Digitizing Citizen Energy Communities

A Platform Engineering Approach

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Abstract

Low acceptance and protests against the increasing expansion of renewable generation capacities by local citizens have repeatedly slowed down the ongoing energy transition in western countries. A promising approach to address this issue is the energy community concept, for which the European Union introduced a regulatory framework within the 'Directive on common rules for the internal market for electricity'. It refers to them communities as Citizen Energy Communities. Within these communities, participants can exchange locally generated energy and the community can be represented by a digital platform, which organizes the community's continuous power distribution and financial flows. In the academic literature, these communities are discussed as a tool to actively integrate citizens into the energy system on a local level. They increase the acceptance by benefiting the local value chain and empower the energy sector's decarbonization. However, there is a lack of research on how Citizen Energy Communities can be implemented in practice and how they perform under real-world conditions. This dissertation's contribution addresses the empirical challenges in the implementation and long-term operating of Citizen Energy Communities. The thesis reports on six studies. In the first study, the necessary IT architecture and digital building blocks are developed based on a literature review and insights from a real-world implementation for Citizen Energy Communities are described. From the resulting experiences, requirements for the individual building blocks and technologies are deducted. Researchers propose that blockchain technology can accelerate the introduction of Citizen Energy Communities. Therefore, a maturity model for blockchain-based Citizen Energy Community projects is established in the subsequent study, which allows assessing the development status of field implementations and identifying necessary next steps. In the third study, a platform-based allocation mechanism is designed, which addresses heterogeneous preferences of participants and thus enables local prices for different local energy sources. Based on an implementation, the mechanism's performance and functionality are evaluated.

Besides the technical functionality, user behavior is of central importance for success. Therefore, seven user interface design principles are deducted in the fourth study based on a structured design science research process with the help of expert interviews and a behavioral laboratory experiment. In the fifth study, it is quantified and evaluated if participants are regularly active within the community, willing to pay premium prices for local renewable sources and whether they are responsive to local price signals as often assumed in the literature. The results show that Citizen Energy Communities need to be tested more thoroughly and that the platform's allocation mechanism require a low complexity or additional support systems like automated agents. As a result, the sixth study evaluates the real-world trading performance of automated agents and their impact on the platform market. The results show that a single agent among human traders can minimize the participant's cost. However, this advantage diminishes with the number of additional automated agents in the market. The thesis is concluded with an outlook and pathway for future research.

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List of Abbreviations

CEC	Citizen Energy Community
CHP	Combined Heat and Power
CMM	Capability Maturity Model
CMMI	Capability Maturity Model Integrated
DQN	Deep Q-Learning Networks
DRL	Deep Reinforcement Learning
DSR	Design Science Research
EER	Enhanced Entity-Relationship
EEX	European Energy Exchange
EC	European Commission
EU	European Union
EV	Electric Vehicle
EXP	Expert
HTTP	Hypertext Transfer Protocol
ICT	Information and Communication Technology
JWT	JSON Web Token
LAN	Local Area Network
LAMP	Landau Microgrid Project
LEM	Local Energy Market
LEC	Local Energy Community
LoRaWAN	Long Range Wide Area Network
MDP	Markow Decision Process
NIMBY	Not In My Backyard
P2P	Peet-to-Peer
PV	Photovoltaic
RL	Reinforcement Learning
RES	Renewable Energy Sources
ReLU	Rectified Linear Unit
SiLU	Sigmoid Linear Unit Function
OTC	Over-the-Counter

Part I.

Fundamentals

Chapter 1.

Introduction

The concentration of greenhouse gases in the atmosphere is at a record level and still rises (US Department of Commerce, 2020). In the Paris Climate Agreement, put into effect in 2016, 191 member states of the United Nations committed themselves to limit global warming to 2° Celsius compared to the pre-industrial level (United Nations, 2016). One of the main drivers of increasing greenhouse emissions is the energy sector (Statista, 2018). Governments, political institutions and state legislators worldwide pursue the goal of net-zero greenhouse emissions by putting policies in place to reach a more sustainable energy generation. The European Commission (EC) declared their intent of net-zero greenhouse gas emissions by 2050 (European Commission, 2019). To achieve the status of net-zero emissions, the European Union (EU) must transform its fossil fuel-based energy system with large power plants into a sustainable system, based on distributed renewable energy sources (RES) such as solar or wind energy (European Commission, 2020). However, the increasing expansion of RES generation capacities has also repeatedly led to local protests and resistance (Schwenkenbecher, 2017). The acceptance of the restructuring process by local citizens decreases and becomes a constraining factor for its success (Wüstenhagen et al., 2007; Batel et al., 2013). The 'not in my backyard' (NIMBY) phenomenon causes that while citizens, in general, support the energy transition, they fear to be negatively affected (Devine-Wright, 2009). They are afraid of decreasing property prices and a lower quality of life due to noise and visual disturbances (Devine-Wright, 2005). This local resistance can significantly impede the progress and success of the energy transition. In Germany, for example, federal states are allowed to set a 1,000-meter minimum distance between wind turbines and residential areas (Schmid, 2020). Such regulation reduces the potential areas for wind turbines and severely hinder the expansion of renewable energy (Stede and May, 2020). Even some already existing turbines cannot be repowered by new ones because they are in the prohibited zone (Meunier, 2019). Therefore, it requires new concepts to foster acceptance by integrating local citizens into the energy sector and by enabling direct participation (Musall and Kuik, 2011; Lienhoop, 2018).

Furthermore, the envisioned transformation of the energy sector requires massive investments in the existing infrastructure. According to estimates by the EU, the energy sector needs annual investments of €260 billion to reduce emissions by 40% by 2030 (European Parliament, 2020). The public sector cannot raise these sums on its own and it needs massive investment from the private sector (Energiewende, 2019). With the ‘Green Deal', the EU aims to mobilize at least €1 trillion until 2027 to foster public and private investments for climate protection and sustainability and also to activate the private sector's financial power (European Parliament, 2020). To activate this financial power, many governments have already introduced incentive programs to stimulate investments in renewable generation capacities. For example, many countries have established a fixed subsidized feed-in tariff for RES power plants (Pyrgou et al., 2016). As a result, private sector groups like households, farmers and small businesses invested in renewable generation capacities at their location. For example, private households with installed rooftop systems have a 70% share of the overall photovoltaic (PV) capacity in Germany (Foederale Energien, 2018). This generation is used for self-consumption and turns the owner from a passive consumer into an active self-sustainer, so-called prosumer (Parag and Sovacool, 2016). However, the subsidized feed-in tariff decreased in the last decade and a large share of older power plants will drop out of the subsidy program in the coming years (Fraunehofer ISE, 2021a). The current regulation provides options like accepting lower feed-in prices based on the wholesale market price (only a temporary option until 2027 in Germany), contracting an energy supplier for the sales process, increasing the self-consumption with additional storage systems, or curtail the surplus generation (Verbraucherzentrale NRW e.V., 2021; Mitteldeutsche Netzgesellschaft Strom GmbH, 2020; Bundestag, 2021). However, each option is connected to either additional investments (e.g., storage system, smart meter hardware), lower profits and additional fees. Therefore, there is a risk that the associated costs will be too high due to high regulatory obstacles, which may result in shutdown or generation curtailment (Lenck et al., 2020). Other alternatives like the direct selling of surpluses to other consumers within a community are not possible. These concepts would be more suitable for most prosumers because small amounts of generation surpluses can be sold easily and directly, without additional bureaucratic costs or investments into storage systems.

However, citizens do not only invest in rooftop solar for self-consumption. They also collectively invested in local RES projects. For instance, many local energy collectives are invested in wind parks that they often operate (Raveling, 2018). Combined, private households, farmers and small businesses represent 50% of the installed renewable capacity in Germany and are hence combined the largest ownership group (Agentur für Erneuerbare Energien, 2021). As with rooftop PV systems, the ongoing economic operation is also a challenge for wind power plants after the feed-in tariff subsidy scheme expires. For example, community power plant projects can only sell the generation to their members for self-consumption or to local consumers in the near vicinity within so-called purchase power agreements. However, these include several fees and additional costs and makes no difference to a commercial sale. Therefore, these additional fees and resulting lower profits may lead to a situation where these power plants are not profitable, resulting in their shutdown. The deconstruction of functional renewable generation capacities due to administrative costs and regulatory requirements is counterproductive in the fight against climate change. Solutions are needed to support prosumers and collectively owned generation plants to sell their surplus energy locally without high costs and thus prevent the curtailment, shutdown, or deconstruction of older renewable generation capacities.

One concept to address the challenges of local resistance and expiring feed-in tariffs is the formation of so-called energy communities (Koirala et al., 2018; Walker and Devine-Wright, 2008). In these energy communities, local citizens organize themselves, invest in their own generation and share self-generated electricity, possibly through market mechanisms. A distinctive social innovation feature of energy communities is the ability to combine the mutual and the public interest (Huybrechts and Mertens, 2014; Bauwens et al., 2016). Citizens can engage in these communities independently of their income and profit directly from local generation, which can increase their acceptance (Koirala et al., 2016; Caramizaru and Uihlein, 2020; Lennon et al., 2019). Inspired by first citizen energy initiatives, the European Union (EU) acknowledged the necessity for better integration of citizens into the energy sector. It introduced the energy community concept in the 2019 issued 'Directive on Common Rules for the Internal Market for Electricity' (Parliament, 2019). According to the directive, energy communities offer citizens the opportunity to generate, consume and share energy directly. These communities can facilitate the introduction of new technologies or consumption patterns and empower citizens to participate in the electricity market directly (Parliament, 2019). The directive aims to create a regulatory framework in all member states, which promotes this self-organization of citizens in energy communities and defines them as Citizen Energy Communities (CEC) (Parliament, 2019). The definition does not contain strict specifications but sets several conditions, which a legal entity must fulfill to be declared as a CEC. First, the CEC's purpose must be to provide environmental, economic, or social community benefits to its members or to the local areas where it operates. Second, participation must be voluntary and open. Third, the CEC must be controlled by its members or shareholder, which are natural persons, local authorities, or small enterprises (Sokołowski, 2020; Parliament, 2019). Overall, a CEC can be described as a community where its participants can engage in investing, generating, consuming and sharing energy (Reijnders et al., 2020). The directive specifies that the community appears to the outside grid and energy market as a single entity. The community operator manages surpluses or additional demand.

There are several advantages associated with the CEC concept. First, its members can jointly invest in renewable energy capacity. In the past, the generated energy was sold for a fixed feed-in tariff or with the help of a third party on an energy market (Brummer, 2018; Reijnders et al., 2020). However, within the CEC, this self-generated electricity can also be distributed directly to the community, thus leading to higher self-consumption and the saving of costs. Besides the self-consumption, reliable returns are no longer paid once feed-in tariffs run out. Therefore, selling generated surplus ensures that older plants can be operated in the long run. Through a higher willingness to pay or by avoiding certain levies, the community-owned generation can amplify investment incentives for additional renewable energy power plants (Caramizaru and Uihlein, 2020). Also, the CEC members can jointly invest in other assets, such as shared storage systems, benefit from them and thereby increase the acceptance for them (Reijnders et al., 2020; Henni et al.; Warren and McFadyen, 2010). Therefore, CECs can actively integrate citizens into the energy system on a local level, empower the energy sector's decarbonization (Schram et al., 2019) and substantially benefit the local value chain and energy system (Zwickl-Bernhard and Auer, 2021; Caramizaru and Uihlein, 2020). In addition, the CEC aggregates consumption and generation within the community and can set incentives or implement mechanisms that support system operators in stabilizing the distribution grid (Reis et al., 2019; de Villena et al., 2020). Since a great share of the RES generation capacity is owned by private individuals and is installed decentrally, grid management becomes an increasingly relevant challenge. The weather dependency of RES creates volatility and peaks in the distribution grids. As a result, the share of the local generation can increase to a point where it exceeds the local demand within the distribution grid. Thus, bi-directional flows from the distribution grid to higher grid levels occur more often and cause additional grid management costs (Zahedi, 2011). Grid operators must balance demand and supply within the system at each moment to prevent blackouts and keep the frequency steady (Stoft, 2002). CECs within the distribution grid can help to reduce load or generation peaks. This balancing can lead to lower grid management costs and fewer transmission losses (De Clercq and Guerrero, 2018; Koirala et al., 2016). In the long-term, this will result in fewer transmission and distribution grid expansions costs and a higher share of locally consumed green electricity (De Clercq and Guerrero, 2018). Both overall grid expansion costs and direct participation in self-generated energy can increase the acceptance of the energy transition (Joos and Staffell, 2018; Lienhoop, 2018).

The full potential of the CEC concept can only be realized with the support of digital technologies, e.g., information and communication technology (ICT), databases, smart meters and software. The EU directive on CECs supports the application of such digital technologies (Parliament, 2019). These digitized CECs may include a trading platform, frequently conceptualized under the umbrella term 'local energy market' (LEM) (Sousa et al., 2019; Bremdal et al., 2017). On these platforms, participants can trade energy with each other directly and a market mechanism organizes the continuous power and financial flow (Mengelkamp et al., 2018a). The additional recorded and processed information can be utilized to add additional services and benefits for the CEC participants. For example, private households have only limited knowledge on how much energy their devices consume at certain times. Their so-called energy literacy is low (Brounen et al., 2013; US Department of Energy, 2017). This knowledge gap leads to a situation in which households would like to behave more ecologically but are unable to do so. Digitized CEC can provide high-resolution load data to consumers and allow them to engage with their own energy consumption. A user application provides the participants with necessary information about their consumption behavior, energy mix and costs (Gupta et al., 2018; Schwartz et al., 2013). Also, currently, private households receive no feedback on how sustainable their consumption decisions are (Bourgeois et al., 2014). Digitized CECs can also incentivize participants to consume energy more sustainably by sending regular feedback on the amount of locally consumed energy. Over a more extended period and regular engagement with the CEC platform, participants can get more familiar with their consumption behavior and habits and can develop a higher environmental awareness and energy literacy (Francisco and Taylor, 2019; Faruqui et al., 2010). In addition, the CEC trading platform provides consumers the opportunity to influence their energy mix and costs by actively bidding on local generation or by adjusting their consumption behavior with respect to their personal preferences or current market situation. According to Morstyn et al. (2018), the advantages of local trading are the 'energy matching', 'preference satisfaction' and 'uncertainty reduction'. The first describes the efficient coordination of local demand and supply. The utilized market mechanism and corresponding local prices set incentives to expand local generation (Mengelkamp et al., 2018a) and storage capacities to support local grid balancing (Ketter et al., 2013). These local price signals may incentive consumers to shift their consumption into local generation peaks and thereby to contribute to grid balancing and management (Faruqui et al., 2017; Zhang et al., 2018). Also, local energy trading allows participants to choose between different local energy sources and enables the mitigation of peak periods (Morstyn et al., 2018). Preference satisfaction focuses on the local consumers' ability to state their willingness to pay for local energy sources and, therefore, influence the origin of their electricity consumption. New market mechanisms incorporate the heterogeneous consumer preferences and allow premium prices for local energy (Zade et al., 2022b), which act as an incentive for generation expansion. Regarding uncertainty reduction, the trading platform offers local generators the opportunity to sell their surpluses locally without high bureaucratic hurdles and, therefore, provides an alternative revenue stream (Mengelkamp et al., 2019c). CECs with trading platforms, therefore, reduce investment uncertainty for prosumers in times of declining subsidized feed-in-tariffs in many countries (OECD, 2019).

With the introduction of the EU directive and the corresponding regulatory frameworks, the development of CECs is now at the transition from the conceptual phase to real-world implementations that can be rolled out on a larger scale. The challenge for CEC operators is that their participants are a heterogeneous group with different backgrounds, preferences and experiences. Most of them are non-experts and the interaction with the platform is not a priority in their daily lives. Furthermore, each individual may have different levels of knowledge, motivation to participate and willingness to invest time resources (Mengelkamp et al., 2018e). However, participants' long-term engagement is essential to ensure the overall functionality of the CEC platform. Low-involved or inactive CEC members will not change their behavior towards more sustainability, react to price signals or benefit from the community. Participants must be able to derive a benefit from using the platform. If they do not understand how the platform functions or the perceived benefits are too small, or the hurdles using it are too high, the participants become inactive and leave the community. As a result, a platform with inactive participants is not able to increase the participants' acceptance for local renewable energy sources. For this reason, the analysis of the user behavior and design of the CEC platform is of particular importance. The analysis of user behavior is essential to assess how participants interact with the platform and to identify drivers of long-term engagement. Otherwise, the platform will remain ineffective. In addition, without a suitable platform design and functioning infrastructure, participants are not able to use the platform effectively and CECs cannot unfold their potential. Thus, it is necessary to avoid design errors in practical implementations. The same applies to the platform's underlying IT architecture. A poor design can lead to malfunctions or misunderstanding of information and, subsequently, wrong decisions by the participants. The results of this dissertation address this field of research and provide novel insights for the scientific community and industry regarding the implementation and design of CECs. This dissertation, therefore, contributes to the energy transition's acceptance within the general population and thus its ultimate success.

1.1. Research Questions and Outline

The dissertation consists of two parts, each containing contributions to the CEC design and analysis of the participant behavior on CECs. The first part discusses the technical building blocks of a digitized CEC and contributes to future implementations by creating knowledge regarding the CEC's IT architecture, blockchain maturity and the platform market mechanism. The second part analyzes the participant behavior on the CEC platform, identifies drivers for long-term engagement and effects of AI-based automated agents.

The core of digitized CECs is the utilization of different digital technologies and their interaction with each other. Therefore, the initial study of the first part analyses the required functionalities for digitized CECs and their underlying IT infrastructure. Besides listing possible functionalities, the existing literature lacks a comprehensive set of modules and processes and technology assessment, which allows the provision of these functionalities in a digitized CEC. The first study contributes to this research gap by identifying necessary modules and processes of the IT infrastructure and by deriving an overall IT architecture for CECs. This architecture is tested in a real-world implementation to assess suitable technologies and their overall performance. Within the context of a real-world project, the experiences with implemented technologies are evaluated to answer the underlying first research question:

Research Question 1 *What are the fundamental modules, processes and a suitable implementation of a CEC IT architecture?*

A central building block of the CEC IT infrastructure is the database. It stores all necessary information and is the foundation for calculating transactions, market prices, or individual costs. Blockchain technology is a promising technology for many researchers and practitioners to represent the database. The excitement around this technology is closely linked to the strengthening interest in CECs. In recent years, many new designs, approaches and pilot projects have focused on this new technology (Wörner et al., 2019a; Mengelkamp et al., 2018a; Vasconcelos et al., 2019). However, the blockchain does not necessarily have to exclusively be a database technology, used to store and distribute the emerging data in the CEC, but it can also execute other tasks like the allocation mechanism linked to a market design. It has unique characteristics which influence the CECs IT architecture and is seen as a key technology to enable CECs in practice. Because of the technology's early deployment status, blockchain-based CECs need a framework to assess their maturity and identify the necessary next steps for the CEC. In the second study, a blockchain maturity model is proposed, which supports the answer to the second research question:

Research Question 2 *How can the current level of maturity of blockchain-based CEC applications be assessed?*

A central element of a digitized CEC with a trading platform is the market mechanism. It allocates locally generated energy within the community to the respective participants. So far, electricity is traded as a homogeneous commodity on wholesale energy markets with a merit order mechanism. However, several studies suggest that consumers differentiate in their willingness to pay for renewable (local) sources (Ma et al., 2015; Borchers et al., 2007; Mengelkamp et al., 2019c). Within the concept of the digitized CEC, it is possible to distinguish electricity based on its origin and price it differently. This situation allows consumers to satisfy their different preferences and enables premium prices for (sustainable) local generators. Therefore, a market mechanism is necessary which can distinguish between different forms of local energy sources. In the last study of the first part, a market mechanism is developed and evaluated regarding the third research question:

Research Question 3 *What is an appropriate market mechanism for a CEC market platform, which can capture different consumer valuations for various types of locally generated electricity?*

The second part of this dissertation focuses on CEC participants and their behavior. The first study concentrates on the user interface, as it is the connection between the participants and the CEC platform. Participants request information over the user interface, such as their own load data or market prices and place bids on the trading platform. For the CECs to reach their full potential, participants must be encouraged to interact and engage with the system over the long-term. Therefore, it is crucial to analyze the user interface and develop it to ensure participants' long-term engagement. The provision and preparation of the available information within the user interface is important, as well as the application design itself. Even minor design errors and incorrect visualizations can lead to misunderstandings or misinterpretations by the participants, which can result in diminishing activity. There is a lack of research on what information the participants utilize and which form of presentation they prefer. To close this research gap, a design science research approach is applied to derive design principles for a CEC user interface, which ensures that participants can utilize the available functionalities and remain engaged in the CEC. The perception and usage by participants are evaluated in a real-world field project to answer the fourth research question:

Research Question 4 *What are fundamental design principles for a CEC user interface and platform that lead to a long-term engagement of participants?*

Due to the missing real-world data, existing research on CECs is based on several assumptions regarding the participants' behavior. For example, studies assume that some participants have different willingness to pay and some are willing to pay premium prices for local energy sources (Zade et al., 2022b; Mengelkamp et al., 2018e). Also, studies assume a regular participant engagement with the CEC and consumption shifts in reaction to price signals (Mengelkamp et al., 2017; Ableitner et al., 2020). It is especially important to assess long-term behavior to exclude the possible novelty bias of the participants, which can lead to false conclusions. The academic community and industry need an understanding of how the participants interact with the CEC in the long run, in which regularity they do so and what the main drivers and obstacles are to interactions. For future CEC operators, it is crucial to understand how information and incentives are perceived by the participants and to understand what leads to interactions with the system. Therefore, a long-term behavior analysis is conducted in the fifth study, which provides insights into how the consumers value local energy sources, their willingness to pay premium prices and how they respond to price signals. The fifth research question focuses on the evaluation of bidding and consumption behavior data from a longitudinal field study.

Research Question 5 *What identified long-term behavior in a CEC can confirm the behavioral assumptions from the literature?*

The results of this dissertation show that some participants lack the willingness or opportunity to invest considerable time and effort into their engagement with the CECs. Automated trading agents are a solution that is proposed in the literature. Such agents have an advantage because they can always track market movements and instantly respond to changing situations based on communicated consumer preferences. Agents equipped with a reinforcement learning algorithm, can trade in place of human participants and reduce the need for the interaction with the system (Mengelkamp et al., 2018c; Staudt et al., 2018). However, there is no research that evaluates the performance of such agents in CEC field implementations. Therefore, in the last study, a reinforcement learning-based automated agent is implemented and evaluated in a real-world project in competition with human traders. In addition, if automated agents provide a competitive advantage, there is an incentive for all participants to implement automated agents. Therefore, a second analysis investigates the performance of exclusively automated agents based on the empirical data from the same field project. Both analyses are used to answer the final research question:

Research Question 6 *Which financial benefit can be achieved by an automated agent i) within a group of human traders and ii) within a group of exclusively automated agents on a CEC market?*

1.2. Thesis Structure

The thesis is structured along the main areas of its contributions and follows the research questions from the previous section. The thesis is organized into four parts. Part I begins with an introduction and motivation to the topic of CECs in Chapter 1. Building on this, Chapter 2 provides the foundations of the power system and describes insights into Germany's current regulatory situation and

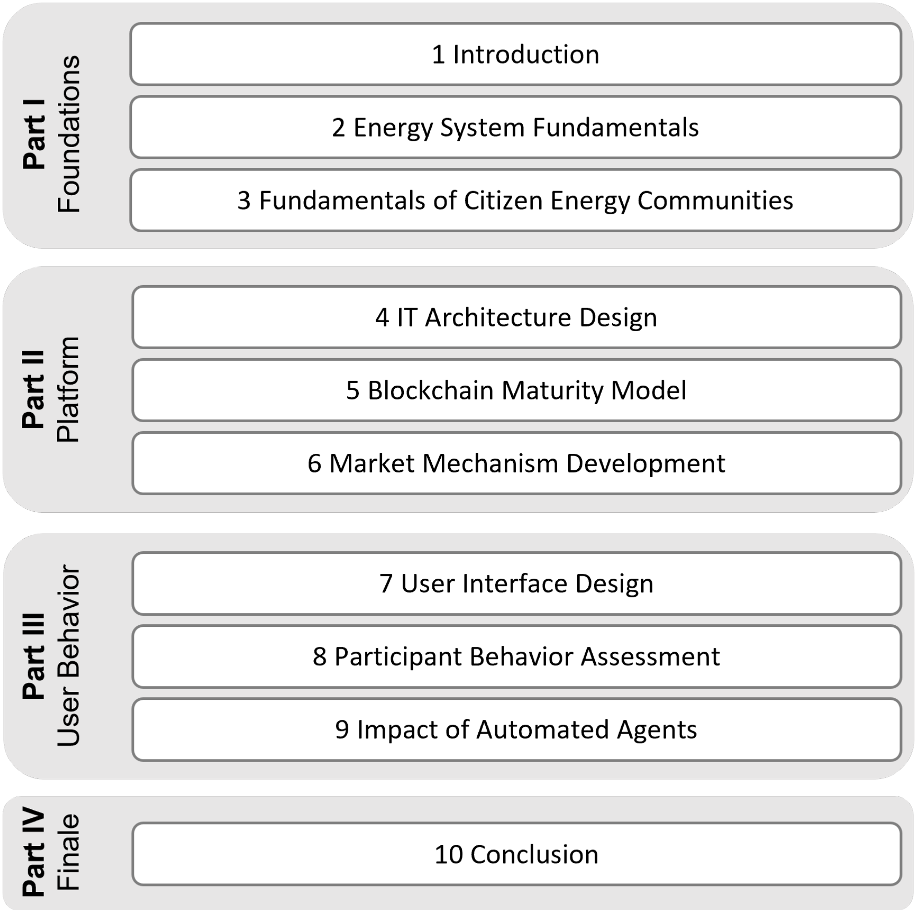

Figure 1.1.: Thesis structure

the CEC regulatory framework by the EU. Chapter 3 presents an overview of the existing research body regarding energy communities, describes the market engineering approach used to engineer the different CEC platform components and introduces the real-world pilot project referenced in this dissertation, the Landau Microgrid Project (LAMP). Part II, *Citizen Energy Communities - Platform*, assesses the platform infrastructure aspects of a CEC. Chapter 4 focuses on deriving a suitable IT architecture for CECs and on experiences from the presented real-world implementation. Building on this, Chapter 5 discusses the maturity of blockchain technology for CECs and presents a maturity model for its evaluation. In Chapter 6, a CEC allocation market mechanism is developed, which allows participants to differentiate between various local power generation technologies. Part III, *Citizen Energy Communities - User Behavior*, focuses on the perception and behavior of CEC participants. Chapter 7 focuses on designing the user application and elaborates generalizable design principles from the implementation and operation phase. Chapter 8 examines the participants' behavior over a one year period, their willingness to pay premium prices and analyzes how they react to different information and price signals. Building on this, Chapter 9 evaluates the performance of an automated agent that acts on a CEC market with non-professional traders. Finally, Part IV concludes this dissertation. It provides an outlook by discussing possible subsequent research areas and future challenges for CECs. Figure 1.1 illustrates the structure of the thesis and its division into four parts with ten chapters

While this dissertation represents an original research contribution, parts of this thesis are based on the contributions of published or unpublished collaborative studies. As these studies are joint efforts of several collaborators, I disclaim these parts clearly and refer to the authors as a group ('we').

Chapter 2.

Energy System Fundamentals

Energy is the foundation of modern, developed economies. It is essential to produce industrial goods, create value in all industrial sectors and, necessary in the daily life of private households. Because of this vital role, the energy sector represents a critical infrastructure, which is highly regulated and faced only a few structural transformations in the past. The latest major transformation was the liberalization at the beginning of the 1990s, which abolished the existing and protected geographical monopolies (Collier, 1998). The goal of the liberalization was to make the energy market more efficient and enable more competition. The result of this transformation is the current value chain of the energy sector. It is divided into a regulated and unregulated area. Natural monopolies such as the electricity grids, which are responsible for power transmission and distribution, represent the regulated area and were separated from the remaining stages of the value chain, through the so-called 'unbundling' (Pielow and Ehlers, 2008). With the increasing importance of climate change, the next transformation process has already started. In this transformation, however, the focus is not strengthening of competition but transformation of the generation structure to make it more sustainable and reduce greenhouse gas emissions (European Commission, 2020). With the increasing expansion of renewable energy capacity, balancing the so-called energy trilemma gets harder to achieve. This trilemma describes the fulfillment of three central, equally important goals. The energy policy must carefully manage the three dimensions of security of supply, energy efficiency and ecological sustainability. Figure 2.1 shows these three targets. With the rapid transition to renewable energy generation, there is a clear shift towards ecological sustainability and a risk of conflicts with the other two targets increases. Therefore, it is essential that new concepts and approaches within the energy transition also consider and contribute to all three dimensions of the trilemma.

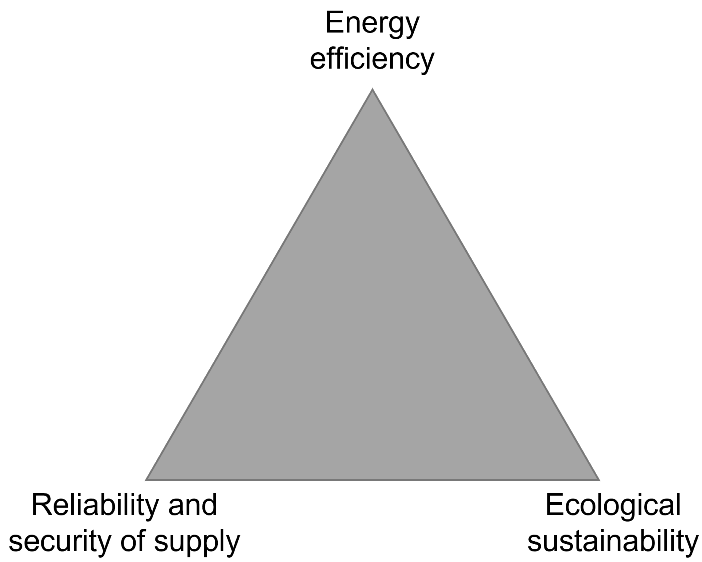

Figure 2.1.: Triangle of targets of the energy system

The first part of this chapter introduces the general structure of the energy sector's value chain. Besides the description, the arising challenges through the transformation towards more sustainability are explained for each stage.

2.1. Energy Sector Value Chain

The current value chain in the energy sector is the result of the liberalization process of the 1990s, where structural monopolies were unbundled. This value chain can be divided into four areas: generation, transmission, distribution and consumption, including energy retail. Figure 2.2 provides an overview of the value chain.

2.1.1. Generation

Traditionally, a large part of the required energy was generated in large conventional power plants using fossil fuels (coal, gas, oil) or uranium. Until today, this approach is predominant and much of the worldwide consumption of energy is based on

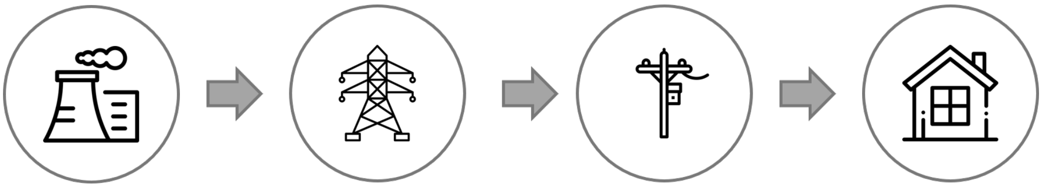

Figure 2.2.: Overview of the energy value chain

these energy sources (Ritchie and Roser, 2020). From the perspective of the abovementioned three policy targets, the primary advantage of conventional power plants is that they can provide a high level of security of supply due to their controllability. At the same time, due to economies of scale, these power plants can generate energy economically efficient. However, against the backdrop of the climate crisis, the focus has changed towards the third goal, sustainability. In recent years, this shift has resulted in a substantial expansion of renewable generation capacities subsidized by the state. This expansion has led to a steady increase in the share of the generation capacity of renewable systems such as PV, wind, hydropower, or biomass. In 2020, renewable generation capacities accounted for 50.5% of the total public net generation in Germany (Fraunehofer ISE, 2021b). The total generation share of renewable systems in 2021 was 46%. Against the background of the German government's climate neutrality targets for 2045, this share have to increase in the coming years (Coalition contract 2021-2025, 2021). Many countries have introduced subsidy schemes for these plants (Haas et al., 2004). For example, Germany has introduced a fixed feed-in tariff price that paid 20 years for electricity generated by renewable systems (Agnolucci, 2006). The goal is to reduce the investment risk and provide incentives for the expansion of renewable generation capacities. As a result of these government subsidies, many private households, businesses and farms have invested in their own plants and became prosumers. These groups together represent with nearly 50% the biggest share of renewable generation capacities in Germany (REN21, 2014). Most of them are either part of an energy cooperative which invested in local wind parks, or they installed own PV systems on their roof. As a result, installed rooftop systems represents 70% of the overall PV capacity in Germany (Foederale Energien, 2018).

The energy sector's generation structure is fundamentally changing with the expansion of renewable generation capacities. Most of them have different characteristics than conventional power plants. The generation capacity of individual plants is much smaller than that of large conventional power plants. Therefore, many small renewable systems are installed decentrally in the grid (Green and Newman, 2017). In contrast to conventional power plants, renewable systems are not controllable and the generation capacity depends on the respective weather conditions such as wind and sun. At the same time, the integration of these new renewable sources into the energy market is more challenging. Traditionally, energy is often marketed via different wholesale markets, such as the European Energy Exchange (EEX) or direct agreements, so-called over-the-counter (OTC) trades (Rademaekers et al., 2008; Graf and Wozabal, 2013). These marketplaces and arrangements are designed for national trades with large trading volumes and corresponding minimum quantities (European Energy Exchange, 2020). Therefore, small generators cannot participate directly on the energy market. So far, this has not been a problem, as most of the small renewable systems received the above-mentioned feed-in subsidy. According to the German Renewable Energy Act, the system operators are obliged to buy the surplus energy at a fixed price and sell it at the wholesale market. However, at the beginning of 2020, prosumers start to drop out of the subsidy. These prosumers have to rely on aggregators and other energy retailers to sell their surplus energy (European Union Agency for the Cooperation of Energy Regulators, 2021). However, these services cause additional costs and lower profits. A key challenge in the near future is to integrate the many small renewable systems into the energy system without relying on government subsidies and, at the same time, prevent plants from being dismantled due to poor marketing opportunities. Energy communities can provide a framework within small power generation capacities to sell surpluses without high market entry costs and subsidies.

2.1.2. Transmission and Distribution

The next step is the transmission of power from the generation site to the area where the energy is consumed, e.g., private households or industrial facilities. Traditionally, the transportation task is divided into two stages, the transmission and distribution of electrical energy, the second and third stages of the value chain (El-Hawary, 2008). The main task of the transmission system is to transmit power from large conventional power plants to the distant distribution grids. The task of the distribution system operator is to organize the delivery of electrical energy to each end consumer in the grid, e.g., private households. The required quantities are taken from the high-voltage grid of the transmission system and distributed to the connection points in the grid (Hensing et al., 2014). In Germany, there are four transmission system operators and over 800 distribution system operators with the majority of these operators operating a network area of less than 30,000 connection points. A connection point represents a single consumer, for example a private household. While the transmission networks in Germany have a total network length of 37,200 kilometers, the entire length of all distribution networks is approximately 1.8 million kilometers (Bundesnetzagentur and Bundeskartellamt, 2021). Due to the high generation capacity of conventional plants, the transmission system operators in Germany have system responsibility and manage the stability of the power grid (11§ EnWG).

Both grids represent a monopolistic bottleneck and are therefore regulated since the liberalization (Knieps, 2016). A monopolistic bottleneck can be described as the combination of a natural monopoly and existing market entry barriers. Both circumstances endow the owner of the natural monopoly with market power, which allows setting prices above the marginal costs and, therefore, to receive a non-competitive higher revenue (Knieps, 2008). There are different approaches to regulate monopolistic bottlenecks and prevent the abuse of market power. In Germany, the government introduced a revenue cap approach with the 'Anreizregulierungsverordnung (ARegV)'. It sets a maximum revenue (cap) for the grid operator based on their cost structure. Every five years, the regulatory authority recalculates the cap (§3 ARegV). For example, in 2021 the resulting network charges for the transport and distribution of energy accounted for 22% of the total electricity price in Germany (Bundesnetzagentur and Bundeskartellamt, 2021).

With the expansion of renewable energy capacity, the traditional roles of both grid operators change. First, the number of large conventional plants decreases (Bundesnetzagentur and Bundeskartellamt, 2021). Instead, many small renewable generation capacities are localized directly in the distribution grids, moving energy generation closer to the consumption areas (Alanne and Saari, 2006). Less energy needs to be transported from the transmission to the distribution grids. Second, the renewable energy systems cannot be controlled, resulting in increasing load peaks in the distribution grid and power flows can reverse at certain times and must be balanced (Ramchurn et al., 2012). However, transmission grid operators, who retain the system responsibility and manage the grid stability, cannot control these systems directly. Energy communities can play a supporting role for grid stability by managing local imbalances and encourage consumption in periods with high generation.

2.1.3. Consumption

The final stage of the value chain is the consumption of the transmitted power. Electricity is consumed in different sectors, for example, in industry, businesses, private households and transport. With 24% and 29%, private households and businesses account for more than 50% of the final consumption (Bundesministerium für Wirtschaft und Energie (BMWi), 2020). Traditionally, in this last stage of the value chain, power retailers organize the energy procurement on the energy wholesale market and supply their customers. These retailers perform organizational tasks, such as forecasting consumption, reporting to the network operator, as well as billing. In the case of private households, the consumption is usually recorded with an analog meter and billed via a fixed volume tariff, which consists of a fixed and volume-based component (European Union Agency for the Cooperation of Energy Regulators, 2021). For the billing process, the consumption data is forecasted by the retailer and compared with the recorded values of the analog meter once a year. Consumers only have a passive role in this traditional setting.

This setting changes due to the ongoing transformation and digitalization process. First, since the beginning of 2020, a statute has been requiring the installation of smart metering systems for modernized or new buildings with an annual consumption of more than 6,000 kWh (Bundesnetzagentur and Bundeskartellamt, 2021). This so-called smart meter rollout has been specified and regulated by the 'Messstellenbetriebsgesetz' since 2017. Despite ongoing lawsuits in 2021, it can be expected that private households will slowly adopt this technology, which allows the real-time recording of consumption data. This has the direct advantage for consumers that they can observe their consumption and draw conclusions regarding their behavior. At the same time, the new data allows energy retailers to forecast the consumption better, to bill consumers directly and in shorter intervals. Second, suppliers have begun to differentiate their tariff types and increasingly offer green electricity tariffs. In these green tariffs, only energy generated in renewable sources is used. Therefore, it provides consumers some information on the energy origin. By choosing these tariffs, consumers can partly influence the origin and sustainability of their consumption. The share of private households with such a tariff was accounted for 29.3% of all tariffs in 2020 (Bundesnetzagentur and Bundeskartellamt, 2021). This trend underscores that sustainable consumption and knowledge about the origin are gaining relevance for private households. In recent years, prices for green tariffs have continued to fall and in 2021 they were almost on a par with the price level of standard tariffs (Bundesnetzagentur and Bundeskartellamt, 2021). This trend will drive the demand for these type of tariffs further in the coming years. Third, with the installation of decentralized renewable energy capacities, an increasing number of households start to become small, local generators for their own consumption (Foederale Energien, 2018). These consumers become temporary generators and are therefore called prosumers. In addition, these prosumers also generate local surpluses, which could be consumed by other private households or companies in the local vicinity, creating local energy communities. Within energy communities utilizing smart meters and other digital technologies, platforms can be provided to consumers to exchange energy and supply each member with individual information on their consumption origin, development and costs. The energy community concept has been discussed for several years. An introduction to the different concepts and the individual building blocks of such a platform is described in the following chapter.

Chapter 3.

Fundamentals of Citizen Energy Communities

This chapter provides an overview of the various concepts behind the term energy community, introduces the regulatory framework for CEC by the EU and then describes the different CEC platform components along the market engineering framework.

3.1. Concepts of Energy Communities

In recent years, the concept of an energy community, where citizens organize themselves locally, has gained attention in both research and practice (Hisschemöller and Sioziou, 2013). A distinctive social innovation feature of community energy is the ability to combine the mutual and the public interest (Bauwens et al., 2016). In this concept, citizens are empowered to form local energy communities, becoming so-called 'energy citizens', sharing energy with each other. The idea has been discussed for several years, mostly under different names including 'local energy community' (Orozco et al., 2019), 'renewable energy community' (Soeiro and Ferreira Dias, 2020), 'sustainable energy community' (Romero-Rubio and de Andrés Díaz, 2015), 'renewable energy cooperative' (Capellán-Pérez et al., 2018), 'citizen energy cooperative' (REScoop, 2021), or 'community microgrid' (Warneryd et al., 2020). Walker and Devine-Wright (2008) explore the variety of interpretations and define two core areas that describe these concepts. First, communities must provide a high level of participation. Second, the community benefits must be distributed to its participants.

The terms mentioned above focus on connecting citizens in communities and providing benefits for its participants but with different characteristics and priorities. Walker (2008) investigates different community concepts that exclusively focus on financing renewable generation capacities without any local energy exchange. He distinguishes between different forms, for example, investing in commercial power plants or joint financing of own facilities that are not used for self-supply. The author refers to these concepts as *energy cooperatives*. Walker (2008) separates these concepts from the energy community concept with a local exchange of energy. The concept of renewable energy cooperative (Capellán-Pérez et al., 2018) and citizen energy cooperatives (REScoop, 2021) also fall under this definition.

Another special form is the concept of ‘community microgrids’, which is also often used in the context of energy communities. Warneryd et al. (2020) define community microgrids as a group of interconnected loads and energy sources that act as a single entity to the grid. Cornélusse et al. (2019) describe the concept as a community in which all members are connected to the same local bus through which they exchange energy with the public grid or among themselves. Gui et al. (2017) define community microgrids as self-contained systems that may be connected to a central grid or function on their own. Within the microgrid, all connection points, e.g., households, small businesses, prosumers are part of the community. Therefore, community microgrid concepts focus on the physical connection of participants and represent a special form of energy communities. In contrast to other concepts, participation in a community microgrid is not voluntary and tied to the grid topology (Perger et al., 2021).

The concepts and descriptions of ’energy cooperatives’ and ‘community microgrid’ can be differentiated from the energy community concept because their focus is exclusively on monetary benefits or participation within them is not voluntary. Other described energy community concepts in the literature are in line with the conditions of free participation and benefits for the community by Walker and Devine-Wright (2008). Orozco et al. (2019) uses the term ’local energy community’ to describe a set of residential and industrial actors connected to the same distribution network to form a community voluntarily. Romero-Rubio and de Andrés Díaz

(2015) refer to the concept as 'sustainable energy community'. They emphasize the collective, sustainable use of own generation facilities and expand the local exchange characteristic to other sectors such as heat or water. The authors argue that the goal of sustainability also includes additional commodities besides electricity. Kunze and Becker (2015) coin the term 'collective and politically motivated renewable energy project'. The authors emphasize that an energy community must have a political purpose and participation should generate benefits for each member. In addition, Gui and MacGill (2018) provide a typology that distinguishes communities between centralized, distributed and decentralized. The authors define energy communities as a social structure fostering a sustainable energy supply. They also extend the community focus to other commodities like heat, transportation, water, or waste management, similar to Romero-Rubio and de Andrés Díaz (2015). Overall, the concept can be characterized as an approach in which citizens voluntarily come together in communities to exchange locally generated energy and thus generate added value that is not necessarily monetary.

In 2019 the European Union has introduced the legal concept of the CEC to group all these different terms and descriptions and provide a regulatory framework (Parliament, 2019). Within the 'Directive on Common Rules for the Internal Market for Electricity' the EU defines the CEC as a legal entity that is based on voluntary and open participation and is effectively controlled by members or shareholders. These can be natural persons, local authorities, municipalities, or small enterprises. Its primary purpose is to provide environmental, economic, or social community benefits to its members or shareholders or to the local areas where it operates, rather than exclusively generating financial profits. The concept covers the generation, distribution and consumption of energy. CECs are platforms that actively integrate citizens into the energy system on a local level, empower the energy sector's decarbonization (Schram et al., 2019) and substantially benefit the local value chain and energy system (Zwickl-Bernhard and Auer, 2021; Caramizaru and Uihlein, 2020). Caramizaru and Uihlein (2020) analyze several European community projects, their goals and experiences. The authors point out that these communities support the energy transition, foster citizens' participation in renewable energy generation and integrate prosumers as well as consumers. They thus allow consumers' access to capital and benefits of decentralization independently of their income. The CEC concepts utilize various digital technologies and optionally include a trading platform to enable their stakeholders to interact with each other and exchange energy. Therefore, the market engineering framework is used in the following to describe and explain the different dimensions of the CEC platform by Weinhardt and Gimpel (2007) displayed in Figure 3.1.

3.2. Market Engineering Framework for digital Citizen Energy Communities

In this chapter, the established market engineering framework by Weinhardt and Gimpel (2007) used to provide an overview of the different dimensions of the CEC trading platform. Figure 3.1 depicts this framework. The framework supports the evaluation and design of markets by breaking them down into their constituent parts and analyzing them accordingly. It consists of five main components: The socio-economic and legal environment, the transaction object, the market structure, the agent behavior and the market outcome. The market structure is divided into three sub-components: the micro structure, the IT infrastructure and the business structure. In the following, each component is described, existing literature regarding this dimension is presented and existing research gaps are connected to contributions of this dissertation.

3.2.1. Socio-economic and Legal Environment

The first component of the framework focuses on the economic and legal environment to provide a broader context and existing limitations and conditions that the platform operator must consider. The legal framework for the CEC platforms within the EU is the 'Directive on Common Rules for the Internal Market for Electricity'. This regulatory environment applies only to the EU member states. Other governments may have different regulatory regimes. Since the focus of this dissertation is not on the regulatory aspects of energy communities, this section describes the EU CEC regulation exclusively, with a special focus on the current regulatory situation in Germany. As already described in Chapter 1, the EU

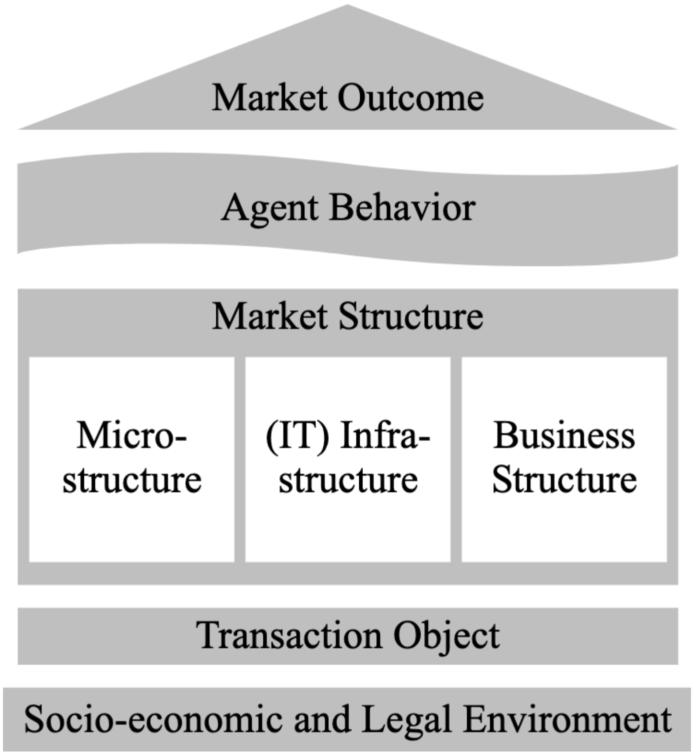

Figure 3.1.: The market engineering framework by Weinhardt and Gimpel (2007)

directive defines the CEC as a legal entity that must be controlled by its members or shareholder, which are natural persons, local authorities, or small enterprises (Sokołowski, 2020; Parliament, 2019). Citizens should voluntarily form and join these communities and these communities appear to the outside grid and energy market as a single entity. Citizens within these communities can engage in investing, generating, consuming and sharing energy (Reijnders et al., 2020). The overall purpose is to provide environmental, economic, or social community benefits to its members or to the local area where it operates. The definitions of the directive are broad in order to give the member states leeway. However, with the directive introduction in 2019, EU member states have been obliged to implement it into national law within the timeframe of two years. The German government passed the deadline and has not yet introduced any changes to the regulatory framework for forming CECs, stating that the existing regulations would be sufficient to form CECs. Various environmental and citizen groups disagree with this view and have already lodged a complaint with the EU (Ullrich, 2021). The following part describes the current German regulatory framework, its corresponding hurdles for introducing CECs in Germany and the existing niche to bypass these restrictions.

Even though liberalization in Germany has opened up the generation and consumption stages of the value chain to competition, there are still regulations and legislative requirements which affect the CEC core functionality. A key element of the CEC concept is the direct exchange of energy between local generation and consumption within the community. However, various legal requirements prevent prosumers from selling their generation surpluses directly to consumers in their vicinity. First, each consumer is guaranteed to be supplied with electricity according to §36 EnWG. However, the regulation prohibits that several energy retailers supply a single consumer in parallel. Therefore, a prosumer who sells energy directly to a local consumer takes the role of an energy retailer from the perspective of the German regulator. Several legal requirements exist for energy retailers. According to these, the prosumer would be responsible for the procurement of the complete consumer's energy demand. This obligation results in the fact that the prosumer would have to buy energy for the consumer on the energy market if there are no generated surpluses. This is a high hurdle for private prosumers who are not professional energy retailers. §40 EnWG states that an energy retailer must also fulfill several administrative requirements and tasks. Examples are the communication of the contract duration, compensation arrangements, information about termination rights and the setting of a price and registration with the local grid operator. Also, the energy retailer must ensure a regular meter reading (§40a EnWG). These requirements create administrative costs, leading to an unprofitable situation for the prosumer.

Nevertheless, there is a possibility of implementing CECs and circumventing existing regulatory hurdles. Under German law, the 'Kundenanlage' (customer system) is such a regulatory niche (§3 No. 24a EnWG). In this context, a grid area can be declared a customer system if it represents a geographically contiguous area and does not affect competition on the wholesale market overall. Following a landmark decision by the German Federal Court of Justice, several criteria were defined, which determine whether a grid area can be declared as a customer system. Regarding the geographical aspect, the court decided that a grid can be declared as a customer system, when there is no need for another power facility to supply all end consumers in the grid. Regarding the competition aspect, the court defined several predefined criteria for a grid area to be declared as a customer system. The first criterion is that the number of end consumers connected to the grid is not higher than a several hundred. Second, the grid area covers approximately 10,000m^2 or smaller. Third, the annual amount of transmitted energy remains under 1,000 MWh and fourth, only one building is connected (Gabler and Pennekamp-Jost, 2020). According to the current jurisdiction, a grid area can be defined as a customer system if it meets the described criteria with the exception that one criterion does not have to be fulfilled. For example, the served area by a potential grid area with 10 end consumers in one building is bigger than 10,000m^2 and the transmitted annual energy also exceeds 1,000 MWh. This grid cannot be defined as a customer system. A similar grid with an annual transmitted energy under 1,000 MWh can be declared as a customer system.

In a customer system, the operator acts as the energy retailer for all consumers in the customer system. The operator, therefore, has to comply to the regulation i.e., being responsible for buying missing residual quantities from or selling surpluses to the public grid. A major advantage of the customer system is that the participants themselves do not have to comply to several regulator's requirements. From the perspective of the public grid, the customer system is a single entity.

From the economic perspective, the customer system has additional advantages, as several components of the electricity price do not apply. First, several levies (e.g., for disconnectable loads) and electricity tax must not be paid by consumers. In addition, the customer system operator is also the network operator for this grid and not bound to the regulation described in Chapter 2. Therefore, the operator can set the network charges on its own Held and Mannsdörfer (2018). For this reason, the electricity price within the customer system was about 16.00 EURct lower than in the public grid in 2021. Table 3.1 displays the different price components. Not only consumers, but also prosumers benefit from an additional monetary incentive to participate in the community. Consumers can expect a lower energy price than in the public grid. At the same time, prosumers can sell their surplus energy at a higher price. The customer system represents a regulatory niche where it is possible to establish CECs under existing regulation.

Components	Average Tariff (2021)	Customer System (2021)
Generation	8.31	6.93
Metering fee	0.49	0.49
Network fees	7.28	0
Concession	1.64	0
Renewable surcharge	6.50	6.50
Other Levies	1.09	0
Electricity tax	2.05	0
Value-added tax	5.20	2.64
Total	**32.56**	**16.56**

Table 3.1.: Cost structure of average tariff and customer system in 2021 (Bundesnetzagentur and Bundeskartellamt, 2021)

3.2.2. Transactional Object

The transaction object is the second component of the market engineering framework and describes the good, which is exchanged over the platform. According to the existing energy community literature, this is not exclusively limited to electrical energy. Romero-Rubio and de Andrés Díaz (2015) include the exchange of other commodities like heat or water. Gui and MacGill (2018) also consider different goods like heat, transportation, water and waste management. While, the transactional object can vary between different communities, the EU directive refers exclusively to electrical energy. In line with the EU directive's definition, this thesis will focus exclusively on electrical energy as the transactional object.

From the physical perspective, electricity can be characterized as a homogenous good. However, Ma et al. (2015) and a choice experiment by Borchers et al. (2007) indicate that consumers start to distinguish between different electricity origins. For example, Kaenzig et al. (2013) shows that consumer prefer different electricity mixes. Mengelkamp et al. (2019c) identify a subgroup of potential community participants who state that they would pay premium prices for local energy, which indicates differentiation between different energy origins. This origin differentiation of the transactional object will be addressed more closely in the following microstructure section and the Chapters 6 and 8.

