} using (8.35) $\forall s \in [SP_{t,n}]$
    Update soc_s^{BTM} using (8.36) $\forall s \in [st, t + TH]$
    Calculate R^n using (8.34)
  if $n \in N^{ch,FTM}$ **then**
    Adjust $a_{t,n}$ according to (8.23), (8.24) and (8.25), obtain $a_{t,n}^{adj}$.
    Determine $e_{s,n}^{in}$ using (8.26), update P_s^{ch} using (8.30) $\forall s \in [SP_{t,n}]$
    Update soc_s^{FTM} using (8.29) $\forall s \in [st, t + TH]$
    Calculate R^n using (8.27)
  if $n \in N^{dc,FTM}$ **then**
    adjust $a_{t,n}$ according to (8.32), (8.24) and (8.25), obtain $a_{t,n}^{adj}$
    Determine $e_{s,n}^{out}$ using (8.33), update P_s^{dc} using (8.35) $\forall s \in [SP_{t,n}]$
    Update soc_s^{FTM} using (8.37) $\forall s \in [st, t + TH]$
    Calculate R^n using (8.34)
  if $n \in N^{FCR}$ **then**
    Update $soc_s^{placeholder}$ using (8.38) $\forall s \in [st, t + 4 \cdot \frac{1}{\Delta t}]$

The SCA then iterates over all actions $a_{t,n}$ in the action vector (line 1). From the available information on requested power and duration, the service period $SP_{t,n} = [st, et]$ is determined in line 2. The SCA then differentiates between charging, discharging, BTM and FTM use cases to process the following in lines 3 to 22. Each action is first adjusted to a value that does not violate any constraints of the BESS or the minimum purchase quantity of the service request. Then, for each time step $s \in SP_{t,n}$, the in-flowing energy $e^{in}_{s,n}$ is determined and the charging power P^{ch}_{s} is updated. Finally, the respective SoC is updated and the resulting revenue of the service request is calculated. For the use case FCR, the action is adjusted in line 24. The reserved FCR capacity soc^{FCR}_{s} is then updated for each time step s within the FCR bidding block $[st, t + \frac{4}{\Delta t}]$ in line 24. Subsequently, the empty capacity needed for negative FCR provision is reserved. The SCA outputs the updated SoC vector, the adjusted action vector A^{adj}_{t}, the service request revenues R_n and the updated power vector P_t.

Reward. The reward is a crucial component of a DRL model, as it is the signal that allows the agent to learn by rewarding good decisions and punishing bad ones. In the case of a multi-use BESS with the goal of maximizing profits, the obvious choice for a reward is the profits that are generated through the acceptance of service requests. The reward signal in time step t is therefore the sum of revenues r^{n}_{t} that result from service requests $n \in N$ at time step t.

$$reward_t = (\sum_{n \in N} r^{n}_{t}) \tag{8.40}$$

One difficulty that the agent faces is that negative reward signals can occur and are often desirable, because only by buying electricity can the BESS operator generate profits from selling said electricity at a later point in time. While this can make it more difficult to learn, DRL algorithms inherently addresses this issue by aiming at a maximization of cumulative profits as shown in (8.1), and by taking the value of the next state into account, which is higher when the BESS is charged. Additional reward components could be included to incentivize specific behavior, i.e., by penalizing unwanted actions or rewarding prioritized services. This type of reward engineering is however difficult to calibrate and we therefore refrain from including further components into the reward.

In the following, we demonstrate the functionality and evaluate the performance of the above introduced theoretical model in a case study. The proposed scheme of a BESS agent that coordinates multiple applications using a DRL algorithm is implemented in python 3.7 using the packages Gym by *OpenAI* (Gym documentation, 2022) and tensorflow 2.0 (Abadi et al., 2015). To solve the problem, the state-of-the-art PPO2 algorithm developed by *stable baselines* (Stable baselines documentation, 2022) is integrated into the implemented environment via a Gym-interface.

8.4 Case Study

To demonstrate the designed and implemented DRL-based BESS service agent, we conduct a case study of a hypothetical community BESS that receives service requests from all four application areas depicted in Figure 2.3. We assume that the BESS is located within a neighborhood and receives requests for storing excess PV generation and supplying household loads from prosumers within the neighborhood as BTM application. We furthermore assume that peak-shaving requests are submitted by a small industrial facility within the network section as second BTM application. Both BTM use cases are assumed to be exempt from taxes and levies when supplied by previously stored exceeds PV generation. The BESS further receives requests to participate in the FCR auction and trade in the intraday spot market. Intraday trading is also assumed to not be burdened with taxes or levies and BTM and FTM electricity quantities are strictly separated. The setup of the case study is shown in Figure 8.4 and described in detail in the following.

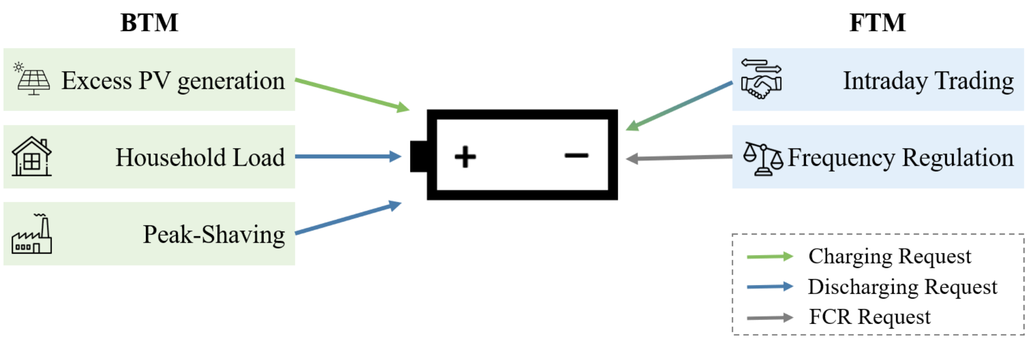

Figure 8.4.: Case study setup

Service requests. The chosen use cases result in up to ten service requests per time period. At 8 a.m., the agent receives six service requests for the FCR auction, one for each 4-hour FCR bidding block of the following day. The service request is always for the maximum possible amount. The FCR prequalification criteria requires a 25% buffer, therefore, in the case of a BESS with 15 kW power capacity, the maximum power bid is 12 kW. For all other use cases, the agent receives up to four service requests at every time step, i.e., one for storing excess PV generation, one for supplying household loads, one for peak-shaving and one for trading on the intraday market. The use cases are thereby aggregated, so that, for example, the household demand of several residents in the neighborhood is submitted as one single service request. Note that only three of these four requests can occur simultaneously, as there is either excess PV generation available or surplus household load, but never both at the same time. This is the case because we assume PV generation is first consumed directly, if possible (compare Chapter 4). For intraday trading, the BESS service agent receives the current intraday price and its maximum available power as service request at each time step. The agent can then choose an action between -1 and 1, where negative values refer to discharging (i.e., selling) and positive values to charging the BESS (i.e., buying electricity). For all other use cases, the agent can choose a continuous action between 0 and 1. We choose an hourly resolution and set the time horizon TH to 40, that is, the agent plans up to 40 hours ahead. This value is chosen because at 8 a.m., the time of the FCR auction, the end of the last FCR bidding block of the following day is exactly 40 hours away.

The duration of all service requests is one hour except in the case of FCR provision, where one block, if accepted, lasts 4 hours. For peak-shaving, we set the minimum purchase quantity to 1, i.e., the service requests can only be fully accepted. All other service requests can be partially accepted as well.

State space. As described in Section 8.3.3, the state space consists of the service request vector $Request_t$, the power vector P_t, the SoC vectors for BTM, FTM and FCR use cases as well as the forecast vectors. In the case study, we include a forecast each for the household load ($Forecast^{H}$), excess PV generation ($Forecast^{PV}$) and intraday prices ($Forecast^{ID}$) in the state space. To reduce the dimension of the state space and thus the complexity of the task that the DRL agent needs to solve, we condense the forecast vectors of household load and PV generation by calculating the mean value of 4 hour time windows. We align these windows with the time slots of the FCR bidding blocks. The vector of a forecast $fc \in [PV, H]$ is therefore defined as follows:

$$Forecast_t^{fc} = [\frac{1}{4}\sum_{s=t}^{t+4} forecast_s^{fc}, \frac{1}{4}\sum_{s=t+4}^{t+8} forecast_s^{fc}..., \\ \frac{1}{4}\sum_{s=t+TH-5}^{t+TH-1} forecast_s^{fc}] \tag{8.41}$$

The intraday forecast is not condensed and included as a vector of length TH. In the following, we describe the case study parameters and the data sources that were used for modeling the service requests.

