Dissertation

Dynamic participation in energy communities with peer-to-peer trading

in fulfilment of the requirements for the degree of
Doktorin der technischen Wissenschaften

submitted at the
Energy Economics Group
Faculty of Electrical Engineering and Information Technology
Technische Universität Wien

by

Dipl.-Ing. Theresia Perger

Supervisor:

Prof. Dr. Johann Auer
Technische Universität Wien

Reviewer and Examiner:

Prof. Dr. Sonja Wogrin
Technische Universität Graz
Graz, Austria

Prof. Dr. Nina Hampl
Wirtschaftsuniversität Wien
Vienna, Austria

Vienna, December 2022

Abstract

Increasing decentralized electricity generation by distributed on-site photovoltaic (PV) systems and the amendment of regulatory frameworks in many countries promote the active participation of prosumers in the energy system. This thesis contributes to this topic by proposing both a peer-to-peer trading concept and a concept for dynamic participation in an energy community. A linear program optimizes peer-to-peer trading between prosumers of a local energy community with PV systems and battery energy storage systems (BESSs) by maximizing the community's welfare. Community members are characterized by their individual willingness-to-pay, which reflects their ambitions to reduce emissions from electricity consumption. For dynamic participation, a bi-level optimization model determines the optimal parameters of possible new participants based on the environmental or economic preferences of the community's original members. Next, the model is extended to a stochastic dynamic program to select new members. The community wants to plan a few years ahead, which includes the following uncertainties: (i) which members are leaving after each period, and (ii) which are the potential new members willing to join the community. The focus lies on the contractual design between the energy community and new entrants; the model calculates the duration of contracts endogenously. The results of a case study show improvements in the overall profitability of PV systems and BESSs and that willingness-to-pay is a promising tool to save emissions from electricity consumption. The results of dynamic participation demonstrate that environment-oriented prosumers opt for a new prosumer with high PV capacities installed and low electricity demand, whereas profit-oriented prosumers prefer a new member with high demand but no PV system capacity, presenting a new source of income. Sensitivity analyses indicate that new prosumers' willingness-to-pay has an important influence when the community must decide between two new members. The last set of results shows a sample energy community's decision-making process over a horizon of several years comparing the stochastic approach with a simple deterministic alternative solution.

Kurzfassung

Zunehmende dezentrale Stromerzeugung durch Vor-Ort Photovoltaikanlagen (PV) und Änderungen der regulatorischen Rahmenbedingungen in vielen Ländern fördern die aktive Beteiligung von Prosumern am Energiesystem. Diese Arbeit leistet einen Beitrag zu dem Thema, indem ein Peer-to-Peer-Handelskonzept und ein Konzept für die dynamische Teilnahme an Energiegemeinschaften entwickelt werden. Ein lineares Programm optimiert den Peer-to-Peer-Handel zwischen Prosumern einer lokalen Energiegemeinschaft mit PV-Anlagen und Batterie-Energiespeichersystemen (BESS) durch Maximierung der Wohlfahrt der Gemeinschaft. Die Mitglieder der Energiegemeinschaft werden durch ihre individuelle Zahlungsbereitschaft charakterisiert, die ihre Ambitionen zur Reduzierung der Emissionen aus dem Stromverbrauch widerspiegelt. Für eine dynamische Beteiligung bestimmt ein Bi-Level Optimierungsmodell die optimalen Parameter möglicher neuer Teilnehmer auf der Grundlage der ökologischen oder wirtschaftlichen Präferenzen der ursprünglichen Mitglieder der Gemeinschaft. Anschließend wird das Modell auf ein stochastisches dynamisches Programm zur Auswahl neuer Mitglieder erweitert. Die Gemeinschaft möchte einige Jahre im Voraus planen, was die folgenden Unsicherheiten beinhaltet: (i) welche Mitglieder nach jeder Periode ausscheiden und (ii) welches die potenziellen neuen Mitglieder sind, die bereit sind, der Gemeinschaft beizutreten. Der Schwerpunkt liegt auf der Vertragsgestaltung zwischen der Energiegemeinschaft und den neuen Mitgliedern; das Modell berechnet die Dauer der Verträge endogen. Die Ergebnisse einer Fallstudie zeigen, dass die Gesamtrentabilität von PV-Anlagen und BESS verbessert wird und dass die Zahlungsbereitschaft ein vielversprechendes Instrument zur Einsparung von Emissionen aus dem Stromverbrauch ist. Die Ergebnisse der dynamischen Beteiligung zeigen, dass umweltorientierte Prosumer sich für einen neuen Prosumer mit hohen PV-Kapazitäten und geringer

Stromnachfrage entscheiden, während gewinnorientierte Prosumer ein neues Mitglied mit hoher Nachfrage, aber ohne eigene PV-Anlagenkapazität bevorzugen, was eine neue Einkommensquelle darstellt. Sensitivitätsanalysen zeigen, dass die Zahlungsbereitschaft der neuen Prosumenten einen wichtigen Einfluss hat, wenn sich die Gemeinschaft zwischen zwei neuen Mitgliedern entscheiden muss. Die letzte Reihe von Ergebnissen zeigt den Entscheidungsprozess einer beispielhaften Energiegemeinschaft über einen Zeitraum von mehreren Jahren und vergleicht den stochastischen Ansatz mit einer einfachen deterministischen Alternativlösung.

Contents

Abbreviations

PV	Photovoltaic
BESS	Battery energy storage system
SoC	State of charge (of an energy storage system)
EV	Electric vehicle
DER	Distributed energy resources
GHG	Greenhouse gas
SME	Small-to-medium sized enterprise
SH	Single house
SAB	Small apartment building
DA	Day-Ahead (market)
DSO	Distribution system operator
EU	European Union
REC	Renewable Energy Community
CEC	Citizen Energy Community
EAG	Erneuerbaren Ausbaugesetz
REDII	Recast Renewable Energy Directive
ED	Electricity Directive
LP	Linear program
MILP	Mixed integer linear program
KKT	Karush-Kuhn-Tucker
MCP	mixed complementarity problem
MPEC	mathematical program with equilibrium constraints

1. Introduction

1.1. Motivation

The transformation of the energy sector toward sustainability is a significant and important challenge for today's society and the following generations, as the energy sector is a main driver for climate change. The Intergovernmental Panel on Climate Change (IPCC) has advised that to combat the impacts of global warming, greenhouse gas (GHG) emissions must be substantially reduced (Masson-Delmotte et al. (2018)). Globally, most of the energy used for electricity, heating and cooling, transport, and in the industry sector is generated by the combustion of fossil fuels, such as oil, natural gas, and coal. Switching to renewable primary energy is a major part of the solution toward sustainability. The electricity system plays an important role in this transformation. Due to sector coupling, other sectors such as transport will be increasingly electrified, which will lead to a high degree of electrification in the future. Therefore, electricity generation from renewable sources is key. In addition to the generation of hydro power, it is anticipated that a large share will be provided by wind and photovoltaic (PV) generation (IEA World Energy Outlook 2018 International Energy Agency (2018)). PV electricity generation on a ground-mounted utility scale and via building attached/-integrated PV systems has become increasingly prevalent in recent years. Notably, on-site PV electricity generation in the building environment accelerates the transition from a centralized energy system to a sustainable, decentralized, and local one.

Decentralized electricity production creates an opportunity for consumers such as households or small businesses to become producers at the same time (called *prosumers*) and thereby become active participants in the energy system. Especially with PV, it is relatively easy for prosumers to simultaneously produce and consume local renewable energy. Because a single prosumer is only a very small player in the system, a step forward for prosumers is to collectively organize themselves in so-called energy communities, where members have the opportunity to share or trade electricity with each other, and take advantage of load aggregation to further optimize the use of resources (Frieden et al. (2019)). There are different settings, in which PV generated electricity can be shared among prosumers. In multi-apartment buildings, tenants can share generation from a joint PV system. Furthermore, a microgrid is well suited to share (or to trade) locally generated electricity with other parties connected to the microgrid. In a more virtual way, renewable energy communities and citizen energy communities allow their participants to share electricity without necessarily being restricted to physical proximity.

The objectives of energy community members are mostly to increase their economic benefits and to contribute to climate change mitigation (Soeiro and Dias (2020b) and Bauwens (2019)). Hence, a fair pricing mechanism and trust in the community are crucial in this aspect. Furthermore, peer-to-peer trading and energy communities are opportunities to create new sustainable business models (F.G. Reis et al. (2021)). There are also opportunities to form local, decentralized electricity markets (Doumen et al. (2021) and Capper et al. (2022)). A common trading approach in scientific literature is peer-to-peer trading, where participants directly buy and sell electricity from/to their "peers" (Bjarghov et al. (2021), Sousa et al. (2019), and Tushar et al. (2021)). Peer-to-peer trading allows participants to increase their consumption of locally generated clean energy and to increase flexibility.

The importance of sustainable energy communities is growing, and the European Union's *Clean Energy Package* Directorate-General for Energy (European Commission) (2019) explicitly mentions energy communities, and acknowledges their great potential. The *Recast Renewable Energy Directive* (REDII, see European Commission, 2018) paves the way to enable renewable energy communities (REC). The therein defined measures will lead to higher acceptance and a better establishment of energy communities in the future, which means not only that the formation of energy communities is facilitated and that entry barriers are reduced, but also that stabilization, medium- and long-term developments, and selection processes in energy communities should be better understood. When transitioning toward a world with a high share of renewables, it can be assumed that local electricity markets, such as peer-to-peer trading or pool markets, are more established and sufficient regulatory framework exists.

This thesis focuses on energy communities that go *beyond the meter* and are not limited to a closed system boundary, such as a multi-apartment building or microgrid. Instead, the participants are located in different buildings, and they match and trade their PV generation and demand profiles via a local public distribution grid. However, it is necessary for the matching and trading algorithm to be governed by certain specifications and detailed rules. In the sense of "energy democratization," participation in an energy community occurs on a voluntary basis, and different incentives are offered to prosumers to entice them to join. In this respect, such incentives are reflected in the individual willingness-to-pay of each prosumer: the stronger the preference to buy local PV generation, the higher the willingness-to-pay. A model is developed in this thesis that optimizes peer-to-peer trading in an energy community while respecting the willingness-to-pay for local PV generation of individual prosumers. The aim of the energy community is not self-sufficiency, as the members of the community are connected to the public grid and they still purchase part of their electricity from the retailer. Instead, the aim of the energy community is to optimally use the resources and thus sustain without requiring any governmental financial support or subsidies. Furthermore, the analyses of this thesis consider existing energy communities wherein a community manager selects optimal new participants for the community in order to maximize benefits of its members.

1.2. Research questions

This thesis aims to answer three research questions related to energy communities. This Section describes each of the research questions in detail and then provides an overview on the relation between the research questions, as illustrated in Figures 1.1 and 1.2.

The core objective of this thesis is the evaluation of local energy communities with peer-to-peer trading and their development over time when members (prosumers) leave the community or new potential members would like to join. Therefore, from the community's point of view, optimal decisions for the selection of new participants have to be made. The objective of this thesis is addressed in three contributions.

In the first contribution of this thesis (Perger et al. (2021)), a linear program to optimally distribute PV generated electricity in an energy community using a peer-to-peer trading approach is developed to answer the first research question.

Research question 1: *How can a peer-to-peer trading approach in energy communities take into account prosumers' individual preferences for saving emissions caused by electricity consumption?*

The research question is aimed to be answered using a linear optimization problem with the objective to maximize community welfare. On one hand, welfare measures how much the community self-consumes its own generation, and on the other hand it measures how generation is distributed amongst members. We consider individual willingness-to-pay of prosumers, which reflect the prosumers' ambitions to reduce emissions from the grid, in the objective to maximize welfare of the community.

The second and third contributions are based on the first contribution and both contributions cover the selection process of energy communities searching for new members. The second contribution (Perger and Auer (2022)) addresses the second research question.

Research question 2: *How would an existing energy community collectively choose an optimal new member/prosumer to engage in peer-to-peer trading?*

The core objective of the second contribution is to investigate and optimize energy communities, wherein prosumers trade self-generated PV electricity with one another (peer-to-peer trading), including members' entry and exit over time. With the model developed in Perger and Auer (2022), it is possible to (i) choose between different prosumers, and (ii) choose the desired parameters of a new prosumer.

The third research question in addressed in the third contribution (Perger et al. (2022)).

Research question 3: *Does knowledge of future developments in energy communities help a community manager make better decisions selecting new participants than without considering future developments?*

The core objective of the third contribution is to optimize the selection process of an energy community over a period of several years including stochastic information. The decision of a community manager considers a portfolio of possible new entrants to the community, who might or might not join in the future. A stochastic dynamic optimization model is developed to answer research question three.

Now that the three research questions that comprise this thesis have been defined, we want to take a closer look on the relation between the research questions. Research question one only considers *static* energy communities. We look at a certain time frame (one year), where the set-up of community members does not change, and optimize PV sharing within the community. PV generation and electricity demand profiles vary hourly over a whole year. With research question two, we start to consider *dynamic* energy communities. In the following year, the energy community is faced with the exit of some existing members and the (possible) entry of new members, on whose acceptance or rejection into the community a decision is made. Research question two extends research question one in two dimensions: time scale and variation of members, see Figure 1.1. The third research question is in its way an extension of the second research question. We consider a longer time horizon (up to five years instead of one year), and a larger portfolio of possible prosumers.

Figure 1.2 shows how the research questions are related from a methodological

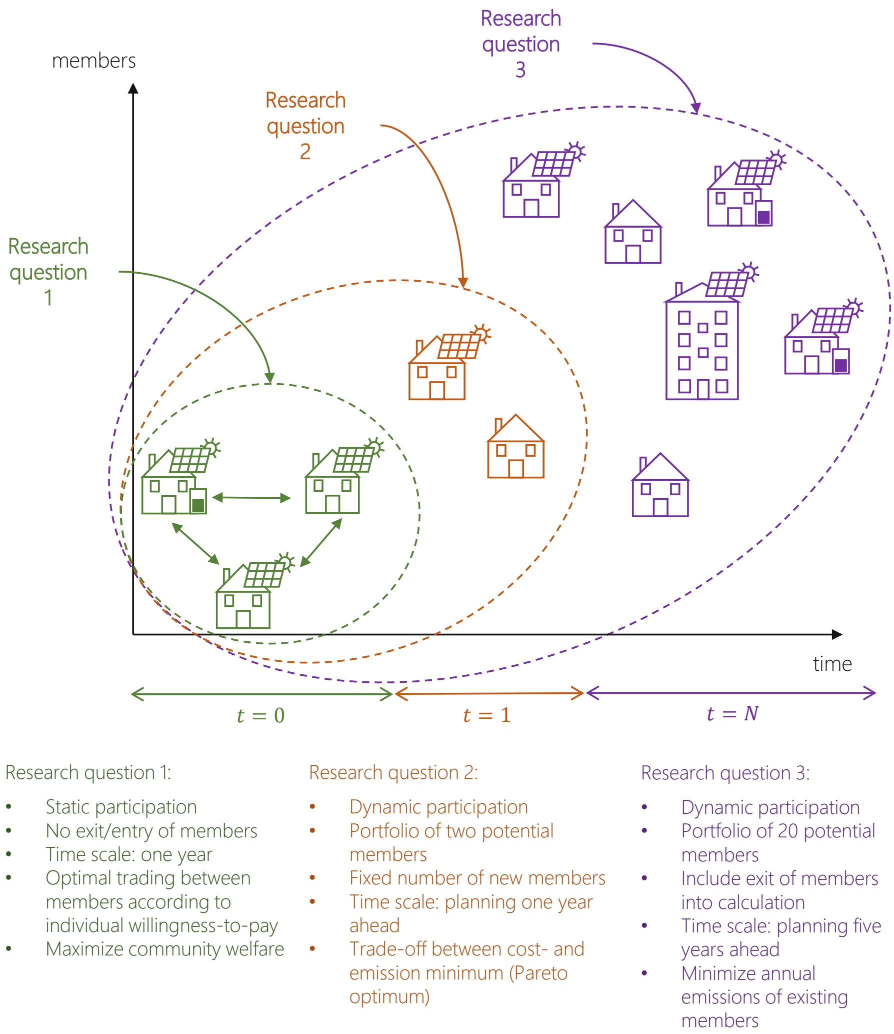


Figure 1.1.: Connection of the research questions from an energy economics point of view

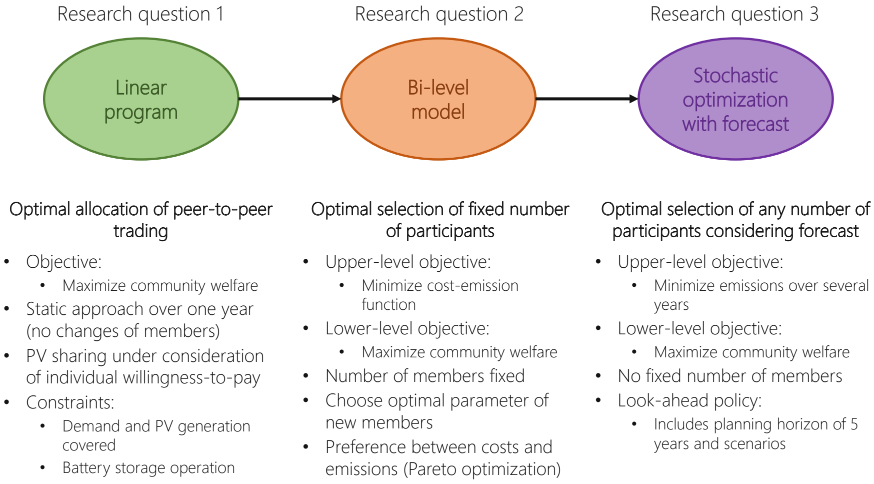


Figure 1.2.: Connection of the research questions from a methodological point of view (evolution of the method)

point of view. The linear program that was developed to answer research question one is the basis of the following modeling extensions: a bi-level model for research question two and a stochastic optimization for research question three. Chapter 3 explains the methods in detail.

1.3. Structure of the thesis

The remainder of this thesis is structures as follows: Chapter 2 presents a comprehensive literature review on energy communities and local electricity markets. The Chapter starts with definitions and regulatory aspects of energy communities, followed by reviews of state-of-the-art energy community modeling, stochastic optimization, and participation in energy communities from social and regulatory perspective. Progress beyond state-of-the-art concludes the Chapter.

Chapter 3 describes the methods applied to answer the research questions: linear program, bi-level model, and stochastic program. Each method is described in a dedicated section starting with overview on the problem followed by detailed mathematical formulation and nomenclature.

The presentation of results is divided into two parts: results of static participation (Chapter 4) and results of dynamic participation (Chapter 5). Chapter 4 presents results outlined by the first research question. A case study is set-up and results of different use cases and sensitivity analyses are shown.

Chapter 5 presents results outlined by the second and third research question. Similar to Chapter 4, case studies are set-up for each research question. The results for different scenarios of dynamic participation in energy communities are shown.

Overall findings with respect to research questions and synthesis of results is presented in Chapter 6. The last Chapter 7 completes the thesis with conclusions and outlook.

2. State-of-the-art and progress beyond

This Chapter provides a review and discussion of recent, relevant scientific literature regarding energy communities and peer-to-peer trading. The chapter starts with an introduction and definition of energy communities in Section 2.1. Next, Section 2.2 provides a discussion of recent scientific literature relevant to modeling of energy communities and peer-to-peer trading. The Section concludes with an overview on practical, real-life peer-to-peer trading implementations. Section 2.3 covers participation and contracts in energy communities from social and policy point of view. This Chapter concludes with the thesis' contribution to the progress beyond state-of-the-art in Section 2.4.

2.1. Energy communities versus microgrids

In Europe, a legal framework has recently been set by the European Commission's Clean Energy Package that promotes active consumer and prosumer participation, self-consumption, and energy communities (see Directorate-General for Energy (European Commission) (2019)).[1] The European Commission introduced the legal terms *Renewable Energy Community (REC)* and *Citizen Energy Community (CEC)* in the 2018 *Recast Renewable Energy Directive* (REDII, see European Commission, 2018) and the 2019 *Electricity Directive* (ED, see European Commission (2019)), respectively. Both REC

[1] The related regulatory frameworks of different EU countries are presented in Campos et al. (2020).

and CEC are legal entities, where members are private persons, small businesses, or local institutions, and participation is on an open and voluntary basis. Both RECs and CECs should offer environmental, economic, or social benefits for the community, and they do not primarily promote financial profits. For the main differences between RECs and CECs, please refer to Urbantschitsch (2020) and COMPILE (2019).

The concept of an energy community is fundamentally different to the concept of a microgrid. A microgrid is a physical distribution grid, or a defined part of a distribution grid, and all connected consumers and producers are part of the microgrid. A microgrid is part of the distribution grid, but it can still be *"disconnected and independently operated"* (see Rakos et al. (2012)). Ali et al. (2017) investigate the policies, incentives, and barriers associated with microgrids in the EU, US, and China, and further definitions, state-of-the-art, and case studies are found in Hossain et al. (2014), Hirsch et al. (2018), and Mohseni and Moghaddas-Tafreshi (2018).

In contrast, an energy community is not necessarily physically constrained to a certain area, and participation is on a voluntary basis. Literature provides different definitions of energy communities. For example, Gui and MacGill (2018) provide a very broad definition of an energy community as a social structure that has the primary goal of ensuring a cleaner energy supply, and the context may also be extended to water, transportation, and waste management. Gui and MacGill (ibid.) also introduce several concepts and typologies relating to energy communities, such as community-scale energy projects, virtual power plants (VPPs), peer-to-peer trading, and integrated community energy systems (ICES).

This thesis focuses on energy communities, where proximity between members is important on the one hand, but on the other hand, an energy community is not restricted to a certain neighborhood, and participation is on a voluntary basis. The technology portfolio includes photovoltaic systems (PV) and battery energy storage systems (BESS).

2.2. Energy communities modeling and implementations

2.2.1. PV sharing and energy communities

With a reduction in (or phasing out of) subsidized feed-in tariffs in many countries, it is necessary to increase the self-consumption of PV generated electricity to ensure that PV systems are still profitable. The load aggregation of multiple prosumers could therefore further increase profitability, and tenant electricity models play a key role in this respect. Fina et al. (vol. 2018) analyze sharing generated PV in multi-apartment buildings, and Roberts et al. (2019a) compare different arrangements, with the aim of maximizing the value of PV in apartment buildings. Then, Roberts et al. (2019b) evaluate the impact of using a shared battery energy storage system (BESS) in apartment buildings. Both a welfare maximization and a game-theoretic model for PV sharing in a multi-apartment building are developed in Fleischhacker et al. (2019), and multi-objective optimization for retrofitting an apartment (building including rooftop PV systems) is modeled in Fan and Xia (2017).

To go beyond a single buildings (and therefore *beyond the meter*), energy communities and peer-to-peer trading play a major role in managing the assets of distributed energy resources (DERs). Lüth et al. (2018) analyze battery flexibility in communities of prosumers and consumers, and Taşcıkaraoğlu (2018) analyzes shared energy storage in neighborhood networks. Furthermore, the study of Zepter et al. (2019) develops an interface to integrate communities of small prosumers into the day-ahead and intraday markets. Energy communities are very diverse, and their sizes, the number of actors involved, and the rules of sharing electricity are not standardized. In Abada et al. (2020), the viability of energy communities is shown to strongly depend on the rules for sharing electricity among the members.

Sharing electricity within a community has a higher potential to reduce GHG emissions than prosumers who act individually, as shown in Schram et al. (2019a). Schram et al. (ibid.) also calculate the greenhouse gas reduction in Austria, Belgium, France, Germany, Italy, the Netherlands, Portugal and

Spain due to the deployment of energy communities. Radl et al. (2020) compare the profitability of PV sharing in renewable energy communities across certain European countries. Collecting empirical evidence from four European countries, Wierling et al. (2018) found that energy cooperatives play an important role as enablers of the energy transition; however, they rely on governmental support to be competitive in the markets.

A net present value maximization for PV sharing in energy communities is performed in Fina et al. (2019) for four characteristic settlement patterns in Austria. Based on this, Fina et al. (2020) then find the cost-optimal potential of energy communities in Austria as a whole. Building on different scenarios for the European energy system in 2030, Zwickl-Bernhard and Auer (2021) analyze the potential influence of local energy communities on the national energy system of three reference countries. The effects of energy communities on the European electricity and heating system are analyzed in Backe et al. (2022), who found that the large scale roll-out of energy communities across Europe causes less capacity expansion across Europe and storage capacity expansion is decreased. Also, generation capacity expansion shifts from building heating capacity towards electricity production capacity.

2.2.2. Peer-to-peer trading models in literature

A comprehensive review of existing literature and modeling approaches in the field of peer-to-peer trading is presented in Soto et al. (2021). Most peer-to-peer trading models consider consumers, prosumers, an energy sharing coordinator, and an electricity supplier/retailer. There are different approaches to implementing the energy exchange and negotiation processes. In Soto et al. (ibid.), they are categorized into trading platforms, blockchain, game theory, simulation, optimization, and algorithms. Different non-cooperative game theory approaches for peer-to-peer trading of prosumers in microgrids with PV systems and battery storage are developed in Paudel et al. (2019) and Zhang et al. (2018). A canonical coalition game for peer-to-peer trading is presented in Tushar et al. (2018), while Fleischhacker et al. (2019) compares a Stackelberg game with a welfare maximization model for PV sharing in multi-apartment peer-to-peers. Continuous double auctioning models for peer-to-peer trading are developed in Li and Ma (2020), Chen et al. (2019), and Lin et al. (2019).

Trading preferences and decision strategies in peer-to-peer trading are evaluated in Hahnel et al. (2020). In order to provide maximum profits, the study of An et al. (2020) examines the optimal pricing strategies for the prosumer and consumer and their peer-to-peer trading partners, and a simulation of a peer-to-peer bidding system is conducted in Zhang et al. (2018). Notably, Sousa et al. (2019) suggest that peer-to-peer trading currently means either: (i) sharing of the excess renewable generation within a community, or (ii) buying electricity directly from a local renewable generator.

To decrease aggregated peak load, Bjarghov et al. (2020) developed a peer-to-peer trading capacity market formulated as a mixed complementarity problem (MCP). Sharing energy in a community-based market structure including fairness indicators is proposed in Moret and Pinson (2019). Jiang et al. (2021) presents a two-stage optimization approach, including social utility maximization in the first stage and payment bargaining in the second stage. Comparing three different models, Henriquez-Auba et al. (2021) found that a sharing economy model in which PV generation is traded among firms in a local spot market is a plausible pathway to maintaining and accelerating investments in PV systems, considering that feed-in programs are likely to be phased-out in the near future. Peer-to-peer markets with product differentiation are introduced in Sorin et al. (2019). In Hashemipour et al. (2021), virtual local energy markets with dynamic allocation of clusters that change on a daily basis are developed. Electric vehicles (EV) are pooled into the market to further increase flexibility.

Potential congestion and voltage problems in the distribution network considering the increasing penetration of DER are addressed in recent papers on peer-to-peer trading. For example, Dynge et al. (2021) analyze the impact of the low voltage grid on local markets. As the physical distribution network is used for trades in local electricity markets, a market clearing approach considering network fees and power losses is introduced in Paudel et al. (2020). The Euclidean distance of the distribution network between peers is included as grid-related costs using a product differentiation method in Orlandini et al. (2019). Another product differentiation approach is presented in Khorasany et al. (2020) in which network constraints are considered using a power transfer distribution factor to represent the contribution of transactions in the line flows. Considering electrical distances between prosumers, Guerrero et al. (2021) include a shortest path algorithm in their peer-to-peer market design and compare stable-matching and continuous double auction allocation mechanisms. An optimization problem solving matching between peers, including least-cost energy path algorithms, is proposed by Jogunola et al. (2020).

2.2.3. Stochastic modeling and optimization of energy communities

In the field of energy system analysis, there are many decisions that require dealing with uncertainty, especially due to growing volatile renewable generation (wind and solar) and price variations. Yue et al. (2018) identified four methods to tackle uncertainties: Monte Carlo analysis, stochastic programming, robust optimization, and modeling to generate alternatives. About one third of the studies reviewed in Yue et al. (ibid.) apply formal uncertainty techniques. The majority of energy system models use sensitivity or scenario analyses to include effects of uncertainty.

We find different stochastic optimization approaches within microgrids and (smart) energy communities in scientific literature. Energy management of a smart community with electric vehicle charging using a scenario-based stochastic model predictive control framework is presented in Zhou et al. (2022). Among other stochastic parameters, moving-horizon probabilistic models are applied for the prediction of the arrival time of EVs. Kara et al. (2022) show a pooled local flexibility market design under demand uncertainty and stochastic bidding process, which can reduce the costs of grid operation. Net-zero communities are modeled in Karunathilake et al. (2019) using a fuzzy multi-criteria decision making approach: Renewable energies are selected based on a life-cycle perspective and under uncertainty. Neyestani et al. (2015) analyze smart local networks, where customers can choose between alternative solutions of energy supply according to their own preferences. Customers' decisions are addressed by a stochastic modeling approach. Robust optimal on-line scheduling of an energy community, where renewable energy sources including a community storage are shared, is accomplished in Scarabaggio et al. (2021) using a stochastic model predictive control (MPC) approach. Uncertainty from forecast of inflexible demand profiles and renewable production curves are included. In Corinaldesi et al. (2020), the operating strategy for the flexibility of end-users is modeled using a rolling horizon approach, including trades at Day-Ahead and Intraday spot markets. A scenario-based stochastic multi-energy microgrid investment planning model to minimize costs is presented in Ehsan and Yang (2019). Again regarding a microgrid, a two-stage program for unit commitment is combined with a Markov decision process in Shin et al. (2017) considering wind uncertainties. Ahmadi et al. (2022) developed a bi-level stochastic optimization for microgrids. Jiao et al. (2022) present a combined robust and stochastic MPC for EV charging stations in microgrids.

In this section, we introduced models that include uncertainty in the planning and the operation of energy communities. We found that stochastic parameters concern, among others, renewable generation profiles, energy demand of prosumers, or EV charging. Some models include individual preferences of prosumers, e.g., in Neyestani et al. (2015), where preferences of customers to choose from alternative energy sources are included in their modeling approach. We found that little attention is paid to individual preferences of prosumers and their willingness to participate in energy communities or local electricity markets.

2.2.4. Practical peer-to-peer model implementations

Park and Yong (2017) introduce peer-to-peer trading concepts and provide a comparative review. Zhang et al. (2017) also review different peer-to-peer trading concepts, for example that of *Piclo* in the UK (see Piclo (2020)), the *Brooklyn Microgrid* (Mengelkamp et al. (2018) and Brooklyn Microgrid Microgrid (2020)), and *Vandebron* in the Netherlands (see Vandebron (2020)). Customers using *Piclo* buy local renewable electricity and generators have full transparency on a half-hourly basis. The *Exergy* platform of the *Brooklyn Mi-*

crogrid allows the prosumer to conduct autonomous electricity transactions almost in real time. *Vandebron* allows producers of renewables to set their own prices, and consumers then select a supplier. *OurPower* is a platform for producers and consumers of renewable, decentralized electricity that is implemented by an Austrian energy cooperative (see OurPower (2020)), and the project *P2PQ* optimizes PV self-consumption and tests peer-to-peer trading concepts via blockchain (see open4innovation (2018)). The *sonnenCommunity* (see sonnenGroup (2020)) in Germany, Austria, Switzerland, and Italy allows prosumers to share their electricity with other members of the *sonnenCommunity*, and members of this community do not need to also use a conventional electricity provider. In addition, people who join *efriends* can invest in PV projects of SMEs and subsequently buy renewable PV generation from there (see eFriends Energy GmbH (2020)). Other recent projects are presented by *BestRES* (see BestRES (2018)).

2.3. Participation in energy communities

2.3.1. Participation in local energy markets or communities from a policy and social perspective

As already mentioned in the beginning of this Chapter in Section 2.1, a number of legal instruments are included in the European Union's Clean Energy Package (Directorate-General for Energy (European Commission) (2019)) introducing the legal framework to establish the sharing/trading of self-generated electricity and to initiate economic incentives for its practice. EU member states are obliged to enable the entrance of these active participants into markets. Furthermore, the Clean Energy Package introduced a definition of *peer-to-peer trading*. Nevertheless, many regulatory aspects of peer-to-peer trading remain unclear. A review of current European policies, legislation, and possible legal issues related to peer-to-peer trading and energy communities in electricity markets is presented in Almeida et al. (2021). The European guidelines of the Clean Energy Package as transposed into Austrian law is analyzed in Fina and Fechner (2021).

Azarova et al. (2019) analyze how to design a Renewable Energy Community to increase social acceptance, finding that acceptance for solar farms and power-to-gas infrastructure is high, mixed for wind farms, and low for gas power plants and power lines. To gain more knowledge regarding individuals' willingness to participate in energy communities, using regression analysis, Koirala et al. (2018) conducted a survey in the Netherlands to determine the importance of factors such as environmental concerns, renewable acceptance, community trust, and resistance (among others). According to the survey, perceived barriers for participation include lack of time, financial reasons, satisfaction with the status quo of the energy system, and no trust in the neighborhood.

According to the analysis in Hackbarth and Löbbe (2020) focusing on intentions of private households to participate in peer-to-peer trading mechanisms in Germany, highly interested potential participants exhibit environmental rather than economic preferences, and are drawn to innovative pricing schemes. Soeiro and Ferreira Dias (2020) find that reliability is a key component and that citizens recognize the added non-monetary values of renewable energy communities.

In contrast to Germany and the Netherlands, there is a delay in the development and integration of RECs in Southern European countries. Using a survey in Spain and Portugal, Soeiro and Dias (2020a) aims to understand the motivations of members in energy communities.

To ensure a just energy transition to a carbon-neutral economy, energy community projects should be observed from a social perspective (Longo et al. (2020)) as well. How vulnerable groups might benefit from renewable energy communities is explored in Hanke et al. (2021), who investigated 71 RECs in Europe. In addition, the inclusion of vulnerable consumers in the energy transition, who are generally underrepresented in REC projects, is discussed in Hanke and Lowitzsch (2020). The enabling framework to support inclusion remains rather unclear and should not languish as an idea on paper; therefore, lawmakers and policymakers should develop incentives targeting both RECs and individual vulnerable consumers. Policy advice for new European rules for RECs are derived in Hoicka et al. (2021).

Regarding peer-to-peer trading concepts in particular, Reis et al. (2020) developed a multi-agent framework to model peer-to-peer electricity within energy communities with an emphasis on vulnerable consumers and members' economic outcomes, considering fairness in the distribution of energy resources. Fair revenue sharing and exit clauses are examined in Fioriti et al. (2021), to identify the optimal sizing of energy communities.

2.3.2. Participation and contracts in energy communities

Main research topics within the field of energy communities and local electricity markets are the barriers and incentives to participation of prosumers in energy communities. In this regard, the contracts and formation of energy communities are key. A literature review summarizing recent publications to derive challenges and barriers in energy communities from a consumer perspective is found in Lazdins et al. (2021). At European level, Boulanger et al. (2021) provide a qualitative overview of energy community concepts and strategies that lead to their creation and growth. Bauwens (2019) make a distinction between incentives of members of small and large communities: Financial motives are most important for members of large communities, while non-economic drivers (environmental, social, and other) dominate for members of smaller, local communities.

Energy communities are opportunities to possibly create new (sustainable) business models (F.G. Reis et al. (2021)). An optimistic outlook on possible business models in the context of energy communities is brought by Cielo et al. (2021), where sizing of PV systems and electrochemical energy storage is optimized solving a mixed integer linear program leading to an internal rate of return of 11%. Investments via consumer stock ownership plans as the prototype business model for renewable energy communities are introduced in Lowitzsch (2020). Roversi et al. (2022) investigate how energy communities and climate city contracts are key interventions to face the ambitious goal of implementing citizens centered and climate-neutral cities.

In local electricity markets and especially in peer-to-peer trading, dynamics and diversity of the actors involved have to be considered. Creating dynamic peer-to-peer clusters for virtual local electricity markets to optimally match load and renewable generation profiles for an EV flexibility marketplace is presented in Hashemipour et al. (2021). Diverse DER portfolio characteristics of prosumers are included in the study of Qiu et al. (2021), who developed a multi-agent deep reinforcement learning approach to address the peer-to-peer trading problem. The concept of so-called (smart) contracts in energy communities or peer-to-peer trading is described, among others, in the following literature: Kirli et al. (2022) reviews smart contracts in energy systems, which are applied, e.g., in peer-to-peer trading, electric vehicle charging, and demand-side response. Kirli et al. (ibid.) propose a systematic model of the smart contracting process to guide researcher and practitioners in this field. Chakraborty et al. (2020) developed an automated peer-to-peer negotiation strategy for settling energy contracts under consideration of prosumers' individual and heterogeneous preferences over societal and environmental criteria. Wang et al. (2020) propose an energy contract based on Shapley values to allocate profits among participants in a fair way. Another automated negotiation process of bilateral energy contracts is presented in Pinto et al. (2018).

An energy community is a small, tangible social unit, wherein trust and confidence in the community are key. Automated, smart contracts for trading, as seen in Kirli et al. (2022), Chakraborty et al. (2020), Wang et al. (2020), Pinto et al. (2018) and virtual energy communities (Hashemipour et al. (2021)) are useful and supporting instruments. This thesis goes beyond these short-term optimal allocation and trading contracts; we also consider the medium- to long-term development of an energy community.

2.4. Contribution to the progress beyond state-of-the-art

In relation to the research questions defined in Section 1.2 and the literature presented in this Chapter, this thesis' contribution to the progress beyond state-of-the-art is presented in the following.

In respect to research question one, a peer-to-peer trading model was developed that considers the willingness-to-pay of individual members. Compared to the variety of modeling approaches shown in Section 2.2.2, the approach developed in this thesis includes the following novelties:

- The prosumers not only share their PV surplus with the community, but the total amount of PV electricity generation is peer-to-peer traded within the community to optimally allocate resources while respecting each of the member's willingness-to-pay. In this respect, prosumers can create a greater profit margin by selling their PV electricity generation to community members who have a higher willingness-to-pay. In addition, prosumers who are interested in minimizing their environmental footprint can purchase greater amounts of clean PV electricity generation. Many different nuances between profit maximization and emission minimization are also possible.

- This concept means that prosumers do not prefer their own PV electricity generation over other prosumers' PV generation and it paves the way for energy communities to attain a sharing economy.

- The individual willingness-to-pay of each community member is a very comprehensible function that is derived directly from GHG emissions having an equivalent CO_2 price in EUR/tCO_2. It is a price that prosumers are willing to pay on top of the electricity price and is their individual and voluntary contribution to emission reduction targets.

- Prosumers are therefore able to calculate the reduction in direct emissions (in tons of CO_2) that is a result of them sharing PV generated electricity. The willingness-to-pay is derived considering marginal emissions which in turn reflect the actual hourly emission savings. With the proposed method, prosumers can individually account for their environmental impact and footprint.