3.2.3. Microstructure

The microstructure component is part of the overall market structure and describes the market sides, its actors and the market mechanism design. It determines how the available resources are allocated and priced (Dauer et al., 2016). For the CEC platform, a market mechanism allocates locally available energy from local suppliers (prosumers/generators) to consumers. The academic community discusses different market mechanisms and trading designs in the literature, often under the term of local energy markets, which represent a special form of the CEC concept. A popular mechanism is the double call-auction (Block et al., 2008; Goncalves Da Silva et al., 2014; Ding et al., 2013; Ampatzis et al., 2014). Block et al. (2008) apply a combinatorial approach to create bids for heat and electricity at the same time. A continuous double auction design is also used by Ding et al. (2013) and Goncalves Da Silva et al. (2014). Ampatzis et al. (2014) set up discrete time intervals in which a continuous double auction takes place. Mengelkamp et al. (2018c) present a discrete double auction (merit order mechanism) with a single clearing price in each period. The same mechanism is used by Holtschulte et al. (2017), Mengelkamp et al. (2018a) and Lezama et al. (2019). This auction type is widely used in wholesale energy markets around Europe. For a deeper insight into these different designs, Mengelkamp et al. (2019a) provide an overview of these different approaches and market mechanisms.

Besides the allocation of local, available energy, a key challenge for the design of the CEC market mechanism are the increasingly differing preferences by consumers for these energy sources, as described in the transaction object section. Several studies in the literature assume that participants have a heterogeneous willingness to pay for different energy sources and pay premium prices for renewable or local energy sources. For example, Perger et al. (2021) assume that CEC participants have heterogeneous goals and a corresponding willingness to pay. The authors differentiate between two agent types, profit-orientated participants with a low willingness to pay for green energy and environmentally concerned participants with a high willingness to pay for green energy. The authors develop a trading mechanism, which incorporates the individual willingness to pay. They create a sample community with a set of arbitrary participants with ten private households and five small businesses and assume different willingness to pay values for each participant to evaluate the performance of their mechanism. Similarly, Zade et al. (2022b) propose an auction-based approach to satisfy community participants' preferences, allowing them to pay premium prices. The authors state that current approaches do not consider heterogeneous user preferences. They propose seven clearing mechanisms and evaluate their performances with the help of a Monte Carlo simulation. Aligned with both studies, in Chapter 6, a newly developed mechanism is presented that incorporates the different valuations of CEC participants and according to these preferences, organizes a market order of the available energy sources.

Besides the allocation of local energy, the security of supply is critical for the CEC. Locally generated energy is not always available, which especially holds true for renewable sources and they depend on weather conditions. As described in the socio-economic and legal environment section, a CEC is a single entity from the perspective of the public grid. This public grid takes over the balancing task in the case of missing generation. At the same time, in case of high local generation, the surplus quantities are supplied to the public grid. These quantities are not traded on the CEC platform. Therefore, the public grid acts as a balancing entity for the CEC.

3.2.4. Business Structure

The component of the business structure is part of the overall market structure and describes the economic value streams for the market operator. It is composed of the business model, pricing and transaction costs (Dauer et al., 2016). Due to its novelty, business models for CEC platforms are not yet clearly defined and an apparent revenue model is missing. According to Mengelkamp et al. (2019b) there is a tendency towards periodic, transactional, or energy volumetric payments. The former describes regular, fixed membership to be part of the community. Transactional payments are fixed fees on each transaction and energy volumetric payments are similar to volumetric tariffs, where the participant has to pay for each bought kWh. In contrast, entry payments seem unlikely because they act as an entry barrier for possible new participants. Besides receiving payments from its participants, the community can sell surpluses from community-owned generations. An alternative approach is that local utilities offer their customers to join CECs that they operate as an additional service. Local utilities might offer this service as it may increase customer loyalty and provide the possibility of selling additional services and products like installing solar panels or energy efficiency services. An important condition regarding the business structure is that it should not focus exclusively on financial benefits. As the CEC directive states, it must additionally provide environmental or social community benefits to its members or shareholders or to the local areas where it operates. Therefore, these benefits must be incorporated into the business structure of the CEC.

3.2.5. IT Infrastructure

The third component of the market structure is the IT infrastructure. It describes the technical basis of the market and underlying process to ensure its functionality. Regarding the CEC platform, it consists of various technologies, hardware and software and systems that involve different stakeholders. These must be coordinated and brought together in the right manner, which is a complex task. The architecture of this IT infrastructure plays a central role for the CEC platform. The architecture needs to describe how to divide the overall information system into various modules with specific tasks. Each module has specific requirements. Within the IT architecture, these modules interact with each other to exchange information (Ross, 2003). Each interaction can be defined as a process. The goal of the IT architecture is to organize the different modules and processes, which ensures the overall functionality of the platform.

In general, IT architectures play an essential role for companies, organizations, or institutions (Ross, 2003; Alonso et al., 2010). Due to the ongoing digitization of many sectors, the structure and functionality of the implemented IS have become more complex and relevant. Thus, the architecture plays a significant role (Schmidt and Buxmann, 2011). There is no clear definition of the term IT architecture and the term is often used synonymously with the term IT infrastructure (Ross, 2003). According to Ross (2003), an IT architecture is ‘the organizing logic for applications, data and infrastructure technologies, [...]'. Schütz et al. (2013) subdivide the IT architecture into three areas to examine the respective level of complexity in more detail: data and information architecture, application architecture and infrastructure technology. Guillemette and Paré (2012) define an 'architectural builder', which builds and organizes the IT infrastructure in such a way that it can implement the required processes while reducing complexity. They describe the IT architecture as individual modules which interact with one another. A defined process represents each interaction and the modules utilize different technologies. The latter is partly independent of the architecture, as it only determines the minimum requirements for the technology. Overall, there is a whole research field in the information system domain that deals with the management and complexity of IT architectures (for an overview, see (Schütz et al., 2013)). Beyer et al. (2004) state that the information system's architecture represents an integral part of the entire socio-technical system and includes the stakeholders' requirements. They present an IT architecture for integrated healthcare networks. The authors use an extensive literature review and stakeholder interviews to identify existing information systems' key challenges and problems for healthcare networks and derive the essential functionalities relevant to the architecture.

Looking at the literature of CEC concepts, there is a multitude of different approaches, shown by the review of Sousa et al. (2019). Different IT architectures are proposed. The corresponding studies focus either on the overall system or the energy management of smaller sub-areas of the grid, e.g., (Khorasany et al., 2018; Anthony Jnr et al., 2020; Gottschalk et al., 2017; Wu et al., 2015). There are already first architecture approaches to integrate CECs into the overall system (Zhang et al., 2018; Andrade et al., 2020). Other approaches show the interaction between the individual stakeholders (Mazzola et al., 2020) or the interaction with the overall system (Zia et al., 2020; Budiman, 2018). Yet, a specific and detailed CEC IT architecture with its different modules and processes is missing. This dissertation addresses this gap in Chapter 4.

3.2.6. Agent Behavior

The agent behavior component describes the interaction between the sellers and buyers on the market, which effects the market outcome. In the context of the CEC platform, the agents are the local generators and consumers. Their behavior on the platform can be described by the accessing individual information and based on this, submitting bid prices or shifting consumption. This behavior is influenced by the user interface and market design of the platform, which is determined in the market structure component. In this dissertation, we analyze the agent behavior regarding the stated CEC benefits. First, we review behavioral assumptions from the literature and comparing them to the real behavior on a CEC platform to determine if the platform and interface design result in the desired behavior, a long-term engagement. Second, we identify factors which support this long-term participant engagement on the CEC.

Regarding the behavioral assumption in the literature, several authors assume diverse willingness to pay for electricity from different energy sources. Another assumption is the CEC participants' activity on the platform. Most studies assume a regular activity of participants in CECs. Mengelkamp et al. (2017); Gazafroudi et al. (2021) analyze bidding strategies given different market mechanisms. However, they assume a regular interaction by the participants and do not incorporate behavioral restrictions, for instance, no activity at night because a human participant would sleep in these periods. Similarly, Chen and Su (2018) model participant behavior with the help of a deep reinforcement learning approach. The authors do not incorporate possible human restrictions, which also influence trading ability. Ableitner et al. (2020) provide first field insights into CEC participants' behavior. The authors cluster participants' behavior into three groups based on their activity. However, the authors do not discuss how participation activity can be influenced and if the behavior changes in the long run as the project ended after the four months period.

The platform price signals indicate the local scarcity of the available energy sources. A common assumption in the literature is that these local price signals can influence the participants' consumption behavior and contribute to system balancing. Mengelkamp et al. (2018a) state that CECs can provide investment incentives and support local grid balancing. However, the authors do not provide any empirical evidence. Zhang et al. (2018) design an energy exchange platform and simulate trading on it. They show that local trading within a community supports balancing local demand and supply. However, their results are based on the assumption that participants are willing to shift their consumption. Faruqui et al. (2017) confirm in their meta-study that consumers reduce their peak load in response to higher peak prices. They also state that this effect gets more potent with enabling technology such as in-home displays, which visualize the load data and prices. In the study by Ableitner et al. (2020), the authors report indications for an increased load-shifting by the participants in their field project. However, these statements are based on interviews and not on quantitative data analysis. This dissertation reviews and tests these assumptions by analyzing the long-term behavior and reaction to price signals on the LAMP platform in Chapter 8.

3.2.7. Market Outcome

The market outcome is the result of the market's structure, its economic and legal environment and the agent behavior. It represents the final step in the framework and can be measured by different indicators. The defined market outcome allows for comparing and assessing different market designs with each other and helps to improve them. Regarding the CEC platform, the market outcome can vary between different CEC concepts. By definition, the regulatory framework for the CEC concept is kept open and thus allows for different objectives. Therefore, the market outcome should be based on the individual goals of the stakeholders and participants.

In the literature, different goals of the market outcome are discussed. The first one is to increase the consumption of self-generated energy within the community (Mengelkamp et al., 2018c; Ilic et al., 2012; Hvelplund, 2006). In line with this, contributing to grid stability can also be an important market outcome. Here, the CEC supports the grid and its stability through active behavior and price changes depending on consumption within the community. Another goal can be the collective financing of new generation or storage units or the provision of other services like charging stations. Despite the different targets stated in the literature, the fundamental aim to achieve any of these goals is a long-term, active engagement on the platform by the community participants. Without this engagement, none of the above goals can be achieved and is therefore a necessary market outcome for CECs. Therefore, this dissertation focuses to analyze and support the long-term engagement of CEC participants. We define 'long-term engagement' as participants who regularly but not constantly interact with the system and engage with the information provided over a long-term period.

3.3. Overview of Real-World Projects

One of the first well-known CEC project with a trading platform is the Brooklyn Microgrid in New York that performed a blockchain-based electricity trade in 2016 (Mengelkamp et al., 2018a). It consists of a digital trading platform based on the tendermit blockchain technology and the market mechanism utilizes a time-discrete double auction with 15 minute trading periods. Mengelkamp et al. (2018a) state that the project team worked closely with the local regulator. However, there is only little information on the existing regulatory situation and economic incentive structure. Also, Mengelkamp et al. (2018a) do not discuss the outcome of the market mechanism, the number of participants (prosumers/consumers) and an assessment of their behavior. In Europe, there are several CEC projects. An overview of different projects is provided by Weinhardt et al. (2019). The 'Energy Collective' is a project in Roskilde, Denmark. Moret and Pinson (2019) introduce a market organization for the community and describe the interactions between a system operator and other CECs. They focus on the transaction object, the role of a community manager and introduce a distributed optimization approach for the operation of energy collectives. The authors assess different market outcomes and mechanism design choices based on simulation results. The required IT architecture, regulatory environment and participants' behavior are not described in further detail.

The authors of Wörner et al. (2019a), Wörner et al. (2019b) and Ableitner et al. (2020) discuss the findings of the 'Quartierstrom' project in the Swiss town of Walenstadt. They describe a user-centric approach focused on the user value proposition and participant preferences by enabling peer-to-peer energy exchange. The project ran for a total of four months and included 37 households. The focus of Wörner et al. (2019a) lies on the agent behavior and market outcome. The authors define electricity as the transaction object and investigate the willingness to pay for renewable energy. Wörner et al. (2019b) discuss the market design and technical structure of the peer-to-peer market. They give an overview of the IT architecture focusing on the implemented blockchain technology (Wörner et al., 2019b). However, there is no further description of the underlying IT infrastructure. Ableitner et al. (2020) combine the results of both publications and the study gives more insight into the project structure and the behavior of the participants.

RegHEE is a CEC project by the TU Munich. The project includes 17 households and the market mechanism consists of a periodic double auction with a quarter-hourly matching (Zade et al., 2022a). Zade et al. (2022a) evaluate the potential of the blockchain technology. The authors show the technology limits in performing market transactions securely and cost-effectively. Agent behavior and market outcome are not described.

The 'SoLAR' project is located in the German city of Allensbach. As presented by Kremers (2020), the project aims to demonstrate the maximization of renewable energy consumption in decentralized energy systems. The author introduces an intelligent energy management system and focuses on the interaction between a real energy system and a digital energy twin. The focus of the infrastructure description is on the specification on energy appliances, such as a PV panel or a combined heat and power (CHP) plant. Instead of a market mechanism, a control system is used to improve self-consumption, grid friendliness and cost benefits.

Vasconcelos et al. (2019) provide an introduction to the structure of the German LEM demonstrator project 'Pebbles' in the Allgäu region. The authors especially focus on possible business models for the different stakeholders, the required legal-regulatory framework in the context of CECs and how they can interact with distribution system operators to enhance reliable grid operation. A preliminary system architecture is also presented and the authors examine possible implementations of blockchain technology. However, the authors do not describe a detailed IT infrastructure that is required to implement their LEM. The overview of the classification of LEM projects in Table 3.2 shows what Market Engineering components the described studies cover.

Project	Socio-economic & Legal Environment	Transaction	Market Structure: Microstructure	Market Structure: Business Structure	Market Structure: IT-Infrastructure	Agent Behavior	Market Outcome
Brooklyn Microgrid	(x)	x	x	(x)			
Energy Collective		x	x				(x)
Quartierstrom		x	x	(x)	(x)	(x)	(x)
RegHEE		x	x		x		
SoLAR		x	x			x	
Pebbles	x		x	x	(x)		

Table 3.2.: Market engineering classification of existing CEC projects

3.4. The Landau Microgrid Project

Parts of the provided insights of this dissertation are based on the results of the LAMP real-world field project. This project has been conducted in a cooperation between the Karlsruher Institute of Technology, the software company Selfbits GmbH and the local utility EnergieSüdwest. Its objective has been to investigate the different requirements and challenges of an implemented CEC. Throughout the project, data has been gathered on the impact of the design, implementation and operation of the CEC platform. In the initial planing, the project IT infrastructure was supposed to be based on blockchain technology. However, due to the low maturity (Heck et al., 2020), the project team switched to a centralized approach, described in Chapter 4. The chosen neighborhood for the project lies within an areal grid, which falls under the previously explained customer system regulation and belongs to the involved utility. The grid has only one connection point to the public distribution grid. There are 118 connection points within the areal grid, the majority of which are private households. At the beginning of the project, the project was advertised in the neighborhood and 11 households decided to participate. Of these, five live in single-family homes and the rest lives in multifamily homes. The household size is between one and five persons. The average age of the participants is 49. The annual consumption of these participants corresponds to about 9% of the total consumption

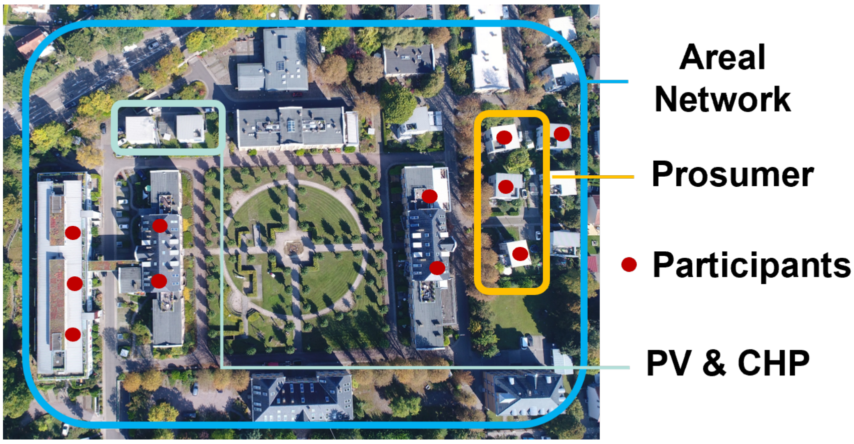

Figure 3.2.: Overview of the Landau Microgrid Project area

in the areal grid. The neighborhood features local generation facilities. A local CHP plant with a capacity of 50kW electrical (85kW thermal) and a PV system with a capacity of 23.56 kWp generate energy locally. The CHP is heat-controlled and supplies the households with heat. Electricity is a by-product. The typical load of the CHP depends on the time of year. It is almost at full load during the winter due to heat demand, while it is mostly inactive in summer. In spring and fall, its operation depends on the weather. The project partner utility owns and operates both installations. In addition, three participants installed a PV system during the project run time and became prosumers. The five power generation units are the only available local power sources and provide the local supply. Figure 3.2 shows the project area and the location of all participants and generation sites. The utility project partner operates the platform and organizes the excess or missing power quantities that cannot be matched locally. Over the course of the project, the local utility standard grid tariff of 23.67 EURct/kWh applies. Comparably, every locally generated kilowatt-hour that cannot be consumed locally is sold to the public grid at the corresponding feed-in tariff. The feed-in tariff is 11.0 EURct/kWh for PV electricity and 8.0 EUR/kWh for CHP. All transactions are recorded by the information system and stored in the database.

Part II.

Citizen Energy Communities - Platform

Introduction to Part II

The digital platform is the central building block to digitize a CEC. Without it, participants would not be able to view their individual consumption data and actively trade with each other, as described in Chapter 3. The core of this digitalization is the platform's IT infrastructure, its architecture, individual components and utilized technologies, which represent and ensure the fundamental functionality. In Chapter 4, the individual technical components of the digital CEC platform are identified, an appropriate IT architecture to organize them is developed and the performance and experience with the utilized technologies in the real-world implementation (LAMP) is analyzed. The ongoing discussion on the use of blockchain technology for CECs is mainly linked to the maturity of the technology, as well as its implementation status within the CEC projects. So far, there is a lack of a model that supports practitioners to determine the maturity level of their own blockchain-based CEC project and to identify appropriate next steps. Therefore, in Chapter 5, a blockchain maturity model for CECs with trading platform is developed. Besides technical functionality and blockchain technology, the goal of the platform is to enable local energy trading between the CEC participants. A unique feature of this local trading is that it allows the differentiation between available local energy sources. Studies show that participants have a different willingness to pay for various energy sources. The last chapter of this part describes a novel market mechanism that considers this difference in the willingness to pay of CEC participants and allocates available energy according to their stated preferences (Chapter 6).

Chapter 4.

IT Architecture Design

This chapter develops a specific and detailed IT architecture for CEC platforms. As described in Chapter 3.2.5, an essential part of the IT infrastructure is its architecture, which defines processes and modules and thereby meets different CEC stakeholder requirements and reduces complexity. Therefore, a CEC IT architecture design is derived in this chapter, consisting of four essential modules and six corresponding processes. It is based on the available literature and existing CEC implementations. The derived IT architecture is tested and assessed in the real-world implementation, the LAMP project. For a detailed description, see Chapter 3.4. Each module and process is implemented and evaluated in the project. In addition, a set of suitable technologies is tested within this real-world setting and the advantages and disadvantages are discussed in detail. The proposed IT architecture can serve as a blueprint for future CEC projects, as it covers the fundamental processes and is at the same time extendable.

This chapter comprises the published article by B. Richter, A. Golla, K. Welle, P. Staudt, C. Weinhardt, *Local Energy Markets - An IT Architecture Design*, Energy Informatics, 2021. cited here as: Richter et al. (2021).

4.1. Introduction

From a technical perspective, the digital CEC trading platform can be described as the information system which organizes the matching between the local generators and consumers. As already described in Chapter 3.2.5, the IT infrastructure of this information system consists of various technologies, modules and systems owned by different CEC stakeholders. These different modules must be organized and work together to perform a specific task and allow the participants to use the platform and interact with other participants or access necessary load and market information. The correct organization and communication between the different modules is a complex task, which underlines the importance of a suitable architecture for the IT infrastructure. It can reduce the complexity by coordinating the interactions and defining the specific tasks of each module. As described in Chapter 3.2.5, there is a lack of IT architecture proposals for CECs in the academic literature. Also, practical experience from real-world implementations is missing. Therefore, it is crucial to discuss the necessary functionalities and the structure of a CEC IT architecture based on the body of literature and experience of real-world implementations. First, we identify the individual modules and processes of a CEC IT architecture based on the existing literature body. Second, building on this, we assess LAMP as an existing real-world CEC project that implements this IT architecture. We describe the architecture in detail and discuss the implemented technologies, including design choices and share our experiences from the LAMP case study. We also elaborate on the advantages and disadvantages of these technologies based on experience from the operation. With this analysis, we answer the research question: *What are the fundamental modules, processes and a suitable implementation of a CEC IT architecture?*

4.2. Identifying the IT Architecture Structure

The development of CECs is still in an early stage and there are many different designs and proposed functionalities. There is already a large variety of literature on CECs. An overview of this is given in Chapter 3. Our analysis of the IT architecture focuses on CECs with a trading platform, also known as LEMs, as these have been discussed and addressed very frequently. We analyze the existing literature for basic functionalities and processes of CECs. Due to the complexity and an often lacking precise formulation of assumptions on the underlying functionality, we also evaluate information from existing CEC implementations to obtain further information on possible architectural building blocks. With both analyses, we determined the basic functionality and the resulting necessary processes. Based on these, we define and describe the required modules of the IT architecture and describe their tasks and related processes. As a result, we have identified four key modules of the IT architecture that literature frequently refers to and which are often present in the analyzed projects. These components are the 'Smart Meter Hardware', 'Market Implementation', 'User Interface' and 'Database'.

4.2.1. Smart Meter Hardware

The first module is the *Smart Meter Hardware*, which many authors implicitly or explicitly mention. Energy trading on a CEC trading platform requires the measured load values of all participants in real-time. Metering infrastructure is necessary to capture load data and specify parts of the CECs functionalities (Ilic et al., 1998; Teotia and Bhakar, 2016; Long et al., 2017). Mengelkamp et al. (2018a) state that each participant requires a smart meter to measure the required load data. Overall, the task of this module is to measure load data and transfer the data to the information system. These measurements take place at the participant's home and the hardware transfers the information with specific communication technology. This module can come with various technology standards, but in the analyzed literature, no author precisely specifies their specific technical approach or mentions possible technical standards. In the related smart meter literature, different technologies are proposed. The most common ones are the data transmission over the mobile network, local area network (LAN) (Kabalci, 2016), or various radio standards like LoRaWAN (Mlynek et al., 2015; Varsier and Schwoerer, 2017). In the case study, we will discuss the advantages and disadvantages of the LoRaWAN technology in more detail. Besides the communication technology, the measuring capability of the smart meter hardware is crucial for market mechanisms. A 15-minute clearing interval requires measurement data in the appropriate resolution or higher (Ilic et al., 1998; Block et al., 2008). Therefore, the smart meter hardware technology's feasible measurement accuracy determines which market mechanisms can be implemented successfully. However, they all share the need for some form of smart metering technology.

4.2.2. User Interface

The connection between the users and the information system plays a minor role in the current literature. Although the individual participant groups like prosumers or private households are described in almost all CEC-related publications, virtually no information is provided on how the participants interact with the information system. Several authors mention an application or user interface (Wörner et al., 2019a; Mengelkamp et al., 2018a; Wörner et al., 2019b; Vasconcelos et al., 2019). However, it is not clear what functionalities this module includes. This is probably caused by the still early development stage of the CECs. Since many CEC concepts are based on active trading and participation by the different stakeholders, the submission of preferences or bids and the reception of market and consumption data is necessary. Each participant must be able to place bids on the market, view and monitor transactions, market results and consumption or generation data (Mengelkamp et al., 2018c; Wörner et al., 2019a; Energy, 2018a,b). Also, the *User Interface* module requires a verification process. Mengelkamp et al. (2018a) state that each participant's identity must be ensured via a verification process. This authentication is an important component, as individual load data is sensitive. Additionally, the information system must prevent the users from viewing each other's individual information or placing bids for someone else, which threats the integrity of the CEC. In the blockchain context, identity management is also mentioned (Wörner et al., 2019b; Mengelkamp et al., 2018d). In the mentioned publications, different identities are assigned with the help of blockchain technology.

4.2.3. Market Implementation

The third module is the *Market Implementation.* The vast majority of publications deals with different approaches and proposals about the allocation mechanism of the market. The literature does not explicitly mention the process needed to execute the market. Most authors do not specify the required data in concrete terms. However, these can usually be derived from the design of the mechanism. In (Mengelkamp et al., 2019a), the authors identify over 30 publications that describe a kind of market mechanism or 'trading design'. There are approaches like auctions (Teotia and Bhakar, 2016; Mengelkamp et al., 2019a; Lezama et al., 2019), P2P designs

(Wörner et al., 2019a; Sousa et al., 2019) or mechanisms that rely on an optimization algorithm (Block et al., 2008; Torbaghan et al., 2016; Holtschulte et al., 2017). For more details see Chapters 3.2.3 and 6. In most cases, the load data and user input (bids, preferences, willingness to pay) are necessary. Overall, the basic function of this architecture module is to request the required information and prepare it for the market mechanism. With this data, the implemented market mechanism software calculates the individual transactions. Then, the market mechanism module passes these transactions back into the information system. It becomes clear that the concrete design of the market mechanism is not relevant for the IT architecture itself and can be substituted as needed. Only the capabilities of the smart meter technology need to be respected by the market mechanism design.

4.2.4. Database

The *Database* module is the last in the proposed architecture. This module, similar to the *User Interface* or *Smart Meter Hardware*, is rarely specifically mentioned or specified in the existing literature even though it is clearly part of the architecture. There are often implicit assumptions, since many authors promote the blockchain or distributed ledger technology in their approaches (Blom and Farahmand, 2018; Mengelkamp et al., 2018d; Wörner et al., 2019b; Mengelkamp et al., 2018a; Wörner et al., 2019a). For instance, the *Smart Meter Hardware* module generates data and stores it in the blockchain database for both the *Market Implementation* and *User Interface* modules. The blockchain is a special type of database which is self-managed locally by all participants. They agree on the current state of the database through a consensus mechanism (Mengelkamp et al., 2018d; Andoni et al., 2019). However, the usage of this technology is much broader than the storage of information. For example, smart contracts execute the market mechanism on the blockchain automatically (Wörner et al., 2019b; Mengelkamp et al., 2018d). The great attention for blockchain technology indicates that data consistency and assignability play an essential role. In each of these descriptions, the blockchain is the central entity that stores, manages and provides the data. Parts of the information are stored or retrieved regularly (load data, transactions) and some irregularly (bids). The *Database* module must be available at all times. Therefore, the *Database* module itself initiates no processes.

However, this module is the central point in the architecture. Each of the other three modules communicates exclusively with the *Database* module.

4.3. Fundamental IT Architecture Overview

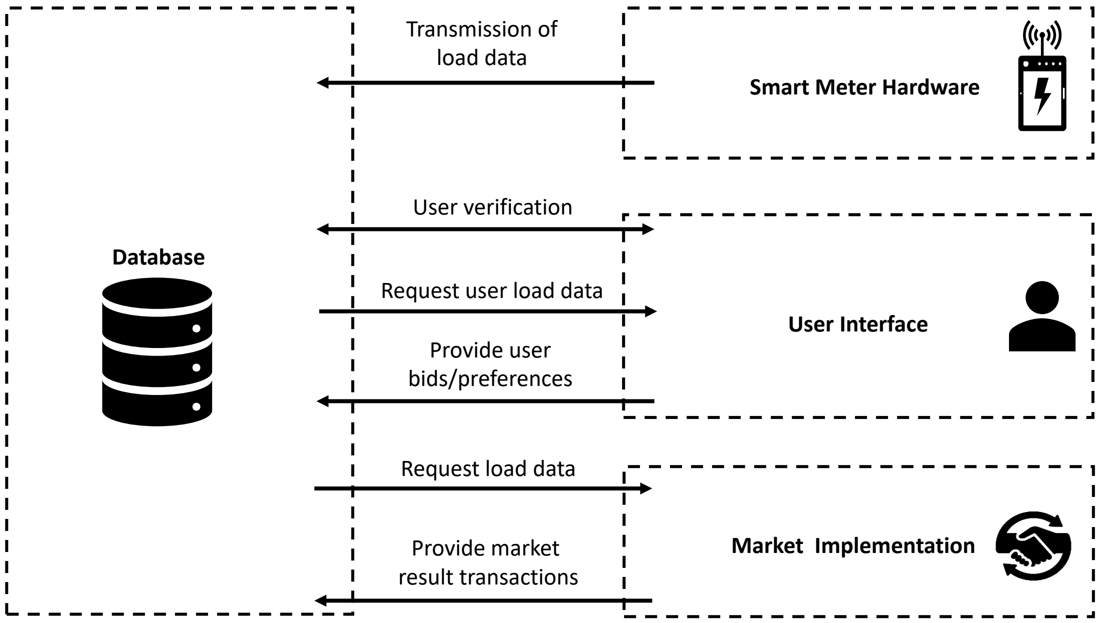

Figure 4.1.: Overview of the fundamental CEC IT architecture

The results of the literature and project analyses are displayed in Figure 4.1 and further explained in Table 4.1. We identify four modules and six processes between them. The modules of the architecture ensure the basic functionality of a CEC and the *Database* module is the central building block of the architecture. Here, all data is stored and distributed. As Figure 4.1 shows, the other modules communicate exclusively with the database. Due to the centralized structure around it, the individual modules influence each other only via the database. This allows the implementation of different market mechanisms and technologies without having to change the underlying structure. Also, it can be extended easily. Different market mechanisms can be exchanged in the module and other modules with additional functionalities can be added. Yet, the technical requirements of these modules or mechanisms, like the resolution of the load data, have to be considered to avoid malfunctions. The proposed modules and processes cover the basic functionality of

CECs. Further functionalities, such as billing or prediction of load values, are partly mentioned in the literature but represent a higher complexity of the CEC IT architecture because regulation has to be considered much more closely. The presented modules with their functionalities should be present in every CEC to ensure its basic functionality. Nevertheless, the gap between academic research and real-world implementations still seems large. Different stakeholders and settings are present in real-world projects. Thus, the IT architecture can differ from our proposed structure. Yet, it should inherit the proposed modules and processes that can be modified or extended.

Module	**Tasks**	**Processes**
Smart Meter Hardware	Recording and processing of load flows	Transmission of load data
User Interface	User identification	User verification
	Visualization of individual load data	Request load data
	Capture user's bids/preferences	Provide user bids/preferences
Market Mechanism	Processing of user and load data	Request load/user data
	Create transaction with market mechansim software	Provide market result transactions
Database	Store and make available all data generated	No outgoing process

Table 4.1.: IT architecture modules, tasks and processes

4.4. Case Study - Modules and Processes of the LAMP IT Architecture

The above presented IT architecture does not describe the modules' internal processes to fulfill their tasks, possible technologies used within the modules and their communication with the database. Besides, it was noticed during the literature analysis that there are no examples of an IT architecture described in detail that has actually been implemented. In the following, we describe an IT architecture of an implemented CEC, the LAMP project, described in Chapter 3.4. We elaborate on the necessary processes, used technologies and discuss their advantages and disadvantages from the experience of a day-to-day operation over two years.

The four distinct modules of the IT architecture previously identified are implemented. First, smart meters with LoRaWAN sensors record the load values of all participants and transfer them (*Smart Meter Hardware*). The local market participants have access to this load data and are able to submit bids to the system through a mobile user application (*User Interface*). The load and bidding data are processed into transactions with the help of a specific market mechanism (*Market Implementation*). A relational database stores all load and market data and manages the access of different users. A representation of the actual architecture with its modules and processes (numbers) is represented by numbers in Figure 4.2. In the following, we describe and discuss each module, its processes and implemented technology in detail.

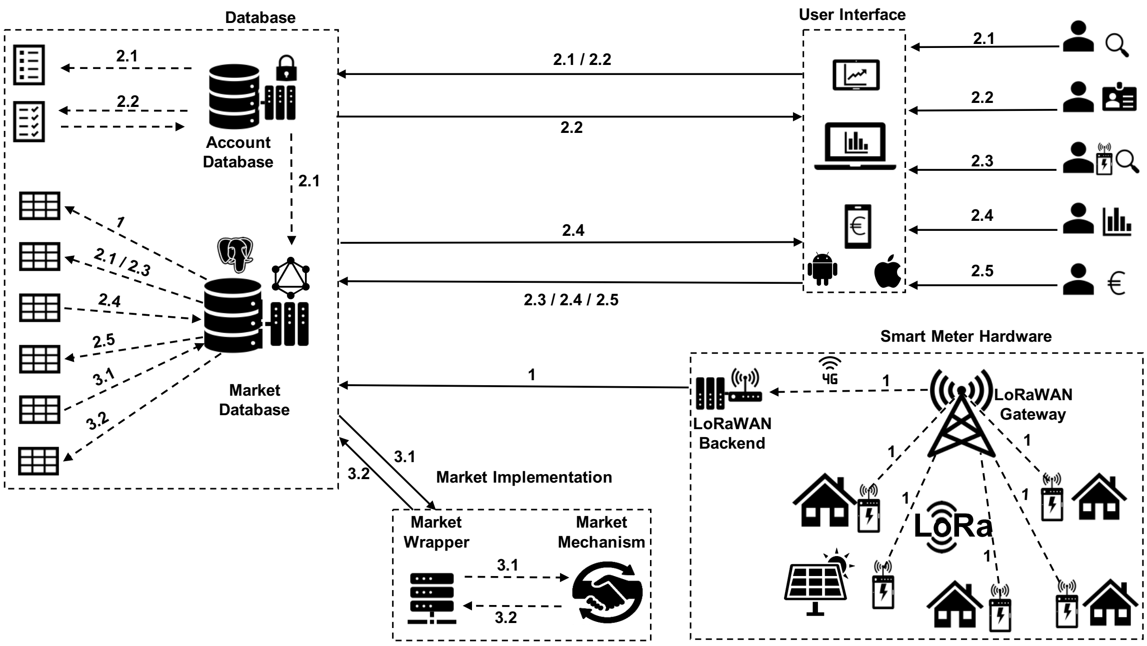

Figure 4.2.: Implementation of IT architecture with corresponding technologies

Smart Meter Hardware: In the LAMP IT architecture, a digital electricity meter records the load data. This meter has a communication module that allows the measured load values to be transmitted to an information system (Process 1). It utilizes the LoRaWAN technology. LoRaWAN stands for 'Long-Range Wide-Area Network' and is a low-power wide area network. The latter describes a network protocol that enables communication over long distances (up to 2-5 kilometers in inhabited areas) and consumes little energy. The architecture of LoRaWAN networks is centralized and organized with one or more gateways as nodes. For a new area, at least one gateway is required in the direct neighborhood. The end devices (LoRa sensors) publish the measured data on the frequency band of 868MHz in 15 minutes intervals. The gateway, which is connected to the internet via the mobile network, receives the signals. Then, it forwards the received data to a network server. Within the LoRaWAN, the network server checks and processes the received data (e.g., deletes duplicate entries) and sends it to an application server where the data is stored. The processing step between the network and application server is necessary because the gateways forward all received LoRa signals. Therefore, it also sends signals from devices that are not intended for the CEC. The network server ensures that only the transmitted load data of the electricity meters is stored. In the last step, the application server transmits the data to the *Database* module via a WebSocket connection. The transfer of load data to the database itself is a process between the *Smart Meter Hardware* and *Database* modules. The system is able to identify the incoming load data of each device. For every active device, the system administrator registers it with a SmartMeterID in the database (more details are presented in Section 4.4).

Technology Discussion: In the project, a digital meter of 'EMH-metering', more precisely, the model LZQJ-XC is used. A LoRa sensor is connected to the meter, reads the load data and broadcasts it over the frequency band which is received by a LoRa gateway, which transmits the data to an information system. A system of LoRa sensors, gateways and back-end servers is called LoRaWAN. A 'Class A' LoRa sensor from the company 'nke-watteco' is used. For the project, a new gateway was installed in the direct neighborhood, as well as the required backend, namely the network and application server. The advantages of the LoRaWAN technology for this application are easy installation, scalability due to the cost per sensor and signal strength. For some participants in the project, the grid connection point is in the basement from which no connection to a mobile network is possible. Therefore, the installation of a regular GSM modem was no option. The advantage of the LoRa technology is that a LoRa sensor has high sensitivity and can transmit much better from underground indoor locations (Alliance, 2020). Since the sensor transmits only a meter reading to the LoRa, the data payload is not very large and the low bandwidth of the technology is not an issue. A further advantage is a simple and inexpensive expansion with further end devices. In an approach based exclusively on the mobile phone network, these modules would have had to be equipped with prepaid mobile credits. Besides, the requirement of privacy and data security is an inbuilt standard by the design of this technology. Since the LoRaWAN technology is a network protocol designed for the Internet of Things, many different end devices located in the reception area of a gateway can be used. The network protocol uses end-to-end encryption to avoid direct access to data and to avoid alteration (man-in-the-middle-attack). The encryption is valid up to the application server and cannot be decrypted by the network server. The network protocol only performs an integrity check to identify transmission errors. A weak point of the LoRaWAN technology is the network architecture. The installation of a single gateway creates a single point of failure. If the gateway fails, there is no transmission of the measured values. This case has occurred during the active operation of the CEC. A storm damaged the gateway, which had to be replaced. However, this problem is overcome by installing a second gateway within the transmission range of the LoRa sensors. As the technology is used for different purposes by the energy provider in the CEC area, better coverage can be expected in the next years. Also, for a better connection between the gateway and the devices, the installation of the former must be at a certain height.

A web socket connection between the *Database* and the *Smart Meter Hardware* module is used in the project to transfer data from the application server to the database. The advantage over a conventional Hypertext Transfer Protocol (HTTP) connection is the web server, which is able to forward new information directly to the client without receiving an initial request. A small disadvantage of the web socket is that a faulty connection, where no data is transferred, can remain if data transmission from the web socket is not checked regularly. However, the risk can be limited by regularly checking the database and restarting the web socket.

Over the project duration, technical problems occurred repeatedly. Besides the LoRaWAN technology, there was no backup data transmission technology in the project. Therefore, no data is transmitted in the event of a malfunction. About 60% of all malfunctions are only one period (15 minutes) long. 85% of all occurring malfunctions are one hour or shorter. We track these malfunction problems back to transmission errors by the LoRa sensor. They are partly related to the distance of the sensor to the antenna. Two participants live near the transmission limit of the antenna and have a significant share of these short-term issues. However, the error also occurred with subscribers who live much closer to the antenna. These circumstances indicate that distance is not the only reason for these short interruptions. Since only the LoRa sensor transmits absolute meter readings and not the difference between two readings, the missing load values from periods with malfunction are automatically captured in the next successful transmitting period. Additionally, to the short-term issues, the installed LoRa sensors show issues in long-term usage and stop transmitting. These malfunctions periods are longer and occur randomly. We solved this problem by restarting the sensors manually. Nevertheless, these issues contributed to longer downtimes that lasted for several days for one participant. However, the proportion of these failures is less than 1%. In addition to these smaller, individual disruptions, there are major technical failures (over several weeks) during the project caused by technical issues of the LoRaWAN antenna. As described previously, a storm damaged the antenna, which had to be repaired. Also, the web socket failed one time and caused a longer interruption. Both problems required repairing or restarting the system. It turns out that LoRa technology is vulnerable to transmission errors and is not a good technology choice for the *Smart Meter Hardware* module. For future projects, we recommend using other smart meter technology (e.g., transmission over the mobile network) or relying on backup systems, like a second antenna, ensuring reliable and steady data transmission.

User Interface: In the derived IT architecture, the module *User Interface* is the connection point between the system and the user. In the case study, this interface is an application that the user can install on a personal computer or smartphone. Therefore, the application is accessible to all participating users. Mobile devices like smartphones and tablets are very popular, therefore a development for the largest platforms like Android and iOS was chosen. An interface via a web application also allows access via a browser, which gives access to the application over a desktop PC. The goal is that the CEC can be reached via different devices. This coverage allows participants to use their usual devices without requiring additional hardware. Addressing the functionality of the module *User Interface*, the architecture distinguishes between five different processes. Figure 4.2 displays all these processes starting with the number 2. Processes 2.1, 2.2 and 2.3 display the user's registration, identification and connection to the smart meter data within the information system. All three processes can be assigned to the user verification process mentioned in the previous section. The application prevents users from viewing the data of other participants or to issue bids in their name. For the user's identification, the information system has to be able to identify the user. This is ensured by the registration process (2.1). In order to enable the unique identification, each participant must register his or her login data (usually only a username and password). For this, the application has a registration menu that can be selected by a new user. The application sends the registration data to the account database over a secure representational state transfer application programming interface (REST-API). The account database first saves the username and password and then creates a new UserID linked to both. In the next step, this ID is saved in the market database, which allows the market database to identify the user. The distinction between the two databases is discussed in the *Database* section, see Chapter 4.4. The registration process only needs to be carried out once by each participant in order to register themselves in the system. As a minor note regarding the login data: It is part of today's standard procedure that the username is an e-mail address of the user, whose possession he has to verify via a confirmation link. This process is not mapped in process 2.1, as this is part of the IT system's security architecture. After successful registration, the system can authenticate the user through the login data. Figure 4.2 illustrates this authentication procedure in process 2.2. The user enters the login data on the login screen when starting the app. In the authentication process, the application sends the credentials to the account database over the same REST-API mentioned in Process 2.1. The account database compares the login data with the registration data. If both are the same, the authentication is successful and the application receives a JSON Web Token (JWT) as an access token from the account database. The access token allows the GraphQL server of the market database to identify a user and accept their requests. For security purposes, the access token is only valid for a certain time. The corresponding device is linked to the UserID in the market database so that a user can view the consumption or generation data. The meter hardware is connected to the UserID. Process 2.3 establishes a connection between the SmartMeterID and UserID in the *Database* module. The user enters the SmartMeterID in the application via a specific interface. The application then transmits this information to the GraphQL server and connects the UserID to the SmartMeterID in the market database. The user only has to perform this process once for each meter. The 'User Interface' module allows the user to view individual consumption and market data (transactions, market prices and past bids) and to place bids. This functionality is illustrated in Figure 4.2 by processes 2.4 and 2.5. Process 2.4 describes the request for individual consumption and market data by the user. The application displays this data in different granularity, for example, daily or weekly consumption. After successful authentication by the user, the application has a valid access token. It sends the data request over the GraphQL API to the GraphQL Server. The server validates the token and accesses the requested data in the database. The database uses aggregates, which are defined as so-called views and the API makes them available. These views contain the pure data of the daily aggregates and are then formatted in the app so that they can be presented in different forms. No data is stored within the app, but it is provided through live queries against the server. The user can visualize the consumption and market data in a non-aggregated form as a table. These modules also request data from the database (2.4) and processes it internally. The last process 2.5, is the submission of bids by the user. The application provides an interface where the user enters a new bid price to buy or sell energy on the energy market. The application transmits the bid via the same GraphQL API to the database. For identification purposes, the application also uses the mentioned token. The server checks the validity of the bid and stores it in the market database with the corresponding timestamp and UserID.

Technology Discussion: In the project, the software partner provided a self-developed application for mobile devices like smartphones and tablets. The application was developed according to the described architecture and specifically tailored to this project. The cross-platform mobile app development framework 'Ionic' was used. This framework provides tools to develop apps on top of standard web technologies like CSS, HTML and JavaScript, which allows a single codebase that can be distributed to the two largest mobile platforms, the Android and iOS operating systems. Furthermore, it allows users to access the app via a web application. The advantages of this design approach are that the users in the project are independent of the operating system and can access the application from nearly any device. In addition, the framework prevents double development costs for both platforms. However, at the beginning of the project, it was not certain whether participants had the appropriate hardware or were willing to use it. For this reason, each participant was given an Android tablet for the sole purpose of participating in the CEC. It had the pre-configured application installed, which ensured access to the local market. The users also got a link to the web interface and the participants had the possibility to use the application via their private devices.

Since the application is publicly available for download in the corresponding app stores, it has a start screen where a user has to register and later authenticate herself (process 2.1, 2.2) to prevent unauthorized access. Both processes are implemented in the project, as described above. The use of the JSON Web Token to authenticate the user against the market database is well suited, as a stateless session can be created. The token transfers all information required for the authentication with the database. Therefore, the database does not need to save the session with the user. This situation is advantageous because as long as the access token is valid, the user remains logged in and can request data without repeating the authentication process. However, the high level of security is perceived as an entry barrier by the participants, which will be discussed in more detail in Chapter 7.

It should be noted that registration and authentication are possible without a smart meter. This design implies that even people who are not participating in the project can have access to CEC data. In the project, we allow access to the market prices and aggregated generation quantities. The user gets access to the individual load data only after registering the smart meter (process 2.3). In the project, the process is similar to the process described above, with an additional security feature. The participants receive a PIN and SmartMeterID from the system administrator. The combination of both prevents an unauthorized person from gaining access to the individual data of a smart meter through trial and error or a brute force method. This design makes it easy to provide the data that is needed by the user, hiding the complexity and structure of the underlying database. By separating the registration process, smart meters can already create devices in the system before the serial number is known. This is relevant in the parallel development process of the CEC between the modules of the *User Interface*, the *Database* and the *Smart Meter Hardware*. If no final decision has yet been made on the model and modification of the metering equipment, it does not prevent the database structure from being set up. Another advantage is that replaced or new devices can be integrated into the application quickly.

The project application provides several interfaces where the user can retrieve load and market data. Figure 4.3 shows four screenshots of the implemented user application design. Since all participants are native German speakers, the language of the application is German. The first two screenshots from the left show individual load data and its composition from local sources. The composition interface distinguishes between power from the CHP plant, PV power system and the backup grid option. The application offers the data for different time resolutions (day, week, month). This can be adapted for other projects within the proposed IT architecture. For each of these periods, the temporal resolution is adjusted accordingly (hours, days, weeks). The reason for the graphical representation is that people can grasp and understand them quicker. We discuss the interface design in more detail in Chapter 7. Additionally, the user can see all her transactions on the market and the corresponding market prices. The two screenshots from the right in Figure 4.3 display this information. The left shows the market prices of the CHP and PV markets. As mentioned earlier, registered users without a smart meter can also use these interfaces. The right illustrates the transactions of the PV power system. It distinguishes between local transaction of the CEC and surplus sales to the grid. Finally, the user also has access to her bid history.

The application uses the views to send predefined data queries from the app to the database. The usage of these views to represent the data has two advantages. First, mobile devices are not optimized for these calculations, so depending on the scaling of the chart, it is beneficial to calculate an aggregate form of the data in the database. Second, the user does not need access to all her time-series data at once. The last functionality is the submission of bids. The process of the submission and storage in the database proceeds, as explained above. The biggest challenges are potential wrong or illogical inputs of bid prices by the user. The entry must be within the specified upper and lower limits of the bidding range, which a user might forget. A graphical feature solves these problems. The consumer can set her bid price for both power sources via a graphical controller. This ensures that the user does not place a bid outside the upper or lower limits. Logically incorrect entries are not possible. Again, these functionalities can be adapted as needed within the proposed IT architecture.

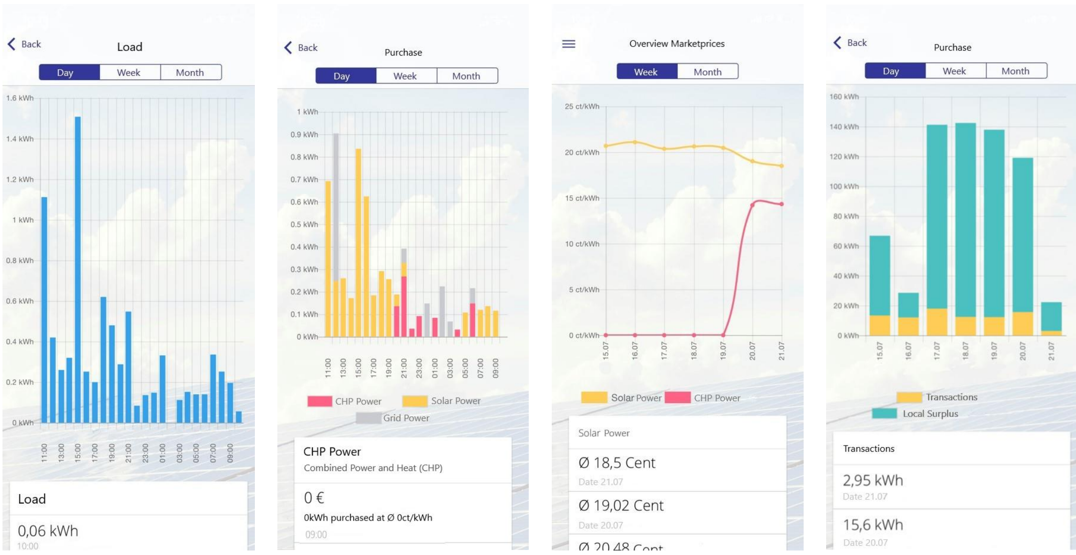

Figure 4.3.: Visualization of the implemented user interface

Market Implementation: Based on the proposed IT architecture, the *Market Implementation* module is implemented using two components: The MarketWrapper and the market mechanism. The market mechanism ensures coordination of demand and supply and decides the allocation of generation. The mechanism used in the project was specifically developed. It distinguishes between the two different types of generation that exist locally (PV and CHP). Each is cleared in a separate market with a uniform price auction. The market mechanism determines the clearing order of the markets based on the incoming bids from the users. The clearing interval is 15 minutes. A detailed description of the market mechanism implemented in the project is provided in Chapter 6. The task of the MarketWrapper is to process the raw data from the *Database* module and to transmit the market results to the database. The input parameters are the bids of all participants and the outputs are the transactions and market prices after a successful matching. For this purpose, the module requests the current bids of all participants of the local market. In the proposed architecture, the database does not store final bids, only its components. Therefore, the market module creates the bids within its structure. The MarketWrapper then creates the bids from the load values of the electricity meters and bid prices of the generators and consumers. The MarketWrapper has fixed reading and writing permissions for certain tables of the database. It makes the requests for the relevant data for the bidding process via the GraphQL API. The GraphQL server then passes the data to the MarketWrapper in a JSON file. It receives a JSON file and processes the raw data into bids. The MarketWrapper then transmits these bids to the market mechanism. In Figure 4.2, process 3.1 displays this procedure. The market mechanism then takes the bids and creates market transactions and market prices. After the market is cleared, the MarketWrapper transfers transactions and market prices via the GraphQL API. It writes each transaction individually to the database. To do this, the MarketWrapper passes each transaction to the GraphQL server in a single request to keep the complexity low.

Technology Discussion: The project distinguishes between market execution and preparation. The advantage of this separation is the division of tasks between different programs. One program communicates with the *Database* module and one executes the actual market matching. This way, malfunctions that occur during communication with the *Database* module do not lead to a crash of the market mechanism. Also, the preprocessing by the MarketWrapper allows for an easy exchange and adjustment of market mechanisms. The separation allows changing the code in one of the two components without affecting the other. However, this separation is not absolutely necessary for a functioning module, but it has become an apparent advantage during the project's development process and operation. Both programs are Java-based and run on a separate server than the database with an Ubuntu operating system. The server connects to the database over the internet using the GraphQL API. The server executes the market mechanism every 15 minutes. The market mechanism differentiates between local trading and the public grid and thus distinguishes between local and external network transactions. The recording of both is important to enable accounting and accurate allocation. The public grid serves as a back-up option for unmatched bids (both generation and consumption) after the execution of the local market. Generation sold into the public grid is rewarded with the national feed-in tariff for PV, consumption from the grid is charged based on the retailer rate.

Database: The architecture's *Database* module consists of two separate databases: the account and the market database. The heart of the system is the market database. The task of the market database is to store all data arising within the CEC and to make it available to others. A server handles the management of the database and processes data requests in a specific programming language like GraphQL. Such a GraphQL server manages and monitors the writing and reading accesses of the other modules. It also manages the requests of the other modules and transmits or receives the data via a GraphQL API. An object-relational database organizes the data with different tables. Each data type has its own table. For instance, a table stores all information related to the user, another table stores all smart meter readings and another table stores all market transactions. An object-relational database was implemented with the open-source database management system PostgreSQL.

