Master's thesis

NTNU
Norwegian University of Science and Technology
Faculty of Economics and Management
Dept. of Industrial Economics and Technology Management

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Expanding the notions of local electricity markets: A study on trading among and within energy communities

Master's thesis in Sustainable Energy Systems and Markets
Supervisor: Pedro Crespo del Granado
Co-supervisor: Naser Hashemipour

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Kunnskap for en bedre verden

Preface

This master's thesis is the result of an international collaboration between NTNU Trondheim and TU Berlin within the master's program SESAM (Sustainable Energy Systems and Markets). We met within the SESAM program and decided early on to work together. In the previous semester, we laid the foundation for our research and great collaborative teamwork in the specialization project, which also served as the starting point for our master's thesis. Our goal in writing this master's thesis was to explore critical aspects of local electricity markets and advance the discussion on this topic. We decided to divide the master's thesis into two individual journal papers that have been or will be submitted to peer-reviewed international journals after discussing it with our supervisor Dr. Pedro Crespo del Granado. We hope that this thesis and the associated papers can contribute to the academic community and to the discussion of potential opportunities that are still unexplored.

We want to express our special thanks to our supervisor Pedro, who provided us with excellent guidance from the beginning of the specialization project until the submission of this thesis. We are grateful for numerous fruitful discussions, constructive feedback, and good advice on academic work and writing. Thank you, Pedro, for your encouraging and inspiring supervision.

We would also like to thank our co-supervisor, Dr. Naser Hashemipour, who was always there for us when we had questions regarding modeling or data. He also participated in our discussions and gave excellent ideas to help us. Thank you, Naser, for the great collaboration and your patience with our many questions.

We also received valuable advice at our meetings at SINTEF, where we presented our ideas and results. Thank you very much for taking the time to give us constructive feedback and useful input.

We would also like to thank Dr. Ruud Egging-Bratseth for handling all the administrative hurdles and making this program possible. In addition, we want to thank TU Berlin for giving Jakob the opportunity to take the dual master's program with NTNU Trondheim.

Last but not least, we would like to thank our families and friends for supporting us on this great journey.

Jakob and Marthe, Trondheim June 2022

Problem Description

In our master's thesis, we investigate potential designs and benefits of local electricity markets with prosumers, consumers, and distributed energy resources. Specifically, we evaluate different trading algorithms applied in competitive local markets. In addition, we develop a new market design to increase the value of plus energy neighborhoods' surplus electricity. To investigate these issues, we applied our models to cases in Norway, the UK, and Germany.

In the first paper, we analyze competitive local electricity markets using the trading algorithms Peer-to-Peer (P2P) and Multi Unit Double Auction (MUDA). To this end, we performed bidding simulations based on a market reference price to create bids and offers required for the trading algorithms. We applied the trading algorithms to a case in Steinkjer (Norway) and London (UK) and compared them to a centralized optimization model, representing a perfect solution. Accordingly, we addressed the following research questions in the first paper:

- Which trading algorithm is fair and realistic in representing an energy community that internally creates a prosumer-to-consumer market?
- How do different bidding simulations affect the outcome of the trading algorithms? What underlying behavior assumptions (e.g., bidding strategies) affect the trading outcome?
- How do different system characteristics and contexts (e.g., country) affect the outcome of the trading algorithms?

Since the internal clearing of LEMs might result in surplus electricity, we want to develop a marketplace where this surplus can be adequately remunerated. Therefore, we created energy communities that first clear their market internally using centralized optimization and subsequently trade their surplus or deficit in the "Community-to-X" (C2X) market. For the C2X market, we chose to use the P2P trading algorithm based on the results from our first paper. Furthermore, we examined the grid impacts in terms of system losses and voltage fluctuations and proposed a method to enable DSOs to participate in the C2X+ market to reduce potential grid problems. Accordingly, we addressed the following research questions in the second paper:

- What new marketplaces will reward the surplus value of solar and wind power after internal LEM clearing? Is C2X a viable option for remunerating surplus energy?
- What impact does LEM trading have on the grid in terms of voltage variations and system losses? What is the role of the DSO in a C2X market?

Abstract

Local electricity markets (LEMs) is an expanding research area that contributes to the green transition of the energy system. With recent advances in Information and Communication Technology (ICT), LEMs can facilitate the increasing deployment of distributed energy resources (DERs) by sharing electricity locally. This also enhances the role of prosumers and accelerates the shift from consumerism to prosumerism.

However, there are still knowledge gaps in the research field of LEMs. One example is the missing research on managing surplus of plus energy neighborhoods to increase the value of their surplus. Furthermore, there is no consensus on how to organize energy sharing within LEMs (e.g., creating a wholesale market), such as assessing the economic efficiency of trading algorithms. We address these issues in two journal papers.

In the first journal paper, we analyze internal LEM clearing for two cases in Norway and the United Kingdom. To do so, we apply the trading algorithms Peer-to-Peer (P2P) and Multi Unit Double Auction (MUDA) and compare the results to a cooperative market clearing (centralized optimization) in terms of self-sufficiency, traded energy, and curtailment. We also develop a market reference price and conduct bidding simulations to establish bids and offers for the trading algorithms. The results indicate significantly higher efficiency of the P2P algorithm than MUDA but also reveal some disadvantages regarding unfair trading. Finally, as a step further in this thesis, we propose a bidding strategy for selling prosumers with battery storage.

In the second journal paper, we propose a new market called "Community-to-X" (C2X) to trade electricity surplus of plus energy neighborhoods. In the C2X market, communities with surplus electricity can enter to sell their surplus to other communities or external players. To further explore this market, we divided the paper into two main parts: First, we modeled LEM trading models for communities and compared the results with a business-as-usual case. Second, we applied the LEM results to the C2X market and analyzed the financial benefits. The market models were simulated on a German distribution network. We find that the C2X market can be economically beneficial for all participants, but communities with higher surpluses benefit the most from selling their electricity. Moreover, the results do not indicate any major grid problems in the low-voltage grid caused directly by LEM trading. However, we extend this market for a future scenario to show how the DSO can interact with market participants to manage potential grid impacts.

In conclusion, this thesis provides new ideas to current notions of how LEMs function internally and externally. Hopefully, this will bring a novel perspective to the implementation of LEMs and provide starting points for further research.

Sammendrag

Lokale elektrisitetsmarkeder (LEM) er et voksende forskningsområde som bidrar til det grønne skiftet innen energisystemer. Med nye fremskritt innen informasjons- og kommunikasjonsteknologi, kan disse markedene nå være med på å styre og effektivisere den økende andelen av distribuerte energiressurser ved å legge opp til lokal energihandel mellom plusskunder og vanlige forbrukere. Dette vil i tillegg forsterke og fremskynde overgangen fra et system med kun forbrukere til et system med plusskunder og lokal energiproduksjon.

Det er imidlertid fortsatt noen kunnskapshull i dette forskningsområdet. Det mangler blant annet forskning på hvordan overskuddsenergi fra disse markedene kan utnyttes videre. I tillegg er det ingen felles enighet om hvordan man skal organisere handelen i disse markedene. I denne masteroppgaven tar vi for oss noen av disse problemstillingene gjennom to forskningsartikler.

I den første artikkelen analyserer vi den interne markeds-klareringen for to systemer i henholdsvis Norge og Storbritannia. Dette gjør vi ved å bruke to handelsalgoritmer, «Peer-to-Peer» (P2P) og «Multi Unit Double Auction» (MUDA), og deretter sammenligne resultatene fra disse mot en referanse-modell. Vi utviklet også en modell for en markedsreferansepris, i tillegg til å simulere strategier for bud og tilbud i algoritmene. Resultatet fra dette indikerer at P2P-algoritmen er betydelig mer effektiv enn MUDA, men at det er visse fordeler og ulemper med begge. Som et siste steg i arbeidet som tilhører denne artikkelen, har vi utarbeidet et forslag for hvordan handelsalgoritmer kan brukes av plusskunder med batterier.

I den andre artikkelen utarbeidet vi et forslag for et nytt market kalt «Community-to-X» (C2X), hvor målet er at de lokale elektrisitetsmarkedene kan kjøpe og selge overskuddsenergi, enten med andre nabolag eller eksterne kjøpere. Dette arbeidet er delt i to hoveddeler: Først modellerte vi ulike lokale elektrisitetsmarkeder for å evaluere økonomiske resultater og fysiske påvirkninger på kraftnettet. I den andre delen ser vi på de økonomiske fordelene ved å fortsette handelen in C2X-markedet. Våre resultater viser at C2X-markedet er fordelaktig for alle deltakere, men de nabolagene med mest overskudd drar mest nytte av å selge sin elektrisitet. Videre finner vi ingen store nettproblemer som en direkte årsak av lokal. Vi ser likevel på et scenario med høyere lokal produksjon for å vise et eksempel på hvordan nettselskaper kan samhandle med nabolag for å håndtere potensielle problemer i nettet.

For å konkludere, gir denne oppgaven nye ideer til gjeldende forestillinger om hvordan lokale elektrisitetsmarkeder fungerer internt og eksternt. Forhåpentligvis vil dette bringe et nytt perspektiv for implementering av LEM i fremtidige systemer, og gi et utgangspunkt for videre forskning på dette området.

Contents

List of Figures

List of Tables

Abbreviation list

BB	Budget Balanced
C2X	Community-to-X
DA	Double Auction
DER	Distributed Energy Resource
EE	Energy Efficient
IC	Incentive Compatibility
ICT	Information and Communication Technology
IR	Individual Rational
KPI	Key Performance Indicator
LEM	Local Electricity Market
MUDA	Multi Unit Double Auction
P2P	Peer-to-Peer
PV	Photovoltaic
TPA	Third Party Access

1 | Introduction

The urgent need to decarbonize the energy sector and slow down global warming is driving the energy transition worldwide. It is a great challenge for humanity to restructure the energy systems and deploy more renewable energies in such a short time. These changes happen at all grid levels, from the interconnection between countries (in the transmission grid) to the installation of small rooftop PV systems (in the low-voltage and distribution grid). In our master's thesis, we take a closer look at the opportunities in the low-voltage and distribution grid from an economic and physical point of view.

Driven by the energy transition and the reduction of investment costs, the deployment of decentralized energy resources (DERs) has increased significantly in recent years. DERs include renewable energy generation, storage, and consumption management technologies such as electric vehicles (EVs) or demand response solutions (IEA, 2022a). In addition, energy systems can benefit from integrating DERs through load shifting and flexibility options to address issues related to voltage regulation, power quality, and network congestion (IRENA, 2019).

In recent years, the idea of local electricity markets (LEMs) that trade locally generated electricity from DERs has emerged and gained popularity in research (Bjarghov et al., 2021; Sousa et al., 2019). These LEMs aim to make optimal use of locally generated energy and encourage the active participation of prosumers who both produce and consume electricity (Merino et al., 2021). However, there are still major knowledge gaps on how to operate local markets optimally, and other fields within the topic, such as surplus trading and DSO interactions, remain more or less unexplored.

In this master's thesis, we expand the current idea of how LEMs can operate, both internally and externally. The fundamental part of this thesis consists of two journal papers that each focus on different areas within the research field of LEMs[1]:

The first paper, *A wholesale market within an Energy Community: Trading algorithms applied to Norway and the UK*, looks at the internal operations of a LEM. Here, two different trading algorithms are applied to the local market-clearing and compared to the outcome of a cooperative market-clearing using centralized optimization. Additionally, different methods of simulating bidding are investigated by creating a reference price for the market participants.

The second paper, *A new marketplace for trading among plus energy neighborhoods: Community-to-X and DSO interactions*, focuses on external trading opportunities of surplus electricity for LEMs after the local clearing. Here, we propose a new market where communities and external players can trade and increase the value of LEM surplus. This is a new research frontier and idea in LEMs. We also provide an example of how the DSO can interact with the players in the market.

[1] Both of these papers are based on the work done in a specialization project at NTNU (TIØ4580) in the fall of 2021.

This thesis contributes to the current research by bringing new ideas to the table, which can open up for further discussion and drive the development and implementation of LEMs. Specifically, we proposed a new concept for inter-community trading through the C2X market, which can increase the value of surplus and facilitate DSO interactions. Furthermore, we provided further research on the market-clearing of non-cooperative LEMs by evaluating the efficiency of two trading algorithms, one of which has never been applied to LEM trading. Finally, the models used in this work are applied to real-life cases in different countries in Europe, namely Norway, the UK, and Germany.

As a framework for the two papers, we present some background and the thematic focus of this thesis in Section 2. Our first paper, *A wholesale market within an Energy Community: Trading algorithms applied to Norway and the UK*, is then presented in Section 3. In Section 4.2, we take a look back at paper 1 to present a way of including bidding strategies for prosumers with batteries, in addition to showing the way towards the second paper. The second paper, *A new marketplace for trading among plus energy neighborhoods: Community-to-X and DSO interactions*, is presented in Section 5. Lastly, in Section 6, we reflect on the findings in this thesis and state our final concluding remarks.

2 Power systems and markets

In the last century, electricity has become an indispensable commodity that plays a crucial role in most people's life. It is now unimaginable to live without access to electricity in modern societies. However, the electricity system is highly complex, from generation to distribution to consumption by the end-user. Moreover, conventional power generation causes large emissions that harm the global climate. This section gives an overview of the challenges and developments in the electricity market and provides insights into the local electricity markets.