In respect to research question two, a method is developed based on the peer-to-peer allocation mechanism presented in Perger et al. (2021) to optimize energy communities with peer-to-peer trading over the years.

- We developed a framework to including members' entry and exit in energy communities.

- A novel peer-to-peer model is proposed that simultaneously provides (i) an allocation mechanism for electricity trades between members and (ii) a new member's selection process. Both (i) and (ii) take the prosumers' individual preferences into account.

- The selection process, which is of particular interest, operates from the perspective of the community members, wherein community members are searching for "optimal fitting participants" as opposed to optimal technologies.

- The insights gained from the results and sensitivity analyses expand the understanding of the importance of participants' individual preferences. These insights offer practical considerations to help establish stable and prosperous local energy communities.

In respect to research question three, the selection process as suggested by Perger and Auer (2022) is extended to include a stochastic forecast of a horizon of five years.

- We consider the medium- to long-term development and stabilization of an energy community. We ask how to assign contracts in energy communities, such that participants are assured that the community is evolving according to their needs, and trust is strengthened.

- To our knowledge, preferences of prosumers to join or leave an energy community as stochastic input are not analyzed in any other paper.

- Finally, the explicit search for optimal participants for an energy community instead of searching for an optimal technology portfolio, as it is state-of-the-art in most papers, is a prominent aspect of this work. With increasing number of prosumers in the energy system and energy communities as an established instrument, selection of participants will become more and more standard practice.

3. Methods

This chapter describes in detail the methods that are developed to answer the research questions defined in Section 1.2. Therefore, this chapter is divided into three parts, each focusing on one of the methods. In Section 3.1, a linear program (LP) to answer the first research question is presented. Next, Section 3.2 presents a bi-level problem to solve dynamic participation as posed by the second research question, and in Section 3.3, a stochastic approach to dynamic participation to answer the third research question is presented. Each section is organized as follows. We start with an overview on the methodology including flow charts, then we continue with a description of the optimization problem including mathematical formulation, and finally we present nomenclature. For some detailed equations, as well as model verification and validation, please refer to Appendix A. First, we provide an overview on the main characteristics of our three methods in Table 3.1.

Table 3.1.: Overview on the methods developed and applied in this thesis

Research question	1	2	3
Method	Linear Program	Bi-level	Stochastic
Time scale:	1 year	1+1 years	1+5 years
New members:	none	fixed number	any number
Selection criteria:	no selection	emissions and costs	emissions
Selection of:	no selection	parameters and members	members
Time resolution:	hourly (one year)	hourly (representative days)	hourly (representative days)
Github repository:	T. Perger (2021)	T. Perger (2021)	T. Perger (2022)

3.1. Peer-to-peer trading model for static participation (linear program)

3.1.1. Overview on the methodology

The linear optimization model[1] developed in this work is described in detail in this section. In general, local energy communities with the following properties are considered:

- Members of the community are either consumers, producers, or both (*prosumers*). For simplicity, all members are referred to as prosumers throughout the paper.
- The members are households or small-to-medium-sized enterprises (SMEs).
- The incentives for participants to join the energy community vary between (i) consuming local PV electricity, (ii) contributing to increasing the community's self-consumption, (iii) improving the PV system's profitability, (iv) avoiding emissions, and (v) others.
- The community is based on fully voluntary participation. Joining or leaving the energy community is on a voluntary basis, and the willingness-to-pay for the community's generated PV electricity is individually set (the minimum price is equal to the retail electricity price).
- The technology portfolio includes PV systems and BESS.
- Each household is connected to the public distribution grid, which is used to conduct peer-to-peer trading. The case study presented in this thesis is a set-up in which all the prosumers are located in the same section of the local distribution system.

[1] Acronym of the model: FRESH:COM (**F**ai**R** **E**nergy **SH**aring in local **COM**munities). The model is currently being developed in the Horizon 2020 project openENTRANCE (see https://openentrance.eu).

- The objective function of the model maximizes the community welfare, and this is expressed in monetary terms.

Figure 3.1 shows a flow chart of the methodology. The sequence used in the modeling approach is as follows:

- Members joining the energy community are defined and the following prosumer input data are collected for the model: electricity demand profile, PV generation profile, and battery parameters. It is important to note that size of the PV system is not optimized for the community.[2] It is assumed that prosumers, who join the community, already have a PV system designed according to their roof top area and orientation, and suitable to their annual demand.

- The willingness-to-pay of each prosumer is calculated as explained in Section 3.1.2.2.

- A linear optimization problem (LP) is set-up, and the objective function and constraints are defined according to Equations (3.3a)-(3.3g).

- The linear optimization problem is solved.

- The results for the community set-up are analyzed with respect to the amount of electricity traded and the revenues and emission savings of the prosumer.

3.1.2. Mathematical formulation

This section explains the optimization model in detail. Community welfare is first defined in this context, willingness-to-pay of prosumers is then explained, and the mathematical formulation of the objective function and constraints of the model are then presented.

[2] Optimal capacity allocation of PV systems and BESSs in energy communities are developed in Fina et al. (2019), for example.

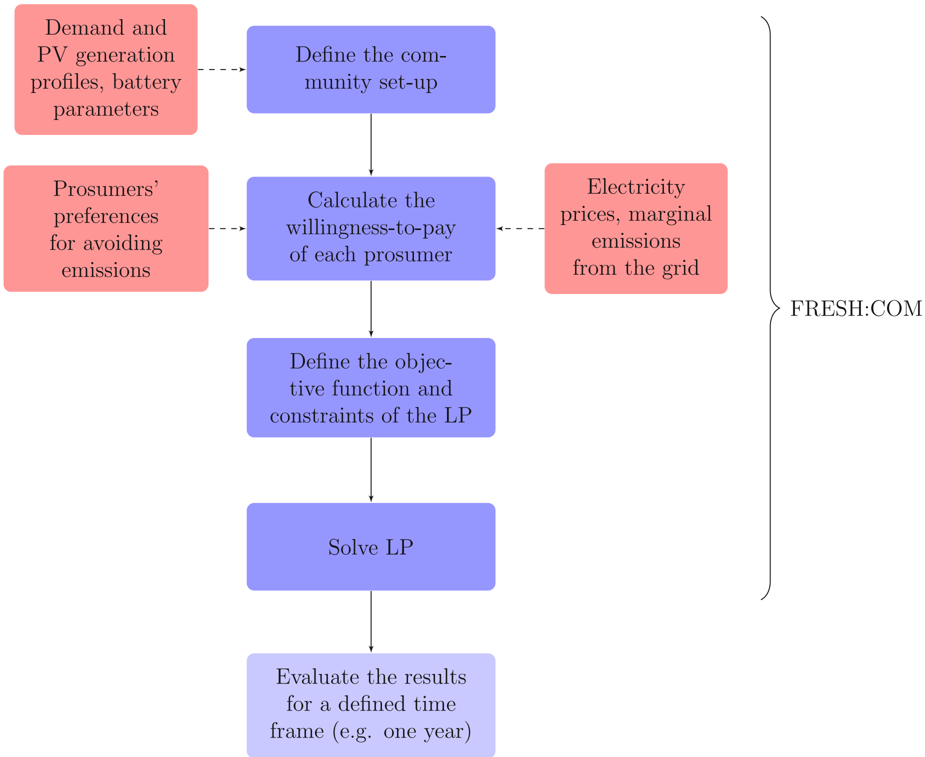


Figure 3.1.: Flow chart of the optimization model FRESH:COM

3.1.2.1. Definition of community welfare

The objective of the model is to maximize the community welfare. To make the abstract term *community welfare* more tangible, the individual members of the energy community are considered on the one hand, and the energy community as a whole is considered on the other hand.[3]

Part I of community welfare measures the optimal resource allocation on the level of the community as a whole, and overall self-consumption is maximized by peer-to-peer trading among members. In other words, the community

[3]The here defined community welfare is based on social welfare, which comprises two parts: producer and consumer welfare. Producer welfare corresponds to part I – the community as a whole acting as a producer to maximize profits. Consumer welfare corresponds to part II and considers the demand function (here: willingness-to-pay).

minimizes its electricity bill from the retailer. Part II of community welfare is maximized when the share of PV generation is optimally assigned to each member of the community under consideration of their individual willingness-to-pay. Community welfare, CW, is defined as

$$CW = \underbrace{\sum_{t\in\mathcal{T},i\in\mathcal{I}} p_t^{G_{out}} q_{i,t}^{G_{out}} - \sum_{t\in\mathcal{T},i\in\mathcal{I}} p_t^{G_{in}} q_{i,t}^{G_{in}}}_{\mathrm{I}} + \underbrace{\sum_{t\in\mathcal{T},i,j\in\mathcal{I}} wtp_{i,j,t} q_{i,j,t}^{share}}_{\mathrm{II}}. \quad (3.1)$$

With this approach, prosumers not only negotiate the PV surplus, but the entire amount of PV electricity generated is traded within the community, without preference for self-consumption, and solely according to each individual's willingness-to-pay. As willingness-to-pay also depends on avoiding GHG emission, community welfare indirectly includes emission preferences.

3.1.2.2. Definition of willingness-to-pay

As explained above, the willingness-to-pay of an individual member determines how much PV generated electricity is shared between the community members and how it is distributed. The main idea behind the willingness-to-pay above the retail electricity price for purchases from the grid relates to an individual's preference for reducing marginal emissions from the grid. Similar to marginal costs, marginal emissions are emitted when another unit of electricity (kWh or MWh) is produced in the wider electricity system, and the time variant vector e_t (in tCO_2/kWh) represents the marginal emissions. This means that the GHG emissions from a marginal power plant are considered instead of the average emission factor. Each prosumer, j, can choose an individual weighting factor, w_j, (in EUR/tCO_2), which represents the amount they are willing to pay on top of the retailer's price, because marginal emissions will be avoided by buying the locally produced PV generated electricity.

The willingness-to-pay can thus be determined in relation to the retailer's electricity price, $p_t^{G_{in}}$, plus the premium for avoiding emissions as a product of the individual weighting factor, w_j, and the marginal emissions, e_t, as

$$wtp_{i,j,t} = p_t^{G_{in}} + w_j \cdot e_t \quad (3.2)$$

$q_{i,j,t}^{share}$ is therefore distributed according to the emission factor w_j of each prosumer. Ultimately, this means that prosumers do not prefer their own PV generation over other prosumers' PV generation.

3.1.2.3. Objective function and constraints

Figure 3.2 shows a sketch of a small, energy-trading community. The figure helps to illustrate the following mathematical representation and formulation of the optimization model, FRESH:COM. Including BESSs and PV systems in the technological portfolio of the community, the optimization problem can be formulated as follows.

$$\max_{\substack{\{q_{i,t}^{G_{in}}, q_{i,t}^{G_{out}}, q_{i,j,t}^{share}, \\ q_{i,t}^{B_{in}}, q_{i,t}^{B_{out}}, SoC_{i,t}\}}} \sum_{t \in \mathcal{T}, i \in \mathcal{I}} p_t^{G_{out}} q_{i,t}^{G_{out}} - \sum_{t \in \mathcal{T}, i \in \mathcal{I}} p_t^{G_{in}} q_{i,t}^{G_{in}} + \sum_{t \in \mathcal{T}, i,j \in \mathcal{I}} wtp_{i,j,t} q_{i,j,t}^{share} \tag{3.3a}$$

$$\text{subject to} \quad q_{i,t}^{load} = q_{i,t}^{G_{in}} + q_{i,t}^{B_{out}} + \sum_{j \in \mathcal{I}} q_{j,i,t}^{share} \tag{3.3b}$$

$$q_{i,t}^{PV} = q_{i,t}^{G_{out}} + q_{i,t}^{B_{in}} + \sum_{j \in \mathcal{I}} q_{i,j,t}^{share} \tag{3.3c}$$

$$SoC_{i,t} = SoC_{i,t-1} + q_{i,t}^{B_{in}} \cdot \eta^B - q_{i,t}^{B_{out}} / \eta^B \tag{3.3d}$$

$$SoC_i^{min} \leq SoC_{i,t} \leq SoC_i^{max} \tag{3.3e}$$

$$q_{i,t}^{B_{in}}, q_{i,t}^{B_{out}} \leq q_i^{B_{max}} \tag{3.3f}$$

$$q_{i,t}^{G_{in}}, q_{i,t}^{G_{out}}, q_{i,j,t}^{share}, q_{i,t}^{B_{in}}, q_{i,t}^{B_{out}}, SoC_{i,t} \geq 0 \tag{3.3g}$$

for all $i, j \in \mathcal{I}$ and $t \in \mathcal{T}$. The objective expressed in Equation (3.3a) to maximize the community welfare described in Section 3.1.2.1. Equations (3.3b) and (3.3c) are constraints for covering the demand and PV generation of each prosumer at each time, and Equation (3.3d) determines the state of charge ($SoC_{i,t}$) of the batteries.[4] Equations (3.3e) and (3.3f) limit the state of charge and the (dis-)charging power to their physical boundaries. Finally, the non-negativity constraints are represented by Equation (3.3g).

[4]Technically, it is possible to simultaneously charge and discharge the BESS using this approach. However, this is avoided here by using the efficiency factor $\eta^B < 1$.

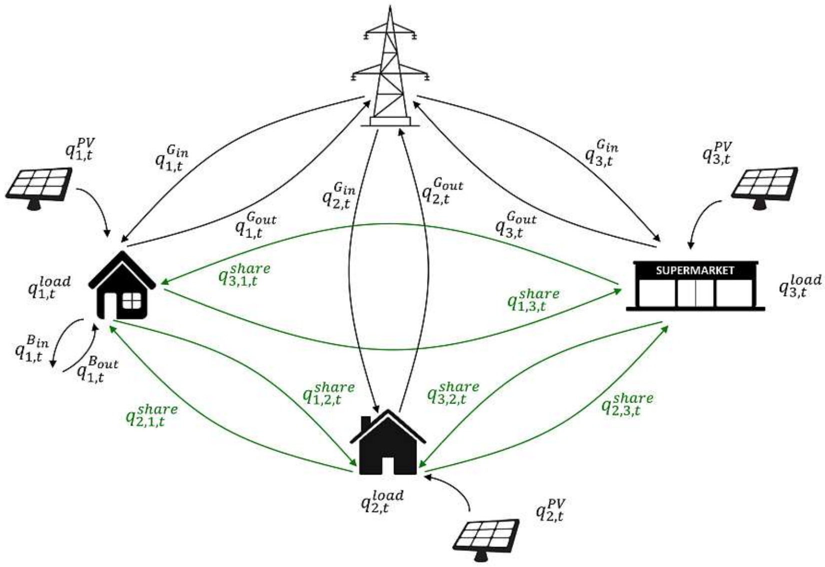


Figure 3.2.: Sketch of electricity trading in a small energy community comprising three members

3.1.3. Nomenclature peer-to-peer trading model for static participation

Variable	Explanation	Unit
$t \in \mathcal{T} = \{1, \ldots, T\}$	Time steps	
$i \in \mathcal{I} = \{1, \ldots, N\}$	Index of the prosumers	
Input		
$q_{i,t}^{PV}$	PV generation of prosumer i	kWh
$q_{i,t}^{load}$	Demand of prosumer i	kWh
SoC_i^{max}	Maximum capacity of prosumer i's battery	kWh
$q_i^{B_{max}}$	Maximum (dis)charging power of prosumer i's battery	kW
η^B	Efficiency of the batteries	
w_j	Prosumer j's weighting factor for marginal emissions	EUR/tCO_2
$wtp_{i,j,t}$	Willingness-to-pay of prosumer j	EUR/kWh
$p_t^{G_{in}}$	Average spot market electricity price	EUR/kWh
$p_t^{G_{out}}$	Retailer's electricity price	EUR/kWh
e_t	Marginal emissions from the grid	tCO_2/kWh
Output		
$q_{i,t}^{G_{in}}$	Purchase of prosumer i from the grid	kWh
$q_{i,t}^{G_{out}}$	Sales from prosumer i to the grid	kWh
$q_{i,j,t}^{share}$	Purchase of prosumer j from prosumer i	kWh
$q_{i,t}^{B_{in}}$	Charging of prosumer i's battery	kWh
$q_{i,t}^{B_{out}}$	Discharging of prosumer i's battery	kWh
$SoC_{i,t}$	State of charge of prosumer i's battery	kWh

3.2. Basic model for dynamic participation (bi-level model)

3.2.1. Overview on the methodology

3.2.1.1. Modeling framework

The framework of the modeling approach is a peer-to-peer electricity trading concept in a local energy community. Prosumers (or consumers or producers) join on a voluntary basis and exchange PV electricity generated by community members with one another. Figure 3.3 presents the basic idea of the peer-to-peer trading concept in this paper. All members are connected to the public distribution grid to be able to cover the community's residual load, to feed in the surplus PV electricity, and to trade with the other community members (green arrows). Participants in the community are either households or small-to-medium-sized enterprises.[5] The technology portfolio includes PV systems and battery energy storage systems (BESSs). In addition, each prosumer has an individual willingness-to-pay for PV electricity generated by community members, which determines the allocation of the peer-to-peer trading.

The aim of this model is to optimize the dynamic participation of prosumers in an energy community; hence, changes in the set-up of members over time (i.e., exit/entry). In Figure 3.3, the orange parts represent a new member joining the community.

In this context, new prosumers are characterized by (i) electricity load/demand, (ii) electricity generation (PV system and BESS size), and (iii) consumer-type (household or small business). Other characteristics include electrical distance from the other community members, the minimum and maximum number of new prosumers, and the length of binding contracts

[5] According to the European Commission's *Recast Renewable Energy Directive* (REDII, see European Commission (2018)), the concept of energy communities should mainly benefit citizens, small businesses, and local authorities (see REScoop (2022)).

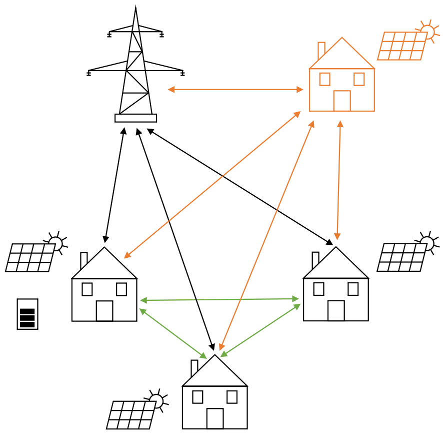


Figure 3.3.: Sketch of the framework of the modeling approach

with the community. The latter is out of scope for this model, but it will follow in Section 3.3.

3.2.1.2. Flow chart

The minimum length of a contract for prosumer participation in energy communities is assumed to be one year. There is a deadline each year; until then, members can decide to leave the community in the next contract period, or decide to stay and extend the contract for another year. In the meantime, prospective new members can declare interest in joining the community until the annual deadline. The flow chart in Figure 3.4 shows the process that is suggested to optimize dynamic participation in energy communities over a horizon of several years.

- The starting point is the "old" community, where some members leave at the end of their contract period.

- The status quo of the remaining members is then captured. The analyses of peer-to-peer electricity trading under the consideration of prosumers' willingness-to-pay from Section 4 demonstrate two important characteristics for a community and its members: Overall community welfare[6], and the annual emissions and costs of each member. These indicators are obtained by solving a linear program (see the model presented in Section 3.1 and Perger et al. (2021)) to maximize community welfare of the original community configuration. The annual costs and emissions are then used as "benchmarks" for the optimization process.

- After decisions about leaving, staying, or joining the community are made by all existing and potential new members, a bi-level optimization problem is solved to determine the optimal configuration of new prosumers. The lower level problem is linear community welfare maximization that was applied to the original community in the previous step to obtain benchmarks. The upper-level problem determines which potential members are selected by the community, and subsequently, the new prosumers' parameters (annual electricity demand and peak capacity of the installed PV systems).[7]

- Finally, the new community is defined and the process repeats in the next year.

The implementation of the proposed method is shown for one period (year) in order to focus on the selection process of the community using the bi-level optimization approach.

3.2.2. Mathematical formulation of the optimization problem

3.2.2.1. Willingness-to-pay of prosumers

Prosumers' individual willingness-to-pay determines how PV generated electricity is distributed among community members as part of the lower level

[6] Community welfare comprises two parts: (i) producer welfare, which considers the community as a whole to maximize producer profits, and (ii) consumer welfare, which considers the individual demand functions (here, willingness-to-pay). Details are explained in Section 3.2.2.2.

[7] The proposed model calculates optimal BESS sizes as well; however, the focus of this work remains on annual demand and PV system size.

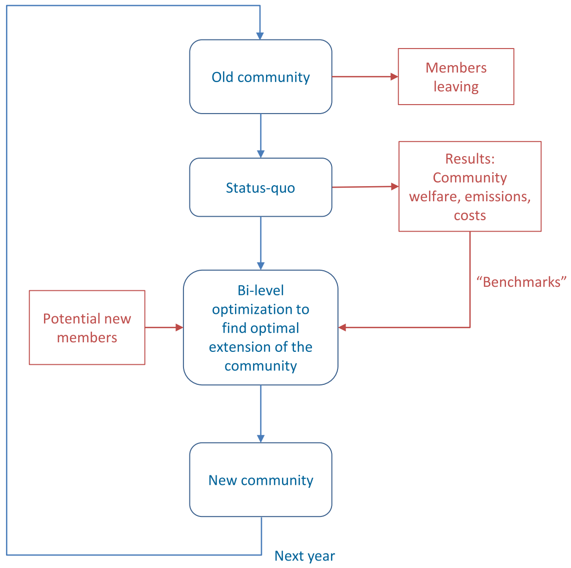


Figure 3.4.: Flow chart of the proposed methodology

objective. The baseline of the willingness-to-pay is the retail electricity price, $p_t^{G_{in}}$, and an individual CO_2-price, w_j, is added on top that relates to the prosumer's preference for reducing emissions from electricity consumption, as it was already introduced in Section 3.1.2.2. In addition, the modeling extension presented in this Section also includes a preference, $d_{i,j} \in [0,1]$, to buy more locally (i.e., buying from a prosumer with the shortest electrical distance). The willingness-to-pay of prosumer j at time t to buy from prosumer i, $wtp_{i,j,t}$, is adapted from Equation (3.2) as follows:

$$wtp_{i,j,t} = p_t^{G_{in}} + w_j(1 - d_{i,j}) \cdot e_t. \tag{3.4}$$

The emissions from the grid, e_t, are represented as a time series using the greenhouse gases emitted into the wider electricity system by the marginal power plant; hence, they are also known as marginal emissions. The local energy community is assumed to be a price taker in the wider electricity system.

3.2.2.2. Community welfare

The aim of peer-to-peer electricity trade and the lower level objective is to maximize community welfare, which is already defined in Section 3.1.2.2.

3.2.2.3. Prosumers' cost-emission function

To evaluate the impact of new prosumers on original prosumers, the following functions are defined:

$$\Delta costs_i = costs_i - costs_{i,old}, \tag{3.5}$$

$$\Delta emissions_i = emissions_i - emissions_{i,old}. \tag{3.6}$$

Equation (3.5) is the deviation of prosumer i's annual costs within the new community set-up compared to the previous status-quo. Similar to Eq. (3.5), Eq. (3.6) represents prosumer i's annual emission increase or decrease. The cost-emission function CE – the upper level objective – is defined next.

$$CE = \sum_{i \in \mathcal{I}_{old}} \alpha_i \Delta costs_i + (1 - \alpha_i) \Delta emissions_i \tag{3.7}$$

Similar to Pareto-optimization, a weighting factor $\alpha_i \in [0, 1]$ is introduced for each prosumer to choose individually. Therefore, α_i determines whether more emphasis is placed on minimizing costs or emissions. By choosing an individual α_i, prosumers can express either a cost-saving or an emission-saving preference. Due to the absolute values of costs and emissions in Eq. (3.5) and (3.6), each prosumer's changes count equally. The cost-emission function CE is the objective to be minimized in the optimization problem.

The costs of each member i of the community over a certain period are calculated as following:

$$\begin{aligned} costs_i = &\sum_{t \in \mathcal{T}} p_t^{G_{in}} q_{i,t}^{G_{in}} - \sum_{t \in \mathcal{T}} p_t^{G_{out}} q_{i,t}^{G_{out}} \\ &+ \sum_{t \in \mathcal{T}, j \in \mathcal{I}} wtp_{j,i,t} q_{j,i,t}^{share} - \sum_{t \in \mathcal{T}, j \in \mathcal{I}} wtp_{i,j,t} q_{i,j,t}^{share}, \end{aligned} \tag{3.8}$$

where $\mathcal{T}$ is the respective time period. The emissions over a certain time are:

$$emissions_i = \sum_{t \in \mathcal{T}} e_t q_{i,t}^{G_{in}} \tag{3.9}$$

Only purchases from the grid are considered in the emissions calculations, because the production of PV electricity does not generate marginal emissions.

3.2.2.4. Bi-level optimization problem

This model solves two main problems: (i) selecting the optimal electricity demand and PV capacity of new prosumers to fulfill certain requirements set by original community members, and (ii) maximizing community welfare, given the new prosumers' parameters selected in (i). Subsequently, this problem can be formulated as a bi-level problem, wherein the leader anticipates the follower's reaction. In the upper-level problem, the *leader*, of the bi-level problem represents (i) and its lower level, the *follower*, (ii).

The leader minimizes the cost-emission function CE with the continuous decision variables $load_i$ and PV_i, and the binary decision variables b_i, for all $i \in \mathcal{I}_{new}$ (see Eq. (3.10a)). The decision variables have lower and upper bounds to ensure a reasonable solution of the model (see Eqs. (3.10b) and (3.10c)). The set of variables

$$Q_{i,t} = \{q_{i,t}^{G_{in}}, q_{i,t}^{G_{out}}, q_{j,i,t}^{share}, q_{i,t}^{B_{in}}, q_{i,t}^{B_{out}}, SoC_{i,t}\}$$

are the lower level primal decision variables. The dual variables of the lower level problem are $\{\lambda_{i,t}^{load}, \lambda_{i,t}^{PV}, \lambda_{i,t}^{SoC}\}$ for equality constraints, $\{\mu_{i,t}^{SoC^{max}}, \mu_{i,t}^{B_{in}^{max}}, \mu_{i,t}^{B_{out}^{max}}\}$ for inequalities, and $\{\beta_{i,t}^{G_{in}}, \beta_{i,t}^{G_{out}}, \beta_{i,j,t}^{share}, \beta_{i,t}^{SoC}, \beta_{i,t}^{B_{in}}, \beta_{i,t}^{B_{out}}\}$ for non-negativities. The objective function of the follower in Eq. (3.10e) maximizes community welfare. The equality constraints (3.10f)-(3.10i) ensure that prosumer i's electricity demand and PV generation are covered at all times. The upper-level decision variables are included in Eq. (3.10h) and (3.10i) for new prosumers. The state of charge of prosumer i's BESS is defined in

Eqs. (3.10j) and (3.10k), and other battery constraints in (3.10l)-(3.10n). Non-negativity conditions are included in (3.10o).

$$\min_{\{load_i, PV_i, b_i, Q_{i,t}\}} \quad \sum_{i \in \mathcal{I}_{old}} \alpha_i \Delta costs_i + (1-\alpha_i)\Delta emissions_i \tag{3.10a}$$

subject to:

$$b_i \cdot load_i^{min} \leq load_i \leq b_i \cdot load_i^{max} \quad \forall i \in \mathcal{I}_{new} \tag{3.10b}$$

$$b_i \cdot PV_i^{min} \leq PV_i \leq b_i \cdot PV_i^{max} \quad \forall i \in \mathcal{I}_{new} \tag{3.10c}$$

$$\sum_{i \in \mathcal{I}_{new}} b_i = n \tag{3.10d}$$

$$\max_{Q_{i,t}} \sum_{t\in\mathcal{T}, i\in\mathcal{I}} p_t^{G_{out}} q_{i,t}^{G_{out}} - \sum_{t\in\mathcal{T}, i\in\mathcal{I}} p_t^{G_{in}} q_{i,t}^{G_{in}} + \sum_{t\in\mathcal{T}, i,j\in\mathcal{I}} wtp_{i,j,t} q_{i,j,t}^{share} \tag{3.10e}$$

subject to:

$$q_{i,t}^{G_{in}} + q_{i,t}^{B_{out}} + \sum_{j\in\mathcal{I}} q_{j,i,t}^{share} - q_{i,t}^{load} = 0 \qquad (\lambda_{i,t}^{load}) \quad \forall i \in \mathcal{I}_{old}, t \tag{3.10f}$$

$$q_{i,t}^{G_{out}} + q_{i,t}^{B_{in}} + \sum_{j\in\mathcal{I}} q_{i,j,t}^{share} - q_{i,t}^{PV} = 0 \qquad (\lambda_{i,t}^{PV}) \quad \forall i \in \mathcal{I}_{old}, t \tag{3.10g}$$

$$q_{i,t}^{G_{in}} + q_{i,t}^{B_{out}} + \sum_{j\in\mathcal{I}} q_{j,i,t}^{share} - load_i q_{i,t}^{load} = 0 \qquad (\lambda_{i,t}^{load}) \quad \forall i \in \mathcal{I}_{new}, t \tag{3.10h}$$

$$q_{i,t}^{G_{out}} + q_{i,t}^{B_{in}} + \sum_{j\in\mathcal{I}} q_{i,j,t}^{share} - PV_i q_{i,t}^{PV} = 0 \qquad (\lambda_{i,t}^{PV}) \quad \forall i \in \mathcal{I}_{new}, t \tag{3.10i}$$

$$SoC_{i,t-1} + q_{i,t}^{B_{in}} \cdot \eta^B - q_{i,t}^{B_{out}}/\eta^B - SoC_{i,t} = 0 \qquad (\lambda_{i,t}^{SoC}) \quad \forall i, t > t_0 \tag{3.10j}$$

$$SoC_{i,t=t_{end}} + q_{i,t_0}^{B_{in}} \cdot \eta^B - q_{i,t_0}^{B_{out}}/\eta^B - SoC_{i,t_0} = 0 \qquad (\lambda_{i,t_0}^{SoC}) \quad \forall i, t = t_0 \tag{3.10k}$$

$$SoC_{i,t} - SoC_i^{max} \leq 0 \qquad (\mu_{i,t}^{SoC^{max}}) \quad \forall i, t \tag{3.10l}$$

$$q_{i,t}^{B_{in}} - q_i^{B^{max}} \leq 0 \qquad (\mu_{i,t}^{B_{in}^{max}}) \quad \forall i, t \tag{3.10m}$$

$$q_{i,t}^{B_{out}} - q_i^{B^{max}} \leq 0 \qquad (\mu_{i,t}^{B_{out}^{max}}) \quad \forall i, t \tag{3.10n}$$

$$\begin{aligned} &-q_{i,t}^{G_{in}}, -q_{i,t}^{G_{out}}, -q_{i,j,t}^{share}, \\ &-q_{i,t}^{B_{in}}, -q_{i,t}^{B_{out}}, -SoC_{i,t} \leq 0 \qquad (\beta_{i,t}^{G_{in}}, \beta_{i,t}^{G_{out}}, \beta_{i,j,t}^{share}, \beta_{i,t}^{SoC}, \beta_{i,t}^{B_{in}}, \beta_{i,t}^{B_{out}}) \quad \forall i, t \end{aligned} \tag{3.10o}$$

with $i, j \in \mathcal{I}$ and $t \in \mathcal{T}$.

A common approach to solving a bi-level optimization problem is the transformation to a mathematical program with equilibrium constraints (MPEC, see Ruiz et al. (2014)). The lower level problem (Eqs. (3.10e)-(3.10o)) is reformulated by its corresponding Karush-Kuhn-Tucker (KKT) conditions, and can be classified as a mixed complementarity problem (MCP) or equilibrium problem, which is parameterized by the leader's decision variables (Dempe and Kue (2017)). The resulting optimization problem is single-level, and it is linear except for binary variables and complementarity constraints. The derivation of the KKT conditions is presented in detail in A.2. The resulting complementarity conditions are then transformed into a mixed integer linear program (MILP) using the Fortuny-Amat method (see A.2.3), also known as the "Big-M approach" (Fortuny-Amat and McCarl (1981), Fischetti et al. (2017), and Pineda et al. (2018)).

3.2.3. Nomenclature basic model for dynamic participation

Sets	
$t \in \mathcal{T} = \{1, \ldots, T\}$	Time steps
$i \in \mathcal{I} = \{1, \ldots, N+n\}$	Index of all prosumers
$i \in \mathcal{I}_{old} = \{1, \ldots, N\}$	Index of old prosumers
$i \in \mathcal{I}_{new} = \{N+1, \ldots, N+n\}$	Index of new prosumers
Parameter	
$q_{i,t}^{load}$	Demand of prosumer i (kWh)
$q_{i,t}^{PV}$	PV generation of prosumer i (kWh)
$load_i^{max}$	Max. annual demand of prosumer $i \in \mathcal{I}_{new}$ (kWh)
$load_i^{min}$	Min. annual demand of prosumer $i \in \mathcal{I}_{new}$ (kWh)
PV_i^{max}	Max. peak PV generation of prosumer $i \in \mathcal{I}_{new}$ (kW)
PV_i^{min}	Min. peak PV generation of prosumer $i \in \mathcal{I}_{new}$ (kW)
SoC_i^{max}	Capacity of prosumer i's battery (kWh)
$q_i^{B_{max}}$	Max. (dis)charging power of prosumer i's battery (kW)
η^B	Efficiency of the batteries
w_j	Prosumer j's emissions weighting factor (EUR/tCO_2)
d_{ij}	Distance factor between prosumer i and j ($\in [0,1]$)
$wtp_{i,j,t}$	Willingness-to-pay of prosumer j (EUR/kWh)
α_i	Upper-level preference factor of prosumer i ($\in [0,1]$)
$p_t^{G_{in}}$	Retailer's electricity price (EUR/kWh)
$p_t^{G_{out}}$	Average spot market electricity price (EUR/kWh)
e_t	Marginal emissions from the grid (tCO_2/kWh)
Decision variables	
$load_i$	Annual demand of prosumer $i \in \mathcal{I}_{new}$ (kWh)
PV_i	Installed PV capacity of prosumer $i \in \mathcal{I}_{new}$ (kW)
b_i	Binary decision variable of prosumer $i \in \mathcal{I}_{new}$
$q_{i,t}^{G_{in}}$	Purchase of prosumer i from the grid (kWh)
$q_{i,t}^{G_{out}}$	Sales from prosumer i to the grid (kWh)
$q_{i,j,t}^{share}$	Purchase of prosumer j from prosumer i (kWh)
$q_{i,t}^{B_{in}}$	Charging of prosumer i's battery (kWh)
$q_{i,t}^{B_{out}}$	Discharging of prosumer i's battery (kWh)
$SoC_{i,t}$	State of charge of prosumer i's battery (kWh)

3.3. Dynamic participation over multiple time steps (bi-level model with stochastic forecast)

3.3.1. Overview on the methodology

The purpose of this third method is to develop a sound framework for energy communities to select from a portfolio of potential members under consideration of uncertainties, which is why a stochastic dynamic programming approach is developed. We consider the (potential) members' preferences to stay, leave, or wanting to join the community as the main uncertainty. Therefore, scenarios are developed and we use probabilities of possible future entries and exits in/from the community. A community manager has to decide what kind of contracts to offer to each of the prosumers. These contracts are binding from the perspective of the community manager (members are not allowed to be kicked out), but members can decide to leave the community before the end of the contract.

The procedure can be summarized as follows: Each year, the community manager captures the existing members and their contracts. Next, information on new possible entrants and their willingness to join the community is collected. Finally, we check if there are any existing members who want to early phase out of their contract and leave the community. Now the community manager has collected all of the certain (deterministic) information. Stochastic input data of future developments are then estimated, considering the following uncertainties: (i) which members are leaving after each period, and (ii) which are the potential new members willing to join the community. A set of scenarios is designed to represent these uncertainties and include them in the optimization problem.

3.3.2. Mathematical formulation of the stochastic dynamic program

This section presents the core of the method, the stochastic dynamic program. The procedure introduced in Section 3.3.1 is now mathematically explained. The dynamic program needs a policy, which is a function to determine decisions given available information in a state. We choose a *look-ahead policy*: Decisions are made explicitly optimizing over a certain time horizon with stochastic forecasts. Figure 3.5 shows an overview of the structure of the dynamic program. The planning horizon corresponds to n years in a set $\mathcal{N}$, the scenarios ω are of a finite sample of potential outcomes Ω, and $i \in \mathcal{I}$ are all (possible) prosumers of a portfolio. The optimization model solves two main problems simultaneously: (i) selecting optimal new participants from the portfolio of possible entrants and assigning contracts to them, and (ii) optimally allocating the trading between participants considering their individual willingness-to-pay. Optimal allocation in (ii) means maximizing the community welfare (see Section 3.3.2.2) considering the participants chosen in (i). Therefore, the problem can be formulated as bi-level problem, wherein the *leader* (i) anticipates the reaction of the *follower* (ii).

3.3.2.1. Upper-level problem

The problem is divided into two steps: The first one, year $n = 1$, represents the "here and now" decision. We know the status-quo of the community and the portfolio of new members, who might or might not want to join, at this time. The second step starts at $n = 2$ until $n = N$, where we use scenarios such that the decision at $n = 1$ can "see" the future within a certain horizon.

Objective function The objective function is minimized considering scenarios and planning horizon:

$$\min_{x_{n,i}(\omega),u_{n,i}(\omega),b_{n,i}(\omega),Q_{i,t,n}(\omega)} \quad F_1 + \sum_{\omega \in \Omega} \sum_{n=2}^{N} p(\omega) F_n(\omega) \tag{3.11}$$

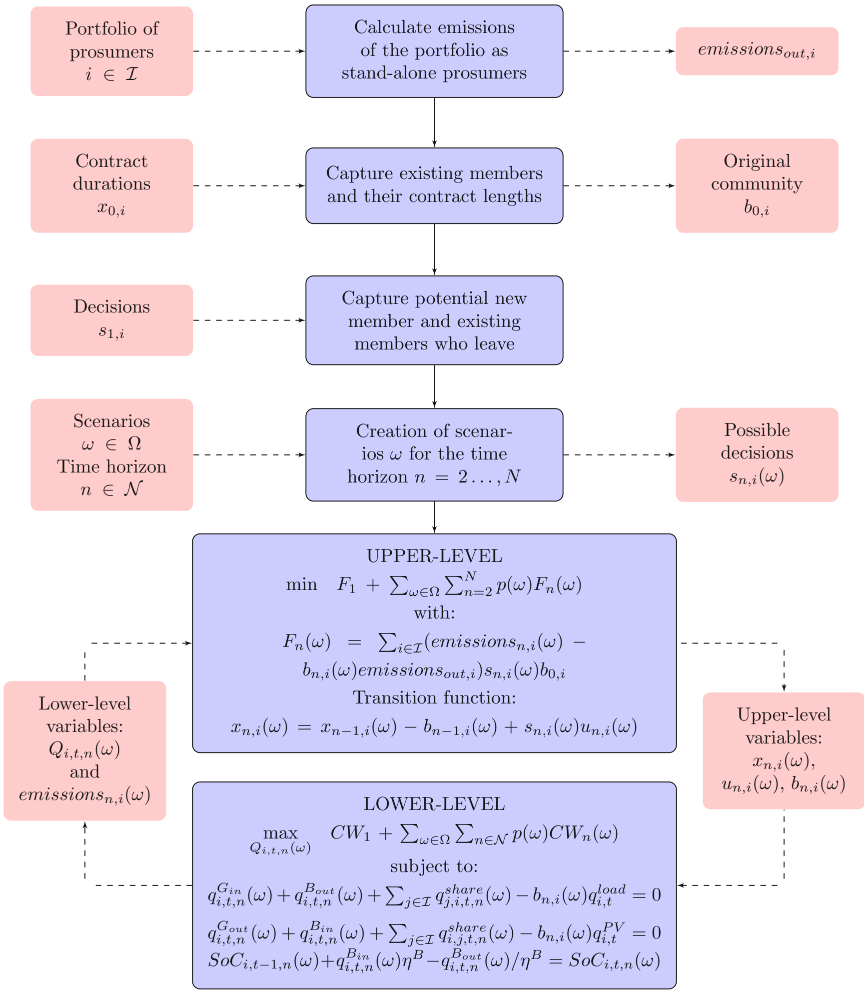


Figure 3.5.: Overview on the stochastic dynamic program

F_1 is the the value of the objective function at $n = 1$ (deterministic; scenarios are not included). $F_n(\omega)$ is the value of the objective function of a certain forecast year n and scenario ω, and $p(\omega)$ is the probability that ω happens.