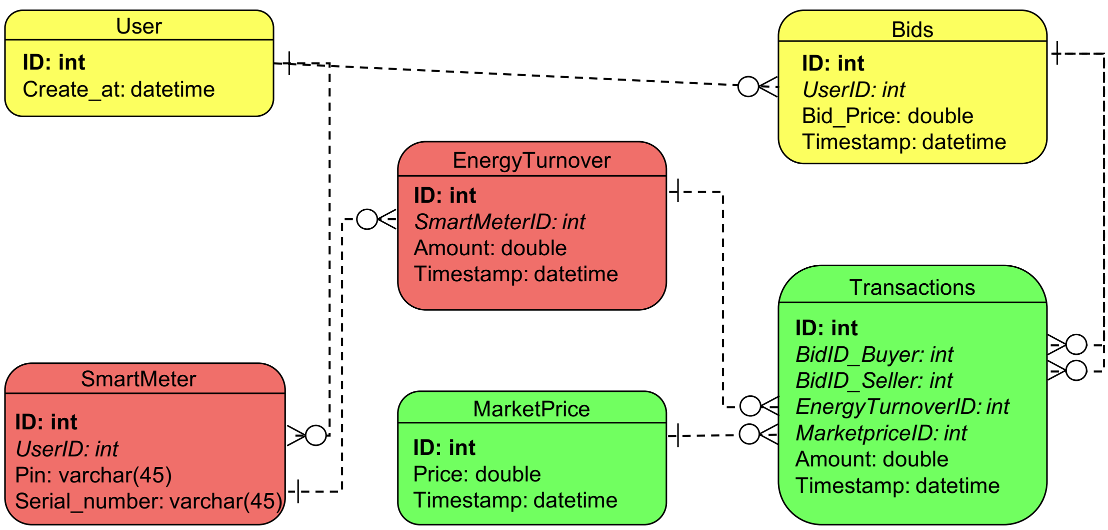

Figure 4.4.: Database setup as EER-model representation

Figure 4.4 shows the Enhanced Entity-Relationship (EER) Model of the market database relations, including intra- and interrelation integrity constraints. The market database has six tables. These are divided into three groups (colors) in relation to the other three modules. This can easily be adjusted with other instantiations of the proposed IT architecture. Each table consists of different attributes, which collect different kinds of additional data. For the *Smart Meter Hardware* module, two tables exist. One for the management of the *Smart Meter Hardware* (e.g., Hardware IDs) and one for the storage of transmitted meter readings (‘EnergyTurnover’). The ‘EnergyTurnover’ table continuously records the meter readings of Process 1. Process 3.2 stores the transactions and market prices in the market database. Therefore, the *Market Implementation* module requires two tables, one for the transactions and one for the market prices. The *User Interface* also has two tables, one to store user information and one for the submitted bids. The latter table stores the bid prices submitted through the application (process 2.5). The account database takes over the process of user registration and authentication. The account database stores the login data and creates a UserID in the registration process. The account database also transfers the UserID to the market database ‘User’ table, which is described in process 2.1. The task of the account database is then to compare the login data with the authentication requests of the users (process 2.2). An authenticated user receives a JSON token from the account database (see *User Interface*) and can use it to make valid queries to the market database (processes 2.3, 2.4, 2.5). Process 2.3 connects the tables ‘SmartMeter’ and ‘User’ to map the corresponding load values. This connection allows the individual data request in process 2.4 and bid submission in process 2.5. As mentioned earlier, for users without a registered smart meter, process 2.4 only requests market prices and aggregated transactions of the generation (PV and CHP power systems). The two right screenshots of Figure 4.3 show the data which these users can access.

Technology Discussion: During the project, the implementation of a blockchain as the database was discussed but dismissed. In initial simulations on the Ethereum Blockchain, the implementation of the market mechanism in smart contracts proved to be a technical challenge (Heck et al., 2020). The proof-of-work algorithm, the resulting block creation time, energy consumption and technical instability, involved too much risk. In addition, the use of LoRaWAN technology would not have been possible. The separation of user authentication and market data has several advantages. First, the login data is stored separately from all other data. No module has access to this data, as it only communicates with the GraphQL server of the database. Also, the market database itself has no access to the account database. In case of errors in the access management or malfunctions, no access to the participants' login data is possible. The *User Interface* module communicates directly with the account database, has no direct access to the stored data and registers or authenticates the user. This design ensures a high level of protection of all participants' login data and their individual load data. One reason for choosing a PostgreSQL-based database over a relational database is the cross-table transactions referential integrity. For example, if an identification number of a smart meter in the table 'SmartMeter' is changed, an inter-relational constraint guarantees that the information is updated in all tables, which are related to this identification number. If a system administrator tries to create an already existing smart meter identification number in the table 'SmartMeter', an intra-relational constraint disables multiple allocations of the same identification number. The lack of licensing costs due to open-source deployment is another reason. An alternative to a relational database would be a so-called NoSQL database system like MongoDB.

4.5. Limitations and Conclusion

A functional and mature information system is essential for the CEC operation and particularly to achieve high customer satisfaction. The architecture of an information system has a central influence on subsequent functionality and performance. We answer our research question with the deduction and discussion of a CEC IT architecture based on extant literature that enables the necessary functionality described in the literature on existing CECs. The majority of the publications focuses on market mechanisms and gives only a partial picture of a CEC's core functionalities and architecture. Regarding the IT architecture, numerous contributions only implicitly mention functionalities and modules. More technical contributions often focus on the usage of blockchain technology. The deduced IT architecture has four central components: The *Smart Meter Hardware*, the *User Interface*, the *Market Implementation* and the *Database*. Our proposed architecture describes how these four components interact with each other to meet the essential CEC functionalities. More sophisticated systems that, for instance, include the flexible control of certain loads can easily be served with the same architecture as the market signals remain the same. More complicated or less complex market mechanisms can also be included in the same architecture. It thus allows for all necessary functionalities, independent of the complexity of the system. Furthermore, we describe a case study that implements the deduced IT architecture as a specific instantiation and discuss the advantages and disadvantages of the implemented technologies. Thus, we fill the research gap of a detailed IT architecture description for a CEC. We do not directly compare different IT architectures to measure the efficiency of our approach, which is a limitation of our work. Due to cost reasons of field experiments, it was not possible to implement several IT architectures in the project and compare them. Also, this analysis does not explicitly measure the effectiveness of the IT architecture. Nevertheless, expert interviews with participants reveal that they did not notice most transmission interruptions and are satisfied with the system's overall reliability. This chapter is intended to be the starting point of a discussion on the IT architecture of CECs and suitable technologies. Thus, it contributes to the maturation of the CEC and a decentralized organization of energy systems and markets and helps practitioners with new CEC projects in their planning process and daily operation.

Chapter 5.

Blockchain Maturity Model

The blockchain technology is a widely discussed approach in the academic community to represent essential parts of the CEC IT infrastructure. Because of its innovative design as a distributed and decentralized information system, blockchain supporters see its it as a potential enabling technology for CECs. However, the technology is in an early development state and lacks widespread adoption in the energy sector. Various approaches, concepts and implementations have different development statuses. Therefore, an assessment of this status, as well as the identification of necessary next steps and improvements, is needed. The current research lacks a transparent model that assesses the current maturity level of such blockchain implementations and supports the overall development process and quality. To this end, a model is developed, which allows analyzing the current maturity level of real-world blockchain based CEC implementations and thus sets the foundation for continuous improvement. The derived model is applied to an early development stage of the LAMP Project. The assessment shows that in its early state, the project is in a premature maturity stage due to missing regulatory rules and standardization.

This chapter comprises the published article by B. Richter, E. Mengelkamp and C. Weinhardt, *Maturity of blockchain technology in local electricity markets*, 2018 15th International Conference on the European Energy Market (EEM), 2018. cited here as: Richter et al. (2018).

5.1. Introduction

Blockchain technology is currently a frequently discussed concept in many sectors, but especially in the energy sector (Pisa and Juden, 2017). As discussed in Chapter 4.2.4, many authors promote the blockchain or distributed ledger technology in their approaches and their studies are a driver of the currently increasing interest around the CEC concept, especially for CECs with a trading platform. For the remainder of this chapter, we refer to this concept as LEM. The blockchain's decentralized, trust-free characteristics are promising as an underlying IT infrastructure for such projects. According to its proponents, blockchain technology may just be the key technology to enable a scalable introduction of these community concepts into energy systems. It allows the implementation without the necessity of a centralized IT system (central intermediary) and connected single point of failure (Sikorski et al., 2017). In addition, it provides transparent and cost-efficient microtransactions and ensures the irreversibility of them (Mengelkamp et al., 2018b). However, there are only a few implemented real-world projects utilizing the blockchain technology (Ableitner et al., 2019; Vasconcelos et al., 2019; Zade et al., 2022a) and these are far from a large scale, sector-wide implementation. There are several reasons for this divergence between interest and implementation of such markets. First, the information system based on the blockchain technology represents a novel approach with its decentralized architecture that still poses many challenges for the implementers and users (Glaser and Bezzenberger, 2015; Mengelkamp et al., 2018b). Second, the strict regulatory requirements have so far prevented a roll-out in the energy sector (Wüstenhagen et al., 2007; Weinhardt et al., 2019). So far, there is a lack of a clear development path for this technology in the LEM context for widespread adoption in the energy sector, as well as the need to identify the different dimensions necessary to continue the maturation process.

For this purpose, we develop a blockchain maturity model for LEMs. We focus exclusively on LEMs utilizing the blockchain technology as the IT infrastructure. We consider the market structure as well as regulatory and economic environment, described in Chapter 3. Based on a comprehensive literature review of current blockchain concepts and LEMs, we follow the approach of Becker et al. (2009) to develop a blockchain maturity model for local energy markets (BMM-LEM). This chapter addresses the following research question: *How can the current level of maturity of blockchain-based CEC applications be assessed?*

We use the well-known capability maturity model (CMM) (Paulk et al., 1993) and two approaches of blockchain maturity models (Hardwin Spenkelink, 2017; Wang et al., 2016a) as a basis. The BMM-LEM follows the five steps of the CMM to determine the current maturity and the requirements for future development to reach a higher level of maturity.

5.2. Related Work

In the following, we first take a look at the blockchain technology, its structure, functionality and characteristics. Second, we describe how LEM approaches utilize the blockchain technology and provide a short overview of blockchain-based implementations. Finally, we provide an overview of existing maturity models.

Blockchain Technology: At its core, a blockchain is a distributed database with a peer-to-peer network, a consensus mechanism and cryptographic methods (Nakamoto, 2008). It allows trust-free transactions over a network without the need for an intermediary. It may increase decentralization in various applications (Sikorski et al., 2017). In addition, it may self-execute code without external supervision (often described as *smart contracts*) (Wattenhofer, 2016). There is no general, clear definition of the blockchain technology. For example, Byström (2016) defines the blockchain as a ledger where its records can never be altered or destroyed. Pilkington (2016) give a more technical definition. The authors define the technology as a chain of transactional records, where a subset of network participants (also known as 'miners') ensures its validity by solving difficult computational problems. These miners compete against each other in the network to solve a mathematical problem and add new records to the blockchain database. This process ensures that every node in the network has the exact version of the database. For this purpose, the database is divided into blocks, which are arranged in chronological order. The consensus mechanism ensures that all nodes in the network extend their database in the same way (Sikorski et al., 2017; Glaser, 2017). A blockchain provides several fundamental properties: transparency, immutability, reliability, disintermediation and availability (Mengelkamp et al., 2018d). Transparency is achieved as each node in the blockchain network has a copy of the (complete) transaction history. Based on the consensus mechanism and database structure, it is difficult to alter the blockchain's records retrospectively and the database becomes immutable. In addition, the blockchain technology utilizes a peer-to-peer network, which has no single point of failure and provides high reliability and availability. The combination of these properties can create an environment in which it is unnecessary to rely on a trustworthy central authority (Sikorski et al., 2017; Glaser, 2017).

Blockchain-based LEMs: An LEM represents a special form of the CEC concept that allows residential households to trade locally generated electricity over a local platform (Mengelkamp et al., 2018a). The platform empowers the community to be more involved in their energy generation and keeps profits within the community (Koirala et al., 2016). Especially, the blockchain's ability to create completely decentralized LEMs raises awareness among researchers and practitioners (Munsing et al., 2017). The concept of local trading with blockchain technology is widely covered in the academic literature (Mengelkamp et al., 2018a; Kirpes et al., 2019; Blom and Farahmand, 2018). Besides energy trading, blockchains are also considered for actually controlling decentralized resources (or microgrids) (Imbault et al., 2017). Aitzhan and Svetinovic (2018) focus on data privacy concerns in blockchain-based trading. The cost of (data) privacy becomes increasingly important in small markets, where the participants know one another (Buchmann et al., 2013). Sikorski et al. (2017) implement a small-scale electricity market between only three participants. Mengelkamp et al. (2018a) describe an LEM on a private blockchain between multiple households. Al Kawasmi et al. (2015) develop a blockchain-based anonymous carbon emission trading system between independent agents on a public blockchain. While public blockchains grant access to all users and thus are open to the public, private blockchains restrict access and are often used in scenarios in which only particular agents shall be granted access (Sikorski et al., 2017).

As LEMs are limited to their geographic or social community, private and permissioned blockchains are a discussed choice to restrict market access to community members only (Sikorski et al., 2017). Simultaneously, this restriction saves computational resources as it limits the number and competition between the miners. Nevertheless, in this early stage of development, public blockchains like Ethereum are used to test the functionality of LEMs as well (Meeus and Nouicer, 2020). Besides the academic research, first pilot projects (see Chapter 3.3) such as the 'Brooklin Microgrid' (Mengelkamp et al., 2018a), 'Pebbles' (Vasconcelos et al., 2019) or 'Quatierstrom' (Ableitner et al., 2019) explore the abilities of the blockchain technology for LEMs in practice. Zhang et al. (2018) and Sousa et al. (2019) give a broad overview of the blockchain LEM projects and point out how blockchain technology plays a central role in many LEM implementations. However, there are no structured approaches to assess LEM blockchain implementations, to evaluate their level of maturity and to identify the necessary next step in their development process. We address this research gap and develop a structured maturity model for the application of blockchain-based LEMs.

Maturity Models: The Capability Maturity Model (CMM) is one of the best-known and most used maturity models (Paulk et al., 1993). After its introduction, CMM was the starting point and basis for many maturity models for different purposes and areas. It was developed in the early 1990s and aims at evaluating the ability to manage software projects. Since then, the model has been widely applied as a general model measuring the maturity of processes. It defines five successive stages of maturity to evaluate the quality of processes and how to improve them. In each step, excluding the first one, the development process meets several requirements, for example, a more detailed standardization or documentation. With each stage, the maturity of the process increases. Maturity is defined as the degree of formality, documentation and optimization of processes (Paulk et al., 1993). The CMM has been expanded and specifically adapted for various areas. For example, Rosemann and De Bruin (2005) developed a business process management maturity model based on the CMM. Furthermore, a management of processes maturity model (de Bruin et al., 2006) and a project management maturity model (Crawford, 2006) are based on the CMM.

Due to this large (and uncomprehensive) amount of individual models, the original CMM was combined with several other models to develop the new capability maturity model integrated (CMMI). The CMMI is a more general maturity model that can be used for most application areas (Gibson et al., 2006). As an additional reaction to the development of various (partly low quality) maturity models, Becker et al. (2009) introduced a comprehensive framework for the development of maturity models. It aims at identifying relevant design and selection processes in the creation process of a maturity model.

5.3. Development of a Blockchain Maturity Model

For the development of an LEM blockchain maturity model, we apply the first four steps of the framework by Becker et al. (2009). Due to feasibility reasons, we omit the last steps because publication, community feedback and adaption were not feasible at the time of the project.

In the first step, we define the problem which the maturity model should solve. To this end, we determine the target domain, stakeholder group, underlying importance and relevance of our maturity model. Subsequently, we identify existing maturity models and compare them to the defined problem to select important attributes and dimensions for the maturity model to be developed. The third step focuses on the determination of a development strategy. In this step, it is decided whether a complete new model is designed, an existing model enhanced, several models combined to create a new model, or contents from existing models are applied to new domains. The fourth step describes the iterative development, its transfer and evaluation process. We also apply the current state of the blockchain technology in the specific context of LEMs on the basis of several use cases and pilot projects. In this last step, we also show at which maturity state the blockchain technology is and what kind of effort is needed to meet the requirements of the next maturity state.

Step 1 - Problem Definition: Utilizing the blockchain technology within an LEM allows for the creation of a completely decentralized local market without an intermediary. As described in Section 5.2, academic research is actively pursuing the idea of blockchain-based LEMs. Yet, despite academia and industry developing innovative concepts of blockchain-based LEMs, projects use different blockchain technologies (e.g., different consensus mechanisms) and have different approaches regarding the functionalities of the market. In addition, the market mechanism, the legal framework and state of development differ widely between the projects. We develop the BMM-LEM to create a comprehensive approach for academia and industry to evaluate blockchain solutions in LEMs in a structured, multidimensional way and assists in the ongoing enhancement process. First approaches in this direction are too generalized or not sufficiently specified to the context of the energy sector (Wang et al., 2016a; Hardwin Spenkelink, 2017).

Step 2 - Comparison of Maturity Models: Besides the well-established CMM by Paulk et al. (1993), our literature review identifies two maturity models focusing on blockchain technology, namely the maturity model for blockchain adoption by Wang et al. (2016a) and the blockchain maturity model by Hardwin Spenkelink (2017). Both maturity models use the CMM and its successor CMMI as a basis. Yet, the approaches use a different taxonomy for the maturity assessment. On the one hand, Hardwin Spenkelink (2017) identify eight risk dimensions which are divided into several individual risks, each represented by a set of maturity questions to determine the maturity stage. On the other hand, Wang et al. (2016a) distinguish between three assessment areas (technology, market and regulation), but the maturity model focuses exclusively on the technology dimension. However, neither maturity model is based on the comprehensive development approach of Becker et al. (2009), or a similar framework. They are also not specifically tailored to the domain of LEMs. Therefore, we utilize both maturity models in the development process of the BMM-LEM.

Step 3 - Determination of Development Strategy: As a starting point for the iterative design development process, we combine the models by Wang et al. (2016a) and Hardwin Spenkelink (2017). They provide a comprehensive structure of key areas as well as different assessments of the maturity level of blockchain applications. Thus, they provide a good baseline to develop a holistic maturity model tailored to blockchain implementations in LEMs. As a second step, we open up the process to review and integrate general maturity models (not specifically based on blockchain technology) and start the iterative development.

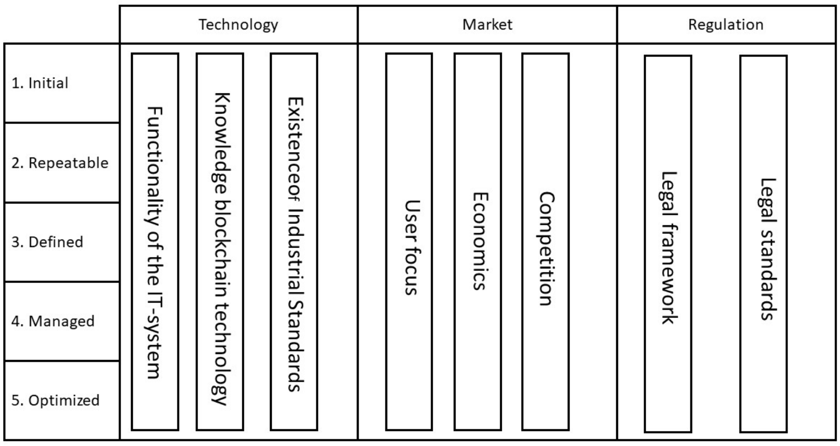

Figure 5.1.: The maturity model for assessing blockchain based CEC applications.

Step 4 - Iterative Maturity Model Development: In the process of developing the maturity model, we conduct four iterative steps. First, we determine and review the initial structure, based on the existing blockchain maturity models. We propose an initial architecture with five maturity stages for the BMM-LEM according to the well known CMM model (Paulk et al., 1993) and the blockchain maturity model by Wang et al. (2016a).

Based on Wang et al. (2016a), our initial approach includes only one dimension, i.e., technology. Utilizing the maturity models of Wang et al. (2016a) and Hardwin Spenkelink (2017), we define three characteristics for this dimension: 1. the functionality of the IT system, 2. the knowledge about blockchain technology, 3. the existence of industrial standards. The functionality of the IT system describes the existence and performance of several IT artifacts (e.g., network architecture, consensus mechanism) of the blockchain technology. The knowledge of the blockchain covers the ability to map given processes and peculiarities of LEMs on the blockchain. The existence of industrial standards considers the development of best practices and standardization as an indicator of the maturity of blockchain-based LEMs. At the end of the first step, we evaluated our framework with several academic researchers from the energy field in workshop discussions. The most important drawback discussed was the inclusion of only one dimension. Technology alone cannot reflect the maturity of a blockchain-based LEM. Further, a mature blockchain could only succeed in a well-regulated environment.

In the second step, we included the additional dimensions, *Market* and *Regulation*, into the BMM-LEM to extend the model with the legislative and market environment. The market dimension reflects the economic environment around and inside the LEM development process. The regulation dimension illustrates the alignment of the developed LEM into the specific and general legal framework and the compliance to regulatory standards.

Thirdly, we used an extensive literature review to identify characteristics for the two new dimensions. We include the characteristics partly from the existing maturity models, partly from own development based on the problems described in the literature. The market dimension is divided into three characteristics: user focus, economics and competition. The user focus describes the ability to address the system user's needs and distinguishes between several groups. It transitions the development focus from technical functionality towards user focus. Economics illustrates the importance and measurement of costs and determines the relevance of optimizing processes. Competition focuses on the degree of competition and market liquidity inside the LEM as an indicator of maturity. In a first approach, we divided regulation into three characteristics: Directly applying laws, overall legal framework and legal standardization. We evaluated the two new dimensions and their characteristics in a group discussion. The feedback was largely positive. Only the characteristics of directly applying laws and general legal framework are criticized. Both describe very similar situations and cannot be clearly distinguished.

Finally, we modify the criticized characteristics directly and combine both into the characteristic legal framework. In the final model, the regulation dimension has two characteristics: legal framework and legal standards. The latter describes the alignment to specified technological requirements like APIs or processes, while the legal framework measures the overall development of the regulatory environment, e.g., blockchain-specific laws. As a result of these four steps, we end up with the first blockchain maturity model for LEMs. Figure 5.1 shows a graphical representation of the developed BMM-LEM. It represents five stages from (1) *Initial* to (5) *Optimized* and contains three dimensions with 2-3 characteristics each. In the following, we describe each maturity stage of the BMM-LEM in more detail.

Initial: In the *Initial* stage (1), most of the IT artifacts only exist in theory, from the technology dimension perspective. The project team focuses on developing these essential artifacts. General knowledge about the blockchain technology exists, yet no reshaping or development toward specific requirements of industry standards occurs. The market environment is rudimentary defined and no targeted user groups exist. Different market mechanisms are evaluated theoretically, focusing on functionality and not on efficiency. The markets are not implemented yet. Thus, competition cannot be evaluated and the regulatory environment is not considering LEMs or corresponding regulation does not exist yet.

Repeatable: The *Repeatable* state (2) contains a more controlled and coordinated development. First IT artifacts exist, mostly implemented as ad-hoc code and initial test runs are successful. Different types of blockchains (e.g., different consensus mechanisms) are evaluated and tested. Hard- and software partly align to industry standards. A first market prototype is tested, focusing on reliability and secure processing. User groups are initially defined. Different incentives and goals of these groups are evaluated. Requirements of the market environment are measured and different market mechanisms and access points are tested. The general and possible blockchain-based LEM regulation is known and discussed.

Defined: The *Defined* stage (3) is achieved when the fundamental functionality like blockchain access (e. g., permissioned, public) or consensus mechanisms are defined. Then, more complex LEM processes (e. g., market mechanisms) can be implemented on the blockchain. Practical experience exists and best practices in troubleshooting are developed. A first LEM with a limited number of participants for testing purposes is implemented. The focus shifts from basic functionality to the safe delivery of services to the user. Processes become standardized to reduce costs. Due to limited access and testing, the degree of competition inside the market is low. The regulatory authorities have started to define rules specified towards blockchain-based LEMs. In the industry, first projects coordinate information exchanges among themselves and the regulator. First attempts towards standardization exist.

Managed: In the *Managed* stage (4) the IT-system runs reliably and implements all essential functionalities. Complex processes can be carried out without any problems. Practical experience is used proactively to improve and expand the IT artifacts. The system is aligned with the established standards of the industry. The market mechanism works properly. Market outcome and performance can be measured. All predefined user groups have access to the LEM. Competition on the LEM increases and significantly affects the market outcome. Processes are optimized to reduce costs and to improve the LEM's reliability. Also, specific laws and standards exist to regulate LEMs.

Optimized: The *Optimized* stage (5) is reached in a situation of the continuous improvement process. Quality measurements to evaluate the performance exist and the system runs reliably and securely. The market works cost-efficiently and competition is high. Possible future user needs are anticipated, evaluated and addressed by developing new services and business models. Regulation is well established and accepted by all participants.

5.4. Case Study - Maturity of the Landau Microgrid Project

In this section, we apply the BMM-LEM to the blockchain-based LEM project, the Landau Microgrid Project. As described in Chapter 3.4, in the project beginning, the blockchain technology was applied and tested. Therefore, the following analysis is based on the experience and state of the art, at that time.

Technology: The technological maturity of the project is at the third level (*Defined*). Decisions over the fundamental functionality and architecture are already made. The infrastructure is a self-developed permissioned blockchain and uses a simple consensus mechanism. Smart contracts are created and deployed to enable the basic functions of the market platform. Documentation is established to secure a knowledge transfer within the project. Also, first practical experiences were collected through several test runs, installations and the solution of minor technical issues. Meters and software are in a first standardization process.

Market: From the perspective of the market dimension, the LAMP project is also on the third maturity level (*Defined*). The users of the system and the market mechanism are defined. The first participants have access to the market over an application for testing purposes. The application is the access point to the market and provides useful services for each user group. For example, consumers can check their electricity purchasing history. Besides the consumers, the project defined three other user groups: prosumers, generators and the network operator. The focus of the market development lies on the reliability of the market and the proper execution of the market mechanism. Competition inside the market is low due to the fact that the market is still being tested.

Regulation: The regulatory maturity stage is on the second level (*Repeatable*). There are no specified laws or regulation for blockchain-based LEMs in Germany. However, existing rules are evaluated in order to estimate the possible scope. In addition, first meetings with industry and regulators on workshops and conferences are held to discuss these topics. Yet, legal standards are far from being developed.

Overall, the maturity state of the project is on the threshold to the third level. From the technology and market dimension perspective, the project meets all requirements and achieves the third stage. The essential IT artifacts and the market platform design are defined, first users test the market and initial practical experience is made. However, the missing of regulatory rules and standardization prevents a complete assignment to the third stage.

5.5. Limitations and Conclusion

This chapter introduces the BMM-LEM, which is based on several established maturity models. Yet, none of them focuses on blockchain-based LEMs. The CMM, a well-known and frequently used maturity model, was initially introduced for software development. The maturity models by Wang et al. (2016a) and Hardwin Spenkelink (2017) provide a more general model but focus only on the technological aspects of the blockchain. In addition, blockchain technology itself is far away from a very mature state. Therefore, the stages 4 *Managed* and 5 *Optimized* of our model are based on common models and technology paths. Yet, no official benchmarks exist so far. Feedback of other projects and the energy community towards the BMM-LEM will show how a general application can be made and, thus, how our model can be improved. For this, the BMM-LEM will need to be applied to additional use cases and tested in-depth for its applicability, versatility and suitability to evaluate blockchain-based LEMs. To answer the research question, we establish a blockchain maturity model for LEMs based on a comprehensive and iterative process. Subsequently, we assess the LAMP project with our maturity model. The developed model provides structured and useful information about the project's current state and next steps. We identify missing regulatory standards as the main hurdle to push the development of blockchain-based LEMs.

Chapter 6.

Market Mechanism Development

In recent years, the valuation of energy sources by private households became more differentiated (Wüstenhagen and Bilharz, 2006; Sangroya and Nayak, 2017). For example, many consumers prefer renewable energy sources (e.g., PV or wind) over conventional generation (Borchers et al., 2007). Consumers also differentiate between renewable energy sources based on personal preferences or negative perceptions (Devine-Wright, 2005). A distinct advantage of CECs, especially LEMs, is the matching of locally available energy sources and the ability to take the preferences of their participants on the demand side into account. However, this ability causes several challenges in the platform market mechanism design. Existing auction mechanisms in the energy sector do not differentiate between energy generation technologies and lead to insufficient market results. Therefore, a two-step mechanism tailored explicitly for the differing consumer valuations is proposed in this chapter. The mechanism interprets the different consumer preferences and applies the Borda Count voting mechanism to determine the chronological execution order of the market. In this chapter, the mechanism is implemented, tested and evaluated using empirical data from the LAMP project.

This chapter comprises the published article by B. Richter, E. Mengelkamp and C. Weinhardt, *Vote for your energy: a market mechanism for local energy markets based on the consumers' preferences,* Proceedings 16th International Conference on the European Energy Market (EEM),2019. cited here as: Richter et al. (2019).

6.1. Introduction

Until recently, the energy origin was not a relevant characteristic of energy consumption. As described in Chapter 3.2.3, energy is characterized as a homogenous good. However, several studies indicate that consumers start to distinguish between different energy origins (Ma et al., 2015; Sangroya and Nayak, 2017; Borchers et al., 2007). Due to rising environmental awareness, private households start to prefer energy from different renewable sources and are willing to pay higher prices to change their energy mix towards their preferences (Kaenzig et al., 2013). Mengelkamp et al. (2019c) show first indications of this shift and increasing willingness to pay higher prices for renewable generation. CECs are a concept that allows local consumers to trade locally generated energy and, to influence the individual energy mix directly. In addition, the local energy trading allows premium for specific generation technologies, from which local generators benefit directly (Mengelkamp et al., 2019c). This new opportunity to directly influence the energy mix according to one's preferences promotes participant acceptance of the CEC concept and the local energy sources it integrates. However, established market mechanisms in the energy sector cannot directly represent the heterogeneity in energy generation technology and efficiently allocate the local, available energy. Therefore, this chapter addresses the following research question: *What is an appropriate market mechanism for a CEC market platform, which can capture different consumer valuations for various types of locally generated electricity and allocate them correspondingly?*

6.2. Related Work

Heterogeneous Preferences: The change of preferences and willingness to pay for different energy origins is actively investigated by the research community. Researchers often differentiate between 'green' renewable energy and conventional energy. For example, Navrud and Bråten (2007) confirm a spread in the willingness to pay for different energy sources, regardless of whether they are renewable or not. Sundt and Rehdanz (2015) conduct a meta-analysis of consumers' willingness to pay according to energy sources. They conclude that the willingness to pay differs by source and increases if the received energy is from renewable sources. Borchers et al.

(2007) and Yoo and Ready (2014) show that consumers prefer green energy but within this group the consumers show a higher willingness to pay for energy from PV generation over wind or biomass. Kaenzig et al. (2013) explore the consumer preferences of different electricity mixes and their preference for different renewable energy sources. The authors conclude that 16% of the surveyed consumers are willing to pay higher prices to receive a more environmentally friendly electricity mix. Overall, it can be stated that the literature assumes that consumers make a distinction in the source of energy and are willing to pay a higher price for renewable sources.

Market Mechanisms: As described in Chapter 3.2.3, the academic community proposes various market mechanisms and trading designs for CECs, especially mechanisms for LEMs. Mengelkamp et al. (2019a) provide a holistic overview of different allocation mechanism and CEC concepts with trading platforms. A widely-used approach is the double call-auction (Ampatzis et al., 2014; Mengelkamp et al., 2018c; Ding et al., 2013). For example, Holtschulte et al. (2017) and Lezama et al. (2019) apply a discrete double call-auction with sealed bids, a similar design to the well-known merit order mechanism, which is used in European energy exchanges. Mengelkamp et al. (2018a) suggest both, a simple closed order book, which is cleared at certain time slots and P2P bilateral markets for local energy markets. Besides energy trading, some research also includes the trading of capacity and flexibility (Ramos et al., 2016; Rosen and Madlener, 2012; Gazafroudi et al., 2021). These approaches focus on the local balancing and support of the overall grid stability. As these concepts are still in an early stage of development and dependent on the legal framework, they are not considered further in this work. Regarding the local energy exchange, none of the approached mentioned above considers local consumers' heterogeneous preferences. Only the work by Zade et al. (2022b) address these heterogeneous preferences. The authors analyze and test seven auction-based corresponding clearing mechanisms. This chapter aims to contribute to this research area by developing a market mechanism that captures different participants' valuations for different types of locally generated electricity.

6.3. Developing a preference-based Market Mechanism

Problem Description: The main challenge in the development of a preference-based market mechanism is that the previously described and established auction mechanisms are not suitable to take different preferences for various energy sources into account. With a preference for a certain energy source, a differentiation is created. This differentiation creates an impression of heterogeneity between the energy sources, which results in a differentiated willingness to pay for these. Yet, the different energy sources are technically perfect substitutes because their demanded load can be met equally well by all available sources. This raises the challenge of how to allocate the local available energy from all sources in a way that each participant receives energy from preferable energy sources. Double-call auction mechanisms, which are established in the energy sector, are designed for markets with homogenous goods. These mechanisms cannot allocate heterogeneous goods simultaneously. Therefore, these mechanisms cannot be utilized for a preference-based market mechanism directly.

Preference satisfying Auction Mechanisms: To address this challenge, we analyze two specific auction mechanisms, which take different valuations into account and combine heterogeneous goods. The first is called *multi-attribute* auction, the second *combinatorial* auction. Combinatorial auctions are an auction type that combines different goods. A bidder can claim any combination of these goods and a mechanism allocates the goods, maximizing revenue (Pekeč and Rothkopf, 2003). Regarding the energy trade, these combinations would consist of different energy mixes for each pre-defined energy amount (e.g., kWh). Several factors increase the possible number of available bundles and combinations. For example, the current availability of the energy source and there are infinite numbers of possible energy mixes. This circumstance increases the number of possible bundle combinations and it is likely that an optimal market outcome cannot be computed fast and easily. Comparable, a multi-attribute auction can also not provide a sufficient market allocation by design. This auction type focus on a single good with several characteristics and is often used in procurement processes (Bichler, 2000). Applied to the described case in this work, supplied energy has different characteristics, like its origin generation type or geographical distance. Consumers can submit bids for energy, where their preferences correspond with the provided characteristics. However, a fundamental assumption of this auction mechanism is that an exact, uniform valuation across all attributes exists (Gimpel and Mäkiö, 2006). Consequently, this condition requires that the preference order (e.g., PV over wind) must be equal for each bidder. This uniform valuation is not given, as each consumer can prefer the sources in a different order. For example, one consumer prefers wind over PV and PV over CHP. Another consumer favors CHP, then PV and the wind is the least favored. As a result, not all consumers value PV energy always strictly higher than energy generated by wind turbines. Therefore, current auction designs are not fully suited for a CEC platform to allocate the locally generated energy according to the consumers' preferences.

Preference based Voting Mechanism: We develop a novel market mechanism to address the challenge of different preference orders between the consumers. We utilize the distinction of different characteristics from the multi-attribute auction design and create so-called 'submarkets' based on these pre-defined characteristics. Typical characteristics of these submarkets can be, for example, the generation types (PV, wind, water, biomass, ...), the geographical distance (local, regional, national), or a combination of both. Within these submarkets, consumers do not distinguish between the supplied energy sources, like energy from two different PV power systems and the traded good can be described as homogeneous. With this step, it is possible to utilize a well-established discrete double-call auction mechanism. Each market determines its own price and consumers can receive their demanded load from the existing submarkets. The traded energy on each market is, from a physical perspective, a perfect substitute regarding the satisfaction of consumers' load demand. Therefore, the different submarkets are dependent on each other. With the assumption that consumers have a different willingness to pay for available energy sources in the different submarkets, the subsequent challenge is to determine a mechanism that organizes the distribution of the consumers over the existing submarkets and the execution of these submarkets.

There are several ways to address this challenge. The straightforward approach is to assign each participant to the appropriate submarket according to the individual highest preference if energy is offered in that submarket. However, this approach has a distinct flaw. If the amount offered in one submarket is insufficient, while local energy is still available in another submarket, consumers will not be supplied with local energy and receive energy from the grid. Therefore, the market mechanism does not ensure that the available local energy is allocated to the consumers and creates an overall mismatch. An alternative approach is to establish a market execution order. In this case, the submarket that is preferred the most by the consumers is executed first. Consumers who do not have their demand met are then transferred to the submarket with the second-highest preference of all consumers. This process continues until all demand is met or no more submarkets are available. An internal voting system can determine the execution order by allowing consumers to vote for their preferred market order.

Most common voting systems focus on a single winner but ignore the preference distribution over all alternatives, which leads to strategic voting. Especially, voters who favor a candidate who is less likely to win have an incentive to vote strategically and not according to their preferences (Ludwin, 1978). Therefore, we choose a ranked voting system, the so-called Borda Count. This voting mechanism was invented by Jean Charles de Borda as an alternative voting concept (Emerson, 2013). The Borda Count system allows voters to rank all choices corresponding to their preferences. The preferred choice gets the highest score and the next alternatives, in descending order, a decreasing lower score. The scores for each alternative are summed up and an overall rank order is determined (Emerson, 2013; García-Lapresta and Martínez-Panero, 2002).

In the context of the proposed market mechanism, all consumers are seen as voters. Every consumer submits a bid for each market. We assume that the individual preference order represents the willingness to pay for each source (bid). For example, a CEC includes three different kinds of energy sources: PV, wind and CHP. A participant prefers PV over wind and energy from wind sources over CHP sources. Following this preference order, the order of the bid prices can be represented by this rank order: $b_{PV} > b_{Wind} > b_{CHP}$. The participant prefers a market order starting with the PV market, then the wind market and in the end, the CHP market. Therefore, PV receives 3 points, wind 2 and CHP 1. This rank order is the participant's

Borda Count vote. If a consumer has the same bid price for two sources, the rank is chosen at random.

Consumer/Source	PV	Wind	CHP
Consumer 1	3	2	1
Consumer 2	2	1	3
Consumer 3	2	3	1
Sum	7	6	5

Table 6.1.: Example of a Borda Count score

Table 6.1 shows an example with the above-mentioned three energy sources and three different consumers. The consumers differ significantly in their energy source preferences. In cases of unmatched bids on the first ranked market are these transferred to the second rank market. This process is repeated until all markets are executed. Unmatched supply and demand bids are then handled by the public grid. A distinct benefit of this mechanism is that it can easily incorporate new participants. If the preference order of a consumer changes over time, the mechanism will be able to take this preference shift into account.

6.4. Market Mechanism Evaluation

The market mechanism explained in Section 6.3 is implemented in the LAMP project described in Chapter 3.4. The case study focuses on the project period from April to September 2020. The case study features two submarkets, for each local energy source (CHP and PV). Each market utilizes the same auction mechanism, a discrete double call-auction with sealed bids. The price determination works as follows: First, all bids from both market sides are collected (supply and demand). A bid consists of a bid price and a quantity. The price determination mechanism sorts all bids by their bid price. The supply-side bids are sorted in ascending order and the demand-side bids in descending order. In the following step, the highest bids from the demand side and the lowest bids from the supply side are matched until the bid price from the demand side exceeds the supply side bid price or until there are no bids left on one side. The market price can be determined in the range between the last matched supply and demand bid price. In the observed period, the last matched supply bid set the market price in the first half of the observed period. In the second half, this was changed to the last matched demand bid. The trading interval is 15 minutes, which is in line with energy trading intervals at European wholesale markets. The market matches the recorded load data from the smart meters with generation. This matching is performed ex-post because the market participants already consumed the energy. However, the design can also match forecast quantities, but these types of CECs require additional systems which deal with forecasting errors. This increases the complexity of the mechanism and is out of scope of this study.

During the observed period, the majority of consumers prefer energy from local PV sources. This majority preference results in the PV market is being executed first. This order does not change throughout the period, even though individual consumers change their preference order. Of all eleven consumers, six consistently prefer local PV power. One consumer is indifferent between the two forms but has a higher preference for local PV energy in the beginning (two days). Also, one consumer consistently prefers local energy from the CHP origin. The remaining three consumers change their preference order during the observed period.

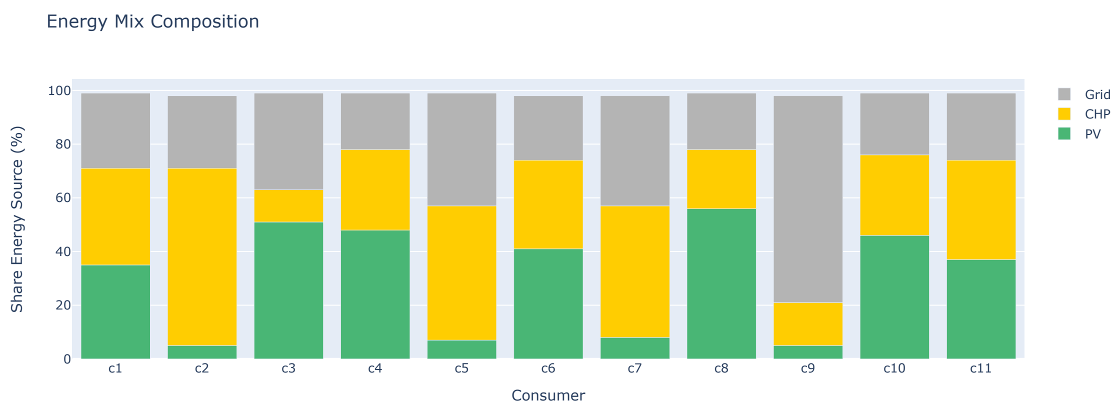

Figure 6.1.: Overall energy mix of all participants from Apr. to Sept. 2020

The order of the markets impacts the energy mix of participants. Figure 6.1 displays the consumers' energy mix in the LAMP project. The figure shows how much of the participants' demanded load on the market is satisfied by the corresponding two available energy sources (PV and CHP) and how much is met by the public grid. The high proportion of grid energy is a result of the fact that the CHP plant does not provide energy continuously, as it focuses on heat provision and electricity is only a by-product (see description in Chapter 3.4). Therefore, local generation is sometimes not available at night and the public grid meets the consumers' energy demand. Also, consumers 5, 7 and 9 have PV power systems (prosumer) and mostly need energy in hours without their own generation. This situation is usually the case in the evening, explaining the high proportion of grid energy in their mix. Looking closer at Figure 6.1, it shows that the energy mix is different between the consumers and corresponds to their respective preferences. Consumers 2 (66%), 5 (50%) and 7 (49%) have a high proportion of CHP in their mix, which corresponds to their preference. Consumers 3 (51%), 4 (48%), 6 (41%) and 8 (56%) have a high percentage of local PV energy in their mix, which also matches their preference. The differences in the energy mix among the consumers with the same preference order can be explained by the varying bid prices. Consumers with the highest bid price are more likely to be supplied. Therefore, situations can arise where consumers have a preference for PV power but are not supplied because there is not enough PV energy available. These consumers' unmatched loads are then transferred to the CHP submarket. Therefore, the mechanism ensures that available local energy is matched if enough local energy is available and consumers' willingness to pay is at least equal to the supply bid prices. The presented results show that the developed market mechanism is able to capture the preferences of the consumers and to adjust to changing supply conditions. It allocates the available energy to the consumers with the highest willingness to pay.

The results show that the energy mix depends on the availability and bid prices. Figure 6.2 displays the energy share the consumers received from their preferred submarket, which corresponds to the highest preference (grid consumption is not considered). Here, consumers 3 (80%) and 5 (86%) have the highest shares. Correspondingly, consumer 3 has the highest PV bid, 25 EURct/kWh, in the PV submarket. In contrast, consumer 5 does not have the highest bid in the CHP submarket but is the only participant who consistently prefers CHP energy. As a result, many consumers with a higher CHP bid price but also a higher PV bid are already supplied on the PV submarket and thus not matched on the CHP submarket. The high share of CHP in the energy mix of consumer 5 shows that the participant is supplied mostly according to the individual preference. On average, 67% of all consumers' electricity consumption was supplied by locally available sources. Of this local consumption, an average of 60% corresponded to the participant's preferred source.

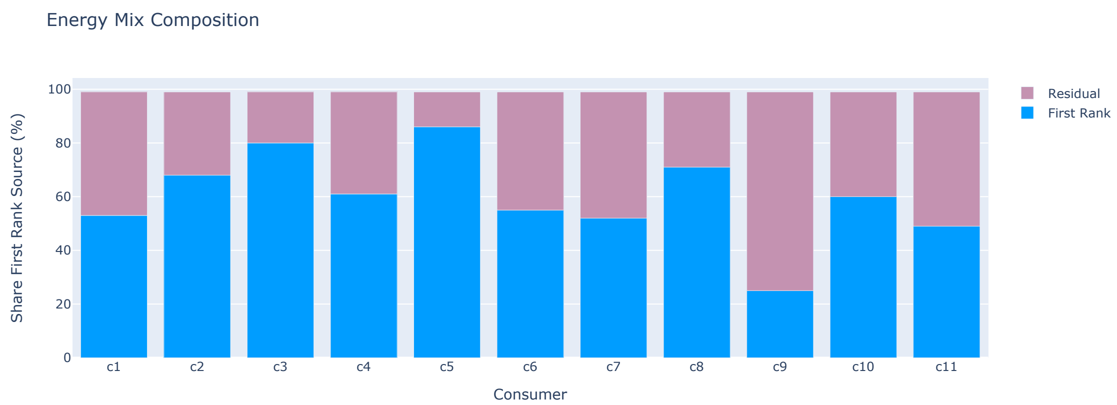

Figure 6.2.: Share of first preference source in energy mix

6.5. Discussion and Limitations

Overall, the lower share regarding the supply by the first preference energy source can be explained, among other things, by the heterogeneous preferences of all consumers and underlying functionality of the Borda Count voting system. First, although some consumers prefer the CHP energy source, they can be matched on the PV submarket because the overall vote of all consumers favors this energy source and the market is executed first. This matching happens if their PV bid price is not below the supply bid prices and the generated amount is sufficient. Therefore, these consumers are supplied by an energy source that they do not prefer the most, even if their preferable source is available. This represents a disadvantage of the developed mechanism. However, these consumers receive, by design, this less preferable energy at a lower price which corresponds to their willingness to pay. Therefore, the mechanism ensures that if consumers receive the energy they prefer less, they pay a lower price. Also, if the supply is not sufficient, the low bid price ensures that these consumers are the first who will not be matched and then transferred to the second submarket with their preferred energy source.

Besides the bid price, the availability of both local sources has a decisive influence. As described above, the CHP plant was not generating energy continuously. The PV plant is dependent on weather conditions and the time of day. During evening hours with CHP generation, all consumers receive energy from this generation source or the public grid regardless of their preference because PV energy is unavailable. Battery storage systems are possibilities to increase the share of local energy and the respective primary preference share. The storage system can increase the availability on the supply side but requires tracking the consumed energy by source.

6.6. Conclusion

In this chapter, a two-step market mechanism for CECs with a trading platform, also known as LEMs, is proposed. With this proposed design, we answer our research question by developing a mechanism, which is able to distinguish between different consumer energy source valuations. In a first step, submarkets are formed based on the different preference characteristics of the consumers (e.g., type of generation, location). Each submarket is cleared on its own, using a discrete double-call auction. In order to reflect the distribution of preferences of all consumers in the community, the second step introduces a voting system that determines the chronological schedule of the markets' execution. This order is calculated with the Borda Count voting mechanism. Each consumer sets a bid price for each market, which can be ordered and considered a vote. The Borda Count mechanism calculates based on all votes the market order. The developed market mechanism is implemented in the LAMP project. We show that the mechanism is able to allocate local energy according to the individual consumer preferences. The individual results are depended on the consumers' willingness to pay, individual bid prices and available supply of the local energy source.

Part III.

Citizen Energy Communities - User Behavior

Introduction to Part III

Besides the design of the market mechanism and the IT architecture of a CEC platform, the user behavior of the participants has an impact on the market outcome. The analysis of the participants' behavior shows how they use the platform and what effect the design has on their behavior. This analysis step is essential as it verifies whether the chosen design of the market structure leads to the desired market outcome. This analysis also allows investigating, which factors influence the behavior and gives conclusions on how the market structure can be adapted to achieve the desired market result. For this reason, the following part analyzes the behavior of CEC participants on the platform and how they can be supported so that they remain committed and part of the community in the long term. First, the connection between platform and user is important. It must be easy for participants to use the platform and to derive an individual benefit from its functions and services. There is little design knowledge in the CEC context, especially on the interface design that connects the platform and the user. Therefore, the design of the user interface is investigated with a design science research approach in Chapter 7. Based on the experience of this iterative process, corresponding design knowledge is generated. Second, the participant behavior on the platform determines whether the benefits assumed in the academic literature, such as system beneficial consumption shifts or higher local profits for prosumers, can be observed (see Chapter 3.2.6). The real-world verification of these assumptions is needed to ensure the successful implementation of CECs in practice. Therefore, Chapter 8 reviews the most common assumptions in the literature through a longitudinal analysis of participant behavior in the LAMP project. Third, the digital platform offers the opportunity to support participants in their activity on the platform, especially when they have limited time and or expertise. In the literature, the use of automated agents has been proposed to solve this challenge. In Chapter 9, the real implementation of such an agent in the LAMP project is described, analyzed and based on the insights, the market design is evaluated.

Chapter 7.

Designing a User Interfaces for Citizen Energy Communities

In this chapter, design knowledge that actively engages participants in the long-term and supports sustainable behavior is derived and evaluated. An important aspect of the CEC concept and corresponding information system is the interface between the participants and the platform, especially its design. It ensures active engagement and periodic use, which are crucial success factors of a CEC and its value propositions for the energy system. Following a design science research approach, seven design principles are derived and evaluated for the CEC concept based on a literature review and extensive feedback from stakeholders and participants of the LAMP project. Six design principles are instantiated in an application, tested in the field for one year by the project participants and evaluated in expert interviews. The seventh design principle is derived a result of the empirical test phase of an online experiment to assess the market mechanism preferences of potential participants. The findings provide applicable design knowledge to advance the transition to a renewable energy system and support future real-world CEC implementations.

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7.1. Introduction

The described benefits of CECs and the corresponding promising impact on the sustainability of consumption behavior discussed in Chapter 3 can only be realized if the participants show a long-term engagement with the platform. This long-term engagement is linked to how much benefit the participants feel that they can derive from the functions and design provided by the platform and in relation to that, whether they can understand and use them. If these benefits seem small or the hurdles to achieve them are high, participants become inactive and may leave the community. Inactive participants, who do not utilize the provided behavioral information, will not make purposeful consumption changes. Therefore, the platform's design, especially the user interface, plays a central role. An inadequate design can lead to participants not finding functionalities or might make it difficult to use them correctly. The provided information by the platform can also be misunderstood and thus lead to unintended, incorrect behavior. Designing a system that fits all relevant community needs is particularly challenging because most of the participants have different levels of knowledge and are non-professionals. Their motivation to participate and their available time differ widely. In addition, the interaction with the platform is not a priority in their daily lives. For this reason, it is important that the platform design supports the participants to easily access and understand the available information and functionalities.

In this chapter, existing design knowledge is acknowledged and new design knowledge is created through a long-term field experiment where participants use the LAMP CEC platform over more than one year. We investigate how participants interact with the implemented information system and which functionalities motivate them in the long-term, thus ensuring a long-lasting effect for more sustainable behavior. This behavior and corresponding awareness are necessary to foster resource conservation and sustainability. As stated in Chapter 3.2.7, we use the term "long-term engagement" to refer to participants who regularly but not constantly interact with the system and engage with the information provided over a long-term period. We elaborate on design principles that a) provide practical experiences for new CEC projects and b) contribute design knowledge in the emerging field of energy communities where long-term involvement supports sustainable behavioral change of non-professional users. We investigate the following research question: *What are fundamental design principles for a CEC user interface and platform that lead to a long-term engagement of participants?*

To answer this research question, we divide it into three sub-questions. The first sub-question focuses on the general understanding of the platform design and the ability to use the provided functionalities correctly. The first sub-question is: *How should a CEC user interface be designed so that participants can understand and use the provided functions?* The second sub-question corresponds to the participants' behavior and their ability to use the information provided by the platform to make behavioral changes corresponding to their preferences: *How should a CEC user interface be designed so that participants can behave according to their preferences?* Finally, this chapter's goal is the generation of design knowledge for long-term engagement of CEC participants. Therefore, the last sub-question is: *How should a CEC platform be designed so that participants generally exhibit a long-term user engagement?* We conduct a Design Science Research (DSR) project based on the approach by Kuechler and Vaishnavi (2008) with three design cycles (Hevner et al., 2004; Kuechler and Vaishnavi, 2008) to address these three sub-questions. We present the results of the three cycles of this project. We design a first prototype based on identified requirements (Cycle 1), derive six design principles based on this design, instantiate them in a full application and evaluate the proposed design after a one year testing period in the LAMP project (Cycle 2). We conduct individual expert interviews with the project participants for the evaluation. Based on the interview feedback, we carry out an online experiment (Cycle 3) to evaluate the market mechanism preferences of potential CEC participants and derive the seventh design principle.

7.2. Related Work

There is corresponding research on the user interface functionality in other contexts and design research. For example, the CEC interface has similarities with energy feedback systems. These systems describe the provision of information (consumption, energy mix and costs) through a (digital) user interface. Several studies show that feedback on energy consumption has a positive impact on more sustainable behavior and that there is a hidden potential within private households to adapt their behavior regarding sustainability and cost reduction when being provided with the corresponding information (Gholami et al., 2020; Karlin et al., 2015). Furthermore, there is research on the design of such energy feedback systems. Ableitner et al. (2017) implement and test different designs of smart shower meters, which give real-time feedback. The authors investigate the impact of different display designs on energy (and water) conservation. The results underline the importance of a carefully designed interface. The study describes the result that a display design with visual elements which shows the environmental impacts of the users' behavior resulted in higher energy consumption. Dalén and Krämer (2017) analyze and improve existing energy feedback solutions focusing on the device level using the DSR approach by Peffers et al. (2007). The authors propose four design principles focusing on the design of smart meter interfaces to promote efficient energy usage in private households and they evaluate a first prototype. Gnewuch et al. (2018) develop design principles for conversational agents for utility service stations regarding user interactions. The design principles' goal is to promote sustainable energy use through the interaction with conversational agents. However, the proposed design principles focus mainly on data processing to enable energy feedback and less on consumers' perceived utility and long-term usage.

Stock trading interfaces are another domain of similar interfaces. Lee and Kim (2002) derive three design principles for stock trading websites. The authors proposed a "Functional Convenience" design principle, which distinguishes between an information-gathering process and an order-making process. The former process needs to include useful and up-to-date information, while the latter focuses on the submission of the order and its effectiveness. In addition, the second design principle by Lee and Kim (2002) focuses partly on the user's delight (Delightfulness), meaning that users will interact with the interface frequently if the interface experience is entertaining and interesting, which creates utility for the user. This description can be interpreted as a form of long-term engagement. However, the authors' design principles cannot be transferred directly to the CEC context. The proposed design principles do not include the intention to enable the users to make purposeful behavior changes towards more sustainability and it addresses expert users.