2.1 The need for a green energy transition

> "We are the first generation to feel the effect of climate change and the last generation who can do something about it." (Barack Obama, Former US President)

In 2015, 196 parties from around the world adopted the legally binding Paris Agreement with the goal of limiting global warming to well below two degrees, preferably 1.5 degrees (UNFCCC, 2022b). Unfortunately, the temperature limit of 1.5 degrees may already be exceeded before 2026 with a probability of 48%, according to new calculations by the WMO (WMO, 2022). This would endanger the climate in several ways and put ecosystems and humans at risk (IPCC, 2022). Therefore, the climate is at stake more than ever, and even more profound actions must be taken. The EU has already reacted to increasing emissions by raising the target for reducing greenhouse gas emissions to 55% by 2030 compared to 1990 (European Commission, 2022).

Especially energy production has a major impact on the climate due to high emissions. This makes the decarbonization of the energy supply inevitable to achieve the climate goals. However, after a slight drop in 2020 due to COVID-19, energy-related CO_2 emissions reached a record high of 36.3 Gt in 2021 (IEA, 2022e). In total, the emissions from electricity and heat generation account for 44% of global emissions (IEA, 2022d), as illustrated in Figure 2.1.

In particular, electricity demand is continuously increasing as more and more energy services are electrified, e.g. electric vehicles and air conditioning. Since electricity is still generated mainly by coal and gas, this also significantly increases CO_2 emissions (IEA, 2022f). However, electrification also offers a major opportunity to reduce these emissions, as coal and gas can be more easily replaced by renewables in electricity generation compared to other sectors.

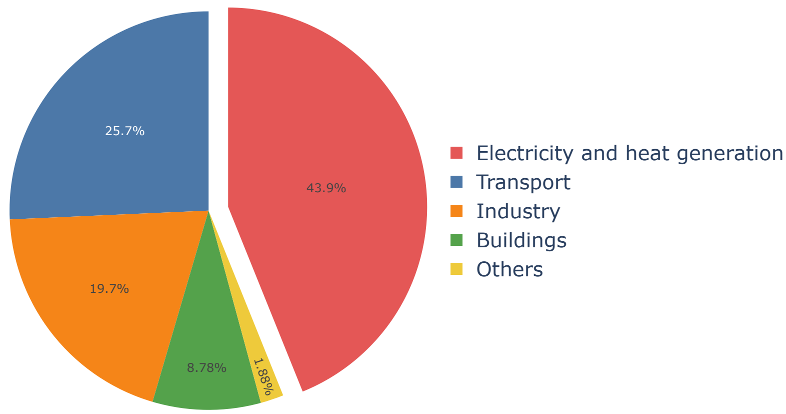


Figure 2.1: CO_2 emissions by sector in 2019, excluding electricity and heat generation from the end-use sector (IEA, 2022d)

2.2 Electricity markets - Developments & Challenges

To increase competition in the European electricity markets and thus improve cost efficiency, a significant transition phase has taken place since the early 1990s. In this context, electricity markets are being liberalized, privatized, and restructured in terms of supply and distribution (Sioshansi, 2006). Consequently, the number of participating financial players increased continuously, and the markets became much more efficient.

To further drive the transition of the European electricity markets, the first Energy Union strategy was published in 2015. The aim was the creation of an energy union that provides consumers with secure, sustainable, and affordable energy (European Comission, 2022). The energy union defines five dimensions that are closely interlinked and mutually reinforcing. Figure 2.2 illustrates these five dimensions.

The formation of the Energy Union has its roots in the 1995 Green Paper, which was based on the 1957 Treaty of Rome and the 1987 Single European Act (Karan and Kazdağli, 2011). It was the first initiative to create a single European energy market. Further efforts were made to establish common rules and promote the liberalization of the energy markets. Accordingly, Directive 96/92/EC came into force, initially introducing unbundling of activities and third party access (TPA) (Meeus, Purchala, and Belmans, 2005). Vertical unbundling separates the grid as a natural monopoly from upstream and downstream sectors. This is crucial for competitiveness as it allows generators to operate in a market where they can make their own investment decisions (Cramton, 2017). The TPA, in turn, ensures that system operators treat all users equally in terms of access to information and use of their network (Meeus, Purchala, and Belmans, 2005).

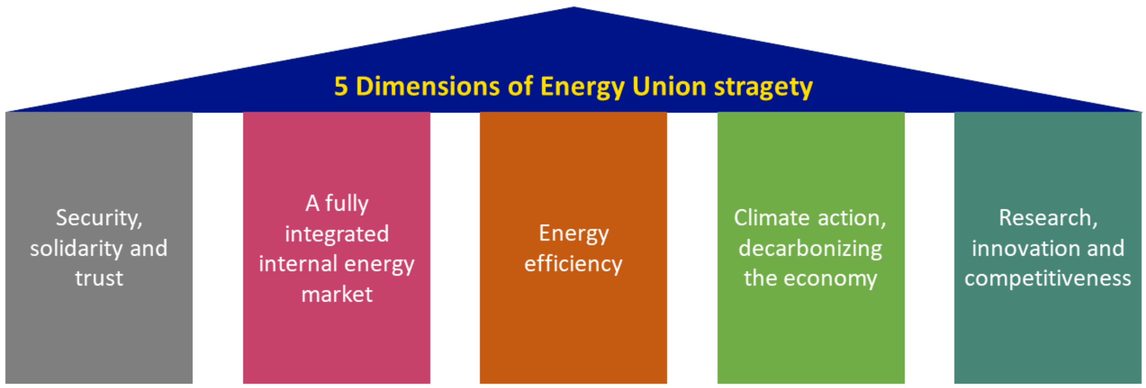


Figure 2.2: Dimensions of the energy union strategy (European Comission, 2022)

Another important contribution to this reform is the Lisbon Strategy of 2000, which sets a more ambitious plan for the following years and emphasizes the importance of improving competitiveness (Karan and Kazdağli, 2011). After that, political attention shifted to energy market integration, security of supply, and environmental objectives.

Pollitt (2009) suggest that an energy market should complete the following stages to become more competitive and efficient. As we explored the evolution of the European energy markets, it has become clear that they are well on their way to passing through these stages.

- Privatization of publicly owned electricity assets
- Opening of the market to competition
- Extension of vertical unbundling of transmission and distribution from the generation and retailing
- Introduction of an independent regulator

The electricity system is highly complex. Thus, several challenges must be overcome when designing an electricity market. The primary objective is to ensure the security of supply, which means the electricity must be available without interruption by resisting and recovering from disturbances and contingencies (IEA, 2022a). To achieve this, a power system should have the characteristics of adequacy, operational reliability, and resilience. Adequacy is the ability to meet the power demand in a specific area constantly. Furthermore, operational security is maintaining a normal state or quickly returning to a normal state after a system disturbance. Lastly, resilience refers to the ability to cope with and recover from short-term shocks, and long-term changes (IEA, 2022c). When these characteristics are not present, extended outages can occur that not only cause economic losses but can also endanger people's lives, such as in the 2021 Texas Blackout.

The 2021 Texas blackout demonstrated the importance of security of supply. This catastrophic event claimed hundreds of lives, forced people into darkness for days, and cost more than $20 billion (Bloomberg, 2022). The power outage from February 15th to 18th exceeded previous events in terms of failed generation capacity, the number of customers affected, and the lowest grid frequency, to name a few. It was caused by disruptions in electricity and natural gas services due to the winter storm “Ur” but had a number of contributing factors that made the event very complex. Contributing factors included the failure of generation technologies and power plants due to the winter storm, incorrect demand and weather forecasts, the rapid deterioration of grid conditions early on February 15th, and the failure of the natural gas system, which exacerbated power problems (Austin, 2021). Such catastrophic events must be prevented in the future, and the power grid and generation technologies must be prepared for further and increasing weather extremes.

To prevent jeopardizing the security of supply, the system must be balanced in real-time, i.e., generation must match demand at all times (Green, 2008). Otherwise, generators or electrical equipment can be damaged, which in the worst case can lead to a system breakdown. Consequently, system operators must constantly monitor the system frequency and voltage level to be able to respond to unexpected changes. To manage those changes and balance supply and demand quickly, system operators use ancillary services already procured in the day-ahead and intraday market (Cramton, 2017).

In addition, storage options can help ensure energy balance and increase system flexibility, and we can divide them into short- and long-term storage options. Short-term storage is primarily used to store electricity for no longer than one day. This type of storage can be applied to achieve “peak-shaving” on the supply side when demand is very high. In contrast, long-term storage typically stores energy for weeks or months. They allow large differences between supply and demand to be balanced and can even shift electricity between seasons (IRENA, 2018). With intermittent renewable energies and higher electrification, the system is more prone to supply and demand fluctuations, increasing the importance of ancillary services and flexibility.

The electricity prices in markets with high shares of VRE can be very volatile, depending on the generation mix in the system (IRENA, 2017). For end-users, this can mean uncertainty in their electricity bill, depending on the type of electricity contract they have. However, the value of flexibility can become more valuable and an attractive option to hedge against big variations in prices. Nevertheless, this incentive relies on price signals that reflect the market situation close to real-time, i.e., from the day-ahead or balancing markets (IRENA, 2017).

2.3 A closer look at Norway, UK and Germany

In this thesis, we analyze cases from Norway, the United Kingdom, and Germany. Therefore, we take a closer look at the electricity markets in these countries to set the context for the upcoming work.

Norway

Norway's energy sector is already net-zero (IEA, 2022b) and dominated by hydropower with a share of 91.8 % of total power production in 2020 (SSB, 2022). However, wind generation is increasing rapidly and was already responsible for 6.4 % of 2020 electricity generation. Statnett is the only transmission system operator (TSO) in Norway and is responsible for settling imbalances in all five Norwegian price zones. Consequently, Statnett also runs the balancing market (OED, 2022). Day-ahead and intraday trading, in contrast, takes place on the Nord Pool exchange. With Nord Pool, Norway introduced an early example for market-based power trading in 1991 (OED, 2022). In 2000, the Nordic market became fully integrated as all Nordic countries joined the Nord Pool exchange market (Pool, 2022b). Today, 15 countries across Northern Europe are part of the Nord Pool day-ahead market (Pool, 2022a). Thus, the history of Nord Pool is a great example of the integration of electricity markets in Europe.

End-users in Norway can generally choose between three different electricity supply contracts: fixed-price, standard variable price, and spot price. Under a fixed-price contract, a fixed electricity price is set for a certain period, and the supplier is bound to deliver the electricity at that price. This is usually the lowest-risk option but tends to be more expensive because suppliers include a risk premium. In the case of a standard variable price contract, electricity prices fluctuate depending on the development of the electricity market. Therefore, the price guarantee period is shorter, but suppliers must inform customers of price changes two weeks in advance. Lastly, Norwegians can choose a spot-price contract, where they buy electricity at Nord Pool market prices plus a markup to cover costs. (OED, 2022)

United Kingdom

The United Kingdom also takes a pioneering role, as it was the first country to realize market liberalization in Europe (Karan and Kazdağli, 2011). In addition, the Electricity Act of 1989 opened the generation, transmission, and retail sectors to competition (Ofgem, 2022b).

UK's electricity generation still has a high share of coal (35.7% in 2020) and nuclear (16.1% in 2020), but renewables capacity is steadily increasing, reaching a record 43% wind and solar electricity in 2020 (BEIS, 2022). Wind power dominated the renewable electricity generation and is expected to grow by 12% between 2022 and

2024, while nuclear and gas are expected to decline by 7% and 6%, respectively (IEA, 2022b). The UK already has large interconnections with continental countries such as France (3 GW) and the Netherlands (1 GW) but plans to expand interconnections to other countries due to fluctuating renewable energy sources (Ofgem, 2022a).

The wholesale electricity market is considered to function well, with a moderate market concentration and a continuously growing number of generators. With 27% in 2018, EDF is the largest electricity producer, followed by RWE (13%) and SSE (9%). To ensure a well-functioning market, including avoiding the exercise of market power and security of supply, the independent Office of Gas and Electricity Markets (Ofgem) monitors and regulates market activities. For end-users, the wholesale market price is still the largest component of the energy bills at 38% in 2018, along with network (24%) and operating (18%) costs, as well as environmental and social obligation costs (11%) and other direct costs. (Ofgem, 2022c)

Other main components of the electricity system are the transmission and distribution networks that transport electricity to end-users. National Grid is responsible for maintaining the high-voltage transmission network, while 14 different DSOs run the distribution network (Ofgem, 2022c).

Germany

Germany also plays a role in integrating European electricity markets, as it initiated the energy reforms in continental Europe with the Directives of the European Commission in the late 1990s (Karan and Kazdağli, 2011). After that, with the first version of the German Renewable Energy Sources Act (EEG) in 2000, a series of laws were launched driving the green energy transition (BMWK, 2022b). To date, it is a largely liberalized electricity market with various unbundled market players and an increasing share of renewable energies (dena, 2022).