8.4.1 Parameters and Data Sources

The parameters of the case study are shown in Figure 8.1. The hyperparameters used for the training of the PPO2 algorithm are shown in Figure 8.2. The BESS size is set to 30 kWh energy capacity and 15 kW power capacity and the efficiency for charging and discharging is set to $\eta = 0.95$, i.e., the round-trip efficiency is 0.95^2. We assume that the neighborhood consists of ten households and features 40 kW of installed PV power capacity, which corresponds to around five typical residential PV systems.

Table 8.1.: Parameters of the case study

Parameter	Assumption	Parameter	Assumption
BESS capacity	30 kWh	Households price	0.32 € kWh^{-1}
BESS power	15 kW	Peak Shaving price	1 € kWh^{-1}
BESS efficiency	95 %	FCR prices	scaled market data
PV capacity	40 kW	Intraday prices	scaled EPEX Spot ID3
PV price	0.8 € kWh^{-1}		

Table 8.2.: Hyperparameters

Hyperparameter	Value	Hyperparameter	Value
cliprange ϵ	0.2	learning rate α	2.50E-05
entropy coefficient β	0.01	# of steps	168
disocunt rate γ	1	# of minibatches	4
λ	0.95	# of epochs	48

The generation data for the PV generation is retrieved from *Renewables.ninja* (Pfenninger and Staffell, 2016, 2021; Staffell and Pfenninger, 2016), where we simulate the generation of a 40 kW solar PV power plant located in Karlsruhe, Germany. We assume a fixed price of 0.8 € kWh^{-1} for buying excess electricity from PV generation, which reflects the opportunity costs of current EEG feed-in-tariffs. The load data for the simulated household demand is retrieved from the dataset *Representative electrical load profiles of residential buildings in Germany* (Tjaden et al., 2021). From this data set, ten households are randomly sampled and aggregated to form the household demand of the community. We assume that PV generation will first be used directly by the households if possible, and therefore obtain the excess PV generation by subtracting the load from the PV generation profile. We assume a fixed remuneration of 0.32 € kWh^{-1} for supplying household load, which is based on the electricity price for German households in 2022 (see Chapter 1). For peak-shaving requests, we use an industrial load profile published by Huber et al. (2019). We assume a fixed price of 1 € kWh^{-1} for the peak-shaving service. This value is deliberately set very high, as the peak shaving requests occur infrequent and follow no obvious pattern. These requests are therefore the hardest to predict for the BESS service agent, so we want to set a high incentive for accepting them. The prices of the FCR auction are retrieved from the publicly available data of the German TSOs on *Regelleistung.net* (50 Hertz et al., 2022). For the intraday prices, we use data from *EPEX SPOT* (EPEX SPOT, 2021). For simplification, we choose the *ID3* to be the available price for intraday action, which is the weighted average price of the intraday transactions of the last three hours prior to delivery.

We sample all the available data into a resolution of one hour. We assume that the actions of the BESS do not influence market prices, i.e., this is a price taker model. As the FCR auction scheme was changed from weekly bidding blocks to daily bidding blocks in July 2019, we only use the market data from July 2019 onward. As we want to include an entire year in our test data, we test on the data from 2021 and train the model on the data from July 2019 until December 2020.

During the training period, the price level and spreads on the day-ahead and intraday markets are quite low, making it difficult for a BESS to generate any profits through trading. We therefore alter the available market data and increase the spreads of the intraday prices by 225 % for the training data and 125% for the test data. The lower value for the test data is chosen because of the unusually high market prices starting in mid 2021 to better align train and test data.

In addition, we scale the FCR prices by multiplying with 0.25 to create more situations in which FCR and PV use cases compete with each other. Especially during the test period, FCR prices had reached levels at which it was optimal to continuously provide full FCR bidding capacity. The near-optimal strategy could thus be easily implemented through a rule-based approach. The assumption of lower FCR prices is further motivated by the limited demand of the FCR auctions of around 600 MW. An analysis by Schäfer, C. (2021) shows that in 2021, already more than half of this demand was supplied by BESSs. We therefore assume that prices will fall as the number of participating BESSs increases and the market becomes saturated.

Forecasts. For the PV generation and household load forecasts that the agent observes during real-time observation, we multiply the true values with a random noise sampled from a normal distribution with a mean error of 0 and a standard deviation of 0.3 (i.e., 30% forecast error). In the case of PV generation and household load, multiplying the noise value with the actual generation value ensures that the forecast will not predict generation during the night. Furthermore, small absolute true values result in smaller forecast errors. In the case of intraday prices however, negative or zero values may occur and smaller values, i.e., prices close to zero, would not necessarily result in smaller forecast errors than higher values. Therefore, to create synthetic forecasts for the intraday prices, we add a random error onto the true values instead of multiplying it. The random error is randomly sampled from a normal distribution with mean zero and standard deviation 1.

8.4.2 Benchmarks

To compare the performance of the developed DRL-based BESS service agent, we consider three benchmarks: a theoretical optimum and two rule-based benchmarks. The theoretical optimum is determined through an optimization of the entire testing period with perfect foresight of all generation, consumption and price data using the Gurobi solver. The optimization solves the optimization problem displayed in (8.42). The decision variables are denoted with x for continuous variables and a for binary variables. Each decision variable is determined for every time step, i.e., every hour h on day d where D is the number of days in the considered time period. The algorithm decides how much electricity to buy ($x^{ID,buy}$) or to sell ($x^{ID,sell}$) on the intraday market, to charge from PV generation (x^{PV}) and to discharge for household consumption (x^{SC}) or peak-shaving (x^{Peak}). Further, the amount of bid capacity for FCR, x^{FCR}, is determined. In the first time step, the SoCs of FTM and BTM use cases, soc^{FTM} and soc^{BTM}, are set to zero (8.42a and b). The reserved capacity for FCR soc^{FCR} amounts to 15 minutes multiplied with the FCR bid capacity (8.42c). Furthermore, a constraint is added which ensures that soc^{FCR} is always smaller than the sum of soc^{FTM} and soc^{BTM} to ensure the ability to provide positive FCR (8.42d). Within each day d, the SoCs for BTM and FTM use cases are updated in (8.42e) and (8.42g), considering the charge and discharge efficiency η. The SoC at the beginning of a day is updated in lines (8.42f) and (8.42h). It is further ensured that the sum of the SoCs is not greater than the BESS's capacity Cap (8.42i), and that the sum of in- and out-flowing electricity is within the power limits (8.42j and k). The electricity charged from PV generation is limited by the available excess PV generation pv in that time step (8.42l). Similarly, the served household and peak load is limited by the household and peak load demand $load^{H}$ (8.42m) and $load^{Peak}$ (8.42n), respectively. We introduce the binary variable a^{Peak} to ensure that peak load can be either served entirely or not at all, in accordance with the minimum purchase quantity of 100% for peak-shaving use cases in the case study. In (8.42o), we ensure that FCR is only provided in blocks. That is, for every hour $b \in [0, 1, 2, 4, 5, 6, 8, 9, 10, 12, 13, 14, 16, 17, 18, 20, 21, 22]$, the FCR capacity bid must be equal to the successive hour. The binary variables $a^{ID,sell}$ and $a^{ID,buy}$ are needed to ensure that electricity is not simultaneously bought and sold on the intraday market in (8.42p) and (8.42q).