Regarding behavioral changes towards more sustainability, the study by Seidel et al. (2013) develops design principles that should support organizational sensemaking in sustainable transformations. Sensemaking of information is crucial for individuals to understand the environmental impact of their behavior and to derive corresponding actions. The authors choose a web interface as instantiations of the derived design principles. They conduct three revisions of their initial set of design principles. However, the final design principles do not address long-term interactions with the web interface and focus more on the organizational aspects and the communication between different users. Several studies, focusing on long-term engagement, can be found in other domains. Wallis et al. (2013) analyze the motives of amateur musicians to use their instruments over a longer period. The authors identified seven properties and transferred them into the field of human-computer interaction, where they can be used in the interface designing process. However, the authors do not derive design principles and design knowledge. Kazhamiakin et al. (2016) present a gamification framework to foster long-term engagement of smart city citizens regarding sustainable behavior. According to the authors, the framework allows the design and execution of gamification solutions, which promote sustainable behavioral changes in the area of urban mobility. Although the authors show concrete instantiations of the presented solutions, they do not propose specific design principles for the interface design. Jain et al. (2012) investigate the connection between interface engagement and reductions in energy consumption. The authors use login data to assess the performance of different interface components. They conduct a six-week study with 43 participants and a prototype interface. The authors confirm that user engagement corresponds to a decrease in energy consumption. While the authors examine different design components, they do not derive design principles from their study results.

Summarizing, design knowledge already exists in other similar contexts, such as the user interface for stock trading and energy feedback systems. Especially design principles of energy feedback systems focus on changing consumption behavior towards more sustainability. Yet, existing CEC research body lacks findings on interface design for CECs and design knowledge for motivating the regular long-term engagement of participants. In addition, there is still a lack of empirically tested implementations and knowledge about effective CEC instantiations. We close this research gap by creating new design knowledge using a DSR approach based in part on the above-mentioned existing design knowledge. Therefore, we follow the call of Seidel et al. (2017) and promote sustainability as well as a practical application of Green Information System research and contribute to the research agenda on the design of Green Information Systems.

7.3. Design Science Research Approach

This study is a DSR project that develops and instantiates design principles for CEC platforms, especially the user interface, to better integrate participants and motivate long-term participation. As mentioned in Chapter 3.3, the first CEC projects are implemented and local community approaches, which may additionally include other consumer commodities such as water, gas, or heat, are on the rise. Therefore, with our DSR project, we aim to generate valuable design knowledge not only for future CEC projects but also for communities that wish to include different consumer commodities. We follow the DSR approach by Kuechler and Vaishnavi (2008) to develop the targeted design principles (DP). Due to the iterative structure of the DSR methodology and the corresponding continuous evaluation of the artifact, as well as the involvement of real users and experts, it supports the process of developing a suitable solution. The approach of DSR is particularly suitable for this purpose, as it allows to identify unknown challenges of the CEC platform and interface design and to address them in later cycles. The starting point of the DSR project is to develop and provide a solution for the LAMP project. Based on our experiences, we transfer generalizable design knowledge within the process. With this approach, we follow *Strategy 2* of Iivari (2015), which focuses on solving a concrete problem in practice and generates design knowledge within this process.

Design Science Research Project: The DSR project consists of three cycles, as shown in Figure 7.1. This study presents the results of these three cycles. It includes the development and testing of a prototype (Cycle 1), refinement of the prototype to a complete application and the implementation as well as evaluation in the LAMP project (see Chapter 3.4 for a description) where we test the artifact (Cycle 2). Based

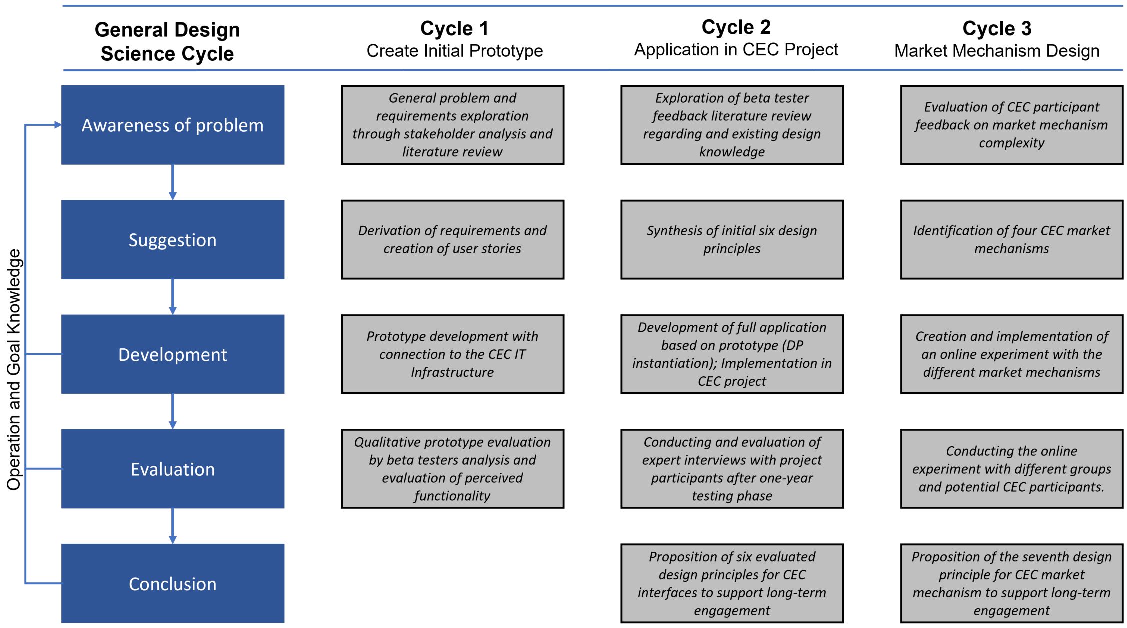

Figure 7.1.: DSR project adopted from Kuechler and Vaishnavi (2008)

on the evaluation results of Cycle 2 regarding the market mechanism complexity, we conduct a third cycle. This third cycle sets up an online experiment where potential participants test different CEC market mechanisms in regards to observations of the previous cycle (Cycle 3). Since the most significant uncertainty for the design lies in the participants' perception, we choose to follow the human risk & effectiveness strategy for the evaluation process (Venable et al., 2016). In this strategy, the evaluation of artifacts is quickly moved from formative, artificial evaluation to more formative, naturalistic evaluations in real settings and real organizational situations. We briefly outline the DSR project and provide further background information in the following.

Cycle 1: In this cycle, a prototype interface is developed in collaboration with the project stakeholders. The goal is to design a functional interface, which provides the necessary functional capabilities of the CEC application that allow the users to obtain detailed information from the CEC platform and to bid actively. In the first cycle's problem awareness phase, we derive stakeholder requirements utilizing insights from a literature review and interviews with project stakeholders. Next, we develop several user stories based on the literature and stakeholder input in the suggestion phase. We leverage the user stories from this step to design a first prototype (interface mock-up). Subsequently, we present this prototype to three selected beta testers and two project managers. All testers evaluate the prototype's design before the project start in Cycle 2. The three beta testers are also participants of the project during the active phase of Cycle 2.

Cycle 2: The second cycle's objective is the design evaluation of the CEC platform and its user interface over a more extended period and to derive generalizable design knowledge regarding long-term engagement of the users. In the awareness of the problem phase, the feedback from the beta testers is evaluated and considered in terms of perceived usability and suggestions for improvements. In addition, a literature review is conducted regarding existing design knowledge for comparable use cases as well as long-term engagement in general. Based on this, we propose six initial design principles in the suggestion phase of Cycle 2. The project team then improved the prototype and created an application with full functionality. All LAMP participants received an individual tablet with the pre-installed application. The duration of Cycle 2 is one year and participants used the provided application during the whole period. Following this period, we collected feedback from all ten participants employing semi-structured interviews and derived and evaluated six design principles which support long-term engagement and meet the stakeholders' requirements. However, the negative effect of the market mechanism's complexity was noticeable feedback from the participants regarding long-term engagement. For most participants, it was challenging to understand the mechanism and effects of their bidding behavior. The arising uncertainty led to lower activity and engagement. Based on this feedback and the stated effect on long-term engagement, we conducted a third cycle, which examines the impact of different market mechanisms on potential participants and investigates their preferences with the help of an online experiment to adapt this final building block of the overall platform design.

Cycle 3: In the third and last cycle, we investigate the perception, understanding and effect of different market mechanisms and identify additional necessary design principles. This cycle is based on the second cycle's findings and is essential to ensure that the developed design principles from the previous cycles can support the participants in their decision process and increase their engagement with the CEC overall. Due to the difficulty of testing different market mechanisms within a real project, an online experiment is conducted in this cycle. Each participant of the experiment tests four different market mechanisms. These correspond to different approaches, such as an auction or time-of-use rate mechanism. Within the experiment, the participants run through various scenarios with the respective market mechanisms. In each of the scenarios, the participants must decide on a bid price and load shifting. The goal is to determine which form of market mechanism the participants prefer that encourages them to interact with it.

7.4. Results

The results from all three cycles are presented below. The first part describes the problem knowledge and the resulting requirements, user stories and the prototype. Based on this, in the second part the solution knowledge and the derived design principles, their instantiation and the structure of the market mechanism experiment is described. The last part includes the evaluation results of the six derived design principles and the market mechanism experiment, which we utilize to derive the seventh design principle.

7.4.1. Problem Knowledge and Requirements

For a structured description of the problem space and the identification of essential requirements, we adopt the conceptual model of Maedche et al. (2019). First, we investigate the underlying needs and problems of the project's stakeholders (CEC operator and participants) by exploring the existing literature and by conducting interviews. On the one side, the need of CEC operators is that participants engage with the platform in the long-term and use it regularly because without interactions, the platform does not generate any benefit or profits. This is inevitably related to the design of the CEC platform and its interface, as it is the only connection between the user and the platform. On the other side, participants have no explicit formal needs because they participate on the platform voluntarily. However, they will interact with the platform and thereby with the CEC interface if first, the provided functionality of the platform is valuable for them, and second, the interface design allows participants to understand the functionality and use it accordingly. These needs lead to the design goal of a CEC platform and its interface: participants derive a personal benefit by using the platform and, consequently, interact with the platform on a regular basis, forming a long-term engagement.

We extract the following requirements from the literature and the project partner's expertise to achieve this goal. First, it is necessary to grant the users access to relevant data from the information system via the platform interface ((Mengelkamp et al., 2018a; Wörner et al., 2019a). This functionality is equivalent to the feedback systems described in the related work section (Dalén and Krämer, 2017; Loock et al., 2013; Tiefenbeck et al., 2019). Besides the individual load data, the system should provide information on the available electricity generation sources to determine the individual electricity mix, the market results and the individual costs. Several existing projects support the latter requirement implicitly by distinguishing between transactions with local resources and external resources (Ableitner et al., 2020; Mengelkamp et al., 2018b; Vasconcelos et al., 2019). Besides, the utility project partner emphasized the importance of such feedback for local generation sources in the stakeholder interview. Based on this information, users can evaluate their behavior and derive actions or desirable behavioral changes. These necessities lead to the first requirement (R1) that users need to be able to access the relevant market and load data in order to be able to evaluate their behavior promptly and react correspondingly.

Second, the possibility to express individual preferences through bidding is another central feature of the CEC concept (Mengelkamp et al., 2018b; Teotia and Bhakar, 2016; Wörner et al., 2019a). In addition to monitoring their behavior, users must be able to respond to changing situations, such as changing weather conditions or market prices (Mengelkamp et al., 2017, 2018a; Wörner et al., 2019b; Weinhardt et al., 2019). This functionality is equally important for local generators. Therefore, the second requirement (R2) is that users must be able to formulate active preferences to purchase or sell electricity on the local market at specific prices or rates and communicate these preferences to the information system. Third, during the interview, the utility partner pointed out that security and privacy are important as load values are sensitive information. Furthermore, existing data protection policies specify that individual load information is sensitive data and needs to be secured. In addition, data leakage, like knowing the bid data from other participants, creates an unintended market advantage and decreases trust in the platform. Therefore, the system must prevent users from accessing other participants' load data or bids.

Consequently, the third requirement (R3) is that users must not be able to access other users' data or place unauthorized bids in their names.

In the evaluation phase of Cycle 1's prototype design, a beta tester recommended to introduce regular notifications and updates. Participants should receive a regular reminder with summarizing information, which allows them to get a quick overview (specifically if time resources are a constraining factor). We transform this suggestion into the fourth requirement (R4) that the system should regularly inform the users with summarizing information about their performance. In the second cycle, we respond to the beta testers' prototype feedback with the fully developed application. With the help of additional participants, we identify specific weaknesses of the first instantiation after a one year field study. Important feedback from the evaluation of Cycle 2 is that the complexity of the implemented market mechanism meant that participants did not always understand the consequences of their actions and this led to inactivity. In the interviews, we could exclude the possibility of design errors in the information representation and understanding. We conclude that it has a strong effect on the participants' long-term engagement if the market mechanism is too complex. Therefore, we derive the fifth requirement (R5) that the platform's market mechanism complexity needs to be kept minimal in order for participants to understand the consequences of their bidding actions. Table 7.1 summarizes all five requirements.

Requirement	**Description**
R1	Users need to be able to access to the relevant market and load data in order to be able to evaluate their behavior promptly and react correspondingly.
R2	Users must be able to formulate active preferences to purchase or sell electricity on the local market at specific prices or rates and communicate these preferences to the information system.
R3	Users must not be able to access other users' data or place unauthorized bids in their names.
R4	The system should regularly inform the users with summarizing information about their performance.
R5	The platform's market mechanism complexity needs to be low in order for participants to understand the consequences of their bidding actions.

Table 7.1.: Overview of stakeholder requirements

7.4.2. Solution Knowledge

Prototype Development and Design: Since there is little previous research on a CEC platform and corresponding interface design, an initial prototype is evaluated in the first cycle. The prototype design contains all the necessary functions derived from the literature input and the first stated stakeholder requirements (R1-R3) but has limited functionality since the underlying IT infrastructure is not yet implemented. We presented the prototype to beta testers. Three of them are households that later participate in the project and already have a smart meter installed. The two project partner employees have access to load data from an electricity meter installed in the project partner's office building. Each of them received a tablet with the pre-installed application prototype. The participants had one hour to familiarize themselves with the application. Before the interviews, all agreed to participate and provided their demographic data. The survey was conducted on-site, with one researcher conducting the interview and the second taking notes.

Design Principles and Artifact Instantiations: The feedback for the prototype design and derived literature insights from related design domains are the basis for the first six initial design principles. Each design principle is connected to the derived requirements from the project stakeholders, which represents the problem space. The first three design principles address R1, DP4 and DP5 address both, R2 and R3, respectively. For R1, we distinguish between three design principles because the intended effect of the feedback differs. For example, information on the consumption behavior has no value regarding a better bidding behavior. Feedback on the energy mix or energy costs, respectively, shows the participants the effects of their behavior regarding sustainability and cost-savings. The sixth design principle addresses R4, which is the result of the stakeholder evaluation of the first cycle. Similarly, the seventh design principle introduced in Cycle 3 is based on R5, which is derived from the second cycle's feedback. We formulate these principles with the framework of (Gregor et al., 2020).

In Cycle 2, each design principle is derived from the prototype feedback and instantiated within the pilot project. The prototype mock-up is transformed to a full-scale application, which represents the artifact. We improve and adapt the initial prototype in the second cycle using the information gained in the evaluation step. Figure

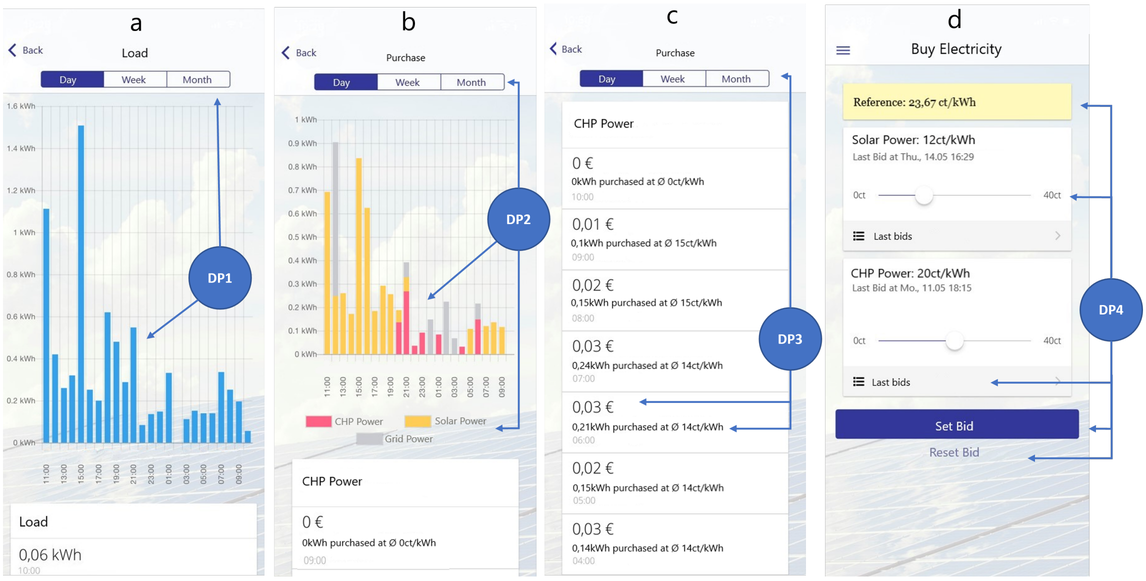

Figure 7.2.: Visualization of the design principles 1-4 instantiations

7.2 shows the improved instantiations of DP1-4 after the feedback in Cycle 1. In the following, we present all seven design principles and their instantiations in LAMP.

As discussed previously, the user feedback system is a central building block of the overall functionality. The academic community already discusses and investigates the effects of 'Energy Feedback Systems' (Karlin et al., 2015). Dalén and Krämer (2017) propose design principles with respect to consumption and monetary savings. However, feedback on the energy mix and environmental impact of energy is not considered. Instead of single devices, we focus on aggregated information as it addresses the overall behavior. Therefore, we partially integrate their approach because they focus on providing information for efficient energy decisions based on consumption values. Additionally, the project stakeholders point out that consumption feedback, which fosters behavioral changes, is a necessary and important functionality. Feedback should enable the users to identify their general, everyday behavior patterns. However, consumption values alone are difficult to understand and many users do not have energy-specific expertise (Brounen et al., 2013; Dalén and Krämer, 2017). Therefore, it is crucial to put it into a sensemaking context (Seidel et al., 2013). The users need a relative reference to judge their power consumption and to compare different periods. Consumption information should be visualized to the users (Froehlich, 2009). It allows them to investigate and assess their consumption behavior more quickly. Regarding individual consumption data, this leads to the following DP1.

> *DP1:* *For CEC operators to design a long-term engaging user interface, which allows participants to draw conclusions on how their individual consumption is affected by the behavior during their everyday life, the interface should provide visualizations of individual historical consumption data because it supports the participants in the understanding of their consumption behavior and identification of saving potentials.*

Instantiation: Figure 7.2a displays the visualization of consumption values through a graph. The users can switch between the displayed periods of a day, week, or month. Below the graphic, a table shows the load value for every period.

Access to individual consumption data alone is not sufficient to judge individual sustainability. Participants cannot retrieve how environmentally friendly their actions are by evaluating the consumption data. As mentioned in the previous section and chapters, environmental awareness and the need to reduce the ecological footprint are becoming more important for private households. The possibility of local (renewable) consumption is a key feature of the different, already existing CEC projects. Besides, studies indicate a higher willingness to pay for local and green electricity in certain population segments (Mengelkamp et al., 2019c; Tabi et al., 2014). This sustainability trend cannot only be observed in the field of electricity. There is also a need for more sustainability in other areas of society like food or transportation. In this sense, the local utility stakeholder points out that the representation of local resources is critical to embrace sustainable local consumption. The target is to incentivize participants for sustainable behavior by encouraging them to increase the individual local and green share. Alternatively, the participants can raise their bids for local sources, which creates higher margins for local generators. Comparable to the first DP, the consumption mix information requires an understandable visualization, which allows a distinction between different sources. Therefore, the application must process the origin of the energy generation, making it easier for the participants to identify their consumption mix and compare it with their individual preferences. The second design principle addresses this as follows.

<u>*DP2:*</u> *For CEC operators to design a long-term engaging user interface, which enables participants to adjust their behavior according to their individual preferences in their everyday life and on the market platform, the interface should provide visualizations of the different individual consumer commodity sources because it supports the participants in their assessment of the sustainability of their behavior and helps them to become more sustainable.*

Instantiation: Figure 7.2b shows the instantiation of DP2 and displays the purchase values. Here, comparable to the Figure 7.2a, load values are shown divided along three different colors, each of which represents a different generation type. In the interface, we make a distinction between local electricity generation from PV power systems and indicate them with the caption ('Solar Power'). Similar, energy from a CHP plant is indicated with the caption ('CHP Power') and energy from the power distribution grid with ('Grid Power').

Apart from different energy generation sources and the individual consumption mix, the costs are essential for households (Mengelkamp et al., 2019c). Due to the lack of smart metering infrastructure, households only have estimations of their own consumption and related costs today. The supplier then invoices the respective deviation at the end of the year. In the worst case, this can lead to high additional, unanticipated payments. Households only receive limited and, above all, no direct cost feedback on their consumption behavior (Vine et al., 2013). In regard to CECs, the general assumptions in almost all contributions are cost-minimizing consumers and profit-maximizing local generators (Mengelkamp et al., 2018c; Wörner et al., 2019a; Ströhle and Flath, 2016). Additionally, the stakeholder interview underlines that displaying costs is necessary to avoid surprisingly high bills for the participants and to establish an economic and perceivable connection between behavior and costs that allows for sensemaking (Seidel et al., 2013). The feedback is necessary for participants to assess their actions from a sustainability and a financial point of view. Therefore, we formulate the third design principle as follows.

<u>*DP3:*</u> *For CEC operators to design a long-term engaging user interface that enables participants to choose cost saving behavior in their everyday life, the interface should provide consumption costs transparently and instantly to allow the participants to connect their behavior to the associated costs.*

Instantiation: Figure 7.2c displays the instantiation of DP3, which is also located within the purchase interface. The instantiation presents the transaction data table and distinguishes the costs by each energy source. The presented figure shows the costs for energy from the CHP plant. Each entry represents an hour of a day and shows the costs, amount and average price (in cent per kWh) of that hour. This representation can also be aggregated for different periods, as described above.

The submission and adjustment of bids, according to individual preferences, is a unique characteristic of markets and a particular argument for CECs. Concerning the two preceding design principles, the participants cannot only influence their consumption mix by behavioral adjustments but also by changing their bid price for specific energy generation sources. In the case of surprising feedback, e.g., a low share of local consumption, the participants can increase their bids and signal a higher willingness to pay. In the CEC literature, nearly every concept relies on consumer involvement and includes a bid submission process (Bremdal et al., 2017; Mengelkamp et al., 2018c; Wörner et al., 2019a). This functionality allows the active integration of consumers and prosumers and promotes allocation efficiency for the local resources. However, a remark from the stakeholder interviews is that consumers have only limited experience with auction mechanisms, which can lead to hesitation and it introduces additional complexity. A risk exists concerning false user inputs and a lacking understanding of how to submit a bid successfully. Therefore, a simple interface is required, supporting the participants by only allowing bids in a reasonable price range and by not requiring constant bid updates. Since different market mechanisms accept different bidding inputs, the information system input mask must prevent wrong or illogical inputs. The evaluation of Cycle 1 resulted in the integration of a reference value to create an orientation point for the consumers and prosumers. DP4 addresses this as follows.

<u>*DP4:*</u> *For CEC operators to design a long-term engaging user interface that facilitates the bid input process on the market platform, they should provide a bid submission interface with required numerical input in a valid and reasonable range for all available energy sources and a reference value because it helps participants in the bidding process and provides an orientation point.*

Instantiation: Figure 7.2d shows the bidding interface as the instantiation of DP4. A controller interface prevents erroneous inputs and users can bid for electricity from local PV and the CHP in a range from 0 to 40 EUR/kWh. A reference value shows the grid tariff. Participants can submit a bid by clicking the *Set Bid* button, or reset their bid if it has not yet been submitted. They can see their past bids to evaluate past actions.

CEC literature does not explicitly mention security functionalities concerning sensitive data. Consumption data of individual households is among the most sensitive personal data as it provides direct insight into individual behavior. For example, energy data allows drawing conclusions about the occupancy of a household (Beckel et al., 2014). For this reason, the utility project partner specified in the interviews that the operator must protect all participants' privacy and it has to be impossible for uninvolved third parties or other participants to have access to individual consumption data. If this cannot be guaranteed, participants may decide not to participate and additionally, this approach may violate the applicable law. Furthermore, the operator must prevent other participants from placing bids on behalf of other participants. Otherwise, the trust in the system and its functionality is at risk. A design principle that describes a comparable functionality can be found in (vom Brocke et al., 2017). It is formulated in the context of a DSR tool-support website. We define the fifth design principle as follows.

<u>*DP5:*</u> *For CEC operators to design a long-term engaging platform for participants to protect sensitive data of the market platform, the platform should ensure privacy through corresponding authentication mechanisms because it establishes trust towards the system and compliance with legal data protection requirements.*

Instantiation: To protect the privacy and sensitive data, in the instantiation of

DP5, each participant is assigned a user account whose access data is an e-mail address and a password. The application contains a login display and after starting the application, the user must enter the access data to log in.

As stated above, the target groups for the CEC information system are not engaging professionally in markets and have no comprehensive domain knowledge. The question arises to what extent and intensity the participants can actively engage with the system. Attention and time are often limiting factors and participants can often only irregularly deal with their performance on the CEC. In the evaluation phase of Cycle 1, beta testers suggest a recurring reminder, which helps the participants to receive information from the system passively. In the evaluation interview at the end of Cycle 1, one beta tester pointed out that reports should provide a quick overview of the data. This reminder should be combined with a summary of aggregated information about individual consumption behavior and market events (see DP1-3). A simple overview of all relevant information allows participants to check the information and decide on appropriate action quickly. Regular intervals allow to compare the aggregated values and in case of substantial deviations, the participants can take direct action. For example, participants who are currently otherwise involved could be informed via a weekly e-mail with the latest information on their behavior and directly identify a week with increased consumption. For this reason, DP6 is defined as follows.

DP6: For CEC operators to design a long-term engaging platform, participants need to receive an overview of their overall performance on the market platform regularly and proactively. The platform should provide an opportunity for participants to activate a notification service that sends aggregated information on a regular basis because it facilitates the participants' engagement with the platform and enables them to track their individual behavior development.

Instantiation: This design principle is instantiated through a weekly report sent via e-mail. This report includes the amount of energy consumed, the power source composition of the individual participant, the overall costs and the individual average electricity price for the last seven days. Additionally, the average price of all participants is communicated to ensure the possibility of comparison (i.e., to enable a better sensemaking (Seidel et al., 2013)).

The interview feedback after Cycle 2 made it clear that the complexity of the market mechanism is an important challenge for the CEC design and participant engagement. The high stated complexity had an impact on the participants' behavior. According to their statements, they could not clearly link their actions (DP4) to the market results (DP1-3). Therefore, a complex market mechanism inhibits the effectiveness of the other design principles as it inhibits sensemaking of participants. Similarly, the high complexity requires participants to study the market mechanism intensively at the beginning in order to understand it clearly. This necessity is an additional hurdle because many participants mention their limited time resources. However, understanding the market mechanism is essential for active participation and a good performance on the platform. According to the interview statements, none or little understanding leads to a decrease in activity and to participants consequently interacting less often with the CEC. The market mechanism's complexity seems to strongly influence the perception and perceived utility of the user. Therefore, we define a seventh design principle in order to deal with this issue as follows.

DP7: For CEC operators to design a long-term engaging platform that supports the participants in understanding the effect of their actions on the market platform, the platform should implement a market mechanism, which is easy to understand and therefore facilitates the interactions with the CEC.

Market Mechanism Experiment: Based on the feedback in Cycle 2, a third cycle was necessary, which explicitly deals with the complexity of the market mechanism for CECs. For this purpose, an online experiment was conducted, in which participants test four different market mechanisms in various scenarios and in random order. The experiment participants are asked to buy energy as cheaply as possible in each game. For bought renewable energy, a donation is made to a charity focusing on environmental sustainability to simulate the additional effects of buying sustainably generated energy. We opted to evaluate this cycle in a laboratory experiment because it allowed for more participants and broader immediate feedback. The experiment was conducted online with 115 participants. Of these, 41 were female (36%) and 74 were male (64%). Within the experiment, the goal for the participants is to develop a feel for how the market mechanisms work and to evaluate which of these mechanisms appeals to them the most. Likewise, we expect better insights into why participants prefer specific market mechanisms to others. This preference is essential information for CEC operators when developing and implementing the platform. In the experiment, four market mechanisms are tested, a time-of-use mechanism (TOU), a real-time pricing mechanism (RTP), a periodic tariff based on individual bids (PET) and an auction mechanism (AUC) as implemented in Cycle 2. Therefore, the market mechanisms can be classified along the amount of interaction (TOU and RTP require no interaction, AUC and PET require user bids) and the frequency of price changes (with TOU and PET prices change infrequently, while with RTP and AUC prices may change in every period). The experimental setup consists of five games. In the first four games, users test each of the different market mechanisms in a randomized order to avoid an impact of the sequence. In the fifth game, the users can choose their preferred mechanism out of the four tested mechanisms at the end of the experiment.

Each game is structured similarly and consists of three days with a corresponding morning, afternoon and evening period. Within each day, there is a fixed amount of renewable and conventional energy available to the CEC, unknown to the participants in advance. The participants compete with two other virtual participants (that simulate the neighbors), which follow fixed bidding strategies. The participants' task in each game is to consume a given amount of energy over the three days. For this, they have a fixed amount of money at their disposal. The payout for the experiment participation is determined by how much money the participants have saved at the end of each game. It provides an incentive for the participants to purchase the necessary supplies as cheaply as possible. The required power quantity that the participants must buy is divided into a fixed and a variable share. The participant must cover the fixed share at the respective time of the day, while the variable portion can be shifted within the day. Shifting demand leads to a small cost for the participant, representing the inconvenience of shifting demand.

The possible amount of RES generation in the respective day segments varies as in real life. The available amount is highest in the afternoon, which is the daytime with the highest solar radiation. Likewise, the participants receive information about the maximum and minimum deviation over the day. Based on this information and a general description of the market mechanism at the beginning of each game, the participants can choose their actions, including shifting demand and individual bids for the PET and AUC mechanisms. Participants are asked various questions regarding their perception of the mechanisms after each game. The experiment is implemented with the open-source framework oTree (Chen et al., 2016).

7.4.3. Evaluation

As mentioned earlier, we select the human risk & effectiveness strategy (Venable et al., 2016). We choose this strategy for the evaluation because the DSR project is user-oriented and the artifact is easy to evaluate with real users in a real-world setting. Its goal is to establish participation and long-term benefits of CECs. The online experiment also fits in this strategy.

We conduct three separate evaluations according to the Kuechler and Vaishnavi (2008) DSR process. We provide necessary background information for the evaluation steps of the three performed cycles in the following. The first cycle evaluates the design of an initial prototype based on the first identified requirements (R1-R3) with three beta testers and two employees of the project partner. Both project partners were part of the stakeholder interview from the problem awareness phase. The second cycle evaluates the derived and instantiated design principles after a one year testing phase within the LAMP project (see description in Chapter 3.4). At the beginning of the project's active phase, the participants receive their own tablet computers on which the application is installed and set up. In addition, each of the participants is able to install the application on their own mobile devices or access it via the web interface. The login data is provided by the project team and communicated individually to the participants.

Before the start of Cycle 2, participants were asked how important the consumption of local green energy is to them, as well as for their reasons for participating. Table 7.2 shows an overview of the responses, which allows a better interpretation of the interview statements. All participants indicated that green energy is important to them. Only two participants provide different answers. Participant 4 is indifferent, while participant 6 indicates that cost is also an important factor besides sustainability. Further reasons for participation vary. However, it can be noticed that especially the direct access to local, green generation, the local character of the community and the access to personal consumption behavior are reasons for participation. It is important to note that these responses were not given anonymously but during personal interviews, which may have led participants to advocate sustainability due to social pressures and norms (Grimm, 2010). However, all participants participated voluntarily and can be considered early adopters, which are especially interested in these topics. Therefore, the selection bias can also be a reason for the sustainable mindset of all participants (Belot and James, 2014). In addition, two participants stated that they are professionally active in the energy sector. The evaluation of the third cycle is based on empirical results of the conducted online experiment.

	Household size	Interest in local green energy	Participation Reasons
Participant 1	3	Important	· Access to local generation of energy · Support research · Support ideas to reduce grid expansions
Participant 2	4	Important	· Insights in the own consumption behavior · General information about market functionality
Participant 3	2	Important	· Access to local generation of energy · Avoiding centralized big power plants · Embrace local autonomy
Participant 4	1	Indifferent	· Insights in the own consumption behavior
Participant 5	2	Important	· Installation of own PV panel · Empower self-generation
Participant 6	2	Important (costs relevant)	· Access to local energy · Insights in the own consumption behavior
Participant 7	2	Important	· Access to local generation of energy · Insights in the own consumption behavior
Participant 8	2	Important	· Be part of a community · Project and research support
Participant 9	3	Important	· Be part of a community · Project and research support
Participant 10	1	Important	· Recommendation of another member · General interest

Table 7.2.: Description of participation reasons

Prototype Design Evaluation: The initial prototype feedback of the beta testers was positive. Many of the functions and representations inspired the users to think about their needs in relation to such systems further. The beta testers indicated that they understood the application's structure quickly and that they studied the different functionalities in detail. The beta testers suggested the following improvements to the interface: Beta testers 2 and 3 mentioned that the abbreviations of the PV system and the CHP plant are unclear. Beta tester 2 emphasized that not all participants have a background in the energy industry and will have difficulties in understanding the abbreviations. Beta tester 1 also remarked that he did not understand the abbreviations. Beta testers 4 and 5 noted that a legend is missing in the electricity mix display to assign the respective colors correctly. Beta tester 3 criticized that there is no reference value displayed for the energy price and suggested that the interface should show grid tariffs from different grid areas. However, after consultation with the project team, this was dismissed, as these are not comparable and depend on the respective network topology and cost structures. Instead, the team agreed to display the network tariff of the local energy supplier and project partner (see Figure 7.2d). The suggestion of beta tester 2 to implement a weather forecast in the prototype was discarded due to the technical effort and costs in relation to the small additional value. Beta tester 1 addressed the possibility of a regular notification, which we further translated into requirement 4 (R4) and adopted in DP6.

Design Principle Evaluation: We utilized the prototype design and its feedback to derive the proposed design principles according to the selected human risk & effectiveness strategy. We developed a full application from this prototype, implemented it into the LAMP project and evaluated the design principles after a one year testing phase.

Evaluation methodology: Every design principle is based on a functional requirement of the stakeholders. If this requirement is met, a participant can derive a benefit from it. This benefit is the basis for participants using the application and thus for a long-term commitment. In the following, each design principle and its instantiation is first examined regarding whether participants were able to use the provided functionality and therefore whether the application fulfills the underlying requirement. We also evaluate whether the implementation motivates participants to engage with the platform in the long-term.

We assessed the design principles derived after Cycle 1 (DP1-DP6) and their instantiations after the one year testing phase by conducting interviews with the participants. We evaluate the instantiations following Kaiser's approach (Kaiser, 2014) with ten project participants, referring to them as experts (EXP). All ten participants have used the application for over a year. The long interaction period under real conditions is ideal for evaluating the instantiation as well as the validity of the design principles and for assessing design features using feedback from the participants. Due to their extended exposure to the CEC platform, all interviewed participants are suitable for expert interviews. Even in the case of low usage of the application, the feedback justifying this behavior can provide insights on how future systems can be improved. Besides the general impression, participants are asked explicitly about the individual instantiations of the design principles and their overall impressions. The expert interviews follow a semi-structured approach that allows interviewers to ask questions on different topics and, based on the answers, allows switching between topics in the guideline. All ten interviews were conducted via telephone due to the COVID-19 pandemic restrictions and were recorded, transcribed and evaluated. Before each interview, the interviewer explained the interview's objective and gave some context information regarding the guideline. The interviewees were informed on their data protection rights and asked for consent to record the interview.

Design principle 1: DP1 is based on the R1, which states that users need access to relevant market and load data in order to be able to evaluate their behavior promptly and to react correspondingly. DP1 focuses on the provision of individual load data and should support participants in the understanding of their own consumption behavior. All participants stated that they accessed their individual load data and investigated their consumption behavior. Therefore, the instantiation of DP1 and thus, the fulfillment of R1 was successful. Regarding the perceived utility, participants state that the visualization of the consumption values is the most interesting for them. In addition, the possibility to study the consumption behavior in a substantially higher time resolution than the provided 15 minutes intervals would have a high value for most participants. EXP5 noted that at the beginning of the project, he was surprised about high consumption in the morning and found that boiling water causes this peak ("*[...] it was also interesting* *and revealed some interesting findings. I was surprised at how much the kettle consumes. So, we have already gained insights from that, which we have then tried to incorporate into our everyday life."*). Similarly, EXP10 expresses a great surprise that some, in her opinion, small devices cause such high consumption. She also stated that she exchanged information with her neighbor (EXP8) about findings on the consumption of household appliances (*"We just looked at it [consumption visualization (DP1)] and his wife said that the dishwasher was on."*). EXP5 even tried to determine the exact power consumption of individual devices with the help of the visualization. EXP2 also used the application to identify the high base load of a dehumidifier in the basement. He remarks that the high consumption surprised him and that the device is now only turned on when necessary (*"The thing needs an insane amount of electricity, although it is not that big. For me, one realization is that when the humidity is at 40-50 percent, that's when you turn it off. That is really helpful."*). EXP9 states that he used the visualization to evaluate the effect of shifting the washing machine's consumption or dishwasher to the daytime hours. EXP1 and EXP6 highlight the report (DP6) with the aggregated consumption value as the primary source of information on consumption behavior and only used the app's visualization in case of substantial deviations from their expectation. EXP2, EXP7, EXP9 and EXP10 mention that over the project duration, they used both forms, the visualization and the report to different degrees depending on the available time and motivation. EXP8 and EXP3 state that individual consumption values are interesting, but they did not change their behavior. The reason given by both is that the value of the time invested for a more active engagement with the topic exceeds the potential savings. EXP6 wants to set the aggregation periods herself (day, week, month) and does not want to be limited to the given aggregation possibilities. EXP2 emphasizes that there is nothing to improve in terms of structure and presentation and that it helped him a lot in understanding his consumption behavior. It is clear that participants have a high interest in the given instantiation of DP1 and, in some cases use it to adjust their behavior. According to their statements, after the high initial interest in everyday life, the participants have increasingly resorted to the regularly monitoring of aggregated consumption values from the weekly reports in order to check their consumption behavior. An interesting realization from the interviews is that although many participants deal with their consumption behavior and, adapt it if necessary, only a few become active on the CEC and change bid prices. DP1 and its instantiation is connected to a high perceived utility by the participants and supports long-term engagement with the system in terms of a regular check of the individual consumption behavior and occasional behavioral adjustments. DP1 also helped to improve the energy literacy of some participants and led to surprising realizations, which also seem to increase their engagement with the system.

Design principle 2: Like DP1, DP2 is also based on R1. It focuses on the consumption mix and energy origin, which should help participants to understand the environmental impact of their consumption better and allow them to adjust it, correspondingly. Again, all participants state that they were able to understand the instantiation of DP2, which confirms the correct functionality. However, the perceived utility from DP2 is different. Although the participants generally welcome the visualization of the electricity mix and market transactions, they use the provided instantiation much less than that related to DP1. In contrast to DP1, the participants report that they increasingly looked in the weekly reports over time. EXP5 and EXP7 state that they had dealt with the visualization in detail and tried to influence their local share by changing the bids. Since the composition of the mix also depends on other external factors such as the weather, it was unclear to the participants whether the renewable share changed because of the changed bid or whether it was just the result of a different weather situation. EXP6 confirms that as the project progressed, report information initiated behavioral changes (*"There were peaks and I thought about what it could be and then actually changed certain behavior."*). EXP10 explains that the share of local energy in her electricity consumption has a high personal value for her. EXP9 examined whether a behavior change affected the proportion of locally purchased energy (*"We pay attention to move the consumption into the sunshine hours."*). Overall, we can say that the aggregated form of information is preferred and the particular time series are not studied more closely. Likewise, participants do not consider the tabular presentation of individual transactions as valuable. However, it was confirmed that DP2 is valid as the corresponding information was accessed through different means (i.e., the reports). Therefore, DP2 helps to foster long-term engagement in terms of information access and sometimes leads to bid activity. Instantiations of DP2 could be more effective if participants receive additional recommendations on how to behave more sustainably.

Design principle 3: DP3 also corresponds to the first requirement (R1). The presentation of cost information should enable participants to assess the costs of their consumption behavior in real time. Participants stated that they had used the provided cost information and that this information is generally important to them. This confirms the importance of DP3. However, regarding the perceived utility of the DP3 instantiation, the participants stated that they did not use the tabular presentation of costs in the application and informed themselves on costs through the weekly report, comparable to the insights of DP2. EXP2, EXP3 and EXP6 declared that electricity costs play an essential role for them and that a higher resolution than the annual billing has a high added value. However, all stated that they are not interested in a cost resolution on a 15-minute basis. They all prefer aggregated values that are easier to compare. EXP6 emphasized that stating her average price and the overall participants' average price in the report helps to derive a better bid adjustment. EXP5 and EXP8 indicated that the costs' high resolution does not significantly impact their view and hence, does not result in a bid adjustment. In detail, EXP8 stated that he has been paying electricity costs for years and only wants to deal with them when there are higher deviations (*"I mean, I have relatively fixed energy costs, which I have paid in the same way for years and I don't give myself any more trouble here at the end. If the data [costs] had possibly been a bit more drastic, you could say, well, now we have to think about whether we do something here. But it just wasn't like that."*). Similarly, EXP5 noted that there is little room for savings and that he does not have the time to look into it more deeply and accurately. Overall, access to individual cost data is important for participants and supports their long-term engagement. However, the instantiation should focus on aggregated data visualization. An additional incentive for participants to engage with the platform are high individual saving possibilities.

Design principle 4 : The fourth design principle is related to the R2, which states that users must be able to formulate active preferences to purchase or sell electricity on the local market at specific prices or rates and be enabled to communicate these preferences to the information system. The opinion of all participants about the bidding interface is consistently positive. EXP2 and EXP3 stated that the slider bidding interface is easy to understand and intuitive. The indication of the reference value above the bidding, an improvement from the first cycle's feedback, was also positively highlighted by EXP10 (*"Yes, that (reference value) helps me. [...] And I have stayed under it, also because neighbors have said that they have stayed under there, too"*). Therefore, the underlying functionality of the DP4 instantiation is given and used by the participants. However, regarding the perceived utility and connected long-term engagement, EXP2, EXP5, EXP7 wish for more transparency and information about the consequences of bid changes. According to their statements, there is a high degree of uncertainty about the consequences of a bid change. All participants stated that the complexity of the market mechanism was too high, which leaded to uncertainty about the 'optimal' bidding behavior (Richter et al., 2022a). All of the participants barely understood the functioning of the mechanism in detail. They stated that the mechanism is complex and a proper understanding would have been too time-consuming. EXP2 suggested that while adjusting the bids, information should be provided regarding the bid's expected effects. The application should notify the user when specific key values (e.g., share of green energy) are exceeded. EXP2 also noted that navigating to the bidding menu was too complicated. It should be noted that the instantiation of DP4 generally achieves the intention of the design principle and supports a long-term engagement with the system. However, the platform's structure, the complexity of the market mechanism and the transparency of the actions' consequences play an important role in whether the participants feel confident using the feature. In this case, more information should be provided using more active decision support systems. We address this further in Cycle 3 and the evaluation of the market mechanism complexity.

Design principle 5: DP5 is based on the R3 that users must not be able to access other users' data or place unauthorized bids in their names. This design principle should foster long-term engagement by establishing trust through sensitive data protection. If participants do not feel their individual data is safe, they will not use the system. In its implementation, DP5 requires users to frequently log in manually into the system on their devices. None of the participants stated that they felt their data were insufficiently protected. Instead, the manual login without an option to store username and password stopped some users from frequent use of the application. EXP3 and EXP6 confirmed this. EXP6 often wanted to check the exact data after a report review but could not remember the login data and did not have the motivation to look it up. All participants mentioned in their interviews that this is a disabling factor (*"In the beginning, yes, we looked into it, but then we always had to log in and this was such a hassle. The easier, the better."* EXP6). It became clear that login is a high hurdle for using the application and participation in the CEC. In respect to long-term engagement, future instantiations should consider the tradeoff between data security and ease of use. On the one hand, high protection measures reduce the perceived utility and therefore reduce long-term engagement. On the other hand, low protection can lead to data leakage and violation of privacy or data protection laws, which results in lower trust in the system. Nevertheless, no participant voiced privacy concerns, which confirms that the design principle was covered in its essence, even though the implementation caused discomfort and should be improved.

Design principle 6: DP6 is based on the prototype input from Cycle 1 and resulting R4, which states that users should receive regular notifications as a reminder, comparable to a newsletter or push notification. The selected design principle instantiation were weekly e-mail reports for each participant. All participants acknowledged these reports as a valuable feature. Therefore, the intended functionality was given. The feedback from all participants is very positive and they agree that a regular reminder in the form of a weekly e-mail report containing all information from DP 1-3 in aggregated form is a good addition. EXP4 stated that the report enabled him to keep track of the project and his power consumption with a low entry barrier. Similarly, EXP3 and EPX10 both emphasized that even without understanding the underlying market mechanism, these recurring values can give a good intuition for one's performance after a short time. As mentioned above, EXP6 used the weekly report to monitor consumption patterns with minimal effort (*"I have to be honest, I always take a quick look at the report and then just check the amount. And only if it is remarkably low or high, then I look at what could have caused it. If it's okay, then I don't look too closely."*). EXP1 also commented positively on the reports and the personal value but noted that the mailing should remain limited to a weekly cycle and there should be no overlap of the aggregated periods. There are different opinions regarding the periodicity of the communication. The majority feels that a weekly cycle is sufficient. EXP5 prefers more frequent messages, while EXP8 and EXP9 favor longer periods. The priority of the different information (DP1-3) within the report is also assessed differently. EXP3, EXP5, EXP7, EXP9 and EXP10 indicated a preference for the electricity mix. EXP 1, EXP2 and EXP6, on the other hand, showed interest in the information about costs and market price development. EXP2 and EXP6 also indicated that they additionally have a strong interest in the weekly consumption numbers (*"The bottom line was that I could do more with the report. You could look back and say: ok, I paid more this week, let's take a look at the costs and the individual transactions, what's the reason for that?"* EXP2). EXP4 stated that he had not used the app at all except for the initial period and then only used the reports' information. Overall, the instantiation of this design principle is a success and represents a major assistance for the participants. The design principle supports participants' long-term engagement as it reminds them of the project on a regular basis and provides comparable consumption information over time that is perceived as useful by the participants. After the project's end, several participants asked whether they could still receive the reports showing the high value for long-term engagement of the DP.

Additional interview feedback from Cycle 2: In addition to the explicit feedback on the design principles, the interview responses include other interesting insights. The provision of their own tablet computer and the possibility to access the app via their own devices was rated very positively. For example, EXP2 mentioned that he installed the application on his cell phone to track load values even during working hours. He criticized the navigation within the app, more precisely, the navigation from the load consumption interface to the bidding interface. Also, EXP2 favors the possibility of directly initiating a bidding process within the visualization or report. Furthermore, all participants mentioned a decreasing activity. The interview partners gave different reasons for this, which can be divided into two categories. First, all participants agreed on the market mechanism's uncertainty and complexity, which resulted in less interest in the market performance. EXP1 and EXP5, for example, explicitly requested more transparency. In principle, the market mechanism's functioning is perceived to be understandable, but there is no clear recommendation for action and the participants express the desire for decision support systems. EXP2 expressed the idea of an automated agent that would continuously adapt the bids to the market conditions corresponding to his objectives. Second, an issue is the role of the CEC in the everyday life of the participants. It became clear that many participants are interested in the topic but do not want to spend much of their time resources on it. Therefore, it is essential to provide an easy-to-use design and to reduce complexity, which allows participants to understand the provided information or possible consequences of bidding actions quickly.

Design principle 7: The feedback from Cycle 2 clearly showed that the application itself was very positively perceived and only needed minor revisions. However, the market mechanism needed to be adapted. In order to address this issue, we decided to evaluate possible market designs in a laboratory experiment to find the most satisfying mechanism. It took the participants about 35 minutes to complete the experiment. A total of 575 games were played by 115 participants. Participants were able to opt out of playing if they felt that the game's complexity was too high and received a fixed payout. They did so in 202 cases (35%). Of the remaining 373 games, participants shifted their variable demand in 340 games (92%). It shows that participants understood the mechanics of the mechanisms and acted correspondingly. On average, people earned the most when playing with RTP. When choosing the fifth game, 58% of the participants opted for the TOU (29%) or RTP (29%) mechanisms. These are the easiest mechanisms where prices are externally communicated. These are followed by the AUC (23%) and the PET (19%) mechanisms, which require explicit bids. This result shows that while there is not one popular mechanism, less complex mechanisms are generally preferred. Within the experiment, participants are also asked to specifically state the perceived satisfaction and complexity of each mechanism on a 7-point Likert scale. Here, the AUC receives the lowest satisfaction scores (4.0) and participants perceive the highest complexity (5.2). RTP pricing got the highest satisfaction score (5.1), followed by TOU (4.8), which are also perceived as the least complex mechanisms (4.5 and 4.8, respectively). When asked which market mechanism participants would prefer in real-life for themselves, 41% indicated TOU, 39% chose RTP and only 12% and 7% chose PET and AUC, respectively. Overall, 67 of the participants indicated a different mechanism in that question than they selected in the fifth game. This information may explain the 23% of the AUC in the selection of the fifth game. Participants seem to have tried again to improve themselves or to understand it better through practical experience. Of all 26 participants who chose the AUC again, only 3 participants indicated that they preferred it in real life. A clear result of this experiment is that simpler and less complex mechanisms are favored and should support the participants' long-term engagement as they can better understand the consequences of their bid actions.

Evaluation Summary: The derived and evaluated design principles as well as exemplary instantiations allow CEC operators to design a CEC user interface and its corresponding platform in a way that participants i) understand and use the provided functions, (ii) can behave according to their preferences in the local market and (iii) generally exhibit a long-term user engagement due to the perceived benefits. DP1-4 address the understanding and usage of the provided function. It can be noted that these design principles achieve a high approval among the interview partners and that the interviewees used all associated features, at least through the weekly reports. None of the participants reported difficulties finding information or submitting bid prices. Regarding the ability to behave according to individual preferences, the instantiations of DP2 and DP3 provide little to no benefit to the participants and were therefore not used after an initial testing phase. The feedback shows that CEC participants are interested in the actual power consumption, energy origin and cost but on different aggregation levels. In the case of power consumption (DP1), the users are interested in temporally granular data, while in the case of power origin and cost, the aggregated information over a defined period is more interesting and helpful. It seems that most participants have learned to intuitively evaluate the data from the reports based on past reports. Focusing on DP4 addressing the bidding process, the feedback shows that market design and complexity play a significant role regarding long-term use. Participants are more willing to adapt or examine their consumption behavior closely than to change their bids actively if the market mechanism is too complex. First, there is a high degree of uncertainty about the new bid's impact and the monetary incentive is not large enough. Second, many participants shy away from the effort to deal with the market dynamics in more detail and therefore either use a trial-and-error approach or only monitor the values after reaching a satisfactory level without further interaction. All of this shows that if the possibility is given to place a bid, it needs to be doable with very little effort and the effects need to be directly perceivable. This makes a case for less complex market mechanisms, which we confirmed using an online experiment, which are formulated in DP7. In contrast, the results regarding DP6 show the vital benefit of proactive notifications. A regular reminder combined with aggregated information allows participants to track the individual metrics easily. It also shows that regardless of the market design, these reports are valuable to participants to monitor and adjust their behavior.

In terms of long-term engagement, fulfilling the first two parts of the research question is essential. If participants cannot use the functions or cannot derive any added value from the information provided to them. They become inactive and do not contribute to the system's objective. DP5, DP6 and DP7 specifically refer to long-term engagement. The feedback to the instantiation of DP5 shows that even small hurdles, such as searching for login data, can lead to participants becoming inactive. This result is in alignment with the result of DP6, as the reports ensure access to valuable information without the necessity of initiating a cumbersome login process by the participants. The study reveals that participants prefer a less complex market mechanism, which is reflected in DP7. High complexity leads to uncertainty and resulting inactivity. In general, market operators have to design a CEC platform with great caution. Due to the limited time each participant is willing and able to invest, simple mechanisms and easily accessible information seem to ensure a higher satisfaction which might initiate more regular activity. All findings are presented in Table 7.3.