In continental Europe's biggest electricity market (Karan and Kazdağli, 2011), coal still accounts for the largest share of electricity generation, at 30.2% in 2021. Other dominant conventional sources are nuclear (12.6%) and natural gas (12.6%). Electricity from renewable sources is mainly generated from wind power (21.5%) and PV (8.7%). Overall, renewables accounted for 42.4% of total electricity production in 2021, almost 5% less than in 2020 (Destatis, 2022). This is mainly due to recovering demand from Covid-19 and low wind speeds. However, the trend is toward further reductions in conventional sources. First, nuclear will be phased out by the end of 2022 (IEA, 2022b). After that, coal is expected to decline rapidly according to Germany's phase out-plans (BMUV, 2022). Renewables, in turn, are projected to increase by 11% by 2024. However, as total electricity generation and thus exports decline, Germany is expected to become a net importer for the first time since 2002 (IEA, 2022b). Due to its central location in Europe, Germany is connected to a total of eleven countries, which facilitates electricity trade with other countries (BMWK, 2022a).

Germany is also home to one of the most important power exchanges, the "European Energy Exchange" (EEX), where both spot and future products are traded (Karan and Kazdağli, 2011). The balancing market is operated by TSOs similar to other countries, but in Germany, there are four different TSOs divided into regulation zones (Netztransparenz.de, 2022).

In Europe, German end-user electricity prices are one of the most expensive. In the second half of 2021, German end-users paid an average of 32.34 ct/kWh, significantly more than the European average (23.69 ct/kWh). One of the main reasons for the high prices is taxes and duties, which accounted for 51 % of the electricity bill in 2021. Other components are power generation and sales (26 %) and network charges (23 %) (BMWK, 2022c).

2.4 Local electricity markets

In the future, renewable energy is expected to grow rapidly. From 2022 to 2024, fossil fuels are projected to decrease by 10% and be replaced by renewables (IEA, 2022b). These fluctuating energy sources increase the pressure on the energy system and make it more difficult to ensure the security of supply. Therefore, measures such as flexibility options or ancillary services become even more critical. Moreover, this raises the argument of self-dependency, which encourages alternatives to the traditional top-down structure.

With the integration of volatile renewable energy sources, we expect the system to become even more challenging in terms of price volatility. For example, in 2021, we experienced an enormous increase in wholesale market prices due to higher gas prices, and this increase is expected to be even higher (IEA, 2022b).

As we have explored in this chapter, electricity systems are complex and in rapid change as we try to move towards a green future. With these changes, and as a result of drastic investment cost reductions, the implementation of DERs is rapidly increasing. This significant increase in DERs encourages the relatively new role of prosumers, which both produce and consume electricity using behind-the-meter technologies, such as renewables and battery storage (Bjarghov et al., 2021). Dukovska, Paterakis, and Slootweg (2018) identify three main goals of prosumers: lower electricity costs, reduced grid dependence, and environmentally friendly consumption.

Local electricity markets (LEMs) is a concept that further empowers prosumers by enabling them to trade their electricity locally with their neighbors using a joint market platform (Mengelkamp and Weinhardt, 2018). Furthermore, LEMs can be divided into three market design categories: Full P2P market, community-based market, and hybrid P2P market (Sousa et al., 2019). In a full P2P market, peers can negotiate directly with each other. In contrast, in the community-based market, a community manager is responsible for trading activities to achieve the optimal outcome from the community's perspective. Lastly, a hybrid P2P market is a combination of the two previously mentioned markets.

By participating in a LEM, prosumers and consumers are less affected by volatile and increasing wholesale prices or supply problems of the main grid. Therefore, the current developments in the electricity market can also accelerate the implementation of local electricity markets.

However, LEMs not only provide benefits for the prosumers and consumers but can also bring significant benefits to the system and other market participants. Moreover, IRENA (2020) lists the following contributions of LEMs to a green energy transformation:

- Increased renewable deployment and flexibility due to consumers' and prosumers' empowerment.
- Balancing and congestion management through better operation of distributed energy resources.
- Provision of ancillary services to the main power grid.
- Improved energy access for consumers in mini-grid set-ups.

Lastly, LEMs are no longer just a theoretical idea. Over time, several pilot projects have been initiated to create LEMs with P2P trading. Table 2.1 gives an overview of some exemplary projects. Further projects can be found in (Zhang et al., 2017; Saif and Khadem, 2020; IRENA, 2020).

Table 2.1: Existing local energy trading projects

Project	Country	Start	Details	Sources
Brooklyn Microgrid	US	2016	A New York-based local electricity market in a microgrid where participants can trade with each other using blockchain-based smart contracts. Participants are prosumers with PV systems who sell surplus energy and consumers who buy electricity via auctions.	(Mengelkamp et al., 2018; BMG, 2022; IRENA, 2020)
Piclo	UK	2014	Piclo is a trading platform that matches prosumer and consumer every half hour based on customer preferences, location, smart meter data, and generator pricing. It also includes a marketplace that supports system operators in procuring and operating flexibility.	(Piclo, 2022; Zhang et al., 2017; IRENA, 2020)
Pebbles	Germany	2018	Pebbles is a research project investigating blockchain-based decentralized trading models and network service exchange for future local electricity markets. Incentives for grid-friendly user behavior are also being analyzed in order to use the distribution grid in the most efficient way.	(Pebbles, 2022)
Quartier-strom	Switzer-land	2019	In Quartierstrom, a LEM is set up with 37 households to share locally generated solar electricity through a Blockchain-based double auction platform. Local consumption is encouraged through grid tariffs that are lower than existing grid tariffs.	(Quartierstrom, 2022; Ableitner et al., 2019; Saif and Khadem, 2020)
SOLshare	Bangla-desh	2014	SOLshare has succeeded in piloting the world's first ICT-enabled P2P trading network for rural households in Bangladesh. Prosumers with PV systems are connected via a mini-grid to sell surplus electricity to consumers without access to electricity.	(UNFCCC, 2022a; SOLshare, 2022; IRENA, 2020)

Paper 1

A wholesale market within an Energy Community: Trading algorithms applied to Norway and the UK

Manuscript submitted to Renewable Energy (Elsevier)

3 | A wholesale market within an Energy Community: Trading algorithms applied to Norway and the UK

Abstract

The development of local electricity markets (LEMs) and energy communities is accelerating the shift from consumerism to prosumerism. However, there is no concrete understanding of how electricity sharing in LEMs should be organized, a local wholesale market within, or centralized sharing? This paper explores trading algorithms that can represent a competitive market and bidding conditions within a LEM. That is, how well can trading algorithms represent the wholesale market of an energy community?; How do different bidding simulations affect the outcome of the trading algorithms? How do the system characteristics affect the outcome of the trading algorithms? We address these questions by analyzing a community (residential buildings) in Steinkjer (Norway) and London (UK), including PV systems and wind turbines. We first determine bids and offers based on different bidding simulations and develop a market reference price. Afterward, we applied the trading algorithms Peer-to-Peer (P2P) and Multi Unit Double Auction (MUDA) for local electricity trading. We compared the results in selected KPIs such as self-sufficiency, traded energy, and curtailment. We find that P2P provides a more economically efficient trading algorithm than MUDA as it generally enables more trading and thus lowers grid imports. However, there are concerns that P2P brings disadvantages such as unfair trading.

3.1 Introduction

Decentralized energy resources (DERs) have recently experienced significant growth in deployment and adoption due to declining technology costs. As a result, DERs are now more affordable and becoming increasingly popular for residential buildings. This has created the opportunity to develop building-to-building energy-sharing systems to efficiently use on-site wind and solar power. Local electricity markets (LEMs) concepts have provided new mechanisms and ideas to facilitate energy trading (Maldet et al., 2022). LEMs provide a platform for prosumers and consumers to trade electricity. This can reduce the peak grid imports, improve DERs utilization, and lower distribution and transmission costs (Bjarghov et al., 2021). For example, Lüth et al. (2018) analyzed LEM benefits for end-users by estimating savings up to 31% on their electricity bill when co-optimizing local electricity trading, compared to a case with no trading. Zheng, Huang, and Lai (2021) in another study demonstrate that Peer-to-Peer (P2P) energy and storage sharing can reduce the net costs by 34.5%.

To further explore the potential of LEMs, it is important to reflect on how to organize LEMs, how the internal market should function, and how the price will potentially be settled between diverse players with different selling and buying price willingness. In the literature, a majority of research on LEMs focuses on centralized optimization and primarily considers power flow analyses or context-specific studies. However, understanding how an internal wholesale market will determine local prices and the related trading algorithms remains an open question. To this end, this paper investigates if certain trading algorithms provide market-based results comparable to the community model (perfect market with centralized optimal decisions) but considering bidding options that incentivize competition (fairer prices). Particularly, the paper focuses on the following research questions:

- Which trading algorithm is fair and realistic in representing an energy community that internally creates a prosumer-to-consumer market?
- How do different bidding simulations affect the outcome of the trading algorithms? What underlying behavior assumptions (e.g., bidding strategies) affect the trading outcome?
- How do different system characteristics and contexts (e.g., country) affect the outcome of the trading algorithms?

To address these questions, we developed two models. The first one is a reference model that uses centralized optimization. The second is a competitive trading model used to investigate the performance of different trading algorithms, namely Peer-to-Peer (P2P) and Multi Unit Double Auction (MUDA). We also developed different bidding simulations to include bidding preferences in the competitive market. These are based on a developed reference price index tailored for LEMs. Then, we analyzed and compared the trading algorithms for two different cases with diverse characteristics. The two cases are used to examine how the algorithms work in different markets and contexts. That is, we implemented the analysis to realistic cases of residential buildings in Norway and the United Kingdom.

The structure of the rest of the paper is as follows: In Section 3.2, we present related literature and outline research contributions. Next, the model formulations and bidding simulations are in Section 3.3, while the case studies and data used are described in Section 3.4. Section 3.5 presents results and the main findings. Lastly, Section 3.6 summarizes main conclusions of the paper.

3.2 Related literature

Recent developments in digitization, such as grid automation and an increase in DERs, have driven the emergence of LEMs. Mengelkamp and Weinhardt (2018) define a LEM as "a geographically distinct and socially close community of residential prosumers and consumers that have access to a joint market platform for trading locally produced electricity among each other." Within LEMs, prosumers can take an active role in electricity trading. They can pursue their individual preferences and objectives through trading strategies (Van Der Schoor and Scholtens, 2015). Accordingly, Dukovska, Paterakis, and Slootweg (2018) note three key prosumer objectives: reduction of electricity bills, less dependence on grid companies, and environmentally friendly consumption. Therefore, LEMs contribute to better utilization of wind and solar power at lower costs and benefit the participants (Bjarghov et al., 2021; Maldet et al., 2022; Herenčić et al., 2022).

3.2.1 Local electricity market clearing

An important design element of LEMs is how the trading should be organized. This includes how sellers and buyers will set the market-clearing within the LEM. The literature tends to focus on two main approaches. The first one is a cooperative approach where the goal is to maximize social welfare, given the utilities and consumption in the system. The second is a non-cooperative approach where the goal is to create an efficient market that stimulates competition. Table 3.1 presents an overview of relevant literature regarding LEMs and trading mechanisms.

For the cooperative approach, previous literature looks at LEMs and their effect on the grid. Here, the market-clearing is usually done using a centralized optimization model. The objective function is to maximize social welfare, usually through the minimization of system costs. Consequently, this method will give the optimal result, seen from a community perspective. For example, Lüth et al. (2018) investigates the role of battery storage in a LEM for a cooperative community model. Dynge et al. (2021) incorporates a power flow analysis to look at the grid impacts of cooperative

Table 3.1: Overview of central literature related to LEM design and trading mechanisms

Reference	Cooperative	Competitive	Strategic	Grid impact	Case	Comment
Lin, Pipattanasomporn, and Rahman (2019)	No	Yes	Yes	No	100 participants in a microgrid using typical residential load. Various PV penetration with typical PV gen profiles.	Compares uniform and discriminatory k-DA with several bidding strategies.
Xu et al. (2021)	No	Yes	Yes	No	5 prosumers in microgrid community with PV and energy storage systems.	Proposes a new auction mechanism based on uniform pricing.
Lüth et al. (2018)	Yes	No	No	No	Including centralized and decentralized energy storage.	Compares cases with centralized and decentralized storage.
Dynge et al. (2021)	Yes	No	No	Yes	52 houses with varying combination of PV and EVs.	Comparing no-trade model with trade model.
Sæther, Granado, and Zaferanlouei (2021)	Yes	No	No	Yes	Industrial site with 5 buildings and a variety of PV, CHP, EV and load shifting.	Investigates role of sharing local flexibility.
Mengelkamp et al. (2017)	No	Yes	Yes	No	Households with PVs that covers total electricity demand over a whole year.	Compares several cases: reference, P2P trading, and P2P trading incl. Shared storage.

trading. Sæther, Granado, and Zaferanlouei (2021) study the role of sharing local flexibility in an industrial site that coordinates peak management centrally.

However, it is unrealistic to assume both buyers (consumers) and sellers (prosumers) aim to lower the community energy cost because individuals often seek to maximize their own profit. Hence, the representation of competitive market designs is also an important research area in the literature. Sousa et al. (2019) suggest three types of design options for competitive markets: Pooled market trading, fully decentralized markets with only bilateral trading, and hybrid markets where a market agent gathers and facilitates bilateral trading. For both the pooled and hybrid market, auctions or other market-clearing mechanisms that consider bids and offers are needed to clear the market xu2021iterative. For example, k-double auctions (k-DA) are widely applied in the LEMs literature xu2021iterative. In double auction mechanisms, there are two ways of establishing trading prices: uniform or discriminatory pricing. In uniform pricing, we have one market-clearing price that applies for all winning participants. As for discriminatory pricing, also known as "pay-as-bid" pricing, each trade has one price, and there is no single market-clearing price. For both these, there is a price coefficient, k, that determines the balance in clearing price between buyer and seller price lin2019comparative.