$$
\begin{array}{llll}
\max & \multicolumn{3}{l}{(\sum_{d=1}^{D}\sum_{h=0}^{23} x_{d,h}^{FCR}\cdot p_{d,h}^{FCR} + x_{d,h}^{SC}\cdot p^{SC} + x_{d,h}^{Peak}\cdot p^{Peak} - x_{d,h}^{PV}\cdot p^{PV}} \\
& \multicolumn{3}{l}{\quad +(a_{d,h}^{ID,sell}\cdot x_{d,h}^{ID,sell} - a_{d,h}^{ID,buy}\cdot x_{d,h}^{ID,buy})\cdot p_{d,h}^{ID})} \\
\text{s.t.} & soc_{1,0}^{FTM} = 0 & & (8.42a) \\
& soc_{1,0}^{BTM} = 0 & & (8.42b) \\
& soc_{d,h}^{FCR} = x_{d,h}^{FCR}\cdot 0.25h & \forall d\in D,\ \forall h\in[0,..,23] & (8.42c) \\
& soc_{d,h}^{FCR} \leq soc_{d,h}^{FTM} + soc_{d,h}^{BTM} & \forall d\in D,\ \forall h\in[0,..,23] & (8.42d) \\
& soc_{d,h+1}^{FTM} = soc_{d,h}^{FTM} + \eta\cdot x_{d,h}^{ID,buy} - \frac{1}{\eta}\cdot x_{d,h}^{ID,sell} & \forall d\in D,\ \forall h\in[0,..,22] & (8.42e) \\
& soc_{d+1,0}^{FTM} = soc_{d,23}^{FTM} + \eta\cdot x_{d,23}^{ID,buy} - \frac{1}{\eta}\cdot x_{d,23}^{ID,sell} & \forall d\in[1,..,n^D-1] & (8.42f) \\
& soc_{d,h+1}^{BTM} = soc_{d,h}^{BTM} + \eta\cdot x_{d,h}^{PV} & & \\
& \qquad -\frac{1}{\eta}\cdot(x_{d,h}^{SC} + x_{d,h}^{Peak}) & \forall d\in D, \forall h\in[0,..,22] & (8.42g) \\
& soc_{d+1,0}^{BTM} = soc_{d,23}^{BTM} + \eta\cdot x_{d,23}^{PV} & & \\
& \qquad -\frac{1}{\eta}\cdot(x_{d,23}^{SC} + x_{d,23}^{Peak}) & \forall d\in[1,..,n^D-1] & (8.42h) \\
& Cap \geq soc_{d,h}^{FTM} + soc_{d,h}^{BTM} + soc_{d,h}^{FCR} & \forall d\in D,\ \forall h\in[0,..,23] & (8.42i) \\
& -power \leq x_{d,h}^{ID,buy} - x_{d,h}^{ID,sell} + x_{d,h}^{PV} & & \\
& \qquad -x_{d,h}^{SC} - x_{d,h}^{Peak} & \forall d\in D,\ \forall h\in[0,..,23] & (8.42j) \\
& power \geq x_{d,h}^{ID,buy} - x_{d,h}^{ID,sell} + x_{d,h}^{PV} & & \\
& \qquad -x_{d,h}^{SC} - x_{d,h}^{Peak} & \forall d\in D,\ \forall h\in[0,..,23] & (8.42k) \\
& x_{d,h}^{PV} \leq pv_{d,h} & \forall d\in D,\ \forall h\in[0,..,23] & (8.42l) \\
& x_{d,h}^{SC} \leq load_{d,h}^{H} & \forall d\in D,\ \forall h\in[0,..,23] & (8.42m) \\
& x_{d,h}^{Peak} = a_{d,h}^{Peak}\cdot load_{d,h}^{Peak} & \forall d\in D,\ \forall h\in[0,..,23] & (8.42n) \\
& x_{d,b}^{FCR} = x_{d,b+1}^{FCR} & \forall d\in D,\ \forall b\in B & (8.42o) \\
& 1 \geq a_{d,h}^{ID,sell} + a_{d,h}^{ID,buy} & \forall d\in D,\ \forall h\in[0,..,23] & (8.42p) \\
& x_{d,h}^{ID,sell} + x_{d,h}^{ID,buy} = a_{d,h}^{ID,sell}\cdot x_{d,h}^{ID,sell} + a_{d,h}^{ID,buy}\cdot x_{d,h}^{buy} & \forall d\in D,\ \forall h\in[0,..,23] & (8.42q) \\
& 0 \leq x_{d,h}^{FCR}, x_{d,h}^{SC}, x_{d,h}^{Peak}, x_{d,h}^{PV}, & & \\
& \qquad x_{d,h}^{ID,sell}, x_{d,h}^{ID,buy} & \forall d\in D,\ \forall h\in[0,..,23] & (8.42r) \\
& power \geq x_{d,h}^{SC}, x_{d,h}^{Peak}, x_{d,h}^{PV}, x_{d,h}^{ID,sell}, x_{d,h}^{ID,buy} & \forall d\in D,\ \forall h\in[0,..,23] & (8.42s) \\
& x_{d,h}^{FCR} \geq power\cdot\frac{1}{1.25} & \forall d\in D,\ \forall h\in[0,..,23] & (8.42t) \\
& a_{d,h}^{ID,sell}, a_{d,h}^{ID,buy}, a_{d,h}^{Peak} \in [0,1] & \forall d\in D,\ \forall h\in[0,..,23] & (8.42u)
\end{array}
\tag{8.42}
$$

Finally, the limits of the decision variables are set. All continuous variables must be greater than 0 (8.42r) and smaller than the power limit (8.42s), with the exception of FCR that requires a safety buffer of 25% and therefore cannot be greater than 12 kW (8.42t).

The two rule-based benchmarks are either (i) the continuous provision of FCR during the entire test period or (ii) the provision of no FCR at all. All requests from PV, household load and peak-shaving services are accepted in the order in which they arrive by both rule-based benchmarks. For the benchmarks, the agent does not trade on the intraday market, as no simple rule-based strategy can be deployed for the uncertain price trajectory while considering the trade-off with the other use cases. Note that the continuous maximum FCR provision does not severely restrict the acceptance of other use cases. As the maximum bid on the auction is 12 kW, only a total of $2 \cdot 0.25h \cdot 12kW = 6kWh$ of energy capacity is unavailable for other use cases, leaving the majority of the BESS's energy capacity of 30 kWh available for other use cases.

8.4.3 Results

We train the developed DRL-based BESS agent for 5 million steps. After around 3 million steps, the reward converges. We then test the trained model on one year of data. Figure 8.5 shows the performance of the DRL-based model in comparison with the rule-based benchmarks and the theoretical optimum. The detailed revenue streams of all five types of service requests are listed in Table 8.3. The DRL-based agent achieves annual profits of 2,184 €, which is 28% better than the benchmark with constant FCR provision and 10% above the benchmark without FCR provision. The DRL-based model further achieves 61% of the theoretical optimum, which is a good performance, considering that the optimum is only theoretical as it is able to exploit every single spread on the intraday market with perfect foresight and to optimally balance all use cases. This also becomes evident in the high profit share of trading revenues in the theoreical optimum. In the optimum, the joint revenues of BTM and FCR use cases is lower than in the case of the DRL agent and the benchmark without FCR provision. It needs to be noted that degradation is not considered and therefore the intraday profits might be overestimated, since it has been suggested that trading leads to overproportional cyclical degradation (Perez et al., 2016).

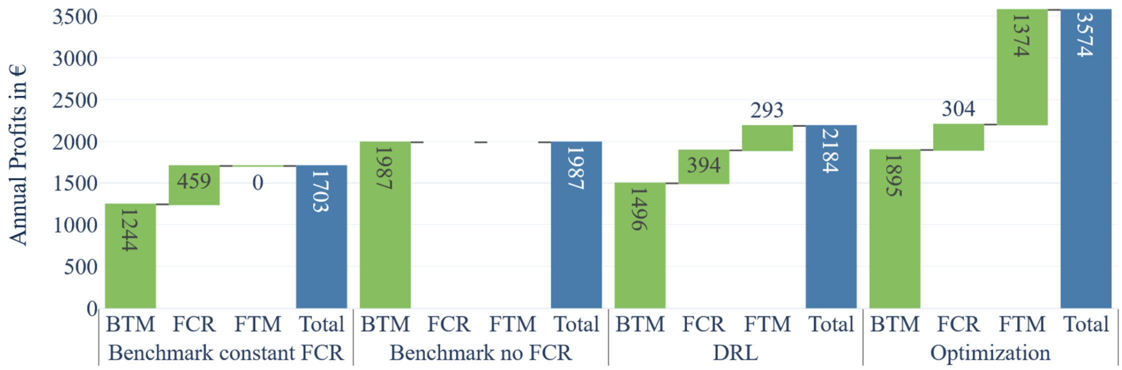

Figure 8.5.: Comparison of the annual profits achieved by the DRL agent, theoretical optimum and rule-based benchmark strategies

The use case peak shaving occurs relatively rarely during the testing period, with a total service request volume of 92 kWh during the entire year. Both rule-based benchmarks and the DRL agent manage to accept roughly half of these requests whereas the theoretical optimum serves around 70 kWh of peak load.

Table 8.3.: Revenues streams of DRL-based BESS agent and benchmarks

Revenues in €	Households	PV	Peak-Shaving	FCR	Trading	Total
Benchmark “constant FCR”	1,669	-466	41	459	0	1,703
Benchmark “no FCR”	2,696	-750	41	0	0	1,987
DRL	2,038	-582	41	394	293	2,184
Optimization	2,532	-707	70	304	1,374	3,574

A closer look at an exemplary week of the SoC occupation of the optimization reveals that at some times, the ideal strategy is to accept FCR requests almost continuously, with the exception of time windows in which the BESS can be fully charged with excess PV generation (compare July 2021 in Figure 8.7). If however intraday price spreads are large enough to generate more profits, significantly less FCR is provided, as seen in the SoC of February 2021 (Figure 8.6).