As reference, we calculate the emissions of all possible members as if they were stand-alone prosumers (not part of the community; hence, no electricity trading with anyone else but the grid, with the objective of maximizing their own self-consumption). The objective function measures the improvement of the community members' emission balances. Therefore, the optimal selection of new members should improve the emission balance of the existing participants. The emissions of each community member i over a year n are calculated as following:

$$emissions_{n,i}(\omega) = \sum_{t \in \mathcal{T}} e_t q_{i,t,n}^{G_{in}}(\omega) \tag{3.12}$$

This definition considers the purchases $q_{i,t,n}^{G_{in}}$ from the grid only, as the production of PV electricity does not generate marginal emissions. $F_n(\omega)$ is composed of $emissions_{n,i}(\omega)$ and $emissions_{out,i}$; the latter are annual emissions of member i as a stand-alone prosumer, as mentioned above.

$$F_n(\omega) = \sum_{i \in \mathcal{I}} (emissions_{n,i}(\omega) - b_{n,i}(\omega) emissions_{out,i}) \cdot s_{n,i}(\omega) \cdot b_{0,i} \tag{3.13}$$

Let us describe Equation (3.13) in detail: We use $b_{0,i}$ and $s_{n,i}(\omega)$[8] to exclude prosumers, who were not part of the original community (i.e., $b_{0,i} = 0$) and those who want to leave the community in scenario ω (i.e., $s_{n,i}(\omega) = 0$), from the calculations. In addition, we use $b_{n,i}(\omega)$ to ensure that the share of prosumer i's emission balance in $F_n(\omega)$ is zero if prosumer i is not part of the new community ($b_{n,i}(\omega) = 0$) in year n and scenario ω.[9] Thus, linearity of the problem, apart from binary variables, is maintained.

Transition function A so-called transition function reflects the system dynamics of a dynamic program. In this work, the transition function calculates the remaining contract length (state variable $x_{n,i}(\omega) \geq 0$) of each prosumer i. It depends on the number of years remaining from the previous year ($x_{n-1,i}(\omega)$) and the control variable $u_{n,i}(\omega) \geq 0$, which is the possible extension of the contract. The transition function is defined as:

$$x_{n,i}(\omega) = x_{n-1,i}(\omega) - b_{n-1,i}(\omega) + s_{n,i}(\omega) u_{n,i}(\omega) \tag{3.14}$$

[8] $b_{0,i}$ and $s_{n,i}(\omega)$ are exogenous parameters.
[9] The model sets all decision variables $Q_{i,t,n}(\omega) = 0$ if $b_{n,i}(\omega) = 0$; hence, $emissions_{n,i}(\omega) = 0$.

valid for $\forall i \in \mathcal{I}, n > 1 \in \mathcal{N}, \omega \in \Omega$. $s_{n,i}(\omega)$ is an exogenous parameter from the scenarios, representing the (possible) choices of the portfolio: staying/joining ($s_{n,i}(\omega) = 1$), or leaving/not joining ($s_{n,i}(\omega) = 0$). Note that when $s_{n,i}(\omega) = 0$, then $x_{n,i}(\omega) = 0$. The binary variable $b_{n,i}(\omega)$ is one if there is a valid contract for prosumer i in year n:

$$b_{n,i}(\omega) = \begin{cases} 1 & \text{if } x_{n,i}(\omega) > 0 \\ 0 & \text{if } x_{n,i}(\omega) = 0 \end{cases} \tag{3.15}$$

$b_{n,i}(\omega) \in \{0, 1\}$ serves two ends: (i) in transition function (3.14), $b_{n,i}$ decreases the contract length of the previous year $x_{n-1,i}(\omega)$ by one year; (ii) $b_{n,i}(\omega)$ can set the lower-level constraints (3.10f) and (3.10g) to zero, thus excluding a prosumer (refer to Section 3.3.2.2 for better understanding). The relationship between $x_{n,i}(\omega)$ and $b_{n,i}(\omega)$ can be expressed by using a big-M approach. For $n = 1$, we use the initial values $x_{0,i}$ and $b_{0,i}$ for the transition function:

$$x_{1,i} = \begin{cases} x_{0,i} - b_{0,i} + s_{1,i} u_{1,i} & \text{if } s_{1,i} = 1 \\ 0 & \text{if } s_{1,i} = 0 \end{cases} \tag{3.16}$$

Note that at $n = 1$, non-anticipativity constraints are imposed:

$$u_{0,i}(\omega) - u_{0,i} = 0 \tag{3.17}$$

Eq. (3.17) means that we have to choose one decision $u_{0,i}$ for the contract length of prosumer i regardless of the outcome ω; hence, we are not allowed to see into the future. Non-anticipativity constraints are included for all other variables too:

$$x_{0,i}(\omega) - x_{0,i} = 0 \tag{3.18}$$

$$b_{0,i}(\omega) - b_{0,i} = 0 \tag{3.19}$$

$$Q_{i,t,0}(\omega) - Q_{i,t,0} = 0 \tag{3.20}$$

There is also a rule implemented that prosumers, that wanted to join the community ($s_{n,i}(\omega) = 1$), but were rejected ($b_{n,i}(\omega) = 0$), are not considered anymore in the following years; hence, $b_{m,i}(\omega) = 0 \; \forall m > n$. We assume that once a prosumer was rejected, they search for other, alternative energy communities to join.

3.3.2.2. Lower-level problem

The dynamic program has to solve a lower-level problem to optimally allocate PV electricity generation within the community according to the participants' individual willingness-to-pay. The lower-level problem is adopted from Perger and Auer (2022); therefore, a very brief overview is presented in the following. For details refer to the original publication.

Willingness-to-pay The willingness-to-pay of prosumer j at time t to buy from prosumer i, $wtp_{i,j,t}$, is as follows:

$$wtp_{i,j,t} = p_t^{G_{in}} + w_j(1 - d_{i,j}) \cdot e_t. \tag{3.21}$$

Community welfare The aim of peer-to-peer electricity trade is to maximize community welfare, which is defined in two parts. Part I of community welfare measures the optimal resource allocation at community level, maximizing self-consumption of the community as a whole over a year. Part II optimally assigns PV generated electricity to each member in consideration of their individual willingness-to-pay; thus, part II represents peer-to-peer trading from one prosumer to another, $q_{i,j,t}^{share}$. Community welfare (CW) within scenario ω over year n is defined as following:

$$CW_n(\omega) = \sum_{t \in \mathcal{T}, i \in \mathcal{I}} \Bigg(\underbrace{p_t^{G_{out}} q_{i,t,n}^{G_{out}}(\omega) - p_t^{G_{in}} q_{i,t,n}^{G_{in}}(\omega)}_{\mathrm{I}} + \underbrace{\sum_{j \in \mathcal{I}} wtp_{i,j,t} q_{i,j,t,n}^{share}(\omega)}_{\mathrm{II}} \Bigg) \tag{3.22}$$

The set of variables

$$Q_{i,t,n}(\omega) = \left\{ q_{i,t,n}^{G_{in}}(\omega), q_{i,t,n}^{G_{out}}(\omega), q_{j,i,t,n}^{share}(\omega), q_{i,t,n}^{B_{in}}(\omega), q_{i,t,n}^{B_{out}}(\omega), SoC_{i,t,n}(\omega) \right\} \tag{3.23}$$

are the lower level primal decision variables. The formulation is found in A.4. The lower level problem is reformulated to its corresponding Karush-Kuhn-Tucker (KKT) conditions in order to solve the bi-level problem.

3.3.3. Nomenclature stochastic dynamic participation model

Sets	
$n \in \mathcal{N} = \{1, \ldots, N\}$	Years (forecasting horizon)
$t \in \mathcal{T} = \{1, \ldots, T\}$	Hourly time steps
$i \in \mathcal{I} = \{1, \ldots, M\}$	Index of prosumers in the portfolio
$\omega \in \Omega = \{\omega_1, \ldots, \omega_{\lvert\Omega\rvert}\}$	Set of scenarios
Parameter	
$q_{i,t}^{load}$	Demand of prosumer i (kWh)
$q_{i,t}^{PV}$	PV generation of prosumer i (kWh)
SoC_i^{max}	Capacity of prosumer i's battery (kWh)
$q_i^{B_{max}}$	Maximum (dis)charging power of prosumer i's battery (kW)
η^B	Efficiency of the batteries
w_j	Prosumer j's preference to avoid emissions (EUR/tCO$_2$)
d_{ij}	Distance preference between prosumers i and j ($\in [0, 1]$)
$wtp_{i,j,t}$	Willingness-to-pay of prosumer j (EUR/kWh)
$p_t^{G_{in}}$	Average spot market electricity price (EUR/kWh)
$p_t^{G_{out}}$	Retailer's electricity price (EUR/kWh)
e_t	Emissions from the grid (tCO$_2$/kWh)
$s_{n,i}(\omega)$	Decision of i to join, stay or leave the community
$p(\omega)$	Probability of scenario ω
Decision variables	
$x_{n,i}(\omega)$	State variable: Remaining contract duration of i in year n
$u_{n,i}(\omega)$	Control variable: Contract extension for i in year n
$b_{n,i}(\omega) \in \{0, 1\}$	Binary variable if i has a valid contract in year n
$q_{i,t,n}^{G_{in}}(\omega)$	Purchase of prosumer i from the grid (kWh)
$q_{i,t,n}^{G_{out}}(\omega)$	Sales from prosumer i to the grid (kWh)
$q_{i,j,t,n}^{share}(\omega)$	Purchase of prosumer j from prosumer i (kWh)
$q_{i,t,n}^{B_{in}}(\omega)$	Charging of prosumer i's battery (kWh)
$q_{i,t,n}^{B_{out}}(\omega)$	Discharging of prosumer i's battery (kWh)
$SoC_{i,t,n}(\omega)$	State of charge of prosumer i's battery (kWh)
$\lambda_{i,t,n}(\omega), \beta_{i,t,n}(\omega), \mu_{i,t,n}(\omega)$	Dual variables of the problem
Functions	
$F_n(\omega)$	Value of objective function at n and ω
$emissions_{n,i}(\omega)$	Annual emissions of prosumer i
$emissions_{out,i}$	Annual emissions of prosumer i if they are not a member
$CW_n(\omega)$	Community welfare

4. Results of static participation in energy communities

This chapter presents the results of the first research question as presented in Perger et al. (2021). Static participation in energy communities is analyzed using a linear program developed for optimal peer-to-peer trading. Section 4.1 explains the case study set-up in detail. Next, Section 4.2 presents the case study with households decomposed into results for a whole year and for a specific time slot during the year. Section 4.3 shows results of the case study with households and business. Finally, sensitivity analyses of static participation are found in Section 4.4.

4.1. Case study set-up

4.1.1. Model implementation

The model is implemented in MATLAB (version R2019b, see MATLAB (2019)) using the optimization toolbox YALMIP (see Löfberg (2004)) and the solver Gurobi (see Gurobi Optimization, LLC (2021)). In this study, the model is applied to different arbitrary energy community set-ups.

4.1.2. PV generation data

The PV generation data were obtained from the open source tool Renewables.ninja (2019) (see also Pfenninger and Staffell (2016) and Staffell and

Pfenninger (2016)), where relevant data can be obtained for any location and for different PV system parameters, such as peak production, azimuth, and tilt. The community set-up used to obtain the results in this paper is situated in the city of Vienna, Austria (latitude 48.2084°N and longitude 16.3725°E). The reference year employed was 2019, and a tilt of 35° was set equally for all PV systems used in these analyses.

4.1.3. Prosumer data and willingness-to-pay

The sample community used to test the proposed linear optimization model, FRESH:COM, comprises a set of (arbitrary) prosumers consisting of ten private households and five small businesses. The electricity demands of the households are generated by using real measured anonymized demand profiles (see EEG (2020)), while the electricity demands of the different types of businesses are derived from so-called Synthetic Load Profiles (see APCS-Austrian Power Clearing and Settlement (2019)), which are also used as a reference in daily electricity market operations, scheduling, clearing, and financial settlements. Table 4.1 shows the parameters of PV orientation and peak output, the BESS capacity, the individual emissions' preference, w_i, and the annual electricity demand of each prosumer, and Figures 4.1 and 4.2 are graphical displays of prosumer household data and those of the five small businesses, respectively. Further information about the demand and generation profiles is provided in B.1 and B.2.

The charging and discharging efficiencies of the batteries is assumed to be $\eta^B = 0.9$, and the maximum (dis)charging power is $q_i^{B_{max}} = 1\,\mathrm{kW}$. The state of charge should not fall below $SoC_i^{min} = 0\,\mathrm{kWh}$.

4.1.4. Marginal emissions and prices

Schram et al. (2019b) presents a time series of marginal emissions from certain European countries in 2017. The hourly values of the German-Austrian price zone are used in this study to remain geographically consistent. Further

Table 4.1.: Relevant data relating to different prosumers

Prosumer	PV orientation	PV peak output [kW]	Storage capacity [kWh]	Emission factor w_i [EUR/tCO_2]	Annual demand [kWh]
Household 1	South	5	-	10	6628
Household 2	East West	6	4	70	4659
Household 3	South	3	-	100	5689
Household 4	South East	5	5	50	5138
Household 5	South	5	-	20	3762
Household 6	-	-	-	80	7700
Household 7	South West	5	6	0	5727
Household 8	-	-	-	100	5889
Household 9	East	5	-	90	5598
Household 10	South	5	6	40	8283
Business	South	10	-	0	14000
Business 0-24 h	East West	10	-	0	22000
Business 8-18 h	South	10	-	0	15000
Shop/Hair dresser	South	10	-	0	18000
Bakery	East West	10	-	0	30000

information about marginal emissions can be found in B.3.

The optimization model also requires the retail electricity price, $p_t^{G_{in}}$, that prosumers pay when buying electricity from the grid, and the remuneration, $p_t^{G_{out}}$, for feeding PV generation to the grid. The average value of the 2019 Austrian retail electricity price (0.20 EUR/kWh[1]) is assumed for $p^{G_{in}}$ (see Eurostat (2022)).

In this case study, all the settings are designed for PV generated electricity without consideration of any subsidies and/or feed-in tariffs. It is assumed that excess PV generation is sold at a spot market price. To retain consistency with data available for marginal emissions,[2] the reference used here is the average value of the base product of the (then) German-Austrian spot market in 2017 (see EXAA Energy Exchange Austria (2020)). Therefore, $p^{G_{out}}$ is set

[1]The exact average value across the country for 2019 was 0.2034 EUR/kWh
[2]The marginal power plant sets the price of the spot market and the marginal emissions.

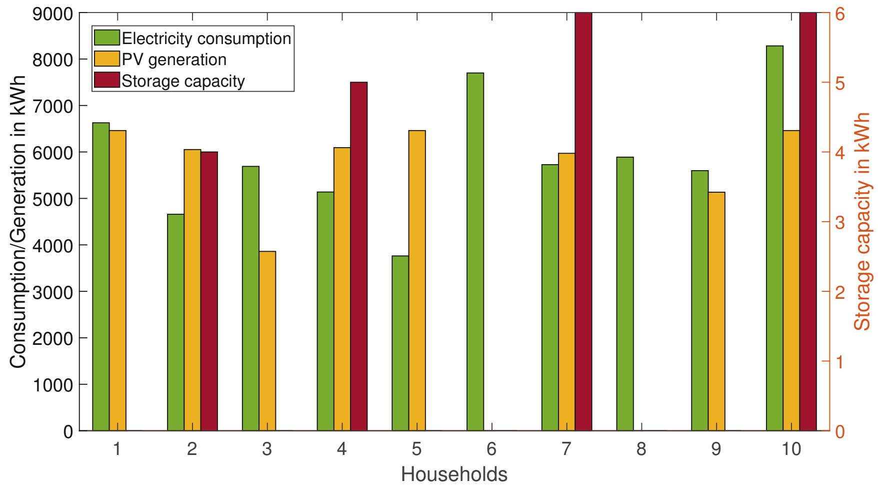


Figure 4.1.: (left axis) Energy consumption and PV generation for one year and (right axis) battery capacity of the test community (households only)

to 0.0345 EUR/kWh.

4.2. Results of energy communities with households

4.2.1. Annual results

Energy Community without BESS In the set-up of prosumers selected (10 households without BESSs), 26% of the electricity is traded within the community, while the share of self-consumption is only 3%, see the pie chart in Figure 4.3. Furthermore, 43% of the electricity is purchased from the retailer and the surplus fed into the grid equals 28%. The objective function of the linear optimization model ensures that the electricity purchased from the retailer is minimized. Furthermore, sharing within the community and self-consumption are preferred compared to selling to the grid.

Peer-to-peer trading is then discussed in detail. The 3D bar plot in Figure 4.4 shows the results of the optimization variable $q^{share}_{j,i,t}$ over one year

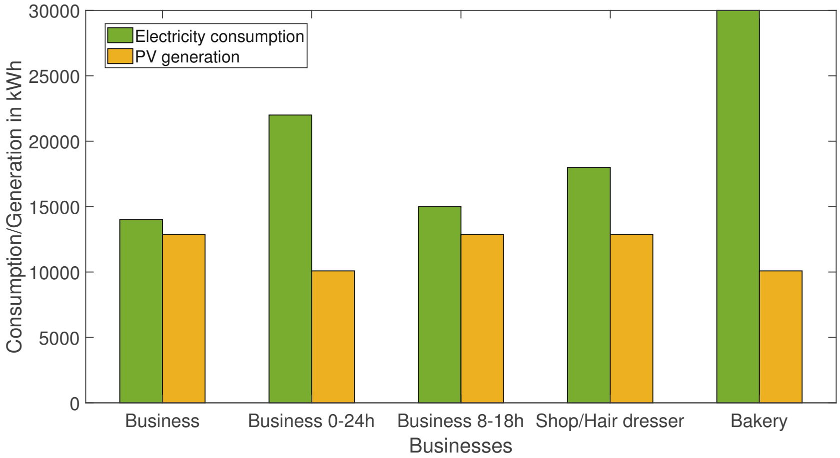


Figure 4.2.: Energy consumption and PV generation of the five small businesses for one year

($\sum_{t \in \mathcal{T}} q_{i,j,t}^{share}$, $\mathcal{T} = 1, \ldots, 8760$), and the amount of PV generated electricity that each prosumer trades with other prosumers is evident. Following the matrix logic of $q_{j,i,t}^{share}$, the diagonal line indicates the self-consumption of each prosumer and their willingness-to-pay decides how the generation is shared.

As each member of the energy community has their own characteristic electricity demand and the dimensions of the PV system vary, the distribution of $q_{j,i,t}^{share}$ not only depends on the willingness-to-pay, but also strongly on the size of each prosumer's PV system. A different perspective is shown in Figure 4.5, where the focus is on the relation between the self-consumption of each prosumer (yellow) and the electricity purchased from the community (green) and from the grid (blue). The PV consumption to demand ratio (the percentage of the annual demand that is covered by PV generation from self-consumption and buying from other community members) is presented on the right axis (in %).

Figure 4.6 shows the correlation between the willingness-to-pay (left axis, blue) and the ratio between the amount of PV electricity consumed and the demand for electricity (right axis, red). The figure indicates that a high

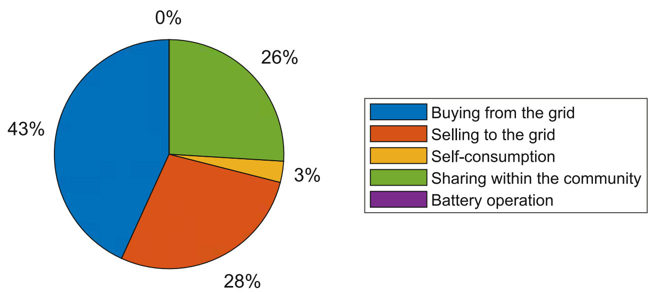


Figure 4.3.: Percentage of annual share of electricity consumed and PV electricity generated (without BESSs)

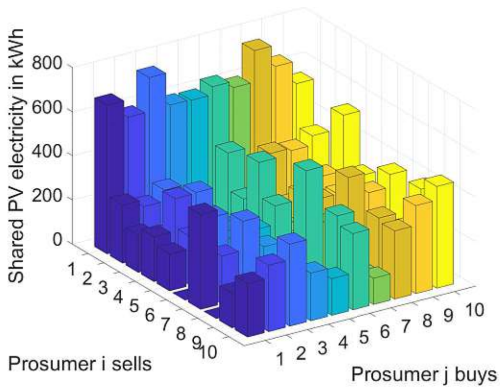


Figure 4.4.: PV generation traded within the community in a year (without batteries)

willingness-to-pay generally leads to a higher share of PV electricity from the community and vice versa. Therefore, the introduction of a willingness-to-pay is a promising tool for allocating the PV electricity generated, especially within an energy community where all of the PV generation is shared, and not just each prosumer's surplus.

The revenues and emissions' savings of each prosumer change when they join the energy community and engage in peer-to-peer trading. To analyze this effect, the revenues and CO_2-emissions are calculated and compared to the revenues and the emissions that the members would generate if they were stand-alone prosumers only, who do not share their PV electricity generation. Participants with a high willingness-to-pay pay more for electricity in the

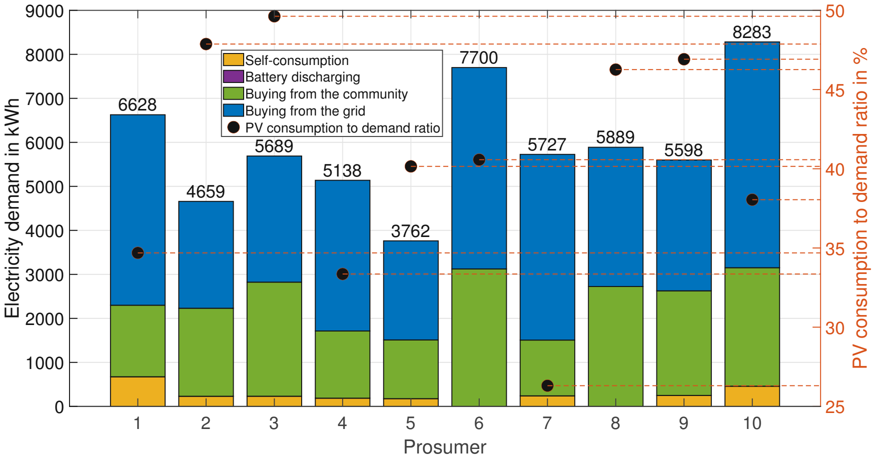


Figure 4.5.: (left axis) Prosumer electricity demand is covered by PV self-consumption (yellow), PV generated by the community (green), and electricity from the grid (blue); (right axis) PV consumption to demand ratio - (without BESSs)

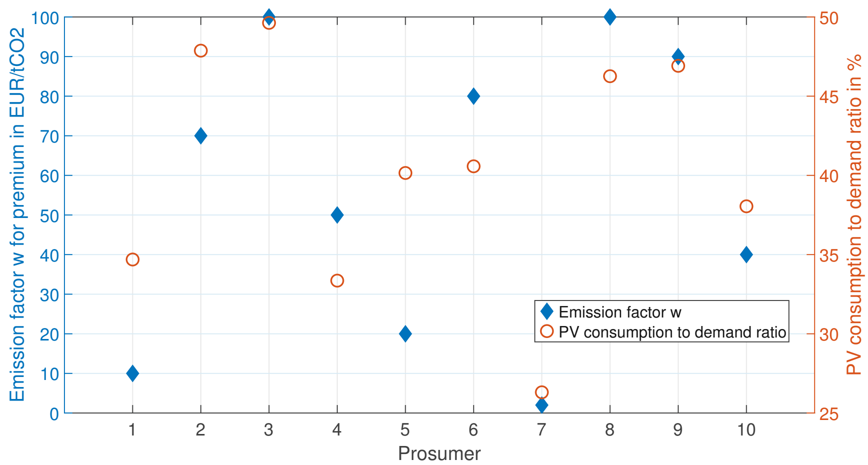


Figure 4.6.: (left axis) Willingness-to-pay; (right axis) ratio between the amount of PV generation consumed and amount of electricity demanded (without BESSs)

peer-to-peer trading scenario and end up with a negative financial balance compared to being a stand-alone prosumer. On the other hand, participants with a relatively low willingness-to-pay generate profits because they sell most of their renewable energy to members who are willing to pay more.

The red bars in Figure 4.7 show the financial savings generated by engaging in peer-to-peer trading. The four prosumers with the highest willingness-to-pay (prosumers 3, 6, 8, and 9) have a negative balance. Prosumers 1 and 7 have the lowest willingness-to-pay and the highest savings, with savings of approximately 38% for prosumer 1.

A similar but opposite tendency can be seen with emissions' savings. The green bars in Figure 4.7 indicate whether a member can save marginal emissions by purchasing from their peers. A high willingness-to-pay leads to emissions' savings because of the implicit preference to purchase emission-free PV generated electricity over that from the retailer. It should be noted that most prosumers in Figure 4.7 follow the same pattern: a positive financial balance but no emission savings, or emission savings but a negative financial balance.

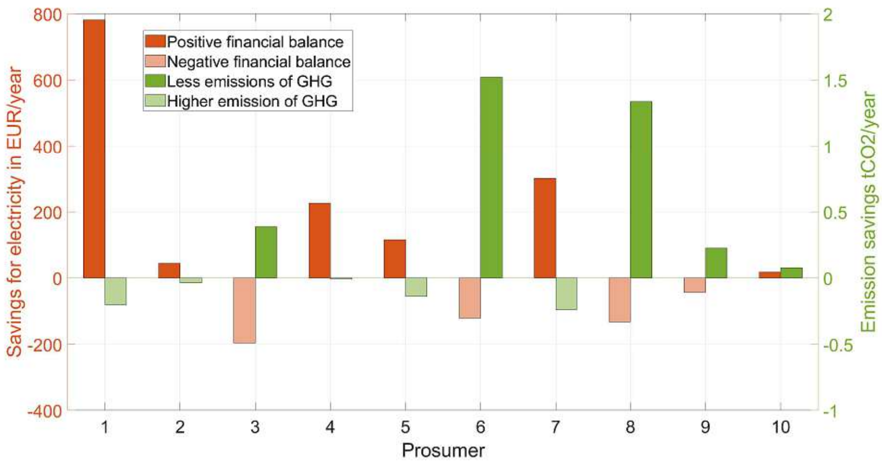


Figure 4.7.: (left axis) Savings in Euros compared to being a stand-alone prosumer; (right axis) emissions' balance (without BESSs)

Energy Community with BESSs This section describes the effects of including BESSs to the technology portfolio. By using BESSs, it is possible to increase the community's shared self-consumption and decrease the amount purchased from the retailer. BESSs are added to the set-up of ten households from the previous section. The pie chart in Figure 4.8 shows the distribution of electricity on an annual level with BESSs operating: 28% of the electricity is shared within the community, 9% is provided by BESSs within the community, and 3% is self-consumption. Purchases from the grid have decreased to 39% due to BESSs, and the amount sold to the grid has reduced to 21%.

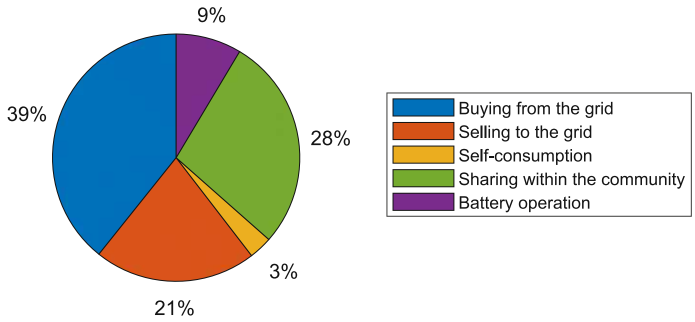


Figure 4.8.: Percentages of annual share of electricity consumed and PV electricity generated (with BESSs)

Figure 4.9 compares the results of community set-ups with and without BESSs showing the differences between the two scenarios, and the following conclusions can be drawn:

- Batteries are charged only when the amount of generated PV electricity exceeds the demand of the whole community; therefore, the amount of electricity used for charging is equal to the difference in the amount sold to the grid.
- Prosumers are not buying from the retailer to charge their batteries - only PV electricity is used. Therefore, the difference in the amount bought from the grid equals the amount discharged by batteries.
- When excess PV electricity is generated, prosumers with BESSs can charge their batteries with the PV electricity they generate, and they can then buy from the community, if required. When there is not enough available PV generation, they can use their batteries to cover their demand, instead of buying from the retailer. With BESSs, the

whole community buys approximately 15% less electricity from the retailer than without BESSs.

- BESSs do no compete with the community's generated PV electricity because only excess electricity generated is stored, and the batteries are discharged only when the amount of PV generation is insufficient for covering the demand. There is only a slight shift between self-consumption and trading with other members.

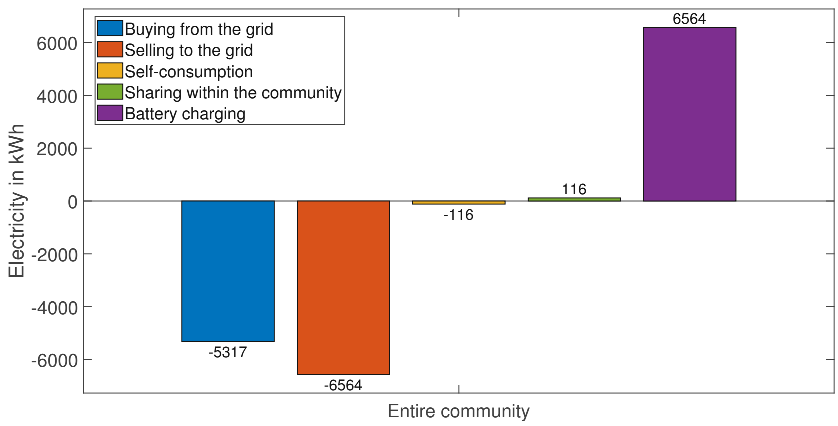


Figure 4.9.: Comparison of community set-ups with and without the inclusion of BESSs

In addition, Figure 4.10 shows that the financial savings of prosumers with BESSs (prosumers 2, 4, 7, and 9) are higher than in Figure 4.7 (without BESSs). Furthermore, prosumers 2, 4, 7, and 9 achieve greater emissions' saving in this new scenario. These positive financial and emissions' balances could thus be incentives to invest in BESS.

4.2.2. Results for one specific hour

Following the results obtained on an annual level, one specific hour is analyzed in detail in this section to gain a better insight into the peer-to-peer trading mechanism. The set-up is the same as that in Section 4.2.1 without BESSs.

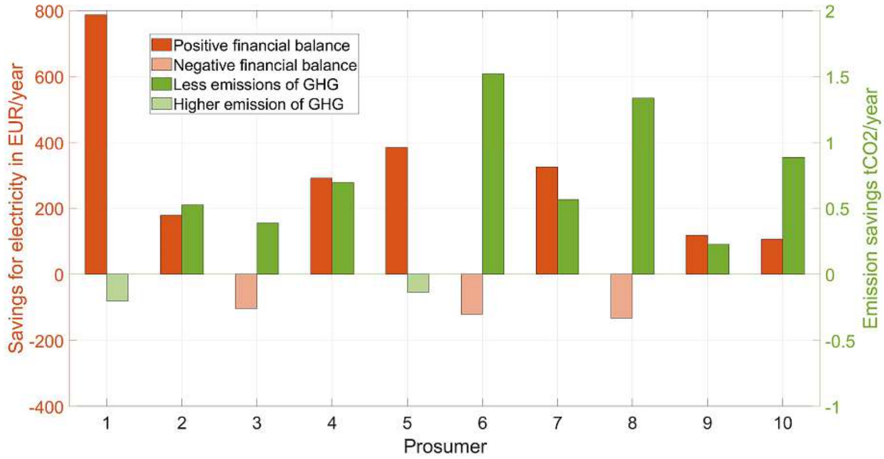


Figure 4.10.: (left axis) Savings in Euros compared to being a stand-alone prosumer; (right axis) emissions' balance (with BESSs)

April 1st between 16:00 and 17:00 is chosen as the timeframe.[3] Production from the PV systems exceeds the total demand of the prosumers (see Figure 4.11) in this hour. The marginal emissions in this hour are 578 gCO_2/kWh and the willingness-to-pay ($wtp_{i,j,t}$) is between 0.20 and 0.26 EUR/kWh (see right axis Figure 4.11). Figure 4.12 shows the peer-to-peer trading results, again as a 3D bar plot. Prosumers 6 and 8 have no PV systems of their own, and they cover their demand by purchasing PV electricity from the community. Prosumer 7 generates high amounts of PV electricity compared to their demand, and is thus selling to prosumer 1 and 8. Other prosumers are also selling proportions of their generated PV electricity to the community. As there is a PV generation surplus, the community does not need to purchase electricity from the retailer during this specific hour.

[3]During nighttime, when no PV electricity is produced, $q_{i,j,t}^{share} = 0$, $\forall i, j \in \mathcal{I}$. Therefore, a time slot during daytime is presented here.

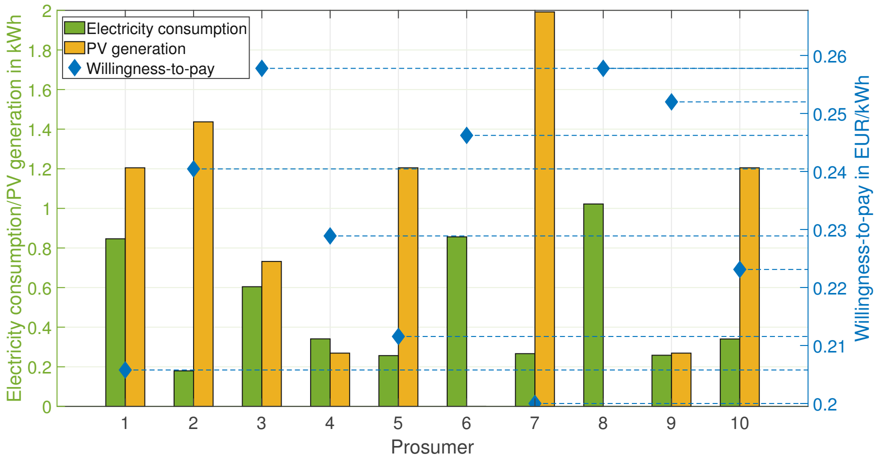


Figure 4.11.: Electricity demand and PV electricity generation - left axis; willingness-to-pay - right axis (one specific hour)

4.3. Energy communities including businesses

Energy communities should not only be an option for private households, but also for small and medium-sized enterprises (SMEs). The original community set-up is extended by five prosumers that have typical commercial load profiles (see Section 4.1). Each new prosumer has a 10 kWpeak PV system, and their w_j is 0 EUR/tCO_2 (the willingness-to-pay therefore corresponds to the retailer's electricity price). First, pie charts compare the annual share of electricity consumed and the PV electricity generated with and without BESSs. As there are no BESSs assigned to the businesses (only to the households), the effects of the BESSs are relatively small in this extended community set-up. The remaining results in this section exclude BESSs. The annual demand and amount of PV electricity generated is much higher for the businesses than for the households; therefore, $q_{j,i,t}^{share}$ is particularly high for the businesses (prosumers 11-15, see Figure 4.14).

Figure 4.15 shows the amount of electricity demanded by each prosumer that is covered by the following: self-consumption, purchases from other community members, and purchases from the grid. The PV electricity consumption to demand ratio (right axis in Figure 4.15 and Figure 4.16) shows that the

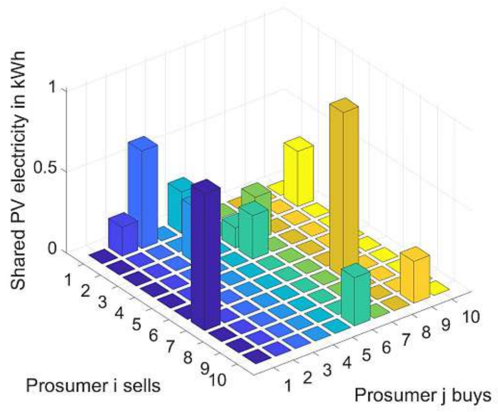


Figure 4.12.: PV generated electricity traded within the community during one specific hour (without BESSs)

household prosumers can increase their share of locally generated PV electricity compared to the previous set-up (with only households), because of the higher amount of available PV generation. The businesses show different characteristics. Prosumer 13 is a business open from 08:00 until 18:00, and it has a high PV electricity consumption to demand ratio. Its demand profile is high during the day, especially around noon, which is a perfect time to consume PV generated electricity. The demands of prosumers 11 and 14 are highest during the day, but they are not as distinctive as prosumer 13; their PV electricity consumption to demand ratios are lower than that of prosumer 13. In contrast, prosumers 12 and 15 have low PV electricity consumption to demand ratios. Prosumer 12 is a business operating 24 hours a day, and the peak demand of the bakery (prosumer 15) is in the early morning hours. Both of their demand profiles do not correlate well with the PV electricity generation profiles.