A central assumption to model competitive markets with auctions is the representation of bids and offers. There are two main approaches: non-strategic and strategic bidding. The non-strategic bidding approach entails randomized bids and offers without any specific strategy and will usually not result in an efficient market mengelkamp2017trading. Strategic bidding is more realistic in a competitive market but requires game-theoretic approaches (see review in bjarghov2021).

Current literature that looks at competitive markets usually includes bidding strategies or provides comparisons of no-strategy and strategic approaches. For example, Lin, Pipattanasomporn, and Rahman (2019) investigates two bidding strategies: the best-offer and the market-power. The first does not consider the market situation in terms of market supply or surplus energy, and participants compete for the best price. In the second strategy, participants have knowledge about market conditions, such as historical PV and demand data, and bid accordingly. Mengelkamp et al. (2017) also compares two agent behaviors: a no-strategy versus an intelligent bidding approach. In the DA literature, Lin, Pipattanasomporn, and Rahman (2019) compares discriminatory and uniform k-DA and concludes that the first provides better market decisions (avg. percentage kWh traded and avg. percentage of households cleared). Mengelkamp et al. (2017) also considers uniform k-DA but compares it to another trading mechanism known as Peer-to-Peer trading (P2P).

The P2P trading algorithm is based on sealed bids and offers that are matched if the buying price is higher than the selling price. There is no single market-clearing price but rather discriminatory prices for each trade that occurs. The algorithm is similar to discriminatory k-DA, but instead of sorting the bids and offers, they are paired randomly. Consequently, P2P might have a higher number of trades than k-

DA as there is a possibility for advantageous matching. The randomness might also reduce market power and unfair competition. However, because of discriminatory pricing, peers might pay different prices for the same product at the same time-step (Mengelkamp et al., 2017). Mengelkamp et al. (2017) based on the early work of Blouin and Serrano (2001) concluded that the P2P with intelligent bidding is the most efficient. Interestingly, this was the only literature available on this specific algorithm regarding LEMs and energy systems in general.

Double auction mechanisms are evaluated based on four characteristics: individual rationality (IR), budget balance (BB), incentive compatibility (IC), and economic efficiency (EE) (Lin, Pipattanasomporn, and Rahman, 2019). A trading algorithm is IR if participants do not derive negative utility from their participation. Moreover, BB implies the balance of money input and output. Furthermore, IC is given when participants have an incentive to bid their true value. Finally, the algorithm must maximize the aggregated utility of the participants to be EE (Lin, Pipattanasomporn, and Rahman, 2019). However, Myerson and Satterthwaite (1983) showed that a DA is not economically efficient if a mechanism is IR, BB, and IC. Nevertheless, many researchers have tried to create auction mechanisms with the highest possible efficiency. For instance, McAfee (1992) proposed a mechanism that achieves an approximate optimization of a single-unit auction. Moreover, a commonly used DA mechanism is the Walrasian mechanism (Rustichini, Satterthwaite, and Williams, 1994). Unfortunately, this mechanism is not IC leading to incentives for misreporting valuations and therefore manipulating the price. Finally, Segal-Halevi, Hassidim, and Aumann (2018) suggested the Multi Unit Double Auction (MUDA) algorithm that is IR, BB, and IC. It approximately optimizes the economic efficiency in sufficiently large markets. The MUDA algorithm was first applied to data from a stock exchange. To the best of our knowledge, the work in this paper is the first attempt to investigate the applicability of the algorithm for LEM trading.

3.2.2 Contributions

In general, LEMs have been an important research area in the last decade. Still, there are research gaps on how to establish and value the development of a wholesale market within LEMs that incentivizes trading (market based). This paper provides the following contributions:

- The comparison of the trading algorithms MUDA and P2P, and centralized optimization under different bidding simulations in LEMs. Although trading algorithms have been studied in the literature, the research on MUDA is new in the context of LEMs. P2P trading has been studied in the literature, but this is the first attempt to compare it to MUDA while creating bidding simulations.

- The paper presents a new method for creating different bidding simulations for prosumers and consumers based on a reference price. We propose a new calculation of a reference price as a starting point for the bidding simulations. A similar approach was pursued by lin2019comparative, but instead of using market prices from previous hours, we consider the current share of renewables in the LEM and an external grid price.

- We provide an early example of applying non-cooperative trading algorithms in a case in both Norway and the UK. Most studies on LEMs used centralized optimization with perfect competition. Therefore, this work contributes by applying trading algorithms on new settings.

- An important finding of this paper is that the P2P algorithm leads to efficient results that are close to centralized optimization. In contrast, MUDA works less efficiently in this case, but might be unfavored due to the relatively small number of participants.

3.3 Methodology

In this chapter, we describe the models used in this paper. We use two models to simulate electricity trading within a LEM: a reference model explained in Section 3.3.1 and a competitive model described in Section 3.3.2. The objective is to compare and evaluate the P2P and MUDA trading algorithms to the reference case. The latter uses centralized optimization, which gives the "perfect" solution from a system perspective. This represents a non-competitive system where a community manager handles all trades through a centralized hub. In contrast, the competitive model represents a market where participants place bids and offers in a trading hub (see Figure 3.1). Social welfare is highest for the community model, but it does not account for the individuals' interests.

The LEM configuration is the same for both models and consists of consumers and prosumers connected through a trading hub. The prosumers have renewable electricity generation (e.g. solar PV) and can trade electricity with other peers. Consumers can only buy from the prosumers. All participants in the market are also connected to the distribution grid to purchase power at a grid price.

The system is also bound to certain simplifications, boundary conditions, and assumptions. Firstly, there are no network constraints within the LEM or in the grid connection. We also use a copper plate model, meaning we neglect all losses. Furthermore, investment costs are disregarded. Moreover, peers cannot sell surplus electricity to the grid. We also assume self-consumption is prioritized before local trading, and local trading is prioritized before buying from the grid, meaning the local price is assumed to be lower than the grid price for any time-step. All the models can operate close to real time subjected to expected demand and local renewable production.

Table 3.2 provides an overview of the variables, parameters, sets, and scalars notations.

Table 3.2: Overview of sets, scalars, parameters and variables used in this paper

Sets	
$t \in T$	Hours t in time horizon T
$h, p \in H$	Houses h and peers p in community H
$b, s \in H$	Buyers b and sellers s in community H

Scalars	
P_p	Export penalty term
ψ	Loss factor for local trading
P_{low}	Lower bound for reference price

Parameters	
$dem^{(t,h)}$	Demand of house h in time-step t
$res^{(t,h)}$	Renewable energy production of house h in time-step t
$p_G^{(t)}$	Price of electricity from the grid in time-step t
$P_{ref}^{(t)}$	Reference price in time-step t
$U^{t)}$	Bids and offers from the uniform distribution in time-step t
$S^{(t)}$	Bids and offers from the skewed normal distribution in time-step t
T_0	Set of random number following a normal distribution
T_1	Set of random number following a normal distribution
λ	Skewness factor of normal distribution
σ	Standard deviation of normal distribution
μ	Mean value of normal distribution

Variables	
$G^{(t,h)}$	Grid consumption of house h in time-step t
$I^{(t,h)}$	Total imported electricity of house h in time-step t
$I_p^{(t,h \leftarrow p)}$	Imported electricity of house h from peer p in time-step t
$X^{(t,h)}$	Total Exported electricity of house h in time-step t
$X_p^{(t,h \rightarrow p)}$	Exported electricity of house h to peer p in time-step t
$p_{p2p}^{(t)}$	Local p2p trading price for a given trade in time-step t
E	Expected value

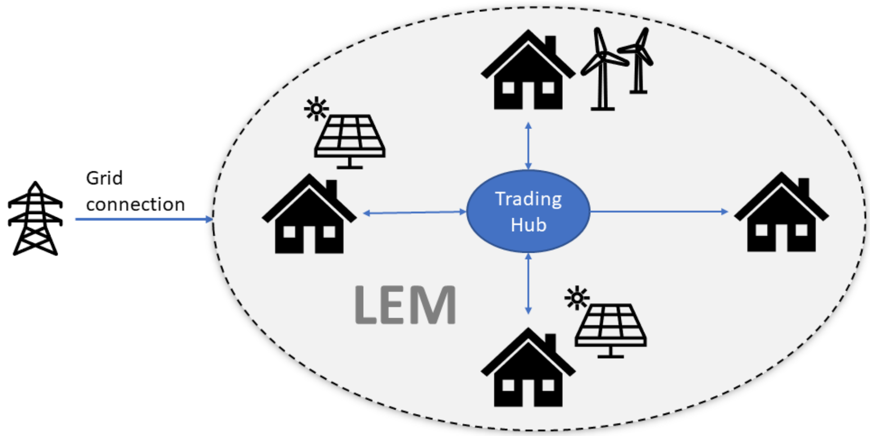


Figure 3.1: Graphical illustration of the community configuration for local trading

3.3.1 Centralized model

The model presented in this section is largely built on the suggested "flexi-user"-model from Lüth et al. (2018). Here, the objective is to minimize the total cost for the community. However, Lüth et al. (2018) only minimizes system costs, while we aim to also look at the amount of energy traded locally. Therefore, to avoid multiple optimal solutions, we have included a penalty term, P_p, to the objective function related to the total sold (exported) energy, $X^{(t,h)}$. This minimizes unnecessary trading while still giving the optimal results in terms of grid import as long as the penalty is appropriately small. Lastly, since all local trades are kept within the market, we do not consider the local trading prices (as they zero out in the summation). The objective function is given in Equation (3.1).

$$min \sum_{h} \sum_{t} [P_G^{(t)} \cdot G^{(t,h)}] + P_p \cdot \sum_{h} \sum_{t} [X^{(t,h)}] \tag{3.1}$$

Furthermore, the objective function is subject to several constraints, including the energy balance between supply and demand for each house. This restriction is given in Equation (3.2). Here, the supply consist of local renewable production $res^{(t,h)}$, grid import $G^{(t,h)}$ and purchased (imported) electricity $I^{(t,h)}$. The demand consist of the demand $dem^{(t,h)}$ and sold (exported) electricity $X^{(t,h)}$.

$$res^{(t,h)} + G^{(t,h)} + I^{(t,h)} \geq dem^{(t,h)} + X^{(t,h)} \qquad \forall t \in T, \quad \forall h \in H \tag{3.2}$$

Moreover, the flow of sold electricity for each participant in the market is defined in Equation (3.3). Here, the total export for house h is defined as the sum of exported electricity of house h to its peers p. There is also a restriction that only allows houses that generate renewable electricity in any given time-step to export electricity in that same time-step. This restriction is defined in Equation (3.4).

$$X^{(t,h)} = \sum_{p \neq h} X_P^{(t,h \rightarrow p)} \tag{3.3}$$

$$X^{(t,h)} = 0 \qquad \forall (t,h) | res^{(t,h)} = 0 \tag{3.4}$$

The purchased electricity of house h from its peers p in time-step t is calculated from the export of each peer, including a loss factor ψ, as given in Equation (3.5). Furthermore, the total imported energy for each house in each time-step is then the sum of imported energy, as given in Equation (3.6).

$$I_p^{(t,h \leftarrow p)} = \psi \cdot X_p^{(t,p \rightarrow h)} \qquad \forall p \neq h \tag{3.5}$$

$$I^{(t,h)} = \sum_{p \neq h} I_p^{(t,h \leftarrow p)} \tag{3.6}$$

Lastly, as the participants cannot sell to the grid, the total quantity sold by all houses must equal the total quantity purchased by all houses for each time-step. We must also account for losses by including the loss factor ψ. This trading balance is given by Equation (3.7).

$$\sum_h \psi \cdot X^{(t,h)} = \sum_h I^{(t,h)} \qquad \forall t \in T \tag{3.7}$$

The loss factor in the model formulation by Lüth et al. (2018) is set to 0.924. However, in this model, it is set to 1[1] to provide a fair comparison with the competitive model that does not account for losses.

3.3.2 Trading algorithms - P2P and MUDA

This paper investigates the double auction algorithms MUDA and P2P in local electricity trading. Double auction is a collective term for various auction mechanisms in which multiple sellers and buyers come together to sell and buy goods. The algorithms are used to simulate competitive behavior in the LEM. Furthermore, details about the algorithms used in this paper can be found in the PyMarket documentation (Kiedanski, Kofman, and Horta, 2022).

For the competitive model, we assume a prioritization of self-consumption over trading. This means that prosumers first consume their own electricity before placing an offer to the trading hub and selling their surplus energy. In case of a power deficit, consumers submit a bid to buy electricity. The model then uses one of the trading algorithms to clear the market for the whole period, one time-step at a time.

[1] The loss factor is only included to avoid arbitrage, and excessive energy trading between participants in the centralized model and is therefore be set close to 1 (i.e., 0.9999).

The bids and offers required for the algorithms to work are established in two steps. First, we derived a reference price reflecting what participants will likely pay, based on the current situation of the LEMs' local generation. Secondly, we conducted bidding simulations in which bids and offers are randomly generated around the reference price using different bidding strategies.