The DRL agent seems to learn an FCR provision pattern similar to the optimum in July for the entire test year. This seems logical, as “optimal” intraday trading is much harder for the agent to learn and it therefore relies on the “safe” earnings from steady FCR provision. The agent leaves out an FCR bid block in the morning, which allows to utilize more of its energy capacity for BTM use cases, i.e., charging excess PV generation.

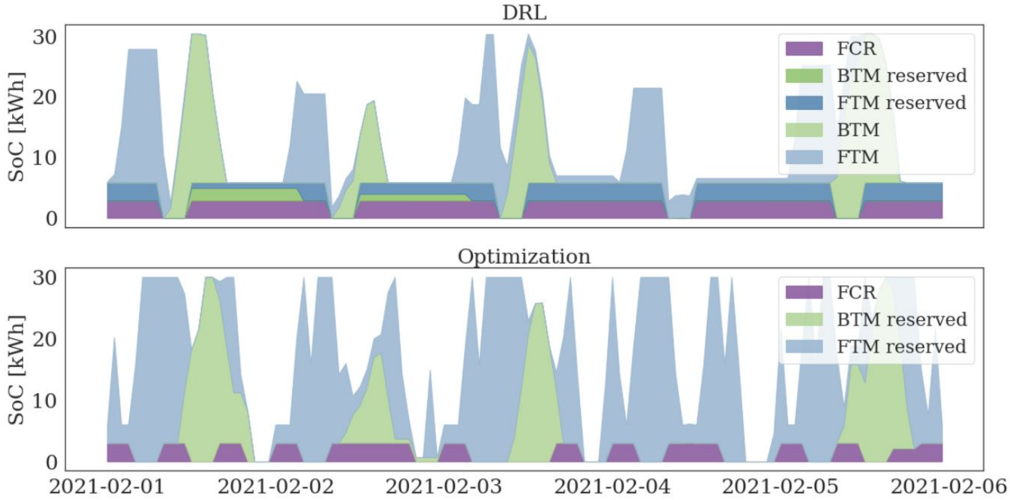

Figure 8.6.: Comparison between the SoC occupation of the DRL-based operation and the theoretical optimum in February

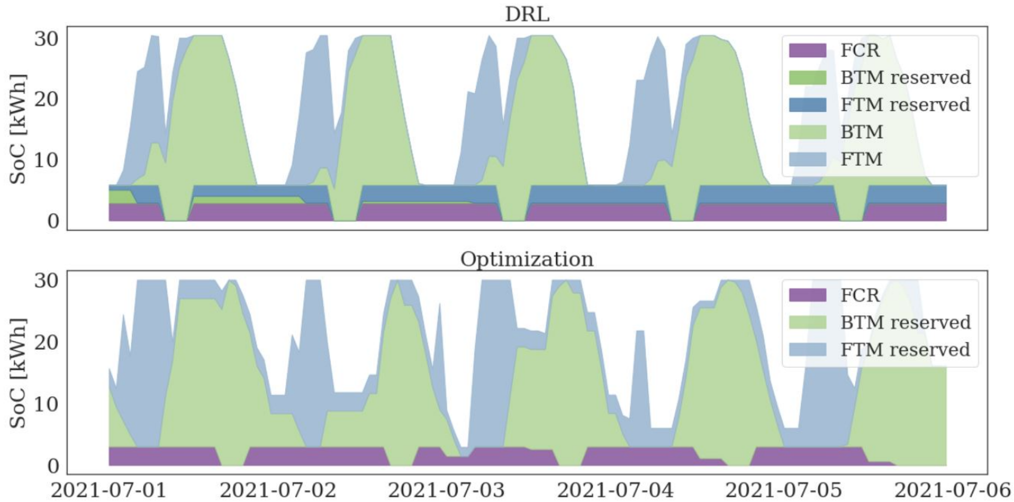

Figure 8.7.: Comparison between the SoC occupation of the DRL-based operation and the theoretical optimum in July

In general, the DRL agent seems to learn various kind of patterns. For example, a similar occupation of FTM use cases can be observed in the first week of July 2021 displayed in Figure 8.7, where the DRL agent uses the times in the morning before PV generation starts to generate profits on the intraday market. This strategy further allows the agent to reserve electricity from FTM use cases instead of BTM use cases, as can be seen by the reserved blocks.

In summary, we show that the DRL outperforms both benchmarks in our case study and is able to handle the complex interplay of several use cases and uncertainties. This is a novel finding as our model is more complex than previous DRL-based multi-use BESS operation strategies and, to the best of our knowledge, we are the first ones to benchmark the performance of the DRL agent against comparable rule-based strategies. In the following, we discuss some limitations of the presented case study.

8.5 Discussion

This chapter shows promising results for the deployment of a DRL algorithm to solve the online operation problem of a multi-use BESS. Moreover, the agent has to handle the use cases as they would appear in reality, i.e., both in the form of continuous requests and auctions that require several actions at one time step. The proposed model could therefore be deployed in practice as well. We further demonstrate a novel modeling approach for BESS operators by modeling use cases as service requests, which are part of the agent's observations. There are however several limitations to this work, which motivate future research in this area.

One drawback of DRL in general is the difficult interpretation of the agent's actions. From Figure 8.7, it seems that the DRL agent learns cyclical patterns at least to some extent. There are however deviations, as can be seen in the SoC of FTM use cases. It is unclear what steers the agent's actions in this regard and, for example, to what extent it relies on the forecasts for its decisions. In the specific case of our multi-use DRL model, the interpretability becomes additionally difficult through the (necessary) deployment of the SCA and BA. Since the agent's actions are altered without the explicit knowledge of the agent, the agent might have difficulties in understanding the consequences of actions in general. This problem is an ongoing topic of research in the DRL discipline. In the context of energy systems, Chen et al. (2021a) propose a first solution to facilitate the learning of DRL agents that need to learn boundaries of physical systems. In the study, a feasibility layer is introduced, which projects a set of chosen actions to the nearest feasible set of actions (constrained by the physical system) through an optimization approach. Since this layer is incorporated into the neural network, in contrast to the clipping approach, the agent can observe the alterations of the actions. Future research could apply this principle to the problem at hand. The introduced case study however uses a quite simple model, and it is subject to future research whether the principle can be applied to more complex models like the one introduced in this chapter.

In our case study, service requests for BTM use cases as well as intraday trading are all handled in real-time, i.e., the service needs to be provided immediately. Other configurations are thinkable here as well, for example, that peak-shaving requests arrive earlier (compare Chapter 7). Furthermore, the submitters of service requests could anticipate other participant's behavior and try to gain advantages through strategic behavior. This interaction of several agents is disregarded in this chapter and could be incorporated through an agent-based simulation in future research.

8.6 Conclusion

In this chapter, we introduce and evaluate the implementation of a StaaS inspired BESS service agent with a DRL-based approach. We demonstrate that the data-driven agent can handle multiple use cases, both from an auction and continuous markets and therefore extend previous research by a more complex model that can be deployed during real-time. Our results show that the DRL agent outperforms comparable rule-based benchmarks by 10 to 28% and achieves 67% of the theoretical optimum in the considered test year.

This chapter concludes Part III of this thesis on data-driven operation strategies for BESSs. On all levels of energy systems, data-driven methods are demonstrated to handle uncertainties during real-time operation. In front of the meter, a classification-based strategy for a renwable operator is designed in Chapter 6 and shown to reduce the operator's financial risk. Behind the meter, risk averse planning behavior based on a probabilistic forecast has relatively low, if any, negative effects on the profitability of an industrial BESS deployed for joint peak-shaving and FCR provision (Chapter 7). Finally, a DRL-based multi-use BESS operation strategy is shown to outperform comparable rule-based operation strategies in Chapter 8.

In the following, a summary of the results and implications of the thesis is given in Chapter 9 and an outlook on promising future research paths is provided in Chapter 10.

Part IV.

Finale

CHAPTER 9

CONTRIBUTION AND IMPLICATIONS

Future low-carbon, largely electrified energy systems will need substantial BESS capacity to integrate large shares of intermittent RESs (Bründlinger et al., 2018; Weitemeyer et al., 2015). The expansion of small-, medium- and grid-scale BESSs must therefore be accelerated while considering the differing goals and requirements of BESS deployment on different levels in the power grid. To this end, this dissertation contributes to a holistic understanding of BESS deployment and operation on all levels of integrated energy systems.