Finally, the financial balances and emissions' savings of the five businesses are shown in Figure 4.17. Interestingly, four out of the five businesses have a negative financial balance. Only prosumer 13 has a positive balance, because their demand profile correlates with PV electricity generation times. Due to the overall dimension of the community's PV systems, the other businesses sell to the grid instead of selling to the community during times of high PV

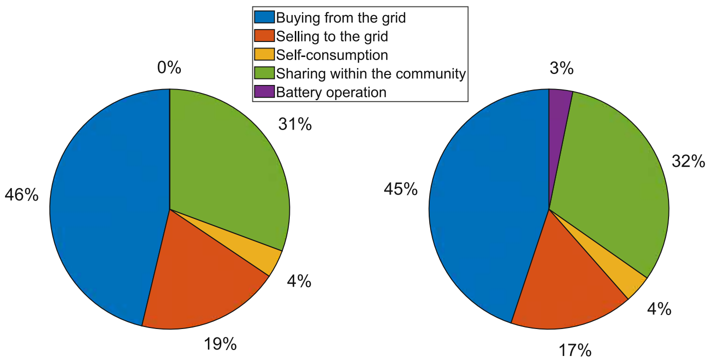


Figure 4.13.: Percentages of annual share of electricity consumed and PV electricity generated within the community (including five small businesses); left: without BESSs; right: with BESSs

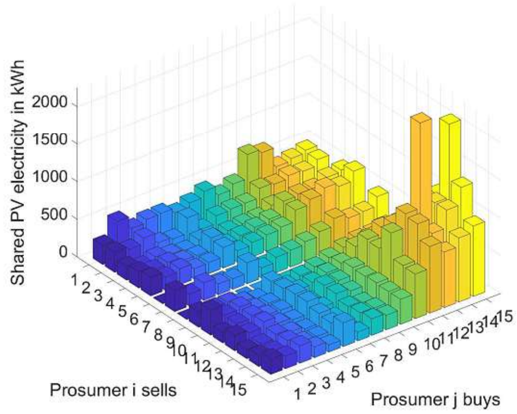


Figure 4.14.: The amount of generated PV electricity traded within the community (including five small businesses) in one year (without BESSs)

electricity generation, which leads to lower profits. Therefore, the community set-up is not ideal for most of the five businesses, because sufficient amounts of PV electricity are already generated. A preferential set-up would thus comprise mostly consumers to whom businesses can sell their PV generated electricity. However, from the perspective of the community, businesses add value because they become the consumers of the PV electricity generated.

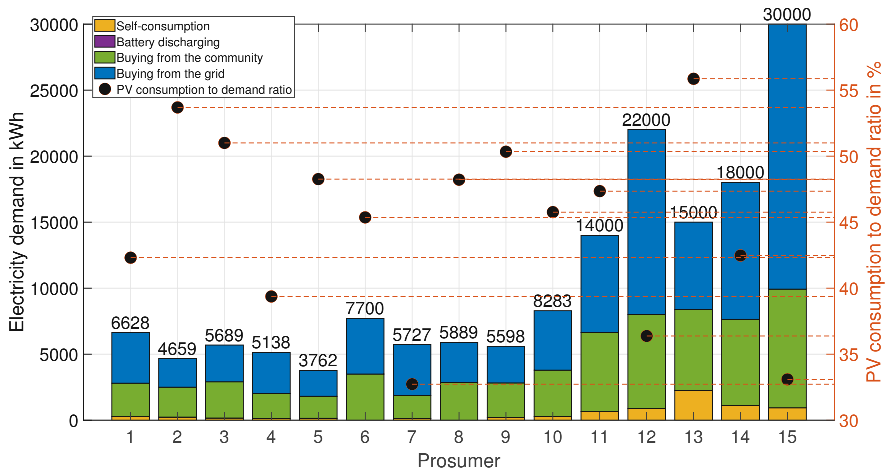


Figure 4.15.: (left axis) Prosumer electricity demand (including that of five small businesses) is covered by PV self-consumption (yellow), PV generated by the community (green), and electricity from the grid (blue); (right axis) PV consumption to demand ratio (without BESSs)

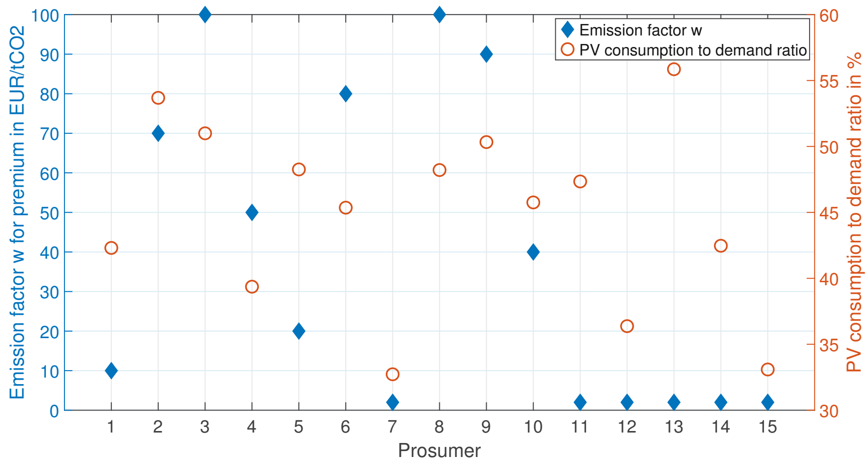


Figure 4.16.: (left axis) Willingness-to-pay; (right axis) ratio between the amount of PV generation consumed and amount of electricity demanded (without BESSs, including five small businesses)

Based on the results of this case study, it is necessary to determine what type of community is the best fit for new potential members and which prosumer

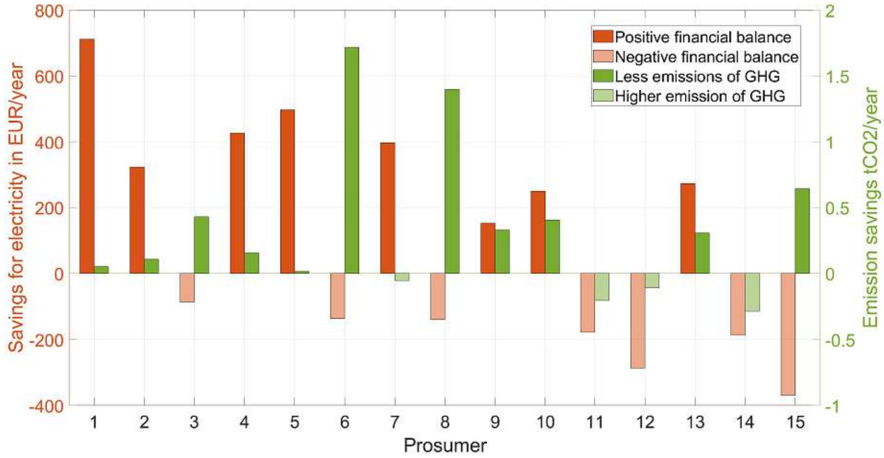


Figure 4.17.: (left axis) Savings in Euros compared to being a stand-alone prosumer; (right axis) emissions' balance (without BESSs, including five small businesses)

characteristics add value to communities. The following parts of this thesis based on the contributions Perger and Auer (2022) and Perger et al. (2022) analyze energy communities in which members drop in and out over several years. It is important to determine criteria that members need to meet prior to joining a community, so that the added value is optimal for the existing community as well as for the new member.

4.4. Sensitivity analysis

In this section, the input parameters and the default set-up of ten households without BESSs (Section 4.2.1) are modified in different sensitivity analyses. The default set-up is located in Vienna, Austria, and some of the parameters (for example the retail electricity price, the average spot market price, and the marginal emissions) are specific to the region. The model presented in this paper is designed to be applied in different regions and countries, and only the location specific input data thus need to be adapted accordingly.

In the following sensitivity analyses, some of the input parameters are varied and the prosumer set-up is modified. In this section, the following four scenarios are modeled and evaluated:

1. *Varying the Retail Electricity Price*

   The average Austrian retail electricity price is just slightly below that of the 2019 EU-28 average value (see Eurostat (2022)). As it would be interesting to determine whether adapting the retail electricity price in the model to that of another European country would change the results of the energy community, the retail electricity price, $p_t^{G_{in}}$, is adapted here to the average German value of 0.3088 EUR/kWh. This is a retail electricity price at the upper end of Europe (due to the high renewable levy share, surcharges, and taxes).

2. *Varying the Remuneration for Excess PV Generation*

   In the default scenario, it is assumed that excess PV generation is sold to the grid at an average spot market price. In this scenario, the results are evaluated when the renumeration is neglectable, i.e. when $p_t^{G_{out}}$ is set to 0. This could occur if excess renewable generation in the current electricity market design is treated rather as a burden than a benefit.

3. *Varying the Marginal Emissions of the External Reference Electricity Market*

   Compared to the Austrian/German electricity system, other electricity systems have different power plant portfolios (for example, they have a high share of nuclear power plants, which are classified as *low-emission* or *emission free* in terms of GHG). As an example, the marginal emissions in the French electricity system are a fraction of the marginal emissions in the Austrian/German electricity market (see Schram et al Schram et al., 2019b). In this sensitivity analysis, the vector of the marginal emissions, e_t, represents the French electricity system instead of the Austrian/German system.

4. *Structural Diversification of the Community*

In this final sensitivity analysis, one member drops out of the community. To best demonstrate the possible impacts of changes in the community set-up, it is considered that a prosumer with a relatively high PV electricity generation and electricity demand leaves (prosumer 7 with a 5 kWpeak South West PV system).

The following Figure 4.18 shows the percentage deviation of the different sensitivity analyses from the default scenario. The output values of social welfare, self-consumption, sharing within the community, and the purchases and sales from/to the grid are compared and the results are as follows:

- Community welfare (in EUR) decreases in all four sensitivity analyses. As per Equation (3.1), the retail price, $p_t^{G_{in}}$, and remuneration, $p_t^{G_{out}}$, influence community welfare. Varying marginal emissions does not alter the weights of the willingness-to-pay, but the prosumers pay proportionally less (or more if marginal emissions increase), and therefore the community welfare result changes. The drop-out of the member decreases welfare because there are only 9 prosumers left to buy and sell the PV electricity generated.

- The amount of electricity (in kWh) available for self-consumption and sharing within the community shifts slightly in scenario 2-4. The only distinctive deviation is noticeable in sensitivity 1, where self-consumption increases and sharing with the community decreases. It is important to note that self-consumption in the default scenario is only a few percent, and thus the relative shift seems high.

- The purchases and sales from/to the grid (in kWh) in sensitivity analyses 1-3 are not different from those in the default scenario, because the prosumer set-up is the same and the community welfare maximization minimizes the purchases/sales from the grid. However, these change in sensitivity analysis 4, when one member leaves the community. The total amount of electricity decreases, because there is a lower electricity demand as well as lower PV electricity generation.

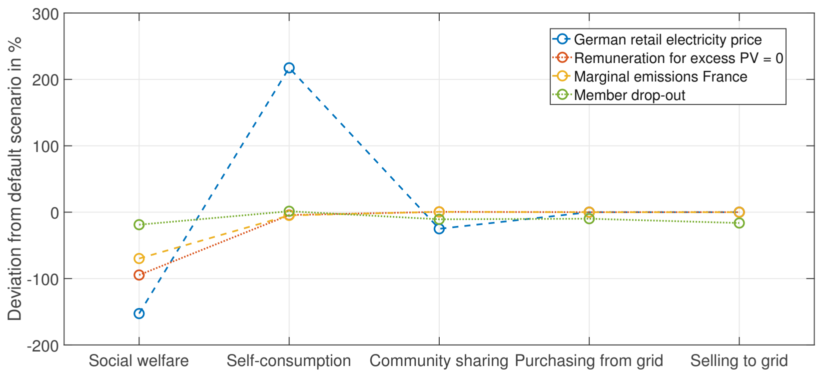


Figure 4.18.: Deviation from default set-up for sensitivity analyses

5. Results of dynamic participation in energy communities

This chapter presents the results of the second and third research questions as presented in Perger and Auer (2022) and Perger et al. (2022), respectively. Both contributions address dynamic participation in energy communities. The second research question, where dynamic participation over one year is considered and a community can choose optimal parameters of new members, is presented in Section 5.1. The case study set-up is found in Section 5.1.1, followed by results for a case study with households in Section 5.1.2 and with businesses in Section 4.3. Sensitivity analyses in Section 5.1.4 conclude the results of the second research question. The third research question, where a stochastic approach to dynamic participation is covered, is presented in Section 5.2. The case study set-up and the set of scenarios are found in Section 5.2.1. The selection of new members in year one using a horizon with stochastic forecasts is shown in Section 5.2.2, and the results of a deterministic and stochastic approach are compared. Finally, the selection process in Section 5.2.3 over five years comparing stochastic and deterministic solution concludes this chapter.

5.1. Dynamic participation over one year

5.1.1. Case study set-up

5.1.1.1. Model implementation

The model is implemented using Python (version 3.7.2; see Van Rossum and Drake (2009)) using the Pyomo package (version 5.7.3; see Hart et al. (2011) and Bynum et al., 2021), and Gurobi (version 9.0.0; see Gurobi Optimization, LLC (2021)) as a solver. Gurobi is a commercial solver; alternatively, the problem can be solved with the open-source solver GLPK (GNU Linear Programming Kit, see GNU project (2021)). The model is available open source on GitHub (see T. Perger (2021)).

5.1.1.2. Input data

To generate the results of a case study, a small community needs to be defined. The electricity demand of each member is obtained from the open-source tool LoadProfileGenerator (version 10.4.0; see Pflugradt and Muntwyler (2017)), which generates artificial data. Different household types categorized by living situation and demographics (single working person, elderly couple, family, etc.) are included in this study.

The PV generation data are obtained from a different open-source tool Renewables.ninja (version v1.3; see Pfenninger and Staffell (2016), and Staffell and Pfenninger (2016)). PV systems' irradiation data and electricity output are location-specific to Vienna, Austria.

While the existing community is characterized by specific input parameters, standardized profiles for the new prosumers are used as input data:

- $q_{i,t}^{load}$ is a standardized load profile (H0 for household, G0 for standard business[1])), which is normalized to 1000 kWh/year. For example, a result of $load_i = 5$ means that the optimal prosumer has an annual demand of 5000 kWh/year. The possible range is between $2000 - 8000$ kWh/year.

- $q_{i,t}^{PV}$ is the generation profile of a $1\,\mathrm{kW_{peak}}$ PV system facing South; hence, the decision variable PV_i is a factor that upscales the PV system size. The possible range is between $0 - 5\,\mathrm{kW_{peak}}$.

A summary of the prosumers' input data can be found in Figure 5.1 and in more detail in Table 5.1. The willingness-to-pay w_i is arbitrarily assigned between the prosumers to cover a range between 0–100 EUR/tCO_2. The electrical distance factors $d_{ij} \in [0,1]$ can be represented by a symmetric matrix with diagonal elements all set to 0 (see Figure 5.2). The values assumed here are dummy values to represent electrical distances within a distribution network because the case study is artificial. The higher the value of d_{ij}, the further the electrical distance between prosumer i and j.

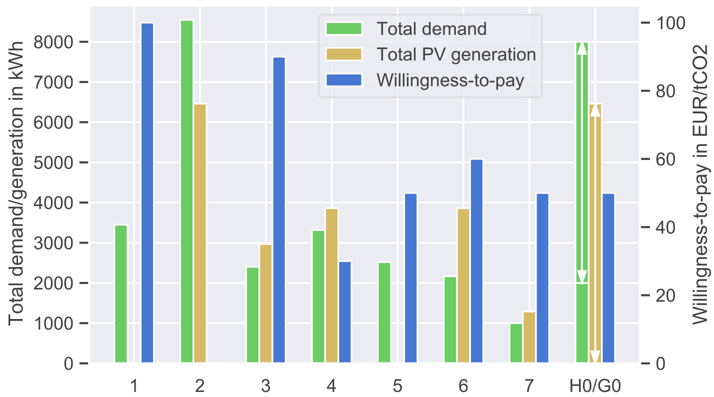


Figure 5.1.: Annual electricity demand and photovoltaic (PV) generation of the prosumers (left axis); willingness-to-pay w_j of each prosumer (right axis)

Input data from the grid includes the following values: $p_t^{G_{in}} = 0.2$ EUR/kWh (the average value of the 2019 Austrian retail electricity price; see Eurostat

[1]The synthetic load profiles of 2019 for household (H0 "Haushalt") and business (G0 "Gewerbe allgemein") are used (see further APCS-Austrian Power Clearing and Settlement (2019)).

Table 5.1.: Parameters of the prosumers of the community ("-" indicates that a technology type is not included). The willingness-to-pay w_i of the new prosumers (H0 and G0) is not optimized, but varied in a sensitivity analysis.

	Annual demand (kWh)	PV orientation	PV peak output (kW)	Storage capacity (kWh)	CO_2-price w_i (EUR/tCO2)
Prosumer 1	3448	-	-	-	100
Prosumer 2	8548	South	5	-	0
Prosumer 3	2403	West	3	-	90
Prosumer 4	3320	South	3	3	30
Prosumer 5	2521	-	-	-	50
Prosumer 6	2167	South	3	-	60
Prosumer H0	$2000 - 8000$	South	$0 - 5$	-	0/50/100
Prosumer G0	$2000 - 8000$	South	$0 - 5$	-	0/50/100

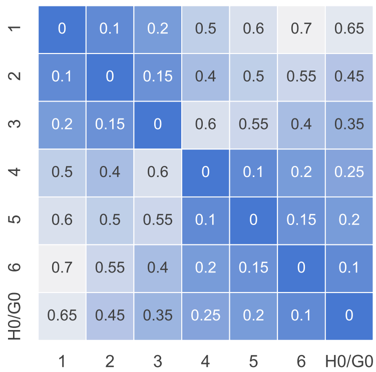


Figure 5.2.: Distance factors d_{ij} between the members (H0 and G0 represent the new prosumers)

(2022)) and $p_t^{G_{out}} = 0.04\,$EUR/kWh (average Austrian spot market price of 2019; see EXAA Energy Exchange Austria (2020)). Marginal emissions e_t are hourly values obtained from Schram et al. (2019b) (Austrian-German spot market), and average hourly values are found in Figure C.2 in the Appendix.

5.1.1.3. Clustering in the time domain

Because MPECs are computationally expensive, an alternative approach is used to represent peer-to-peer trading within a community over a whole year. The input data that is available in hourly resolution for a whole year is transformed to three representative days using a k-means algorithm (Teichgraeber and Brandt (2019)) of the Python *tslearn* package (Tavenard et al. (2020)). The optimization model then determines the optimum using the three representative days considering the weight (each day represents a number of days of the year, which is then used to weight each representative day in the process of upscaling back to annual values; all three days represent the whole year) of each day in both the upper and lower level objective functions.

5.1.2. Results of bi-level optimization of a case study with households

5.1.2.1. Status-quo of the original community

It is first necessary to take a deeper look into the original community's peer-to-peer trading. The original community consists of six households with consumers and prosumers. The annual results (kilowatt-hours of electricity bought and sold, emissions, and costs) of all members are presented in Table 5.2. Figure 5.3 presents the peer-to-peer traded electricity (in kWh/year) in detail as a heat map; rows represent the amount a prosumer sells to each peer, and columns are the respective purchases.

Compared to all other participants, prosumer 1 buys the most from the community, with the highest share coming from prosumer 2, who is prosumer 1's closest peer and has a $5\,\mathrm{kW_{peak}}$ PV system installed. Prosumer 1 does not own a PV system and has the highest willingness-to-pay. Prosumer 3 has the second-highest willingness-to-pay; however, they also have their own PV system installed, and mostly consume their own generation. Prosumer 2 prefers to sell to prosumer 1, with a higher willingness-to-pay than prosumer 3. Prosumer 2 clearly has the highest electricity demand within the

Table 5.2.: Summary of the results of peer-to-peer trading (original community set-up)

Prosumer	1	2	3	4	5	6
Buying grid (kWh)	1140.3	4871.6	1379.3	1080.4	1436.3	854.6
Selling grid (kWh)	0	818.3	1680.0	573.5	0	2286.9
Battery charging (kWh)	0	0	0	870.0	0	0
Battery discharging (kWh)	0	0	0	721.5	0	0
Self-consumption (kWh)	0	3341.5	1016.7	1400.7	0	1282.9
Buying community (kWh)	2308.1	334.6	6.5	117.4	1084.5	29.6
Selling community (kWh)	0	2300.8	274.3	1015.5	0	290.0
Emissions (tCO_2)	0.6	2.6	0.7	0.6	0.8	0.5
Costs (EUR)	790.0	449.3	154.5	-8.2	527.7	24.0

community; therefore, the highest annual (marginal) CO_2 emissions of the community, despite having large PV system capacities installed.

Prosumer 5, who is a consumer only, prefers to buy from their closest peers, prosumers 4 and 6. Prosumer 6 has very low annual electricity costs due to high-self-consumption and being able to sell electricity to other members of the community. Prosumer 4 is the only participant with a BESS and is able to further minimize their electricity costs, achieving negative annual costs.

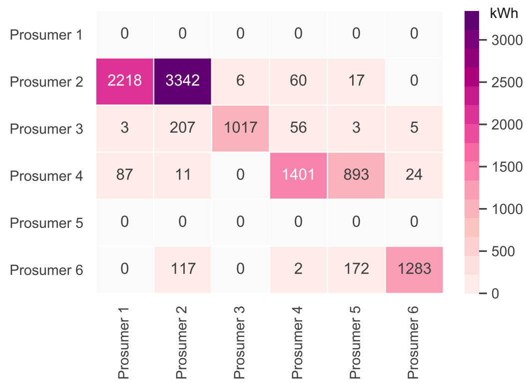


Figure 5.3.: Heatmap of the peer-to-peer electricity trading between the prosumers

5.1.2.2. Cost- vs. emission-saving preference of prosumers

One new prosumer with a household electricity demand profile (prosumer H0) is added to the original community of six households described above. The potential new member is characterized by a willingness-to-pay of 50 EUR/tCO_2 (mid-range compared to the other prosumers) and by electrical distances as defined in Fig. 5.2. Minimizing the objective function of the upper-level problem will determine the ideal parameters of the new prosumer. Annual electricity demand might vary between 2000 kWh/year to 8000 kWh/year, and PV capacity between 0 kW_{peak} to 5 kW_{peak}. The variable n (number of new prosumers) is set to one; hence, with one potential new prosumer the binary variable b_i automatically equals one (see Eq. (3.10d)).

The first set of results shows two distinct cases; (i) where all members have an emission-saving preference ($\alpha_i = 0$), and (ii) where all members have a cost-saving preference ($\alpha_i = 1$). A third case (iii) with mixed preferences will be presented in Section 5.1.2.3.

(i) Minimizing emissions In the first case, it is assumed that all community members care about minimizing their annual emissions, but have no preference regarding cost savings; $\alpha_i = 0$ is set for all prosumers $i \in \mathcal{I}_{old}$. The result of the new prosumer's PV system size is not surprising. The PV capacity is set to its maximum $PV_{new} = PV_{new}^{max} = 5\,\mathrm{kW_{peak}}$. At the same time, the optimal electricity demand of the new prosumer is at its minimum $load_{new} = load_{new}^{min} = 2000\,\mathrm{kWh/year}$. The new annual peer-to-peer trading values are shown in Fig. 5.4. The annual results (kilowatt-hours of electricity bought and sold, marginal emissions, and costs) of all members are presented in Appendix Table C.1.

Cost-wise, the newly added PV capacity can be seen as a competition with other members' PV systems. Part of the revenue from selling electricity to consumers transfers to the new prosumer instead of old members, whose earnings now decrease. Notably, the annual emissions of all prosumers involved are reduced. Due to the newly added PV capacity, prosumers are able to buy more electricity from the community. The electricity demand of the

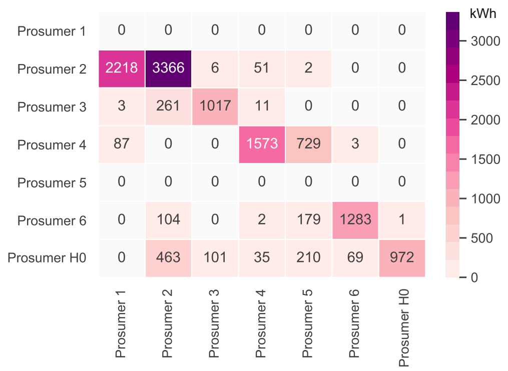


Figure 5.4.: Heatmap of the peer-to-peer electricity trading between the prosumers – all $\alpha_i = 0$

new prosumer is low, such that there is little competition in consuming PV electricity.

The Sankey diagram in Figure 5.5 demonstrates that members of the original community ($\mathcal{I}_{old}$) cover their electricity demand through self-consumption, buying from other community members or buying from the grid. The left side represents the old community without the new prosumer, and the right side shows the new community. The new prosumer's PV generation primarily substitutes purchases from the grid, which is desirable if the common goal is to reduce emissions. Prior to adding the new prosumer, community members purchase 10 700 kWh from the grid. Adding a new prosumer with a 5 kW_{peak} PV system installed, this amount can be reduced by around 8%. Prosumer 4, who has battery storage installed, can also increase their self-consumption.

The next Figure 5.6 presents the annual cost and emission increase (or decrease) of each prosumer of the original community, comparing Eqs. (3.5) and (3.6). Annual costs (left axis in red) increase slightly by a few EUR for most prosumers, whereas emissions significantly decrease, as desired.

(ii) Minimizing costs The other distinct case is setting all $\alpha_i = 1$, indicating that prosumers seek to minimize annual electricity costs. The optimal result of the bi-level problem is a prosumer with the maximum pos-

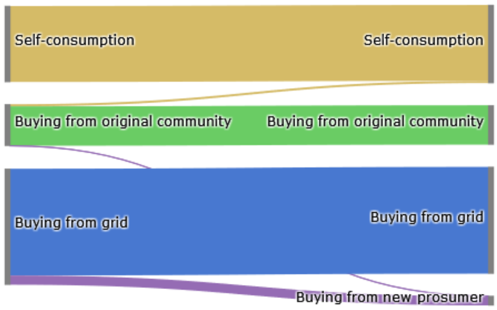


Figure 5.5.: Sankey diagram of the electricity consumption of prosumers

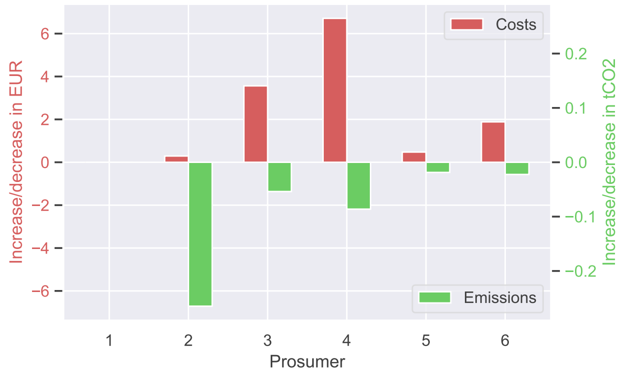
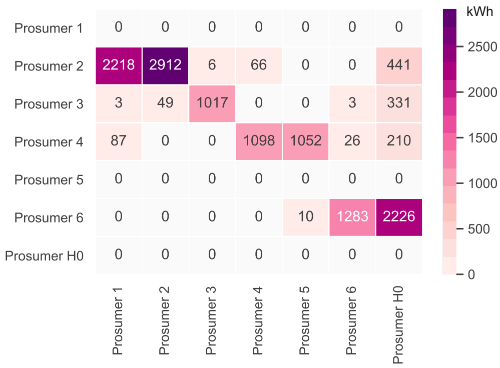


Figure 5.6.: Cost- and emission balances of the prosumer of $\mathcal{I}_{old}$ – all $\alpha_i = 0$

sible annual electricity demand $load_{new} = load_{new}^{max} = 8000\,\mathrm{kWh/year}$. At the same time, the new prosumer's optimal PV capacity is at its minimum $PV_{new} = PV_{new}^{min} = 0\,\mathrm{kW_{peak}}$; hence, the new member is a consumer, who buys PV electricity from the community, which generates additional revenue for the other members. The new annual peer-to-peer trading values are shown in Fig. 5.7. The annual results (kilowatt-hours of electricity bought and sold, marginal emissions, and costs) of all members are presented in Appendix Table C.2.

The Sankey diagram in Figure 5.8 demonstrates that members can increase their income by selling a significant amount of their generation to the new prosumer, which was previously sold to the grid because the new prosumer's



	Prosumer 1	Prosumer 2	Prosumer 3	Prosumer 4	Prosumer 5	Prosumer 6	Prosumer H0
Prosumer 1	0	0	0	0	0	0	0
Prosumer 2	2218	2912	6	66	0	0	441
Prosumer 3	3	49	1017	0	0	3	331
Prosumer 4	87	0	0	1098	1052	26	210
Prosumer 5	0	0	0	0	0	0	0
Prosumer 6	0	0	0	0	10	1283	2226
Prosumer H0	0	0	0	0	0	0	0

Figure 5.7.: Heatmap of the peer-to-peer electricity trading between the prosumers-all $\alpha_i = 1$

willingness-to-pay is higher than the remuneration for selling PV generation into the grid $wtp_{i,new,t} > p_t^{G_{out}}$.

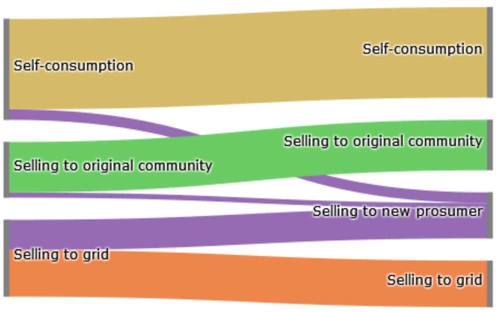


Figure 5.8.: Sankey diagram of the electricity generation of prosumers

In total, about 40% of the community's surplus PV production is sold to the new prosumer in this scenario, resulting in cost savings for prosumers with PV systems (see Figure 5.9). This is especially evident for prosumer 6, who is the closest neighbor of the new prosumer. The consumers of the community, prosumers 1 and 5 do not experience major changes. Emission balances offer another interesting result; the lower the willingness-to-pay (e.g., prosumer 2 with $w_2 = 0\,\mathrm{EUR/tCO_2}$), the higher the annual CO_2 emissions. Prior to adding the new member with a high electricity demand, higher amounts of PV generated electricity remained available for prosumers with low willingness-to-pay, which are now sold to the new member. Prosumer 6, the closest neighbor of the new prosumer, achieves the highest cost decrease.

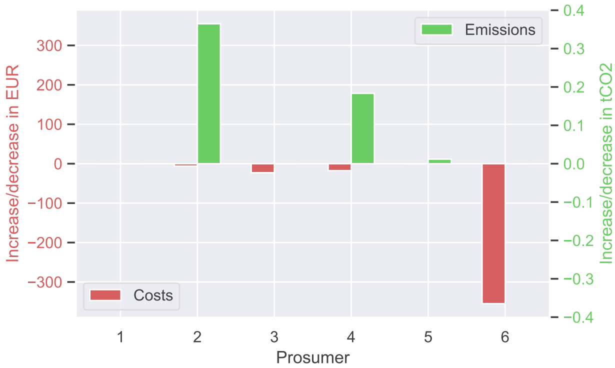


Figure 5.9.: Cost and emission balances of the prosumer of $\mathcal{I}_{old}$ – all $\alpha_i = 1$

5.1.2.3. Prosumers with mixed emission and cost-saving preferences

While the prosumers' choices of α_i are uniform in both cases (i) and (ii) in Section 5.1.2.2, this Section introduces non-uniform values of α_i. There is an extremely large number of possible combinations, many of which lead to the same results as either case (i) or (ii). Other combinations lead to different results; for example, $[\alpha_1, \alpha_2, \alpha_3, \alpha_4, \alpha_5, \alpha_6] = [1, 1, 0, 1, 1, 0]$, which is presented here as case (iii). The optimal parameters of the new prosumer are set by the model to maximum PV capacity and maximum annual electricity demand, $PV_{new} = 5\,\mathrm{kW_{peak}}$ and $load_{new} = 8000\,\mathrm{kWh/year}$, respectively. The detailed peer-to-peer trading in Figure 5.10 shows that the new prosumer trades electricity with the other members, but predominantly self-consumes their PV generated electricity due to their own high annual electricity demand. This differs from case (i) in the previous Section, wherein the new prosumer has a low electricity demand and sells larger volumes of electricity to the other members, comparing Fig. 5.11 with Fig. 5.5.

Due to the high share of self-consumption in case (iii), the new prosumer

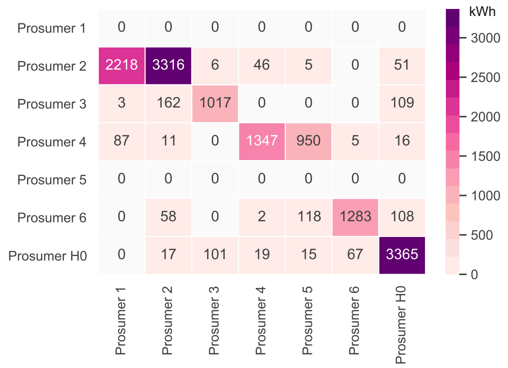


Figure 5.10.: Heatmap of the peer-to-peer electricity trading between the prosumers – mixed α_i

buys only small volumes of electricity from the community (see Fig. 5.12). In general, there are less interactions/trades with the community, which is reflected in the annual cost-emission balances as well. Figure 5.13 shows very small deviations from the previous status quo. Annual emissions decrease for prosumers 3 and 6, which is congruent with their preferences on saving emissions ($\alpha_{3,6} = 0$). Annual cost differences are negligible (less than 2 EUR per year). The annual results (kilowatt-hours of electricity bought and sold, marginal emissions, and costs) of all members are presented in Appendix Table C.3.

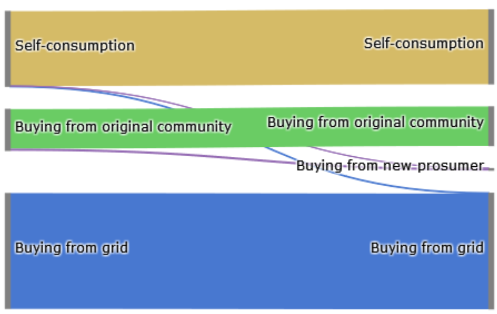


Figure 5.11.: Sankey diagram of the electricity consumption of prosumers

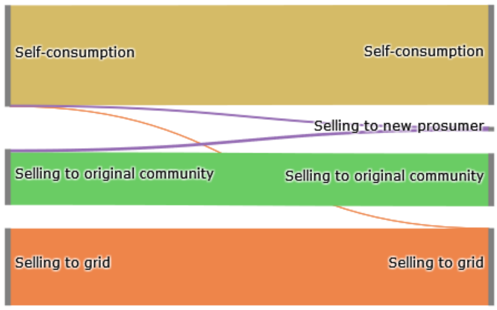


Figure 5.12.: Sankey diagram of the electricity generation of prosumers

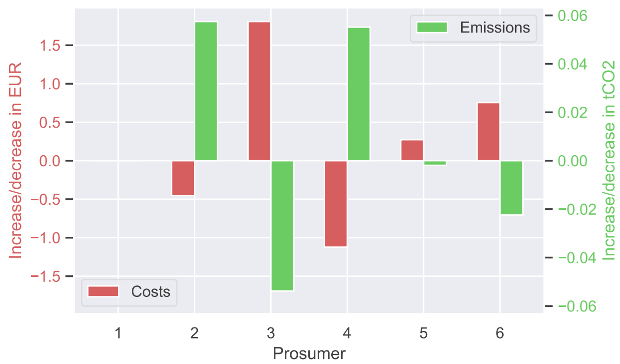


Figure 5.13.: Cost- and emission balances of the prosumer of $\mathcal{I}_{old}$ – mixed α_i

5.1.3. Results of bi-level optimization of a case study with households and businesses

Next, another potential new prosumer with the electricity demand profile of a standard business (prosumer G0) is compared to prosumer H0. The results are unchanged when the case study from Section 5.1.2 is conducted with prosumer G0 instead of H0; therefore, the binary decision variables are actively used in this step and the model is run with two potential new prosumers $\mathcal{I}_{new} = \{\text{prosumer H0}, \text{prosumer G0}\}$ to determine which prosumer type is preferred by the community. There is only one possible choice:

$$\sum_{i \in \mathcal{I}_{new}} b_i = 1. \tag{5.1}$$

We start the analyses by minimizing the individual emissions again, as in case (i). The community prefers the household profile with the same parameters as seen in Section 5.1.2: PV_{new} =5 kW$_{\text{peak}}$ and $load_{new}$ = 2000 kWh/year. The annual peer-to-peer trading is shown in Figure 5.14 (left), wherein the business (prosumer G0) is not part of the community. The other cases, (ii) and (iii), minimizing the prosumers' costs and mixed preferences elicit a different result. The business is a better match with PV generation profiles than the household (see Figures C.2 and C.3 in the Appendix) and is, therefore, a better opportunity to sell surplus PV generation to. In case (ii) the business is a consumer only, with an annual electricity demand of 8000 kWh (see Figure 5.14, right). The results are summarized in Table 5.3.

Table 5.3.: Choosing between different prosumer types H0 and G0

prosumer type	H0	G0
(i) individual emissions	✓	-
(ii) individual costs	-	✓
(iii) mixed α_i	-	✓

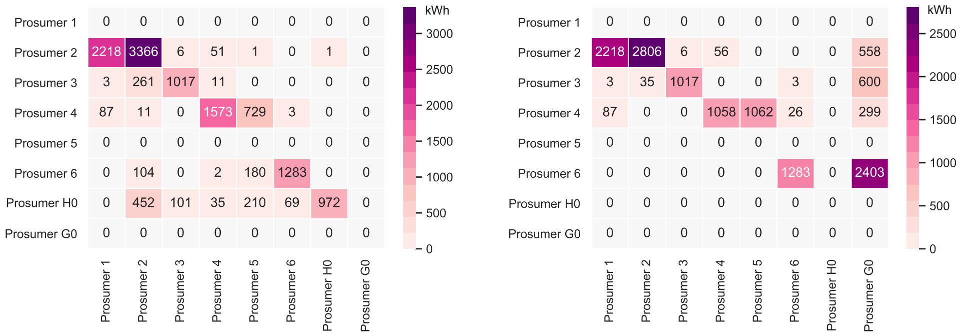


Figure 5.14.: Choosing between prosumer types; $\alpha_i = 0$ (left) vs. $\alpha_i = 1$ (right)

5.1.4. Sensitivity analysis

This Section presents sensitivity analyses to complete the results of this study. In Section 5.1.4.1, differing levels of the new prosumer's willingness-to-pay are applied to the case study to determine possible changes in the results. In

Section 5.1.4.2, the distances of the new prosumer to the other members are altered.