Multiple-unit double auction (MUDA) trading algorithm

Segal-Halevi, Hassidim, and Aumann (2018) introduced the MUDA algorithm aiming to create an economically efficient (EE) trading algorithm that is at the same time individually rational (IR), budget balanced (BB), and incentive compatible (IC).

The algorithm first creates two sub-markets, a left, and a right sub-market. The bids and offers are then divided between two sub-markets with a probability of 0.5. After that, the market equilibrium price is calculated on each sub-market with an aggregated demand and supply curve. Subsequently, each sub-market trades with the market equilibrium price of the other sub-market. Consequently, the bids and offers of the left sub-market trade at the market prices of the right sub-market and vice versa. For successful matching, the bid must be higher (or equal) and the offer must be lower (or equal) than the market equilibrium price.

MUDA does not prevent an imbalance between supply and demand in each sub-market. The algorithm can lead to greater demand or supply (long side) in the sub-markets. While the short side can trade all bids or offers, bids or offers from the long side remain. There are different variations of MUDA on how to deal with the excess on the long side. In this paper, we use "Vickrey"-MUDA. Here, the bids or offers with the highest profit are selected first (highest bids or lowest offers). In the next step, the selected traders have to pay a trading fee. The trading fee is determined by the potential profits of the traders who are pushed out of the market.

With MUDA, participants cannot manipulate the price through strategic reporting since bids and offers are traded at an exogenously determined market price. Consequently, they only have an incentive to submit their true value, and therefore, the trading algorithm fulfills the IC requirement. Moreover, the agents do not lose through their participation, so the algorithm is IR. Furthermore, the "Vickrey"-MUDA is weakly budget balanced as the market-maker can make profits through trading fees but never losses. Finally, MUDA approximately optimizes the economic efficiency in sufficiently large markets (Segal-Halevi, Hassidim, and Aumann, 2018). However, it has not been applied to local electricity trading so far. Figure 3.2 presents a simplified illustration of the MUDA algorithm.

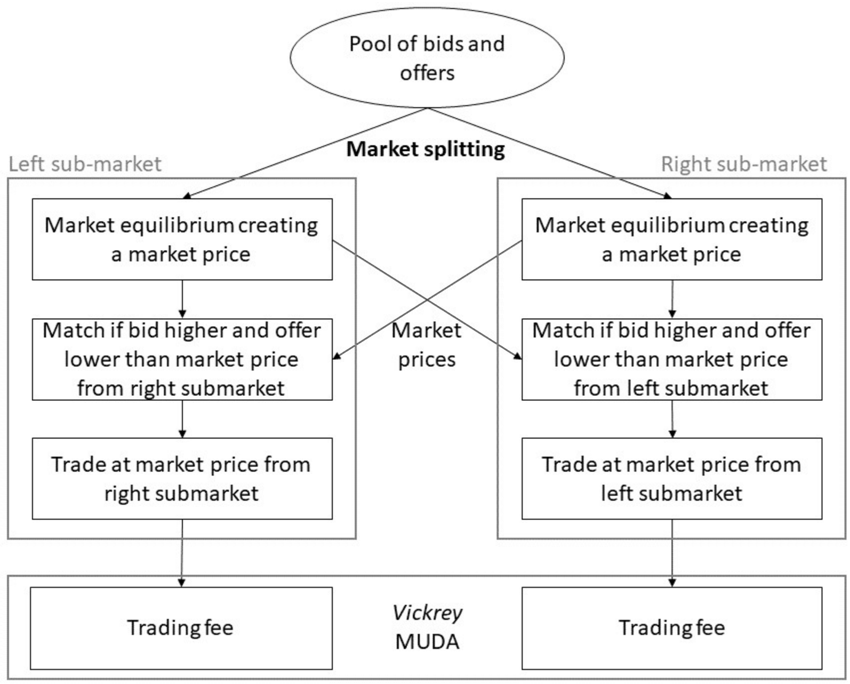


Figure 3.2: Graphical illustration of the MUDA algorithm

Peer-to-Peer (P2P) trading algorithm

The P2P algorithm is based on the work by Blouin and Serrano (2001) and has previously been implemented for LEMs by Mengelkamp et al. (2017). Similarly to MUDA, the P2P trading algorithm works by peers submitting bids and offers into a central trading hub. These bids are then randomly paired and matched if the bidding price is higher than the offer price.

The trading price for each match is determined by Equation (3.8), and thus depends on the price coefficient, k. If $k = 1$ all profit goes to seller, if $k = 0$ all profit goes to buyer. For this project, we use a price coefficient of 0.5.

$$p_{p2p}^{(t)} = p_b^{(t)} \cdot k + (1 - k) \cdot p_s^{(t)} \qquad k \in [0, 1] \tag{3.8}$$

Since all bids might not be matched in the first run, the algorithm does several iterations, as illustrated in Figure 3.3. This means that if a peer's bid or offer is not matched in the first iteration, or not all quantity is traded, they will participate in the next iteration. These iterations will go on until all unmatched participants either trade all their quantity or no available pairs are left in the trading hub.

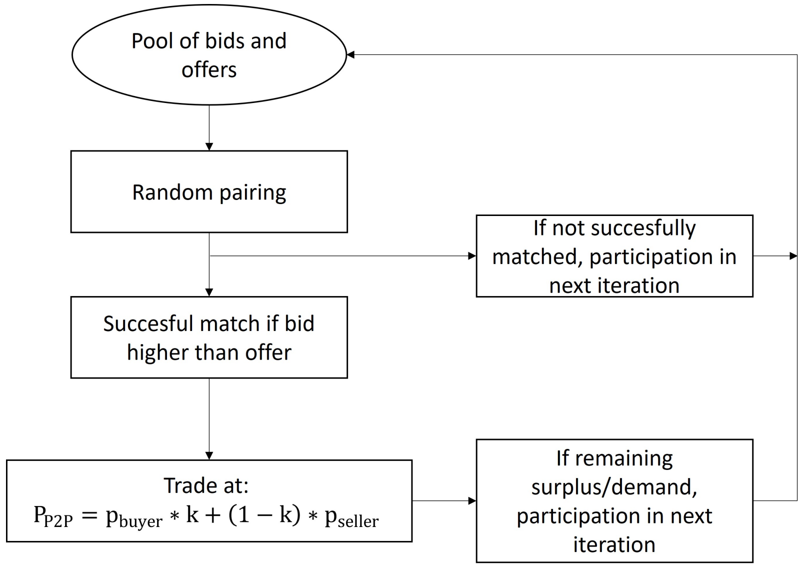


Figure 3.3: Graphical illustration of the P2P algorithm

An important characteristic of this algorithm, and possibly a drawback, is the price and quantity variations. Since all trades have an individual price, instead of a market price, different peers can end up with largely different prices for the same quantities in the same time-step. This means the algorithm can be perceived as unfair to some participants. However, the P2P trading algorithm does not provide incentives to manipulate bids and offers. On the one hand, buyers try to bid as low as possible, but they must not bid too low to find a trading partner. Otherwise, they have to buy more costly electricity from the grid. Sellers, on the other hand, try to drive the price up, but they need an even higher buying price. So their offer should also not be too high.

Reference price

The reference price reflects the situation of the local market in terms of renewable electricity availability, demand, and wholesale prices. It is a simplified representation of an algorithm that predicts market prices using historical weather and wholesale market data. Assuming that participants have a high level of information about the market, the reference price therefore also reflects the price a participant is willing to bid.

The reference price should change according to the availability of renewable energy. In times of high availability and thus high supply, the reference price should decrease. If, in contrast, renewable generation is scarce, the reference price should increase and converge to the wholesale market price. However, the reference price should never exceed the grid price, as *rational* consumers would always choose the cheapest option.

The proposed Equation (3.9) follows the described principles. In addition, a lower bound P_{low} is added in Equation (3.10) to avoid low offering prices that might not be realistic.

$$P_{ref}^{(t)} = (1 - \frac{\sum_h res^{(t,h)}}{\sum_h dem^{(t,h)}}) \cdot P_G^{(t)} \tag{3.9}$$

$$P_{ref}^{(t)} \geq P_{low} \tag{3.10}$$

Bidding simulations

Based on the reference price, bidding simulations are performed to generate bids and offers that incorporate some randomness. The idea behind these bidding simulations is to obtain bids and offers that represent the market conditions of the LEM under the assumption that participants have relatively good information about the competition but still have some variety in risk preferences. Therefore, we performed two bidding simulations to simulate the participants' bidding and offering: uniform distribution and skewed normal distribution.

The uniform distribution does not involve strategic bidding of buyers and sellers. Consequently, each participant bids randomly around the reference price without anticipation. In this bidding simulation, the bids and offers range from 10 % below to 10 % above the reference price, as can be seen in Equation (3.11). Here, $U^{(t)}$ are uniformly distributed random numbers generated within the range of 0.9 to 1.1.

$$U^{(t)} = \hat{Y_U} \cdot P_{ref}^{(t)} \qquad \forall b, s \in H \tag{3.11}$$

The skewed normal distribution aims to represent the strategic bidding behavior of the participants. We assume that participants want to stay in the market because they can reduce their electricity costs by trading locally compared to buying from the main grid. For both trading algorithms, higher bids and lower offers can potentially increase the number of successful trades. Therefore, we assume that buyers tend to bid slightly higher than the reference price and sellers slightly lower.

We generate two sets of random numbers according to Equation (3.12), one for bids (with positive λ) and one for offers (with negative λ). T_0 and T_1 are independent random numbers following a standard normal distribution. λ, σ, and μ are the parameters of the skewed normal distribution. If λ is set to zero, the resulting random numbers follow a normal distribution with the mean of μ and standard deviation of σ. Consequently, λ is the parameter determining the skewness of the distribution, as well as the expected value of the generated numbers, as shown in (3.13).

$$S^{(t)} = \mu + \sigma \cdot (\frac{\lambda}{\sqrt{1+\lambda^2}} \cdot |(T_0)| + T_1 \cdot \sqrt{1 - (\frac{\lambda}{\sqrt{1+\lambda^2}})^2}) \tag{3.12}$$

$$E[Y] = \mu + \sqrt{\frac{2}{\pi}} \sigma \frac{\lambda}{\sqrt{1+\lambda^2}} \tag{3.13}$$

The μ and σ are set to the reference price ($P_{ref}^{(t)}$) and 15 % of the reference price, respectively. The λ that should not be unrealistically large but still reflect the effect of higher bids and lower offers is set to 0.25. Finally, Figure 3.4 illustrates the skewed normal distribution for 1000 randomly generated bids and offers with the selected parameters.

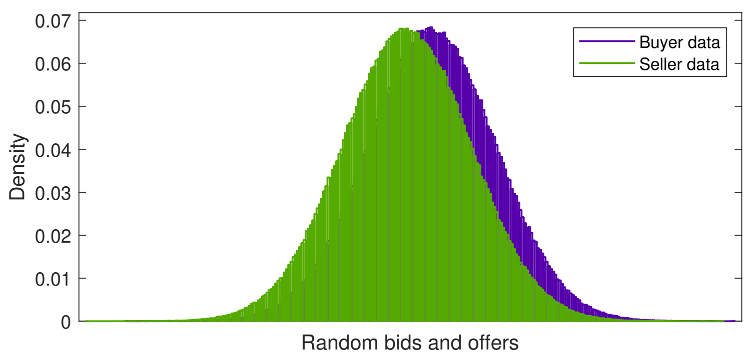


Figure 3.4: Distribution of random bids and offers in the skewed normal distribution

3.4 Case studies and Data

To analyze the MUDA and P2P trading algorithms and determine their efficiency, we examined a case from Norway and the UK. The cases differ in the number of houses, the distribution of renewable energy generation among the houses, and the solar radiation. To investigate detailed effects, a period of 20 days from mid-June to early July is considered.

3.4.1 Steinkjer case

In the Steinkjer case, the trading algorithms are applied in a small neighborhood in Steinkjer, Norway. The data is based on Dynge et al. (2021) but has been adjusted in some respects, e.g., with newly added small wind turbines, more PV systems, and battery storage were removed. This increases the overall generation of renewable energy and contributes to a more variable generation profile.

The load profiles are actual consumption data collected from a smart grid project in Steinkjer. The data set includes 54 households connected through a distribution network, which in turn is connected to the main grid. The load profiles has a time granularity of 15 minutes and was retrieved over a period of 20 days from mid-June to early July. However, to match the time granularity of renewable energy generation and grid prices (hourly), the load profiles were aggregated into an hourly demand. Furthermore, the average household demand during this period is comparatively high at 1 147 kWh.

The grid price consists of the fluctuating wholesale market price and the annually constant grid tariff. The wholesale market price was retrieved from NordPool's historical data (NordPool, 2022). Here, we have selected 20 days that are consistent with the consumption data but from 2019. Furthermore, we have used the 2019 private household grid tariff from the DSO in Steinkjer, which is 0.42 NOK/kWh (AS, 2022).

Moreover, we extracted generation profiles for wind and PV from renewables.ninja (Pfenninger and Staffell, 2016; Staffell and Pfenninger, 2016), which provides meteorological PV and wind data from the NASA MERRA-2 database (Rienecker et al., 2011). Here, we selected 20 days in summer of 2019. In total, we have equipped 35 households with PV systems of varying capacities and a panel tilt of 45°. Additionally, we have equipped ten households with wind turbines of the Siemens SWT 2.3 82 model. Although the turbine model originally had a higher capacity and hub height, the data is realistic at the house level as we scaled down the capacity to 2.3 kW, see a similar approach in (Crespo del Granado, Wallace, and Pang, 2014).