On the individual level, I investigate the promotion of BESS deployment and analyse how existing resources can be deployed more effectively by connecting several individuals in an energy community. I analyse BESS requirements on the system level, which can guide policy-makers in the design of an appropriate regulatory framework that further incentivizes investments on the lower aggregation levels. Furthermore, I design and investigate data-driven operational strategies that facilitate a real-time operation of BESSs at these various levels of energy systems for FTM, BTM and combined applications. In this chapter, the findings of this dissertation are summarized along the seven research questions proposed in Chapter 1.

In Part II of this thesis, BESS deployment across all aggregation levels is analysed. Residential decision-makers who contribute to the expansion of BESSs on an individual level are in the focus of Chapter 3. I find that an informative website on energy-related technologies in buildings significantly increases the intention to use and to recommend the website if it contains vivid and interactive features (as opposed to a static website with purely textual information). Likewise, the perceived knowledge of users is higher when using the animated website, although this does not apply to the measured objective knowledge. This validates the identical information content of the two tested treatments and gives clues about the importance of the subjective user experience. While the observed effects can directly be attributed to the vivid design elements, the effects of interactive features are inconclusive, as they may pose an additional cognitive burden to users. The results provide important insights for the design of information material to promote residential BESS installation and to increase energy literacy among non-experts. Interactive features should be designed carefully and future research could investigate target-group specific effects and requirements.

On a higher aggregation level, individuals can be connected to form an energy community and to increase the utilization and profitability of PV-coupled BESSs. In Chapter 4, I show that on average, 615 € of annual profits can be realized in a community of five households with annual electricity consumption magnitudes that are typical for German households. Accordingly, the utilization of BESSs within the community can be increased from an average of 280 to 320 annual cycles. However, the profits of the community vary significantly and participants of such a sharing community should be carefully selected depending on load patterns and properties. In addition, I show that a set of fixed prices for the shared goods can ensure a fair distribution of profit shares among participants in most cases. In the study, I assume that the neighborhood is allowed to operate in a setting of privileged self-consumption. The regulation therefore would have to be adapted in the case of energy communities to facilitate the demonstrated local integration of RESs and a higher utilization of idle storage capacities, which is envisioned by the European Union under the term of Citizen Energy Communities.

In order to design the correct incentive schemes, it is important to know how much BESS capacity is necessary on a system level. On this level, I design a bottom-up methodology to determine BESS requirements in integrated energy systems that allows to consider particularities on lower aggregation levels. In a case study for the state of BW, I show that in a scenario with a 95% share of RES generation, 6.8 GWh of BESS energy capacity are required under central planning while 128 GWh are needed under decentral planning. The LCOE more than double from

42 € MW^{-1} to 94 € MW^{-1} under central vs. decentral planning. Realizing the low costs of central planning would however require an extreme concentration of RESs within few selected regions within BW, some of which are already known to be in opposition to certain power installations. An in-between planning approach leads to storage requirements of 52 GWh and LCOE of 64 € MW^{-1}. These results motivate future research on the acceptance of transition paths towards decarbonized energy systems, and the quantification of the benefit of increased acceptance in terms of acceptable additional costs.

In summary, Part II of this thesis contributes to a holistic understanding of BESS deployment on different aggregation levels of integrated energy systems. In this regard, three key contributions can be derived from these analyses: First, since individual decision-makers take a center stage in the expansion of BESS, they need to be provided with transparent information to increase energy literacy and subsequently evaluate investment decisions on energy-related technologies, including PV-coupled BESSs. This information can be conveyed through an informative website in an engaging manner, using vivid visualization elements and (carefully designed) interactive features. Second, once individuals have invested in storage capacity its utilization should be maximized. In order to increase BESS utilization and subsequently to realize more profitable investments, consumers and prosumers within a residential neighborhood could engage in a sharing economy for decentral RES and BESS resources. The suitability of participants and agreements for profit-sharing mechanisms need to be carefully evaluated and chosen in these settings. This way, (citizen) energy communities can contribute optimally to the BESS requirements of an integrated energy system. These requirements have to be analysed on a system level to guide policy-makers in the design of regulatory measures. Therefore, third, when planning pathways towards low-carbon integrated energy systems, the view of a central planner should be expanded by decental perspectives in order to discuss and factor in cost trade-offs and acceptance issues regarding the spatial distribution of RES and BESS capacities at an early stage.

These findings therefore have important implications for policy-makers as well. Transparent information needs to be available and accessible for individuals to facilitate decision processes. An exemplary tool in this regard is the "Energy Atlas

Baden-Württemberg" provided by the government of BW (LUBW, 2022). These kind of tools and websites need to be designed according to the needs of potential users to facilitate a dissemination of the available information. Furthermore, individuals should be able to connect decentrally and to engage in a joint utilization of available generation, consumption and BESS resources. On this level, regulation could further provide incentives that ensure a grid-friendly operation of decentral resources. Finally, policy-makers need to take local and regional acceptance into account when designing pathways towards decarbonized energy systems. The view of a central planner disregards potentials in areas with greater acceptance and may lead to an extreme spatial concentration of RES and BESS capacities within a system and a corresponding high burden for the affected communities. These factors need to be taken into account at an early stage by policy-makers.

BESS deployment needs to be planned and promoted on all aggregation levels of integrated energy systems. For an effective utilization of these BESS resources, online operational strategies are needed to address uncertainties that lead to inefficiencies during real-time operation. Therefore, in Part III of this thesis, I design, evaluate and discuss data-driven operation strategies for the real-time operation of BESSs, thereby considering the differing requirements of stakeholders on different aggregation levels participating in various BTM and FTM use cases. In Chapter 6, I take the perspective of a large renewable operator in front of the meter who uses a grid-scale BESS to reduce the risks of directly marketing her generation on the day-ahead spot market. The results show that a classification-based heuristic operation strategy can reduce the CVaR between 28% and 57% and on average by 38.5% in the five (summer) months that were considered in the case study. In this study, I assume that the BESS can be accessed as service provider, which motivates research on the perspective of such a BESS service agent and which is addressed in Chapter 8.

Behind the meter, an industrial plant operator can increase the utilization of a BESS deployed for industrial peak-shaving utilization by simultaneously participating in the FCR auction. In Chapter 7, I show that risk-averse planning behavior, realized through a probabilistic forecast, has no or only small negative effects on the annual revenue streams in the analysed case studies of four companies. Only in the case of one company, planning on the 95^{th} forecast percentile results in 10% lower profits, whereas the risk of missing a critical peak is substantially reduced. In one case, moderate risk-averse planning behavior (i.e., planning on the 75^{th} or 90^{th} forecast percentile) even slightly increases the annual profits by 3% because times of peak demand could be better anticipated than in the case of risk-neutral planning. Overall, the results indicate that risk-averse planning can be a reasonable operational strategy for industrial BESS operators for peak-shaving. Future research could take other application areas, e.g., spot market trading into account to further increase the BESS's utilization and profitability. This will however likely lead to larger monetary trade-offs when relying on risk-averse vs. risk-neutral planning strategies, as more uncertainties come into play.

Combining several BTM and FTM applications, several small- and medium-scale BESSs could be pooled together by means of a StaaS platform that allocates service requests. In Chapter 8, I design and evaluate an environment for a DRL-algorithm that handles these service requests during real-time operation. Combining all four application areas introduced in Figure 2.3, the results show that through its ability to better coordinate between applications, the DRL algorithm achieves 10 to 28% higher annual profits than a comparable rule based benchmark strategy.

The research in Part III of this thesis contributes to the development of online operation strategies for BESSs that can be deployed during real-time operation through the utilization of data-driven approaches. For a large renewable operator, a rule-based strategy based on a classification approach can substantially reduce the risk associated with the direct marketing of generation from RESs. In the case of an industrial plant, planning based on a probabilistic forecast reduces the risk of missing critical peaks while still allowing the generation of substantial revenues through FCR provision. Finally, I show the potentials of DRL, a promising data-driven approach for sequential decision-making that can be applied to the case of a multi-use BESS and deployed during real-time. These findings show the potential of data-driven approaches to facilitate BESS operation across all aggregation levels of power systems and to address various stakeholder needs in the process. In this respect, policy-makers are challenged to create the necessary regulatory framework to allow a versatile deployment of BESSs, e.g., by ensuring that all BESSs are given (unbureaucratic) access to local applications as well as to wholesale markets. Only in this way can idle capacities be avoided and BESSs be deployed as effectively as possible in integrated energy systems. Innovative business models, such as a StaaS platform as proposed in Section 2.6, are also needed to pool and efficiently allocate decentral resources.