5.1.4.1. Influence of willingness-to-pay

The first set of sensitivity analyses observes the effect of the new prosumer's willingness-to-pay on the community decision. First, we compare the outputs of the bi-level model for different cases of prosumer preferences α_i, as seen in Sections 5.1.2.2 and 5.1.2.3, varying the new prosumer's willingness-to-pay. Table 5.4 presents the results of cases (i)-(iii), where w_{new} is altered from one side of the spectrum of willingness-to-pay, $w_{new} = 0\,\mathrm{EUR/tCO_2}$, to the other, $w_{new} = 100\,\mathrm{EUR/tCO_2}$. There is no noticeable influence of w_{new} in cases (i) and (ii) (see Table 5.4). With either all $\alpha_i = 0$ or $\alpha_i = 1$, the parameters of the new prosumer, $2000\,\mathrm{kWh}/5\,\mathrm{kW_{peak}}$ and $8000\,\mathrm{kWh}/0\,\mathrm{kW_{peak}}$, respectively, are clearly specified by the upper-level cost-emission objective function (CE), regardless the new prosumer's willingness-to-pay.

In contrast, w_{new} can be a decisive factor when α_i are mixed. With $w_{new} = 100\,\mathrm{EUR/tCO_2}$, the new prosumer's optimal annual electricity demand decreases to 2000 kWh, whereas lower willingness-to-pay leads to 8000 kWh. Prosumer 6 has a preference to lower emission ($\alpha_6 = 0$) in case (iii). When $w_{new} > w_6 = 60\,\mathrm{EUR/tCO_2}$, the peer-to-peer allocation assigns higher volumes of PV generated electricity to the new prosumer instead of prosumer 6, negatively impacting the cost-emission function CE and lowering the optimum electricity demand of the new prosumer.

Next, the community decides between two potential new members (similar to Section 5.1.3) with opposite levels of willingness-to-pay to analyze the influence of the willingness-to-pay on the community's choice. The first example is two household (H0) prosumers, who are identical except for the willingness-to-pay, $w_{H0,0} = 0$ vs. $w_{H0,100} = 100$. The community's choices can be seen in Table 5.5, column two (highlighted). In cases (i) and (iii), a prosumer with a low willingness-to-pay is preferred, whereas, in case (ii), the community opts for the prosumer with high willingness-to-pay. The two subsequent columns on the right, which compares household (H0) and business (G0) prosumers,

Table 5.4.: Influence of the willingness-to-pay on the results (new prosumer is a household). w_{new} is the individual CO_2-price of the new prosumer, $load_{new}$ and PV_{new} the resulting optimal annual electricity demand and PV capacity of the new prosumer, respectively.

	$w_{new} = 0$		$w_{new} = 50$		$w_{new} = 100$	
	$load_{new}$ kWh	PV_{new} kW_{peak}	$load_{new}$ kWh	PV_{new} kW_{peak}	$load_{new}$ (kWh)	PV_{new} (kW_{peak})
(i) ind. emissions	2000	5	2000	5	2000	5
(ii) ind. costs	8000	0	8000	0	8000	0
(iii) mixed pref.	8000	5	8000	5	2000	5

repeat this pattern.

Table 5.5.: Influence of the willingness-to-pay on the choice of the community. w_{new} is the individual CO_2-price of the new prosumers.

prosumer type w_i in EUR/tCO_2	H0 0	H0 100	H0 0	G0 100	G0 0	H0 100
(i) individual emissions	✓	-	✓	-	✓	-
(ii) individual costs	-	✓	-	✓	-	✓
(iii) mixed preferences	✓	-	✓	-	✓	-

An assertion can be drawn from the first set of sensitivity analyses that while willingness-to-pay is not a decisive factor in terms of choosing a new prosumer's optimal parameters, it is crucial when deciding between two otherwise identical or similar prosumers. This leads to the assumption that willingness-to-pay is a more significant parameter than prosumer type.

5.1.4.2. Influence of distance criteria

The second type of sensitivity analysis alters the geographical location of the new prosumer with respect to the old community members. The altered distance factors, $\tilde{d}$, of the new prosumer are mirrored compared to the original configuration, d:

$$\tilde{d}_{new,j} = d_{new,(N+1)-j}, \tag{5.2}$$

where j are the indices of prosumers in $\mathcal{I}_{old}$; hence, the new prosumer is (geographically) on the other side of the community. The closest community member is prosumer 1, the furthest is prosumer 6. Note that the distances within the original community remain equal. The new distance factors can be found in Figure 5.15.

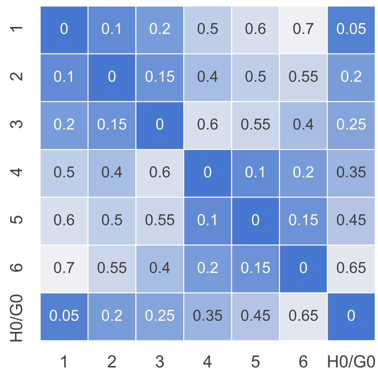


Figure 5.15.: Distance factors d_{ij} between the members (H0 and G0 represent the new prosumers)

Cases (i)-(iii) are once again analyzed and the new prosumer is a household prosumer type with a willingness-to-pay $w_{new} = 50\,\text{EUR/tCO}_2$. Deviation from the previous distance set-up is noticeable in case (iii), where the PV capacity changes to zero, whereas the other two cases remain the same, see Table 5.6. In cases (i) and (ii), the location of the new prosumer does not influence the community's decision. To analyze the community's decision in the mixed-preference (case (iii)), Figure 5.16 compares the prosumer's volumes of traded electricity in two different scenarios: (a) the optimal output of case (iii) ($load_{new} = 8000\,\text{kWh/year}$ and $PV_{new} = 0\,\text{kW}_{\text{peak}}$) and (b) the non-optimal parameters of the new prosumer ($load_{new} = 8000\,\text{kWh/year}$ and $PV_{new} = 5\,\text{kW}_{\text{peak}}$) in Section 5.1.2.3, both with new distance factors $\tilde{d}_{new,j}$. The optimal parameters in scenario (a) lead to an increase in purchases from the community and a decrease in sales for the new prosumer (H0) compared to (b). Therefore, the prosumers of $\mathcal{I}_{old}$ considerably increase sales volumes, particularly prosumer 2 with a cost-saving preference ($\alpha_2 = 1$), which compensates for the small decrease in purchases of prosumer 3 and prosumer 6, who have an emission-saving preference ($\alpha_3, \alpha_6 = 0$) in case (iii).

Table 5.6.: Influence of the willingness-to-pay on the community's choice. d_{new} and $\tilde{d}_{new}$ are the unmodified and modified distance factors, respectively; $load_{new}$ and PV_{new} are the the resulting optimal annual electricity demand and PV capacity of the new prosumer, respectively.

	old distances d_{new}		new distances $\tilde{d}_{new}$	
	$load_{new}$ (kWh)	PV_{new} (kW_{peak})	$load_{new}$ (kWh)	PV_{new} (kW_{peak})
(i) ind. emissions	2000	5	2000	5
(ii) ind. costs	8000	0	8000	0
(iii) mixed preferences	8000	5	8000	0

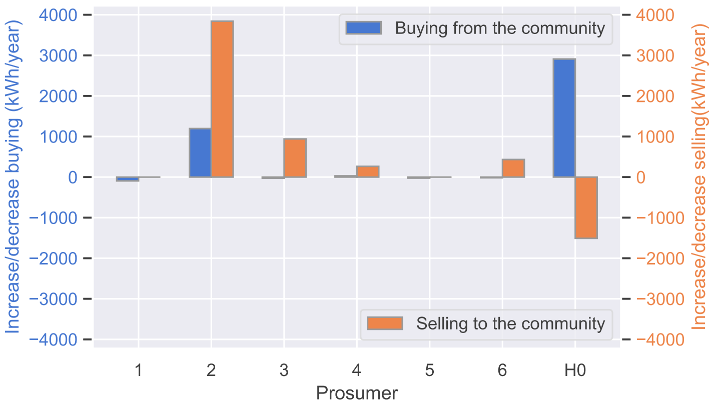


Figure 5.16.: Deviation of buying/selling

5.2. Stochastic dynamic participation with a horizon of several year

5.2.1. Case study set-up

5.2.1.1. Model implementation and run time

The open-source model[2] is implemented using Python (version 3.9.7; Van Rossum and Drake (2009)), the Pyomo package (version 6.2; see Hart et al. (2011) and Bynum et al., 2021), and the commercial[3] solver Gurobi (version 9.5.0; see Gurobi Optimization, LLC (2021)). The stochastic dynamic program is very computationally expensive; with a time horizon of five years considering four scenarios, the case study presented in the following paragraphs takes 7 hours and 36 minutes to solve on a standard computer with Intel(R) Core(TM) i7 CPU. A deterministic solution of the same problem without forecast and scenarios takes 47 seconds.

5.2.1.2. Data and assumptions

In this case study, a portfolio of 20 artificial prosumers consisting of ten single houses (SH), eight small apartment buildings (SAB), and two small businesses (SME) is considered. Single houses have PV systems with up to 5 kW_{peak} installed, and apartment buildings and businesses up to 8 kW_{peak}. Additionally, some prosumers own a battery storage system (BESS). Not all prosumers have their own PV systems; hence, they are consumers only. The detailed data including PV system orientation and willingness-to-pay (CO_2-price w_j) can be found in Table 5.7. w_j covers a range between 0–100 EUR/tCO_2,[4] depending on how strong a prosumer's environmental am-

[2] https://github.com/tperger/PARTICIPATE

[3] Alternatively, the problem can be solved with the open-source solver GLPK (see GNU project, 2021).

[4] With average emissions of 132 gCO_2/kWh from electricity generation in Austria and, for example, $w_j = 100$ EUR/tCO_2, the willingness-to-pay is 1.32 cent/kWh above the retail electricity price.

bitions are. The distance preferences $d_{i,j}$ between prosumers are arbitrarily assigned within $d_{i,j} \in [0, 1]$. The distances are symmetric, thus $d_{i,j} = d_{j,i}$.

The initial set-up consists of ten prosumer (five SHs, four SABs, and one SME); from there, the different scenarios are developed as shown in Section 5.2.1.3. Electricity demand data and PV production data are obtained from open-source tools. Residential demand profiles (LoadProfileGenerator version 10.4.0, see Noah Pflugradt, 2021 and Pflugradt and Muntwyler, 2017) represent different living situations and demographics. Renewables.ninja (see Renewables.ninja, 2019, Pfenninger and Staffell, 2016, and Staffell and Pfenninger, 2016) provides electricity output data from PV systems; in this case study, data from Vienna, Austria from 2019 is applied. To represent demand profiles of businesses, a synthetic load profile for standard businesses (G0 "Gewerbe allgemein") is used (see APCS-Austrian Power Clearing and Settlement (2019)).

Other parameter of the case study concern electricity prices and emissions from the grid. Prosumers buy remaining electricity, which they could not buy from other community members or self-generate, from the retailer. The average residential electricity price in Austria was $p_t^{G_{in}} = 0.22\,\mathrm{EUR/kWh}$ in 2021 (see Eurostat (2022)). This value is constant over all $t \in \mathcal{T}$ and $n \in \mathcal{N}$. The excess PV generation, which prosumers could not sell to other community members or self-consume, is sold to the grid at Day-Ahead (DA) market prices. $p_t^{G_{out}}$ are Austrian DA prices from 2019 (see ENTSO-E (2022)). These values are time-variant over $t \in \mathcal{T}$; the time series is re-used for all $n \in \mathcal{N}$. Emissions from the grid are calculated using again data from ENTSO-E (ibid.) for Austria. The calculation considers the amount of electricity generated per hour and per generation type to account for the corresponding emissions. e_t are hourly average values in $\mathrm{gCO_2/kWh}$; this time series is again used for all $n \in \mathcal{N}$.

Annual hourly data that is available for a whole year is transformed into three representative days using the Python *tslearn* package (Tavenard et al. (2020)), which is based on a k-means clustering algorithm (Teichgraeber and Brandt (2019)). This step is necessary to reduce computational efforts, because solving MPECs is already very time-consuming. Per year, 8760 time

Table 5.7.: Parameters of the prosumers of the portfolio ("-" indicates that a technology type is not included).

	Annual demand (kWh)	PV orientation	PV peak (kW)	BESS (kWh)	CO_2-price (EUR/tCO2)
Prosumer SH 1	3336	South	5	3	100
Prosumer SH 2	4538	South	5	0	0
Prosumer SH 3	5253	-	-	-	90
Prosumer SH 4	5824	South	3	3	30
Prosumer SH 5	6337	South	5	0	50
Prosumer SH 6	6833	South	5	3	60
Prosumer SH 7	7346	-	-	-	40
Prosumer SH 8	7917	South	3	3	80
Prosumer SH 9	8632	South	5	0	20
Prosumer SH 10	9834	-	-	-	100
Prosumer SAB 1	6258	South	8	3	100
Prosumer SAB 2	8513	West	8	0	0
Prosumer SAB 3	9854	-	-	-	90
Prosumer SAB 4	10926	South	5	3	30
Prosumer SAB 5	11888	East	8	0	50
Prosumer SAB 6	12820	West	8	3	60
Prosumer SAB 7	13782	-	-	-	40
Prosumer SAB 8	14854	South	5	3	80
Prosumer SME 1	16195	South	8	0	10
Prosumer SME 2	18450	-	-	-	20

steps are reduced to 72 time steps only. The resulting representative days reflect a summer, a winter, and a spring/fall day. The input data sets that are clustered mainly vary during different times of the day and the year (i.e., seasons). This information is preserved in the representative time series, therefore the clustering approach is reasonable in our application.

5.2.1.3. Scenarios

We use a finite set of scenarios to represent possible developments of the portfolio of possible prosumers. Considering in total 20 prosumers, their possible decisions, and a time horizon of a few years, a large number of permutations are obtained. Therefore, a scenario tree with all possibilities would be very large. Due to the high computational efforts of stochastic programming, we do not aim at using the full scenario tree for our research. Instead, a relatively small set of completely different scenarios is developed to represent the wide spectrum of possibilities.[5] This decision is also justified by the fact that in the objective function in Eq. (3.11), the scenarios are weighted with their probabilities $p(\omega)$. As a result, with increasing number of scenarios, the probabilities of each single scenario drop.

The use case that will be shown in the results section considers different building and prosumer types: single houses (SH), small apartment buildings (SAB), and small businesses (SME). At the beginning, the initial set-up contains five SHs, four SABs, and one SME. The present contract lengths with the community $x_{0,i}$ vary between zero (in the portfolio, but not a member) and three years. From there, four different scenarios are considered:

- ω_1: additional SABs might want to join in the upcoming years
- ω_2: the SABs might want to phase-out in the upcoming years
- ω_3: additional SHs might want to join in the upcoming years
- ω_4: the SHs might want to phase-out in the upcoming years

Figure 5.17 shows a graphical representation of each scenario $\omega \in \Omega$ from year one to year five (blue – $s_{n,i}(\omega) = 1$; yellow – $s_{n,i}(\omega) = 0$; highlighted in red - changes compared to the original community). The original community consists of the following prosumers: SH 1, SH 2, SH 3, SH 6, SH 7, SAB 3, SAB 4, SAB 5, SAB 7, SME 1.

5.2.2. Selection of new members in year one using a horizon with stochastic forecasts

The energy community that is investigated in the case study considers a portfolio of 20 (possible) prosumers. The portfolio is diverse: different build-

[5] The values of $s_{n,i}(\omega)$ are randomly assigned.

Scenario ω1

Year 1	Year 2	Year 3	Year 4	Year 5
SH 1	SH 1	SH 1	SH 1	SH 1
SH 2	SH 2	SH 2	SH 2	SH 2
SH 3	SH 3	SH 3	SH 3	SH 3
SH 4	SH 4	SH 4	SH 4	SH 4
SH 5	SH 5	SH 5	SH 5	SH 5
SH 6	SH 6	SH 6	SH 6	SH 6
SH 7	SH 7	SH 7	SH 7	SH 7
SH 8	SH 8	SH 8	SH 8	SH 8
SH 9	SH 9	SH 9	SH 9	SH 9
SH 10	SH 10	SH 10	SH 10	SH 10
SAB 1	SAB 1	SAB 1	SAB 1	SAB 1
SAB 2	SAB 2	SAB 2	SAB 2	SAB 2
SAB 3	SAB 3	SAB 3	SAB 3	SAB 3
SAB 4	SAB 4	SAB 4	SAB 4	SAB 4
SAB 5	SAB 5	SAB 5	SAB 5	SAB 5
SAB 6	SAB 6	SAB 6	SAB 6	SAB 6
SAB 7	SAB 7	SAB 7	SAB 7	SAB 7
SAB 8	SAB 8	SAB 8	SAB 8	SAB 8
SME 1	SME 1	SME 1	SME 1	SME 1
SME 2	SME 2	SME 2	SME 2	SME 2

Scenario ω2

Year 1	Year 2	Year 3	Year 4	Year 5
SH 1	SH 1	SH 1	SH 1	SH 1
SH 2	SH 2	SH 2	SH 2	SH 2
SH 3	SH 3	SH 3	SH 3	SH 3
SH 4	SH 4	SH 4	SH 4	SH 4
SH 5	SH 5	SH 5	SH 5	SH 5
SH 6	SH 6	SH 6	SH 6	SH 6
SH 7	SH 7	SH 7	SH 7	SH 7
SH 8	SH 8	SH 8	SH 8	SH 8
SH 9	SH 9	SH 9	SH 9	SH 9
SH 10	SH 10	SH 10	SH 10	SH 10
SAB 1	SAB 1	SAB 1	SAB 1	SAB 1
SAB 2	SAB 2	SAB 2	SAB 2	SAB 2
SAB 3	SAB 3	SAB 3	SAB 3	SAB 3
SAB 4	SAB 4	SAB 4	SAB 4	SAB 4
SAB 5	SAB 5	SAB 5	SAB 5	SAB 5
SAB 6	SAB 6	SAB 6	SAB 6	SAB 6
SAB 7	SAB 7	SAB 7	SAB 7	SAB 7
SAB 8	SAB 8	SAB 8	SAB 8	SAB 8
SME 1	SME 1	SME 1	SME 1	SME 1
SME 2	SME 2	SME 2	SME 2	SME 2

Scenario ω3

Year 1	Year 2	Year 3	Year 4	Year 5
SH 1	SH 1	SH 1	SH 1	SH 1
SH 2	SH 2	SH 2	SH 2	SH 2
SH 3	SH 3	SH 3	SH 3	SH 3
SH 4	SH 4	SH 4	SH 4	SH 4
SH 5	SH 5	SH 5	SH 5	SH 5
SH 6	SH 6	SH 6	SH 6	SH 6
SH 7	SH 7	SH 7	SH 7	SH 7
SH 8	SH 8	SH 8	SH 8	SH 8
SH 9	SH 9	SH 9	SH 9	SH 9
SH 10	SH 10	SH 10	SH 10	SH 10
SAB 1	SAB 1	SAB 1	SAB 1	SAB 1
SAB 2	SAB 2	SAB 2	SAB 2	SAB 2
SAB 3	SAB 3	SAB 3	SAB 3	SAB 3
SAB 4	SAB 4	SAB 4	SAB 4	SAB 4
SAB 5	SAB 5	SAB 5	SAB 5	SAB 5
SAB 6	SAB 6	SAB 6	SAB 6	SAB 6
SAB 7	SAB 7	SAB 7	SAB 7	SAB 7
SAB 8	SAB 8	SAB 8	SAB 8	SAB 8
SME 1	SME 1	SME 1	SME 1	SME 1
SME 2	SME 2	SME 2	SME 2	SME 2

Scenario ω4

Year 1	Year 2	Year 3	Year 4	Year 5
SH 1	SH 1	SH 1	SH 1	SH 1
SH 2	SH 2	SH 2	SH 2	SH 2
SH 3	SH 3	SH 3	SH 3	SH 3
SH 4	SH 4	SH 4	SH 4	SH 4
SH 5	SH 5	SH 5	SH 5	SH 5
SH 6	SH 6	SH 6	SH 6	SH 6
SH 7	SH 7	SH 7	SH 7	SH 7
SH 8	SH 8	SH 8	SH 8	SH 8
SH 9	SH 9	SH 9	SH 9	SH 9
SH 10	SH 10	SH 10	SH 10	SH 10
SAB 1	SAB 1	SAB 1	SAB 1	SAB 1
SAB 2	SAB 2	SAB 2	SAB 2	SAB 2
SAB 3	SAB 3	SAB 3	SAB 3	SAB 3
SAB 4	SAB 4	SAB 4	SAB 4	SAB 4
SAB 5	SAB 5	SAB 5	SAB 5	SAB 5
SAB 6	SAB 6	SAB 6	SAB 6	SAB 6
SAB 7	SAB 7	SAB 7	SAB 7	SAB 7
SAB 8	SAB 8	SAB 8	SAB 8	SAB 8
SME 1	SME 1	SME 1	SME 1	SME 1
SME 2	SME 2	SME 2	SME 2	SME 2

Figure 5.17.: Choice of the prosumers $s_{n,i}(\omega)$ depending on the scenarios $\omega \in \Omega$ (blue - $s_{n,i}(\omega) = 1$; yellow - $s_{n,i}(\omega) = 0$; red highlighted - changes compared to the original community)

ing types (single houses and apartment buildings), residential and commercial consumers, different PV system sizes, etc. are included. Initially, the community consists of ten members; the other ten prosumers are not members (yet), but part of the portfolio. It is up to the community manager to define who could be a potential new member in the future. Observing a neighborhood or a district, buildings currently under construction or newly constructed buildings could be potential new members in a few years or even sooner. Also, growing interest in energy communities per se is considered. Residents of existing buildings with already installed PV systems might notice the advantages of joining forces in a community. With some expertise, such portfolio can be created. The next step involves the development of plausible scenarios. If and when a potential new prosumer might announce their willingness to join the community are estimated. This does not have to be exact, because uncertainties can be represented in the different scenarios.

5.2.2.1. Original community

Initially, the status-quo of the original community is observed to create a starting point for the further evaluations of the results. Figure 5.18 shows the peer-to-peer traded electricity (in kWh/year) in detail; columns represent the purchases of each member, and rows the respective sales. The allocation is based on the participants' willingness-to-pay: Prosumers sell self-generated PV electricity to those members with highest willingness-to-pay. Table 5.8 shows the quantitative, annual results (kilowatt-hours of electricity bought and sold, emissions, and costs) of all members. The community consists of six prosumers, who own PV systems (three of them own an additional BESS), and four consumers, who cannot sell electricity; they rely on purchases from the grid or from the community.

5.2.2.2. Stochastic solution

The first set of results shows the selection process for one year in detail. A time horizon of five years with stochastic forecasts from year $n = 2, \ldots, 5$ is included in the decision at year $n = 1$. For each scenario within the time horizon, different decisions are made depending on which configuration is optimal *within each scenario*. The resulting numbers of prosumers are shown

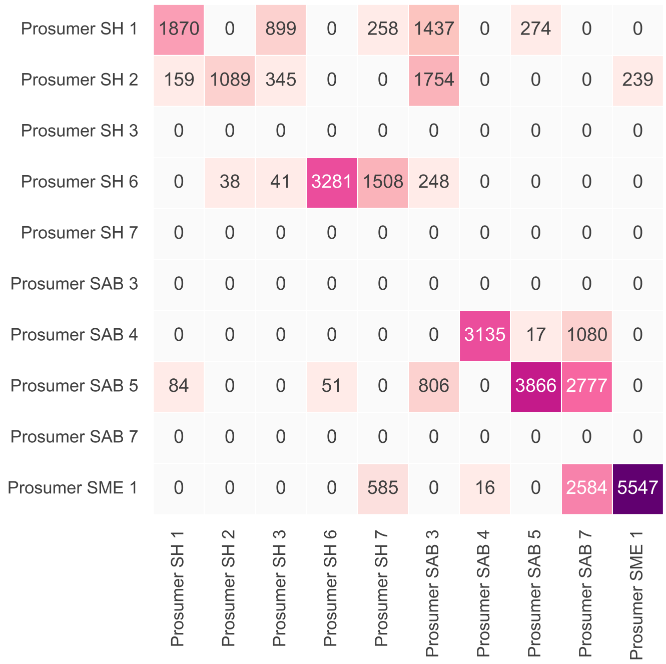


Figure 5.18.: Peer-to-peer trading annual results of the original community in kWh/year

in Figure 5.19, grouped into the following categories: the numbers of existing members (blue) and newly added members (green) are counted on the positive y-axis, and the numbers of prosumers, who are part of the portfolio but no members of the community (yellow), and those leaving the community (red) are counted on the negative part of y-axis. The scenarios $\omega_1, \omega_2, \omega_3, \omega_4$ are shown one below the other. Note that in year one, there is only one joint decision for all scenarios together because of the non-anticipativity constraints imposed in Eq.s (3.17)-(3.20).

As shown in Figure 5.19, the decision at year one involves three prosumers who join the community, and two prosumers who leave. Prosumer SAB 3 and prosumer SAB 7 left on a voluntary basis ($s_{1,i} = 0$). At $n = 1$, decisions on the potential participation of prosumer SH 5, prosumer SAB 8, and prosumer SME 2, who show interest in joining the community ($s_{1,i} = 1$), are made. The stochastic dynamic program under consideration of all four scenarios accepts the new prosumers into the community. Prosumer SH 5 and SAB 8 bring

Table 5.8.: Summary of the peer-to-peer trading results of the original community

Prosumer	SH 1	SH 2	SH 3	SH 6	SH 7
Buying grid (kWh)	479.5	3369.5	3961.1	2712.2	4933.7
Selling grid (kWh)	815.3	2857.8	0	469.9	0
Battery charging (kWh)	880.0	0	0	880.0	0
Battery discharging (kWh)	747.4	0	0	776.8	0
Self-consumption (kWh)	1877.5	1099.2	0	3291.2	0
Buying community (kWh)	231.2	68.8	1291.4	53.1	2412.5
Selling community (kWh)	2887.9	2503.7	0	1819.6	0
Emissions (tCO_2)	0.1	0.5	0.5	0.4	0.7
Costs (EUR)	-531.0	78.4	1169.6	184.5	1637.1
Prosumer	SAB 3	SAB 4	SAB 5	SAB 7	SME 1
Buying grid (kWh)	5601.8	6984.5	7741.2	7338.9	10452.5
Selling grid (kWh)	0	1319.5	665.8	0	1584.0
Battery charging (kWh)	0	880.0	0	0	0
Battery discharging (kWh)	0	783.0	0	0	0
Self-consumption (kWh)	0	3148.5	3855.7	0	5532.1
Buying community (kWh)	4252.5	10.0	291.4	6443.3	210.7
Selling community (kWh)	0	1112.7	3720.0	0	3221.0
Emissions (tCO_2)	0.7	0.9	1.1	1.0	1.4
Costs (EUR)	2227.1	1249.7	910.2	3083.2	1578.7

PV systems to the community, which facilitates acceptance. Prosumer SME 2 on the other hand presents an interesting case: Not owning PV systems, but having the highest electricity demand within the community, prosumer SME 2 is not the ideal candidate for this community with the objective of minimizing emissions. In our case study, there is sufficient excess PV generation available for prosumer SME 2 to be included in the community without worsening the objective function, because prosumer SAB 3 and SAB 7, who are both consumers only, left. We take a look at Figure 5.20, where increase (or decrease) of annual costs and emissions comparing the original community and the community at $n = 1$ are illustrated. Costs and emissions of prosumers that left the community (prosumer SAB 3 and SAB 7), and of those who joined the community (prosumer SH 5, SAB 8, and SME 2), are compared with the costs/emissions of stand-alone prosumers. Without the community, emissions due to electricity consumption of prosumers SAB 3

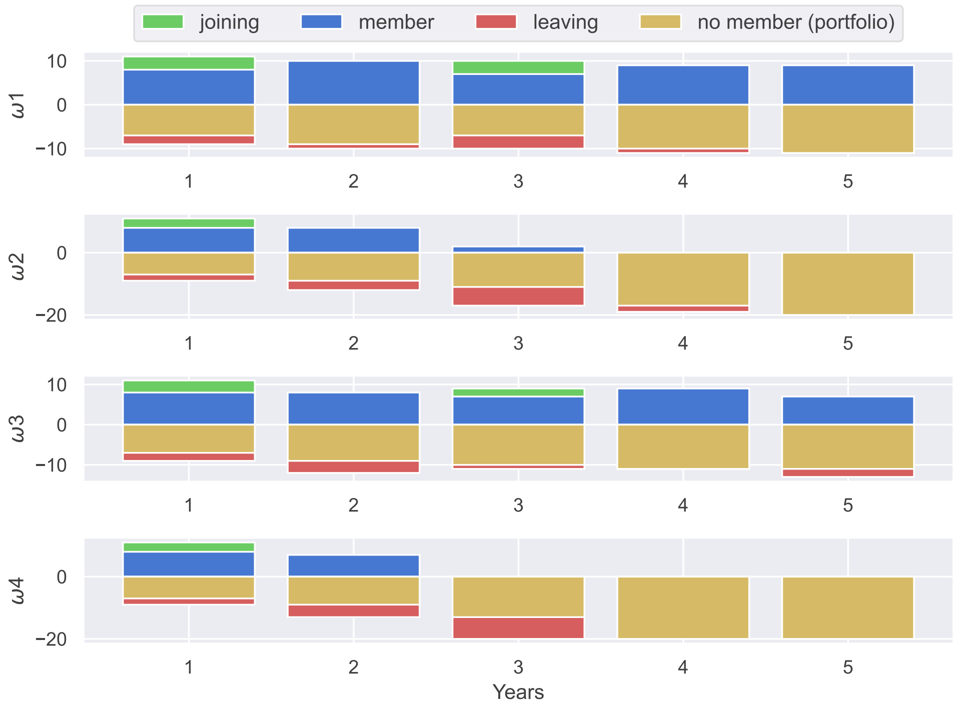


Figure 5.19.: Acceptance/dropping out per scenario considering all prosumers in the portfolio - stochastic solution

and SAB 7 highly increase in $n = 1$. All other emission balances are negative except for prosumer SME 1, thus most prosumers can avoid emissions by trading electricity with other community members. The only prosumer with significant cost increase in year one is prosumer SAB 5, who buys from the new members who joined the community at $n = 1$.

Returning to Figure 5.19, we now compare the scenarios from year two to year five. There is a distinct difference between the scenarios starting from year three: In scenario ω_1 and ω_3, new prosumers show interest in joining the community, while in ω_2 and ω_4, some existing members leave the community, without replacement by new prosumers. This diversity within the scenarios is also reflected in the selection process. Single houses have higher PV capacities installed in relation to their annual electricity demand than apartment buildings or businesses. Therefore, single houses share more PV generated

Figure 5.20.: Difference of annual costs and emissions between original community and new community at $n = 1$ (red - annual costs; green - annual emissions); increase of costs and emissions counted positive, decrease negative

electricity with the community than other prosumer types. In scenario ω_4, five single houses, which were part of the original community, leave in year $n = 3$. The remaining members are then left with a community without sufficient PV capacities to actually benefit from peer-to-peer trading. Hence, the remaining prosumers leave too. The explanation for scenario ω_2 is similar.

Let us now discuss the development of the original community's annual emissions over five years. The contributions of each scenario to the expected emission are shown in Figure 5.21. In this graph, only emissions of active members count; thus, emissions in scenarios ω_2 and ω_4 converge to zero. Additional SABs joining at $n = 3$ in scenario ω_1 increase emissions of the original community members, while staying well below the baseline, the emissions without sharing electricity in the community (dashed black line). In scenario ω_3, the annual emission decrease, because the newly added SHs provide more PV generated electricity, relative to their own demand, to trade with the community.

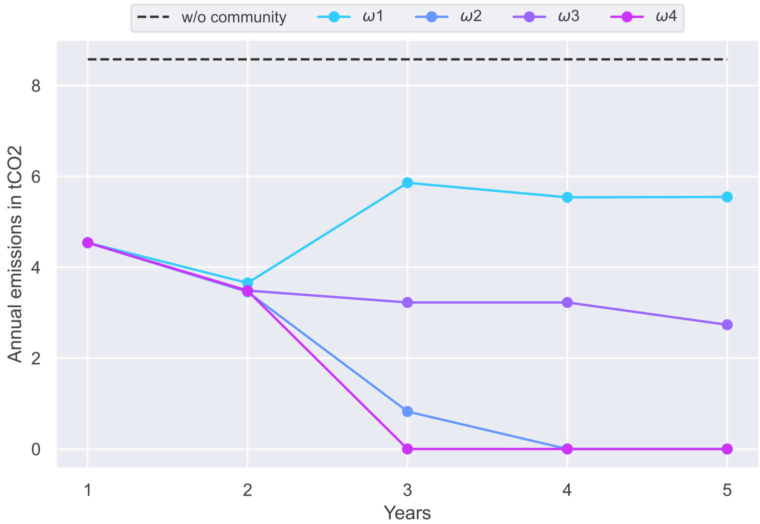


Figure 5.21.: Emissions over five years by scenario $\omega_1, \omega_2, \omega_3, \omega_4$ - stochastic solution

5.2.2.3. Deterministic solution

Next, we compare the selection of the stochastic approach with a simplified, deterministic approach. The deterministic implementation is as following: First, the existing members and potential new members are captured. The optimization is executed knowing all relevant parameters of year $n = 1$, but not considering any future developments. The simplified version of Eq. (3.11) is:

$$\min_{x_{n,i}, b_{n,i}, u_{n,i}, Q_{i,t,n}} F_n \tag{5.3}$$

Constraint and lower level problem remain unchanged to those presented in Section 3.3.2, however, the scenarios ω are missing. Figure 5.22 compares stochastic and deterministic solutions of the problem by showing the decision for each prosumer separately. While prosumers SH 5 and SME 2 are accepted into the community as in the stochastic solution, prosumer SAB 8 is rejected using a deterministic approach, which is the only distinction between the two cases.

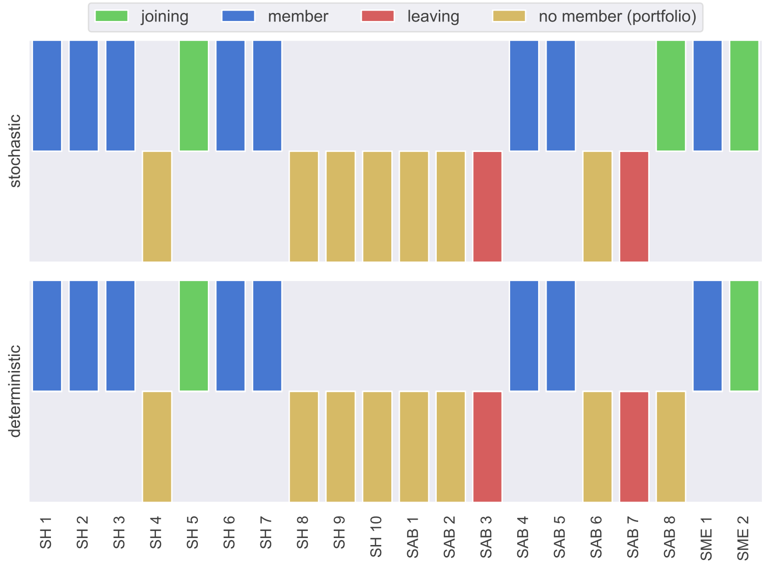


Figure 5.22.: Selection of prosumers in year $n = 1$ (top - stochastic approach; bottom - deterministic)

5.2.3. Selection process over five years comparing stochastic vs. deterministic solution

Recalling the research question of this paper, we want to find out if the stochastic approach to dynamic participation in energy communities leads to different selection of prosumers than a more simple, deterministic approach. For this purpose, the optimization model is applied over several consecutive years using the deterministic implementation briefly explained in the previous section. The consecutive execution of the deterministic program is performed as following: We optimize using Eq. (5.3) with $n = 1$ as our objective function, knowing all the relevant parameters of year one, but not considering any future developments. The resulting configuration of members is the new so-called original community for the following year and the contract lengths are updated. We use scenario ω_1 as a reference scenario, which we assume will actually happen, meaning

$$s_{n,i} = s_{n,i}(\omega_1). \tag{5.4}$$

The optimization is repeated year by year for all $n \in \mathcal{N}$. Afterwards, the whole procedure is again repeated for the other scenarios $\omega_2, \omega_3, \omega_4$.

Figure 5.23 presents the decisions of the deterministic approach comparing all four scenarios one below the other. In year one, all scenarios deliver the same results, because the same parameters are assumed. Comparing with Figure 5.19, it is interesting to notice that in the deterministic solution for scenarios ω_2 and ω_4, there are still members in the community at $n = 5$, which is not the case in the stochastic solution. This can be explained as follows: The objective function F_n takes into account the emission balances of all members of the original community. The deterministic approach updates the community each year, thus the set-up of original members changes as well. The stochastic results from the previous Section 5.2.2 are obtained from the decision at year one and only considers the original community at the starting point. The corresponding emissions are shown in Figure 5.24.

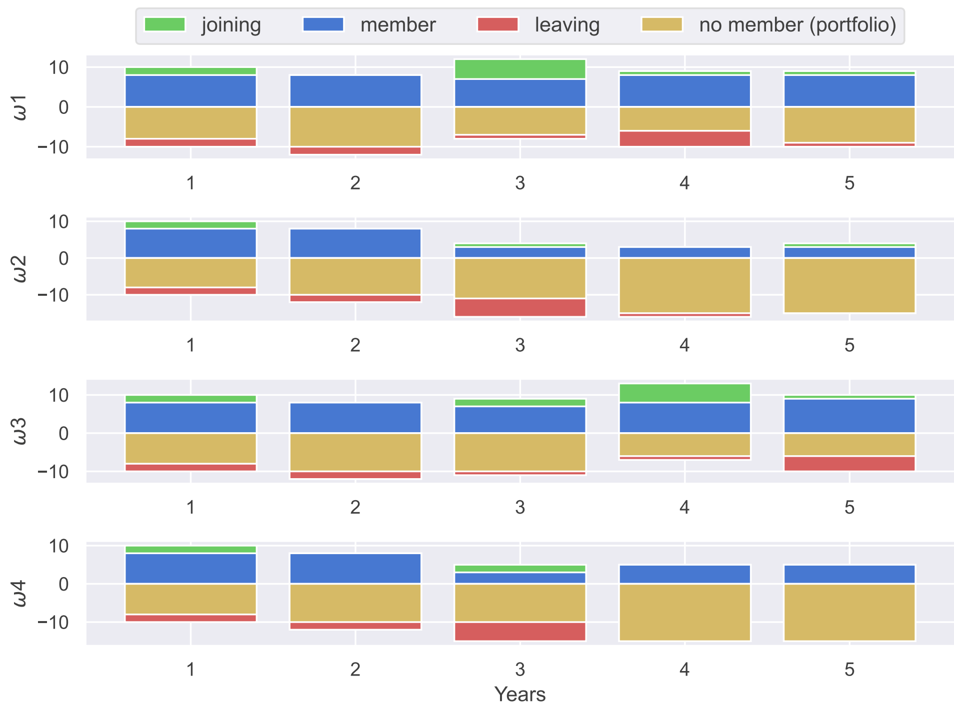


Figure 5.23.: Acceptance/dropping out per scenario considering all prosumers in the portfolio - deterministic solution

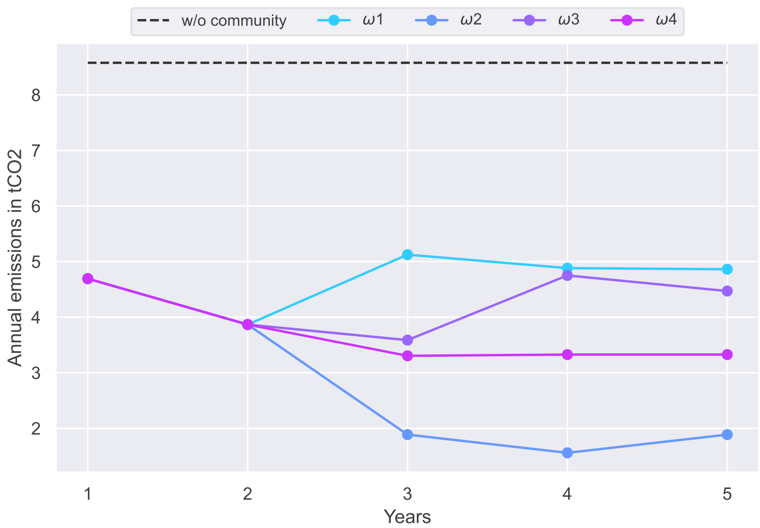


Figure 5.24.: Emissions over five years by scenario $\omega_1, \omega_2, \omega_3, \omega_4$ - deterministic solution

6. Discussion and synthesis of results

This Chapter provides a synthesis and discussion of the results that are presented in the previous Chapters 4 and 5. Starting with Section 6.1, the findings with respect to the research questions, which we defined in Section 1.2, are elaborated. The following Section 6.2 provides a discussion of the limitations and strengths of the proposed methods. The final Section 6.3 of this Chapter discusses upscaling and transferability of the methods in Sections 6.3.1 and 6.3.2, and then participation in energy communities from a system perspective in Section 6.3.3. Figure 6.1 shows an overview of the topics covered in this Chapter, and how they relate to each other.