Table 3.3 summarizes distribution of renewable energy generation for the 54 households.

Table 3.3: Steinkjer case - Distribution of renewable generation units among the 54 households in the community

Production unit	**Quantity**
4 kW PV	15
6 kW PV	14
8 kW PV	2
10 kW PV	4
2.3 kW wind	10

3.4.2 London case

The second case investigates the trading algorithm in a community of 200 households in London, United Kingdom. The load profiles are based on the consumption data from the low Carbon London project that took place from 2011 to 2014 (Networks, 2022). All data sets have a half-hour time resolution and are taken from a 20 day period from mid June to early July.

The grid prices for the London case were created in two steps. First, wholesale electricity prices were retrieved from ENTSO-E (2022). Secondly, the network charges have to be taken into account to obtain the actual grid prices. Therefore, similar to Hashemipour, Granado, and Aghaei (2021), wholesale prices were scaled up to reach an average price of 15 pence/kWh.

The consumption data includes house types with different demand patterns in terms of demographics, social factors, population, and consumption behavior. This data set comprises 164 affluent and 78 comfortable houses. Affluent houses tend to have higher electricity consumption compared to comfortable houses. The average consumption of the selected affluent houses for the 20 day period is 209 kWh. In contrast, the comfortable houses have an average consumption of 165 kWh. However, both house types are rather wealthy and were selected because they are more likely to be able to afford renewable energy generation or live in a community where renewable energy is available.

Solar generation profiles were calculated based on solar irradiation, and temperature data in London from 2013 (data, 2022; Data and DISC), 2015) for different capacities with an efficiency of 21 % and a panel tilt of 35°. Many new profiles are generated by adding random vectors to the original one to increase the diversity of the solar generation in the community. The upper and lower bounds of the random vectors are calculated in a similar way to (Hashemipour, Granado, and Aghaei, 2021). Indeed, first, ten scenarios are generated to cover different possibilities (Crespo Del Granado, Wallace, and Pang, 2016). Then, the normalized standard deviation per time-step is employed to determine a confidence level between upper bound and lower bound. Wind data was derived from wind speed data from an area near London. The generation profile was then calculated by fitting a curve to the power-to-wind-speed profile of a 2.3 kW turbine (similar to (Lüth et al., 2018)).

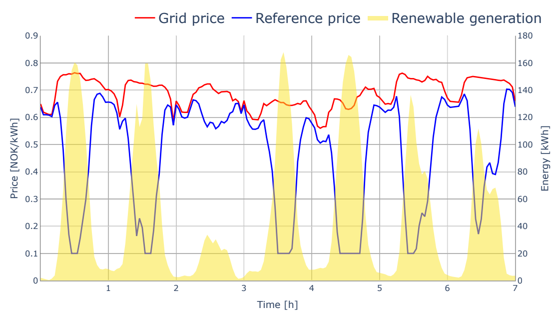
Table 3.4 summarizes distribution of renewable energy generation among the 200 households.

Table 3.4: London case - Distribution of renewable generation units among the 200 households in the community

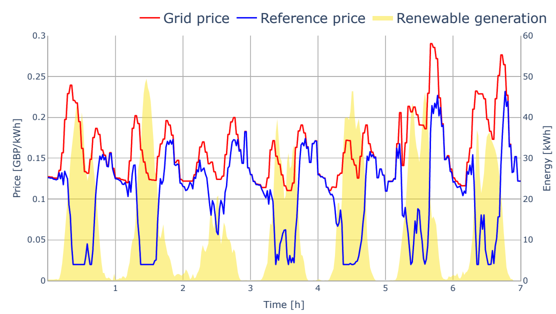
Production unit	**Quantity**
2 kW PV	15
4 kW PV	10
5 kW PV	5
2.3 kW wind	4

3.4.3 Bidding simulation

As described in Section 3.3.2, the application of the trading algorithms requires bids and offers. For this purpose, we developed a reference price according to Equation 3.9 and then generated the bids and offers randomly around the reference price using the uniform and skewed normal bidding simulation. Figure 3.5 illustrates the reference price for both cases in the first week. As expected, the reference price depends strongly on the share of renewable generation. This leads to high variations of the reference price, both over time and in the two cases. In times of low renewable generation, especially at night, the reference price converges towards the grid price. But in times of high local generation, the reference price is close to or equal to the lower bound. The chosen lower bounds, P_{low}, are 10 NOK/kWh for the Steinkjer case and 0.25 GBP/kWh for the London case.



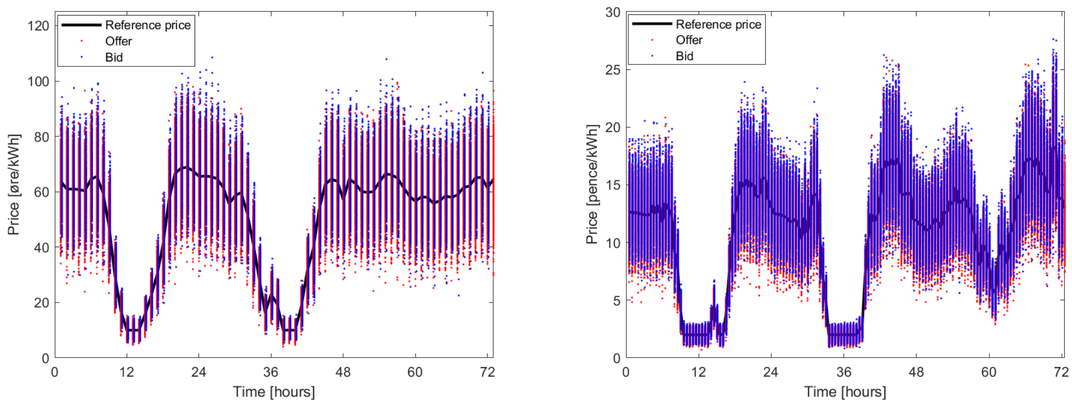
a) Steinkjer



b) London

Figure 3.5: Reference price in the communities compared to grid price and renewable generation

In the next step, we generated 1000 bids and offers based on the reference price using the bidding simulations. As described earlier, the uniform distribution results in bids and offers randomly generated around the reference price for each time-step. Figure 3.6 presents the generated bids and offers from the skewed normal distribution for the first three days for both cases. The Figure illustrates the desired effect of the bidding simulation, i.e., the bids (blue dots) tend to be slightly higher than the offers (red dots). Furthermore, because of the random nature of the simulation, there are also some deviations.



a) Steinkjer b) London

Figure 3.6: Sample of the first 72 hours of calculated bids and offers from the skewed normal distribution

3.5 Results and analysis

This section analyzes the trading algorithms MUDA and P2P in the Steinkjer and London case. Here, centralized optimization is used as a reference for MUDA and P2P as it provides optimal results for local trading from a community perspective. The main objective of this section is to analyze and compare the trading algorithms for both cases. For illustrative purposes, the first seven days of the simulation period are shown in the figures. These representative days include periods with both higher and lower renewable generation and should therefore represent the market sufficiently.

3.5.1 KPI definitions

The trading algorithms are compared under the consideration of various Key Performance Indicators (KPIs), see Table 3.5. The KPIs provide relevant information to determine the efficiency of a particular trading algorithm.

3.5.2 Steinkjer case

In the Steinkjer case, many houses have PV systems to cover the high demand, but the power generation per unit is small due to relatively low solar radiation. In the following, we present the results for centralized optimization, followed by the MUDA and P2P trading algorithms.

Table 3.5: Definition of KPIs used in this paper

KPI	Definitions
Total system cost	Sum of grid import times the wholesale market price for each time-step.
Grid import	Sum of all electricity imported from the grid.
Self-consumption	Sum of community demand minus sum of grid import.
Curtailment	Sum of renewable energy generation minus the sum of self-consumption.
Energy traded	Sum of the energy traded among the peers.

Community model - Centralized Optimization

The centralized optimization results in total system costs of 27 037 NOK, which is the cheapest solution for supplying households with the electricity they demand. With the given generation of renewable energy, the community can cover 36.1 % of its consumption by itself. Participants prioritize self-generated electricity over trading, but 2 506 kWh is still traded locally between the households. However, a large share of 63.9 % is also imported from the main grid. Since centralized optimization represents the optimal solution, we can see that 2.7 % curtailment of the generation is unavoidable.

Figure 3.7 shows the grid import, self-consumption, and curtailment of the community in the first week. During the day, there are high shares of self-consumption, while at night, the electricity grid almost exclusively covers the electricity demand. An exception appears in day three when there was a lower renewable energy generation.

Since the optimization aims to cover the demand of all households as cheaply as possible, and there are no local trading losses, all the local production will be shared among the households in the community. As there is no battery storage in the system, there will be curtailment if the renewable generation exceeds demand at any time-step. This is the case on the fourth, fifth and sixth day in Figure 3.7.

Moreover, Figure 3.7 also illustrates the optimal traded energy of the community in the first week. Peaks in the energy traded occur during the day when the local generation, and thus self-consumption, is high. At these times, the prosumers' electricity generation exceeds their demand, so they share their surplus with other peers. Furthermore, no energy trading takes place on the third day. This is most likely because the prosumers' own generation does not exceed their demand, hence they cannot offer surplus energy for trading.

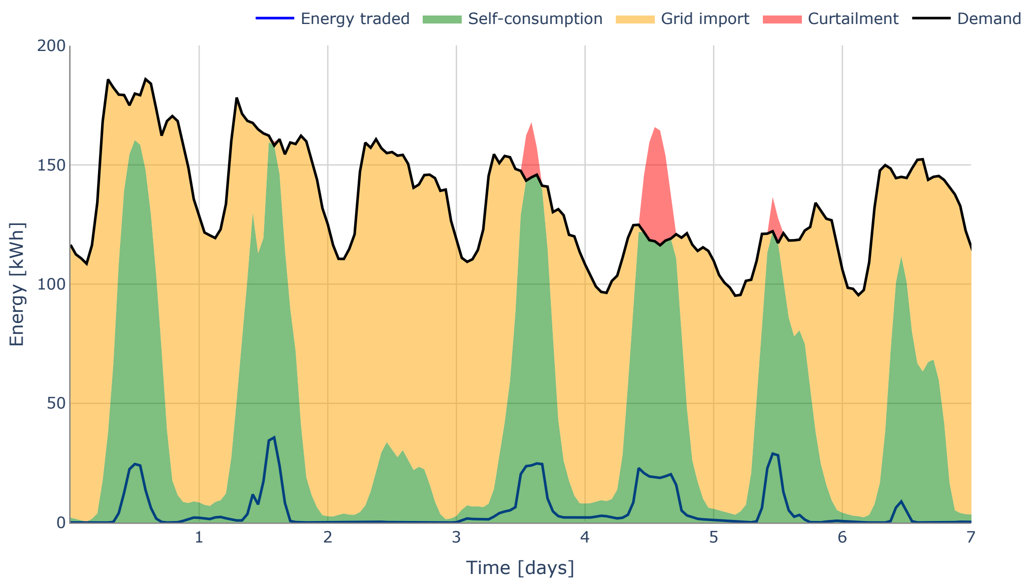


Figure 3.7: Steinkjer case - Grid import, energy traded, self-consumption, curtailment and demand for the first seven days of the centralized model

Competitive model - Trading algorithms

In this section, we examine and compare the efficiency of the MUDA and P2P trading algorithms. The model was implemented using both bidding simulations: the uniform and the skewed normal distribution. As expected, results show a higher efficiency in terms of traded energy when using the skewed normal distribution. This is because the skewed normal distribution results in more matches between bids and offers. Consequently, more trades are made, the community's self-consumption increases, and finally, the system costs for the community decrease. Based on this, we chose to focus mainly on the skewed normal distribution for the results, as we try to simulate the expected behavior of the participants, i.e., peers wanting to stay in the market to trade cheaper electricity. Nonetheless, the KPIs for the uniform distribution are in Table A.1, in Appendix A.

Table 3.6 presents the KPIs of the skewed normal distribution. The results of the P2P algorithm are relatively close to the solution of centralized optimization. The KPIs of the MUDA algorithm, in contrast, have a significantly greater gap to the centralized optimization. Accordingly, the traded energy when using MUDA is lower compared to using P2P. This results in higher curtailment with MUDA as less electricity is distributed between the households. Consequently, using MUDA gives a lower self-consumption, and more electricity must be imported from the main grid. Finally, a higher grid import results in higher system costs when using MUDA.

Table 3.6: Steinkjer case - Comparison of KPIs for centralized, MUDA and P2P for the skewed normal bidding simulation

KPI	Centralized	MUDA	P2P
System cost [NOK]	27 037	28 091	27 229
Grid import [kWh] (%)	39 553 (63.9)	41 073 (66.3)	39 829 (64.3)
Self-consumption [kWh] (%)	22 388 (36.1)	20 868 (33.7)	22 112 (35.7)
Curtailment [kWh] (%)	615 (2.7)	2 135 (9.3)	891 (3.8)
Energy traded [kWh]	2 506	986	2 230

To examine the driving factors behind the KPIs in more detail, we can look at Figure 3.8 and Figure 3.9. They show the grid import, self-consumption, curtailment and energy traded in relation to the community demand in the first week using MUDA and P2P.