In conclusion, this thesis analyses and recommends measures for the promotion and facilitation of BESS deployment in energy systems with intermittent renewable generation. The results support policy-makers in designing corresponding regulation, aggregators and storage operators in their operation strategies and researchers in investigating future low-carbon energy system scenarios. Thereby, this thesis contributes to the promotion and efficient utilization of BESS resources and it thus supports the integration of high shares of sustainable power generation in low-carbon energy systems.

CHAPTER 10

OUTLOOK

The results of this thesis point to promising avenues for future research.

First, when planning BESS deployment in integrated energy systems, all aggregation levels must be considered. This particularly includes the lower aggregation levels and individual, non-expert decision-makers. German households have driven the expansion of PV and BESS in past years and hold the potential to further accelerate this movement (Weitemeyer et al., 2015). The research in Chapter 4 of this thesis provides first insights into the design of engaging informative websites to increase energy literacy of individual, residential decision-makers. However, as the energy transition progresses, a diverse spectrum of individuals has to be reached and accordingly, the needs of various target groups have to be addressed. According to the diffusion of innovation process by Rogers (2003), the adapters of innovative technologies such as PV and BESSs can be divided in the sub-groups “Innovators”, “Early Adopters”, “Early Majority”, “Late Majority” and “Laggards”. In past research, these stages of adoption could be linked to media coverage and other communication channels in the case of PV installations (Dehler et al., 2019). Future research should establish an understanding of current and future adopter characteristics in the case of residential BESSs and subsequently derive requirements to reach and engage these target groups. To include diverse perspectives and backgrounds throughout this process, *Citizen Science* is a promising research approach to engage relevant target groups and to design measures according to their needs.

Second, in this thesis, a centralized planning approach of RES and BESS expansion requirements is critically examined and contrasted with a decentralized approach. Many questions in the field of local acceptance research follow from these observations. In particular, a quantification of the negative or positive effects of absent or existing acceptance is missing. In purely techno-economic planning models, decentralized planning approaches inevitably lead to higher costs than centralized approaches. However, the centralized approaches do not consider the price of social opposition low public acceptance in the process of RES or BESS expansion. This can lead to significant delays in the realization of RES and BESS projects and thus also cause significant costs and negative climate effects. It is therefore questionable, whether a central planning approach is indeed the most cost-efficient option. While a decentral planning approach does not necessarily lead to more acceptance, it is a first step towards a more equal inclusion of different regions into the transition towards a decarbonized energy supply. Future research should develop cost mechanisms addressing the acceptance and categorize regions according to their acceptance potential, similar to what is already being done with physical potential in the case of RESs, e.g., through the "Energy Atlas Baden-Württemberg" (LUBW, 2022). Likewise, targeted measures to increase general acceptance or reduce opposition need to be developed and implemented to facilitate the transition towards decarbonized integrated energy systems.

Third, this thesis proposes several data-driven strategies to facilitate real-time BESS operation and to achieve the goals of various stakeholders. In a smart, integrated energy system, decentral resources could be pooled together through a StaaS platform. First insights into potential agent behavior on this platform are presented in this thesis. It is worthwhile to also model and analyse the interactions of different agents on such a platform. This could be implemented and investigated through an agent-based model of the StaaS platform. In particular, the bidding behavior of the participants, the coordination and allocation algorithms of the platform, and the pricing model of the platform operator are aspects that should be further considered. Additionally, the potential of aggregators and automated bidding agents should also further be investigated.

From a regulatory perspective, policy-makers face several challenges but also opportunities to accelerate BESS deployment across all levels of power systems and to facilitate an effective utilization of existing resources. On an individual level, besides transparent and engaging information, concrete financial programs can leverage the expansion of decentral technologies, similar to feed-in tariffs for renewable generation. Furthermore, the regulatory framework for the deployment of BESSs needs a holistic revision and adjustments in several aspects. Based on the synthesis of the expert interviews on innovative storage regulation, a list of recommendations for regulatory adaptions is derived (see Appendix 1.3), supported by a legal assessment regarding the implementability of the suggestions in German law. These suggestions are a starting point for a discussion on regulatory changes that allow easy access to markets and multi-use deployment for BESSs on all levels of energy systems. Lastly, local and global decision-makers are challenged to facilitate a widespread deployment of RESs and BESSs, not only through regulatory changes, but also by transparently communicating goals and necessary actions to achieve those goals. This is the foundation for creating the necessary acceptance and for involving all citizens in the design of a low-carbon energy system.

Appendices

APPENDIX 1.1: LITERATURE REVIEW SEARCH STRING AND TABLE

Search string for the structured literature review on multi-use BESS deployment.

TITLE(BESS* OR „energy storage“ OR „electricity storage“ OR „storage system“ OR „battery storage“ OR „battery system“ OR „stationary battery“ OR („battery“ AND („arbitrage“ OR „ancillary service“ OR „frequency regulation“ OR „frequency containment“ OR „peak shaving“ OR „self consumption“ OR „multi“ OR „energy system“))) AND

(Battery) Storage

ABSTRACT(„multi* service“ OR „multi* use“ OR „multi* objective“ OR multitask* OR „combin* application“ OR „multiple applications“ OR „multiple revenue“ OR „aggregat* services“ OR „sharing economy“ OR „shar* storage“) AND

Multi-Use

ABSTRACT(„frequency control“ OR „frequency regulation“ OR „ancillary services“ OR „self consumption“ OR „arbitrage“ OR „peak shaving“ OR „peak load“ OR „peak demand“ OR „load shifting“ OR auction* OR „control reserve“ OR „spinning reserve“ OR „standby power“ OR „balancing market“ OR „power market“ OR „wholesale W/2 market“)

Application Area

APPENDIX 1.2: EXPERT INTERVIEW QUESTIONNAIRE

All questions are translated from original German.

1. General BESS deployment and in the context of the expert's organisation
    a) In which concrete projects or applications is the deployment of BESSs realized or researched by [organisation name]?
    b) How do you assess the future potential for the deployment of BESSs?
    c) Which stakeholders do you see in the role of the storage operator?
    d) In your opinion, what is the approximate share of the following battery storage applications for achieving the climate targets (80 to 95% RESs)? Residential BESSs, Community BESSs, Grid-scale BESSs
    e) Which application area of stationary BESSs do you think has the greatest potential for growth in terms of capacity in Germany by 2025?
    f) In your opinion, what are the greatest regulatory challenges for an economic storage operation in Germany?
2. Assessment of the current regulation
    a) Which regulatory barriers does your organisation currently face regarding BESS deployment?
    b) What will the amendment to the EnWG and EEG 2021 change for you in this regard?
        i. Does this open up new application areas and economic potentials for your organisation?
        ii. How do you assess the dynamization and a reform of the network charge system?

c) How do you assess the current regulation for BESS deployment regarding other stakeholders (e.g., residential and community BESSs and their operators)?

d) Which other bureaucratic hurdles do BESS projects face (e.g., citizens' initiatives)?

3. Requirements for future regulation

a) If you could completely"rethink" regulation for (battery) storage, how do you envision innovative regulation that would make it possible to meet the requirements for (battery) storage in future, decarbonized energy systems?

b) What would be the most important aspects for you that this regulation would have to include (3-5 points)?

c) Let's go back to the current regulation. Which regulatory changes are still necessary for the meaningful deployment of BESSs by [your organisation] and other stakeholders?

i. How should surcharges and network fees be dealt with during spot market trading?

ii. What will change as a result of the fact that, according to the coalition agreement, energy storage systems will be anchored as fourth pillar in the energy law?

iii. Which bureaucratic hurdles can be removed?

iv. Which regulatory changes are needed to enable multi-use deployment of BESSs (e.g., for self-consumption, electricity trading, and flexibility services) beyond the current possibilities?

d) How can multi-use BESS deployment be realized without balance sheet manipulation?

e) How can regulation incentivize grid-friendly BESS deployment, e.g., as flexibility service provider?

f) Are government or private subsidy projects needed to stimulate more BESS expansion?

g) Should the heterogeneous regulatory environment within the EU be harmonized?

4. Realization of innovative Regulation

   a) What possibilities exist at the state level (especially Baden-Württemberg) to implement these regulatory changes?

   b) How can a constant development of the regulation be ensured (e.g., via an expert council à la California)? How can it be ensured that the regulation remains up to date?

   c) Do you have any further remarks that you would like to share?

APPENDIX 1.3: RECOMMENDATIONS FOR ACTIONS ON REGULATORY CHANGES TO SUPPORT STORAGE EXPANSION

This list of recommendations for regulatory changes towards regulation that facilitates storage expansion was derived from eight expert interviews along the questionnaire from Appendix 1.2. Note that not all recommendations are supported by all experts, and that some experts even were explicitly against some of the gathered recommendations. The recommendations are specifically targeted at supporting a wide-spread storage expansion. It is then up to the regulator and policy-makers to decide how much storage expansion is wanted and which measures are desireable to achieve this expansion.