6.1. Findings with respect to the research questions

The detailed key findings referring to each research question are outlined in this Section. We will state the research questions once again and answer them with the findings and insights gained in this work. We start with research question one.

Research question 1: *How can a peer-to-peer trading approach in energy communities take into account prosumers' individual preferences for saving emissions caused by electricity consumption?*

The results show that the implementation of individual willingness-to-pay as an allocation mechanism in peer-to-peer trading, as proposed in this thesis, promotes the desired outcomes for the prosumers. Participation in energy communities creates added values depending on the needs of the prosumer:

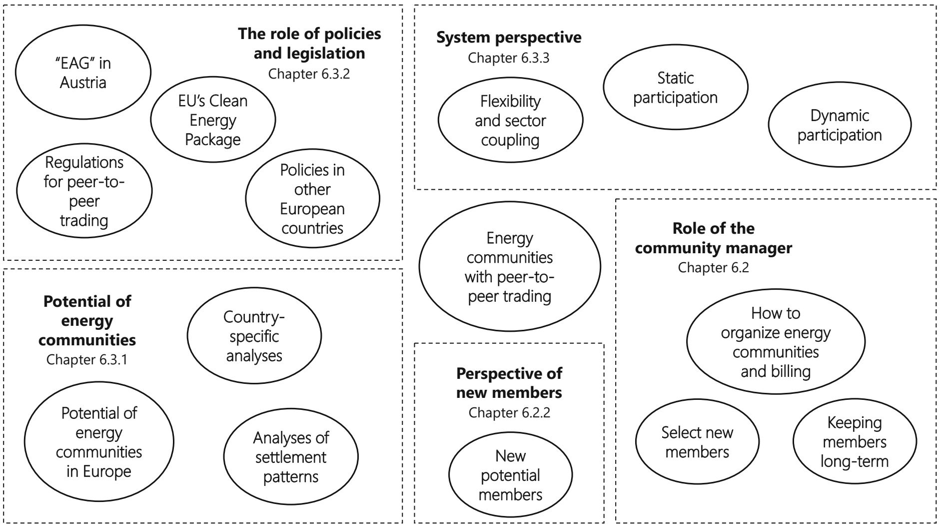


Figure 6.1.: An overview on the topics discussed in this Chapter

financial savings for profit-orientated prosumers with a low willingness-to-pay, and high emissions' savings for environmentally concerned prosumers with a high willingness-to-pay.

Notably, the algorithm ensures that generated PV electricity is perfectly allocated, not only to prosumers according to their willingness-to-pay, but it is also optimized for the entire community by minimizing purchases and sales from/to the retailer.

In addition, battery energy storage systems (BESSs) increase flexibility and are therefore able to reduce the community's purchases from the grid and increase profitability for prosumers owning BESSs.

The findings of the sensitivity analyses show that the retail electricity price has a great influence of the overall results. A higher retail price, for example in Germany, decreases community welfare because the community members generally have to pay more for electricity; however, local self-consumption becomes more valuable and therefore the profitability of sharing PV increases.

The set-up of the community (with respect to the installed PV capacities, the number of prosumers vs. consumers, and the demand profiles) has a strong impact on the performance of the entire community and of each prosumer. As shown in the sensitivity analysis, members leaving the community may decrease the community's welfare and the amount of PV electricity generation that is shared in the community. While this may not be significant when only one prosumer leaves, the effects are likely to increase when there is greater variation in the community set-up. This motivates the next research question to further investigate changes in the portfolio of community members.

Research question 2: *How would an existing energy community collectively choose an optimal new member/prosumer to engage in peer-to-peer trading?*

The bi-level model developed to answer research question two is able to choose the optimal parameters of a new member. This is the first step for gaining useful information on the kind of prosumer (e.g., consumer only or prosumer, high or low PV capacity, level of annual electricity demand, including or excluding BESS (the latter aspect was not shown in this research)) that is preferred by the community. Simultaneously, the model can determine whether the participation of a new member in the community is accepted or rejected; hence, a choice between potential members can be made. In Section 5.1, where the results of research question two are presented, the case study was limited to one new addition to the community. However, it is possible to introduce a portfolio of new members without limiting the number of new members, which is useful for the next research question three. The model determines simultaneously the optimal number of new members and which ones are selected. This is possible because there are binary variables attached to each new member that determine acceptance or rejection. The optimal number differs based on the portfolio of members and the needs of the old community.

The community's choice reflects well the different needs of the members. We can see that a community with environmental-oriented members opts for a prosumer with a large PV system, while profit-oriented choose a consumer with high electricity demand they can sell electricity to and thereby generate profits. Geographical distance and the new prosumer's willingness-to-pay also influence the decision. With mixed preferences, the needs of environment- and profit-oriented prosumers are balanced. There is, of course, also the possibility for the community to define a common goal, such as saving the community's total emissions. In that case, the community must ensure that new prospective members commit to the same target.

The tool developed to answer research question two is only a basic model for dynamic participation, because it shows only one year of the selection process. It can be considered as a basis for dynamic participation over several years (annual phase-in and phase-out of members). Also, it helps an energy community to optimally select prosumers from a given portfolio without considering possible future developments of the community. To improve planning of the community, this matter is addressed by the next research question.

Research question 3: *Does knowledge of future developments in energy communities help a community manager make better decisions selecting new participants than without considering future developments?*

For the purpose of answering research question three, a stochastic dynamic program with a look-ahead policy is developed. The model is based on the bi-level optimization model developed to answer the second research question, which is able to select the most suitable new members for an energy community and its optimal parameters. To answer the third research question, the model is further developed so that the decision made in the *here and now* includes a forecasting horizon that extends into the future.[1] Future parameters are stochastic and scenarios are used to adequately represent possible future developments. The results compare the selection of a community manager with forecast and without forecast.

It is important to choose the scenarios carefully and make them as realistic as possible. For example, it is up for debate whether it makes sense to include scenarios that contradict each other, since they might cancel each other out when weighted equally. Moreover, one should not attach too much

[1] Note that we have simplified the model to a choice between predefined prosumers of a portfolio, since the stochastic approach with forecast is already very complex.

importance to a scenario that is very unlikely to occur.

We noticed that in some scenarios, the model does not extend contracts of members whose emission balances have strongly declined. This is equivalent to members leaving the community because they are dissatisfied with the community's development. We have observed this problem in scenarios where it is endogenously given to the model that a larger number of members leave, leaving the remaining community members abandoned. A follow-up research question could address how to prevent this.

Core characteristic of our approach to the selection process is the community members' objective to minimize emissions from electricity consumption. The peer-to-peer trading mechanism maximizes self-consumption – and therefore also minimizes emissions from electricity consumption – of the community as a whole while considering prosumers' individual willingness-to-pay. When selecting prosumers from a portfolio of potential new members, the original community aims at further avoiding emissions. It is up for discussion if energy community members are more interested in improving economic (e.g., by saving annual costs for electricity) or environmental benefits. Because literature often indicates that environmental incentives play a particularly important role for participants of energy communities, and because individual willingness-to-pay that determine peer-to-peer trading in our work include a preference to save emissions, the elaboration of research question three focuses entirely on environmental interests. Therefore, we made a conscious decision *not against* minimizing costs, but *for* minimizing emissions in the objective function, which is a distinguishing feature of this particular analysis.

6.2. Limitations and strengths of the proposed methods

This Section discusses the limitations and strengths of the methods proposed in this thesis. We highlight the limitations that require further consideration and investigation, first in terms of static participation and then in terms of dynamic participation, in Sections 6.2.1 and 6.2.2, respectively. The strengths of the methods are presented in Section 6.2.3.

6.2.1. Limitations regarding static participation

The discussion of the limitations of the proposed methods begins with a critical analysis of the peer-to-peer trading model, i.e., static participation in energy communities. While energy communities typically have a positive impact on their members, other parties indirectly involved, for example the distribution system operator (DSO), might experience a decrease in the revenue due to local PV self-consumption. Naturally, DSOs are in favor of increasing the fixed component of the grid tariff in case of an increase in self-consumption of PV electricity generation by prosumers and communities. A reduction in the variable grid tariff component also negatively impacts the profitability of energy communities, as this component of the grid tariff directly relates to the retail electricity price. Therefore, future studies should focus on different compositions of fixed versus variable charges of grid tariffs and their corresponding influences on energy community results.

Starting with research question two, we add a so-called distance factor, $d_{i,j} \in [0, 1]$, to the prosumers' willingness-to-pay. This distance-related factor considers that the matching of widely dispersed PV generation and load is disadvantageous, while closer matching is preferred.[2] Equation (3.4) shows how the distance between two members of the community influences the willingness-to-pay: The larger $d_{i,j}$, the smaller the premium that is added on top of the retail electricity price. In our approach, $d_{i,j}$ is an artificial factor; in real applications of peer-to-peer trading it should represent either (i) an individual preference to buy from certain members of the community and not from others, or (ii) a physical parameter such as distance in meters or electrical distance[3] between prosumers. Our approach does not specify how

[2] There are at least two reasons to introduce the distance factor in our work: (i) grid-friendliness and (ii) support of local and decentralize energy supply.

[3] There are different measures of electrical distance for power networks; one example is the absolute value of the inverse of the system admittance matrix (see Blumsack et al. (2009)).

exactly the distance factor can be interpreted and quantified. This ambiguity is a limitation of our peer-to-peer trading model. We leave it open for those who actually want to implement this type of energy community.

6.2.2. Limitations regarding dynamic participation

We continue the discussion on the limitations of the proposed methods by focusing on dynamic participation. Related to the bi-level model that was developed to answer research question two, we found the following discussion points. The objective function of the bi-level model is based on a Pareto optimization approach that includes two objectives, emission and cost minimization, in the same objective function. Both objectives are expressed in different units; emissions in tCO_2 and costs in EUR. These units are often associated with each other when it comes to CO_2-prices (such as in CO_2-taxes or certificate prices), but they are not easily comparable.

Another limitation regarding research question two is that our analyses show only one year in which the community selects new participants. Hence, this is only the basis on which dynamic participation with yearly entry and exit of members is built. Also, the length of the binding contract between participants and community is exactly one year (and can be extended for another year after expiration); therefore, variations in contract lengths are not included in the decision process. These issues are addressed in research question three.

Regarding research question three, the analyses showed that the stochastic approach to optimize a selection process of energy community members is cumbersome. Not only are stochastic dynamic programs computationally expensive, but also the creation of adequate scenarios, data collection and estimation of existing members and potential new ones is a complex procedure in real-life situations. Though, including scenarios that are most likely to happen as a forecast in the decision process is recommended. The exact contractual design between community members and the community as a legal entity is subject to further research, which should include real test sites and the investigation of legal aspects.

Related to both research questions that analyze dynamic participation in energy communities, research questions two and three, the following problems are found. Both models have in common that they find a *joint optimum* for all members by adding the objective of each member to the objective function. A joint optimum does not mean that the individual optimum for each participant is reached and it could mean a degradation for individual participants. Interesting future work could investigate dynamic participation from a game theoretic point of view.

An energy community must be able to attract suitable potential new members to guarantee its performance over the years. If members leave the community and cannot be replaced by new members who restore or improve the status quo, the satisfaction of existing members with the community decreases. In fact, this is a limitation of this thesis. The selection process is made solely from the perspective of the original community, assuming the availability of potential new prosumers who fit well into the community. This issue is addressed – but only indirectly and partially – in the third research question by creating different scenarios in which different types of prosumers are included in the portfolio of potential participants.

Our dynamic participation models allow an energy community to reject potential members, which is in some way a contradiction to the environmental preference attested to the community members. On the one hand, an energy community should be a small, socially tangible entity of manageable size. A sense of belonging, trust, and confidence are easier maintained in a small and selective community. Therefore, boundaries are consciously drawn. On the other hand, the suggested selection process is not a one-size-fits-all approach. Energy communities can have different sizes, goals, and diversity of actors involved. Setting no limits and accepting all interested prosumers into the community would eventually lead to a (single) large energy community for an entire country, which is not a socially tangible entity anymore. The possibility to actively participate and to engage in the energy system according to one's own preferences would be lost.

And lastly, in real implementations of energy communities it might be difficult to find a common criteria that will determine if a potential new prosumer is allowed to join the community or not.

6.2.3. Strengths of the proposed methods

After the discussion of the limitations, we continue with the strengths of the proposed methods. We start again with the peer-to-peer trading model, i.e., static participation in energy communities. One of the strengths of the peer-to-peer trading approach presented here is that the billing should be relatively easy to implement in real life. Time resolution is one hour, therefore hourly smart meter data of all community members is sufficient to ex-post account cash flows. This is an advantage compared to other peer-to-peer trading concepts that rely on blockchain technologies.[4]

The idea to allocate electricity within the community based on individual willingness-to-pay contributes to the strengths of the methods. The objective function to maximize community welfare ensures that the community's resources are optimally utilized by the members. Individual willingness-to-pay enable the community to exactly account cash flows among its members. Also, when PV systems produce less electricity than is demanded, the community's generation is assigned to those with highest willingness-to-pay, i.e., those members are prioritized. Another distinctive feature of our peer-to-peer trading model is that prosumers not only share their surplus with the community, but the total amount of PV electricity generation is traded with the community, which creates more opportunities for buying and selling. It follows that the peer-to-peer trading concept endorses the concept of energy communities contributing to a sharing economy. Interested participants can consume locally generated PV electricity without having to own a PV system, and other prosumers can sell their PV generation to those who wish to consume it. There is a potential for new business models to be created and for the promotion of investments in PV systems.

We now move to dynamic participation in energy communities and discuss the strengths of our modeling approach in this regard. Our dynamic par-

[4]Of course, blockchains offer some advantages such as privacy protection of prosumers and a fully decentralized application.

ticipation models are able to simultaneously maximize community welfare, i.e., optimally distribute PV electricity within the community, and select new members. This way, all known parameters of a potential new member, such as willingness-to-pay and distance to other members, can be included in the selection process and the optimum can be found in one model run.

Although it is only possible to find a common optimum for the entire community that does not guarantee individual optima of all members, it is important that the objectives of all members are taken into account. In research question two, each member can prioritize saving costs, saving emissions, or a mixed preference.

Incorporating a stochastic forecast into the selection process, while computationally quite difficult, is an important step for energy communities to take if they are to survive in the long term. Planning ahead as an energy community will become especially important now that we are in the early stages of introducing energy communities.

6.3. Upscaling, transferability, and system perspective

The research questions, which this thesis aims to answer, each consider the perspective of single energy communities. By definition, energy communities are not closed systems and they are not self-sufficient. Participants are connected to the distribution grid and usually purchase electricity to cover residual demand from the electricity supplier. Therefore, analyses of energy communities are only complete if the system perspective is also discussed. In this Section, we discuss the following aspects: upscaling the potential for energy communities in Section 6.3.1, transferability in Section 6.3.2, and participation in energy communities from a system perspective in Section 6.3.3.

6.3.1. Upscaling the potential for energy communities

The peer-to-peer model (FRESH:COM) for static participation presented in the first contribution of this thesis, Perger et al. (2021), is also applied in a case study within the Horizon 2020 project openENTRANCE (see openENTRANCE (2022)), where, among other things, the theoretical potential of energy communities in Europe is analyzed. Based on five European reference countries,[5] the number of energy communities is derived according to the building stock and the following settlement patterns: city, town, suburban, and rural areas. Settlement patterns are characterized by population density, prevalent building type (single family house, small and large apartment buildings), rooftop areas available for installation of PV, and electricity demand of residents. For this type of analysis, an accurate data base of the residential building stock is key and a high special resolution is desirable to correctly classify areas into settlement patterns.

Results of the analysis of the project's case study show that participants of energy communities can cut down their annual electricity costs and emissions. Cost savings correlate with retail electricity prices, i.e. the higher the costs per kilo-watt-hour, the higher the savings, and they correlate with the amount of PV electricity generated by the community in total. Due to increasing consumption of (clean) PV electricity, emissions of prosumers participating in an energy community decrease.

The evaluation of the potential for energy communities as conducted in the project's case study adds value to this thesis too. Investigating peer-to-peer trading in different settlement patterns shows where participants benefit most from participation in energy communities. The average prosumer in a rural community saves a larger portion of their annual costs and emissions than average prosumers in other settlement patterns. Moreover, the results from different countries show that where prices are highest, financial benefits for community members are also highest. Equivalently, most emissions are saved in countries with a high fossil share in power generation.

[5] Five countries are selected for the case study: Austria, Greece, Norway, Spain, and England, to represent Central Europe, South-Eastern Europe, Scandinavia, Iberian Peninsula and Great Britain, respectively.

6.3.2. Transferability

The case studies that are shown in this thesis investigate energy communities that are located in Austria, and therefore, the parameters such as electricity prices and PV generation profiles are specific to Austria. As mentioned in the previous Section 6.3.1, the peer-to-peer trading model can be applied to different settings, for example different countries, settlement patterns, or sizes of communities, when input parameters are adapted accordingly. In Austria, the legal framework for the concepts of Renewable Energy Community (REC) and Citizen Energy Community (CEC) was created in the *Erneuerbaren Ausbaugesetz* (EAG, see Republik Österreich (2022)). When analyzing other countries, their country-specific regulatory frameworks relevant to energy communities need to be considered. Member states of the European Union have to transpose the new European rules of the recast of the Renewable Energy Directive (REDII, see European Commission (2018)) into national law (see also Hoicka et al. (2021)). In this process, the individual member states are at different starting points from a regulatory and market point of view. For example, in 2015 the roll-out of sustainable energy communities was relatively advanced in Germany compared to other counties such as Spain, where collective ownership of renewable energy infrastructures is rare (see Romero-Rubio and de Andrés Díaz (2015)). The diffusion of energy communities not only depends on policies and regulatory framework, but also on energy mix, market structure, and social attitude (see Sciullo et al. (2022) for a comparison of six European countries). Further comparisons of the regulatory framework for energy communities across Europe can be found in Frieden et al. (2019).

While the regulatory framework for energy communities is emerging in most European countries, the concept of peer-to-peer trading in particular is not as developed. In Austria for example, it is not yet possible to directly buy or sell electricity from/to other prosumers, because the corresponding rules must be created first. However, there are already some providers who are simulating trading between private producers and consumers, based on the currently applicable rules of the energy market. At least, as part of the *Clean Energy for all Europeans* package of the EU, the aforementioned REDII and the Electricity Directive on common rules for the internal market for electricity

(ED, see European Commission (2019)) define the role of citizens as active participants in the energy system and specify that consumers are allowed to store, sell and consume their self-generated electricity (see Uhde (2022)).

Furthermore, we need to ask how peer-to-peer trading, as presented in this thesis, can be managed and organized. The energy community needs an organizational unit, for example a community manager, who is responsible for billing, clearing, and accepting new members, among other things. A community manager may charge a service fee that reduces members' profitability. It is also necessary to develop an algorithm that performs clearing, for example a centralized matching algorithm. Using a decentralized method is an option too, for example blockchain technology. However, it requires additional energy, which is – in relation to the small amounts of energy that are traded between peers in one transaction – not negligible.

Another point of discussion concerning transferability of the proposed methods is the following: How can we include the perspective of potential new members into dynamic participation in energy communities? Our dynamic participation models only consider the perspective of the old community, whose members have to make a decision about the acceptance or rejection of new members. A new member would expect certain benefits from joining the community; we could extend our modeling approach to ensure that certain minimum requirements, for example expected emission savings, are met. Another (very different) idea would be to reverse dynamic participation and examine prosumers' search for an ideal community. This was out of scope for this thesis, but could present interesting future work.

6.3.3. Participation in energy communities from a system perspective

Due to strong dependence on weather conditions, electricity production from power plants using renewable energy sources such as wind and solar is typically characterized by volatile generation profiles. Especially when power plants are bundled at one location, high renewable penetration creates stress on electricity grids, because production (or lack thereof) occurs at the same time and at the same place. Therefore, large capacities of installed PV systems can temporarily strain the distribution grid. Increasing flexibility in the system can be useful to flatten peak loads, so-called peak shaving, but also to avoid heavy amounts of excess PV generation to burden the distribution grid. There is a variety of flexibility options. Among others, there is the possibility to utilize storage (for example battery energy storage system, BESS), demand response, sector coupling, or PV curtailment.

Now we want to discuss the influence of energy communities on distribution grid operation. PV systems are the most established technologies for energy communities, because they are relatively easy to implement and the barriers to operate them are low. The generation profiles of PV systems are very characteristic; they produce the highest outputs around noon, while there is no generation at night. In the evenings, when demand typically peaks, PV generation is low and peak demand cannot be significantly reduced by PV alone without flexibility options. There are also seasonal characteristics: low production in winter, high production in summer.

If grid-friendliness is an objective of the community, the operation of an energy community can help balance grids. There are couple of scientific papers on the grid impact of energy communities. For example, Sudhoff et al. (2022) found that a grid-friendly operation strategy of a renewable energy community can reduce peak power at the low-voltage substation by 23–55%. Comparing with an operation strategy that maximizes the members' economic benefits, the grid-friendly operation shows a cost-saving reduction of less than one percent. Hence, aiming at reducing peak power as a community require small compromises only. Weckesser et al. (2021) included a power flow analysis and found that with the right operating strategy the energy community can reduce the low-voltage grid loading by up to 58%. For the case of peer-to-peer trading, Bjarghov et al. (2020) developed subscribed capacity tariff where end-users pay for a capacity level with a high excess energy term in order to incentivize grid-friendly consumption profiles.

Another aspect that could increase flexibility is the fact that energy community members are active participants in the energy system. They tend to be better informed about electricity markets, energy efficiency, and other related issues than traditional consumers. Therefore, awareness of flexibility needs develops more quickly among energy community members and creates a willingness to participate in flexibility-improving activities. For example, innovative pricing schemes that reward peak load shaving can be integrated into an energy community's internal billing system.

While grid-friendliness was not an objective of this thesis, our peer-to-peer trading model shows a few advantages that could help balance distribution grids. First, the technology portfolio of the community includes BESS, which can shift electricity generated by PV systems to a different hour of the day when its most needed, and therefore members are not only bound to just-in-time consumption. Also, community welfare maximization ensure that the electricity bill of the community is minimized and therefore the internal resources are utilized as much as possible. Next, although flexibility through sector coupling is not included in the analyses of this thesis, some sector coupling mechanisms can be included easily (e.g., electric vehicle charging, operation of heat pumps, etc.) without fundamental change of the modeling approach. Another aspect that could help balance the grid is the prosumers' willingness-to-pay, which includes a preference for buying locally generated electricity, i.e., the closer to another community member, the higher the willingness-to-pay.

The main focus of this thesis is dynamic participation in energy communities, and for this purpose the peer-to-peer trading model was extended to include phase-in and phase-out of members. We would now like to conclude this chapter with a discussion of our dynamic participation models, where new members are selected to join an existing community, from a systems perspective. The objective function reflects the desires of the community members, such as minimizing costs or emissions, which they would like to see fulfilled by adding new members. We would now like to ask whether the community's decision also brings benefits to the energy system. There is potential that this type of selection process could also be beneficial to grid-friendliness of the community, if system perspective and community needs correlate. Incentives for communities to choose prosumers who are best from a system perspective need to be created. A positive side effect would be that investments in PV systems (or other renewable energy generation systems) are triggered where they are most needed.

7. Conclusions and outlook

Energy communities create opportunities for prosumers to actively participate in the energy system. This thesis contributes to this topic by proposing both a peer-to-peer trading concept and a concept to evaluate the selection process to search for new members for an energy community. We start with the conclusions of this thesis from the methodological point of view and then from a thematic perspective. Finally, we present the outlook on future work.

The methods presented in this thesis fulfill two main tasks. The first task is the peer-to-peer trading algorithm to optimally allocate PV generated electricity to the community members. Compared to more basic allocation mechanisms in energy communities, peer-to-peer trading has the advantage that individual participants are granted more autonomy and decision-making power, here in the form of individual pricing. Nevertheless, the overall benefit of the community is maximized, meaning all resources are used as best as possible within the community and no kilowatt-hours are sold "unnecessarily" to the grid.

The allocation mechanism is determined by the individual willingness-to-pay of prosumers, which in our case is even higher than the retail electricity price. That's because in our approach, the entire PV electricity generation is put on the internal community market, where it is allocated based on the prosumers' demand curve. So it may happen that prosumers, instead of self-consuming, sell their own generation to other participants with a higher willingness-to-pay than themselves. Other energy community models typically assume that the community-internal electricity price is somewhere between feed-in tariff and retail price, so that both buyers and sellers benefit, and it only makes selling surplus generation attractive. In our case on the other hand, it is mostly sellers who benefit because of the prosumers' willingness-to-pay above retail price. In this context, the question arises whether it is realistic that participants of an energy community will actually have an increased willingness-to-pay, especially in times of already high electricity prices. In principle, our suggested peer-to-peer allocation mechanism also works with willingness-to-pay below retail price, but then only surplus generation is shared because in order to put the entire PV generation on the market, producers must be compensated at least at the retail price. There is a risk that our approach could be only a niche application for particularly environmentally conscious individuals.

The second task is the selection process of new members from the perspective of an existing community. Our model selects the best entrants from a portfolio of potential new members. The best new entrant should improve the annual costs and emissions balances of the old members of the community. A challenge in the practical implementation of energy communities will be the collection of relevant data. For the selection process, the dynamic participation models need at least an estimation of hourly data of demand and (PV) generation of potential new members. Especially in our stochastic approach to dynamic participation that includes forecasts of several years, it is difficult to realize.

The bi-level models developed in this thesis are complex procedures for relatively small applications, and they are also computationally expensive. These types of bi-level models could also be applied to other problems related to electricity markets, such as whether or not a market area should be expanded or whether or not market areas should be merged.

While we are still in the introductory phase of energy communities, it is first important that consumers and prosumers are willing to create energy communities together and that they can easily overcome regulatory and other organizational barriers. Then, energy communities have to find a way to remain relevant in the future. To accomplish this, we suggest in this thesis to optimize the selection process of new members from the perspective of an existing energy community. However, our proposed selection procedure will only be relevant in the future if enough potentially interested new members can be found.

Therefore, energy communities must be able to sustain themselves and remain attractive to prosumers, preferably without the help of government subsidies. In addition, energy communities must prove that the concept will survive in the long term. It is important to investigate which regulatory aspects are helpful for energy communities and which are not. For example, electricity tariff design can play a major role; with discounts on the network tariff, prosumers and consumers can be encouraged to participate in energy communities, whereas with high fixed components in electricity prices, energy communities become economically less attractive.

However, the main purpose of energy communities, by definition, is not financial gain, which means that other aspects besides economic attractiveness, such as awareness about environmental issues, increasing self-sufficiency, or consumption of locally generated electricity, should be focused on as incentives for participation in energy communities.

In addition to revealing insights into dynamic participation in energy communities, this thesis may provide suggestions for follow-up research questions. Since our studies are limited to the electricity sector, a concept that incorporates the ideas presented in this thesis (mainly individual willingness-to-pay and dynamic participation) for holistic energy communities that include heating, cooling and other energy related aspects such as transport, (waste) water, or disposal of general waste could be created. It is worth investigating closer the contractual arrangements between energy communities as a legal entities and their members. The exact design of contracts also depends on legal and regulatory aspects and is therefore an interdisciplinary challenge. Also, it would be interesting to see if our selection process could be turned around and prosumers search for their ideal community, hence, energy communities can compete when it comes to finding new participants.

8. References

Books

Bynum, Michael L., Gabriel A. Hackebeil, William E. Hart, Carl D. Laird, Bethany L. Nicholson, John D. Siirola, Jean-Paul Watson, and David L. Woodruff (2021). *Pyomo–optimization modeling in python*. Third. Vol. 67. Springer Science & Business Media (cit. on pp. 67, 84).

International Energy Agency (2018). *World Energy Outlook 2018*, p. 661. DOI: 10.1787/weo-2018-en. URL: https://www.oecd-ilibrary.org/content/publication/weo-2018-en (cit. on p. 2).

MATLAB (2019). *(R2019b)*. Natick, Massachusetts: The MathWorks Inc. (cit. on p. 47).

Van Rossum, Guido and Fred L. Drake (2009). *Python 3 Reference Manual*. Scotts Valley, CA: CreateSpace. ISBN: 1441412697 (cit. on pp. 67, 84).

Journal Articles

Abada, Ibrahim, Andreas Ehrenmann, and Xavier Lambin (2020). "On the Viability of Energy Communities". In: *The Energy Journal* 41. ISSN: 1944-9089. DOI: 10.5547/01956574.41.1.iaba. URL: http://www.iaee.org/en/publications/ejarticle.aspx?id=3454 (cit. on p. 12).

Ahmadi, Seyed Ehsan, Delnia Sadeghi, Mousa Marzband, Abdullah Abusorrah, and Khaled Sedraoui (2022). "Decentralized bi-level stochastic optimization approach for multi-agent multi-energy networked micro-grids with multi-energy storage technologies". In: *Energy* 245, p. 123223. ISSN: 0360-5442. DOI: https://doi.org/10.1016/j.energy.2022.123223.

URL: https://www.sciencedirect.com/science/article/pii/S0360544222001268 (cit. on p. 16).

Ali, Amjad, Wuhua Li, Rashid Hussain, Xiangning He, Barry W. Williams, and Abdul Hameed Memon (2017). "Overview of Current Microgrid Policies, Incentives and Barriers in the European Union, United States and China". In: *Sustainability* 9 (7), p. 1146. DOI: 10.3390/su9071146 (cit. on p. 11).

Almeida, Lucila de, Nikolas Klausmann, Henri van Soest, and Viola Cappelli (2021). "Peer-to-Peer Trading and Energy Community in the Electricity Market - Analysing the Literature on Law and Regulation and Looking Ahead to Future Challenges". In: *Robert Schuman Centre for Advanced Studies Research Paper No. RSCAS 2021/35*. DOI: 10.2139/ssrn.3821689. URL: https://ssrn.com/abstract=3821689 (cit. on p. 17).

An, Jongbaek, Minhyun Lee, Seungkeun Yeom, and Taehoon Hong (2020). "Determining the Peer-to-Peer electricity trading price and strategy for energy prosumers and consumers within a microgrid". In: *Applied Energy* 261, p. 114335. ISSN: 0306-2619. DOI: 10.1016/j.apenergy.2019.114335 (cit. on p. 14).

Azarova, Valeriya, Jed Cohen, Christina Friedl, and Johannes Reichl (2019). "Designing local renewable energy communities to increase social acceptance: Evidence from a choice experiment in Austria, Germany, Italy, and Switzerland". In: *Energy Policy* 132, pp. 1176–1183. ISSN: 0301-4215. DOI: https://doi.org/10.1016/j.enpol.2019.06.067. URL: https://www.sciencedirect.com/science/article/pii/S0301421519304379 (cit. on p. 18).

Backe, Stian, Sebastian Zwickl-Bernhard, Daniel Schwabeneder, Hans Auer, Magnus Korpås, and Asgeir Tomasgard (2022). "Impact of energy communities on the European electricity and heating system decarbonization pathway: Comparing local and global flexibility responses". In: *Applied Energy* 323, p. 119470. ISSN: 0306-2619. DOI: https://doi.org/10.1016/j.apenergy.2022.119470. URL: https://www.sciencedirect.com/science/article/pii/S0306261922007954 (cit. on p. 13).

Bauwens, Thomas (2019). "Analyzing the determinants of the size of investments by community renewable energy members: Findings and policy implications from Flanders". In: *Energy Policy* 129, pp. 841–852. ISSN:

0301-4215. DOI: https://doi.org/10.1016/j.enpol.2019.02.067. URL: https://www.sciencedirect.com/science/article/pii/S0301421519301570 (cit. on pp. 3, 19).

Bjarghov, Sigurd, Markus Löschenbrand, A. U. N. Ibn Saif, Raquel Alonso Pedrero, Christian Pfeiffer, Shafiuzzaman K. Khadem, Marion Rabelhofer, Frida Revheim, and Hossein Farahmand (2021). "Developments and Challenges in Local Electricity Markets: A Comprehensive Review". In: *IEEE Access* 9, pp. 58910–58943. DOI: 10.1109/ACCESS.2021.3071830 (cit. on p. 3).

Boulanger, Saveria Olga Murielle, Martina Massari, Danila Longo, Beatrice Turillazzi, and Carlo Alberto Nucci (2021). "Designing Collaborative Energy Communities: A European Overview". In: *Energies* 14.24. ISSN: 1996-1073. DOI: 10.3390/en14248226. URL: https://www.mdpi.com/1996-1073/14/24/8226 (cit. on p. 19).

Campos, Inês, Guilherme Pontes Luz, Esther Marin-Gonzalez, Swantje Gährs, Stephen Hall, and Lars Holstenkamp (2020). "Regulatory challenges and opportunities for collective renewable energy prosumers in the EU". In: *Energy Policy* 138, p. 111212. ISSN: 0301-4215. DOI: 10.1016/j.enpol.2019.111212. URL: http://www.sciencedirect.com/science/article/pii/S0301421519307943 (cit. on p. 10).

Capper, Timothy, Anna Gorbatcheva, Mustafa A. Mustafa, Mohamed Bahloul, Jan Marc Schwidtal, Ruzanna Chitchyan, Merlinda Andoni, Valentin Robu, Mehdi Montakhabi, Ian J. Scott, Christina Francis, Tanaka Mbavarira, Juan Manuel Espana, and Lynne Kiesling (2022). "Peer-to-peer, community self-consumption, and transactive energy: A systematic literature review of local energy market models". In: *Renewable and Sustainable Energy Reviews* 162, p. 112403. ISSN: 1364-0321. DOI: https://doi.org/10.1016/j.rser.2022.112403. URL: https://www.sciencedirect.com/science/article/pii/S1364032122003112 (cit. on p. 3).

Chakraborty, Shantanu, Tim Baarslag, and Michael Kaisers (2020). "Automated peer-to-peer negotiation for energy contract settlements in residential cooperatives". In: *Applied Energy* 259, p. 114173. ISSN: 0306-2619. DOI: https://doi.org/10.1016/j.apenergy.2019.114173. URL: https://www.sciencedirect.com/science/article/pii/S0306261919318604 (cit. on p. 20).

Chen, Kaixuan, Jin Lin, and Yonghua Song (2019). "Trading strategy optimization for a prosumer in continuous double auction-based peer-to-peer market: A prediction-integration model". In: *Applied Energy* 242, pp. 1121–1133. ISSN: 0306-2619. DOI: https://doi.org/10.1016/j.apenergy.2019.03.094. URL: https://www.sciencedirect.com/science/article/pii/S0306261919305045 (cit. on p. 14).

Cielo, A., P. Margiaria, P. Lazzeroni, I. Mariuzzo, and M. Repetto (2021). "Renewable Energy Communities business models under the 2020 Italian regulation". In: *Journal of Cleaner Production* 316, p. 128217. ISSN: 0959-6526. DOI: https://doi.org/10.1016/j.jclepro.2021.128217. URL: https://www.sciencedirect.com/science/article/pii/S0959652621024343 (cit. on p. 19).

Corinaldesi, Carlo, Daniel Schwabeneder, Georg Lettner, and Hans Auer (2020). "A rolling horizon approach for real-time trading and portfolio optimization of end-user flexibilities". In: *Sustainable Energy, Grids and Networks* 24, p. 100392. ISSN: 2352-4677. DOI: https://doi.org/10.1016/j.segan.2020.100392. URL: https://www.sciencedirect.com/science/article/pii/S2352467720303234 (cit. on p. 16).

Dempe, S. and F. Mefo Kue (2017). "Solving discrete linear bilevel optimization problems using the optimal value reformulation". In: *Journal of Global Optimization* 68, pp. 255–277. ISSN: 1573-2916. DOI: 10.1007/s10898-016-0478-5 (cit. on p. 38).

Dynge, Marthe Fogstad, Pedro Crespo del Granado, Naser Hashemipour, and Magnus Korpås (2021). "Impact of local electricity markets and peer-to-peer trading on low-voltage grid operations". In: *Applied Energy* 301, p. 117404. ISSN: 0306-2619. DOI: https://doi.org/10.1016/j.apenergy.2021.117404. URL: https://www.sciencedirect.com/science/article/pii/S0306261921008035 (cit. on p. 14).

Ehsan, Ali and Qiang Yang (2019). "Scenario-based investment planning of isolated multi-energy microgrids considering electricity, heating and cooling demand". In: *Applied Energy* 235, pp. 1277–1288. ISSN: 0306-2619. DOI: https://doi.org/10.1016/j.apenergy.2018.11.058. URL: https://www.sciencedirect.com/science/article/pii/S0306261918317665 (cit. on p. 16).

F.G. Reis, Inês, Ivo Gonçalves, Marta A.R. Lopes, and Carlos Henggeler Antunes (2021). "Business models for energy communities: A review of key issues and trends". In: *Renewable and Sustainable Energy Reviews* 144, p. 111013. ISSN: 1364-0321. DOI: https://doi.org/10.1016/j.rser.2021.111013. URL: https://www.sciencedirect.com/science/article/pii/S1364032121003038 (cit. on pp. 3, 19).