With centralized optimization, we can observe unavoidable curtailment only on the fourth, fifth and sixth day. With MUDA, in contrast, curtailment occurs every day except the third day when there is no energy trading, as indicated in Figure 3.8. Furthermore, we can observe that grid import and curtailment occur at the same time-steps. This means that MUDA fails to match a significant number of bids and offers. As a result, households have to import more expensive electricity from the grid, and locally produced electricity has to be unnecessarily curtailed.

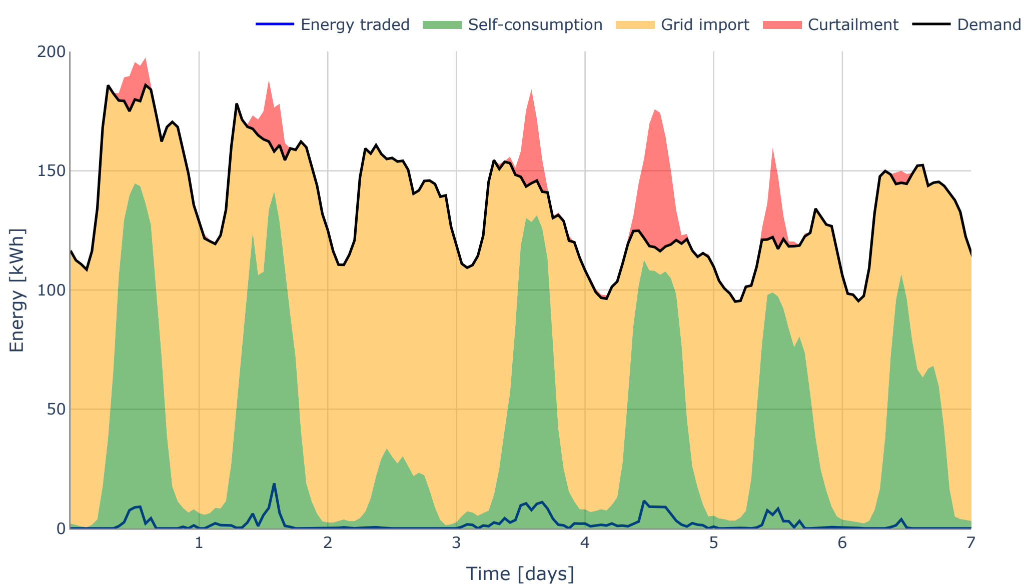


Figure 3.8: Steinkjer case - Grid import, energy traded, self-consumption, curtailment and demand for the first seven days when using the MUDA algorithm

Figure 3.9 shows that using the P2P algorithm results in more traded energy than MUDA. Therefore, the community's self-consumption is significantly higher, and curtailment is reduced. However, we can still observe that P2P does not match all bids and offers, resulting in more curtailment than the centralized optimization. For example, on the second day, there are grid imports and curtailment, which means that available renewable electricity could not be used because the bids and offers were not successfully matched.

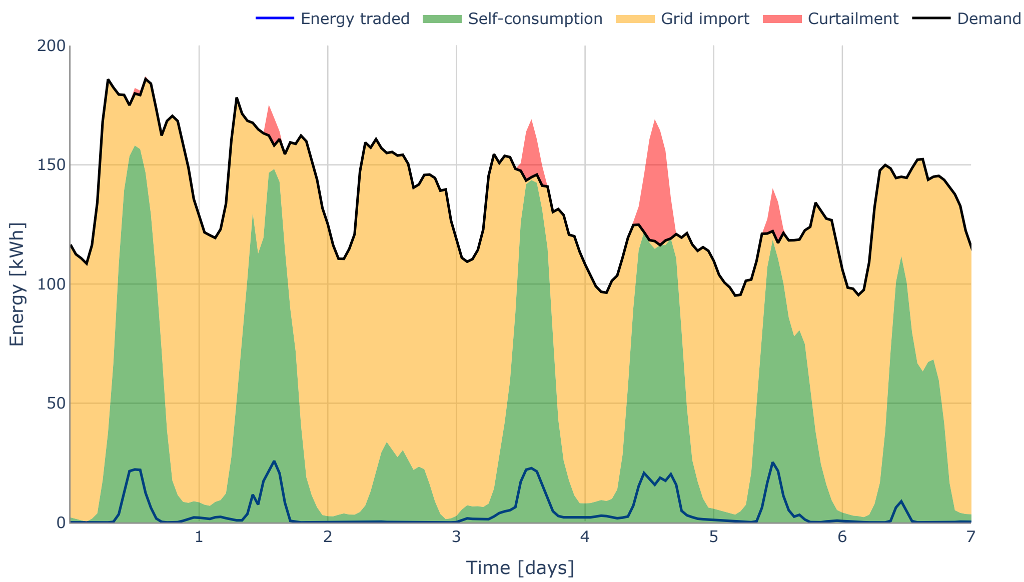


Figure 3.9: Steinkjer case - Grid import, energy traded, self-consumption, curtailment and demand for the first seven days when using the P2P algorithm

Figure 3.10 illustrates the average prices of the trades in each time-step for both MUDA and P2P. Here, we can observe two different effects caused by the different characteristics of the algorithms. First, the average price of the MUDA algorithm is higher than the P2P average price and the reference price in most time-steps, especially when the reference price is high. This is supported by the calculation of the average prices of all trades. For MUDA, the average price of all transactions is 0.31 NOK/kWh. In contrast, the average price when using P2P is 0.23 NOK/kWh. However, it can also be seen that the average prices of the MUDA algorithm never exceed the grid prices. Secondly, we can observe more fluctuating average prices for P2P, particularly at high reference prices. In contrast, in times of high generation, the average prices converge to the reference prices when using P2P.

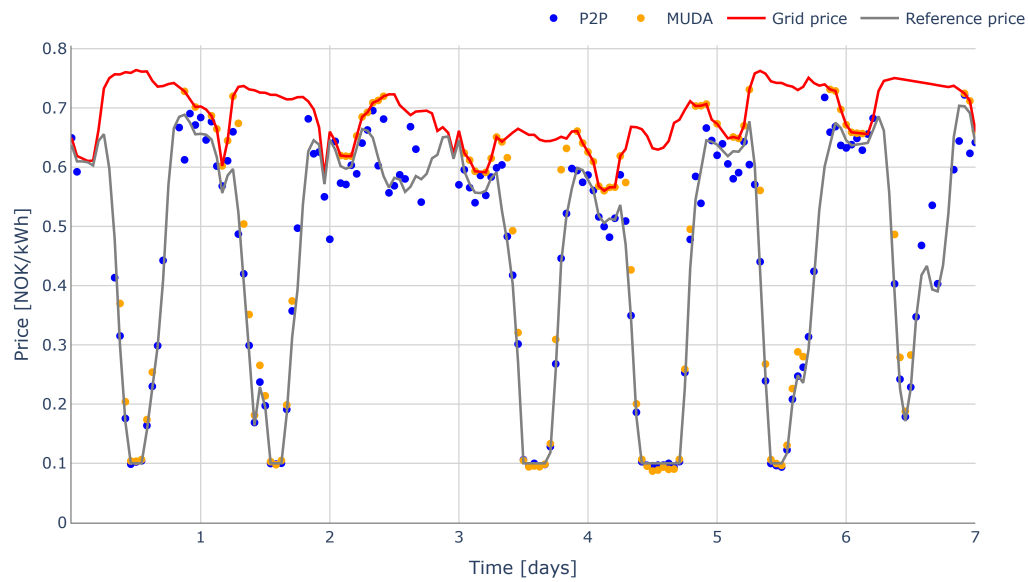


Figure 3.10: Steinkjer case - Average Prices for each time-step in addition to grid price and reference price for the first week of the simulation

3.5.3 London case

Compared to the Steinkjer case, this case contains a larger community (200 households) in London. Another important difference is the higher solar irradiance in London, leading to higher electricity generation per installed PV capacity. The average electricity demand per household is significantly lower in the UK and the time resolution in the London case is half-hourly.

Community model - Centralized Optimization

Compared to the Steinkjer case, we observe significant differences in the results of the London case. A central difference is the higher traded energy in the London case. At 8 193 kWh, the traded energy is more than three times higher than in the Steinkjer case. This is because electricity generation of the prosumers is higher and the average demand per household is lower. Consequently, there is more surplus electricity that can be traded to other households in the community. Accordingly, Figure 3.11 reveals that high shares of self-consumption are covered by traded energy. Furthermore, if the surplus electricity is optimally distributed, curtailment can be kept at a low level of 4.3 % of the total electricity generated.

Moreover, Figure 3.11 also shows similar effects as in the Steinkjer case in terms of self-consumption and grid import. During the day, we observe a high share of self-consumption due to the higher solar irradiation. In contrast, at night, the electricity supply is mainly covered by grid imports. The centralized optimization in the London case results in a self-consumption of 34.7 % and grid import of 65.3 %, very similar to the Steinkjer case. Finally, the system costs amount to 3 844 GBP, representing the cheapest solution for the community.

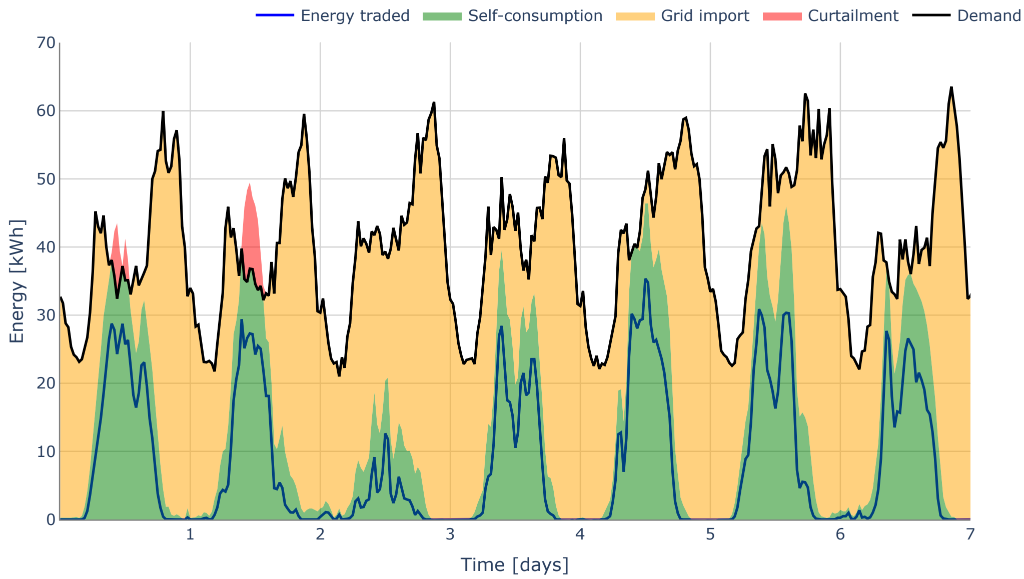


Figure 3.11: London case - Grid import, energy traded, self-consumption, curtailment and demand for the first seven days of the centralized model

Competitive model - Trading algorithms

In this section we analyze the MUDA and P2P trading algorithm for the London case. As in the Steinkjer case, we solved the model with both bidding simulations, but focused on the results of the skewed normal distribution for the same reasons as described in Section 3.5.2. The KPIs for the uniform distribution can be found in Table A.2, in Appendix A.

Table 3.7 shows the KPIs of the trading algorithm with skewed normal distribution compared to centralized optimization for the London case. Similar to the Steinkjer case, the KPIs of P2P are much closer to centralized optimization relative to MUDA. Accordingly, the use of P2P also leads to a relatively high self-consumption (32.3 %) and thus a low grid import (67.7 %). Using MUDA, in contrast, leads to a significant decrease in self-consumption (24.9 %) and an increase in grid import (75.1 %). As a result, the system costs for MUDA (4 423 GBP) are considerably higher than for P2P (3 981 GBP). However, with both trading algorithms, there is a substantial increase in curtailment. When using P2P, 10.8 % of the generated electricity is curtailed, and with MUDA the curtailment increases to 31.3 %. This is most likely due to the different characteristics of the London case, where more surplus energy is generated, and more local trading is required to achieve the optimal solution. As a result, we can see large quantities of traded energy but also more curtailment due to unsuccessful trading attempts.

Table 3.7: London case - Comparison of KPIs for centralized, MUDA and P2P for the skewed normal bidding simulation

KPI	Centralized	MUDA	P2P
System cost [GBP]	3 844	4 423	3 981
Grid import [kWh] (%)	25 063 (65.3)	28 817 (75.1)	25 970 (67.7)
Self-consumption [kWh] (%)	13 295 (34.7)	9 542 (24.9)	12 389 (32.3)
Curtailment [kWh] (%)	596 (4.3)	4 350 (31.3)	1 503 (10.8)
Energy traded [kWh]	8 193	4 439	7 286

Looking at Figure 3.12 and Figure 3.13, we can observe similar effects as in the Steinkjer case. However, due to the characteristics of the London case and the increased energy surplus, the impacts of the trading algorithms are even stronger. Figure 3.12 shows high grid imports and curtailment occurring in the same time-steps when using MUDA. Simultaneously, the self-consumption is significantly lower with MUDA compared to centralized optimization. This means that a large amount of locally generated electricity is curtailed unnecessarily, and costly electricity has to be supplied from the main grid.