7.5. Discussion

The contribution of our study is situated within the 'exaptation' area of the DSR knowledge contribution framework (Gregor and Hevner, 2013). Table 7.4 provides an overview of the components of our design principles, in line with (Gregor et al., 2020). CECs are a new concept and there are not many implementations, apart

DP	Key findings regarding the instantiation in Cycle 2
DP 1	· Helps participants in monitoring their own behavior and devices · Supports long-term involvement and motivation · Helps participants in evaluating their consumption behavior
DP 2	· The energy mix is a relevant information for some participants · Aggregated information has a higher value to participants
DP 3	· Costs are an important information for the participants · Aggregated information has a higher value to participants
DP 4	· Complexity and lack of decision support system prevents bidding activity · Effects of bids must be directly perceivable
DP 5	· Login is a high hurdle for participation · Tradeoff between security and usability
DP 6	· Allows to monitor individual metrics and performance easily · Helps participants to quickly develop an intuitive evaluation of the data · Supports long-term acceptance of the CEC
DP 7	· Mechanism with constant activity might not be functional in the long run · Participants are willing to hand over responsibility to trusted entities · Preference of simpler mechanism with lower involvement

Table 7.3.: Summary key findings of the expert interviews

from pilot projects. In the domain of Green Information System, researchers call for more experience from practical implementations, real-world projects and prototypes with the help of DSR approaches (vom Brocke et al., 2013; Gholami et al., 2020). Therefore, our study follows the call of Seidel et al. (2017) and promotes sustainability as well as a practical application of Green Information System research. We contribute to the proposed research agenda on the design of green information systems with our newly derived and evaluated design principles (Seidel et al., 2013). The derived design principles align themselves with and build upon the previous contributions to green information systems. The platform's functionality is partly composed of other, well-known fields (e.g., energy feedback system) and there are certain similarities to individual design principles from other studies. The design principles presented in this study differ from the existing design principles in their focus on ensuring the long-term engagement of participants. For example, the design principles from Dalén and Krämer (2017) focus primarily on the process of smart meter data recording and processing in order to provide users with meaningful information. Only the last design principle of their study focuses on providing cost information without evaluating whether participants use the provided information in the long-term. In addition, their design principles do not mention behavioral changes towards more sustainability. In contrast, the derived design principles from our study can be seen as a subsequent design step. Here, the focus lies on utilizing the data to provide additional utility to the participants and, therefore, to foster long-term engagement. Furthermore, it enables users to learn from this data and adjust their consumption behavior in a sustainable way.

The first three design principles are in part based on Gnewuch et al. (2018), who aim to provide consumers with information so that they can behave more sustainably. Especially the first design principle of their study is similar to the design principles 1 and 6 of our study as we built on this existing design knowledge. However, in addition to the effect on consumption behavior, the design principles we present have been evaluated for whether they support long-term engagement. This analysis, as well as a fully functional instantiation and field test, is missing in the study of Gnewuch et al. (2018). In comparison to the presented design principles by Seidel et al. (2013), there are several differences. Again, the first design principle of their paper shows similarities to DP1 of our study, but with a focus on providing information that creates disruptive ambiguity to surprise the user and accordingly make them think. In contrast, DP1-3 of our study focuses on providing information to specifically change their behavior. The resulting benefits for participants result in long-term use.

7.6. Limitations

Even though we have followed the established guidelines for the implementation of DSR projects, some limitations need to be discussed. First, we tested the design principles only in one field study. It is unclear whether the participant structure or the market design strongly influenced the results and whether these effects occur in other CEC setups. A common shortcoming of similar studies is that a selection bias exists because only interested households participate in the project. Even if certain biases cannot be excluded, the provided answers hold interesting guidance for the design of CEC platforms and corresponding user interfaces and more generalizable design knowledge for communities with several consumer commodities like water, gas, or heat. The evaluation of design principles in different settings with, e.g., other

DP	Aim	Context	Mechanism	Rationale
1	For CEC operators to design a long-term engaging user interface, which allows participants to draw conclusions on how their individual consumption is affected by the behavior	during their everyday life	the interface should provide visualizations of individual historical consumption data	because it supports the participants in the understanding of their consumption behavior and identification of saving potentials
2	For CEC operators to design a long-term engaging user interface, which enables participants to adjust their behavior according to their individual preferences	in their everyday life and on the market platform	the interface should provide visualizations of the different individual consumer commodity sources	because it supports the participants in their assessment of the sustainability of their behavior and helps them to become more sustainable.
3	For CEC operators to design a long-term engaging user interface that enables participants to choose cost saving behavior	in their everyday life	the interface should provide consumption costs transparently and instantly	to allow the participants to connect their behavioral changes with the associated costs.
4	For CEC operators to design a long-term engaging user interface that facilitates the bid input process	on the market platform	they provide a bid submission interface with required numerical input in a valid and reasonable range for all available energy sources, and a reference value	because it helps participants in the bidding process and provides an orientation point
5	For CEC operators to design a long-term engaging platform for participants to protect sensitive data	of the market platform	the platform should ensure privacy through corresponding authentication mechanisms	because it establishes trust towards the system and compliance with legal data protection requirements
6	For CEC operators to design a long-term engaging platform participants need to receive an overview of their overall performance [...] regularly and proactively	on the market platform	The platform should provide an opportunity for participants to activate a notification service that sends aggregated information on a regular basis	because it facilitates the participants' engagement with the platform and enables and enables them to track their individual behavior development
7	For CEC operators to design a long-term engaging platform that supports the participant in understanding the effect of their actions	on the market platform	the platform should implement a market mechanism, which is easy to understand	and therefore facilitates the interactions with the CEC

Table 7.4.: Design principle components following Gregor et al. (2020)

demographics or commodities can supplement the presented findings.

7.7. Conclusion

To answer the research question of this chapter, we conduct a DSR study that focuses on design principles for a CEC platform and its interface, which support long-term engagement of participants. It consists of three cycles. In the first cycle, we identify four requirements through stakeholder interviews and literature research and evaluate a prototype design. In the second cycle, we propose and evaluate six initial design principles based on Cycle 1. The prototype is improved towards a full application and tested in a real implementation with ten participants over one year. At the end of this phase, the participants are interviewed regarding the design principles in semi-structured interviews. The design principles are positively evaluated as they allow the participants to improve the understanding of their energy consumption behavior and foster long-term engagement with the CEC. The instantiations of some of the design principles within the application need slight improvements but the complexity of the market mechanism is specifically criticized and seems to inhibit the use of the platform. Regarding the market mechanism's complexity, we state a fifth requirement and derive a seventh design principle in the third cycle. In this third design cycle, we show that simple market mechanisms are preferred and increase the users' satisfaction. In conclusion, the derived design principles and the feedback on the instantiations can help researchers and practitioners to design CEC platforms and corresponding user interfaces. We contribute valuable design knowledge as a first starting point for future research, provide experiences for practical CEC implementation and extend the research on energy feedback solutions as developed in (Dalén and Krämer, 2017; Gnewuch et al., 2018; Seidel et al., 2013). Furthermore, this design knowledge can be generalized for similar information systems of other consumer commodities (e.g., water, gas, heat). Thus, we contribute from practical experiences and provide insights that can lead to a more sustainable energy consumption.

Chapter 8.

Participant Behavior Assessment in Citizen Energy Communities

According to literature, CECs promote investment incentives and introduces local price signals, to which the participants respond with behavioral changes. However, there is a lack of long-term, empirical data on participants' behavior in such communities, which is crucial to assess the CECs' overall performance and functionality. This chapter addresses this research gap. Long-term empirical CEC participant behavior is analyzed based on a one year observation period of LAMP and the corresponding project's recorded data and expert interviews with its participants. In three analyses, the participants' initial willingness to pay premium prices for local green power, their overall activity on the CEC and responses to information nudges or price signals are evaluated. The results show that the integration and engagement of participants in CECs is more challenging than hitherto assumed and both market complexity and automation play a central role for success.

This chapter comprises the the unpublished article by B. Richter, P. Staudt, C. Weinhardt, *Citizen Energy Communities - Insights into Long-term Participant Behavior from a Field Study*, Working Paper 2022. cited here as: Richter et al. (2022a).

8.1. Introduction

The current literature associates several properties with the CEC concept which support the energy transition. First, they are assumed to enable a better integration of local RES because prosumers can directly sell their surplus energy to local consumers for a premium price above the fixed feed-in tariffs or wholesale market prices (Parag and Sovacool, 2016). These local prices provide investment incentives for additional local renewable expansion (Koirala et al., 2016) and gives CEC participants the opportunity to support local energy sources directly, which in turn promotes their acceptance. Second, the allocation mechanism introduces local prices, which incentivize participants to contribute to local balancing and, thus, overall grid stability (Ilic et al., 2012; Stadler et al., 2016). Third, the CEC platform provides the participants detailed information on their consumption behavior and energy origin, improving their environmental awareness and enabling them to behave more environmentally friendly (Koirala et al., 2016). It also supports their acceptance for renewable expansion.

However, most of these proposed benefits are based on assumptions on the participant behavior. As described in Chapter 3.2.3, 3.2.6 and 6.1, first studies indicate that CEC participants distinguish between different energy sources and are willing to pay premium prices for local energy sources. Regarding grid stability and local balancing, researchers assume that CEC participants are willing to shift consumption and react to price signals. Also, most studies assume a regular activity of its participants, which is crucial for the platform functionality (see Chapter 7). Nevertheless, it remains unclear whether regular activity and grid stabilizing behavior persists over longer timer periods. Overall, the actual CEC participants' behavior and the resulting effects on CEC performance are largely unknown. First implementation studies (Chapter 3.3) have investigated the CEC participants' empirical activity but focused mainly on the user's bidding activity or participation drivers (Ableitner et al., 2020) and only observed a shorter time period. Whether the reported activity levels remain equally high in the long run is unclear. CEC participants' long-term, empirical behavior and its effects on associated indicators (premium prices for local sources, bid adjustments and consumption shifts) are unknown and require additional research.

Against this backdrop, we assess the long-term behavior of participants in the LAMP project with two local energy sources (see Chapter 3.4 for a detailed project description). We investigate whether the platform design can incentivize participants to shift their consumption significantly, whether they are willing to pay premium prices for local renewable energy in the long-run and we evaluate the overall activity of the participants. In order to draw a comprehensive picture of the participants' behavior, we further enrich the results drawn from the quantitative data analysis with insights from conducted qualitative interviews. The study answers the following research questions: *What identified long-term behavior in a CEC can confirm the behavioral assumptions from the literature?*

For a more detailed understanding, the research question is divided into three sub-questions based on the most prominent behavioral assumptions in the literature. The first analysis focuses on the participants' preferences for different local energy sources. We analyze the submitted bid prices to determine which of the two local sources the participants prefer and assess their willingness to pay for these power sources. As described in Chapters 3.2.3 and 6, an often discussed and highlighted advantage of CECs and especially LEMs is that they enable local trading and differentiation between different local energy sources. Different prices for different local energy sources and possible premiums allow, consumers to change their energy mix according to their own preferences and give local generators an opportunity for sales prices above the feed-in tariff or wholesale market prices. However, whether the willingness to pay for local sources is higher in practice and whether this will persist over a longer period of time is unclear. Therefore, the first sub-question is: *Does the willingness to pay for local energy sources change over time?*

The second analysis concentrates on the CEC participants' platform activity. We analyze the bidding behavior and how participants react to different information nudges by evaluating the participants' interview statements and analyzing bidding data. As described in Chapter 3.2.6, most studies assume a regular activity of participants in CECs. The study by Ableitner et al. (2020) investigates first behavioral insights from a real-world CEC implementation and identifies different activity levels between the participants. However, the authors do not discuss how activity can be influenced and whether the behavior changes in the long run. Their project ended after four months and long-term behavioral statements could not be deducted. To analyze the reaction of participants, we introduce several information nudges through the project to trigger bidding behavior and investigate the reaction of the participants. Therefore, the second sub-question is: *What is the long-term overall activity and how participants respond to information nudges?*

Since local grid balancing is a central value proposition of the CEC concept, the last analysis examines the participants' consumption behavior in reaction to different price signals. As illustrated in Chapter 3.2.6, it is a common assumption that consumers react to local price signals by changing their consumption behavior. There is a lack of real-world experience in regards to this assumption. Ableitner et al. (2019) only qualitatively analyze the willingness of CEC participants to shift consumption. However, these participants were not exposed to targeted price signals and corresponding consumption analysis. The last analysis examines the participants' consumption behavior for different price signals and evaluates the consumer reactions qualitatively and quantitatively. The last sub-question is: *How much do consumers shift their consumption in reaction to price signals?* In addition, based on specific prosumer interview statements, the last analysis also investigates how participants who become prosumers adapt their consumption behavior compared to their former role as consumers.

8.2. Data Evaluation

Trading Phase Description: As mentioned above, different information nudges and price signals, were executed throughout the LAMP project. In the following, we refer to the differentiated signals as trading phases. Table 8.1 provides an overview of all phases. Over the first four trading phases A to D, we introduced sequential information nudges as the amount of information in the weekly report was steadily increased from phase to phase. This information increase allows us to assess how participants react to different types of information with their bids and consumption. Only information on the total weekly consumption and the individual absolute and average costs was provided in phase A. In the second phase, the individual energy mix (PV, CHP, Grid) was included. In phase C, a list of household appliances and their average consumption was added to the report. In phase D, the report included the overall average costs per kWh across all participants to allow a comparison of the individual performance in regard to the group. Each of these reports was sent out once per week. In trading phases E to H, deliberate price signals were placed in order to examine their effects on participants. These treatments aim to investigate whether participants react to such signals with a bid price change or load shift, e.g., shifting loads within the day or between days. During these phases, the report frequency was increased to twice per week. Each report in phase E announced a fixed PV market price for the subsequent days until the following report. This temporal fixed market price changed with each report and corresponded to the lowest bid price of all successful bids since the last report. In phase F, the PV market prices were shifted between two values. On each day from 10 a.m. to 2 p.m. the PV market price was reduced to the level of the feed-in tariff. At any other time, the price was set to 20.0 EURct/kWh. In phase G, the market price on the PV market was reduced to 11.0 EURct/kWh on one day between two reports and 20.0 EURct/kWh on all other days. The day with the longest sunshine hours was selected as the low price day based on weather forecasts and announced to the participants. In trading phase H, the market mechanism was changed so that the demand side determined the market price with the bid price of the last successful demand-side bid. In the final trading phase I, participants were provided with additional information on their performance. For this purpose, we calculated and communicated potential savings retrospectively for each participant, given that their market behavior would have been optimal.

Methodology: Eleven participants took part in the LAMP project, eight as consumers (participants 1-4, 6, 8, 10, 11) and three as prosumers (participants 5, 7, 9). The small sample makes it hard to deduct statistically significant results, which is a particular problem in extensive field studies. Additionally, there is no experimental control group and other external effects are present in this project, such as the selection bias or unobserved influences on behavior (Bhattacherjee, 2012). Therefore, we follow the suggestion of Bhattacherjee (2012) and use a mixed-method approach for the evaluation by analyzing the data and behavior quantitatively and, additionally, perform semi-structured interviews with the participants to assess and validate the observed data. The quantitative approach is focused on identifying interesting behavior apparent in the data and on drawing

Phase ID	**Phase Name**	**Description**	**Duration**	**Interval** (per Week)
A	Consumption Cost	Consumption amount and individual costs	21.08.2019 17.09.2019	1
B	Energy Mix	A + Percentage share of each energy source (PV / CHP / Grid)	18.09.2019 15.10.2019	1
C	Household Appliances Load	B + List with average load values of typical household appliances	16.10.2019 04.02.2020	1
D	Community Consumption Costs	B + Average energy cost of all community members	05.02.2020 31.03.2020	1
E	Consumer Bid Market Prices	D + Announcement of a fixed market price for the upcoming period	01.04.2020 30.04.2020	2
F	Intraday Low-Price Period	D + Daily PV market price drop between 10 a.m and 2 p.m	01.05.2020 31.05.2020	2
G	Low-Price Day	D + Announcement of one low PV market price day in each period	01.06.2020 30.06.2020	2
H	Dynamic Market Prices	D + Change in the mechanism such that demand bids set the market price	01.07.2020 05.08.2020	2
I	Optimal Behavior	D + Information about the ex-post potential cost savings and how much the participant had achieved	06.08.2020 13.09.2020	2

Table 8.1.: Overview and description of trading phases

possible conclusions. The qualitative analysis helps us in interpreting the observed phenomena from the quantitative analysis and provides further insights into the background of the participant behavior.

The available project data includes load data of the participants, power generation data, the bid prices entered via the user application, as well as the transactions and market prices determined by the market mechanism. The processed data is examined for anomalies and analyzed with regard to the three subquestions. We conducted semi-structured expert interviews as proposed by Kaiser (2014) at the end of the project for the qualitative analysis. The interviews follow a guideline that allows the interviewers to ask questions on different topics and switch between the guideline topics based on the answers. The interviews are conducted via telephone, recorded and transcribed. The quantitative study is divided into three thematic areas: the analysis of participants' preferences, the analysis of the bidding strategy in the trading phases and the analysis of consumption reactions to price signals. In addition to the quantitative analysis, we add interview statements from the participants to better understand specific observed behavior.

8.2.1. Evaluation of Participant Bids - Preferences and Bidding Behavior

The first analysis focuses on the participants' bid prices for the two local sources (PV & CHP) and we differentiate between consumer and prosumer participants. Different studies suggest that participants have different preferences regarding the energy origin (Zade et al., 2022b; Navrud and Bråten, 2007; Sundt and Rehdanz, 2015). Based on this assumptions, we state our first hypothesis that participants have different preferences for local sources (H1.1). Second, (Mengelkamp et al., 2019c; Perger et al., 2021; Zade et al., 2022b) suggest that some participants are willing to pay premium prices for local energy sources, which we state as our second hypothesis (H1.2). We define a *premium price* as a bid price above the known reference price for energy from the public grid that is also displayed prominently in the user interface. Both hypotheses correspond to the first subquestion of the divided research question.

Consumers: Figure 8.1 gives an overview of the consumer participants' bidding behavior within the project over the entire duration. In the beginning, all except for participant 10 exhibits a higher preference for energy from the local PV system than the local CHP. The mean value of all initial PV price bids is 25.1 EURct/kWh, while the mean value of all initial CHP bid prices is 19.7 EURct/kWh. Therefore, at the start of the project, the consumers show a higher preference for local PV power, which confirms our first hypothesis (H1.1). However, we observe a negative trend in the bid prices throughout the project. In the end, the average bid price for PV energy is 20.1 EURct/kWh, which is 5.0 EURct/kWh lower than at the beginning of the project. The lowest PV bid was submitted by participant 1 with 12.0 EURct /kWh. The dynamic is similar for CHP bid prices. On average, the bid prices decreased by 2.6 EURct /kWh from 19.7 EURct/kWh to 17.1 EUR/kWh. We observe a higher preference for the local PV generation than the CHP generation, but the price gap between both sources decreases from 5.3 EURct/kWh to 3.0 EURct/kWh. Therefore, we conclude that while participants make a difference between local energy sources, differences slightly loses meaning over time. Nevertheless, the result confirms our first hypothesis (H1.1). Most participants hold this order of preference through the

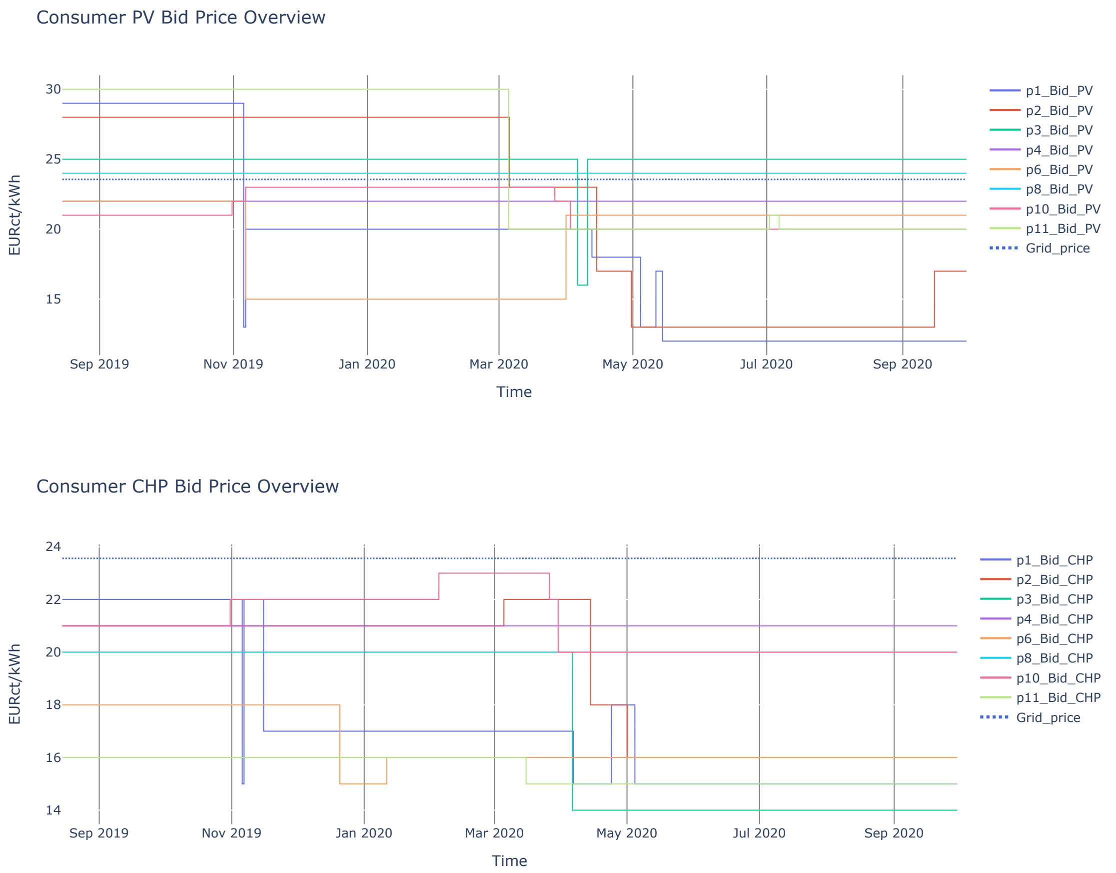

Figure 8.1.: Overview of the consumer bid price changes throughout the project duration

project and there are only isolated temporary deviations from this order of individual participants. In addition, we conclude from the decreasing bidding price trend that the willingness to pay for local sources seems to diminish throughout the project.

This negative trend also impacts the premium prices participants are willing to pay for local energy. The initial PV bids show that some consumers were willing to pay premium prices. Five of the eight consumers set a higher bid price than the stated reference price. In contrast, all initial CHP bid prices were below the reference price. Thus, the analysis shows that initially, some participants were willing to pay a premium for PV generation while no participant bid a premium price for local CHP energy. However, throughout the project, the average PV bid price decreased below the reference price, as Figure 1 displays. Only two out of eleven participants retained a higher bid price than the reference price. Based on

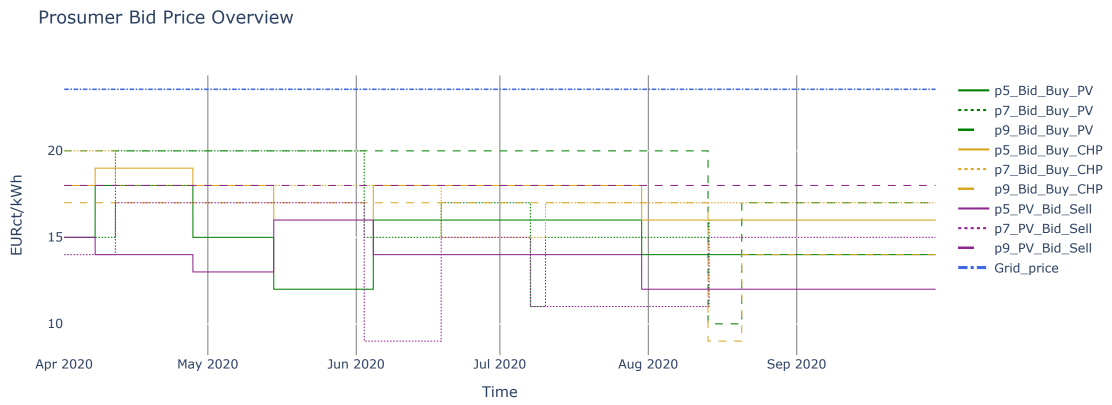

Figure 8.2.: Overview of the prosumer bid price changes throughout the project duration

our observations, we can conclude that the initial high willingness to pay premium prices for local green energy diminishes over time. Therefore, we have to reject our hypothesis regarding premium prices (H1.2). These results challenge research result by Mengelkamp et al. (2019c). The authors identify in their survey that premium prices only apply to a subgroup of potential participants. The identified subgroup seems to be smaller than the current research assumes because participants initially show the willingness to pay premium prices but do not uphold this willingness over a longer period. One explanation for the negative trend could be the market itself. Long-term, repeated markets interactions undermine the participants' moral values and intentions (Falk and Szech, 2013). For example, participant 1 first lowered the bid prices for both sources and then increased them again shortly after, but on a lower level. It seems that the participant tried to influence his individual prices. The interview confirmed that he tested the market mechanism for a better understanding and cost reduction. This observation supports the previously mentioned invalidating effect of the market on individual intentions.

Prosumers: The analysis of the prosumers' bidding behavior shows a similar picture compared as for the consumers. In addition to the possibility of buying local energy, they can also sell their PV surplus and submit a PV selling bid price. As mentioned above, there are only three prosumers in the project (participants

5, 7, 9). The observation period for the prosumers is limited to five months from April to September 2020 due to the need for technical adjustments to the platform infrastructure caused by the installation of the PV panels. Figure 8.2 shows all submitted bid prices by the prosumers. In contrast to the consumers, all three prosumers start and remain with buying bid prices below the reference price. However, prosumers had previously participated as consumers and therefore might have already adjusted their bid prices. We can confirm the negative trend from the previous consumer analysis, but it is less pronounced. The average PV buying bid price starts at 16.7 EURct/kWh and decreased to 15.7 EURct/kWh. Similarly, the average CHP buying bid price decreased from 18.0 EURct/kWh to 15.7 EURct/kWh. Again, the bid price gap between PV and CHP is reduced for prosumers over time. Interestingly, prosumers seem to favor local power from the CHP system over power from the PV system, which is different behavior in comparison to the consumers. A reason for this could be the fact that they generate PV energy by themselves and might not want to buy external PV energy. However, due to the small sample size, we cannot rule out a selection bias or other external effects. Nevertheless, prosumers initially differentiate between local energy sources confirming H1.1. Since all buying bid prices are below the reference price, we reject the premium price hypothesis (H1.2) for prosumers as well. Prosumers are not willing to pay premiums on prices for local, green energy. In addition, the PV selling prices are lower or equal to the buy bid for local PV power. This observation confirms that prosumers understood the underlying market mechanism and are willing to sell their surplus energy at lower prices than the prices at which they would buy it.

Summary: The first analysis shows that local PV sources are seemingly preferred by consumers over local CHP and some set market prices at a premium above the reference price, especially at the beginning of the project. Consumers and prosumers alike show a negative trend regarding their bidding prices over time, which might be rooted in the repeated interaction with the market mechanism. All but one of the participants were unwilling to pay a premium for local, green energy over the project duration. Therefore, it cannot generally be assumed that there is a willingness to pay premiums on local, green energy. Additionally, an initial willingness to pay premiums might not persist in the long-term.

8.2.2. Evaluation of Bidding Behavior - Response to Price and Information Signals

The second analysis focuses on the participants' activity and reactions to different information and market price changes. First, we examine the bidding activity in detail and assess the underlying rationales through the interviews. Regular activity is a key success factor for CECs as continuous behavior adaption helps to balance the grid and it is often implicitly assumed in the literature Mengelkamp et al. (2017); Morstyn et al. (2018); PankiRaj et al. (2019). Therefore, based on the literature assumption we state the first hypothesis that participants interact with the market platform on a regular basis (H2.1). Second, participants in the LAMP project suggested a report to receive aggregated information regularly and are intended to support the participants in evaluating their bidding strategy. Based on this suggestion, we state that the individual information in the reports encourages participants to evaluate their bidding strategy and to adjust their bids (H2.2). For this analysis, we evaluate the trading periods A-E, H and I. We exclude phases F and G because those trading phases focus on incentivizing consumption shifts with price signals, which are the focus in the third analysis. Both hypotheses correspond to the second subquestion of the divided research question.

Consumers: The bidding behavior analysis reveals that the participants do not exhibit extensive bidding activity. As Figure 8.1 shows, the maximum number of individual adjustments is 12 for participants 1 over the entire year. In contrast, participants 4 and 8 have not adjusted their bid prices once. Participant 3 made three adjustments. Participants 6 and 11 changed their bids four times, participant 10 and 2 eight and seven times. We observe three consumer bid adjustments per month on average, which indicates a low bidding activity. This observation shows that consumers rarely acted on the platform in terms of bid adjustments. However, this does not mean that participants were consistently inactive. We conclude from the interview statements that participants mainly used the regular reports to check individual data and to follow the project progress. We identify two main reasons for the low activity: the perceived market complexity linked to insufficient market feedback and participants' available time resources. Some participants stated that they were reluctant to actively adjust bid prices as it was not always clear what effect this might have. Participants 6 and 11 stated that they perceived the market mechanism as too complex and did not understand the possible outcomes of bid price changes (see statements in Chapter 7). This uncertainty resulted in the low number of bid adjustments by these two participants. In contrast, participants 1 and 2 stated that they had become more familiar with the market by testing it and had dealt more intensively with it. Participant 11 indicated that he had only limited time resources and the results from the weekly reports were satisfactory. Participant 6 monitored her consumption data with the help of the reports but was hesitant to act. Participant 8 justified his inactivity, saying that the financial saving potential on the market is too small. In addition, some participants stated that they often forgot the project until they received a new report. Participant 4 indicated that the functionality of the reports and the app to monitor individual load data and costs was sufficient and there was no need for bid adjustments from his perspective. He also mentioned a lack of time. The available time seems to be a crucial factor for the participants. Participants 8 and 11 explicitly stated that they did not want to use their limited time to understand the market mechanism in more detail. Overall, we partly reject the first hypothesis of this analysis (H2.1). Consumers show a low bidding activity due to the perceived market complexity and available time resources. However, they monitor their data with the help of regular reports. Therefore, the participants show interest in the community but are less active than the literature would suggest (Morstyn et al., 2018; Olivella-Rosell et al., 2018; Teotia and Bhakar, 2016; Mengelkamp et al., 2017).

According to the statements of individual participants, the regular reports were helpful to follow the project and interact with it. This insight is also visible in the data analysis. Despite the general low frequency of bid submissions, about 50% of the bid adjustments by participants 1, 10 and 11 occur within a 24-hour window after receiving a report. For participants 2 and 3, this share is 33% and 25% for participant 6. It seems that reports enable the participants to evaluate their bidding strategy better and therefore trigger interactions. In a more detailed analysis, we investigate the bidding responses to the different trading phases to assess their effectiveness. In the first two trading phases, where the reports include consumption costs (A) and consumption costs + the energy mix (B), there is no bid price adjustment at all. This suggests that either the information provided in both phases did not cause the participants to change their preferences, or the information did not offer any added value. In contrast to the first two phases, we identify two clusters of increased activity in the following trading phases C and D. In phase C, the report included the information of the previous phase (B) and additional information about the average consumption of household appliances. At the beginning of this phase, we identify twelve bid price adjustments, seven directly after a report. Later in this phase, there is only one interaction of participant 6. In phase D, the participants additionally received the community average consumption costs for locally consumed energy. In the beginning of this phase, we cannot observe any bidding activity. However, on the day of the fourth report mailing (5th March), participants 2 and 11 adjusted their bids. In the subsequent period of this day, we identify a higher bidding activity. However, it is unclear if the provided information nudges triggered a reaction or other external events.

In contrast to the previous trading phases, phase E did not provide any additional information but allowed consumers to influence the PV market price actively. The PV market price was determined and fixed between two report periods. Its value was then equal to the lowest successful consumer bid price since the last report. During this phase, they adjusted their bid prices seven times in total, two times directly after a report, four times shortly before a report mailing and only once without any connection to a report. Especially, the four adjustments before the report suggest that the participants specifically tried to change the market price actively. Both report in the interview that they tried different bid prices to better understand the market mechanism. However, only these two participants reacted to the incentive in this phase. Therefore, we conclude that the temporarily fixed market prices and the ability to influence them can trigger engagement but addresses only a small group of participants. The recorded behavior also supports this conclusion in trading phase H. In this trading phase, the market mechanism was changed in a way that the lowest successful demand-side bid price continuously set the market price. However, a reaction in phase H was only recorded from participant 11, directly after sending a report. Therefore, we conclude from phases E and H that influenceable dynamic market price changes do not necessarily trigger bidding activity. This result might indicate that customers prefer an external pricing mechanism. In phase I, which featured information on the optimal bidding behavior, no activity was recorded. The interview statements support these observations. Participants stated that they primarily monitored their individual data and performance via the reports and only interacted with the market if they felt that something went wrong. Regular reports seem to have an impact on the participants' overall activity level. A certain proportion of the low number of bid price adjustments are in the period after the report mailing, showing that they can encourage a reaction. We conclude that the reports in general, but no specific information act as reminders to encourage participants to re-engage with the CEC. Therefore, we partly confirm the second hypothesis (H2.2). However, the overall data shows that the participants become more inactive with increasing project progress. This is a surprising finding because most literature assumes a regular activity and does not regard the fact that the novelty effect wears out (Nisi et al., 2011).

Prosumers: The prosumers show a higher bidding activity compared to the consumers. We recorded six bid adjustments per month on average. In the interview statements, the prosumers mentioned the lack of time and market complexity as central obstacles to become more active, similarly to the consumers. Participant 9 stated that he followed the project via the reports but was often too lazy to adjust the bids. He also explained his low activity level by the perceived time-benefit ratio. Participant 5 suggested changing the market mechanism to a mechanism with more direct feedback. Participant 9 suggested more automation and less complexity. The analysis of the report's responses reveals that all bid adjustments occurred within 24 hours of the report being mailed. This suggests that the prosumers react more strongly to external triggers and rarely become active by themselves. However, the small sample is again a limiting factor. No specific trading phase results in higher bidding activity. Each prosumer has a different active period. Overall, the regular reports in general seem to support bidding reactions by the prosumers and are therefore a useful functionality.

Summary: The analysis of the bidding phases reveals that the overall bidding activity of all participants is relatively low. While prosumers seem to be slightly more active than consumers, none of them adjusts bids daily or weekly. In addition, we observe that participants become more inactive over time, which needs to be taken into account when designing CEC platforms. The participants mainly stated a lack of time, savings potential and the market complexity as reasons for their inactivity. Regular reports have been shown to somewhat stimulate participant activity. However, this seems not to be caused by any specific information or incentives contained in the reports but rather by the report itself serving as a reminder. In the interviews, participants stated that they generally use the reports to monitor their overall individual performance and for cost control.

8.2.3. Evaluation of Consumption Behavior - Response to Price Signals

As described in Chapter 3.2.6, the literature suggests that price signals incentivize participants to shift their consumption into periods with lower prices (Faruqui et al., 2017). In our final analysis, we therefore investigate whether participants respond to price signals by shifting their consumption to times with lower prices. In this analysis, we do not distinguish between prosumers and consumers. We introduced time-varying PV market prices in the trading phases F and G. Each day in trading phase F featured a low priced window to incentivize participants to shift consumption into the period during which PV generation is usually highest. The corresponding first hypothesis of this analysis is that participants move parts of their daily consumption into the low priced period (H3.1). In trading phase G, we announced a day with low PV market prices between two reports. The second hypothesis is that participants shift their consumption into the low priced day (H3.2). In the last part of this analysis, we hypothesize that the prosumers have an increased consumption share during daylight hours compared to their consumption from the previous year as consumers (H3.3). We investigate whether consumers increase their consumption during the daytime hours and thus the hours with PV generation, when they become prosumers. All three hypotheses correspond to the third subquestion of the divided research question.

In contrast to the previous analyses, identifying changes in consumption behavior is a more difficult task. On the one hand, external effects such as weather or external events, or public holidays can cause consumption behavior to change significantly from one day to the next. On the other hand, weeks from different months cannot be easily compared either, due to seasonal fluctuations. For this reason, we establish two benchmarks for each participant. The first benchmark is the week before the start of each trading phase. By selecting the benchmarks close to the respective observation period, we minimize misjudgments due to seasonal fluctuations. Since this single week may not represent the participants' behavior fully, we establish the second benchmark. This benchmark also represents a week, but each weekday is the average of the four same weekdays from the previous month.

Participant	**F - Benchmark 1**	**F - Benchmark 2**	**G - Benchmark 1**		**G - Benchmark 2**	
	Average Consumption Shift	Average Consumption Shift	Average Consumption Shift	Number of Days	Average Consumption Shift	Number of Days
1	1.9%	0.6%	-7.7%	1	-12.7%	0
2	4.7%	3.2%	-28.2%	0	-14.9%	0
3	0.8%	-0.3%	-9.3%	1	-29.6%	1
4	1.7%	0.1%	-48.7%	0	-45.2%	0
5	-3.4%	-1.1%	-2.6%	3	-4.05%	0
6	7.7%	3.1%	-18.2%	0	-27.7%	1
7	1.9%	3.0%	-5.5%	1	-7,8%	1
8	1.7%	-0.8%	-6.3%	2	-30.8%	0
9	0.4%	0.8%	22.4%	2	28.7%	2
10	-5.5%	-1.0%	-19.8%	1	-12.8%	1
11	-4.8%	-1.9%	-6.3%	0	-16.8%	2

Table 8.2.: Overview of the participants' consumption shift analysis results

Trading Phase F: Trading phase F consists of four weeks and three days. Each day in this trading phase has a low priced period (10 a.m.- 2 p.m.) in the PV market. In this period, the PV market price is fixed at 10.0 EURct/kWh. Outside the period, it is raised to 20.0 EURct/kWh. We compare each day i with its respective weekday m from the benchmark. For this, we calculate the relative consumption share during the low priced period of each day d_i. Then we derive the difference between this share and the relative consumption share of the respective benchmark weekday b_m, to see if participants increased or decreased their consumption in the low priced period. In the last step, we calculate the average deviation $\overline{x}_F$ of all days n in trading phase F. The following formula displays the calculation: $\overline{x}_F = \frac{1}{n}\sum_{i=1}^{n}(d_i - b_m)$. When the average value $\overline{x}_F$ is negative, it means that the consumer reduced her consumption in the low priced period and vice versa. Table 8.2 displays each participant's average deviation over all days in trading phase F.

The analysis of both benchmarks for phase F reveals a positive consumption shift for most participants. Regarding benchmark 1, two participants seem to shift a significant share of their consumption into the low priced period. Participants 6 and 2 have the highest average shift into the low priced period with 7.7% and 4.7%. Besides these two, participants 1, 3, 4, 7, 8 and 9 show only a small positive shift on average (under 2%) towards the low priced periods. In contrast, we observe the opposite effect for participants 5, 10 and 11. They shift their consumption outside the low priced period and show on average a substantial negative deviation of –3.4%, -5.5% and -4.8%, respectively. Therefore, the first benchmark analysis seems to suggest that at least two participants directly react to the price signals and shift parts of their consumption, but three participants behave contrarily by decreasing consumption in the low priced period. Benchmark 2 supports these observations. Participants 5, 10 and 11 still display a negative shift but less pronounced. Participants 2 and 6 show the highest positive consumption shifts. From the remaining participant group with shifts below 2%, all values remain roughly in the same range. Participants 3 and 8 show a small negative shift regarding benchmark 2. In general, the observed shifts become smaller. Therefore, the analysis cannot confirm that participants react to low price incentives and that they shift their consumption within the day. Although many participants show a positive shift, these might be rather coincidental results, which is confirmed through the interviews. Similarly, we assume that the negative consumption shifts were unintentional, which is also confirmed by interview statements. Overall, we cannot confirm the hypothesis that price signals incentivize a consumption shift within a day (H3.1).

Trading Phase G: Through trading phase G, we investigate whether low priced days incentivize participants to shift their consumption into these days. Table 8.2

displays the analysis of trading phase G with both benchmarks. There were eight low priced days in total in this phase. The first column shows the average consumption change for all eight low priced days. We compare the absolute consumption of each day with the corresponding weekday of each benchmark. To ensure that an observed low consumption is the result of a consumption shift and not from an overall higher consumption week, we additionally check whether the consumption on the low priced day is higher than on the benchmark weekday and whether the consumption on the days previous to the low priced day are lower than the respective benchmark days. If both conditions are fulfilled, this is an indication of a possible consumption shift. The number of low price days, which fulfill these conditions, are displayed in the second column of table 8.2.

The analysis of both benchmarks provides a clear picture. Trading phase G does not induce any apparent consumption shifts. There are participants who have a higher average consumption on single low priced days, however, the majority shows a decreased consumption on these days on average. Participant 9 is the single outlier with increased average consumption. However, this participant shows only a consumption shift in two of the eight days, indicating that he does not shift his consumption in response to the price signal. Therefore, we assume this result is random and does not indicate an intended consumption shift. Overall, we conclude that low price announcements seem not to cause consumption shifts between days and reject the second hypothesis of this analysis (H3.2). The interview responses confirm this result. For example, participant 11 states that he noticed the announcement and reports, but they did not result in any behavioral changes.

Participant	**Consumer Consumption Share**	**Prosumer Consumption Share**	**Difference**
5	53.94%	53.55%	-0.39%
7	56.51%	52.39%	-4.12%
9	59.83%	53.35%	-6.48%

Table 8.3.: Overview of the prosumers' consumption share change

Prosumers Role Change: Finally, we evaluate whether consumers change their power consumption patterns as they become prosumers. Based on the prosumer interview statements, the hypothesis (H3.3) is that prosumers have increased their consumption share during the daylight hours compared to their consumption behavior as consumers in the previous year. With this consumption shift towards the daylight hours, they can consume more of their self-generated energy from the PV panels. For the analysis, two months (May & June) from the project phase are compared to the identical months from the previous year. Access to the previous year's data is possible because consumption was recorded before the project's official start. During this time, the three prosumers had not yet installed their own PV systems. An average week is created from each of the two months as consumers and prosumers. For each day, the consumption share during daylight hours is determined. Regarding the available daylight in both months, we consider the period from 9 a.m. to 6 p.m. as daylight time to ensure PV power systems generate sufficient power. Table 8.3 shows the average consumption share during this time as consumers and prosumers. The proportion of consumption during daylight time reveals that, contrary to the prosumers' statements and impressions, the participants slightly reduced their consumption in the relevant time period. Participant 5 has almost not changed consumption (-0.39%). Participants 7 and 9 show a higher reduction in consumption during the daylight time of -4.12% and -6.48%, respectively. The individual analysis of the weekdays does not show a clear picture either. Therefore, we have to conclude that the prosumers in our project did not significantly change their consumption behavior towards the consumption of more renewable generation when transforming from a consumer to a prosumer. We reject the third hypothesis (H3.3). Additionally, our results show that although the participants consciously tried to move their consumption into the times of the day with PV generation and actually reported this behavior change, the effect does not show in the data and is blurred by everyday necessities and habitual behavior, as participant 5 states in the interview.

Summary: The analysis of the participants' consumption behavior in response to different price signals is surprising from an economic perspective. In trading phase F, individual participants seem to have increased and thus shifted their consumption share during the announced low priced phase. However, these effects are small, are not observed for all participants and only apply to a subgroup. This result suggests that targeted, individual price signals are unlikely to lead to direct consumption shift responses. The analysis results of trading phase G show that participants are not willing to shift their consumption across several days into low priced days. Finally, the last analysis reveals that consumers who become prosumers do not change their consumption behavior fundamentally. Although the participants state in the interviews that they pay more attention to trying to consume more during hours with possible self-consumption from PV generation, these effects cannot be validated in the data analysis. It can therefore be concluded that the effects resulting from conscious behavioral changes caused by prices or self-generation are very small or non-existing.

8.3. Discussion

We provide first insights into long-term participant behavior within a CEC and compare the observed behavior with assumptions from the literature. For the discussion, a summary of the results is presented in Table 8.4.

Analyses	Hypotheses	Description	Results
1	H1.1	Different preference for local sources	Converging trend for both sources over time and different between prosumers and consumers.
	H1.2	Willingness to pay premium prices	Initial willingness to pay premium prices is high but diminishes fast.
2	H2.1	Regular interaction with the platform	Overall, participants show a low bidding activity. It is stated that this is caused by a lack of time and market complexity. Participants monitor their behavior regularly but show less interest in adjusting their bidding strategy.
	H2.2	Report Information	Participants do not react to specific information or price changes from reports by adjusting their bidding strategy. Regular reports foster bidding activity and participants perceive them as a useful tool.
3	H3.1	Intra Day	Insignificant consumption shifts into low-price period within a day.
	H3.2	Between Day	No observable effect.
	H3.3	Prosumer Change	Perceived behavioral change by the prosumers cannot be identified in the consumption data.

Table 8.4.: Overview of stated hypotheses and analysis results

In the first analysis, we observe that the participants in the project have different preferences for local energy sources and are initially willing to pay premium prices for local PV energy. However, participants reduce their bids throughout the project. This finding is in contrast with interview studies stating that consumers are willing to pay premium prices for local renewable energy (e.g., Mengelkamp et al. (2019c)). This is an important finding, as the initial observations in the project seemed to confirm this assumption. However, we were able to show that the willingness to pay premiums does not persist over the period of one year. The long duration of our study is an advantage over other studies on the same subject. We explain this negative trend by the need for repeated interactions on the market, which leads the participants to abandon their intentions to pay high prices for local sources and to act more economically (Falk and Szech, 2013). It affects the long-term effectiveness of CECs and lowers investment incentives and it increases the prosumers' investment uncertainty (Morstyn et al., 2018). Operators of CECs need to examine the extent to which participants are willing to pay premium prices more closely in advance and whether this would persist. Alternatively, fixed sales prices could be established abandoning the idea of a market mechanism. An open question is whether the initially high bid prices and their reduction can be observed repeatedly in other projects and whether the market mechanism might be the cause for this. In addition, alternative solutions or countermeasures should be further analyzed to prevent the unwillingness to pay premiums in the long-term.

Our second analysis shows that the recorded bidding activity is rather low and heterogeneously distributed across the participants. It appears that although participants showed an initial willingness to engage with the system, this declines over time. This result is comparable with the reported activity in the study by Ableitner et al. (2020). In the interviews, participants mentioned several reasons for the decreasing activity. The most limiting factor for the participants is the time they are willing to allocate to deal with the system. Participants also reported a high market mechanism complexity and that the market results were unclear in many cases. This resulted in uncertainty, inhibiting some participants from actively participating in the bidding process. This is a very important finding because many different market mechanisms are developed and studied in the literature (Mengelkamp et al., 2019a). However, most participants seem to favor a stable mechanism with simple rules and less dynamic pricing. The results show that an easy-to-use system with low complexity is paramount for the success of CECs. In addition, participants state and their behavior shows that regular reminders, like reports, can foster activity and improve the participants' engagement. However, we could not identify specific information or price signals, which trigger activity. Therefore, regular reports may constitute helpful means to foster overall activity and engagement of participants. The main challenge for future CECs remains its participants' activation and regular interaction.

In our final analysis, we evaluate how price signals can incentivize consumption shifts. We cannot confirm a reaction to the price signals sent in the trading phases F and G. It becomes evident that consumption shifts into a day rarely occur and the shifted amounts are small. Participants do not integrate shifts within their daily routine. Since load shifting is listed in the literature as an important advantage of CECs (Koirala et al., 2016; Ableitner et al., 2020), further research is needed in this regard. Consumption shifts between days cannot be observed at all. The goal must be to find ways to use the local price signals to incentivize consumption shifts of the participants, possibly by implementing automated systems. Intelligent control systems managing large consumers such as electric vehicles, storage devices, or heat pumps might have potential. Simply announcing periods of low prices is not sufficient and the manual reactions of consumers appear ineffective.

8.4. Limitations

Even though we are confident that our results will inspire future researchers and strengthen the research strand of CECs, our study is subject to several limitations. First, the number of observed participants in this study is limited. Eleven participants represent a rather small sample, meaning that statistically significant effects cannot be deducted. To this end, we conducted semi-structured interviews with all participants to complement the quantitative analysis and to explain the findings in greater detail. Furthermore, we assume a certain degree of self-selection bias as participants were recruited through a local event and the participation was voluntary. Participants show environmental awareness in the interviews and are interested in green energy. For this reason, it is not clear whether the results also apply to communities, in which other values and interests are represented.

In addition, we only record bid changes and not logins to the user application in this project. Therefore, our statements about the inactivity are based on the bid submission. It cannot be ruled out that participants were more active than indicated by the data. For example, participants can check their individual consumption data or market prices without making any bid changes. Participants stated they used the reports and application regularly to check their individual load values. Therefore, the real activity could be higher than assumed but it cannot be determined exactly based on the available data in this study. Nevertheless, it has to be noted that such activity does not contribute to the balancing advantages of CECs when the consumption behavior is not adjusted.

8.5. Conclusion

Our research yields the first longitudinal insights on participant behavior in CECs with a trading platform. The corresponding field experiment featured eleven participants, of which three are prosumers and eight are consumers. We conduct three analyses, which focus on different assumptions on CECs in the literature to answer the stated research question. Our analyses evaluate the participants' preferences and willingness to pay premium prices for local energy sources, their activity on the CEC platform and behavioral responses to different provided information. We further investigate the effects of different price signals on the participants' consumption behavior and how consumers change it when they become prosumers. We use a mixed-method approach, combining quantitative data recorded in the project with semi-structured interviews with the participants after the project. Regarding the first subquestion, we observe that participants differentiate between local energy sources and show an initial willingness to pay premium prices for local PV power. However, this willingness diminishes fast and nearly all participants' bid submissions show a negative trend. Participants become more inactive throughout the project for varying reasons. The most prominently stated reasons are a lack of time and overwhelming market complexity. However, regular reports and reminders support the participants in interacting with the community and are perceived as helpful. Furthermore, price signals do not trigger load shifting within or between days. Contrary to self-assessment, consumers show no behavioral consumption change when they become prosumers.

Regarding the stated research question, our results show that literature assumptions on user behavior within CECs need to be tested more closely in practice At the same time, there is a need for additional decision support systems that allow participants to easily and regularly become active on the platform. A complex and time-consuming platform will likely result in inactive participants, which in turn will result in the actual goal of increasing acceptance not being achieved. Similarly, there is a need for better integration of automated systems that take over consumption shifts for the participants. Overall, it can be seen that there is still a great need for research to transfer CECs into practice, while preserving the expected benefits.

Chapter 9.

Impact of Automated Agents in Citizen Energy Communities

As shown in Chapter 8, most residential households have neither the expertise nor time to regularly interact on a CEC platform market, resulting in little market activity and hence, little reaction to market signals. Automated computational agents can be a solution to this shortcoming. However, there are currently no empirical field experiments with such agents designed to evaluate their performance in these markets. This chapter comprises the empirical implementation of a novel deep reinforcement learning approach for an automated computational agent that is tested in the field. The results indicate that a single automated agent among human traders can minimize the participant's cost and exploits static bid prices of the human market participants. Therefore, the implementation is beneficial from the perspective of a single participant. A subsequent simulation investigates the effects of exclusively automated computational agents on the platform. It can be shown that competition between automated agents cancels the individual advantage of the single automated agent among human traders. The increased competition leads to game-theoretically derived market results. The results therefore suggest that a tariff scheme representing the theoretically optimal market outcomes should replace a market mechanism in such an environment.

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Richter et al. (2022c).

9.1. Introduction

A key issue is for the introduction and operation of CECs is that participants are non-professionals, have limited experience with trading energy and the interaction with the market platform is voluntary (Pouttu et al., 2017). As described in Chapter 8, not all participants are willing to allocate time to deal intensively with the platform, which is also observed by other field studies (Ableitner et al., 2020). In addition, many participants cannot be active at night or during working hours. Therefore, market participants cannot constantly monitor the market and react to changing situations (Mengelkamp et al., 2018c). One approach to address these 'human' constraints is the use of automated computational agents (Bose et al., 2021), which we refer to as automated agents in the following. These agents act on the platform in the interests of the participants. From a technical perspective, the automated agent is software that acts autonomously. At its core, an algorithm selects the optimal actions based on the input it receives. This approach has been studied for several years in the field of financial markets and is known under the term 'Algorithmic Trading' (Nuti et al., 2011). It has been shown that these automated agents have an advantage over human traders (Chaboud et al., 2014) and can develop new pricing strategies of their own (Chakole et al., 2021). The associated advantage for CECs is that participants only have to communicate their preferences and constraints (e.g., maximum local price or share of green energy) and the automated agent trades correspondingly (Mengelkamp et al., 2017). Participants do not have to become active on the platform market themselves. Furthermore, an in-depth understanding of the market mechanism by the participants becomes unnecessary. They can change their preferences at any time without developing a new bidding strategy.

In the literature, automated agents are widely considered. Many researchers evaluate their developed CEC approaches and designs with the help of simulations, in which automated agents mimic the behavior of the participants (Mengelkamp et al., 2019a). However, it is unclear how well automated agents perform in field studies. Field evaluations are still rare and there is no field implementation of a fully automated agent within a field study (Weinhardt et al., 2019). Therefore, we aim to close this research gap by implementing an automated agent and evaluating its performance against human traders within the LAMP project. We show that subsequently, with the introduction of one automated agent, other participants have an incentive to switch to automated agents as well. We therefore, utilize the data from the observed LAMP project in a second step to simulate a market with exclusively automated agents. We answer the following research question: *Which financial benefit can be achieved by an automated agent i) within a group of human traders ii) within a group of exclusively automated agents on a CEC market?*

The chapter is divided into three parts. First, we model the LAMP market from a game-theoretical perspective and derive theoretically optimal strategies for both prosumers and consumers. We show that the demand side has two dominant strategies, depending on the market supply. The result is used as a benchmark to evaluate the behavior of the automated agent. Second, we implement an automated agent based on a deep reinforcement learning Dueling DQN algorithm. The agent then acts in place of one human participant within the LAMP market, in real-time over an extended period. In the second analysis, we utilize the two-months operation period and simulate a situation in which each participant is replaced by an automated agent to study the effect on the market outcomes. Based on our findings, we discuss alternative solutions that reduce the complexity of markets while maintaining their efficiency and incentive effect on their participants.