Fan, Yuling and Xiaohua Xia (2017). "A multi-objective optimization model for energy-efficiency building envelope retrofitting plan with rooftop PV system installation and maintenance". In: *Applied Energy* 189, pp. 327–335. ISSN: 0306-2619. DOI: 10.1016/j.apenergy.2016.12.077 (cit. on p. 12).

Fina, B. and H. Fechner (2021). "Transposition of European Guidelines for Energy Communities into Austrian Law: A Comparison and Discussion of Issues and Positive Aspects." In: *Energies* 14. DOI: doi.org/10.3390/en14133922 (cit. on p. 17).

Fina, Bernadette, Hans Auer, and Werner Friedl (2019). "Profitability of PV sharing in energy communities: Use cases for different settlement patterns". In: *Energy* 189, p. 116148. ISSN: 0360-5442. DOI: 10.1016/j.energy.2019.116148 (cit. on pp. 13, 25).

— (2020). "Cost-optimal economic potential of shared rooftop PV in energy communities: Evidence from Austria". In: *Renewable Energy* 152, pp. 217–228. ISSN: 0960-1481. DOI: https://doi.org/10.1016/j.renene.2020.01.031. URL: https://www.sciencedirect.com/science/article/pii/S0960148120300288 (cit. on p. 13).

Fina, Bernadette, Andreas Fleischhacker, Hans Auer, and Georg Lettner (vol. 2018). "Economic Assessment and Business Models of Rooftop Photovoltaic Systems in Multiapartment Buildings: Case Studies for Austria and Germany". In: *Journal of Renewable Energy* 2018. DOI: 10.1155/2018/9759680 (cit. on p. 12).

Fioriti, Davide, Antonio Frangioni, and Davide Poli (2021). "Optimal sizing of energy communities with fair revenue sharing and exit clauses: Value, role and business model of aggregators and users". In: *Applied Energy* 299, p. 117328. ISSN: 0306-2619. DOI: https://doi.org/10.1016/j.apenergy.2021.117328. URL: https://www.sciencedirect.com/science/article/pii/S0306261921007376 (cit. on p. 19).

Fischetti, Matteo, Ivana Ljubić, Michele Monaci, and Markus Sinnl (2017). "A New General-Purpose Algorithm for Mixed-Integer Bilevel Linear Programs". In: *Operations Research* 65.6, pp. 1615–1637. DOI: 10.1287/

opre.2017.1650. eprint: https://doi.org/10.1287/opre.2017.1650. URL: https://doi.org/10.1287/opre.2017.1650 (cit. on p. 38).

Fleischhacker, A., H. Auer, G. Lettner, and A. Botterud (July 2019). "Sharing Solar PV and Energy Storage in Apartment Buildings: Resource Allocation and Pricing". In: *IEEE Transactions on Smart Grid* 10.4, pp. 3963–3973. DOI: 10.1109/TSG.2018.2844877 (cit. on pp. 12, 13).

Fortuny-Amat, José and Bruce McCarl (1981). "A Representation and Economic Interpretation of a Two-Level Programming Problem". In: *The Journal of the Operational Research Society* 32.9, pp. 783–792. ISSN: 01605682, 14769360. DOI: 10.2307/2581394. URL: http://www.jstor.org/stable/2581394 (cit. on p. 38).

Guerrero, Jaysson, Bunyim Sok, Archie C. Chapman, and Gregor Verbič (2021). "Electrical-distance driven peer-to-peer energy trading in a low-voltage network". In: *Applied Energy* 287, p. 116598. ISSN: 0306-2619. DOI: https://doi.org/10.1016/j.apenergy.2021.116598. URL: https://www.sciencedirect.com/science/article/pii/S0306261921001380 (cit. on p. 15).

Gui, Emi Minghui and Iain MacGill (2018). "Typology of future clean energy communities: An exploratory structure, opportunities, and challenges". In: *Energy Research & Social Science* 35. Energy and the Future, pp. 94–107. ISSN: 2214-6296. DOI: 10.1016/j.erss.2017.10.019 (cit. on p. 11).

Hackbarth, André and Sabine Löbbe (2020). "Attitudes, preferences, and intentions of German households concerning participation in peer-to-peer electricity trading". In: *Energy Policy* 138, p. 111238. ISSN: 0301-4215. DOI: 10.1016/j.enpol.2020.111238 (cit. on p. 18).

Hahnel, Ulf J.J., Mario Herberz, Alejandro Pena-Bello, David Parra, and Tobias Brosch (2020). "Becoming prosumer: Revealing trading preferences and decision-making strategies in peer-to-peer energy communities". In: *Energy Policy* 137, p. 111098. ISSN: 0301-4215. DOI: 10.1016/j.enpol.2019.111098 (cit. on p. 14).

Hanke, F. and J Lowitzsch (2020). "Empowering Vulnerable Consumers to Join Renewable Energy Communities—Towards an Inclusive Design of the Clean Energy Package". In: *Energies*. DOI: 10.3390/en13071615 (cit. on p. 18).

Hanke, Florian, Rachel Guyet, and Marielle Feenstra (2021). "Do renewable energy communities deliver energy justice? Exploring insights from 71

European cases". In: *Energy Research & Social Science* 80, p. 102244. ISSN: 2214-6296. DOI: https://doi.org/10.1016/j.erss.2021.102244. URL: https://www.sciencedirect.com/science/article/pii/S2214629621003376 (cit. on p. 18).

Hart, William E, Jean-Paul Watson, and David L Woodruff (2011). "Pyomo: modeling and solving mathematical programs in Python". In: *Mathematical Programming Computation* 3.3, pp. 219–260 (cit. on pp. 67, 84).

Hashemipour, Naser, Pedro Crespo del Granado, and Jamshid Aghaei (2021). "Dynamic allocation of peer-to-peer clusters in virtual local electricity markets: A marketplace for EV flexibility". In: *Energy* 236, p. 121428. ISSN: 0360-5442. DOI: https://doi.org/10.1016/j.energy.2021.121428. URL: https://www.sciencedirect.com/science/article/pii/S0360544221016765 (cit. on pp. 14, 20).

Henriquez-Auba, Rodrigo, Patricia Hidalgo-Gonzalez, Patricia Pauli, Dileep Kalathil, Duncan S. Callaway, and Kameshwar Poolla (2021). "Sharing economy and optimal investment decisions for distributed solar generation". In: *Applied Energy* 294, p. 117029. ISSN: 0306-2619. DOI: https://doi.org/10.1016/j.apenergy.2021.117029. URL: https://www.sciencedirect.com/science/article/pii/S0306261921004918 (cit. on p. 14).

Hirsch, Adam, Yael Parag, and Josep Guerrero (2018). "Microgrids: A review of technologies, key drivers, and outstanding issues". In: *Renewable and Sustainable Energy Reviews* 90, pp. 402–411. ISSN: 1364-0321. DOI: https://doi.org/10.1016/j.rser.2018.03.040. URL: http://www.sciencedirect.com/science/article/pii/S136403211830128X (cit. on p. 11).

Hoicka, Christina E., Jens Lowitzsch, Marie Claire Brisbois, Ankit Kumar, and Luis Ramirez Camargo (2021). "Implementing a just renewable energy transition: Policy advice for transposing the new European rules for renewable energy communities". In: *Energy Policy* 156, p. 112435. ISSN: 0301-4215. DOI: https://doi.org/10.1016/j.enpol.2021.112435. URL: https://www.sciencedirect.com/science/article/pii/S0301421521003050 (cit. on pp. 18, 109).

Hossain, Eklas, Ersan Kabalci, Ramazan Bayindir, and Ronald Perez (2014). "Microgrid testbeds around the world: State of art". In: *Energy Conversion and Management* 86, pp. 132–153. ISSN: 0196-8904. DOI: 10.1016/

j.enconman.2014.05.012. URL: http://www.sciencedirect.com/science/article/pii/S0196890414004233 (cit. on p. 11).

Jiang, Aihua, Huihong Yuan, and Delong Li (2021). "A two-stage optimization approach on the decisions for prosumers and consumers within a community in the Peer-to-peer energy sharing trading". In: *International Journal of Electrical Power & Energy Systems* 125, p. 106527. ISSN: 0142-0615. DOI: https://doi.org/10.1016/j.ijepes.2020.106527. URL: http://www.sciencedirect.com/science/article/pii/S0142061520319906 (cit. on p. 14).

Jiao, Feixiang, Yuan Zou, Xudong Zhang, and Bin Zhang (2022). "Online optimal dispatch based on combined robust and stochastic model predictive control for a microgrid including EV charging station". In: *Energy* 247, p. 123220. ISSN: 0360-5442. DOI: https://doi.org/10.1016/j.energy.2022.123220. URL: https://www.sciencedirect.com/science/article/pii/S0360544222001232 (cit. on p. 16).

Jogunola, Olamide, Weizhuo Wang, and Bamidele Adebisi (2020). "Prosumers Matching and Least-Cost Energy Path Optimisation for Peer-to-Peer Energy Trading". In: *IEEE Access* 8, pp. 95266–95277. DOI: 10.1109/ACCESS.2020.2996309 (cit. on p. 15).

Kara, Güray, Paolo Pisciella, Asgeir Tomasgard, Hossein Farahmand, and Pedro Crespo del Granado (2022). "Stochastic local flexibility market design, bidding, and dispatch for distribution grid operations". In: *Energy* 253, p. 123989. ISSN: 0360-5442. DOI: https://doi.org/10.1016/j.energy.2022.123989. URL: https://www.sciencedirect.com/science/article/pii/S0360544222008921 (cit. on p. 15).

Karunathilake, Hirushie, Kasun Hewage, Walter Mérida, and Rehan Sadiq (2019). "Renewable energy selection for net-zero energy communities: Life cycle based decision making under uncertainty". In: *Renewable Energy* 130, pp. 558–573. ISSN: 0960-1481. DOI: https://doi.org/10.1016/j.renene.2018.06.086. URL: https://www.sciencedirect.com/science/article/pii/S0960148118307389 (cit. on p. 15).

Khorasany, Mohsen, Yateendra Mishra, and Gerard Ledwich (2020). "A Decentralized Bilateral Energy Trading System for Peer-to-Peer Electricity Markets". In: *IEEE Transactions on Industrial Electronics* 67.6, pp. 4646–4657. DOI: 10.1109/TIE.2019.2931229 (cit. on p. 15).

Kirli, Desen, Benoit Couraud, Valentin Robu, Marcelo Salgado-Bravo, Sonam Norbu, Merlinda Andoni, Ioannis Antonopoulos, Matias Negrete-Pincetic, David Flynn, and Aristides Kiprakis (2022). "Smart contracts in energy systems: A systematic review of fundamental approaches and implementations". In: *Renewable and Sustainable Energy Reviews* 158, p. 112013. ISSN: 1364-0321. DOI: https://doi.org/10.1016/j.rser.2021.112013. URL: https://www.sciencedirect.com/science/article/pii/S1364032121012764 (cit. on p. 20).

Kleinert, Thomas, Martine Labbé, Fr¨ank Plein, and Martin Schmidt (2020). "Technical Note—There's No Free Lunch: On the Hardness of Choosing a Correct Big-M in Bilevel Optimization". In: *Operations Research* 68.6, pp. 1716–1721. DOI: 10.1287/opre.2019.1944 (cit. on p. 145).

Koirala, Binod Prasad, Yashar Araghi, Maarten Kroesen, Amineh Ghorbani, Rudi A. Hakvoort, and Paulien M. Herder (2018). "Trust, awareness, and independence: Insights from a socio-psychological factor analysis of citizen knowledge and participation in community energy systems". In: *Energy Research & Social Science* 38, pp. 33–40. ISSN: 2214-6296. DOI: https://doi.org/10.1016/j.erss.2018.01.009. URL: https://www.sciencedirect.com/science/article/pii/S2214629618300641 (cit. on p. 18).

Lazdins, R, A Mutule, and D Zalostiba (2021). "PV Energy Communities—Challenges and Barriers from a Consumer Perspective: A Literature Review". In: *Energies* 14.16. DOI: 10.3390/en14164873 (cit. on p. 19).

Li, Zhenpeng and Tao Ma (2020). "Peer-to-peer electricity trading in grid-connected residential communities with household distributed photovoltaic". In: *Applied Energy* 278, p. 115670. ISSN: 0306-2619. DOI: https://doi.org/10.1016/j.apenergy.2020.115670. URL: http://www.sciencedirect.com/science/article/pii/S0306261920311661 (cit. on p. 14).

Lin, Jason, Manisa Pipattanasomporn, and Saifur Rahman (2019). "Comparative analysis of auction mechanisms and bidding strategies for P2P solar transactive energy markets". In: *Applied Energy* 255, p. 113687. ISSN: 0306-2619. DOI: https://doi.org/10.1016/j.apenergy.2019.113687. URL: https://www.sciencedirect.com/science/article/pii/S0306261919313741 (cit. on p. 14).

Longo, Danila, Giulia Olivieri, Rossella Roversi, Giulia Turci, and Beatrice Turillazzi (2020). "Energy Poverty and Protection of Vulnerable Consumers. Overview of the EU Funding Programs FP7 and H2020 and Future Trends in Horizon Europe". In: *Energies* 13.5. ISSN: 1996-1073. DOI: 10.3390/en13051030. URL: https://www.mdpi.com/1996-1073/13/5/1030 (cit. on p. 18).

Lowitzsch, Jens (2020). "Consumer Stock Ownership Plans (CSOPs)—The Prototype Business Model for Renewable Energy Communities". In: *Energies* 13.1. ISSN: 1996-1073. DOI: 10.3390/en13010118. URL: https://www.mdpi.com/1996-1073/13/1/118 (cit. on p. 19).

Lüth, Alexandra, Jan Martin Zepter, Pedro Crespo del Granado, and Ruud Egging (2018). "Local electricity market designs for peer-to-peer trading: The role of battery flexibility". In: *Applied Energy* 229, pp. 1233–1243. ISSN: 0306-2619. DOI: 10.1016/j.apenergy.2018.08.004 (cit. on p. 12).

Luthander, Rasmus, Joakim Widen, Daniel Nilsson, and Jenny Palm (2015). "Photovoltaic self-consumption in buildings: A review". In: *Applied Energy* 142, pp. 80–94. ISSN: 0306-2619. DOI: 10.1016/j.apenergy.2014.12.028 (cit. on p. 139).

Masson-Delmotte, V. et al. (2018). "IPCC, 2018: Global warming of 1.5°C. An IPCC Special Report on the impacts of global warming of 1.5°C above pre-industrial levels and related global greenhouse gas emission pathways, in the context of strengthening the global response to the threat of climate change, sustainable development, and efforts to eradicate poverty". In: URL: https://www.ipcc.ch/sr15/download/ (cit. on p. 2).

Mengelkamp, Esther, Johannes Gärttner, Kerstin Rock, Scott Kessler, Lawrence Orsini, and Christof Weinhardt (2018). "Designing microgrid energy markets: A case study: The Brooklyn Microgrid". In: *Applied Energy* 210, pp. 870–880. ISSN: 0306-2619. DOI: 10.1016/j.apenergy.2017.06.054 (cit. on p. 16).

Mohseni, Soheil and Seyed Masoud Moghaddas-Tafreshi (2018). "A multi-agent system for optimal sizing of a cooperative self-sustainable multi-carrier microgrid". In: *Sustainable Cities and Society* 38, pp. 452–465. ISSN: 2210-6707. DOI: 10.1016/j.scs.2018.01.016. URL: http://www.sciencedirect.com/science/article/pii/S2210670717312817 (cit. on p. 11).

Moret, Fabio and Pierre Pinson (2019). "Energy Collectives: A Community and Fairness Based Approach to Future Electricity Markets". In: *IEEE Transactions on Power Systems* 34.5, pp. 3994–4004. DOI: 10.1109/TPWRS.2018.2808961 (cit. on p. 14).

Neyestani, Nilufar, Maziar Yazdani-Damavandi, Miadreza Shafie-khah, Gianfranco Chicco, and João P. S. Catalão (2015). "Stochastic Modeling of Multienergy Carriers Dependencies in Smart Local Networks With Distributed Energy Resources". In: *IEEE Transactions on Smart Grid* 6.4, pp. 1748–1762. DOI: 10.1109/TSG.2015.2423552 (cit. on pp. 15, 16).

Park, Chankook and Taeseok Yong (2017). "Comparative review and discussion on P2P electricity trading". In: *Energy Procedia* 128. International Scientific Conference "Environmental and Climate Technologies", CONECT 2017, 10-12 May 2017, Riga, Latvia, pp. 3–9. ISSN: 1876-6102. DOI: 10.1016/j.egypro.2017.09.003 (cit. on p. 16).

Paudel, Amrit, Kalpesh Chaudhari, Chao Long, and Hoay Beng Gooi (2019). "Peer-to-Peer Energy Trading in a Prosumer-Based Community Microgrid: A Game-Theoretic Model". In: *IEEE Transactions on Industrial Electronics* 66.8, pp. 6087–6097. DOI: 10.1109/TIE.2018.2874578 (cit. on p. 13).

Paudel, Amrit, L. P. M. I. Sampath, Jiawei Yang, and Hoay Beng Gooi (2020). "Peer-to-Peer Energy Trading in Smart Grid Considering Power Losses and Network Fees". In: *IEEE Transactions on Smart Grid* 11.6, pp. 4727–4737. DOI: 10.1109/TSG.2020.2997956 (cit. on p. 14).

Perger, T and H Auer (2022). "Dynamic participation in local energy communities with peer-to-peer trading [version 1; peer review: 1 approved]". In: *Open Research Europe* 2.5. DOI: 10.12688/openreseurope.14332.1 (cit. on pp. 5, 6, 22, 45, 62, 66).

Perger, Theresia, Lukas Wachter, Andreas Fleischhacker, and Hans Auer (2021). "PV sharing in local communities: Peer-to-peer trading under consideration of the prosumers' willingness-to-pay". In: *Sustainable Cities and Society* 66, p. 102634. ISSN: 2210-6707. DOI: https://doi.org/10.1016/j.scs.2020.102634. URL: https://www.sciencedirect.com/science/article/pii/S2210670720308519 (cit. on pp. 5, 21, 33, 47, 108, 144).

Perger, Theresia, Sebastian Zwickl-Bernhard, Antonia Golab, and Hans Auer (2022). "A stochastic approach to dynamic participation in energy communities”. In: *e & i Elektrotechnik und Informationstechnik*. DOI: https://doi.org/10.1007/s00502-022-01069-2 (cit. on pp. 6, 62, 66).

Pfenninger, Stefan and Iain Staffell (2016). “Long-term patterns of European PV output using 30 years of validated hourly reanalysis and satellite data”. In: *Energy* 114, pp. 1251–1265. ISSN: 0360-5442. DOI: 10.1016/j.energy.2016.08.060 (cit. on pp. 47, 67, 85, 148).

Pflugradt, Noah and Urs Muntwyler (2017). “Synthesizing residential load profiles using behavior simulation”. In: *Energy Procedia* 122. CISBAT 2017 International ConferenceFuture Buildings & Districts - Energy Efficiency from Nano to Urban Scale, pp. 655–660. ISSN: 1876-6102. DOI: https://doi.org/10.1016/j.egypro.2017.07.365. URL: https://www.sciencedirect.com/science/article/pii/S1876610217329697 (cit. on pp. 67, 85).

Pineda, S., H. Bylling, and J. M. Morales (2018). “Efficiently solving linear bilevel programming problems using off-the-shelf optimization software”. In: *Optimization and Engineering* 19, pp. 187–211. ISSN: 1573-2924. DOI: 10.1007/s11081-017-9369-y (cit. on p. 38).

Qiu, Dawei, Yujian Ye, Dimitrios Papadaskalopoulos, and Goran Strbac (2021). “Scalable coordinated management of peer-to-peer energy trading: A multi-cluster deep reinforcement learning approach”. In: *Applied Energy* 292, p. 116940. ISSN: 0306-2619. DOI: https://doi.org/10.1016/j.apenergy.2021.116940. URL: https://www.sciencedirect.com/science/article/pii/S0306261921004189 (cit. on p. 20).

Radl, Johannes, Andreas Fleischhacker, Frida Huglen Revheim, Georg Lettner, and Hans Auer (2020). “Comparison of Profitability of PV Electricity Sharing in Renewable Energy Communities in Selected European Countries”. In: *Energies* 13.19. ISSN: 1996-1073. DOI: 10.3390/en13195007. URL: https://www.mdpi.com/1996-1073/13/19/5007 (cit. on p. 13).

Roberts, Mike B., Anna Bruce, and Iain MacGill (2019a). “A comparison of arrangements for increasing self-consumption and maximising the value of distributed photovoltaics on apartment buildings”. In: *Solar Energy* 193, pp. 372–386. ISSN: 0038-092X. DOI: 10.1016/j.solener.2019.09.067 (cit. on p. 12).

— (2019b). “Impact of shared battery energy storage systems on photovoltaic self-consumption and electricity bills in apartment buildings”.

In: *Applied Energy* 245, pp. 78–95. ISSN: 0306-2619. DOI: 10.1016/j.apenergy.2019.04.001 (cit. on p. 12).

Romero-Rubio, Carmen and José Ramón de Andrés Díaz (2015). "Sustainable energy communities: a study contrasting Spain and Germany". In: *Energy Policy* 85, pp. 397–409. ISSN: 0301-4215. DOI: https://doi.org/10.1016/j.enpol.2015.06.012. URL: https://www.sciencedirect.com/science/article/pii/S030142151500230X (cit. on p. 109).

Roversi, Rossella, Andrea Boeri, Serena Pagliula, and Giulia Turci (2022). "Energy Community in Action - Energy Citizenship Contract as Tool for Climate Neutrality". In: *Smart Cities* 5.1, pp. 294–317. ISSN: 2624-6511. DOI: 10.3390/smartcities5010018. URL: https://www.mdpi.com/2624-6511/5/1/18 (cit. on p. 19).

Ruiz, Carlos, Antonio J. Conejo, J. David Fuller, Steven A. Gabriel, and Benjamin F. Hobbs (2014). "A tutorial review of complementarity models for decision-making in energy markets". In: *EURO Journal on Decision Processes* 2, pp. 91–120. ISSN: 2193-9446. DOI: 10.1007/s40070-013-0019-0 (cit. on p. 38).

Schram, Wouter, Atse Louwen, Ioannis Lampropoulos, and Wilfried van Sark (2019a). "Comparison of the Greenhouse Gas Emission Reduction Potential of Energy Communities ". In: *Energies* 12 (23). DOI: 10.3390/en12234440 (cit. on p. 12).

Sciullo, Alessandro et al. (2022). "Exploring Institutional and Socio-Economic Settings for the Development of Energy Communities in Europe". In: *Energies* 15.4. ISSN: 1996-1073. DOI: 10.3390/en15041597. URL: https://www.mdpi.com/1996-1073/15/4/1597 (cit. on p. 109).

Shin, Joohyun, Jay H. Lee, and Matthew J. Realff (2017). "Operational planning and optimal sizing of microgrid considering multi-scale wind uncertainty". In: *Applied Energy* 195, pp. 616–633. ISSN: 0306-2619. DOI: https://doi.org/10.1016/j.apenergy.2017.03.081. URL: https://www.sciencedirect.com/science/article/pii/S0306261917303227 (cit. on p. 16).

Soeiro, Susana and Marta Ferreira Dias (2020b). "Community renewable energy: Benefits and drivers". In: *Energy Reports* 6. The 7th International Conference on Energy and Environment Research—"Driving Energy and Environment in 2020 Towards A Sustainable Future", pp. 134–140. ISSN: 2352-4847. DOI: https://doi.org/10.1016/j.egyr.2020.11.087.

URL: https://www.sciencedirect.com/science/article/pii/S2352484720315122 (cit. on p. 3).

Soeiro, Susana and Marta Ferreira Dias (2020). "Renewable energy community and the European energy market: main motivations". In: *Heliyon* 6.7, e04511. ISSN: 2405-8440. DOI: https://doi.org/10.1016/j.heliyon.2020.e04511. URL: https://www.sciencedirect.com/science/article/pii/S2405844020313554 (cit. on p. 18).

Sorin, Etienne, Lucien Bobo, and Pierre Pinson (2019). "Consensus-Based Approach to Peer-to-Peer Electricity Markets With Product Differentiation". In: *IEEE Transactions on Power Systems* 34.2, pp. 994–1004. DOI: 10.1109/TPWRS.2018.2872880 (cit. on p. 14).

Soto, Esteban A., Lisa B. Bosman, Ebisa Wollega, and Walter D. Leon-Salas (2021). "Peer-to-peer energy trading: A review of the literature". In: *Applied Energy* 283, p. 116268. ISSN: 0306-2619. DOI: https://doi.org/10.1016/j.apenergy.2020.116268. URL: https://www.sciencedirect.com/science/article/pii/S0306261920316585 (cit. on p. 13).

Sousa, Tiago, Tiago Soares, Pierre Pinson, Fabio Moret, Thomas Baroche, and Etienne Sorin (2019). "Peer-to-peer and community-based markets: A comprehensive review". In: *Renewable and Sustainable Energy Reviews* 104, pp. 367–378. ISSN: 1364-0321. DOI: 10.1016/j.rser.2019.01.036 (cit. on pp. 3, 14).

Staffell, Iain and Stefan Pfenninger (2016). "Using bias-corrected reanalysis to simulate current and future wind power output". In: *Energy* 114, pp. 1224–1239. ISSN: 0360-5442. DOI: 10.1016/j.energy.2016.08.068 (cit. on pp. 47, 67, 85, 148).

Sudhoff, Robin, Sebastian Schreck, Sebastian Thiem, and Stefan Niessen (2022). "Operating Renewable Energy Communities to Reduce Power Peaks in the Distribution Grid: An Analysis on Grid-Friendliness, Different Shares of Participants, and Economic Benefits". In: *Energies* 15.15. ISSN: 1996-1073. DOI: 10.3390/en15155468. URL: https://www.mdpi.com/1996-1073/15/15/5468 (cit. on p. 111).

Taşcıkaraoğlu, Akın (2018). "Economic and operational benefits of energy storage sharing for a neighborhood of prosumers in a dynamic pricing environment". In: *Sustainable Cities and Society* 38, pp. 219–229. ISSN: 2210-6707. DOI: 10.1016/j.scs.2018.01.002. URL: http://www.

sciencedirect.com/science/article/pii/S2210670717315111 (cit. on p. 12).

Tavenard, Romain, Johann Faouzi, Gilles Vandewiele, Felix Divo, Guillaume Androz, Chester Holtz, Marie Payne, Roman Yurchak, Marc Rußwurm, Kushal Kolar, and Eli Woods (2020). "Tslearn, A Machine Learning Toolkit for Time Series Data". In: *Journal of Machine Learning Research* 21.118, pp. 1–6. URL: http://jmlr.org/papers/v21/20-091.html (cit. on pp. 70, 85).

Teichgraeber, Holger and Adam R. Brandt (2019). "Clustering methods to find representative periods for the optimization of energy systems: An initial framework and comparison". In: *Applied Energy* 239, pp. 1283–1293. ISSN: 0306-2619. DOI: https://doi.org/10.1016/j.apenergy.2019.02.012. URL: https://www.sciencedirect.com/science/article/pii/S0306261919303022 (cit. on pp. 70, 85).

Tushar, Wayes, Tapan Kumar Saha, Chau Yuen, Paul Liddell, Richard Bean, and H. Vincent Poor (2018). "Peer-to-Peer Energy Trading With Sustainable User Participation: A Game Theoretic Approach". In: *IEEE Access* 6, pp. 62932–62943. DOI: 10.1109/ACCESS.2018.2875405 (cit. on p. 13).

Tushar, Wayes, Chau Yuen, Tapan K. Saha, Thomas Morstyn, Archie C. Chapman, M. Jan E. Alam, Sarmad Hanif, and H. Vincent Poor (2021). "Peer-to-peer energy systems for connected communities: A review of recent advances and emerging challenges". In: *Applied Energy* 282, p. 116131. ISSN: 0306-2619. DOI: https://doi.org/10.1016/j.apenergy.2020.116131. URL: https://www.sciencedirect.com/science/article/pii/S0306261920315464 (cit. on p. 3).

Uhde, Helena (2022). "Peer-to-peer electricity trading in China and the EU – A comparative evaluation of key policy documents". In: *Research in Globalization* 4, p. 100078. ISSN: 2590-051X. DOI: https://doi.org/10.1016/j.resglo.2021.100078. URL: https://www.sciencedirect.com/science/article/pii/S2590051X21000435 (cit. on p. 110).

Wang, Yahui, Xiaorui Wu, Yong Li, Ruifeng Yan, Yi Tan, Xuebo Qiao, and Yijia Cao (2020). "Autonomous energy community based on energy contract". In: *IET Generation, Transmission & Distribution* 14.4, pp. 682–689. DOI: https://doi.org/10.1049/iet-gtd.2019.1223 (cit. on p. 20).

Weckesser, Tilman, Dominik Franjo Dominković, Emma M.V. Blomgren, Amos Schledorn, and Henrik Madsen (2021). “Renewable Energy Communities: Optimal sizing and distribution grid impact of photo-voltaics and battery storage”. In: *Applied Energy* 301, p. 117408. ISSN: 0306-2619. DOI: https://doi.org/10.1016/j.apenergy.2021.117408. URL: https://www.sciencedirect.com/science/article/pii/S0306261921008059 (cit. on p. 111).

Wierling, August, Valeria Jana Schwanitz, Jan Pedro Zeiß, Celine Bout, Chiara Candelise, Winston Gilcrease, and Jay Sterling Gregg (2018). “Statistical Evidence on the Role of Energy Cooperatives for the Energy Transition in European Countries”. In: *Sustainability* 10.9. ISSN: 2071-1050. DOI: 10.3390/su10093339. URL: https://www.mdpi.com/2071-1050/10/9/3339 (cit. on p. 13).

Yue, Xiufeng, Steve Pye, Joseph DeCarolis, Francis G.N. Li, Fionn Rogan, and Brian Ó. Gallachóir (2018). “A review of approaches to uncertainty assessment in energy system optimization models”. In: *Energy Strategy Reviews* 21, pp. 204–217. ISSN: 2211-467X. DOI: https://doi.org/10.1016/j.esr.2018.06.003. URL: https://www.sciencedirect.com/science/article/pii/S2211467X18300543 (cit. on p. 15).

Zepter, Jan Martin, Alexandra Lüth, Pedro Crespo del Granado, and Ruud Egging (2019). “Prosumer integration in wholesale electricity markets: Synergies of peer-to-peer trade and residential storage”. In: *Energy and Buildings* 184, pp. 163–176. ISSN: 0378-7788. DOI: 10.1016/j.enbuild.2018.12.003 (cit. on p. 12).

Zhang, Chenghua, Jianzhong Wu, Chao Long, and Meng Cheng (2017). “Review of Existing Peer-to-Peer Energy Trading Projects”. In: *Energy Procedia* 105. 8th International Conference on Applied Energy, ICAE2016, 8-11 October 2016, Beijing, China, pp. 2563–2568. ISSN: 1876-6102. DOI: 10.1016/j.egypro.2017.03.737 (cit. on p. 16).

Zhang, Chenghua, Jianzhong Wu, Yue Zhou, Meng Cheng, and Chao Long (2018). “Peer-to-Peer energy trading in a Microgrid”. In: *Applied Energy* 220, pp. 1–12. ISSN: 0306-2619. DOI: 10.1016/j.apenergy.2018.03.010 (cit. on pp. 13, 14).

Zhou, Fenglin, Yaoyu Li, Wenyi Wang, and Chao Pan (2022). “Integrated energy management of a smart community with electric vehicle charging using scenario based stochastic model predictive control”. In: *Energy and*

Buildings 260, p. 111916. ISSN: 0378-7788. DOI: https://doi.org/10.1016/j.enbuild.2022.111916. URL: https://www.sciencedirect.com/science/article/pii/S0378778822000871 (cit. on p. 15).

Zwickl-Bernhard, Sebastian and Hans Auer (2021). "Citizen Participation in Low-Carbon Energy Systems: Energy Communities and Its Impact on the Electricity Demand on Neighborhood and National Level". In: *Energies* 14.2. ISSN: 1996-1073. DOI: 10.3390/en14020305. URL: https://www.mdpi.com/1996-1073/14/2/305 (cit. on p. 13).

Conference Papers

Bjarghov, S., M. Askeland, and S. Backe (Sept. 2020). "Peer-to-peer trading under subscribed capacity tariffs - an equilibrium approach". In: *2020 17th International Conference on the European Energy Market (EEM)*, pp. 1–6. DOI: 10.1109/EEM49802.2020.9221966 (cit. on pp. 14, 111).

Blumsack, S., P. Hines, M. Patel, C. Barrows, and E. Cotilla Sanchez (2009). "Defining power network zones from measures of electrical distance". In: *2009 IEEE Power & Energy Society General Meeting*, pp. 1–8. DOI: 10.1109/PES.2009.5275353 (cit. on p. 103).

Doumen, Sjoerd C., Phuong Nguyen, and Koen Kok (2021). "The State of the Art in Local Energy Markets: a Comparative Review". In: *2021 IEEE Madrid PowerTech*, pp. 1–6. DOI: 10.1109/PowerTech46648.2021.9494859 (cit. on p. 3).

Frieden, Dorian, Andreas Tuerk, Josh Roberts, Stanislas D'Herbemont, Andrej F. Gubina, and Benjamin Komel (2019). "Overview of emerging regulatory frameworks on collective self-consumption and energy communities in Europe". In: *2019 16th International Conference on the European Energy Market (EEM)*, pp. 1–6. DOI: 10.1109/EEM.2019.8916222 (cit. on pp. 3, 109).

Löfberg, J. (2004). "YALMIP : A Toolbox for Modeling and Optimization in MATLAB". In: *In Proceedings of the CACSD Conference*. Taipei, Taiwan (cit. on p. 47).

Orlandini, Tommaso, Tiago Soares, Tiago Sousa, and Pierre Pinson (2019). "Coordinating Consumer-Centric Market and Grid Operation on Distribution Grid". In: *2019 16th International Conference on the European*

Energy Market (EEM), pp. 1–6. DOI: 10.1109/EEM.2019.8916247 (cit. on p. 14).

Pinto, Angelo, Tiago Pinto, Francisco Silva, Isabel Praça, Zita Vale, and Juan Manuel Corchado (2018). "Automated combination of bilateral energy contracts negotiation tactics". In: *2018 IEEE Power & Energy Society General Meeting (PESGM)*, pp. 1–5. DOI: 10.1109/PESGM.2018.8586003 (cit. on p. 20).

Rakos, B., P. Stumpf, and I. Nagy (Sept. 2012). "Investigation of the effects of nonlinear model of super-capacitors in local DC microgrids supplied by renewables". In: *2012 15th International Power Electronics and Motion Control Conference (EPE/PEMC)*, DS3b.11-1-DS3b.11–8. DOI: 10.1109/EPEPEMC.2012.6397331 (cit. on p. 11).

Reis, I. F. G., I. Gonçalves, M. A. R. Lopes, and C. Henggeler Antunes (2020). "A study of the inclusion of vulnerable consumers in energy communities with peer-to-peer exchanges". In: *2020 International Conference on Smart Energy Systems and Technologies (SEST)*, pp. 1–6. DOI: 10.1109/SEST48500.2020.9203312 (cit. on p. 19).

Scarabaggio, Paolo, Raffaele Carli, Jan Jantzen, and Mariagrazia Dotoli (2021). "Stochastic Model Predictive Control of Community Energy Storage under High Renewable Penetration". In: *2021 29th Mediterranean Conference on Control and Automation (MED)*, pp. 973–978. DOI: 10.1109/MED51440.2021.9480353 (cit. on p. 16).

Soeiro, S. and M. F. Dias (Sept. 2020a). "Motivations for Integrating a Renewable Energy Community: Evidence for Spain and Portugal". In: *2020 17th International Conference on the European Energy Market (EEM)*, pp. 1–6. DOI: 10.1109/EEM49802.2020.9221887 (cit. on p. 18).

Urbantschitsch, Wolfgang (2020). "Die Transformation der Energiewirtschaft aus regulatorischer Sicht". In: 16.Symposium Energieinnovation, Graz/Austria. URL: https://www.tugraz.at/events/eninnov2020/nachlese/download-beitraege/plena/#c279208 (cit. on p. 11).

Other sources

APCS-Austrian Power Clearing and Settlement (2019). *Synthetic load profiles.* https://www.apcs.at/en/clearing/physical-clearing/

synthetic-load-profiles. [Online; accessed 24-October-2019] (cit. on pp. 48, 68, 85, 147).

BestRES (2018). *Best practices and implementation of innovative business models for renewable energy aggregators.* URL: bestres.eu (cit. on p. 17).

COMPILE (2019). *Collective self-consumption and energy communities: Overview of emerging regulatory approaches in Europe.* URL: https://www.compile-project.eu/ (cit. on p. 11).

Directorate-General for Energy (European Commission) (2019). *Clean energy for all Europeans.* DOI: 10.2833/9937 (cit. on pp. 3, 10, 17).

EEG (2020). *Energy Economics Group, TU Wien, Internal Data Base* (cit. on p. 48).

eFriends Energy GmbH (2020). *eFriends.* URL: www.efriends.at (cit. on p. 17).

ENTSO-E (2022). *ENTSO-E Transparency Platform.* https://transparency.entsoe.eu/. [Online; accessed 14-April-2022] (cit. on p. 85).

European Commission (2018). *Directive (EU) 2018/2001 of the European Parliament and of the Council of 11 December 2018 on the promotion of the use of energy from renewable sources.* URL: http://data.europa.eu/eli/dir/2018/2001/oj (cit. on pp. 3, 10, 31, 109).

— (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 (recast).* URL: http://data.europa.eu/eli/dir/2019/944/oj (cit. on pp. 10, 110).

Eurostat (2022). *Electricity price statistics.* https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Electricity_price_statistics. [Online; accessed 12-April-2022] (cit. on pp. 49, 63, 68, 85).

EXAA Energy Exchange Austria (2020). URL: https://www.exaa.at/de/marktdaten/historische-daten (cit. on pp. 49, 69).

GNU project (2021). *GLPK (GNU Linear Programming Kit).* URL: https://www.gnu.org/software/glpk/ (cit. on pp. 67, 84).

Gurobi Optimization, LLC (2021). *Gurobi Optimizer Reference Manual.* URL: http://www.gurobi.com (cit. on pp. 47, 67, 84).

Microgrid, Brooklyn (2020). *Brooklyn Microgrid - Community Powered Energy.* URL: https://www.brooklyn.energy/ (cit. on p. 16).

Noah Pflugradt (2021). *LoadProfileGenerator*. https://www.loadprofilegenerator.de/. [Online; accessed 08-February-2022] (cit. on p. 85).

open4innovation (2018). *P2PQ - Peer2Peer im Quartier*. URL: https://nachhaltigwirtschaften.at/de/sdz/projekte/peer2peer-im-quartier.php (cit. on p. 17).

openENTRANCE (2022). *openENTRANCE - open ENergy TRansition ANalyses for a low-Carbon Economy*. https://openentrance.eu/. [Online; accessed 12-July-2022] (cit. on p. 108).