The recommendations were legally assessed by a law firm in the field of energy regulation regarding their implementability. Two categories were assessed: (i) Compatibility with higher-ranking law and (ii) system conformity/complexity. The rating is displayed below with the help of a traffic light categorization. The colors have the following meanings:

- Green: (i) There are no concerns with regard to compatibility with higher-ranking or (ii) the recommendation for action fits into the existing regulatory system or the implementation is rather less complex.
- Yellow:(i) There are some concerns with regard to compatibility with higher-ranking or (ii) the recommendation for action does not necessarily fit into the existing regulatory system or the implementation is rather complex.
- Red: (i) There are strong concerns with regard to compatibility with higher-ranking or (ii) the recommendation for action does not fit into the existing regulatory system or the implementation is almost impossible.

1. There should be an independent, technology-neutral storage definition in the German energy law. [Compatibility, Complexity]

2. The EnWG must be amended to include the definition of temporal displacement. This should be oriented along the model of the Directive (EU) 2019/944 for the Internal Electricity Market. [Compatibility, Complexity]

3. The provision of storage power capacity or the procurement of corresponding services via third parties should be included in the network development plan. [Compatibility, Complexity]

4. The verification obligation (*Nachweisverpflichtung*) of peak capping must already take effect at 1%, instead of at 3%. [Compatibility, Complexity]

5. The 25% rule from the EEG 2004, regarding the connection of generation plants to the grid, has to be be adapted to the current investment costs of PV plants or the grid expansion must be extended by a flexibility mechanism. [Compatibility, Complexity]

6. The still existing double burdens for battery storage should be removed. [Compatibility, Complexity]

7. BESSs are to be completely exempted from surcharges and grid fees when engaging in spot market trading. [Compatibility, Complexity]

8. The grid charges need to include a power price component with a charge per kW. [Compatibility, Complexity]

9. A storage market should be implemented analogously to the market for reserve energy (§ 13e EnWG). (was not subject to legal assessment)

10. When a BESS is installed in combination with a PV system, a bonus cent should be awarded on top of the feed-in tariff. [Compatibility, Complexity]

11. For BESSs that are subsidized by the "PV + storage" program, the inverter can currently be curtailed to 50% of its output instead of the usual 70%. This should be abolished, as it is an incentive not to acquire a BESS. [Compatibility, Complexity]

12. A principle of "mutual recognition" should be implemented regarding distribution system operators (DSO) in order to reduce bureaucratic hurdles. In this way, the inspection and approval of a BESS's operation by one DSO would suffice (in contrast to, in the worst case, the approval of all 900 German DSOs).

13. In order to secure customer rights and to set clear deadlines to the DSOs, the systematics of the "supplier change" (*Lieferantenwechsel*) should be transferred to the following processes: Direct marketing of PV electricity and access to flexibility markets for BESSs. [Compatibility, Complexity]

14. Multi-use BESS operation should be possible when applications are separately acocunted for. This can be realized through the 2-meter approach of the BVES.

15. It must be possible to account for green electricity in the BESS in order to solve the solve the problem of the "exclusivity principle" *Ausschließlichkeitsprinzip* ([Compatibility). Complexity]

16. Regulation for energy communities, especially with regard to community BESSs, must be simplified and formulated in a way that is understandable for non-experts, so that no external, legal companies need to be consulted. (was not subject to legal assessment)

17. Federal states should be able to set deadlines for the federal government regarding the realization of BESS projects. [Compatibility, Complexity]

APPENDIX 3.1: ADAPTED ITEMS, VALIDITY AND RELIABILITY INDICATORS

Results for second experiment (replicability study with prolific participant tool) are reported in brackets: *(value)*

Constructs	Items (adapted)		Outer Loadings	α	CR	AVE
Interactivity*	INT1	I am able to interact with the energy information website.	.899 *(.907)*	.828 *(.817)*	.919 *(.916)*	.850 *(.845)*
	INT2	The presented information can respond to my input on this website.	.945 *(.931)*			
Vividness*	VIV1	The presentation of energy related technologies on the EIW is animated.	.837 *(.885)*	.881 *(.906)*	.918 *(.934)*	.737 *(.780)*
	VIV2	The presentation of energy related technologies on the EIW is lively.	.930 *(.953)*			
	VIV3	I can acquire information on the EIW from different sensory channels.	.820 *(.805)*			
	VIV4	The EIW contains information about energy related technologies exciting to senses.	.843 *(.884)*			
Perceived usefulness**	PU1	Using the EIW improved my informedness towards energy related technologies.	.930 *(.972)*	.915 *(.975)*	.940 *(.983)*	.798 *(.952)*
	PU2	The presentation of energy related technologies on the EIW is lively.	.932 *(.979)*			
	PU3	Using the EIW make it easier to be informed about energy related technologies.	.900 *(.976)*			
	PU4	I find the EIW to be useful in being informed about energy related technologies.	.806 *(rem.)*			

Intention to use***	IU1	Assuming I have access to the EIW, I intend to use it next time I want to inform myself about energy related technologies.	.978 *(.982)*	.979 *(.975)*	.985 *(.983)*	.957 *(.952)*
	IU2	Assuming I have access to the EIW, I predict I would use it next time I want to inform myself about energy related technologies.	.983 *(.978)*			
	IU3	Assuming I have access to the EIW, I plan to use it next time I want to inform myself about energy related technologies.	.974 *(.967)*			
Intention to recommend^{+}	IR1	I will recommend to my friends to visit the EIW.	.947 *(.958)*	.941 *(.934)*	.962 *(.958)*	.895 *(.884)*
	IR2	Because I had a good experience with it I will recommend my friends to visit the energy information website.	.969 *(.964)*			
	IR3	I would recommend the energy information website to someone who seeks my advice.	.921 *(.896)*			
Knowledge improvement^{++}	K1	The EIW increases my knowledge	.729 *(.821)*	.816 *(.796)*	.871 *(.867)*	.575 *(.621)*
	K2	I catch the basic ideas of the knowledge taught.	.719 *(.802)*			
	K3	I try to apply the gained knowledge directly in the EIW.	.807 *(.715)*			
	K4	The EIW motivates the user to integrate the knowledge taught.	.852 *(rem.)*			
	K5	I want to know more about the knowledge taught.	.672 *(.809)*			

Enjoyment+++	ENJ1	The use of the EIW is a fun activity.	.923 *(.953)*	.908 *(.925)*	.871 *(.947)*	.693 *(.817)*
	ENJ2	The user interface of the EIW is enjoyable.	.802 *(.836)*			
	ENJ3	The use of the EIW arouses my curiosity.	.930 *(.928)*			
	ENJ4	The use of the EIW stimulates my imagination.	.885 *(.895)*			
Perceived diagnosticity*	DIAG1	The EIW is helpful for me to evaluate energy related technologies.	.823 *(.887)*	.778 *(.810)*	.871 *(.888)*	.693 *(.726)*
	DIAG2	The EIW is helpful in familiarizing me with energy related technologies.	.863 *(.873)*			
	DIAG3	The EIW is helpful for me to understand the performance of energy related technologies.	.809 *(.794)*			

CR = Composite Reliability, α = Cronbach's alpha, AVE = Average Variance Extracted, rem. = item removed to establish discriminant validity

*: Jiang and Benbasat (2007)
**: Venkatesh and Davis (2000)
***: Venkatesh et al. (2003)
+: Naranjo-Zolotov et al. (2019)
++: Fu et al. (2009)
+++: Martínez-Torres et al. (2008)

APPENDIX 3.2: ADDITIONAL SCALES (TRANSLATED FROM ORIGINAL GERMAN)

Constructs	Items (adapted)
Acceptance of renewable energies in general*	In principle, I am a person in favor of renewable energies.
	In principle, I am opposed to renewable energy.
	In all, I am in favor of renewable energy plants in my immediate area.
	In principle, I am opposed to renewable energy systems in my city/town.
Energy awareness*	For shorter trips (up to 2km), I leave the car behind whenever possible and ride my bike or walk.
	When buying new household electrical appliances, I pay attention to low power consumption.
	I mainly use energy-saving appliances.
	In winter, I only use forced ventilation (short, intensive airing).
	When shopping, I make sure to buy regional products as much as possible.
	When I do not need devices (e.g. TV, PC), I switch them off completely (no stand-by mode).
	I adapt my energy consumption behavior to the overall demand (e.g. do not run the washing machine at peak times).
Participation information*	When planning a renewable energy plant, it is important to me to be informed regularly.
	It is important to me to be informed about planned renewable energy plants at an early stage.
	When implementing renewable energy plants, transparency of the planning processes is very important.
Participation evaluation*	Sufficient information materials on renewable energy plants are available.
	The opinion of the population on renewable energy plants is obtained.
	Decisions in the realization of renewable energy plants are made together with the population.
Decision confidence (adapted, original English)**	I am confident in my answer.
	I am confident that I gave the correct answer.
	I feel confident with my answer.
Perceived technology-specific knowledge	How informed are you with regards to energy-related technologies, such as [photovoltaic/battery storage/heat pumps/insulation]?