9.2. Related Work

Agent Behavior: As observed and described in Chapters 8.2 and 7, the overall bidding activity of the LAMP participants is lower than existing literature would be suggest. We observed four bid adjustments on average per month over the duration of one year, with a declining trend. Low available time and the complexity of the market mechanism are the barriers for more engagement. Similar observations are made in other field studies. Ableitner et al. (2020) point out that the activity of participants within the CEC varies largely. The described behavior ranges from several interactions a day to complete inactivity over the project duration. In their study, more than a third of the participants (35%) show little to no activity. The authors describe an average of six price changes per user in three months. This inactivity reduces the effectiveness of the community because inactive participants cannot respond to changing market situations and price signals. Mengelkamp et al. (2018c) state that trading is complex and time-consuming and should be automated. The results of Chapter 8 support this statement. Bose et al. (2021) describe energy as a low involvement good and that participants lack the expertise to trade for themselves on a CEC trading platform. Both studies (Mengelkamp et al., 2018c; Bose et al., 2021) propose automated agents which incorporate market information and represent the participants on the market.

Automated Agents: Automated agents gained increasing attention in recent years. An automated agent is an algorithm that determines the action on the market in place of a human participant. They were originally proposed for financial and e-commerce markets (Preist, 1999). Energy-related research utilizes their principle. In agent-based simulations, such automated agents are used to assess market designs. Mengelkamp et al. (2017) analyze bidding strategies given different market mechanisms. They differentiate between zero-intelligence and intelligent behavior. The former is displayed by random bidding and the latter is based on a reinforcement learning algorithm. Similarly, Okwuibe et al. (2020) evaluate different trading platform design factors by utilizing autonomous agents and a simulation framework. The authors of Etukudor et al. (2020) use an autonomous agent model to capture the preferences of different participant groups. Bose et al. (2021) are the first who explicitly focus on the application of automated agents as a replacement for human participants on a CEC platform, using a reinforcement learning (RL) algorithm. However, their results are based on a simulation model and instead of field data.

Reinforcement Learning: RL algorithms are a subgroup of machine learning algorithms (Sutton and Barto, 2018). The combination of RL with neural networks is called *Deep Reinforcement Learning (DRL)* (Mousavi et al., 2018; Nguyen et al., 2020). This approach shows good performance in different areas like mastering the game GO (Silver et al., 2016), different Atari games (Mnih et al., 2015), controlling a robotic arm (Zhang et al., 2015), managing data center networks (Sun et al., 2020) or predicting protein structures (Senior et al., 2020). Furthermore, DRL approaches are often utilized in energy research. Nakabi and Toivanen (2021) assesses the potential of seven different DRL algorithms to manage a microgrid with flexible demand. The algorithms' tasks are to prioritize resources, to send demand control signals and to set energy prices. The results show that the different DRL algorithms' performances differ widely. The *actor–critic* algorithm achieves the highest scores. Chen and Bu (2019) implement a DRL algorithm for a realistic peer-to-peer energy trading model for microgrids and test the algorithm on a one year data set. The results show that the algorithm performs significantly better than rule-based approaches. Chen and Su (2018) model an event-driven local energy market and evaluate different modeled prosumer energy trading strategies with a DRL algorithm. The authors conclude that the learning algorithm performs better than any used benchmark.

It becomes clear that automated agents utilizing RL approaches are already widely used in research. With the continuing expansion of CEC implementations (Weinhardt et al., 2019) and the rising popularity of isolated communities with trading platforms in developing countries, numerous markets with human traders might exist in the future. However, the individual benefit for a single user relying on an automated agent has not yet been evaluated in the field. Furthermore, the impact of automated traders on such inefficient markets and the possible scale of a first-mover advantage are unclear. For this reason, we implement a DRL-based automated agent in the LAMP project. We compare the agent's actions with the optimal behavior derived from a game-theoretical model of the market and assess the market outcome and individual benefit in a situation with only automated agents.

9.3. Economic Model of the Market Mechanism

The implementation of the automated agent and analysis is based on the LAMP project, described in Chapter 3.4. In the following, we focus our analysis exclusively on the PV market because the implemented automated agent in this chapter is only active on this market. Nevertheless, the results can be applied to the CHP market as well. Before the automated agent's implementation, the project was running over a period of 1.5 years. Within this time, all participants set their bid prices manually. This data is the basis for the training of the automated agent within a simulation environment. The trained automated agent replaces then a single actual human participant in the project. Over the course of two months, it set a bid price in each trading period on the participant's behalf. For the performance evaluation of the automated agent, we determine the economically optimal behavior in the market based on the game theoretic approach. The derived optimal behavior is transferable to other projects with a similar market mechanism.

9.3.1. Game-theoretic Model

We formalize the market platform and behavior for the game-theoretic modeling and make necessary assumptions. In the market, local participants trade their generated energy. On the demand side, there is a set of local consumer agents $C = \{C_1, C_2, \ldots, C_n\}$ and the supply side is represented by local generator agents $G = \{G_1, G_2, \ldots, G_m\}$. Participation is voluntary for the agents of both sides. They can leave at any time and market their energy demand or generation outside the market. Therefore, the potential outcomes of their actions outside the market represent the opportunity costs for generators and consumers. On the consumer side, this is the commercial grid tariff p_{grid}. All consumer agents can exit the CEC and purchase energy at this rate from the utility. Similarly, local generator agents have opportunity costs for selling energy in the local market. Many countries have subsidies for renewable energy generation in the form of feed-in tariffs (OECD, 2019). These subsidies are usually higher than the marginal generation costs for generators with renewable energy sources. Consequently, the generators' opportunity cost is the feed-in tariff $p_{feed-in}$ offered by the distribution grid operator.

For each trading period t, with $t \in \{1, \ldots, T\}$ and T being the number of the trading periods, a consumer agent C_i submits one bid $h^C_{i,t}$. Each bid consists of a bid quantity q and a bid price b, such that $h^C_{i,t} = (b^C_{i,t}, q^C_{i,t})$. Similarly, the bid $h^G_{j,t}$ of a generator agent G_j at a time t is $h^G_{j,t} = (b^G_{j,t}, q^G_{j,t})$. Before each trading period, each agent chooses a bid price. The bid quantities $q^G_{j,t}$ and $q^C_{i,t}$ correspond to the generated energy by the generators and to the required energy by the consumers, respectively. We assume that both sides cannot influence or change their bid quantity. In practice, a change in the consumption quantity might be an additional value proposition of the CEC platform, but consumers require technologies like battery storage devices or controllable heat pumps (Torbaghan et al., 2016). These technologies are already used in private households but not often utilized for providing flexibility (Bose et al., 2021; Jabir et al., 2018). Therefore, the automated agent only manipulates the bid price. In order to evaluate the optimal behavior on the market, we define the overall demand and supply in a trading period t as the sums of the individual bid quantities of generators and consumers.

$$D_t = \sum_{i=1}^{n} q_{i,t}^{C} \tag{9.1}$$

$$S_t = \sum_{j=1}^{m} q_{j,t}^{G} \tag{9.2}$$

Market Situations: As described above, the CEC is embedded within the overall energy system and connected to the public grid, which serves as a backup option. This is a common CEC feature for most implementations (Mengelkamp et al., 2018a; Ableitner et al., 2020). Regarding the aggregated bid quantities, three market situations can occur. First, the aggregated supply S_t in the CEC is larger than the demand D_t. This situation might occur, for example, during midday hours, when there is high PV generation and low demand. In this case, more local energy is available than is consumed, i.e. $D_t < S_t$. We refer to this market situation as *supply excess* in the following. The CEC cannot allocate the residual supply. Therefore, the connected public distribution grid buys this surplus at the feed-in tariff $p_{feed-in}$. Second, there is insufficient local supply to meet the local demand, i.e. $D_t > S_t$. In this situation, there is a demand surplus, which will be supplied from the public distribution grid at the grid tariff p_{grid}. We refer to this market situation as *supply shortage*. The third, more hypothetical case represents equal demand and supply i.e., $D_t = S_t$. There is no need for the public distribution grid to provide balancing in this case. The aggregated supply can meet the aggregated demand. Due to the non-controllability of renewable generation resources and the continuous stochastic nature of supply and demand, this case is unlikely to occur in practice, and therefore, we only focus on the two market situations of supply excess and supply shortage.

$$D_t < S_t : supply\ excess$$
$$D_t > S_t : supply\ shortage$$
$$D_t = S_t : equilibrium$$

Market Mechanism and Price Determination: The market mechanism used in this model corresponds to the implemented mechanism in the LAMP project (described in Chapter 6) and is a discrete double-call auction with sealed bids. The mechanism can be described as a double call auction with uniform pricing mechanism. At the beginning of each trading period t, the agents submit sealed bids. The market mechanism sorts bids from both sides based on the bid price. Demand-side bids $(h^C_{1,t}, ..., h^C_{n,t})$ are sorted in descending order and supply bids $(h^G_{1,t}, ..., h^G_{m,t})$ in ascending order. The mechanism matches the higher demand bids with the lower supply bids. This process proceeds until a bid price of the supply side exceeds a bid price of the demand side or until one side runs out of tradable bids, meaning that there is no more supply or all demand is covered. We define the last matched supply bid on the market as $h^G_{l,t}$ and the last served bid from the demand side as $h^C_{k,t}$. The market price $p_{market,t}$ equals the bid price of the last matched demand side bid price $b^C_{k,t} = p_{market,t}$. At the end of each trading period t, the market mechanism creates the transactions and all agents receive their payoffs for the trading period. For a consumer agent, these are the costs of purchasing energy either from the market at the market price $p_{market,t}$ or from the public network at the grid tariff p_{grid}. The supply agent receives a profit in each period t, which is the sum of the sales to the CEC at the local market price $p_{market,t}$ or to the public grid at the feed-in tariff $p_{feed-in}$.

9.3.2. Modelling Agent Behavior

Since we assume that agents do not adjust their bid quantity, the only remaining behavioral parameter is adjusting the bid price. Here, the opportunity costs represent the bid's upper and lower bound for individually rational agents with no preferences. Consumer agents participate in the market if they can purchase their required energy more cheaply than from the public grid. Therefore, for a rational consumer agent C_i, the grid tariff p_{grid} is equal to the maximum bid price, since this corresponds to the agent's opportunity costs. Local generators only participate in the market if they earn higher profits than their opportunity costs, the feed-in tariff. Therefore, the minimum bid of a rational generator agent G_j is the feed-in tariff $p_{feed-in}$. If all agents behave rationally, the market price $p_{market,t}$ lies between $p_{feed-in}$ and p_{grid}, where $p_{feed-in}$ is the lowest possible market price and p_{grid} is the highest. Below the feed-in tariff, local generators will not offer energy and above the grid tariff, consumers will not buy the energy. In the following, we analyze whether there are dominant bidding strategies for the respective market situations for both agent types. In the first step, we assume perfect foresight of the agents with regard to total supply and demand. On both the supply and the demand side, we assume rational agents and competition and these agents only participate if the utility from the market is equal or higher than from outside the market.

Generator Agents (Supply Side): Since the bid price $b^C_{k,t}$ of the last matched demand bid $h^C_{k,t}$ sets the market price, the supply agents do not directly influence market prices and rather compete for being in the market. As described above, the market mechanism first matches the supply side's low bid prices. Therefore, a rational supply agent has an incentive to set a low bid above the lower bound $p_{feed-in}$ in order to sell its energy on the market. With this bid price, a supplier agent has the greatest chance to trade the generated quantity locally and to possibly profit from a higher market price because the bid is only matched if the supply bid price is lower than the last matched demand bid price ($b^G_{j,t} \leqq b^C_{k,t}$). A deviation towards a bid $b^G_{j,t} = p_{feed-in} + \delta$ with $\delta > 0$ would lead to a higher probability of being pushed out of the market. With this bidding strategy, the profit of the market participation equals or is higher than the profit of its opportunity to sell the energy outside the market for $p_{feed-in}$. As mentioned above, the demand bid price $b^C_{k,t}$ from the last matched demand bid $h^C_{k,t}$ of consumer k sets the market price, which can therefore not be influenced by the generator agents directly. Therefore, the agents' single goal is to stay in the market if profits higher than the feed-in tariff are possible and thus its bidding strategy is independent of the actual market situation. The single

Nash Equilibrium for a rational generator agent is to set a bid price equal to the feed-in tariff ($b^G_{j,t} = p_{feed-in}$). No agent has an incentive to deviate from this bidding behavior because the agent can only be worse off, or the payout remains identical. The bidding strategy results in the submitted bid:

$$h^G_{j,t} = (p_{feed-in}, q^G_{j,t}) \tag{9.3}$$

Consumer Agents (Demand Side): Comparable to the generator agents, a consumer agent would only participate in the market, if the market price $p_{market,t}$ is lower than the opportunity cost of buying energy from the grid with p_{grid}. The consumer agents compete against each other to buy energy within the CEC and we assume perfect competition. In this market setup, they are able to set the market price with their bid price. Therefore, there are different bidding strategies depending on the market situation.

Supply Excess: In this case, each consumer agent knows that its individual demand $q^C_{i,t}$ can be supplied locally. At the same time, the agent does not have to worry about dropping out of the market as long as its bid price is greater than or equal to the last traded bid price $b^G_{l,t}$ on the supply side. Since the lowest supplied demand bid determines the market price $p_{market,t}$, a consumer agent C_i has an incentive to lower the bid price to the point where it is equal to the supply side bid price $b^G_{l,t}$. As described above, the dominant bidding strategy for the generator agents is a bid price of $p_{feed-in}$. If the consumer agent anticipates this dominant supply-side strategy, the dominant demand-side strategy is to bid the feed-in tariff as well. With this strategy, the consumer agent can decrease the market price and thus the individual costs. A deviation to $b^C_{i,t} = p_{feed-in} - \delta$ with $\delta > 0$ would lead to a market dropout, since the bid price would be below all supply agent bid prices. A market dropout results in higher energy costs due to the high grid tariff. A deviation to $b^C_{i,t} = p_{feed-in} + \delta$ with $\delta > 0$ is possible, but could lead to a higher market price and corresponding costs. Therefore, the bidding strategy for the demand agent C_i in a market situation with supply excess is:

$$h^C_{i,t} = (p_{feed-in}, q^C_{i,t}) \quad \text{if } D_t < S_t \tag{9.4}$$

Supply Shortage: In the case of supply shortage, all consumer agents compete against each other for the scarce amount of local energy and not all participants can be served. Therefore, a high bid price corresponds to a higher probability of being matched in the market. The highest rational bid price equals the grid tariff p_{grid}. With this bid price, a consumer agent has the greatest chance to receive locally generated energy in the local market. Similarly to the generator agent, a deviation towards a bid $b_{i,t}^{C} = p_{grid} - \delta$ with $\delta > 0$ would potentially lead to being pushed out of the market, which leads to having to pay the corresponding grid tariff p_{grid}. A deviation $b_{i,t}^{C} = p_{grid} + \delta$ with $\delta > 0$ results in a higher bid price than the previously described opportunity costs for the demand agent. Therefore, there is one Nash Equilibrium in the market situation of supply shortage, which is bidding the grid tariff.

$$h_{i,t}^{C} = (p_{grid}, q_{i,t}^{C}) \quad \text{if } D_t > S_t \tag{9.5}$$

Summary: The strategy for the consumer agents differs between the market situations. In the case of supply excess, the agents bid a price equal to the feed-in tariff and thus the strictly dominant bidding strategy of the supply side $b_{i,t}^{C} = p_{feed-in} = b_{j,t}^{G}$. In the case of a supply shortage, the dominant consumer agent strategy is a bid price equal to the network tariff $b_{i,t}^{C} = p_{grid}$. With this bid, the agent has the highest probability of purchasing energy from the market and paying a lower market price. At the same time, the worst (most expensive) market outcome for the agent corresponds to its opportunity cost, making it indifferent between the two payoffs. Therefore, the optimal bidding strategy depends on the expected market situation.

$$h_{i,t}^{C} = \begin{cases} (p_{feed-in}, q_{i,t}^{C}) & \forall t \in T \mid D_t \leqq S_t \\ (p_{grid}, q_{i,t}^{C}) & \forall t \in T \mid D_t > S_t \end{cases} \tag{9.6}$$

It becomes clear that generator agents have a dominant strategy and always set a bid price equal to the feed-in tariff because the last consumer bid price determines the market price. In contrast, agents on the demand side have two bidding strategies, depending on the market situation. If all agents on the market behave individually rational and there is no uncertainty about the supply-demand ratio, only two market prices can occur. In market periods with a supply excess, the market price corresponds to the feed-in tariff and in case of supply shortage, it corresponds to the grid tariff.

$$p_{market,t} = \begin{cases} p_{feed-in} & \forall t \in T \mid D_t \leqq S_t \\ p_{grid} & \forall t \in T \mid D_t > S_t \end{cases} \tag{9.7}$$

Effect of Incomplete Information: The assumption of complete information is not necessarily always practical in the case of fluctuating energy demand and intermittent supply. In reality, the agent does not know the market situation with certainty before submitting the bid. This is irrelevant for agents on the supply side because there is only one dominant strategy for all market situations. However, the situation is different for consumer agents. If there is a misjudgment by an agent, it chooses a suboptimal bid strategy. If there is a supply excess in the market, but a rational consumer agent C_z assumes that there is a supply shortage, it submits a bid price at the level of the grid tariff $b^C_{z,t} = p_{grid}$. If all other agents evaluate the situation correctly and submit a bid price at the level of the feed-in tariff $b^C_{i,t} = p_{feed-in}$ with $i \neq z$, the deviating bid is the highest bid $b^C_{z,t} = p_{grid} > p_{feed-in}$ and served first. Since there is a surplus situation, the bids of the other agents will also be served and the market price will again be at the level of the feed-in tariff $p_{market,t} = p_{feed-in}$. Thus, the agent C_z is not penalized for the misjudgment and has no higher cost due to the deviating bid price. Even if multiple demand agents in the market misjudge the situation, this does not change the market outcome as long as not all agents make the same mistake. The latter is a borderline case worth mentioning. If all demand agents misjudge the situation independently, a market price at the level of the grid tariff will occur $p_{market,t} = p_{grid} = b^C_{k,t}$ and thus, suppliers will receive the entire market rent. In the opposite case, a consumer agent C_z predicts a supply shortage as a supply excess and sets a bid price at the level of the feed-in tariff $b^C_{z,t} = p_{feed-in}$. All other agents set a bid price at the level of the grid tariff $b^C_{i,t} = p_{grid}$ with $i \neq z$, making the bid price of the agent C_z the lowest. Due to the limited supply quantity available in the market, the misjudging agent is not served by the market and the agent receives the energy demand from the grid p_{grid}. However, since the grid price is equal to the market price on the market, in this situation, the payoffs are also identical. Again, there is also a comparable situation regarding the behavior of all other agents. Unlike the misconception of a supply excess situation, not all agents must be subject to a wrong prediction to change the market price. It only takes a critical number of consumer agents with a misconception so that not all of them can drop out of the market due to the low bid price. As a result, at least one of these agents will be matched in the local market, leading to a lower market price $p_{market,t} = p_{feed-in}$. All participants inside the CEC can procure their energy at lower price $p_{market} = p_{feed-in} < p_{grid}$. This situation enables the possibility of collusive behavior, which we do not consider in this analysis.

Effect of Static Bids: As mentioned in Section 9.2 and described in Chapter 8, first pilot projects analyze the behavior of human participants. These studies show that human traders have different activity patterns and react very slowly to changing market situations. Participants change their bids with a low frequency and do not switch between different bid prices daily. The analysis of the bidding prices in the LAMP project examined in this chapter shows a low number of bid changes recorded over the 1.5 years trading period. The observed bid prices often do not match the above derived two optimal bid prices. In addition, the participants do not directly react to changing market situations. This situation results in fluctuating market prices throughout the day, especially in the morning and evening hours, when PV generation cannot fully cover demand. Figure 9.1 shows an exemplary price trajectory over a week in the project. It shows the ongoing increasing and decreasing market prices throughout each day. An automated agent can take these static bids into account and try to minimize the market price during supply shortage situations by adjusting the bid price accordingly. In the beginning of the project, several participants submit premium bid prices. However, only two demand-side participant remain with the bid price above the grid tariff, which does not match the above derived optimal bid prices. These participant stated that they support the local green generation and are willing to pay a premium. However, these participants also reduced the bid price below the grid tariff at the end of the

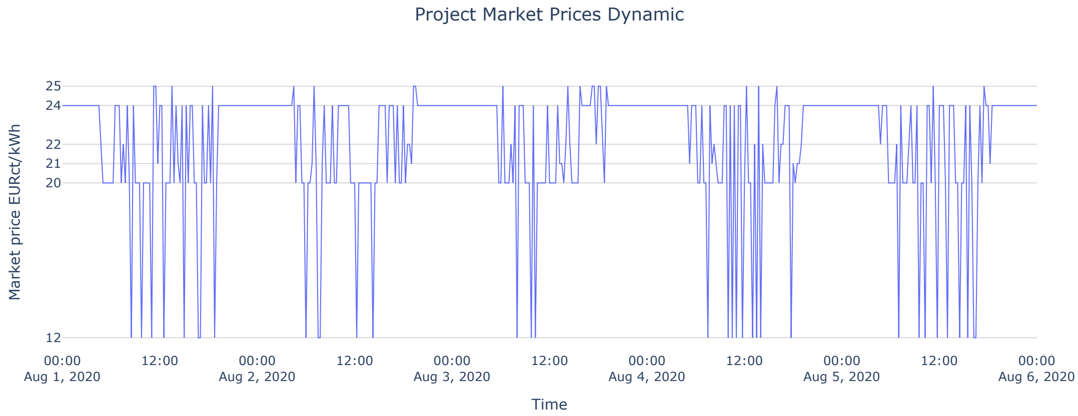

Figure 9.1.: Visualization of the market prices from 01.08.2020 to 06.08.2020

project's duration. Figure 9.1 displays market price peaks at the beginning and end of a day, in a late project phase.

9.4. Development and Implementation of the Automated Agent

For the pratical implementation, we develop an automated agent on the basis of the Duelling-DQN algorithm of Wang et al. (2016b). The agent's task is to automate the bidding activity and its goal is to minimize the overall costs of a consumer agent. We model the action, state and reward function for the LAMP project context based on the foundations by Sutton and Barto (2018). In each market period, the agent has the opportunity to submit a new bid price. Therefore, the agent's action space A is the number of possible bid prices. As described in Chapter 3.4, participants can choose bid prices between 0 and 40 EURct/kWh in steps of 1 EURct. We further reduce the action space's upper limit from 40 to 32 EURct/kWh because it is the highest recorded bid price during the project's 1.5 years duration. We define a specific state s from the state space S as the market price, the distance between market prices and bid, aggregate supply and aggregate demand. Each state consists of these values from the last four market periods. Therefore, the state space contains a high number of possible states, which is the reason for the chosen deep learning approach. After each market period, the agent receives its market transaction, including the market price, costs and consumed amount. Based on this transaction, a reward function calculates the reward r for the agent. With this reward, the agent can evaluate if the overall goal is achieved in the respective market period.

We model a reward function for the applied Dueling-DQN algorithm, which rewards the agent for minimizing the market price (see equation 9.8). However, the agent submits a bid that does not determine the market price, the agent needs an indicator that signals how close the bid is to the market price. If the agent hits the market price in a period t, then the agent will get a positive reward depending on the market price and a bonus reward θ. If not and the bid price is above the market price, the agent C_i receives a negative reward depending on the difference between the market price $p_{market,t}$ and the submitted bid $b^C_{i,t}$. If the bid price is below the market price, the agent drops out of the market and has to pay the grid tariff ($p_{grid} =$ 24 EURct/kWh). The reward function differentiates between a bid that is below the market price or a bid above the market price. We avoid additional punishment of the agent for market dropouts because first tests indicate that such punishment results in random bid behavior by the agent. After different tests, a bonus reward of 2θ for the agent is added if the agent decreases the market price because it shows a better performance in regard to the human static bid prices. If the agent's bid is equal to the market price ($b^C_{i,t} = p_{market,t}$) and its bid is lower than the minimum of its recent ($j \in 1, 2, 3 \ldots$) previous bids, with $b^C_{i,t-j} = p_{market,t-j}$, then the agent will receive a bonus reward $2\theta + \frac{-p_{market,t}}{100}$. This *bonus* further incentivizes the agent to reduce the market price. We train the automated agent algorithm with this reward function.

$$r(b^C_{i,t}, p_{\text{market},t}) = \begin{cases} -(b^C_{i,t} - p_{\text{market},t})^2, & \text{if } b^C_{i,t} > p_{\text{market},t} \\ -(b^C_{i,t} - p_{grid})^2, & \text{if } b^C_{i,t} < p_{\text{market},t} \\ \frac{p_{\text{market},t}}{100} + \theta, & \text{if } b^C_{i,t} = p_{\text{market},t} \\ \frac{p_{\text{market},t}}{100} + 2\theta, & \text{if } b^C_{i,t} = p_{\text{market},t} \text{ and} \\ & b^C_{i,t} < \min(b^C_{i,t-j}, \ldots, b^C_{i,t-1}) \\ & \mid b^C_{i,t-j} = p_{\text{market},t} \end{cases} \tag{9.8}$$

We choose two identical architectures for the neural networks for the Dueling-DQN architecture. Both are feed-forward networks consisting of only one input layer, one hidden layer and one output layer. We use the sigmoid linear unit function (SiLU) as the activation function. The SiLU activation function has been proven to be successful in the case of DRL and can significantly outperform the commonly used Rectified Linear Unit (ReLU) function (Elfwing et al., 2018). Each neural network utilizes the mean squared error loss function and optimizes its parameters with the Adam Optimizer (Kingma and Ba, 2017). Each neural network input layer takes a tensor of the above-described feature set: market prices, the distance between market prices and bid, aggregated demand and aggregated supply of the last four market periods. The output layer provides a so-called 'Q-Value' for each possible action $a \in A$, which are bid prices between 0 and 32 EURct/kWh. During the active period in the LAMP market, the automated agent selects the bid price with the highest Q-Value.

Agent Training: The implementation of an untrained algorithm in the project would result in the agent selecting an ineffective and random bidding strategy. Neural network approaches require a large amount of training data. Only a total of 96 market periods per day are possible within LAMP due to the 15-minutes resolution of the market. For this reason, we extend the existing data set and utilize a simulation environment to train the algorithm. Since one year only covers 37,920 periods, expanding the existing data set was necessary because these types of algorithms require much larger training data volumes for the correct approximation of the Q-values. We bootstrapped the data set to 1.5 million periods by extending the existing load data with additional values. Each artificial value is derived from existing data modified by a value from a uniform distribution function within an interval of 20% of the original value. The simulation environment allows the agent training. The environment receives the agent's bids, processes them and calculates the respective market price and transactions. This data is then fed back to the algorithm, which calculates the reward. The agent's goal is to minimize the market price. The agent must be able to predict the previously derived market situations for each trading interval and learn the corresponding bidding behavior. For the training of the DQN, we utilize the epsilon greedy strategy (Wunder et al., (2010). The epsilon greedy strategy determines that the agent chooses a random action with a ε probability and the action with the highest Q-Value, otherwise. We set the agent's preference for future rewards with a γ of 0.999. The loss function is the mean squared error. In the first tests, we achieved the best training results with $\theta = 0.5$ in the reward function. During the training, the algorithm does not update the neural network's weights after each market period but after a so-called *episode*. Each episode describes a sequence of four market periods where the automated agent tries to reduce the market price. After the episode ends, the agents reassess the past actions of the episode and their corresponding rewards. Both networks calculate and update all weights and biases to the collected rewards (back-propagation). This additional step, the introduction of episodes, is necessary for the training to ensure convergence. We also use a Replay Buffer and a Target Network to prevent unstable training and address the issue of training data that is not independent and identically distributed (Mnih et al., 2015). The batch size in the training is limited to 32 periods and the agent is initialized with a 0.9 epsilon and 0.0006 % reduction each episode. Therefore, the agent has a long exploration phase, especially at the beginning of the training. The algorithm is implemented in python3.7 using the *pytorch* framework. The simulation environment is based on *Java 11* with an interface for the Python application.

Implementation: The trained automated agent replaces a human participant in the project over two months, from February 1st, 2021, to April 4th 2021. We refer to the observed phase with the automated agent in online operation as the *implementation phase*. The automated agent replaces a single participant, which we name participant α in the following. According to his own statement, this participant has not been active on the market and is interested in his consumption data rather than market participation. After the consultation and agreement, the automated agent was assigned with the authentication data and connected to the CEC information system. Each market period, the agent is executed on a server. The agent receives the latest features from the last market trading period in the first step. This feature query is done via a REST interface. Then, the agent calculates the Q-Values. Finally, the agent uses the maximum Q-Value output to determine the bid price. The agent starts a script based on the Python Selenium package for the bid submission. This script accesses the CEC web interface, navigates to the appropriate menu for bidding and sets and confirms the bid price specified by the algorithm. The process is then terminated and starts again in the next trading period.

Multi-Agent Simulation: To answer the second research question, we use the available data from the implementation period, replace each participant with an automated agent and rerun all market periods. Each automated agent bids independently for the respective participant. We refer to this phase as the *multi-agent phase.* The applied algorithm architecture is identical for each agent, as described above. We also simplified the reward function by removing the bonus term $\frac{p_{market,t}}{100} + 2\theta$ because there are no static human bids in the simulation. The automated agent from the implementation phase is trained with the human bidding data from the project. Therefore, each automated agent in the multi-agent phase requires its own training and has to learn to react to the bidding behavior of the other automated agents, which are also learning. We use the load and generation data from the above described extended project data for the training. All agents are trained independently but simultaneously within the simulation environment. After the training, we test the automated agents with data from the implementation phase. In the simulation environment, all automated agents compete against each other by independently determining their bid price. Then, the agent-based simulation calculates the market price for the respective period based on the data and corresponding input from the automated agents and creates the transactions. We compare the results to the implementation phase for the performance evaluation and focus on the bidding behavior, individual costs of participant α and market prices.

9.5. Results

For the analysis of the automated agent's performance, we evaluate the market price and the automated agent's individual costs in live operation. The static bids by human non-expert traders result in different market prices for supply shortage situations. This allows the automated agent to optimize its behavior in these market situation environments by taking the static bid prices into account. We compared the agent's performance with the individual costs from a previous period to evaluate its performance. In addition, we simulate the implementation period again, without the automated agent and with the static bids of participant α and compare the individual costs and market prices. In the second analysis, we rerun the implementation phase in a simulation with exclusively automated agents to assess the effects on the individual performance, market prices and outcomes.

9.5.1. Implementation

For the analysis, we compare the results of the implementation phase with two benchmark phases, which we call *simulation phase* and *human phase*. The human phase describes a market phase prior to the implementation phase, where only human traders were active. The simulation phase incorporates the same period as the simulation phase but without the automated agent and participant α's static bid.

Agent Bidding Behavior: The implementation phase has a total of 5980 market periods. 4021 (67%) periods have no PV generation and there is no trading of local energy. For the analysis, we call these night periods. Night periods represent a particular case of the market situation with supply shortage. During these periods, the public grid ensures supply. Besides these night periods, there are 1959 periods (33%) with local PV generation. In 1113 of these periods (57%), there is a supply excess market situation. Correspondingly, we identify 846 periods (43%) with supply shortage. To assess the results from the implementation phase, we evaluate the bidding behavior of the automated agent in a first analysis and then compare the market prices and individual costs with the result of the described benchmarks.

The first step is evaluating the bidding behavior. The focus is on whether the RL agent can adjust and react to the changing market situations. According to the derived optimal behavior from Chapter 9.3, we evaluate if the automated agent sets low bid prices in periods of supply excess in order to lower the market price. Furthermore, we check whether the agent increases the prices in periods of supply shortage to ensure market participation or takes advantage of the other human participants' quasi-static bids by lowering the market prices strategically. In night periods, the 24 EURct/kWh (67.25%) and 23 EURct/kWh (31.61%) bid prices dominate. An explanation for the high number of 23 EURct/kWh bids is that the agent repeatedly submits a bid price of 23 EURct/kWh during the night and then corrects it to 24 EURct/kWh in the following period. A reason for this behavior can

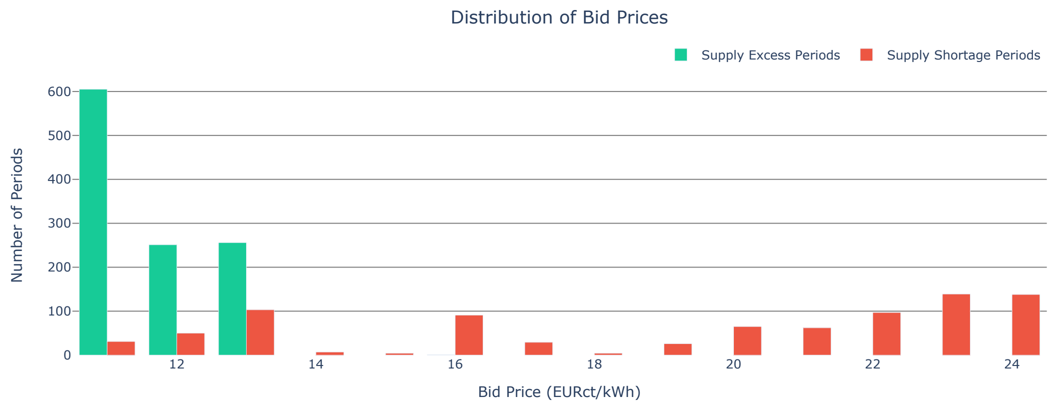

Figure 9.2.: Overview of the submitted bid prices in the implementation phase

be the agent's algorithm architecture. The feature set does not include the current time of the day, which means that the agent has no way of knowing if it is likely that local supply will be available soon. However, the high bid prices are without a disadvantage for participant α because there is no local supply available. For our analysis, we focus on periods with local supply.

Agent Bidding Behavior - Supply Shortage: Figure 9.2 displays the distribution of bid prices in market periods with local supply (excluding night periods) to assess the automated agent's behavior in these periods. The bid analysis shows a deviation of the derived dominant strategy in supply shortage periods with local generation. The agent bids the low bid price of 13 EURct/kWh in a total of 103 (12.17%) of all supply shortage periods. Likewise, the bid price of 16 EURct/kWh is frequently represented with 10.76%. The reason for this surprising distribution is that the automated agent intends to profit from the static bids of the other human participants. Most human bid prices are above 20 EURct/kWh. However, two human traders have static bids prices of 12 EURct/kWh and 17 EURct/kWh. The automated agent seems to take these static bids into account and to react to these. However, the 24, 23, 22 and 21 EURct/kWh bid prices still represent the largest share in the upper range with 138 (16.31%), 139 (16.43%), 97 (11.47%) and 62 (7.33%). These already account for 51.54% of all bid prices in this market situation.

Agent Bidding Behavior - Supply Excess: Focusing on supply excess periods in Figure 9.2, it becomes clear that in this market situation, the agent only selects a bid price between 13 EURct/kWh and 11 EURct/kWh. These correspond to the three lowest possible bid prices, which demonstrates that the automated agent tries to minimize the market price in these periods. The agent selects the 11 EURct/kWh bid price in 605 of the 1113 periods (54.36%). The agent submits the other two bid prices, 12 EURct/kWh and 13 EURct/kWh, about the same number of times, 251 (22.55%) and 256 (23%). We identify a difference between the average bid prices of each market situation. The average bid price of the agent is highest in night periods with 23.7 EURct/kWh. In periods with local generation but supply shortage, the bid price is 4.5 EURct/kWh lower, with 19.2 EURct/kWh and it is 11.7 EURct/kWh on average in periods with supply excess. The extent to which this lower market price has affected individual costs is examined in the next section.

Overall, the analysis of bidding behavior reveals three interesting aspects. First, the agent cannot classify when the market becomes active again in the sense that local PV generation is available. Therefore, there are periodic bid price reductions in night periods, which are related to the architecture of the DQN-algorithm. Second, the automated agent generally sets high bid prices in night periods and periods with a supply shortage, which is expected from the economic modeling. The bid prices of supply shortage with PV generation are more distributed. The agent seems to take the static bids of the other participants into account. In these market situations, the agent tries to reduce the market price closer to the feed-in tariff strategically. Thus, the automated agent learned the behavior described in Section 9.3 and can perform the corresponding strategies in a market environment with static bids. Third, in market situations with supply excess, the agent selects low bid prices, which also correspond to the dominant strategy. In the next step, we analyze the impact of the automated agent on the energy prices of the represented participant α.

Agent Performance Evaluation: For the evaluation of the automated agent's performance, we utilize two different benchmarks. First, we compare participant α's average costs from the implementation phase, where the automated agent interacts on the market, with the average cost of a former period. This analysis is based on the two months of November and December preceding the implementation phase, which we call the *human phase*. It is equally long as the implementation phase. Since the PV generation and the participant's consumption differ between both phases, we only focus on the individual average costs and share of local energy. Second, we rerun the implementation phase in a simulation but without the automated agent. Within the simulation, we set participant α's initial bid price of 22 EURct/kWh and do not change it. The bid price corresponds to the past bid price of the participant. The simulation recalculates the market prices and transactions for all periods within the implementation phase based on the participants' submitted bids, generation and load values. In the following, we refer to this phase as the *simulation phase*. A weakness of this second analysis is that possible reactions of the other participants to the new market prices cannot be observed since these are endogenous and thus unknown. However, looking at past bidding behavior, it can be assumed that this endogenous effect is negligible because participants only rarely adapted their bids. We compare the simulation phase's market results and individual costs with the implementation phase.

	Implementation Phase	**Human Phase**	**Difference**
All Periods	21.8 EURct/kWh	22.3 EURct/kWh	-0.5 EURct/kWh
Local supply periods	16.3 EURct/kWh	18.6 EURct/kWh	-2.3 EURct/kWh

Table 9.1.: Comparison of average market prices between the implementation and human phase

Human Phase Analysis: The choice of this phase as a benchmark serves to compare the performance of the automated agent with real recorded data in a period in which it was not active. However, the comparison has a downside. Both periods have some differences within the generation and load values and the number of specific market periods. The human phase has 5761 market periods, of which 2016 include a local PV supply (34.9%). The implementation phase consists, as described earlier, of 5980 market periods with only 1959 periods (33%) with PV generation. The overall PV generation is about 53% higher in the implementation phase due to better weather conditions and higher solar irradiation. In addition, the overall demand within the implementation phase is about 16% lower compared to the human phase. Both factors influence the overall market results and distribution of market situations. Therefore, we omit a market price analysis and only focus on individual average costs of participant α. Table 9.1 displays and compares these average costs of the implementation and human phase. participant α's average costs are 21.8 EURct/kWh during the implementation phase, while they are 0.5 EURct/kWh higher during the human phase, with 22.3 EURct/kWh. Focusing only on periods with local PV generation, the average costs in the implementation phase are 16.3 EURct/kWh, while they are 18.6 EURct/kWh in the human phase, which is 2.3 EURct/kWh higher. The results are the first indicator that the automated agent seems to create an economic advantage for participant α.

Simulation Phase Analysis: The second analysis confirms this observation. Table 9.2 compares the average market prices of each market situation and average costs between the implementation and simulation phase.

Average Market Price	**Implementation Phase**	**Simulation Phase**	**Difference**
All Periods	21.1 EURct/kWh	21.3 EURct/kWh	-0.2 EURct/kWh
Local supply periods	15.1 EURct/kWh	15.6 EURct/kWh	-0.5 EURct/kWh
Supply Shortage periods	19.9 EURct/kWh	20.4 EURct/kWh	-0.5 EURct/kWh
Supply Excess periods	11.5 EURct/kWh	12.0 EURct/kWh	-0.5 EURct/kWh
Average Costs / kWh			
All Periods	21.8 EURct/kWh	21.9 EURct/kWh	-0.1 EURct/kWh
Local supply periods	16.2 EURct/kWh	16.4 EURct/kWh	-0.2 EURct/kWh

Table 9.2.: Comparison of average market price and costs of the implementation and simulation phase

On average, the simulation phase's market price is 0.2 EURct/kWh higher than in the implementation phase. A closer look at periods with local PV generation shows that the average difference increases to 0.5 EURct/kWh between the implementation phase (15.1 EURct/kWh) and the simulation phase (15.6 EURct/kWh). A differentiation between the two market situations (supply excess and supply shortage) reveals an even clearer picture. In market periods with a supply shortage, the average market price during the implementation phase is 0.5 EURct/kWh lower than in the simulation phase. The average market price in supply excess phases shows that the automated agent achieves its goal to minimize the market price. Here, the simulation phase shows an average market price of 12.0 EURct/kWh. While the market price is 0.5 EURct/kWh lower in the implementation phase. The simulation phase's average 12.0 EURct/kWh market price results from a static 12.0 EURct/kWh bid price by another participant in the market. Since the aggregated demand can be met entirely by local supply in supply excess market periods, the lowest demand bid determines the market price. Therefore, the average market price below the 12.0 EURct/kWh indicates that the automated agent learned to push the market price down in these market periods. In market situations with supply shortage, the average market price during the implementation phase is 19.9 EURct/kWh and 20.4 EURct/kWh for the simulation phase. Both average market prices are significantly lower than the derived market prices for supply shortage phases in Section 9.3. However, the human participants showed low activity and submitted bid prices below the grid tariff of 24 EURct/kWh, which explains the lower average market prices. The automated agent considers these static bid prices because the average market price in supply shortage phases of the implementation phase is 0.5 EURct/kWh lower compared to the simulation phase. This observation is supported by the fact that we observed more market dropouts by the automated agent in the implementation phase. A market dropout happens if the bid price of an agent is too low and the market mechanisms allocates the scarce quantity to other, higher bidding. Nevertheless, the automated agent can lower the market price in the supply shortage phases despite the increased dropouts. The comparison of individual costs from Table 9.2 also displays a similar picture. The agent has 0.1 EURct/kWh lower average costs per kilowatt-hour in each market period in the implementation phase. Looking only at periods with local generation, the average value increases by 0.2 EURct/kWh from 16.4 EURct/kWh to 16.2 EURct/kWh. The rather small deviation can be explained by the static bid price of a human participant (12.0 EURct/kWh). With the uniform pricing mechanism, this bid price represents the market price in supply excess phases, which applies to all participants. Therefore, the automated agent had little room for improvement.

The analysis shows that an automated agent can reduce the average market price and individual costs of the participant and thus generate an economic benefit for the individual participant, which answers the first research question. With an average of 0.2 EURct/kWh lower costs in each period with local supply, participant α saved on average 10.3 EURct over an average day (96 Periods). Over the whole implementation period with its 1959 periods, this advantage amounts to 211.9 EURct. The amount and size of the added value strongly depend on the bids of the other participants and the availability of PV generation. Even when the possible economic margin is small due to low static bids, which are close to the optimal behavior in supply excess situations, the automated agent exploits the slight differences and reduces costs for the participant. Furthermore, the trained agent adapts to static bid prices and reacts correspondingly.

9.5.2. Multi-Agent Simulation

The implementation of an automated agent represents an economic advantage for the participants. It saves time, can directly react to changing market situations and shows an overall better economic performance than manual trading. Therefore, human participants have an incentive to implement an automated agent, assuming that the implementation costs are low. Assuming that all participants behave rationally, they will be represented by automated agents in the long-term. In the third analysis, we therefore conduct an additional simulation with several automated agents to evaluate their behavior and the corresponding effects on the market price. The goal is to investigate wether the derived behavior from Section 9.3 can be observed.

Figure 9.3 displays the distribution of the submitted bid prices by the automated agent of participant α when competing with other automated agents. The bidding behavior analysis of the multi-agent phase reveals that the automated agent of participant α shows a different behavior compared to the competition with human traders. In supply shortage situations, the automated agent submits a bid price of 24 EURct/kWh in 73.52% of the periods and 11 EURct/kWh in 17.14% of the periods. The remaining submitted bid prices are predominantly bid prices of 18 EURct/kWh and 19 EURct/kWh. The automated agent shows more distinct behavior towards the 24 EURct/kWh in supply shortage situations compared to the competition with human traders in Figure 9.2. The reason for this is that the static bid prices of the

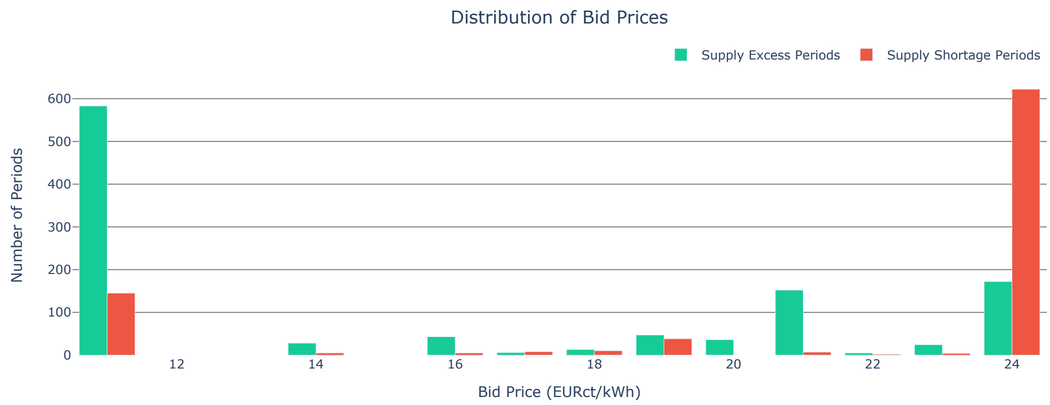

Figure 9.3.: Overview of the submitted bid prices in the multi-agent phase

other participants do not exist in the multi-agent phase and therefore, the automated agents do not take them into account. In the presence of dynamic bid changes, the algorithm shows a clear approximation towards the optimal behavior described in Section 9.3. However, the results show the uncertainty of the market as the agent sometimes misinterprets a supply shortage for a supply excess.

In the supply excess situations, the distribution looks different. Here, 52.57% of all submitted bid prices are 11 EURct/kWh and 15.51% are 24 EURct/kWh. The remaining bid prices are predominantly 21, 19 and 16 EURct/kWh. In this market situation, the variance is higher compared to the supply shortage situation. The implemented uniform pricing mechanism explains this more diverse behavior in supply excess situations. It requires only one agent to bid a low bidding price in supply excess market situations to set a low market price. It seems that the automated agent struggles in the transition phases between the two market situations. However, the optimal behavior of 11 EURct/kWh bid price is set in 52.51% of all supply excess situations. Overall, we observe a more distinct bidding behavior towards the game-theoretic optimum described in Section 9.3.

The analysis of the bidding behavior of the other automated agents paints a comparable picture in market situations with supply shortage. The other agents show comparable shares of 24 EURct/kWh bid prices in supply shortage market situations. In addition, we observe a more diverse bidding behavior in supply excess situations. Some automated agents rarely bid 11 EURct/kWh and show a much higher share of the bid price of 24 EURct/kWh and other bid prices such as 17 EURct/kWh. It seems that some agents require longer training times to distinguish the market situations correctly.

Average Market Price	**Multi-Agent Phase**	**Implementation Phase**	**Difference**
All Periods	21.7 EURct/kWh	21.1 EURct/kWh	0.6 EURct/kWh
Local supply periods	17.0 EURct/kWh	15.1 EURct/kWh	1.9 EURct/kWh
Supply Shortage periods	21.7 EURct/kWh	19.9 EURct/kWh	1.8 EURct/kWh
Supply Excess periods	13.4 EURct/kWh	11.5 EURct/kWh	1.9 EURct/kWh
Average Costs / kWh EURct/kWh			
All Periods	22.3 EURct/kWh	21.8 EURct/kWh	0.5 EURct/kWh
Local supply periods	18.0 EURct/kWh	16.2 EURct/kWh	1.8 EURct/kWh

Table 9.3.: Comparison of average market price and costs of the multi-agent and implementation phase

However, this suboptimal bidding behavior in the supply excess periods also has an impact on market prices and results. Regarding the market results, Table 9.3 compares the average market prices and individual costs of participant α in the multi-agent phase with the implementation phase. The less distinct supply excess market periods can also be seen in the average market prices. With 13.4 EURct/kWh, it is 1.9 EURct/kWh higher than the market price in the implementation phase with 11.5 EURct/kWh. The result shows that the automated agents equally misjudge the market situation. This higher price indicates that the automated agents do not successfully lower the bid price in this phase more than the individual agent. Again, the static bid price of 12.0 EURct/kWh from the implementation phase seems to have an anchor effect, which supports the agent in lowering the market prices. Also, due to the lack of static bids, the market price in market periods with supply shortage increases to 21.73 EURct/kWh, which is closer to the derived optimal market price of 24 EURct/kWh if perfect foresight would exist. The higher average market price impacts the individual average costs in both market situations. The average costs per kilowatt-hour are 22.3 EURct/kWh and therefore about 0.5 EURct/kWh higher in the multi-agent phase and even 1.6 EURct/kWh higher considering only the market periods with local supply. We conclude that the intense competition between the automated agents has neutralized the advantage from the competition with human traders. Figure 9.4 displays the distribution of the market prices within the multi-agent phase. It can be seen that the derived market prices 11 EURct/kWh and 24 EUR/kWh from Section 9.3 are dominating in the respective market situations and

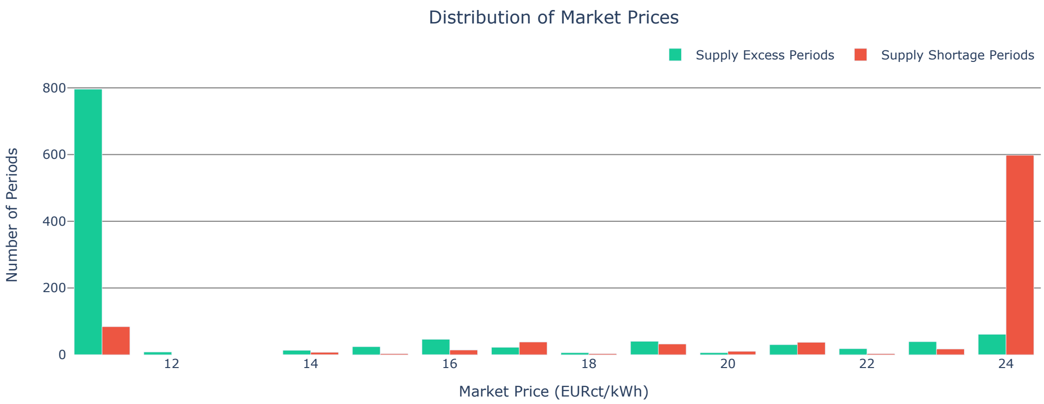

Figure 9.4.: Overview of the market prices in multi-agent phase

only a small amount of the market prices falls in between these two values. However, there is a share in both areas that are assigned to the opposite situation. It turns out that in these situations, all agents have assumed the respective other market situation and behaved accordingly. This explains the inferior market outcome in the supply excess market situations and describes the proportion of periods that the agents collectively failed to predict correctly.

Regarding the second subquestion, the analysis shows that the lack of static bids makes it harder for automated agents to decrease the market price in market situation of supply excess. Automated agents seem to struggle more in forecasting a supply excess market situation. Therefore, the bidding behavior in these situations varies from the derived dominant strategies in Section 9.3. As a result, the average market price in supply excess market situation is higher than in the implementation phase. Nevertheless, the automated agents can recognize the market's economic logic and behave optimally within the scope of the existing uncertainty. However, the participant's individual advantage from the implementation phase diminishes due to the rising competition with the other automated agents and corresponding missing static bids.

9.6. Discussion

The implementation of an automated agent creates an interesting situation. A single participant has an incentive to implement an automated agent to gain an individual advantage. This advantage motivates other participants to do the same, which levels the advantage. Likewise, it can be seen that with the elimination of static bids, the costs for participant α and for all other participants increase since the average market prices rise in the periods with local generation when only automated agents interact on the market. However, this perceived worsening for consumers represents an overall correction of an existing imbalance. The static bids of human participants are the reason why suppliers receive too little profit in scarcity situations in the first place. Single consumers reduce the costs for the demand side in specific supply shortage market situations by becoming the last matched participant with a bid price lower than the grid tariff. This has the effect of weakening the incentive to expand local generation capacity on the supply side, leading to local undersupply in the long run and insufficient expansion. In addition, the lower profits for generators weaken the CEC value propositions for prosumers. The introduction of automated agents can fix this issue but at the price of an overall high complexity and additional cost, as implementation and operation are not free in reality. Our results demonstrate that planners and operators should investigate the effects of automated agents carefully and in detail. Participants pursue bidding strategies only to a small extent and these do not correspond to the derived dominant strategies. In contrast, automated agents are able to exploit this situation and generate an economic advantage for the participant they replace on the platform with other human traders. Also, automated agents learn and follow the corresponding dominant strategies even in a dynamic market environment with exclusively automated agents.

As a result, the derived two equilibrium market prices are realized more often and the market price alternates between the feed-in tariff and grid price. However, the dynamic market environment also introduces uncertainty and the automated agents struggle to predict some supply excess and shortage market situations, resulting in poorer market outcomes. The derived and observed efficient market results can also be achieved with lower complexity. A two-price tariff design, which differentiates between both market situations, is based on the dominant strategies from Section

9.3 and approximates the optimal market results. In market situations with supply excess, the tariff price could be set to 11 EURct and in all other periods, the market price is set to 24 EURct. This tariff design can replicate the optimal market results and its incentives but would be less complex for all participants. Also, it would prevent the exploitation of static bid prices and remove individual incentives to implement an automated agent.