OurPower (2020). *OurPower - die Energiecooperative*. URL: https://www.ourpower.coop/ (cit. on p. 17).

Piclo (2020). *Piclo - Building a smarter energy future*. URL: https://piclo.energy/ (cit. on p. 16).

Renewables.ninja (2019). *Renewables.ninja*. https://renewables.ninja. [Online; accessed 06-April-2022] (cit. on pp. 47, 85).

Republik Österreich (2022). *Bundesgesetz über den Ausbau von Energie aus erneuerbaren Quellen (Erneuerbaren-Ausbau-Gesetz – EAG)*. https://www.ris.bka.gv.at/GeltendeFassung.wxe?Abfrage=Bundesnormen&Gesetzesnummer=20011619. [Online; accessed 21-August-2022] (cit. on p. 109).

REScoop (2022). *Energy Communities under the Clean Energy Package*. https://www.clientearth.org/media/rr1aqpji/energy-communities-transposition-guidance.pdf. [Online; accessed 25-October-2022] (cit. on p. 31).

Schram, Wouter, Atse Louwen, Ioannis Lampropoulos, and Wilfried van Sark (2019b). *The hourly emission factor profiles of Belgium, Spain, France, Italy, The Netherlands, Portugal, Germany and Austria for 2017*. URL: www.mdpi.com/1996-1073/12/23/4440/s1 (cit. on pp. 48, 63, 69, 149).

sonnenGroup (2020). *sonnenCommunity*. URL: https://sonnengroup.com/sonnencommunity/ (cit. on p. 17).

T. Perger (2021). *FRESH:COM v2.0*. URL: https://github.com/tperger/FRESH-COM (cit. on pp. 23, 67).

— (2022). *PARTICIPATE*. URL: https://github.com/tperger/PARTICIPATE (cit. on p. 23).

Vandebron (2020). *Vandebron: Duurzame energie van Nederlandse bodem*. URL: https://www.vandebron.nl (cit. on p. 16).

Appendices

Appendix A.

Appendix to Chapter 3

A.1. Validation of peer-to-peer trading modeling approach

In this section, the model is validated by testing its basic functionalities. Section A.1.1 presents the model validation with respect to sharing excess PV electricity generation only, but not considering willingness-to-pay. The functionality of the willingness-to-pay is then verified in Section A.1.2.

A.1.1. Model Validation by Sharing Excess PV Electricity Generation Only

The first model validation verifies the model when considering that only the prosumers' excess PV electricity generation is shared with the other community members, and that the willingness-to-pay for PV generation by the community is equal to the retailer's electricity price. To model this case, the willingness-to-pay, $wtp_{i,j,t}$, is adapted compared to Equation (3.2):

$$wtp_{i,j,t} = p_t^{G_{in}}, \tag{A.1a}$$

$$wtp_{i,i,t} = p_t^{G_{in}} + \epsilon_i. \tag{A.1b}$$

By adding a small term, ϵ_i, to $p_t^{G_{in}}$ for self-consumption, it can be noticed that self-consumption is preferred before buying from other members. No further changes are added to the model. The prosumers in this set-up are the same ten households those presented in Table 4.1. The diagonal line in the 3D bar plot in Figure A.1 indicates the self-consumption of each prosumer. Prosumers owning a PV system have very high self-consumption, and the amount of excess PV generated electricity is shared mostly with members who have no PV systems of their own.

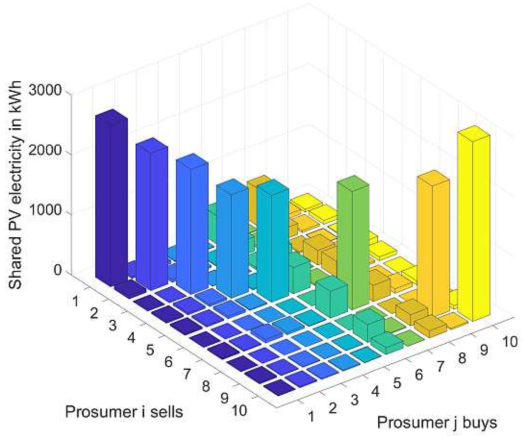


Figure A.1.: Model sharing excess PV generation only (without BESSs)

Luthander et al. (2015) summarize different studies that have researched typical values for prosumer self-consumption and the effects of BESSs on self-consumption. As shown in Figure A.2, the values for self-consumption in this scenario lie between 25%-40%, which is in agreement with the values presented in ibid. Prosumer 3 has over 50% self-consumption and is an outlier because of their small PV system. When including batteries (prosumers 2, 4, 7, and 9), the self-consumption of those prosumers operating BESSs increases by 20%-25% (see Figure A.3).

A.1.2. Validating the Functionality of the Willingness-to-Pay

The next step is to validate the functionality of the willingness-to-pay. The community set-up consists of ten households with the parameters shown in

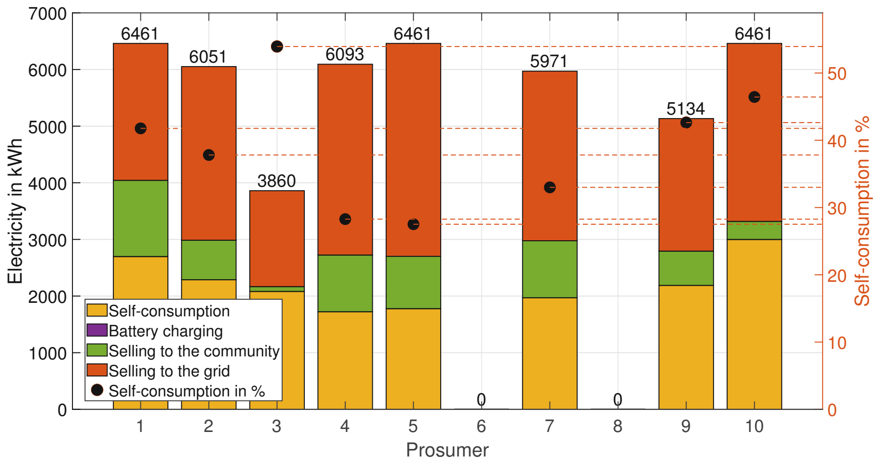


Figure A.2.: Community sharing excess PV generated electricity only (without BESSs)

Table 4.1, except that only prosumer 10 has a PV system (and all BESSs are neglected). The 3D bar plot in Figure A.4 shows that the PV generated electricity of prosumer 10 is traded within the community according to the willingnesses-to-pay of the prosumers (i.e. who pays most, buys most), and prosumer 3, 8, and 9 are the most willing to pay. Figure A.1 shows the results relating mostly to self-consumption, where only excess PV generation is distributed within the community. However, compared with the scenario shown in Figure A.4, it is highly evident how the willingness-to-pay enables and determines peer-to-peer trading.

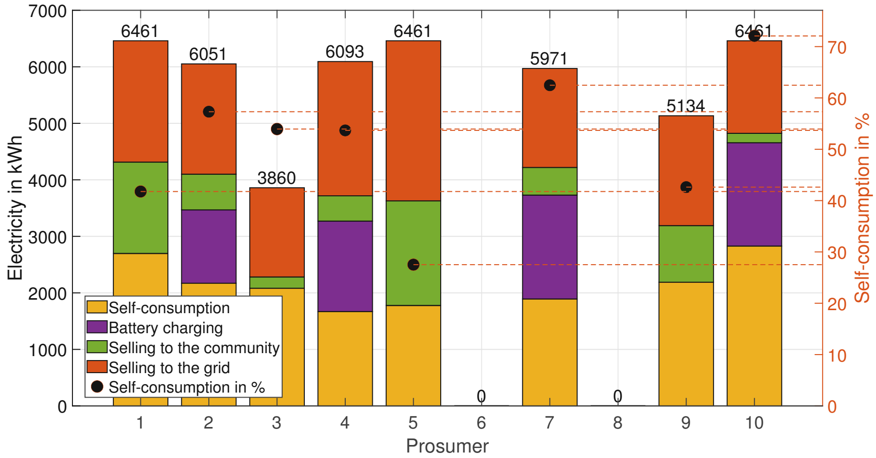


Figure A.3.: Community sharing excess PV generated electricity only (with BESSs)

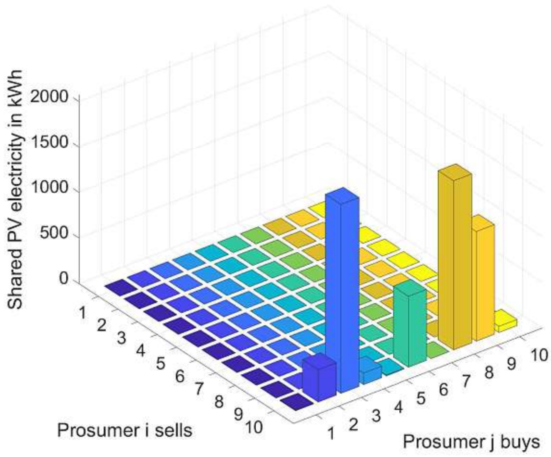


Figure A.4.: Only one prosumer has a PV system (without BESSs)

A.2. Formulation of the KKT conditions of the lower level problem

A.2.1. Lagrangian function

To derive the KKT conditions, the Lagrangian function $\mathcal{L}$ must be formulated:

$$
\begin{aligned}
&\mathcal{L}(q_{i,t}^{G_{in}}, q_{i,t}^{G_{out}}, q_{i,j,t}^{share}, q_{i,t}^{B_{in}}, q_{i,t}^{B_{out}}, SoC_{i,t})\\
&= - SW\\
&\quad + \lambda_{i,t}^{load}(q_{i,t}^{G_{in}} + q_{i,t}^{B_{out}} + \sum_{j \in \mathcal{I}} q_{j,i,t}^{share} - q_{i,t}^{load})\\
&\quad + \lambda_{i,t}^{PV}(q_{i,t}^{G_{out}} + q_{i,t}^{B_{in}} + \sum_{j \in \mathcal{I}} q_{i,j,t}^{share} - q_{i,t}^{PV})\\
&\quad + \lambda_{i,t>t_0}^{SoC}(SoC_{i,(t>t_0)-1} + q_{i,t>t_0}^{B_{in}} \cdot \eta^B - q_{i,t>t_0}^{B_{out}}/\eta^B - SoC_{i,t>t_0})\\
&\quad + \lambda_{i,t_0}^{SoC}(SoC_{i,t=t_{end}} + q_{i,t_0}^{B_{in}} \cdot \eta^B - q_{i,t_0}^{B_{out}}/\eta^B - SoC_{i,t_0})\\
&\quad + \mu_{i,t}^{SoC^{max}}(SoC_{i,t} - SoC_i^{max})\\
&\quad + \mu_{i,t}^{B_{in}^{max}}(q_{i,t}^{B_{in}} - q_i^{B^{max}})\\
&\quad + \mu_{i,t}^{B_{out}^{max}}(q_{i,t}^{B_{out}} - q_i^{B^{max}})\\
&\quad - \beta_{i,t}^{G_{in}} q_{i,t}^{G_{in}} - \beta_{i,t}^{G_{out}} q_{i,t}^{G_{out}} - \beta_{i,j,t}^{share} q_{i,j,t}^{share} - \beta_{i,t}^{B_{in}} q_{i,t}^{B_{in}} - \beta_{i,t}^{B_{out}} q_{i,t}^{B_{out}} - \beta_{i,t}^{SoC} q_{i,t}^{SoC}
\end{aligned}
\tag{A.2}
$$

A.2.2. Formulation of KKT conditions

Stationarity of the Lagrangian function:

$$\partial\mathcal{L}/\partial q_{i,t}^{G_{in}} = p_t^{G_{in}} + \lambda_{i,t}^{load} - \beta_{i,t}^{G_{in}} = 0 \tag{A.3a}$$

$$\partial\mathcal{L}/\partial q_{i,t}^{G_{out}} = -p_t^{G_{out}} + \lambda_{i,t}^{PV} - \beta_{i,t}^{G_{out}} = 0 \tag{A.3b}$$

$$\partial\mathcal{L}/\partial q_{i,j,t}^{share} = -wtp_{i,j,t} + \lambda_{i,t}^{PV} + \lambda_{j,t}^{load} - \beta_{i,j,t}^{share} = 0 \tag{A.3c}$$

$$\partial\mathcal{L}/\partial q_{i,t}^{B_{in}} = \lambda_{i,t}^{PV} + \lambda_{i,t}^{SoC} \cdot \eta_B + \mu_{i,t}^{B_{in}^{max}} - \beta_{i,t}^{B_{in}} = 0 \tag{A.3d}$$

$$\partial\mathcal{L}/\partial q_{i,t}^{B_{out}} = \lambda_{i,t}^{load} - \lambda_{i,t}^{SoC}/\eta_B + \mu_{i,t}^{B_{out}^{max}} - \beta_{i,t}^{B_{out}} = 0 \tag{A.3e}$$

$$\partial\mathcal{L}/\partial SoC_{i,t<t_{end}} = -\lambda^{SoC}_{i,t} + \lambda^{SoC}_{i,t+1} + \mu^{SoC^{max}}_{i,t} - \beta^{SoC}_{i,t} = 0 \quad \text{(A.3f)}$$
$$\partial\mathcal{L}/\partial SoC_{i,t_{end}} = -\lambda^{SoC}_{i,t_{end}} + \lambda^{SoC}_{i,t_0} + \mu^{SoC^{max}}_{i,t} - \beta^{SoC}_{i,t} = 0 \quad \text{(A.3g)}$$

Substituting $\beta^{G_{in}}_{i,t}, \beta^{G_{out}}_{i,t}, \beta^{share}_{i,j,t}, \beta^{B_{in}}_{i,t}, \beta^{B_{out}}_{i,t}\beta^{SoC}_{i,t}$, the stationarity of the Lagrangian function (A.3a)-(A.3g) can be formulated with complementarity conditions as well (see Eq.s (A.4a)-(A.4g)). Eq.s (A.4h)-(A.4n) are the complementarity conditions of the lower level problem's constraints.

$$p^{G_{in}}_t + \lambda^{load}_{i,t} \geq 0 \perp q^{G_{in}}_{i,t} \geq 0 \quad \text{(A.4a)}$$
$$-p^{G_{out}}_t + \lambda^{PV}_{i,t} \geq 0 \perp q^{G_{out}}_{i,t} \geq 0 \quad \text{(A.4b)}$$
$$-wtp_{i,j,t} + \lambda^{PV}_{i,t} + \lambda^{load}_{j,t} \geq 0 \perp q^{share}_{i,j,t} \geq 0 \quad \text{(A.4c)}$$
$$\lambda^{PV}_{i,t} + \lambda^{SoC}_{i,t} \cdot \eta_B + \mu^{B^{max}_{in}}_{i,t} \geq 0 \perp q^{B_{in}}_{i,t} \geq 0 \quad \text{(A.4d)}$$
$$\lambda^{load}_{i,t} - \lambda^{SoC}_{i,t}/\eta_B + \mu^{B^{max}_{out}}_{i,t} \geq 0 \perp q^{B_{out}}_{i,t} \geq 0 \quad \text{(A.4e)}$$
$$-\lambda^{SoC}_{i,t} + \lambda^{SoC}_{i,t+1} + \mu^{SoC^{max}}_{i,t} \geq 0 \perp SoC_{i,t<t_{end}} \geq 0 \quad \text{(A.4f)}$$
$$-\lambda^{SoC}_{i,t_{end}} + \lambda^{SoC}_{i,t_0} + \mu^{SoC^{max}}_{i,t} \geq 0 \perp SoC_{i,t_{end}} \geq 0 \quad \text{(A.4g)}$$
$$q^{G_{in}}_{i,t} + q^{B_{out}}_{i,t} + \sum_{j\in\mathcal{I}} q^{share}_{j,i,t} - q^{load}_{i,t} = 0 \perp \lambda^{load}_{i,t} \quad \text{(A.4h)}$$
$$q^{G_{out}}_{i,t} + q^{B_{in}}_{i,t} + \sum_{j\in\mathcal{I}} q^{share}_{i,j,t} - q^{PV}_{i,t} = 0 \perp \lambda^{PV}_{i,t} \quad \text{(A.4i)}$$
$$SoC_{i,t>t_0-1} + q^{B_{in}}_{i,t>t_0} \cdot \eta^B - q^{B_{out}}_{i,t>t_0}/\eta^B - SoC_{i,t>t_0} = 0 \perp \lambda^{SoC}_{i,t>t_0} \quad \text{(A.4j)}$$
$$SoC_{i,t=t_{end}} + q^{B_{in}}_{i,t_0} \cdot \eta^B - q^{B_{out}}_{i,t_0}/\eta^B - SoC_{i,t_0} = 0 \perp \lambda^{SoC}_{i,t_0} \quad \text{(A.4k)}$$
$$0 \leq SoC^{max}_i - SoC_{i,t} \perp \mu^{SoC^{max}}_{i,t} \geq 0 \quad \text{(A.4l)}$$
$$0 \leq q^{B^{max}}_i - q^{B_{in}}_{i,t} \perp \mu^{B^{max}_{in}}_{i,t} \geq 0 \quad \text{(A.4m)}$$
$$0 \leq q^{B^{max}}_i - q^{B_{out}}_{i,t} \perp \mu^{B^{max}_{out}}_{i,t} \geq 0 \quad \text{(A.4n)}$$

A.2.3. Transformation of complementarity conditions applying the Fortuny-Amat method

The complementarity constraints are reformulated as a mixed-integer program applying the Fortuny-Amat method. The following set of equations shows the transformation of Eq. (A.4a), the other complementarity constraints, Eq.s (A.4b)-(A.4n), are transformed in the same way.

$$p_t^{G_{in}} + \lambda_{i,t}^{load} \geq 0 \tag{A.5a}$$

$$q_{i,t}^{G_{in}} \geq 0 \tag{A.5b}$$

$$p_t^{G_{in}} + \lambda_{i,t}^{load} \leq (1 - u_{i,t}^{G_{in}}) M_1^{G_{in}} \tag{A.5c}$$

$$q_{i,t}^{G_{in}} \leq u_{i,t}^{G_{in}} M_2^{G_{in}} \tag{A.5d}$$

$$u_{i,t}^{G_{in}} \in \{0, 1\} \tag{A.5e}$$

The value of M are $M_1 = 5000$ and $M_2 = 2000$, which were determined empirically, ensure the feasibility of the model and effectively no numerical problems.

A.3. Validation of the bi-level modeling approach

In the bi-level optimization approach shown above, the lower level problem maximizes the welfare of the community and optimally distributes the PV generated electricity within the community. This linear problem is replaced by its corresponding KKT conditions to solve the bi-level problem. The lower level KKT formulation is validated by setting the upper-level objective function to a constant (e.g., $F(x) = 1$) and $\mathcal{I} = \mathcal{I}_{old}$. With this configuration, the results of the bi-level problem are compared to the solution of the lower level problem without upper-level function, variables, and constraints (which equals the solution of the linear optimization problem based on the model presented in Perger et al. (2021)).

The difference of all participants' annual results (amount of electricity bought and sold, emissions, and costs) is calculated comparing the two solution methods. The box plot in Figure A.5 presents the distribution of each category of results. The differences between the two solution methods are negligibly small in the scale of 10^{-13} and the KKT formulation of the lower level problem sufficiently substitutes the ordinary LP, which means that the Big-M method is appropriately applied (see Kleinert et al. (2020)).

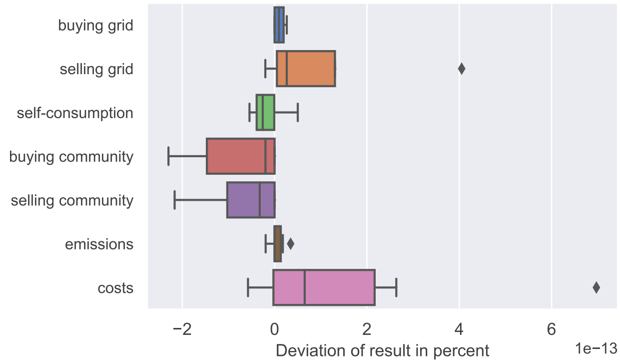


Figure A.5.: Validation of the Karush-Kuhn-Tucker (KKT) conditions

A.4. Lower-level problem formulation of bi-level model with stochastic forecast

The formulation of the lower-level problem of the bi-level model with stochastic forecast is:

$$\max_{Q_{i,t,n}(\omega)} \quad CW_1 + \sum_{\omega \in \Omega} \sum_{n \in \mathcal{N}} p(\omega) CW_n(\omega) \tag{A.6a}$$

subject to:

$$q^{G_{in}}_{i,t,n}(\omega) + q^{B_{out}}_{i,t,n}(\omega) + \sum_{j \in \mathcal{I}} q^{share}_{j,i,t,n}(\omega) - b_{n,i}(\omega) q^{load}_{i,t} = 0 \qquad (\lambda^{load}_{i,t,n}(\omega)) \quad \forall i,t,n \tag{A.6b}$$

$$q^{G_{out}}_{i,t,n}(\omega) + q^{B_{in}}_{i,t,n}(\omega) + \sum_{j \in \mathcal{I}} q^{share}_{i,j,t,n}(\omega) - b_{n,i}(\omega) q^{PV}_{i,t} = 0 \qquad (\lambda^{PV}_{i,t,n}(\omega)) \quad \forall i,t,n \tag{A.6c}$$

$$SoC_{i,t-1,n}(\omega) + q^{B_{in}}_{i,t,n}(\omega) \cdot \eta^B - q^{B_{out}}_{i,t,n}(\omega)/\eta^B - SoC_{i,t,n}(\omega) = 0$$
$$(\lambda^{SoC}_{i,t,n}(\omega)) \quad \forall i, t > t_0, n \tag{A.6d}$$

$$SoC_{i,t=t_{end},n}(\omega) + q^{B_{in}}_{i,t_0,n}(\omega) \cdot \eta^B - q^{B_{out}}_{i,t_0,n}(\omega)/\eta^B - SoC_{i,t_0,n}(\omega) = 0$$
$$(\lambda^{SoC}_{i,t_0,n}(\omega)) \quad \forall i, t = t_0, n \tag{A.6e}$$

$$SoC_{i,t=t_{end},n}(\omega) - SoC_{init} = 0 \qquad (\lambda^{SoC_{init}}_{i,t_{end},n}(\omega)) \quad \forall i, t = t_{end}, n \tag{A.6f}$$

$$SoC_{i,t,n}(\omega) - b_{n,i} SoC^{max}_i \leq 0 \qquad (\mu^{SoC^{max}}_{i,t,n}(\omega)) \quad \forall i,t,n \tag{A.6g}$$

$$q^{B_{in}}_{i,t,n}(\omega) - b_{n,i} q^{B^{max}}_i \leq 0 \qquad (\mu^{B^{max}_{in}}_{i,t,n}(\omega)) \quad \forall i,t,n \tag{A.6h}$$

$$q^{B_{out}}_{i,t,n}(\omega) - b_{n,i} q^{B^{max}}_i \leq 0 \qquad (\mu^{B^{max}_{out}}_{i,t,n}(\omega)) \quad \forall i,t,n \tag{A.6i}$$

$$-q^{G_{in}}_{i,t,n}(\omega), -q^{G_{out}}_{i,t,n}(\omega), -q^{share}_{i,j,t,n}(\omega), -q^{B_{in}}_{i,t,n}(\omega), -q^{B_{out}}_{i,t,n}(\omega), -SoC_{i,t,n}(\omega) \leq 0$$
$$(\beta^{G_{in}}_{i,t,n}(\omega), \beta^{G_{out}}_{i,t,n}(\omega), \beta^{share}_{i,j,t,n}(\omega), \beta^{SoC}_{i,t,n}(\omega), \beta^{B_{in}}_{i,t,n}(\omega), \beta^{B_{out}}_{i,t,n}(\omega)) \quad \forall i,t,n \tag{A.6j}$$

Appendix B.

Appendix to Chapter 4

B.1. Load profile data

The hourly average values of the household demand electricity profiles are shown in Figure B.1; the corresponding total annual demand of each household is shown in Table 4.1; and the hourly average value of small and medium-sized enterprises (SMEs) are shown in Figure B.2. From information obtained

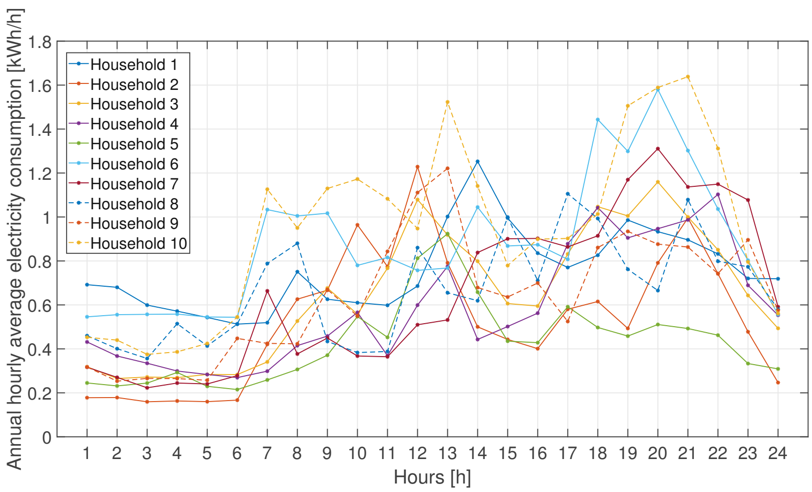


Figure B.1.: Household demand profiles, average hourly value

in APCS-Austrian Power Clearing and Settlement (2019), the following synthetic load profiles were derived:

- G0 – Business
- G1 – Business 0-24 h
- G3 – Business 8-18 h
- G4 – Shop/Hairdresser
- G5 – Bakery

The year of reference is 2019. The demand profiles are normalized to an annual consumption of 1000 kWh for graphical purposes. To obtain the results in Section 4, the synthetic load profiles are upscaled to the prosumers' annual demand (see Table 4.1).

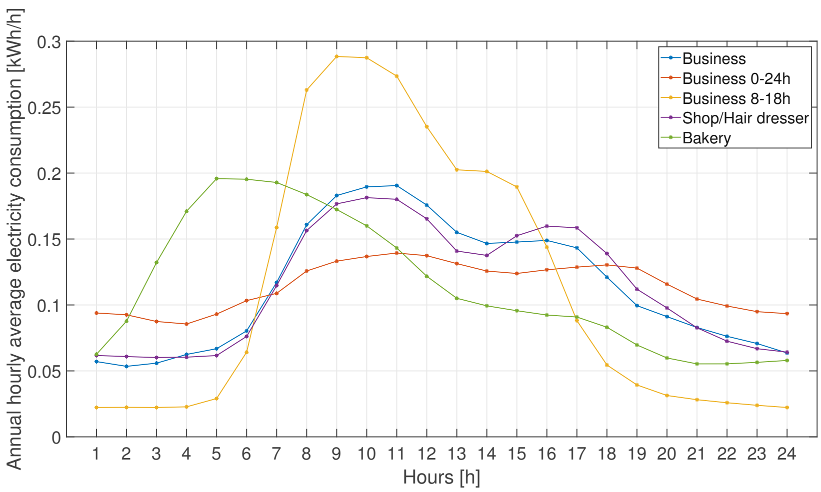


Figure B.2.: Business demand profiles, average hourly value, normalized to an annual consumption of 1000 kWh

B.2. PV generation data

The PV generation data were obtained from Renewables.ninja (Pfenninger and Staffell, 2016 and Staffell and Pfenninger, 2016) with the following parameters:

- Location coordinates: 48.2084°N, 16.3725°E (Vienna, Austria)
- Dataset: MERRA-2 (global)
- Year: 2019
- System loss: 0.1
- Tilt: 35°
- Azimuth:
  - South: 180°.
  - East: 90°.
  - West: 270°.
  - South-East: 135°.
  - South West: 225°.

B.3. Marginal emissions

The marginal emissions for Austria and Germany used to conduct the results in Section 4 are obtained from Schram et al., 2019b. The data contain hourly values in $kgCO_2$/MWh for 2017. Data for other countries are also available: Belgium, Spain, France, Italy, Netherlands, and Portugal. The marginal emissions of France are used in the sensitivity analysis in Section 4.4. Figure B.4 and B.5 show the average hourly values for Austria/Germany and France, respectively.

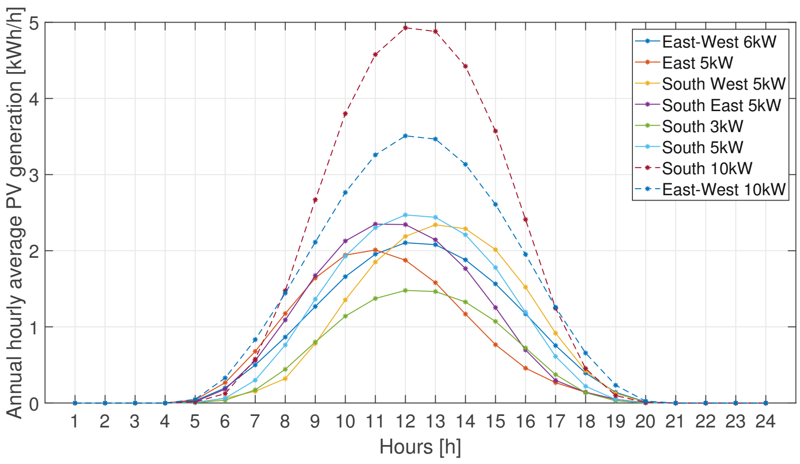


Figure B.3.: PV generation profiles for different PV system sizes and orientations – average hourly value

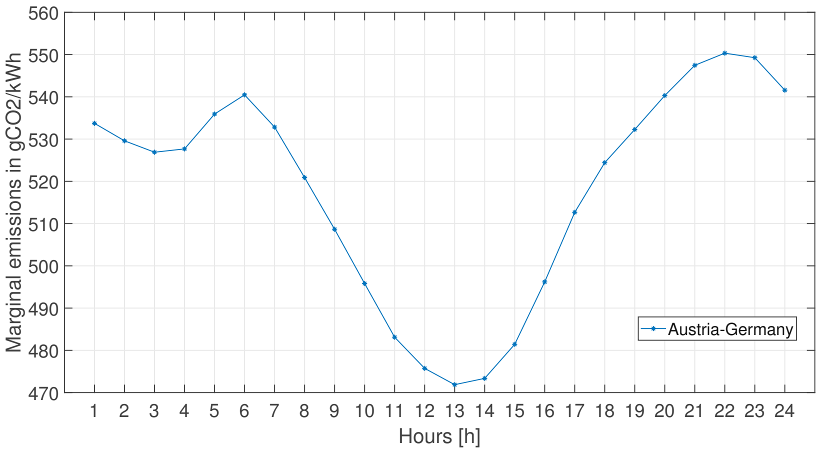


Figure B.4.: Marginal emissions in Austria and Germany (2017) – average hourly value

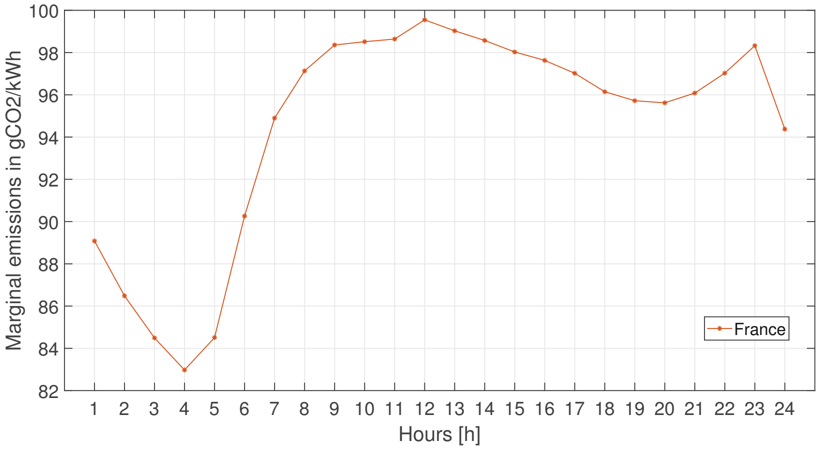


Figure B.5.: Marginal emissions in France (2017) – average hourly value

Appendix C.

Appendix to Chapter 5

C.1. Input parameter of the community and the grid

The hourly input data of the case study is presented in the form of hourly average values. The original community prosumers' electricity demand is shown in Fig. C.1. The average electricity output values of a 5 kW_{peak} PV system is shown in Fig. C.2 (left axis), together with the marginal emissions from the grid (right axis). Fig. C.3 shows the standardized load profiles of household H0 and business G0, which are used in the case study to represent the potential new members.

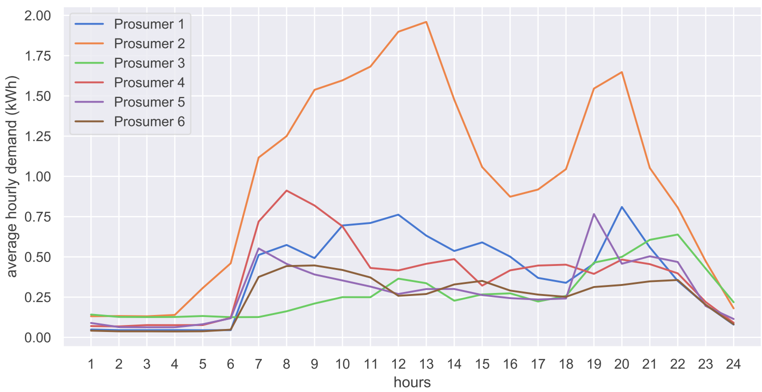


Figure C.1.: Average hourly electricity demand of prosumers

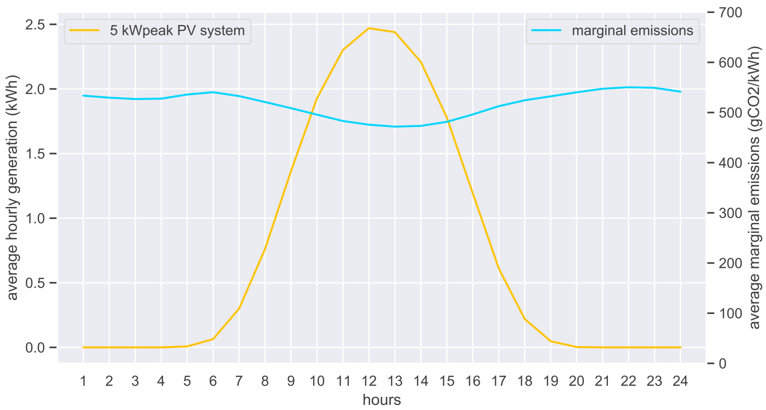


Figure C.2.: Average hourly electricity PV generation (left) and marginal emissions (right)

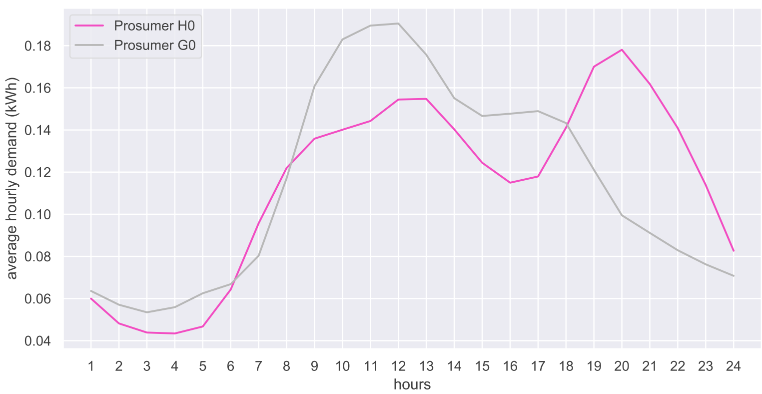


Figure C.3.: Average hourly electricity demand of new prosumers (normalized to an annual electricity demand of 1000 kWh)

C.2. Annual results of cases (i)-(iii) in detail

Tables C.1-C.3 present the annual results of purchases/sales from/to the grid and the community, self-consumption, battery operation, emissions, and costs for all prosumers 1-6 and prosumer H0. The tables are split into cases (i)-(iii) from Sections 5.1.2.2 and 5.1.2.3.

Table C.1.: Summary of the results of peer-to-peer trading – case (i)

Prosumer	1	2	3	4	5	6	H0
Buying grid (kWh)	1140.3	4354.7	1278.2	917.5	1401	812.6	1027
Selling grid (kWh)	0	818.3	1680	584.6	0	2291.6	4611
Battery charging (kWh)	0	0	0	882.6	0	0	0
Battery discharging (kWh)	0	0	0	731.4	0	0	0
Self-consumption (kWh)	0	3365.6	1016.7	1573.4	0	1282.9	972
Buying community (kWh)	2308.1	827.4	107.6	97.8	1119.8	71.6	0.9
Selling community (kWh)	0	2276.8	274.3	819.2	0	285.4	877.7
Emissions (tCO_2)	0.6	2.3	0.7	0.5	0.8	0.4	0.6
Costs (EUR)	790	449.5	158.1	-1.4	528.2	25.8	-165

Table C.2.: Summary of the results of peer-to-peer trading – case (ii)

Prosumer	1	2	3	4	5	6	H0
Buying grid (kWh)	1140.3	5587.5	1379.3	1432.6	1459.1	854.6	4792.1
Selling grid (kWh)	0	818.3	1568.3	516.1	0	341.2	0
Battery charging (kWh)	0	0	0	870	0	0	0
Battery discharging (kWh)	0	0	0	723.6	0	0	0
Self-consumption (kWh)	0	2911.6	1016.7	1098.2	0	1282.9	0
Buying community (kWh)	2308.1	48.6	6.5	65.6	1061.7	29.6	3207.9
Selling community (kWh)	0	2730.8	386	1375.4	0	2235.8	0
Emissions (tCO_2)	0.6	3.0	0.7	0.8	0.8	0.5	2.6
Costs (EUR)	790	443.2	131.6	-25.8	527.6	-331	1663.1

Table C.3.: Summary of the results of peer-to-peer trading – case (iii)

Prosumer	1	2	3	4	5	6	H0
Buying grid (kWh)	1140.3	4983.7	1278.2	1185.8	1432.9	812.6	4351
Selling grid (kWh)	0	818.3	1680	573.5	0	2291.6	2876.6
Battery charging (kWh)	0	0	0	870	0	0	0
Battery discharging (kWh)	0	0	0	720.1	0	0	0
Self-consumption (kWh)	0	3315.6	1016.7	1347.5	0	1282.9	3365
Buying community (kWh)	2308.1	248.4	107.6	66.6	1088	71.6	284
Selling community (kWh)	0	2326.7	274.3	1068.8	0	285.4	219.1
Emissions (tCO_2)	1	2.7	0.7	0.6	0.8	0.4	2.3
Costs (EUR)	790	448.8	156.3	-9.3	528	24.7	767.4