*: Petra Schweizer-Ries et al. (2010)

**: Phillips et al. (2014); Aldag and Power (1986)

APPENDIX 3.3: OBJECTIVE KNOWLEDGE ASSESSMENT

Introductory Description (translated from German):

Please imagine you are the manager of a typical office building in Germany. You have received a limited budget to conduct energy-related renovation measures and now have to decide to implement one of the following measures. Please choose the measure that you think will be the best if your primary goal is to...

Knowledge assessment before usage of EIW:

Questions	Multiple choice answer possibilities
Q1: ...reduce the annual variable energy costs of the building.	Install a small photovoltaic plant (8,3 watt peak-power/m2).
Q2:...reduce the annual CO2 emissions	Install a combined heat and power plant.
Q3:...reduce the annual energy consumption of the building	Retrofit with modern LED lighting.
	Install a heat pump.

Knowledge assessment after usage of EIW:

Questions	Multiple choice answer possibilities
Q1: ...reduce the annual variable energy costs of the building.	Install a large photovoltaic plant (25 watt peak-power/m2).
Q2:...reduce the annual CO2 emissions	Carry out building insulation with high quality insulation material.
	Utilise waste heat
Q3:...reduce the annual energy consumption of the building	Change to an electricity tariff with electricity from renewable energies.

APPENDIX 3.4: EXPERIMENTAL RESULTS

Exact p-values of experiments:

Hypothesis	p-values experiment KIT	p-values experiment prolific
H1	0.000	0.000
H2	0.000	0.000
H3a	0.849	0.037
H3b	0.510	0.078
H4a	0.000	0.000
H4b	0.000	0.008
H5	0.000	0.000
H6	0.001	0.001
H7	0.000	0.045
H8	0.000	0.000
H9	0.000	0.000

Complete Results of Replicability Experiment:

Test for group differences for dependent variables:

	Static				Animated			MWU
Construct	Mean	SD	SW		Mean	SD	SW	**p-value**
INT	4.69	1.46	0.009**		6.1	0.73	<.001***	<.001***
VIV	2.45	1.29	<.001***		4.91	1.01	.26	<.001***
PU	4.21	1.29	.75		5.78	0.91	<.005**	<.001***
ENJ	3.34	1.46	.069*		5.21	1.06	.027**	<.001***
DI	5.41	0.85	.04*		5.9	0.83	.009*	.007**
IU	4.63	1.54	.002**		5.47	1.35	<.001***	.004**
IR	3.9	1.59	.073*		5.06	1.18	.047*	<.001***
KI	4.69	1.11	.04*		5.34	0.89	.12	.005**
*p < .05; **p < .01; ***p < .001;								
SW = p-values from Shapiro-Wilk test, MWU = Mann-Whitney U-test								

Test for group differences for general sustainability attitudes variables:

	Static			Animated			
Construct	Mean	SD	Shapiro-Wilk	Mean	SD	Shapiro-Wilk	**p-value**
Acceptance RE	2.92	0.18	<.001***	2.94	0.22	<.001***	.951[b]
Energy Awareness	3.55	0.74	.348	3.41	0.67	.692	.353[a]
*p > .05; **p > .01; ***p > .001;							
SD = Standard Deviation, Shapiro Wilk = p-value from Shapiro Wilk test depending on whether the data is normally distributed: a. Two-Sided Welch Two Sample T-test, b. Two-Sided Mann-Whitney U Test.							

Additional measures before (t(0)) and after (t(1)) interaction with the EIW:

	Technology-specific knowledge		Correct answer share per participant (objective knowledge assessment)		Decision confidence		Technology-specific attitudes		Partici-pation rating	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Static EIW t(0)	2.21	0.82	0.11	0.17	3.65	1.52	4.23	0.56	3.08	0.67
Static EIW t(1)	2.59	0.69	0.52	0.28	4.41	1.25	4.61	0.49	3.13	0.75
Animated EIW t(0)	2.11	0.6.	0.12	0.17	3.22	4.76	4.21	0.68	2.99	0.73
Animated EIW t(1)	2.6	0.5	0.51	0.32	1.32	0.97	4.31	0.51	3.18	0.74

APPENDIX 7.1: NUMERICAL RESULTS OF CASE STUDY IN CHAPTER 7

Simulation results of Company 1 in base case scenario:

C1	**PI**	**peak costs [€]**	**FCR revenue [€]**	**PI (size x0.9)**	**PI (size x1.1)**
1 foresight	2.13	1403	240	2.14	2.12
25^{th}	1.94	1430	240	1.95	1.94
50^{th}	1.94	1430	240	1.95	1.94
75^{th}	1.91	1434	240	1.95	1.77
90^{th}	2.00	1403	222	2.01	1.99
95^{th}	1.92	1403	211	1.93	1.90
ps only	0.43	1403	0	0.44	0.43
fcr only	0.76	1601	240	0.77	0.76
no BESS	0.00	1601	0	0.00	0.00

Simulation results of Company 2 in base case scenario:

C2	**PI**	**peak costs [€]**	**FCR revenue [€]**	**PI (size x0.9)**	**PI (size x1.1)**
1 foresight	1.66	91,150	11,037	1.75	1.58
25^{th}	1.53	91,933	11,041	1.60	1.46
50^{th}	1.53	91,933	11,041	1.60	1.46
75^{th}	1.58	91,150	10,619	1.67	1.51
90^{th}	1.58	91,150	10,601	1.67	1.51
95^{th}	1.55	91,150	10,456	1.64	1.47
ps only	-0.22	91,150	0	-0.13	-0.29
fcr only	1.01	95,476	11,405	1.01	1.00
no BESS	0.00	95,476	0	0.00	0.00

Simulation results of Company 3 in base case scenario:

C3	**PI**	**peak costs [€]**	**FCR revenue [€]**	**PI (size x0.9)**	**PI (size x1.1)**
1 foresight	1.68	21,145	7,856	1.78	1.70
25^{th}	1.35	22,936	7,878	1.44	1.27
50^{th}	1.35	22,936	7,878	1.44	1.27
75^{th}	1.35	22,936	7,878	1.44	1.27
90^{th}	1.35	22,936	7,878	1.44	1.27
95^{th}	1.34	22,936	7,852	1.44	1.27
ps only	0.25	20,668	0	0.25	0.17
fcr only	0.56	27,155	7,878	0.57	0.56
no BESS	0.00	27,155	0	0.00	0.00

Simulation results of Company 4 in base case scenario:

C4	**PI**	**peak costs [€]**	**FCR revenue [€]**	**PI (size x0.9)**	**PI (size x1.1)**
1 foresight	2.29	45,145	6,092	2.45	2.15
25^{th}	1.58	47,496	6,101	1.67	1.52
50^{th}	1.58	47,496	6,101	1.67	1.52
75^{th}	1.58	47,496	6,101	1.67	1.52
90^{th}	1.58	47,496	6,101	1.67	1.52
95^{th}	1.58	47,496	6,094	1.66	1.51
ps only	0.45	45,145	0	0.61	0.31
fcr only	1.01	49,461	6,101	1.03	1.00
no BESS	0.00	49,461	0	0.00	0.00

Simulation results of Company 5 in base case scenario:

C5	**PI**	**peak costs [€]**	**FCR revenue [€]**	**PI (size x0.9)**	**PI (size x1.1)**
1 foresight	1.10	9,700	1,266	1.16	1.05
25^{th}	1.10	9,700	1,266	1.16	1.05
50^{th}	1.10	9,700	1,266	1.16	1.05
75^{th}	1.10	9,700	1,266	1.16	1.05
90^{th}	1.10	9,700	1,266	1.16	1.05
95^{th}	1.00	9,700	1,186	1.03	0.97
ps only	-0.52	9,700	0	-0.47	-0.57
fcr only	0.63	10,089	1,266	0.63	0.63
no BESS	0.00	10,089	0	0.00	0.00

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