9.7. Limitations

Several assumptions are made within this chapter. First, we focus on a single market mechanism with uniform pricing. While this mechanism is implemented and tested in the project, there are various other approaches described in the literature (Khorasany et al., 2018). The optimal behavior described in Section 9.3 applies only to a market mechanism with uniform pricing and will be different for other projects with other mechanisms. These mechanisms, for example, pay-as-bid, involve a higher potential for strategic behavior and set different prices for each market participant. However, we assume that RL-algorithms can optimize their behavior even better in environments with individual market prices. The assessment of different pricing mechanisms is a task for future research.

The automated agent's performance depends heavily on the available training data. Specific training data reflects only a specific time section of the market activities with the respective number of participants and generation units. If the number of participants changes or new power generation units are connected, the training data might lose parts of its validity. Likewise, the structure of the training data plays an important role. The market price movement described in Section 9.3 can already be observed in training data with static bids. However, static bid prices lead to corresponding market prices in between, which the automated agents recognize in the learning process. These static bid prices allow the agent to quickly anticipate and exploit the corresponding market situation. However, if the behavior of the other participants change, for example, in the transition from human traders to automated agents, the underlying situation for the trained automated agent changes. Therefore, implementing and training automated agents without updating them to changing conditions can result in poorer performance in the long run. In reality, there will be a transition phase in which automated agents gradually replace human traders. How already implemented agents can adapt to these changes in the transition phase is a task for future research. In addition, the required amount of training data represents a challenge for the implementation.

We have assumed that consumers cannot influence or shift their consumption. In practice, a change in the consumption quantity might be an additional benefit of the CEC platform, but as described in Chapter 9, consumers seemingly unwilling to react to price signals and it requires technologies like battery storage or controllable heat pumps to finally exploit demand flexibility. These technologies allow consumers to automatically change their behavior and to shift flexible loads in periods with low market prices. The automated agent could also control this shifting to achieve better results (Golla et al., 2020). Both, the effect of controllable loads on the market results and their management are a task for future research. Furthermore, consumers might collude to reduce prices on the market. CEC platforms are small markets with a limited number of participants who may know each other. This implies the risk that participants might join forces and try to gain an advantage. Staudt et al. (2018) have already shown that automated agents based on simple RL models are able to engage in tacit collusion. The possibility of whether automated agents can recognize and exploit market power is a task of future research.

Finally, the presented approach of replacing automated agents and the market with a tariff model serves to reduce complexity and, at the same time to reduce the weakening of investment incentives by static bids. However, the tariff model does not reflect different preferences for different local sources. Therefore, future work should look more closely at the implications of such a tariff model.

9.8. Conclusion

We investigate the economic advantage of automated agents based on deep reinforcement learning on a CEC market platform with human traders. Additionally, we evaluate how market results change with only automated trading agents interacting on the market. First, we apply a game-theoretical approach to derive the optimal behavior of each participant within the market. Second, we train and implement an automated agent based on the Dueling DQN algorithm. Third, the agent replaces a single participant within LAMP in real-time. Our results show that the automated agent is able to identify the different market situations and shows the appropriate bidding behavior. However, besides the derived dominant bidding strategy, the agent also submits other bid prices, exploiting other static bid prices by human traders. We conclude that an automated agent represents an advantage for participants because they show better performance than competing human traders and save time for the represented participant. As a result, all participants have an incentive to implement an automated agent. Therefore, we finally evaluate the effects of multiple automated agents by simulating this situation with the data from the agent competition with human traders. The analysis shows that the agents learn to approximate the derived optimal behavior from the game-theoretical analysis. A market with several automated agents leads to higher competition on the demand side and decreases the economic advantage of a single automated agent. Since the implementation of agents in practice involves costs and not all participants can implement this on their own, alternatives are needed. Therefore, we discuss that CEC planers and operators should carefully investigate their market design and consider different approaches like a tariff design that generates similar market results without additional costs and complexities for the participants. In addition, this reduced complexity can be an incentive for participants to interact with the platform more often, increasing their long-term engagement with the CEC.

Part IV.

Finale

Chapter 10.

Conclusion

The steady expansion of RES generation capacity has led to local resistance and decreasing acceptance among citizens. With the 'Directive on common rules for the internal market for electricity', the EU has created a regulatory framework to address this issue by enabling citizens to form energy communities, defined as CECs. This concept enables citizens to participate directly in the transition process. The CEC concept has been developed and discussed in academic research under different terms for a few years. It allows citizens to collectively invest in their own generation capacity and share the generated energy. With the utilization of digital technologies, the CEC concept can provide additional benefits for its participants, like high-resolution load data and a trading platform. With the creation of the regulatory framework in the EU, the subsequent step is the implementation and operation of CECs in practice. However, there is no practical experience and knowledge regarding the long-term implementation and operation of CECs. This dissertation is a contribution to close this research gap by addressing crucial challenges for the practical implementation and operation of digitized CECs. Its contribution is divided into two parts. In the first part, a suitable CEC design is derived and evaluated. The CEC IT infrastructure's essential building blocks, processes and architecture are identified, implemented in practice and evaluated. Besides the IT architecture, the first part of the dissertation provides a maturity model for blockchain-based CECs to identify necessary next steps within the implementation process and develops a market mechanism for the CEC trading platform to satisfy heterogeneous preferences. In the second part, the participants' perception of the CEC user interface and their behavior on the trading platform are analyzed. Essential design principles for the user interface are derived, drivers and barriers for long-term engagement are analyzed and the impact of automated agents as support systems for the participants are investigated.

10.1. Summary and Implications

The following chapter summarizes the contributions of this dissertation along the structure and research questions from Chapter 1. In Chapter 2, a basic understanding of the general functionality and value chain of the power system is described. Building on this, Chapter 3 presents an overview of the body of literature regarding energy communities as a new concept within the power system value chain. The market engineering framework is utilized to present the different components of a CEC platform. In this chapter, a detailed description of different real-world CEC implementations and the Landau Microgrid Project (LAMP) is provided. This first fundamental part is followed by the two parts that contain the main contributions of the dissertation.

In these subsequent two parts, the structure and functionality of the CEC design are developed and evaluated. With respect to research question 1, in Chapter 4, necessary processes and components of the CEC's IT infrastructure based on a literature review and stakeholder requirements from the LAMP project are derived and evaluated. Overall, four basic modules and six essential processes ensure the platform's functionality. The four modules are the database, smart meter hardware, user interface and market mechanism. The smart meter hardware collects and transmits the recorded load data, the user application provides individual information and market data to the participants and captures the bid price information. The market mechanism determines the market prices from the recorded load data, captures bid price specifications and calculates the respective transactions. The presented architecture shows a star-shaped structure with the database in its center. The other modules and their processes are exclusively connected to the database module. This structure allows the CEC to be extended with additional functionalities without restructuring the architecture. More sophisticated local systems can easily be added to the same architecture. The structure of each module can be adjusted. For example, more complicated or less complex market mechanisms can also be included in the same architecture. In addition to the architecture, requirements for digital technologies suitable for each of these modules are determined based on the experiences of the LAMP project are reported. A limitation of this chapter is that different IT architectures are not compared regarding their efficiency. Due to the focus on the LAMP implementation and testing, it was not possible to implement several IT architectures.

In recent years, due to its special decentralized structure and self-management, the blockchain technology received increasing awareness from academia as a central technology to enable practical CEC implementations with a trading platform. To answer on research question 2, a maturity model is developed in Chapter 5 to determine the current state of real-world projects based on this technology. The maturity model consists of five phases along three dimensions, which determine the actual implementation and maturity status of a project. The technology dimension evaluates specific information technology aspects, like the existence of industrial standards and specific knowledge. The market and regulatory dimensions assess the alignment of developed CEC within the existing regulation and underlying economics within the CEC. The model is applied to the LAMP project. Overall, the maturity model provides structured and helpful information about the current state of the project and necessary next steps. A limitation is that in its current form, the maturity model is tailored to blockchain based CECs with a trading platform. Future research should focus on the generalization of the maturity model to support bigger groups of real-world CEC implementations.

Many authors assume that consumers have a varying preference for different energy generation sources. These preferences transform the former homogeneous good energy into a heterogeneous good and allow price differentiation. Current tariffs in the energy sector address a differentiation between renewable and non-renewable energy sources but cannot distinguish between specific energy sources (e.g., PV, wind, biomass or CHP), which would allow participants to select their preferred source directly. Research question 3 addresses this and a market mechanism for the CEC trading platform is developed in Chapter 6 that differentiates between energy from different specific energy sources. The developed mechanism considers the participants' differentiated willingness to pay and matches bids for various energy sources separately. For each energy origin, a separate market is established, on which only energy from one source is traded. The applied matching mechanism is based on the merit order mechanism, which is widely used in the energy sector. Since the markets cannot be cleared simultaneously, the developed mechanism determines the order of market clearing based on the bid prices of the demand side. A key advantage of the proposed market mechanism is that it flexibly adapts to changing preferences of participants. At the same time, this adaptability allows it to be used in CECs with different local energy sources and preferences. The analysis shows that participants can influence the origin of their energy consumption regarding their individual preferences. However, other factors like availability and bid prices also affect the energy mix. A limitation of this work is that the developed market mechanism is only tested in a single project and further implementations in other CEC projects are necessary.

Besides the technical functionality of the CEC, the participants' behavior on the platform is essential for its success. It is necessary to investigate how participants interact with the platform and to analyze whether the behavior corresponds to the literature's assumptions. The CEC's user interface is analyzed in more detail in Chapter 7. A design science research approach is applied and seven design principles are derived and evaluated in three cycles to answer research question 4. In the first cycle, requirements for the user interface are derived based on a literature review and a stakeholder survey on a prototype for the LAMP implementation. Five project stakeholders tested the prototype. The second cycle involved i) the derivation and instantiation of six design principles and ii) the transfer of the prototype into a functional user application. Within LAMP, the instantiated user application was tested by the participants over one year and evaluated with the help of expert interviews. In the expert interviews, the participants positively evaluated the instantiations of the design principles in the user application. Additional feedback from individual participants showed that the high complexity of the implemented market mechanism inhibited bidding activity. For this reason, a third cycle was conducted in which a seventh design principle was derived based on this feedback and evaluated with the help of an online experiment. It is found that potential participants of CECs prefer simpler market mechanisms. A limitation of the generated design knowledge is that its evaluation is only based on the interview feedback from the eleven CEC participants and 115 participants of a laboratory experiment. The results of a behavioral laboratory experiment show that less complex market mechanisms are preferred for

CECs. Especially, the results from the field experiment are based on a small sample and a selection bias cannot be ruled out. However, even if certain biases cannot be excluded, the provided answers hold interesting guidance for the design of CEC platforms and corresponding user interfaces.

A purposeful design of the CEC platform and its interface is the foundation to enable interactions of participants on the platform. However, there is a lack of observed real-world behavior in a CEC and unclear how participants behave on these platforms. Researchers made several fundamental assumptions about this participant's behavior in the past. It is unknown whether these assumptions hold in practice. In Chapter 8, these assumptions are examined and compared to observed behavior in LAMP. In this chapter, the willingness to pay premium prices for local energy, the bidding activity, responses to information nudges and the impact of price signals on consumption behavior are analyzed. The analyses show that consumers start with a willingness to pay premium prices for local PV power. However, this willingness quickly vanishes and almost all participants end up with bid prices below the reference price in the long run. The decline can be observed for both available energy sources in the project. Overall, consumers prefer local PV electricity over local CHP electricity. In addition, all participants showed little bidding activity in the project, which declined even further over the project's duration. Participants did not respond with consumption shifts to different price signals. In the additional expert interviews, participants stated that the two main barriers were the high market complexity and the general low availability of time or willingness to invest time to deal with the platform. Complexity seems to increase the participants' uncertainty about the impact of a bidding decision, which leads to inactivity. Participants point out that weekly reports on their CEC trading activity support them in monitoring their own performance. However, reducing complexity and supporting participants in the bid submission process is a key challenge for CECs. A limitation of the analysis is, again, the number of only eleven observed participants in this study, which represents a small sample, meaning that statistically significant effects cannot be deducted. However, the analyzed data represents the first empirical long-term study on CEC participant behavior.

Based on the participant feedback that time is a scare resource when dealing with a CEC, the impact of automated agents acting on behalf of these participants is analyzed in Chapter 9. First, an automated agent based on a deep reinforcement learning algorithm is developed, trained and deployed in LAMP. Over two months, the agent controlled the bidding behavior of a single participant and tried to reduce the energy costs. The analysis shows that the automatic agent uses the static bids of the competing human participants as an anchor and can generate an economic advantage for the individual participant. Thus, an incentive exists for CEC participants to implement automated agents. The second analysis in Chapter 9 evaluates a situation with only automated agents. The results show that the individual advantage vanishes as competition increases, but emerging market prices align with the game-theoretic results. Based on this, possible alternatives are discussed, such as a tariff system, which leads to the same market results but is associated with considerably less complexity and costs. A limitation of this chapter is the focus on a single market mechanism and the behavior of the agent regarding other mechanisms is unknown. However, as the performance of the automated agents indicates, it can optimize its behavior even better in environments with individual market prices.

This dissertation is a contribution to the transfer of the CEC concept into practical implementations. The individual contributions aim to ensure the overall long-term functionality of CEC trading platforms. First, by providing a suitable IT architecture and ensuring that the platform functionality meets the requirements of its stakeholders. Second, by identifying drivers and barriers for favorable user behavior on CECs. The practical experiences and findings are the starting point for further research directions. A clear limitation of this thesis is the focus on a single field project with small number of participants. As the existing literature indicates, there are various other CEC approaches with different participant numbers, local energy sources and market mechanisms. Nevertheless, the conducted analyses show fundamental requirements of the participants for the CEC platform design, such as a market mechanism with low complexity and the need for support systems, which also hold for other CEC concepts. In addition, the studies have shown what information participants use, what goals they pursue within the CEC and how they behave in the long-term, which are important insights for future CEC projects.

10.2. Outlook

The complexity of the allocation is the central challenge for the operation of a CEC platform. A key finding of this dissertation is that many participants do not invest much of their free time in engaging with the trading platform. They also had little or no experience in submitting bids on a platform and had trouble understanding the market prices that were occurring, which led to inactivity. A major challenge is to reduce the complexity, so participants can comprehend the mechanism and participate in the CEC platform more easily. A possible approach is the introduction of several tariff designs, which participants can choose from. The advantage is that CEC participants are already familiar with tariff designs from their electricity contracts. Another approach is the introduction of support systems, which help participants in their decision-making. The main focus for this approach should be on how participants can access and understand the available information quickly and on how the system can support the participants in their decision-making. A promising starting point is the regular report, which was part of the LAMP implementation and received positive feedback from the participants. In the expert interviews, participants have already asked directly for similar, more advanced support systems. For example, it was noted that active support in the form of additional information during the individual bidding process would have been helpful. Future research opportunities are primarily in the effectiveness assessment of different support systems and the perception and identification of design principles so that these encourage and support CEC participants to engage with the platform regularly.

In the context of support systems, the impact of AI-based automated agents is evaluated in this dissertation. Automated agents are able to reduce costs for individual participants. Here, further investigation is needed to determine whether the systems are transferable to other CEC platforms with different market mechanisms. Likewise, investigation of AI-based automated agents with other objective functions, such as a higher local green power share or a multi-objective optimization (e.g., financial benefit and green share), are promising avenues as participants have non-financial objectives. The simulation analysis with exclusively automated agents shows that increasing competition diminishes the individual benefit. However, automated agents can make an important contribution if they can activate participants' consumption flexibility and market it on their behalf. In combination with an energy management system, automated agents based on AI algorithms can respond directly to (price) signals and provide flexibility to the local grid. This local flexibility is an essential factor for the energy transition, as it solves imbalances directly at lower voltage levels and thus contributes to grid stability. In this context, field-testing is crucial to ensure that participants understand and accept it.

The EU exclusively focuses in their directive on CEC with electricity. However, the concept can be applied to other locally available goods, for example, heat or mobility. Over 70% of a private household's energy demand is needed for heat provision. In Germany, a large part of this heat demand is met with conventional natural gas, thus generating emissions. CECs can contribute to a corresponding decarbonization by facilitating the joint investment in a local heating networks or sustainable generation facilities. Such a CEC heat community can also enable the exchange of locally generated heat between the participants and foster a more efficient usage of heat generation technologies. In addition to heat, the CEC concept can also be used for other services, like the integration of charging station infrastructure or shared car fleets. The platforms can enable the organization of car-sharing for community participants and allow a joint investment in charging station infrastructure. Both extensions of the CEC concept increase the individual benefit and thus incentivize participants to remain and engage themselves in the community or attract new members.

Last, the observed user behavior results are based on a single field study. In this context, the composition of participants, demographic data, social background and income are not representative for each CEC. Therefore, the results cannot be fully applied to other environments, such as urban environments with participants from other social structures. Since the observed activity and behavior depends mainly on the participants, there is a need to identify different types of participants and their behavior on the platform. Future research should more closely examine the composition of different participant types in CECs. Citizen Science is a promising methodology in this context. Given the results of this dissertation, further research in the area of CECs is needed in order for them to become an important component of future sustainable energy systems.

Appendices

Appendix A - Expert Interviews Guide

A. Fragen zur Demografie

1. Bitte geben Sie ihr Alter an.
2. Wie viele Personen wohnen mit ihnen in ihrem Haushalt?
3. In welchem Haustyp wohnen Sie (Einzel-/Mehrfamilienhaus)?

B. Fragen zur Teilnehmermotivation & Teilnehmerklassifizierung

1. Warum haben Sie sich entschlossen bei LAMP teilzunehmen?
2. Warum haben Sie sich entschlossen bei LAMP teilzunehmen?
3. Haben Sie eine Idee, welche Ziele verfolgt LAMP?
4. Haben Sie in ihrem Haushalt und/oder in der Nachbarschaft sich über das LAMP Projekt ausgetauscht? Z.B. Familie, Nachbarschaft oder Freunde.
5. Würden Sie LAMP an Freunde/Nachbarn oder Verwandte empfehlen?
6. Welche Gründe sprechen gegen LAMP?
7. Was gefällt Ihnen besonders an LAMP?
8. Wie wichtig ist es Ihnen Strom aus lokalen, ggf. grünen Quellen zu beziehen?
9. Haben Sie ihre monatlichen/jährlichen Stromkosten vor der Teilnahme bei LAMP bewusst verfolgt und waren Ihnen diese bekannt?

10. Welche neuen Erkenntnisse haben Sie durch LAMP über ihre Stromkosten gewonnen? JA – Können Sie hier ein Beispiel geben? / Nein – Was würde Sie dazu veranlassen Ihr Verhalten zu ändern?

C. LAMP – Preisbildung & Herkunft des Stroms

1. Wie haben Sie, generell, die Preisbildung in LAMP wahrgenommen?
2. Wie fair empfinden Sie die Preisbildung in LAMP?
3. Wie bewerten Sie den einheitlichen Preis in LAMP im Vergleich zu einer Preisbildung, bei der für jeden Teilnehmer ein individueller Preis ermittelt wird?
    a) Pro Individualpreis - Warum präferieren Sie einen individuellen Preis?
    b) Pro Individualpreis - Wie würde ein individueller Preis sich auf Ihr Gebotsverhalten und Stromverbrauchsverhalten auswirken?
    c) Pro Einheitspreis - Warum präferieren Sie einen Einheitspreis?
4. Wie wichtig ist es Ihnen zu erfahren, welche Menge und aus welcher lokalen Quelle (oder Nachbarn) Sie ihren Strom beziehen?
5. Haben Sie die Marktpreise verfolgt und hatte der Preis und dessen Entwicklung dazu geführt, dass Sie Gebote angepasst haben?
    a) Nein - Weshalb haben Sie dennoch ihre Gebote angepasst?
    b) Ja - Wie haben Sie auf den Preis reagiert? Können Sie ein Beispiel geben?
6. Vor LAMP hatten Sie mit ihrem Energieversorger einen festen Tarif. Wie bewerten Sie einen solchen festen Tarif im Vergleich zu einem Strompreis, der sich wie bei LAMP alle 15 Minuten verändern kann?
7. Welche Periodenlänge (Zeit, in der sich der Preis nicht verändert) wäre Ihrer Meinung passend?

D. LAMP – Verständnis der Preisbildung

1. Konnten Sie die Mechanik der Preisbildung nachvollziehen?

2. Nein - Weshalb konnten Sie die Preisbildung nicht nachvollziehen? / Welche zusätzlichen Informationen oder Erklärungen haben gefehlt und hätte Ihnen geholfen?

3. Welche der zwei eingesetzten Formen der Preisbildung in LAMP präferieren Sie?

4. Haben Sie auf die vorab kommunizierte Preisbildung in den Handelsphasen 5,6 und 7 reagiert?
   a) Nein - Was sind die Gründe hierfür?
   b) Ja - Können Sie uns konkrete Beispiele geben?

5. Bezogen auf das Verständnis, haben Sie die bereitgestellte Information über die Preisbildung (Beschreibung im Report) vor einer Gebotsabgabe genutzt?
   a) Nein - Welche weiteren Informationen hätten Sie benötigt?
   b) Ja - Würden Sie sich zusätzliche Informationen wünschen?

E. LAMP – Handelsphasen & Reports

1. Wie haben Sie, generell, die Handelsphasen in LAMP wahrgenommen?

2. Welchen Nutzen hatten die wöchentlichen Reports für Sie?

3. Haben Sie ihr ihre Gebotssetzung oder Stromverbrauchsverhalten auf Grundlage der in den Reports bereitgestellten Informationen, in einer oder mehreren Handelsphasen angepasst?
   a) Ja - In welchen Handelsphasen ist dies geschehen?
   b) Nein - Haben Ihnen Informationen gefehlt, um dies zu tun?

4. In den Handelsphasen 1,2,3 und 4 haben Sie jeweils zusätzliche Informationen über ihren Stromverbrauch, die individuellen Stromzusammensetzung, potenzielle „Stromfresser“ im Haushalt und ihren durchschnittlichen Strompreis im Vergleich zu den restlichen Teilnehmern erhalten. Wie hilfreich empfanden Sie diese?

a) Haben Sie die bereitgestellten Informationen genutzt, um Ihre Verbrauchsverhalten anzupassen?

b) Haben Sie die bereitgestellten Informationen genutzt, um Ihren Energiemix zu verändern (lokal / grün)?

c) Haben Sie die bereitgestellten Informationen genutzt, um Ihre Energiekosten zu senken?

5. In Handelsphase 5, 6 und 7 wurden die Gebotspreise der PV-Anlage angepasst und damit vorab die Marktpreise kommuniziert. War dieses vorhersagbare Verhalten für Sie relevant? [Zeiträume nennen und genauer erklären]

   a) Haben Sie die bereitgestellten Informationen genutzt, um Ihre Verbrauchsverhalten anzupassen?

   b) Haben Sie die bereitgestellten Informationen genutzt, um Ihren Energiemix zu verändern, indem Sie ihr Gebot angepasst haben (lokal / grün)?

   c) Haben Sie die bereitgestellten Informationen genutzt, um Ihre Energiekosten zu senken?

6. In Handelsphase 9 haben wir rückwirkend berechnet, wie hoch ihre Einsparung bei einem optimalen Verhalten in LAMP sein könnte. War diese Information für Sie relevant?

7. Haben Sie die bereitgestellten Informationen genutzt, um Ihre Energiekosten zu senken?

8. Welche Informationen im Report empfanden Sie als besonders hilfreich?

9. Mit den Reports wurde eine Visualisierung der Marktperioden mit der Darstellung aller Gebote und Marktpreise für beide Märkte (Photovoltaik und Blockheizkraftwerk) versendet. Welchen Mehrwert konnte Ihnen diese Grafik bieten?

10. Was sollten wir ihrer Meinung nach von den Reports für die App übernehmen?

F. LAMP – Applikation

1. Wie haben Sie die LAMP-App wahrgenommen und wie Sie diese genutzt?
2. Bezogen auf den Energieverbrauch, in der App wird der persönliche Stromverbrauch unter dem Reiter „Verbrauchsdaten“ dargestellt, wie haben Sie dieses Feature genutzt?
   a) Nutzen Sie die grafischen Darstellungen der individuellen Verbrauchswerte?
   b) Wie hilfreich/nützlich sind Sie die grafischen Darstellungen der individuellen Verbrauchswerte?
   c) Erhalten Sie durch die grafische Darstellung der Verbrauchswerte ein besseres Verständnis über ihr eigenes Verbrauchsverhalten?
   d) Haben Sie basierend auf diesen Informationen aktiv versucht ihr Verhalten anzupassen. (z. B. Waschmaschine später angestellt)
   e) Haben Sie durch die Grafik Geräte oder eigenes Verhalten identifiziert, welches einen hohen Stromkonsum verursacht hat?
   f) Welch weiteren Formen der Visualisierung wäre aus ihrer Sicht hilfreich?
3. Bezogen auf die die Zusammensetzung des Strommix, also der Herkunft des Storms. In der App wird der dieser unter dem Reiter „Transaktionen“ dargestellt. Wie haben Sie dieses Feature genutzt?
   a) Nutzen Sie die grafische Darstellung der Zusammensetzung des Strommix?
   b) Wie hilfreich sind die grafische Darstellung der Transaktionen und Zusammensetzung der Strombestandteile, um Informationen über den individuellen Strommix zu erhalten.
   c) Haben Sie basierend auf den Informationen zu Ihren Transaktionen und Energiemix ihre Gebote angepasst, um die Zusammensetzung ihres Energiemix zu verändern (z.B. ein höheres Gebot für PV eingestellt)?
   d) Haben Sie basierend auf den Informationen zu Ihren Transaktionen und Energiemix ihre Gebote verändert, um den Anteil an lokaler Energie zu erhöhen?

e) Haben Sie basierend auf den Informationen zu Ihren Transaktionen und Energiemix ihre Gebote verändert, um den Anteil an lokaler, grüner Energie zu erhöhen?

f) Welch andere Formen der Visualisierung wäre aus ihrer Sicht hilfreich?

4. Die Kosten, diese wurden ebenfalls unter dem Reiter „Transaktionen“ in tabellarischer Form dargestellt. Wie haben Sie dieses Feature genutzt?

   a) Nutzen Sie die tabellarische Darstellung der Energiekosten, sowie Marktpreise, um Informationen über die Kosten ihres Energieverbrauchs und Gebotsverhalten zu erhalten?

   b) Wie hilfreich ist die tabellarische Darstellung der Energiekosten, sowie Marktpreise, um Informationen über die Kosten ihres Energieverbrauchs und Gebotsverhalten zu erhalten?

   c) Wie hat sich ihr Verständnis Sie mit der Hilfe der grafischen Darstellung der Energiekosten besseres Verständnis über die Auswirkungen ihres Energieverbrauchs und Gebotsverhalten gewonnen?

   d) Haben Sie, basierend auf den Informationen zu Ihren Energiekosten und Marktpreise, ihr Verhalten verändert, um die Energiekosten zu verändern (z.B. ein höheres Gebot für PV eingestellt, Verbrauch reduziert)?

   e) Haben Sie basierend auf den Informationen zu Ihren Energiekosten und Marktpreise ihr Gebot verändert, um die Marktpreise zu beeinflussen?

   f) Welch andere Formen der Visualisierung wäre aus ihrer Sicht hilfreich?

5. In Lamp wurden alle 15 minuten Marktpreise ermittelt. Diese Darstellung finden Sie unter „Marktpreise“. Haben Sie dieses Feature genutzt?

   a) Wie haben Sie die grafische Darstellung genutzt?

   b) Welch andere Formen der Visualisierung wäre aus ihrer Sicht hilfreich?

6. Wie einfach und intuitiv bewerten Sie die grafische Oberfläche zu Abgabe von Geboten?

7. Inwiefern hat die Zusatzinformation (Hinweis zum ESW Tarif) Ihnen bei der Festlegung eines neuen Gebotspreises geholfen?

8. Welch andere Formen der Visualisierung wäre aus ihrer Sicht hilfreich?
9. Welche zusätzlichen Informationen hätten Sie sich für die Gebotsabgabe gewünscht?
10. Zuletzt, wir haben mitbekommen, dass es Probleme beim Login gab. Können Sie diese spezifizieren?
11. Durch das Login Feature haben Sie keinen Zugriff auf andere Accounts erhalten und konnten nicht Gebote im Namen anderer Teilnehmer abgeben
12. Welche weiteren Anmerkungen / Anregungen haben Sie zu dem Projekt?

Bibliography

Ableitner, L., Meeuw, A., Schopfer, S., Tiefenbeck, V., Wortmann, F., Wörner, A., 2019. Quartierstrom – Implementation of a real world prosumer centric local energy market in Walenstadt, Switzerland. arXiv:1905.07242 URL: http://arxiv.org/abs/1905.07242.

Ableitner, L., Tiefenbeck, V., Hosseini, S., Schöb, S., Fridgen, G., Staake, T., 2017. Real-world impact of information systems: the effect of seemingly small design choices. WITS 2017 Proceedings , 387–402URL: http://cocoa.ethz.ch/downloads/2018/01/2393_WITS_2017_HPL_CRV.pdf.

Ableitner, L., Tiefenbeck, V., Meeuw, A., Wörner, A., Fleisch, E., Wortmann, F., 2020. User behavior in a real-world peer-to-peer electricity market. Applied Energy 270. URL: http://www.sciencedirect.com/science/article/pii/S0306261920305730, doi:10.1016/j.apenergy.2020.115061.

Agentur für Erneuerbare Energien, 2021. Neue Studie zeigt: Bürgerenergie bleibt zentrale Säule der Energiewende. URL: https://www.unendlich-viel-energie.de/presse/pressemitteilungen/studie-buergerenergie-bleibt-zentrale-saeule-der-energiewende.

Agnolucci, P., 2006. Use of economic instruments in the German renewable electricity policy. Energy Policy 34, 3538–3548. URL: https://www.sciencedirect.com/science/article/pii/S0301421505002181, doi:10.1016/j.enpol.2005.08.010.

Aitzhan, N.Z., Svetinovic, D., 2018. Security and Privacy in Decentralized Energy Trading Through Multi-Signatures, Blockchain and Anonymous Messaging Streams. IEEE Transactions on Dependable and Secure Computing 15, 840–852.

URL: https://ieeexplore.ieee.org/document/7589035/, doi:10.1109/TDSC.2016.2616861.

Al Kawasmi, E., Arnautovic, E., Svetinovic, D., 2015. Bitcoin-based decentralized carbon emissions trading infrastructure model. Systems Engineering 18, 115–130. URL: https://onlinelibrary.wiley.com/doi/10.1002/sys.21291, doi:10.1002/sys.21291.

Alanne, K., Saari, A., 2006. Distributed energy generation and sustainable development. Renewable and Sustainable Energy Reviews 10, 539–558. URL: https://linkinghub.elsevier.com/retrieve/pii/S1364032105000043, doi:10.1016/j.rser.2004.11.004.

Alliance, L., 2020. LoRaWAN and NB-IoT : competitors or complementary | LoRa Alliance®. URL: https://lora-alliance.org/resource-hub/lorawan-and-nb-iot-competitors-or-complementary.

Alonso, I.A., Verdun, J.C., Caro, E.T., 2010. The IT implicated within the enterprise architecture model: Analysis of architecture models and focus IT architecture domain, in: 2010 IEEE International Conference on Service-Oriented Computing and Applications (SOCA), IEEE, Perth, Australia. pp. 1–5. URL: http://ieeexplore.ieee.org/document/5707174/, doi:10.1109/SOCA.2010.5707174.

Ampatzis, M., Nguyen, P.H., Kling, W., 2014. Local electricity market design for the coordination of distributed energy resources at district level, in: IEEE PES Innovative Smart Grid Technologies, Europe, IEEE, Istanbul, Turkey. pp. 1–6. URL: http://ieeexplore.ieee.org/document/7028888/, doi:10.1109/ISGTEurope.2014.7028888.

Andoni, M., Robu, V., Flynn, D., Abram, S., Geach, D., Jenkins, D., McCallum, P., Peacock, A., 2019. Blockchain technology in the energy sector: A systematic review of challenges and opportunities. Renewable and Sustainable Energy Reviews 100, 143–174. URL: http://www.sciencedirect.com/science/article/pii/S1364032118307184, doi:10.1016/j.rser.2018.10.014.

Andrade, R., Garcia-Rodriguez, S., Praca, I., Vale, Z., 2020. A Two Tier Architecture for Local Energy Market Simulation and Control, in: De La Prieta, F., Mathieu, P., Rincón Arango, J.A., El Bolock, A., Del Val, E., Jordán Prunera, J., Carneiro, J., Fuentes, R., Lopes, F., Julian, V. (Eds.), Highlights in Practical Applications of Agents, Multi-Agent Systems, and Trust-worthiness. The PAAMS Collection. Springer International Publishing, Cham. volume 1233, pp. 302–313. URL: http://link.springer.com/10.1007/978-3-030-51999-5_25, doi:10.1007/978-3-030-51999-5_25.

Anthony Jnr, B., Abbas Petersen, S., Ahlers, D., Krogstie, J., 2020. API deployment for big data management towards sustainable energy prosumption in smart cities-a layered architecture perspective. International Journal of Sustainable Energy 39, 263–289. URL: https://www.tandfonline.com/doi/full/10.1080/14786451.2019.1684287, doi:10.1080/14786451.2019.1684287.

Batel, S., Devine-Wright, P., Tangeland, T., 2013. Social acceptance of low carbon energy and associated infrastructures: A critical discussion. Energy Policy 58, 1–5. URL: https://linkinghub.elsevier.com/retrieve/pii/S0301421513001729, doi:10.1016/j.enpol.2013.03.018.

Bauwens, T., Gotchev, B., Holstenkamp, L., 2016. What drives the development of community energy in Europe? The case of wind power cooperatives. Energy Research & Social Science 13, 136–147. URL: https://linkinghub.elsevier.com/retrieve/pii/S2214629615300943, doi:10.1016/j.erss.2015.12.016.

Beckel, C., Sadamori, L., Staake, T., Santini, S., 2014. Revealing household characteristics from smart meter data. Energy 78, 397–410. URL: https://linkinghub.elsevier.com/retrieve/pii/S0360544214011748, doi:10.1016/j.energy.2014.10.025.

Becker, J., Knackstedt, R., Pöppelbuß, J., 2009. Developing maturity models for IT management: a procedure model and its application. Business & Information Systems Engineering 1, 213–222. URL: http://link.springer.com/10.1007/s12599-009-0044-5, doi:10.1007/s12599-009-0044-5.

Belot, M., James, J., 2014. A new perspective on the issue of selection bias in randomized controlled field experiments. Economics Letters 124, 326–328.

URL: https://linkinghub.elsevier.com/retrieve/pii/S0165176514002122, doi:10.1016/j.econlet.2014.06.001.

Beyer, M., Kuhn, K.A., Meiler, C., Jablonski, S., Lenz, R., 2004. Towards a flexible, process-oriented IT architecture for an integrated healthcare network, in: Proceedings of the 2004 ACM symposium on Applied computing - SAC '04, ACM Press, Nicosia, Cyprus. p. 264. URL: http://portal.acm.org/citation.cfm?doid=967900.967958, doi:10.1145/967900.967958.

Bhattacherjee, A., 2012. Social science research: Principles, methods, and practices. University of South Florida. URL: http://repository.out.ac.tz/504/1/Social_Science_Research-_Principles_Methods_and_Practices.pdf.

Bichler, M., 2000. An experimental analysis of multi-attribute auctions. Decision Support Systems 29, 249–268. URL: https://linkinghub.elsevier.com/retrieve/pii/S0167923600000750, doi:10.1016/S0167-9236(00)00075-0.

Block, C., Neumann, D., Weinhardt, C., 2008. A market mechanism for energy allocation in micro-CHP grids, in: Proceedings of the 41st Annual Hawaii International Conference on System Sciences (HICSS 2008), IEEE, Waikoloa, HI. pp. 172–172. URL: https://ieeexplore.ieee.org/document/4438876/, doi:10.1109/HICSS.2008.27.

Blom, F., Farahmand, H., 2018. On the scalability of blockchain-supported local energy markets, in: 2018 International Conference on Smart Energy Systems and Technologies (SEST), IEEE, Sevilla. pp. 1–6. URL: https://ieeexplore.ieee.org/document/8495882/, doi:10.1109/SEST.2018.8495882.

Borchers, A.M., Duke, J.M., Parsons, G.R., 2007. Does willingness to pay for green energy differ by source? Energy Policy 35, 3327–3334. URL: https://www.sciencedirect.com/science/article/pii/S0301421506005131, doi:10.1016/j.enpol.2006.12.009.

Bose, S., Kremers, E., Mengelkamp, E.M., Eberbach, J., Weinhardt, C., 2021. Reinforcement learning in local energy markets. Energy Informatics 4, 7. URL: https://energyinformatics.springeropen.com/articles/10.1186/s42162-021-00141-z, doi:10.1186/s42162-021-00141-z.

Bourgeois, J., van der Linden, J., Kortuem, G., Price, B.A., Rimmer, C., 2014. Conversations with my washing machine: an in-the-wild study of demand shifting with self-generated energy, in: Proceedings of the 2014 ACM International Joint Conference on Pervasive and Ubiquitous Computing, Association for Computing Machinery, New York, NY, USA. pp. 459–470. URL: https://doi.org/10.1145/2632048.2632106, doi:10.1145/2632048.2632106.

Bremdal, B.A., Olivella-Rosell, P., Rajasekharan, J., Ilieva, I., 2017. Creating a local energy market. CIRED - Open Access Proceedings Journal 2017, 2649–2652. URL: https://digital-library.theiet.org/content/journals/10.1049/oap-cired.2017.0730, doi:10.1049/oap-cired.2017.0730.

vom Brocke, J., Fettke, P., Gau, M., Houy, C., Maedche, A., Morana, S., Seidel, S., 2017. Tool-support for design science research: Design principles and instantiation. Available at SSRN 2972803 URL: https://www.researchgate.net/profile/Jan-Vom-Brocke/publication/317185121_Tool-Support_for_Design_Science_Research_Design_Principles_and_Instantiation/links/59ca436a0f7e9bbfdc3678d6/Tool-Support-for-Design-Science-Research-Design-Principles-and-Instantiation.pdf.

vom Brocke, J., Watson, R.T., Dwyer, C., Elliot, S., Melville, N., 2013. Green information systems: Directives for the IS discipline. Communications of the association for information systems 33, 30. doi:10.17705/1CAIS.03330.

Brounen, D., Kok, N., Quigley, J.M., 2013. Energy literacy, awareness, and conservation behavior of residential households. Energy Economics 38, 42–50. URL: https://linkinghub.elsevier.com/retrieve/pii/S0140988313000327, doi:10.1016/j.eneco.2013.02.008.

de Bruin, T., Rosemann, M., others, 2006. A model to measure business process management maturity and improve performance. Business Process management: practical guidelines to successful implementations. J. Jeston and J. Nelis. Oxford, Butterworth-Heinemann .

Brummer, V., 2018. Community energy – benefits and barriers: A comparative literature review of Community Energy in the UK, Germany and the USA, the benefits it provides for society and the barriers it faces. Renewable and Sustainable Energy Reviews 94, 187–196. URL: https://www.sciencedirect.com/science/article/pii/S1364032118304507, doi:10.1016/j.rser.2018.06.013.

Buchmann, E., Kessler, S., Jochem, P., Bohm, K., 2013. The Costs of Privacy in Local Energy Markets, in: 2013 IEEE 15th Conference on Business Informatics, IEEE, Vienna, Austria. pp. 198–207. URL: http://ieeexplore.ieee.org/document/6642877/, doi:10.1109/CBI.2013.36.

Budiman, I., 2018. Enabling Community Participation for Social Innovation in the Energy Sector. Indonesian Journal of Energy 1. URL: https://ije-pyc.org/index.php/IJE/article/view/23, doi:10.33116/ije.v1i2.23.

Bundesministerium für Wirtschaft und Energie (BMWi), 2020. Energieeffizienz in Zahlen 2020. Technical Report. Bundesministerium für Wirtschaft und Energie (BMWi). URL: https://www.bmwi.de/Redaktion/DE/Publikationen/Energie/energieeffizienz-in-zahlen-2020.pdf?__blob=publicationFile&v=20.

Bundesnetzagentur, Bundeskartellamt, 2021. Monitoringbericht 2021. Technical Report. Bundesnetzagentur. Bonn. URL: https://www.bundesnetzagentur.de/SharedDocs/Mediathek/Monitoringberichte/Monitoringbericht_Energie2021.pdf?__blob=publicationFile&v=2.

Bundestag, D., 2021. Gesetz für den Ausbau erneuerbarer Energien (Erneuerbare-Energien-Gesetz - EEG 2021). URL: https://www.gesetze-im-internet.de/eeg_2014/.

Byström, H., 2016. Blockchains, real-time accounting, and the future of credit risk modeling. Ledger 4. URL: https://ledgerjournal.org/ojs/ledger/article/download/100/149.

Capellán-Pérez, I., Campos-Celador, A., Terés-Zubiaga, J., 2018. Renewable Energy Cooperatives as an instrument towards the energy transition in Spain. Energy Policy 123, 215–229. URL: https://linkinghub.elsevier.com/retrieve/pii/S0301421518305937, doi:10.1016/j.enpol.2018.08.064.

Caramizaru, A., Uihlein, A., 2020. Energy communities: an overview of energy and social innovation. Publications Office of the European Union. URL: https://publications.jrc.ec.europa.eu/repository/handle/JRC119433.

Chaboud, A.P., Chiquoine, B., Hjalmarsson, E., Vega, C., 2014. Rise of the machines: algorithmic trading in the foreign exchange market. The Journal of Finance 69, 2045–2084. URL: https://onlinelibrary.wiley.com/doi/10.1111/jofi.12186, doi:10.1111/jofi.12186.

Chakole, J.B., Kolhe, M.S., Mahapurush, G.D., Yadav, A., Kurhekar, M.P., 2021. A Q-learning agent for automated trading in equity stock markets. Expert Systems with Applications 163. URL: https://linkinghub.elsevier.com/retrieve/pii/S0957417420305856, doi:10.1016/j.eswa.2020.113761.

Chen, D.L., Schonger, M., Wickens, C., 2016. oTree—An open-source platform for laboratory, online, and field experiments. Journal of Behavioral and Experimental Finance 9, 88–97. URL: https://linkinghub.elsevier.com/retrieve/pii/S2214635016000101, doi:10.1016/j.jbef.2015.12.001.

Chen, T., Bu, S., 2019. Realistic peer-to-peer energy trading model for microgrids using deep reinforcement learning, in: 2019 IEEE PES Innovative Smart Grid Technologies Europe (ISGT-Europe), IEEE, Bucharest, Romania. pp. 1–5. URL: https://ieeexplore.ieee.org/document/8905731/, doi:10.1109/ISGTEurope.2019.8905731.

Chen, T., Su, W., 2018. Local energy trading behavior modeling With deep reinforcement learning. IEEE Access 6, 62806–62814. URL: https://ieeexplore.ieee.org/document/8496766/, doi:10.1109/ACCESS.2018.2876652.

Coalition contract 2021-2025, 2021. Mehr Fortschritt wagen - Bündnis für Freiheit, Gerechtigkeit und Nachhaltikeit. Technical Report. Die Bundesregierung. Berlin. URL: https://www.spd.de/fileadmin/Dokumente/Koalitionsvertrag/Koalitionsvertrag_2021-2025.pdf.

Collier, U., 1998. Liberalisation in the energy sector, environmental threat or opportunity? Deregulation in the European Union: Environmental Perspectives , 93–113.

Cornélusse, B., Savelli, I., Paoletti, S., Giannitrapani, A., Vicino, A., 2019. A community microgrid architecture with an internal local market. Applied Energy 242, 547–560. URL: https://linkinghub.elsevier.com/retrieve/pii/S0306261919305173, doi:10.1016/j.apenergy.2019.03.109.

Crawford, J.K., 2006. Project management maturity model. Auerbach Publications. URL: https://www.taylorfrancis.com/books/9780849379468, doi:10.1201/9780849379468.

Dalén, A., Krämer, J., 2017. Towards a user-centered feedback design for smart meter interfaces to support efficient energy-use choices: a design science approach. Business & Information Systems Engineering 59, 361–373. URL: http://link.springer.com/10.1007/s12599-017-0489-x, doi:10.1007/s12599-017-0489-x.

Dauer, D., vom Scheidt, F., Weinhardt, C., 2016. Towards smart distribution grids: a structured market engineering review. 6th Karlsruhe Service Summit, Karlsruhe, Germany; Grin Publishing: München, Germany URL: https://service-summer.ksri.kit.edu/downloads/Session_1A1_KSS_2016_paper_25.pdf.

De Clercq, S., Guerrero, C., 2018. Life cycle analysis (LCA) of the improved business models. BestRES project Deliverable 3. URL: http://bestres.eu/wp-content/uploads/2019/01/BestRES_D3.5.pdf.

Devine-Wright, P., 2005. Beyond NIMBYism: towards an integrated framework for understanding public perceptions of wind energy. Wind Energy 8, 125–139. URL: https://onlinelibrary.wiley.com/doi/10.1002/we.124, doi:10.1002/we.124.

Devine-Wright, P., 2009. Rethinking NIMBYism: The role of place attachment and place identity in explaining place-protective action. Journal of Community & Applied Social Psychology 19, 426–441. URL: https://onlinelibrary.wiley.com/doi/abs/10.1002/casp.1004, doi:https://doi.org/10.1002/casp.1004.

Ding, Y., Neumann, M.A., Budde, M., Beigl, M., Da Silva, P.G., Zhang, L., 2013. A control loop approach for integrating the future decentralized power markets and grids, in: 2013 IEEE International Conference on Smart Grid Communications (SmartGridComm), IEEE, Vancouver, BC, Canada. pp. 588–593. URL: http://ieeexplore.ieee.org/document/6688022/, doi:10.1109/SmartGridComm.2013.6688022.

El-Hawary, M.E., 2008. Introduction to electrical power systems. volume 50. John Wiley & Sons.

Elfwing, S., Uchibe, E., Doya, K., 2018. Sigmoid-weighted linear units for neural network function approximation in reinforcement learning. Neural Networks 107, 3–11. URL: https://linkinghub.elsevier.com/retrieve/pii/S0893608017302976, doi:10.1016/j.neunet.2017.12.012.

Emerson, P., 2013. The original Borda count and partial voting. Social Choice and Welfare 40, 353–358. URL: http://link.springer.com/10.1007/s00355-011-0603-9, doi:10.1007/s00355-011-0603-9.

Energiewende, A., 2019. European Energy Transition 2030: The Big Picture. Agora Energiewende , 104URL: https://www.agora-energiewende.de/fileadmin/Projekte/2019/EU_Big_Picture/153_EU-Big-Pic_WEB.pdf.

Energy, L., 2018a. Exergy - Business Whitepaper. URL: https://lo3energy.com/wp-content/uploads/2018/04/Exergy-BIZWhitepaper-v11.pdf.

Energy, L., 2018b. Exergy - Electric Power Technical Whitepaper. URL: http://www.truevaluemetrics.org/DBpdfs/Initiatives/Exergy/Exergy-2018-Technical-Whitepaper-v8.pdf.

Etukudor, C., Couraud, B., Robu, V., Früh, W.G., Flynn, D., Okereke, C., 2020. Automated negotiation for peer-to-peer electricity trading in local energy markets. Energies 13, 920. URL: https://www.mdpi.com/1996-1073/13/4/920, doi:10.3390/en13040920.

European Commission, 2019. The European Green Deal. URL: https://eur-lex.europa.eu/legal-content/EN/TXT/?qid=1596443911913&uri=CELEX:52019DC0640#document2.

European Commission, 2020. EU strategy on energy system integration. URL: https://eur-lex.europa.eu/legal-content/EN/TXT/HTML/?uri=CELEX:52020DC0299&from=EN.

European Energy Exchange, 2020. EEX OFT Contract Specifications. Technical Report. European Energy Exchange. URL: https://www.eex.com/fileadmin/EEX/Downloads/Trading/OTF_Market/EEX_OTF_Contract_Specifications/DE/20200101-eex-otf-contract-spezifications-002a-final-data.pdf.

European Parliament, 2020. Europe's one trillion climate finance plan | News | European Parliament. URL: https://www.europarl.europa.eu/news/en/headlines/society/20200109STO69927/europe-s-one-trillion-climate-finance-plan.

European Union Agency for the Cooperation of Energy Regulators, 2021. Annual Report on the Results of Monitoring the internal Electricity and Natural Gas Markets 2020. Technical Report. European Union Agency for the Cooperation of Energy Regulators. Ljubljana. URL: https://extranet.acer.europa.eu//Official_documents/Acts_of_the_Agency/Publication/ACER%20Market%20Monitoring%20Report%202020%20%E2%80%93%20Electricity%20Wholesale%20Market%20Volume.pdf.

Falk, A., Szech, N., 2013. Morals and markets. Science 340, 707–711. URL: https://www.sciencemag.org/lookup/doi/10.1126/science.1231566, doi:10.1126/science.1231566.

Faruqui, A., Sergici, S., Sharif, A., 2010. The impact of informational feedback on energy consumption—A survey of the experimental evidence. Energy 35, 1598–1608. URL: https://www.sciencedirect.com/science/article/pii/S0360544209003387, doi:10.1016/j.energy.2009.07.042.

Faruqui, A., Sergici, S., Warner, C., 2017. Arcturus 2.0 : A meta-analysis of time-varying rates for electricity. The Electricity Journal 30, 64–72. URL: https://linkinghub.elsevier.com/retrieve/pii/S1040619017302750, doi:10.1016/j.tej.2017.11.003.

Foederale Energien, 2018. Neu installierte Leistung Photovoltaik - Anteil Dachanlagen - Solar - Übersicht zur Entwicklung Erneuerbarer Energien in allen Bundesländern. URL: https://www.foederal-erneuerbar.de/uebersicht/bundeslaender/BW|BY|B|BB|HB|HH|HE|MV|NI|NRW|RLP|SL|SN|ST|SH|TH|D/kategorie/solar/auswahl/978-neu_installierte_lei/ordnung/2018.

Francisco, A., Taylor, J.E., 2019. Designing community-scale energy feedback. Energy Procedia 158, 4178–4183. URL: https://www.sciencedirect.com/science/article/pii/S1876610219308525, doi:10.1016/j.egypro.2019.01.812.

Fraunehofer ISE, 2021a. Aktuelle Fakten zur Photovoltaik in Deutschland. URL: https://www.ise.fraunhofer.de/de/veroeffentlichungen/studien/aktuelle-fakten-zur-photovoltaik-in-deutschland.html.

Fraunehofer ISE, 2021b. Public net electricity generation in germany 2020: share from renewables exceeds 50 percent. Technical Report. Fraunhofer-Gesellschaft zur Förderung der angewandten Forschung e.V. URL: https://www.ise.fraunhofer.de/en/press-media/news/2020/public-net-electricity-generation-in-germany-2020-share-from-renewables-exceeds-50-percent.html.

Froehlich, J., 2009. Promoting energy efficient behaviors in the home through feedback: The role of human-computer interaction, in: Proc. HCIC Workshop, pp. 1–11. URL: https://dada.cs.washington.edu/research/tr/2009/02/UW-CSE-09-02-01.PDF.

Gabler, A., Pennekamp-Jost, A., 2020. BGH konkretisiert Begriff der Kundenanlage. URL: https://www.hoffmannliebs.de/blog/Kundenanlage.

García-Lapresta, J.L., Martínez-Panero, M., 2002. Borda count versus approval voting: A fuzzy approach. Public Choice 112, 167–184. URL: https://www.academia.edu/download/47089235/Borda_Count_Versus_Approval_Voting_A_Fuz20160707-13264-8kplxc.pdf. publisher: Springer.

Gazafroudi, A.S., Khorasany, M., Razzaghi, R., Laaksonen, H., Shafie-khah, M., 2021. Hierarchical approach for coordinating energy and flexibility trading in local energy markets. Applied Energy 302, 117575. URL: https://linkinghub.elsevier.com/retrieve/pii/S0306261921009521, doi:10.1016/j.apenergy.2021.117575.

Gholami, R., Emrouznejad, A., Alnsour, Y., Kartal, H.B., Veselova, J., 2020. The impact of smart meter installation on attitude change towards energy consumption behavior among northern ireland households:. Journal of Global Information Management 28, 21–37. URL: http://services.igi-global.com/resolvedoi/resolve.aspx?doi=10.4018/JGIM.2020100102, doi:10.4018/JGIM.2020100102.

Gibson, D.L., Goldenson, D.R., Kost, K., 2006. Performance results of CMMI-based process improvement. Technical Report. Carnegie-Mellon Univ Pittsburgh Pa Software Engineering Inst. URL: https://apps.dtic.mil/sti/pdfs/ADA454687.pdf.

Gimpel, H., Mäkiö, J., 2006. Towards multi-attribute double auctions for financial markets. Electronic Markets 16, 130–139. URL: http://www.electronicmarkets.org/fileadmin/user_upload/doc/Issues/Volume_16/Issue_02/V16I2_Towards_Multi-Attribute_Double_Auctions_for_Financial_Markets.pdf.

Glaser, F., 2017. Pervasive decentralisation of digital infrastructures: a framework for blockchain enabled system and use case analysis, in: Proceedings of the 50th Hawaii International Conference on System Sciences (HICSS-50), Waikoloa Village, Hawaii. URL: https://scholarspace.manoa.hawaii.edu/bitstream/10125/41339/paper0190.pdf.

Glaser, F., Bezzenberger, L., 2015. Beyond cryptocurrencies-a taxonomy of decentralized consensus systems, in: 23rd European conference on information systems (ECIS), Münster, Germany. URL: https://scholar.archive.org/work/47gagwsgpbhtnfbisxy4wnqnti/access/wayback/https://aisel.aisnet.org/cgi/viewcontent.cgi?referer=&httpsredir=1&article=1056&context=ecis2015_cr.

Gnewuch, U., Morana, S., Heckmann, C., Maedche, A., 2018. Designing conversational agents for energy feedback, in: International Conference on Design Science Research in Information Systems and Technology, Springer. pp. 18–33. doi:https://doi.org/10.1007/978-3-319-91800-6_2.

Golla, A., Henni, S., Staudt, P., 2020. Scaling the concept of citizen energy communities through a platform-based decision support system. European Conference on Information Systems (ECIS) URL: https://www.researchgate.net/profile/Armin-Golla/publication/341287276_Scaling_the_Concept_of_Citizen_Energy_Communities_through_a_Platform-based_Decision_Support_System/links/5eb93352a6fdcc1f1dd0102b/Scaling-the-Concept-of-Citizen-Energy-Communities-through-a-Platform-based-Decision-Support-System.pdf.

Goncalves Da Silva, P., Ilic, D., Karnouskos, S., 2014. The impact of smart grid prosumer grouping on forecasting accuracy and its benefits for local electricity market trading. IEEE Transactions on Smart Grid 5, 402–410. URL: http://ieeexplore.ieee.org/document/6684330/, doi:10.1109/TSG.2013.2278868.

Gottschalk, M., Uslar, M., Delfs, C., 2017. The smart grid architecture model – SGAM, in: The Use Case and Smart Grid Architecture Model Approach. Springer International Publishing, Cham, pp. 41–61. URL: http://link.springer.com/10.1007/978-3-319-49229-2_3, doi:10.1007/978-3-319-49229-2_3.

Graf, C., Wozabal, D., 2013. Measuring competitiveness of the EPEX spot market for electricity. Energy Policy 62, 948–958. URL: https://linkinghub.elsevier.com/retrieve/pii/S0301421513006952, doi:10.1016/j.enpol.2013.07.052.

Green, J., Newman, P., 2017. Citizen utilities: The emerging power paradigm. Energy Policy 105, 283–293. URL: http://www.sciencedirect.com/science/article/pii/S0301421517300800, doi:10.1016/j.enpol.2017.02.004.

Gregor, S., Hevner, A.R., 2013. Positioning and presenting design science research for maximum impact. MIS quarterly , 337–355URL: https://www.academia.edu/download/45589610/Positioning_and_presenting_design_scienc20160512-6120-1a2fjqf.pdf.

Gregor, S., Kruse, L., Seidel, S., 2020. Research perspectives: the anatomy of a design principle. Journal of the Association for Information Systems 21, 1622–1652. URL: https://aisel.aisnet.org/jais/vol21/iss6/2/, doi:10.17705/1jais.00649.

Grimm, P., 2010. Social desirability bias URL: https://onlinelibrary.wiley.com/doi/10.1002/9781444316568.wiem02057, doi:10.1002/9781444316568.wiem02057.

Gui, E.M., Diesendorf, M., MacGill, I., 2017. Distributed energy infrastructure paradigm: Community microgrids in a new institutional economics context. Renewable and Sustainable Energy Reviews 72, 1355–1365. URL: https://linkinghub.elsevier.com/retrieve/pii/S1364032116307006, doi:10.1016/j.rser.2016.10.047.

Gui, E.M., MacGill, I., 2018. Typology of future clean energy communities: An exploratory structure, opportunities, and challenges. Energy Research & Social Science 35, 94–107. URL: https://linkinghub.elsevier.com/retrieve/pii/S221462961730347X, doi:10.1016/j.erss.2017.10.019.

Guillemette, M.G., Paré, G., 2012. Toward a new theory of the contribution of the IT function in organizations. MIS Quarterly , 529–551doi:https://doi.org/10.2307/41703466.

Gupta, R., Barnfield, L., Gregg, M., 2018. Exploring innovative community and household energy feedback approaches. Building Research & Information 46, 284–299. URL: https://doi.org/10.1080/09613218.2017.1356130, doi:10.1080/09613218.2017.1356130. publisher: Routledge _eprint: https://doi.org/10.1080/09613218.2017.1356130.

Haas, R., Eichhammer, W., Huber, C., Langniss, O., Lorenzoni, A., Madlener, R., Menanteau, P., Morthorst, P.E., Martins, A., Oniszk, A., 2004. How to promote renewable energy systems successfully and effectively. Energy Policy 32, 833–839.

Hardwin Spenkelink, Dennis de Vries, M.B., 2017. Blockchain Maturity Model. URL: https://assets.kpmg.com/content/dam/kpmg/nl/pdf/2017/advisory/

block\protect\discretionary{\char\hyphenchar\font}{}{}chain-maturity-model.pdf.

Heck, K., Mengelkamp, E., Weinhardt, C., 2020. Blockchain-based local energy markets: Decentralized trading on single-board computers. Energy Systems URL: http://link.springer.com/10.1007/s12667-020-00399-4, doi:10.1007/s12667-020-00399-4.

Held, J., Mannsdörfer, A., 2018. Der weite Begriff der Kundenanlage in § 3 nr. 24a enwg: Garant oder Hemmnis eines wirksamen Wettbewerbs. REE , 11URL: https://www.roedl.de/de-de/de/medien/publikationen/fachaufsaetze/energiewirtschaft/documents/weite-begriff-kundenanlage-held-mannsd%C3%B6rfer.pdf.

Henni, S., Staudt, P., Weinhardt, C., . A sharing economy for residential communities with PV-coupled battery storage: Benefits, pricing and participant matching. Applied Energy 301. URL: https://linkinghub.elsevier.com/retrieve/pii/S0306261921007583, doi:10.1016/j.apenergy.2021.117351.

Hensing, I., Pfaffenberger, W., Ströbele, W., 2014. Energiewirtschaft. Oldenbourg Wissenschaftsverlag.

Hevner, March, Park, Ram, 2004. Design science in information systems research. MIS Quarterly 28, 75. URL: https://www.jstor.org/stable/10.2307/25148625, doi:10.2307/25148625.

Hisschemöller, M., Sioziou, I., 2013. Boundary organisations for resource mobilisation: enhancing citizens' involvement in the Dutch energy transition. Environmental Politics 22, 792–810. URL: http://www.tandfonline.com/doi/abs/10.1080/09644016.2013.775724, doi:10.1080/09644016.2013.775724.

Holtschulte, D., Erlangga, A.S., Ortjohann, E., Kortenbruck, J., Leksawat, S., Schmelter, A., Premgamone, T., Morton, D., 2017. Local energy markets in Clustering Power System Approach for smart prosumers, in: 2017 6th International Conference on Clean Electrical Power (ICCEP), IEEE, Santa Margherita Ligure, Italy. pp. 215–222. URL: http://ieeexplore.ieee.org/document/8004818/, doi:10.1109/ICCEP.2017.8004818.

Huybrechts, B., Mertens, S., 2014. The relevance of the cooperative model in the field of renewable energy. Annals of Public and Cooperative Economics 85, 193–212. URL: https://onlinelibrary.wiley.com/doi/10.1111/apce.12038, doi:10.1111/apce.12038.

Hvelplund, F., 2006. Renewable energy and the need for local energy markets. Energy 31, 2293–2302. URL: https://linkinghub.elsevier.com/retrieve/pii/S0360544206000417, doi:10.1016/j.energy.2006.01.016.

Iivari, J., 2015. Distinguishing and contrasting two strategies for design science research. European Journal of Information Systems 24, 107–115. URL: https://www.tandfonline.com/doi/full/10.1057/ejis.2013.35, doi:10.1057/ejis.2013.35.

Ilic, D., Da Silva, P.G., Karnouskos, S., Griesemer, M., 2012. An energy market for trading electricity in smart grid neighbourhoods, in: 2012 6th IEEE International Conference on Digital Ecosystems and Technologies (DEST), IEEE, Campione d'Italia, Italy. pp. 1–6. URL: http://ieeexplore.ieee.org/document/6227918/, doi:10.1109/DEST.2012.6227918.

Ilic, M., Galiana, F., Fink, L. (Eds.), 1998. Power Systems Restructuring: Engineering and Economics. Power Electronics and Power Systems, Springer US. URL: https://www.springer.com/gp/book/9780792381631, doi:10.1007/978-1-4757-2883-5.

Imbault, F., Swiatek, M., de Beaufort, R., Plana, R., 2017. The green blockchain: Managing decentralized energy production and consumption, in: 2017 IEEE International Conference on Environment and Electrical Engineering and 2017 IEEE Industrial and Commercial Power Systems Europe (EEEIC / I&CPS Europe), IEEE, Milan, Italy. pp. 1–5. URL: http://ieeexplore.ieee.org/document/7977613/, doi:10.1109/EEEIC.2017.7977613.

Jabir, H., Teh, J., Ishak, D., Abunima, H., 2018. Impacts of demand-side management on electrical power systems: A review. Energies 11, 1050. URL: http://www.mdpi.com/1996-1073/11/5/1050, doi:10.3390/en11051050.

Jain, R.K., Taylor, J.E., Peschiera, G., 2012. Assessing eco-feedback interface usage and design to drive energy efficiency in buildings. Energy and Buildings 48, 8–17. URL: https://linkinghub.elsevier.com/retrieve/pii/S0378778811006499, doi:10.1016/j.enbuild.2011.12.033.

Joos, M., Staffell, I., 2018. Short-term integration costs of variable renewable energy: Wind curtailment and balancing in Britain and Germany. Renewable and Sustainable Energy Reviews 86, 45–65. URL: https://www.sciencedirect.com/science/article/pii/S1364032118300091, doi:10.1016/j.rser.2018.01.009.

Kabalci, Y., 2016. A survey on smart metering and smart grid communication. Renewable and Sustainable Energy Reviews 57, 302–318. URL: https://linkinghub.elsevier.com/retrieve/pii/S1364032115014975, doi:10.1016/j.rser.2015.12.114.

Kaenzig, J., Heinzle, S.L., Wüstenhagen, R., 2013. Whatever the customer wants, the customer gets? Exploring the gap between consumer preferences and default electricity products in Germany. Energy Policy 53, 311–322. URL: https://linkinghub.elsevier.com/retrieve/pii/S0301421512009469, doi:10.1016/j.enpol.2012.10.061.

Kaiser, R., 2014. Qualitative Experteninterviews: Konzeptionelle Grundlagen und praktische Durchführung. Springer-Verlag.

Karlin, B., Zinger, J.F., Ford, R., 2015. The effects of feedback on energy conservation: A meta-analysis. Psychological Bulletin 141, 1205–1227. URL: http://doi.apa.org/getdoi.cfm?doi=10.1037/a0039650, doi:10.1037/a0039650.

Kazhamiakin, R., Marconi, A., Martinelli, A., Pistore, M., Valetto, G., 2016. A gamification framework for the long-term engagement of smart citizens, in: 2016 IEEE International Smart Cities Conference (ISC2), IEEE, Trento, Italy. pp. 1–7. URL: http://ieeexplore.ieee.org/document/7580746/, doi:10.1109/ISC2.2016.7580746.

Ketter, W., Collins, J., Reddy, P., 2013. Power TAC: A competitive economic simulation of the smart grid. Energy Economics 39, 262–270.

URL: https://linkinghub.elsevier.com/retrieve/pii/S0140988313000959, doi:10.1016/j.eneco.2013.04.015.

Khorasany, M., Mishra, Y., Ledwich, G., 2018. Market framework for local energy trading: a review of potential designs and market clearing approaches. IET Generation, Transmission & Distribution 12, 5899–5908. URL: https://digital-library.theiet.org/content/journals/10.1049/iet-gtd.2018.5309, doi:10.1049/iet-gtd.2018.5309.

Kingma, D.P., Ba, J., 2017. Adam: a method for stochastic optimization. URL: https://arxiv.org/abs/1412.6980.

Kirpes, B., Mengelkamp, E., Schaal, G., Weinhardt, C., 2019. Design of a microgrid local energy market on a blockchain-based information system. it - Information Technology 61, 87–99. URL: https://www.degruyter.com/document/doi/10.1515/itit-2019-0012/html, doi:10.1515/itit-2019-0012.

Knieps, G., 2008. Wettbewerbsökonomie: Regulierungstheorie, Industrieökonomie, Wettbewerbspolitik. Springer-Verlag.

Knieps, G., 2016. Network Economics. Springer.

Koirala, B.P., Araghi, Y., Kroesen, M., Ghorbani, A., Hakvoort, R.A., Herder, P.M., 2018. Trust, awareness, and independence: Insights from a socio-psychological factor analysis of citizen knowledge and participation in community energy systems. Energy Research & Social Science 38, 33–40. URL: https://linkinghub.elsevier.com/retrieve/pii/S2214629618300641, doi:10.1016/j.erss.2018.01.009.

Koirala, B.P., Koliou, E., Friege, J., Hakvoort, R.A., Herder, P.M., 2016. Energetic communities for community energy: A review of key issues and trends shaping integrated community energy systems. Renewable and Sustainable Energy Reviews 56, 722–744. URL: https://linkinghub.elsevier.com/retrieve/pii/S1364032115013477, doi:10.1016/j.rser.2015.11.080.

Kremers, E., 2020. Intelligent local energy management through market mechanisms: Driving the German energy transition from the bottom-up. Energy

Reports 6, 108–116. URL: https://linkinghub.elsevier.com/retrieve/pii/S2352484720302092, doi:10.1016/j.egyr.2020.03.004.

Kuechler, B., Vaishnavi, V., 2008. On theory development in design science research: anatomy of a research project. European Journal of Information Systems 17, 489–504. URL: https://www.tandfonline.com/doi/full/10.1057/ejis.2008.40, doi:10.1057/ejis.2008.40.

Kunze, C., Becker, S., 2015. Collective ownership in renewable energy and opportunities for sustainable degrowth. Sustainability Science 10, 425–437. URL: http://link.springer.com/10.1007/s11625-015-0301-0, doi:10.1007/s11625-015-0301-0.

Lee, Y., Kim, J., 2002. From design features to financial performance: a comprehensive model of design principles for online stock trading sites. J. Electron. Commer. Res. 3, 128–143. URL: http://www.jecr.org/sites/default/files/03_3_p03.pdf.

Lenck, T., Podewils, C., Jahn, A., 2020. Wie weiter nach der EEG-Förderung? Solaranlagen zwischen Eigenverbrauch und Volleinspeisung. Technical Report. Agora Energiewende. URL: https://static.agora-energiewende.de/fileadmin/Projekte/2020/2020_06_goldenes_solarende/A-EW_188_Weiterbetrieb_PV-Anlagen_WEB.pdf.

Lennon, B., Dunphy, N.P., Sanvicente, E., 2019. Community acceptability and the energy transition: a citizens' perspective. Energy, Sustainability and Society 9, 35. URL: https://doi.org/10.1186/s13705-019-0218-z, doi:10.1186/s13705-019-0218-z.

Lezama, F., Soares, J., Hernandez-Leal, P., Kaisers, M., Pinto, T., Vale, Z., 2019. Local energy markets: paving the path toward fully transactive energy systems. IEEE Transactions on Power Systems 34, 4081–4088. URL: https://ieeexplore.ieee.org/document/8411502/, doi:10.1109/TPWRS.2018.2833959.

Lienhoop, N., 2018. Acceptance of wind energy and the role of financial and procedural participation: An investigation with focus groups and choice experiments.

Energy Policy 118, 97–105. URL: https://www.sciencedirect.com/science/article/pii/S0301421518301964, doi:10.1016/j.enpol.2018.03.063.

Long, C., Wu, J., Zhang, C., Cheng, M., Al-Wakeel, A., 2017. Feasibility of Peer-to-Peer energy trading in low Voltage electrical distribution networks. Energy Procedia 105, 2227–2232. URL: https://linkinghub.elsevier.com/retrieve/pii/S1876610217306860, doi:10.1016/j.egypro.2017.03.632.

Loock, C.M., Staake, T., Thiesse, F., 2013. Motivating energy-efficient behavior with green IS: An investigation of goal setting and the role of defaults. MIS Quarterly 37, 1313–1332. URL: http://www.jstor.org/stable/43825794.

Ludwin, W.G., 1978. Strategic voting and the borda method. Public Choice 33, 85–90. URL: http://link.springer.com/10.1007/BF00123946, doi:10.1007/BF00123946.

Ma, C., Rogers, A.A., Kragt, M.E., Zhang, F., Polyakov, M., Gibson, F., Chalak, M., Pandit, R., Tapsuwan, S., 2015. Consumers' willingness to pay for renewable energy: A meta-regression analysis. Resource and Energy Economics 42, 93–109. URL: https://www.sciencedirect.com/science/article/pii/S0928765515000536, doi:10.1016/j.reseneeco.2015.07.003.

Maedche, A., Gregor, S., Morana, S., Feine, J., 2019. Conceptualization of the problem space in design science research, in: International conference on design science research in information systems and technology, Springer. pp. 18–31. URL: https://www.researchgate.net/profile/Jasper-Feine/publication/333083808_Conceptualization_of_the_Problem_Space_in_Design_Science_Research/links/5ce39f8e299bf14d95abc089/Conceptualization-of-the-Problem-Space-in-Design-Science-Research.pdf.

Mazzola, L., Denzler, A., Christen, R., 2020. Towards a peer-to-peer energy market: an overview. arXiv preprint arXiv:2003.07940 URL: https://arxiv.org/pdf/2003.07940.

Meeus, L., Nouicer, w.A., 2020. How to put the citizen at the centre of the energy transition?, in: Chapters. Edward Elgar Publishing, pp. 153–163. URL: https://ideas.repec.org/h/elg/eechap/19187_8.html.

Mengelkamp, E., Diesing, J., Weinhardt, C., 2019a. Tracing local energy markets: A literature review. it - Information Technology 61, 101–110. URL: https://www.degruyter.com/document/doi/10.1515/itit-2019-0016/html, doi:10.1515/itit-2019-0016.

Mengelkamp, E., Gärttner, J., Rock, K., Kessler, S., Orsini, L., Weinhardt, C., 2018a. Designing microgrid energy markets. Applied Energy 210, 870–880. URL: https://linkinghub.elsevier.com/retrieve/pii/S030626191730805X, doi:10.1016/j.apenergy.2017.06.054.

Mengelkamp, E., Gärttner, J., Weinhardt, C., 2018b. Decentralizing energy systems through local energy markets: The LAMP-Project, in: Multikonferenz Wirtschaftsinformatik, Lüneburg, Germany. pp. 924–930. URL: https://mkwi2018.leuphana.de/wp-content/uploads/MKWI_90.pdf.

Mengelkamp, E., Gärttner, J., Weinhardt, C., 2018c. Intelligent agent strategies for residential customers in local electricity markets, in: Proceedings of the Ninth International Conference on Future Energy Systems, Association for Computing Machinery, Karlsruhe, Germany. pp. 97–107. URL: https://doi.org/10.1145/3208903.3208907, doi:10.1145/3208903.3208907.

Mengelkamp, E., Notheisen, B., Beer, C., Dauer, D., Weinhardt, C., 2018d. A blockchain-based smart grid: towards sustainable local energy markets. Computer Science - Research and Development 33, 207–214. URL: http://link.springer.com/10.1007/s00450-017-0360-9, doi:10.1007/s00450-017-0360-9.

Mengelkamp, E., Schlund, D., Weinhardt, C., 2019b. Development and real-world application of a taxonomy for business models in local energy markets. Applied Energy 256. URL: http://www.sciencedirect.com/science/article/pii/S0306261919316009, doi:10.1016/j.apenergy.2019.113913.

Mengelkamp, E., Schönland, T., Huber, J., Weinhardt, C., 2019c. The value of local electricity - A choice experiment among German residential customers. Energy Policy 130, 294–303. URL: https://linkinghub.elsevier.com/retrieve/pii/S0301421519302447, doi:10.1016/j.enpol.2019.04.008.

Mengelkamp, E., Staudt, P., Garttner, J., Weinhardt, C., 2017. Trading on local energy markets: A comparison of market designs and bidding strategies, in: 2017 14th International Conference on the European Energy Market (EEM), pp. 1–6. doi:10.1109/EEM.2017.7981938.

Mengelkamp, E., Staudt, P., Gärttner, J., Weinhardt, C., Huber, J., 2018e. Quantifying factors for participation in local electricity markets, in: 2018 15th International Conference on the European Energy Market (EEM), IEEE. pp. 1–5. URL: https://www.researchgate.net/profile/Esther-Mengelkamp/publication/328166584_Quantifying_Factors_for_Participation_in_Local_Electricity_Markets/links/5bd9dd8a4585150b2b944db0/Quantifying-Factors-for-Participation-in-Local-Electricity-Markets.pdf.

Meunier, C., 2019. Geplante Abstandsregeln für Windräder gefährden Klimaziele. URL: https://www.umweltbundesamt.de/themen/geplante-abstandsregeln-fuer-windraeder-gefaehrden.

Mitteldeutsche Netzgesellschaft Strom GmbH, 2020. Vergütung nach EEG - Welche Faktoren bestimmen die Vergütung im Verteilernetz der Mitnetz Strom. URL: https://www.mitnetz-strom.de/netzanschluss/stromerzeugung/betrieb/stromverg%c3%bctung/verg%c3%bctung-nach-eeg.

Mlynek, P., Misurec, J., Fujdiak, R., Kolka, Z., Pospichal, L., 2015. Heterogeneous networks for smart metering – power line and radio communication. Elektronika ir Elektrotechnika 21, 85–92. URL: http://eejournal.ktu.lt/index.php/elt/article/view/11515, doi:10.5755/j01.eee.21.2.11515.

Mnih, V., Kavukcuoglu, K., Silver, D., Rusu, A.A., Veness, J., Bellemare, M.G., Graves, A., Riedmiller, M., Fidjeland, A.K., Ostrovski, G., Petersen, S., Beattie, C., Sadik, A., Antonoglou, I., King, H., Kumaran, D., Wierstra, D., Legg, S., Hassabis, D., 2015. Human-level control through deep reinforcement learning. Nature 518, 529–533. URL: http://www.nature.com/articles/nature14236, doi:10.1038/nature14236.

Moret, F., Pinson, P., 2019. Energy Collectives: A community and fairness based approach to future electricity markets. IEEE Transactions on Power Systems 34, 3994–4004. URL: https://ieeexplore.ieee.org/document/8301552/, doi:10.1109/TPWRS.2018.2808961.

Morstyn, T., Farrell, N., Darby, S.J., McCulloch, M.D., 2018. Using peer-to-peer energy-trading platforms to incentivize prosumers to form federated power plants. Nature Energy 3, 94–101. URL: https://www.nature.com/articles/s41560-017-0075-y, doi:10.1038/s41560-017-0075-y.

Mousavi, S.S., Schukat, M., Howley, E., 2018. Deep reinforcement learning: An overview, in: Proceedings of SAI Intelligent Systems Conference (IntelliSys) 2016. volume 16, pp. 426–440. URL: http://link.springer.com/10.1007/978-3-319-56991-8_32, doi:10.1007/978-3-319-56991-8_32.

Munsing, E., Mather, J., Moura, S., 2017. Blockchains for decentralized optimization of energy resources in microgrid networks, in: 2017 IEEE Conference on Control Technology and Applications (CCTA), IEEE, Mauna Lani Resort, HI, USA. pp. 2164–2171. URL: http://ieeexplore.ieee.org/document/8062773/, doi:10.1109/CCTA.2017.8062773.

Musall, F.D., Kuik, O., 2011. Local acceptance of renewable energy—A case study from southeast Germany. Energy Policy 39, 3252–3260. URL: https://www.sciencedirect.com/science/article/pii/S0301421511001972, doi:10.1016/j.enpol.2011.03.017.

Nakabi, T.A., Toivanen, P., 2021. Deep reinforcement learning for energy management in a microgrid with flexible demand. Sustainable Energy, Grids and Networks 25, 100413. URL: https://linkinghub.elsevier.com/retrieve/pii/S2352467720303441, doi:10.1016/j.segan.2020.100413.

Nakamoto, S., 2008. Bitcoin: A peer-to-peer electronic cash system. Decentralized Business Review URL: https://www.debr.io/article/21260.pdf.

Navrud, S., Bråten, K.G., 2007. Consumers' preferences for green and brown electricity: a choice modelling approach. Revue d'economie politique Vol. 117, 795–811. URL: https://www.cairn.info/revue-d-economie-politique-2007-5-page-795.htm, doi:https://doi.org/10.3917/redp.175.0795.

Nguyen, T.T., Nguyen, N.D., Nahavandi, S., 2020. Deep Reinforcement Learning for Multiagent Systems: A Review of Challenges, Solutions, and Applications. IEEE Transactions on Cybernetics 50, 3826–3839. doi:10.1109/TCYB.2020.2977374.

Nisi, V., Nicoletti, D., Nisi, R., Nunes, N.J., 2011. Beyond eco-feedback: using art and emotional attachment to express energy consumption, in: Proceedings of the 8th ACM conference on Creativity and cognition - C&C '11, ACM Press, Atlanta, Georgia, USA. p. 381. URL: http://dl.acm.org/citation.cfm?doid=2069618.2069706, doi:10.1145/2069618.2069706.

Nuti, G., Mirghaemi, M., Treleaven, P., Yingsaeree, C., 2011. Algorithmic trading. Computer 44, 61–69. URL: http://ieeexplore.ieee.org/document/5696713/, doi:10.1109/MC.2011.31.

OECD, 2019. Renewable energy feed-in tariffs. URL: https://stats.oecd.org/Index.aspx?DataSetCode=RE_FIT#.

Okwuibe, G.C., Wadhwa, M., Brenner, T., Tzscheutschler, P., Hamacher, T., 2020. Intelligent bidding strategies in local electricity markets: a simulation-based analysis, in: 2020 IEEE Electric Power and Energy Conference (EPEC), IEEE. pp. 1–7. URL: https://ieeexplore.ieee.org/document/9320067/, doi:10.1109/EPEC48502.2020.9320067.

Olivella-Rosell, P., Lloret-Gallego, P., Munne-Collado, I., Villafafila-Robles, R., Sumper, A., Ottessen, S.O., Rajasekharan, J., Bremdal, B.A., 2018. Local flexibility market design for aggregators providing multiple flexibility services at distribution network level. Energies 11, 822. URL: https://www.mdpi.com/1996-1073/11/4/822, doi:10.3390/en11040822.

Orozco, C., Lilla, S., Borghetti, A., Napolitano, F., Tossani, F., 2019. An ADMM approach for day-ahead scheduling of a local energy community, in: 2019 IEEE Milan PowerTech, IEEE, Milan, Italy. pp. 1–6. URL: https://ieeexplore.ieee.org/document/8810578/, doi:10.1109/PTC.2019.8810578.

PankiRaj, J.S., Yassine, A., Choudhury, S., 2019. An auction mechanism for profit maximization of peer-to-peer energy trading in smart grids. Procedia Computer

Science 151, 361–368. URL: https://linkinghub.elsevier.com/retrieve/pii/S1877050919305125, doi:10.1016/j.procs.2019.04.050.

Parag, Y., Sovacool, B.K., 2016. Electricity market design for the prosumer era. Nature Energy 1, 1–6. URL: https://www.nature.com/articles/nenergy201632, doi:10.1038/nenergy.2016.32.

Parliament, E., 2019. Directive (EU) 2019/944 of the European Parliament and of the Council of 5 June 2019 on common rules for the internal market for electricity and amending Directive 2012/27/EU. URL: http://data.europa.eu/eli/dir/2019/944/oj/eng. Code Number: 158 Library Catalog: EUR-Lex.

Paulk, M., Curtis, B., Chrissis, M., Weber, C., 1993. Capability maturity model, version 1.1. IEEE Software 10, 18–27. URL: http://ieeexplore.ieee.org/document/219617/, doi:10.1109/52.219617.

Peffers, K., Tuunanen, T., Rothenberger, M.A., Chatterjee, S., 2007. A design science research methodology for information systems research. Journal of management information systems doi:https://doi.org/10.2753/MIS0742-1222240302.

Pekeč, A., Rothkopf, M.H., 2003. Combinatorial auction design. Management Science 49, 1485–1503. URL: http://pubsonline.informs.org/doi/abs/10.1287/mnsc.49.11.1485.20585, doi:10.1287/mnsc.49.11.1485.20585.

Perger, T., Wachter, L., Fleischhacker, A., Auer, H., 2021. PV sharing in local communities: Peer-to-peer trading under consideration of the prosumers' willingness-to-pay. Sustainable Cities and Society 66, 102634. URL: https://linkinghub.elsevier.com/retrieve/pii/S2210670720308519, doi:10.1016/j.scs.2020.102634.

Pielow, J.C., Ehlers, E., 2008. Ownership unbundling and constitutional conflict: a typical German debate. European Review of Energy Markets 2, 55–88. URL: https://www.eeinstitute.org/european-review-of-energy-market/EREM%206%20-%20Article%20Pielow%20-%20Ehlers.pdf.

Pilkington, M., 2016. Blockchain technology: principles and applications, in: Research Handbook on Digital Transformations. Edward Elgar Publishing, pp. 225–

253. URL: http://www.elgaronline.com/view/9781784717759.00019.xml, doi:10.4337/9781784717766.00019.

Pisa, M., Juden, M., 2017. Blockchain and economic development: Hype vs. reality. Center for Global Development Policy Paper 107, 150. URL: https://emsdialogues.org/wp-content/uploads/2020/02/blockchain-and-economic-development-hype-vs-reality.pdf.

Pouttu, A., Haapola, J., Ahokangas, P., Xu, Y., Kopsakangas-Savolainen, M., Porras, E., Matamoros, J., Kalalas, C., Alonso-Zarate, J., Gallego, F.D., Martin, J.M., Deconinck, G., Almasalma, H., Clayes, S., Wu, J., Meng Cheng, Li, F., Zhipeng Zhang, Rivas, D., Casado, S., 2017. P2P model for distributed energy trading, grid control and ICT for local smart grids, in: 2017 European Conference on Networks and Communications (EuCNC), IEEE, Oulu, Finland. pp. 1–6. URL: http://ieeexplore.ieee.org/document/7980652/, doi:10.1109/EuCNC.2017.7980652.

Preist, C., 1999. Economic agents for automated trading, in: Software Agents for Future Communication Systems. Springer Berlin Heidelberg, Berlin, Heidelberg, pp. 207–219. URL: http://link.springer.com/10.1007/978-3-642-58418-3_8, doi:10.1007/978-3-642-58418-3_8.

Pyrgou, A., Kylili, A., Fokaides, P.A., 2016. The future of the feed-in tariff (FiT) scheme in europe: The case of photovoltaics. Energy Policy 95, 94–102. URL: https://linkinghub.elsevier.com/retrieve/pii/S0301421516302257, doi:10.1016/j.enpol.2016.04.048.

Rademaekers, K., Slingenberg, A., Morsy, S., 2008. Review and analysis of eu wholesale energy markets. ECORYS Netherlands, EU DG TREN Final Report URL: https://ec.europa.eu/energy/sites/ener/files/documents/2008_eu_wholesale_energy_market_historical.pdf.

Ramchurn, S.D., Vytelingum, P., Rogers, A., Jennings, N.R., 2012. Putting the'smarts' into the smart grid: a grand challenge for artificial intelligence. Communications of the ACM 55, 86–97. URL: http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.570.92&rep=rep1&type=pdf.

Ramos, A., de Jonghe, C., Gómez, V., Belmans, R., 2016. Realizing the smart grid's potential: Defining local markets for flexibility. Utilities Policy 40, 26–35. doi:https://doi.org/10.1016/j.jup.2016.03.006.

Raveling, J., 2018. Wem gehören Windkraftanlagen? URL: https://www.wfb-bremen.de/de/page/stories/windenergie-bremen/wem-gehoeren-windkraftanlagen.

Reijnders, V.M., van der Laan, M.D., Dijkstra, R., 2020. Energy communities: a Dutch case study, in: Behind and Beyond the Meter. Elsevier, pp. 137–155. URL: https://linkinghub.elsevier.com/retrieve/pii/B9780128199510000062, doi:10.1016/B978-0-12-819951-0.00006-2.

Reis, I.F.G., Gonçalves, I., Lopes, M.A.R., Antunes, C.H., 2019. Residential demand-side flexibility in energy communities: a combination of optimization and agent modeling approaches, in: 2019 International Conference on Smart Energy Systems and Technologies (SEST), pp. 1–6. doi:10.1109/SEST.2019.8849152.

REN21, 2014. Renewables 2014 Global Status Report. Technical Report. Renewable Energy Policy Network for the 21st Century. Paris. URL: https://www.ren21.net/Portals/0/documents/Resources/GSR/2014/GSR2014_full%20report_low%20res.pdf.

REScoop, 2021. REScoop. URL: https://www.rescoop.eu/.

Richter, B., Golla, A., Welle, K., Staudt, P., Weinhardt, C., 2021. Local energy markets - an IT-architecture design. Energy Informatics 4, 35. URL: https://energyinformatics.springeropen.com/articles/10.1186/s42162-021-00164-6, doi:10.1186/s42162-021-00164-6.

Richter, B., Mengelkamp, E., Weinhardt, C., 2018. Maturity of blockchain technology in local electricity markets, in: 2018 15th International Conference on the European Energy Market (EEM), IEEE. pp. 1–6. doi:https://doi.org/10.1109/EEM.2018.8469955.

Richter, B., Mengelkamp, E., Weinhardt, C., 2019. Vote for your energy: a market mechanism for local energy markets based on the consumers' preferences, in: 2019

16th International Conference on the European Energy Market (EEM), IEEE, Ljubljana, Slovenia. pp. 1–6. URL: https://ieeexplore.ieee.org/document/8916544/, doi:10.1109/EEM.2019.8916544.

Richter, B., Staudt, P., Weinhardt, C., 2022a. Citizen Energy Communities - Insights Into Long-Term Participant Behavior From a Field Study. preprint. In Review. URL: https://www.researchsquare.com/article/rs-1299588/v1, doi:10.21203/rs.3.rs-1299588/v1.

Richter, B., Staudt, P., Weinhardt, C., 2022b. Designing Local Energy Market Applications. Scandinavian Journal of Information Systems Working Paper - Under Review.

Richter, B., Wohlfarth, J., Rörhle, D., Staudt, P., Weinhardt, C., 2022c. Impact of automated computational agents in local energy markets. ACM SIGENERGY Energy Informatics Review - Working Paper Under Review.

Ritchie, H., Roser, M., 2020. Energy. Our World in Data URL: https://ourworldindata.org/energy.

Romero-Rubio, C., de Andrés Díaz, J.R., 2015. Sustainable energy communities: a study contrasting Spain and Germany. Energy Policy 85, 397–409. URL: https://www.sciencedirect.com/science/article/pii/S030142151500230X, doi:10.1016/j.enpol.2015.06.012.

Rosemann, M., De Bruin, T., 2005. Towards a business process management maturity model, in: ECIS 2005 proceedings of the thirteenth European conference on information systems, Verlag and the London School of Economics. pp. 1–12.

Rosen, C., Madlener, R., 2012. An auction mechanism for local energy markets: Results from theory and simulation, in: 2012 Complexity in Engineering (COMPENG). Proceedings, IEEE, Aachen, Germany. pp. 1–4. URL: http://ieeexplore.ieee.org/document/6242961/, doi:10.1109/CompEng.2012.6242961.

Ross, J.W., 2003. Creating a strategic it architecture competency: Learning in stages. SSRN Electronic Journal URL: http://www.ssrn.com/abstract=416180, doi:10.2139/ssrn.416180.

Sangroya, D., Nayak, J.K., 2017. Factors influencing buying behaviour of green energy consumer. Journal of Cleaner Production 151, 393–405. URL: https://linkinghub.elsevier.com/retrieve/pii/S0959652617304444, doi:10.1016/j.jclepro.2017.03.010.

Schmid, S., 2020. Deutscher Bundestag - Bundestag vereinheitlicht Energieeinsparrecht für Gebäude. URL: https://www.bundestag.de/dokumente/textarchiv/2020/kw25-de-energieeinsparrecht-698640.

Schmidt, C., Buxmann, P., 2011. Outcomes and success factors of enterprise IT architecture management: empirical insight from the international financial services industry. European Journal of Information Systems 20, 168–185. URL: https://www.tandfonline.com/doi/full/10.1057/ejis.2010.68, doi:10.1057/ejis.2010.68.

Schram, W., Louwen, A., Lampropoulos, I., van Sark, W., 2019. Comparison of the greenhouse gas emission reduction potential of energy communities. Energies 12. URL: https://www.mdpi.com/1996-1073/12/23/4440, doi:10.3390/en12234440.

Schwartz, T., Denef, S., Stevens, G., Ramirez, L., Wulf, V., 2013. Cultivating energy literacy: results from a longitudinal living lab study of a home energy management system, in: Proceedings of the SIGCHI Conference on Human Factors in Computing Systems, ACM, Paris France. pp. 1193–1202. URL: https://dl.acm.org/doi/10.1145/2470654.2466154, doi:10.1145/2470654.2466154.

Schwenkenbecher, A., 2017. What is wrong with nimbys? renewable energy, landscape impacts and incommensurable values. Environmental Values 26, 711–732. doi:10.3197/096327117X15046905490353.

Schütz, A., Widjaja, T., Gregory, R., 2013. Escape from winchester mansion–toward a set of design principles to master complexity in it architectures, in: Thirty Fourth International Conference on Information Systems (ICIS), Milan. URL: https://aisel.aisnet.org/icis2013/proceedings/EngagedScholarship/2/.

Seidel, S., Bharati, P., Fridgen, G., Watson, R.T., Albizri, A., Boudreau, M.C.M., Butler, T., Chandra Kruse, L., Guzman, I., Karsten, H., Lee, H., Melville, N., Rush, D., Toland, J., Watts, S., 2017. The sustainability imperative in information systems research. Communications of the Association for Information Systems 40, 40–52. URL: http://aisel.aisnet.org/cais/vol40/iss1/3/, doi:10.17705/1CAIS.04003.

Seidel, S., Recker, J., Brocke, J.v., 2013. Sensemaking and sustainable practicing: functional affordances of information systems in green transformations. MIS Quarterly 37, 1275–1299. URL: http://www.jstor.org/stable/43825792.

Senior, A.W., Evans, R., Jumper, J., Kirkpatrick, J., Sifre, L., Green, T., Qin, C., Žídek, A., Nelson, A.W.R., Bridgland, A., Penedones, H., Petersen, S., Simonyan, K., Crossan, S., Kohli, P., Jones, D.T., Silver, D., Kavukcuoglu, K., Hassabis, D., 2020. Improved protein structure prediction using potentials from deep learning. Nature 577, 706–710. URL: http://www.nature.com/articles/s41586-019-1923-7, doi:10.1038/s41586-019-1923-7.

Sikorski, J.J., Haughton, J., Kraft, M., 2017. Blockchain technology in the chemical industry: Machine-to-machine electricity market. Applied Energy 195, 234–246. URL: https://linkinghub.elsevier.com/retrieve/pii/S0306261917302672, doi:10.1016/j.apenergy.2017.03.039.

Silver, D., Huang, A., Maddison, C.J., Guez, A., Sifre, L., van den Driessche, G., Schrittwieser, J., Antonoglou, I., Panneershelvam, V., Lanctot, M., Dieleman, S., Grewe, D., Nham, J., Kalchbrenner, N., Sutskever, I., Lillicrap, T., Leach, M., Kavukcuoglu, K., Graepel, T., Hassabis, D., 2016. Mastering the game of Go with deep neural networks and tree search. Nature 529, 484–489. URL: http://www.nature.com/articles/nature16961, doi:10.1038/nature16961.

Soeiro, S., Ferreira Dias, M., 2020. Renewable energy community and the European energy market: main motivations. Heliyon 6. URL: https://linkinghub.elsevier.com/retrieve/pii/S2405844020313554, doi:10.1016/j.heliyon.2020.e04511.

Sokołowski, M.M., 2020. Renewable and citizen energy communities in the European Union: how (not) to regulate community energy in national laws and policies. Journal of Energy & Natural Resources Law 38, 289–304. URL: https://www.tandfonline.com/doi/full/10.1080/02646811.2020.1759247, doi:10.1080/02646811.2020.1759247.

Sousa, T., Soares, T., Pinson, P., Moret, F., Baroche, T., Sorin, E., 2019. Peer-to-peer and community-based markets: A comprehensive review. Renewable and Sustainable Energy Reviews 104, 367–378. URL: https://linkinghub.elsevier.com/retrieve/pii/S1364032119300462, doi:10.1016/j.rser.2019.01.036.

Stadler, M., Cardoso, G., Mashayekh, S., Forget, T., DeForest, N., Agarwal, A., Schönbein, A., 2016. Value streams in microgrids: A literature review. Applied Energy 162, 980–989. URL: https://www.sciencedirect.com/science/article/pii/S0306261915013082, doi:10.1016/j.apenergy.2015.10.081.

Statista, 2018. CO2-Ausstoß weltweit nach Sektoren. URL: https://de.statista.com/statistik/daten/studie/167957/umfrage/verteilung-der-co-emissionen-weltweit-nach-bereich/.

Staudt, P., Gärttner, J., Weinhardt, C., 2018. Assessment of market power in local electricity markets with regards to competition and tacit collusion. Tagungsband Multikonferenz Wirtschaftsinformatik 2018 , 912–923URL: https://mkwi2018.leuphana.de/wp-content/uploads/MKWI_85.pdf.

Stede, J., May, N., 2020. Way Off: The Effect of Minimum Distance Regulation on the Deployment of Wind Power. SSRN Scholarly Paper ID 3603933. Social Science Research Network. Rochester, NY. URL: https://papers.ssrn.com/abstract=3603933, doi:10.2139/ssrn.3603933.

Stoft, S., 2002. Power system economics. Journal of Energy Literature 8, 94–99. Publisher: The Oxford Institute for Energy Studies.

Ströhle, P., Flath, C.M., 2016. Local matching of flexible load in smart grids. European Journal of Operational Research 253, 811–824. URL: https://linkinghub.elsevier.com/retrieve/pii/S037722171630114X, doi:10.1016/j.ejor.2016.03.004.

Sun, P., Guo, Z., Liu, S., Lan, J., Wang, J., Hu, Y., 2020. SmartFCT: Improving power-efficiency for data center networks with deep reinforcement learning. Computer Networks 179, 107255. URL: https://linkinghub.elsevier.com/retrieve/pii/S1389128620300384, doi:10.1016/j.comnet.2020.107255.

Sundt, S., Rehdanz, K., 2015. Consumers' willingness to pay for green electricity: A meta-analysis of the literature. Energy Economics 51, 1–8. URL: https://linkinghub.elsevier.com/retrieve/pii/S0140988315001784, doi:10.1016/j.eneco.2015.06.005.

Sutton, R.S., Barto, A.G., 2018. Reinforcement learning: An introduction. MIT press.

Tabi, A., Hille, S.L., Wüstenhagen, R., 2014. What makes people seal the green power deal? — Customer segmentation based on choice experiment in Germany. Ecological Economics 107, 206–215. URL: https://linkinghub.elsevier.com/retrieve/pii/S0921800914002742, doi:10.1016/j.ecolecon.2014.09.004.

Teotia, F., Bhakar, R., 2016. Local energy markets: Concept, design and operation, in: 2016 National Power Systems Conference (NPSC), pp. 1–6. doi:10.1109/NPSC.2016.7858975.

Tiefenbeck, V., Wörner, A., Schöb, S., Fleisch, E., Staake, T., 2019. Real-time feedback promotes energy conservation in the absence of volunteer selection bias and monetary incentives. Nature Energy 4, 35–41. URL: http://www.nature.com/articles/s41560-018-0282-1, doi:10.1038/s41560-018-0282-1.

Torbaghan, S.S., Blaauwbroek, N., Nguyen, P., Gibescu, M., 2016. Local market framework for exploiting flexibility from the end users, in: 2016 13th International Conference on the European Energy Market (EEM), pp. 1–6. doi:10.1109/EEM.2016.7521304.

Ullrich, S., 2021. Verbände verklagen Bundesregierung in Brüssel: EU-Recht nicht umgesetzt - ERNEUERBARE ENERGIEN. URL: https://www.erneuerbareenergien.de/politik/energiepolitik/verbaende-verklagen-bundesregierung-bruessel-eu-recht-nicht-umgesetzt.

United Nations, 2016. Key aspects of the Paris Agreement | UNFCCC. URL: https://unfccc.int/process-and-meetings/the-paris-agreement/the-paris-agreement/key-aspects-of-the-paris-agreement.

US Department of Commerce, 2020. Global Monitoring Laboratory - Carbon Cycle Greenhouse Gases. URL: https://gml.noaa.gov/ccgg/trends/.

US Department of Energy, 2017. Energy literacy: essential principles for energy education. URL: https://www.energy.gov/eere/education/energy-literacy-essential-principles-energy-education.

Varsier, N., Schwoerer, J., 2017. Capacity limits of LoRaWAN technology for smart metering applications, in: 2017 IEEE International Conference on Communications (ICC), IEEE, Paris, France. pp. 1–6. URL: http://ieeexplore.ieee.org/document/7996383/, doi:10.1109/ICC.2017.7996383.

Vasconcelos, M., Cramer, W., Schmitt, C., Amthor, A., Jessenberger, S., Ziegler, C., Armstorfer, A., Heringer, F., 2019. The PEBBLES project – enabling blockchain based transactive energy trading of energy & flexibility within a regional market. CIRED 2019 URL: https://www.cired-repository.org/handle/20.500.12455/363, doi:10.34890/591.

Venable, J., Pries-Heje, J., Baskerville, R., 2016. FEDS: a Framework for Evaluation in Design Science Research. European Journal of Information Systems 25, 77–89. URL: https://www.tandfonline.com/doi/full/10.1057/ejis.2014.36, doi:10.1057/ejis.2014.36.

Verbraucherzentrale NRW e.V., 2021. Was tun mit der Ü20 PV-Anlage, wenn die EEG-Förderung endet? URL: https://www.verbraucherzentrale.de/wissen/energie/erneuerbare-energien/was-tun-mit-der-ue20-pvanlage-wenn-die-eegfoerderung-endet-50846.

de Villena, M.M., Boukas, I., Mathieu, S., Vermeulen, E., Ernst, D., 2020. A framework to integrate flexibility bids into energy communities to improve self-consumption, in: 2020 IEEE Power Energy Society General Meeting (PESGM), pp. 1–5. doi:10.1109/PESGM41954.2020.9282036.

Vine, D., Buys, L., Morris, P., 2013. The effectiveness of energy feedback for conservation and peak demand: a literature review. Open Journal of Energy Efficiency 2, 7–15. doi:https://doi.org/10.4236/ojee.2013.21002.

Walker, G., 2008. What are the barriers and incentives for community-owned means of energy production and use? Energy Policy 36, 4401–4405. URL: https://linkinghub.elsevier.com/retrieve/pii/S0301421508004576, doi:10.1016/j.enpol.2008.09.032.

Walker, G., Devine-Wright, P., 2008. Community renewable energy: What should it mean? Energy Policy 36, 497–500. URL: https://www.sciencedirect.com/science/article/pii/S0301421507004739, doi:10.1016/j.enpol.2007.10.019.

Wallis, I., Ingalls, T., Campana, E., Vuong, C., 2013. Amateur musicians, long-term engagement, and HCI, in: Holland, S., Wilkie, K., Mulholland, P., Seago, A. (Eds.), Music and Human-Computer Interaction. Springer London, London, pp. 49–66. URL: http://link.springer.com/10.1007/978-1-4471-2990-5_3, doi:10.1007/978-1-4471-2990-5_3.

Wang, H., Chen, K., Xu, D., 2016a. A maturity model for blockchain adoption. Financial Innovation 2, 12. URL: http://jfin-swufe.springeropen.com/articles/10.1186/s40854-016-0031-z, doi:10.1186/s40854-016-0031-z.

Wang, Z., Schaul, T., Hessel, M., Hasselt, H., Lanctot, M., Freitas, N., 2016b. Dueling network architectures for deep reinforcement learning, in: Balcan, M.F., Weinberger, K.Q. (Eds.), Proceedings of The 33rd International Conference on Machine Learning, PMLR, New York, New York, USA. pp. 1995–2003. URL: https://proceedings.mlr.press/v48/wangf16.html.

Warneryd, M., Håkansson, M., Karltorp, K., 2020. Unpacking the complexity of community microgrids: A review of institutions' roles for development of microgrids. Renewable and Sustainable Energy Reviews 121, 109690. URL: https://linkinghub.elsevier.com/retrieve/pii/S1364032119308950, doi:10.1016/j.rser.2019.109690.

Warren, C.R., McFadyen, M., 2010. Does community ownership affect public attitudes to wind energy? A case study from south-west Scotland. Land Use Policy 27, 204–213. URL: https://linkinghub.elsevier.com/retrieve/pii/S0264837709000039, doi:10.1016/j.landusepol.2008.12.010.

Wattenhofer, R., 2016. The science of the blockchain. Inverted Forest Publishing. URL: https://lib.hpu.edu.vn/handle/123456789/28113.

Weinhardt, C., Gimpel, H., 2007. Market Engineering: An interdisciplinary research challenge, in: Jennings, N., Kersten, G., Ockenfels, A., Weinhardt, C. (Eds.), Negotiation and Market Engineering, Internationales Begegnungs- und Forschungszentrum für Informatik (IBFI), Schloss Dagstuhl, Germany, Dagstuhl, Germany. pp. 1–15. URL: http://drops.dagstuhl.de/opus/volltexte/2007/988.

Weinhardt, C., Mengelkamp, E., Cramer, W., Hambridge, S., Hobert, A., Kremers, E., Otter, W., Pinson, P., Tiefenbeck, V., Zade, M., 2019. How far along are local energy markets in the DACH+ region?: A comparative market engineering approach, in: Proceedings of the Tenth ACM International Conference on Future Energy Systems, ACM, Phoenix AZ USA. pp. 544–549. URL: https://dl.acm.org/doi/10.1145/3307772.3335318, doi:10.1145/3307772.3335318.

Wu, F.F., Varaiya, P.P., Hui, R.S., 2015. Smart grids with intelligent periphery: An architecture for the energy internet. Engineering 1, 436–446. URL: https://linkinghub.elsevier.com/retrieve/pii/S2095809916300248, doi:10.15302/J-ENG-2015111.

Wunder, M., Littman, M.L., Babes, M., (2010). Classes of multiagent q-learning dynamics with epsilon-greedy exploration, in: ICML, pp. 1167–1174. URL: https://icml.cc/Conferences/2010/papers/191.pdf.

Wörner, A., Ableitner, L., Meeuw, A., Wortmann, F., Tiefenbeck, V., 2019a. Peer-to-peer energy trading in the real world: market design and evaluation of the user value proposition, in: 40th International Conference of Information Systems, p. 1221. URL: https://aisel.aisnet.org/icis2019/sustainable_is/sustainable_is/2.

Wörner, A., Meeuw, A., Ableitner, L., Wortmann, F., Schopfer, S., Tiefenbeck, V., 2019b. Trading solar energy within the neighborhood: field implementation of a blockchain-based electricity market. Energy Informatics 2, 11. URL: https://doi.org/10.1186/s42162-019-0092-0, doi:10.1186/s42162-019-0092-0.

Wüstenhagen, R., Bilharz, M., 2006. Green energy market development in Germany: effective public policy and emerging customer demand. Energy Policy 34, 1681–1696. URL: https://linkinghub.elsevier.com/retrieve/pii/S030142150400237X, doi:10.1016/j.enpol.2004.07.013.

Wüstenhagen, R., Wolsink, M., Bürer, M.J., 2007. Social acceptance of renewable energy innovation: An introduction to the concept. Energy Policy 35, 2683–2691. URL: https://www.sciencedirect.com/science/article/pii/S0301421506004824, doi:10.1016/j.enpol.2006.12.001.

Yoo, J., Ready, R.C., 2014. Preference heterogeneity for renewable energy technology. Energy Economics 42, 101–114. URL: https://linkinghub.elsevier.com/retrieve/pii/S0140988313002909, doi:10.1016/j.eneco.2013.12.007.

Zade, M., Feroce, M., Guridi, A., Lumpp, S.D., Tzscheutschler, P., 2022a. Evaluating the added value of blockchains to local energy markets—Comparing the performance of blockchain-based and centralised implementations. IET Smart Grid , stg2.12058URL: https://onlinelibrary.wiley.com/doi/10.1049/stg2.12058, doi:10.1049/stg2.12058.

Zade, M., Lumpp, S.D., Tzscheutschler, P., Wagner, U., 2022b. Satisfying user preferences in community-based local energy markets — Auction-based clearing approaches. Applied Energy 306, 118004. URL: https://linkinghub.elsevier.com/retrieve/pii/S0306261921013003, doi:10.1016/j.apenergy.2021.118004.

Zahedi, A., 2011. A review of drivers, benefits, and challenges in integrating renewable energy sources into electricity grid. Renewable and Sustainable Energy Reviews 15, 4775–4779. URL: https://www.sciencedirect.com/science/article/pii/S1364032111003194, doi:10.1016/j.rser.2011.07.074.

Zhang, C., Wu, J., Zhou, Y., Cheng, M., Long, C., 2018. Peer-to-peer energy trading in a microgrid. Applied Energy 220, 1–12. URL: https://linkinghub.elsevier.com/retrieve/pii/S0306261918303398, doi:10.1016/j.apenergy.2018.03.010.

Zhang, F., Leitner, J., Milford, M., Upcroft, B., Corke, P., 2015. Towards vision-based deep reinforcement learning for robotic motion control doi:arXiv:1511.03791.

Zia, M.F., Benbouzid, M., Elbouchikhi, E., Muyeen, S.M., Techato, K., Guerrero, J.M., 2020. Microgrid transactive energy: Review, architectures, distributed ledger technologies, and market analysis. IEEE Access 8, 19410–19432. URL: https://ieeexplore.ieee.org/document/8966274/, doi:10.1109/ACCESS.2020.2968402.

Zwickl-Bernhard, S., Auer, H., 2021. Citizen participation in low-carbon energy systems: Energy communities and its impact on the electricity demand on neighborhood and national level. Energies 14, 305. URL: https://www.mdpi.com/1996-1073/14/2/305, doi:10.3390/en14020305.