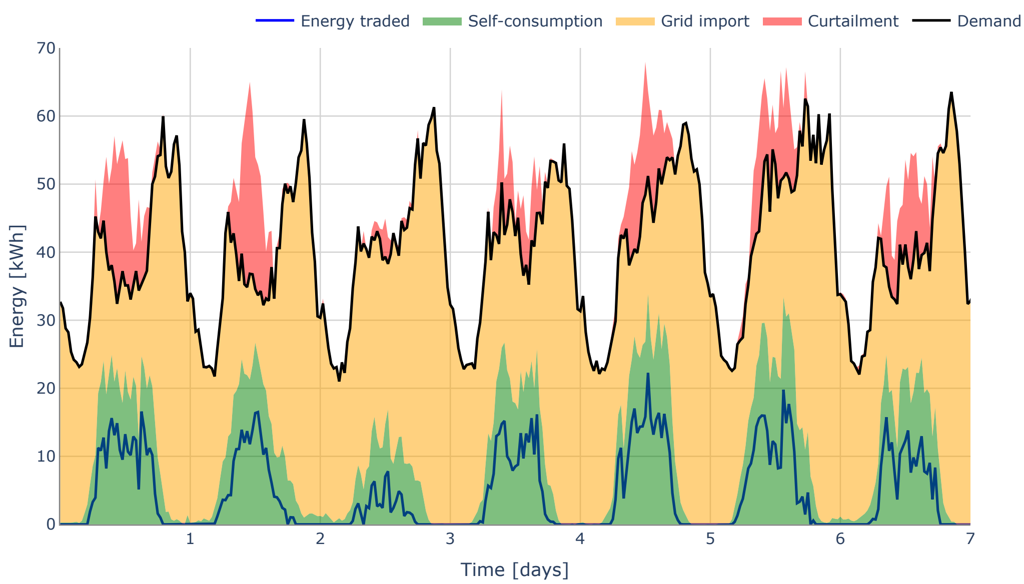


Figure 3.12: London case - Grid import, energy traded, self-consumption, curtailment and demand for the first seven days when using the MUDA algorithm

Figure 3.13 displays that grid import and curtailment also occur in the same time-step when using P2P. However, this happens less frequently and to a smaller extent. Consequently, self-consumption is significantly higher with P2P when renewable generation is high, leading to almost complete self-sufficiency in some time-steps.

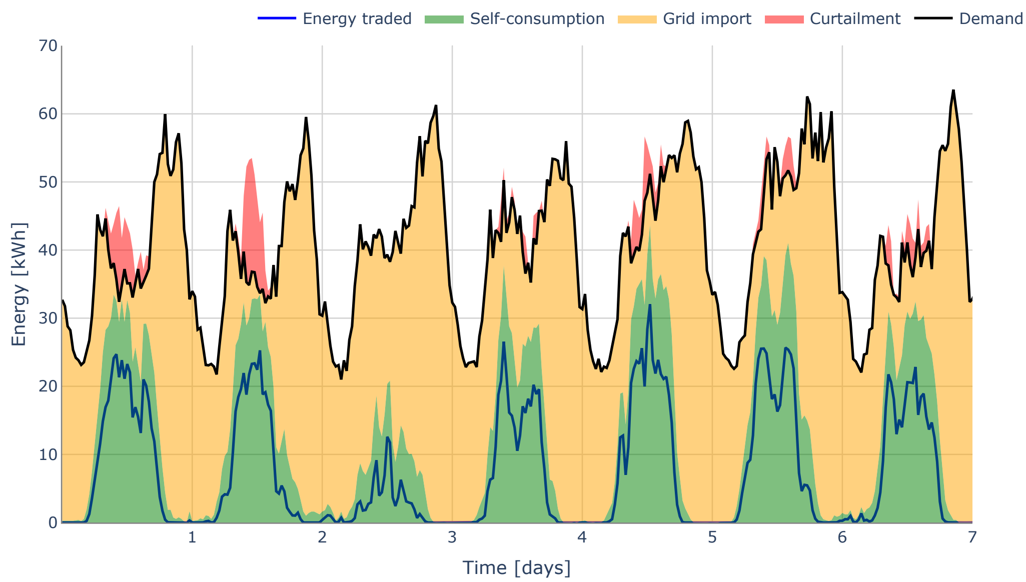


Figure 3.13: London case - Grid import, energy traded, self-consumption, curtailment and demand for the first seven days when using the P2P algorithm

Figure 3.14 illustrates the average prices of trades in the first week relative to the reference price and grid price. As in the Steinkjer case, when MUDA is used, the average prices are mostly higher than the reference prices and the P2P average prices, especially in time-steps with low renewable generation. Again, the average price for all transactions when using MUDA is higher (0.050 GBP/kWh) than P2P (0.049 GBP/kWh). Nevertheless, the average prices of MUDA and P2P are much closer in the London case compared to the Steinkjer case. Furthermore, we can also observe the effect of fluctuating P2P average prices. However, this effect is weaker compared to the Steinkjer case.

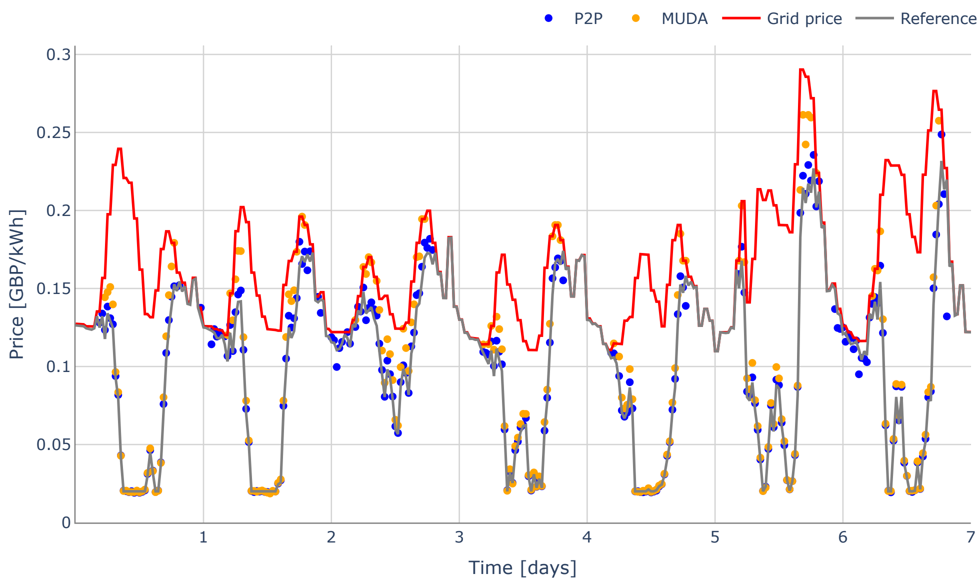


Figure 3.14: London case - Average Prices for each time-step in addition to grid price and reference price for the first week of the simulation

3.5.4 Comparison of the trading algorithms

Overall, the results indicate a significantly lower efficiency of MUDA compared to P2P in terms of engaging local trading and avoiding curtailment. The reason for this is most likely in the characteristics of the trading algorithms. With MUDA, the successful matching of bids and offers depends on the market equilibrium of the other sub-market. For example, if the market price of the right sub-market is higher than a bid or lower than an offer of the left sub-market, they cannot participate in the trading. Another reason for unsuccessful matching with MUDA is that random market splitting can lead to an uneven demand and supply side on each sub-market. This can lead to residual bids or offers remaining on each sub-market, which are also pushed out of trading.

Furthermore, in times of low renewable generation, there is a large surplus of bids and only a few offers. Consequently, there are only a few selected bids, which means that many other bids cannot be traded. With "Vickrey"-MUDA, this leads to an increase in trading fees and higher prices for buyers. The trading fees can even drive the prices for buyers above the grid prices. In this case, buyers would choose to buy electricity from the grid, and local generation would have to be curtailed.

Compared to the result of MUDA, the use of P2P leads to significantly more trading. The P2P algorithm allows multiple iterations of random matching of bids and offers. Therefore, there is a higher probability of a bid finding an offer to trade with. However, the results show strong fluctuations in the average prices. This is because bids and offers are traded at the price midway between them, and therefore the trading prices of simultaneous trades from different peers vary. These average price fluctuations are smaller when renewable generation is high and more bids and offers are submitted. It indicates that average prices converge towards the reference price when the number of bids and offers is higher. In times of low generation, the number of offers is limited, and only a few trades determine the average prices leading to stronger fluctuations in the average prices. Comparing the two cases confirms this, as the effect is much stronger in the Steinkjer case, where there are fewer households and, thus, fewer bids and offers.

After analyzing the trading algorithms and investigating the underlying characteristics, it should also be examined to what extent their performance changes between the Steinkjer and London case. The cases have some key differences, e.g., the number of households, the distribution of renewable generation, and the average household demand. These differences are expected to influence the results and the performance of the trading algorithm.

Table 3.8: Difference of the trading algorithms to centralized optimization in percentage

	Steinkjer			*London*		
KPIs	**Cent.**	**MUDA**	**P2P**	**Cent.**	**MUDA**	**P2P**
System cost	27 037	+3.9	+0.7	3 845	+15.0	+3.6
Grid import	39 553	-6.8	-1.2	25 063	-28.2	-6.8
Self-consumption	22 388	+3.8	+0.7	13 295	+15.0	+3.6
Curtailment	615	+247.4	+44.9	596	+630.0	+152.2
Energy traded	2 506	-60.7	-11.0	8 193	-45.8	-11.1

To compare the performance of the trading algorithms between the Steinkjer and London cases, we calculated the percentage gap to centralized optimization for MUDA and P2P, as shown in Table 3.8. This again shows that both trading algorithms perform less effectively in the London case, as more energy has to be traded, which is described in Section 3.5.3.

As further analysis, we calculated to which extent the performance of the trading algorithm differs between the cases. To this end, we divided the percentage gap of the system costs when using MUDA by the percentage gap of the system costs when using P2P. This shows us how much more efficient the P2P algorithm is for a given case compared to MUDA. In the Steinkjer case, the difference from the centralized optimization is 5.48 times higher for MUDA than for P2P. In contrast, in the London case, the difference is considerably lower at 4.24. This indicates that MUDA increases the performance in larger markets with more participants.

3.6 Conclusion

In this paper, we studied the market efficiency of two trading algorithms applied to LEMs. We looked at how to represent local electricity trading in a LEM using the MUDA and P2P trading algorithms. Based on real-case data from Steinkjer and London, we simulated trading in a LEM for both algorithms vis-a-vis a reference case (based on centralized optimization).

In general, we found that P2P gives better results in terms of trading efficiency compared to MUDA in both cases. This is reflected in less curtailment and more traded electricity when using P2P. However, P2P might sometimes be unfair as random pairing can lead to a large difference in trading prices for the same product. In addition, the "Vickrey"-MUDA results in higher average prices due to trading fees. The higher buying costs can make local trading less attractive, but this revenue can be used for further investments in the community that benefits the participants.

Furthermore, the trading algorithms have lower efficiencies in the London case, in which more electricity trading occurs. This implies that curtailment increases when a higher energy surplus at the household level is up for trading. However, when comparing the two cases, MUDA reduces the gap (compared to the centralized optimization) in the London case, indicating that MUDA works better with a larger number of participants.

The paper also focused on how the underlying behavioral assumptions of participants (bids and offers) affect the trading outcome. Therefore, we simulated bids and offers based on a uniform and a skewed normal distribution. We can see from the KPIs that the skewed normal distribution works better for both trading algorithms. Consequently, incorporating participants' behavioral assumptions affects the outcome and improves the results when the generated bids and offers favor the trading algorithm.

In short, we found that P2P is an efficient trading algorithm that results in relatively much electricity trading and less curtailment. MUDA seems more fair than P2P but has lower market efficiency. Nevertheless, it can still be beneficial in larger communities if trading fees are adequately used. Furthermore, bidding simulations affect the outcome of trading algorithms and improve market efficiency if the underlying assumptions favor the trading algorithm. The results indicate that trading fees in the "Vickrey" MUDA can lead to higher prices that may even exceed the grid prices, resulting in fewer matches of bids and offers. Therefore, there is reason to believe that other MUDA variants, such as the "Lottery" MUDA, where bids and offers are randomly selected without trading fees, may be more suitable for LEMs.

An important point for further research is to consider flexibility of the participants. Batteries, such as electric vehicles, can allow for a more dynamic and strategic trading process, as participants are not always forced to sell when they have a surplus or buy when they are not producing. Another relevant aspect to consider is the trade-off between the costs of batteries and costs of curtailment. In addition, demand response can be included to analyze the price responsiveness of participants.

4 | Moving onwards

In our first paper, presented in Chapter 3, we explored the possibility of using different trading algorithms in a local electricity market in Norway and the UK. However, there are still many unanswered questions in this research field. Therefore, we want to take one step further and address unexplored areas of this field.

Firstly, we only allocated renewable generation to prosumers and did not consider battery storage. Nevertheless, battery storage is becoming increasingly common, especially when a household already has fluctuating renewable generation, such as PV. Therefore, in Chapter 4.1, we propose a bidding strategy for individual sellers with renewable generation and battery storage.

Secondly, we concluded that clearing LEMs often results in large amounts of surplus electricity. To avoid curtailing this surplus or selling it at a relatively low feed-in tariff, we propose a new way to create more value for this surplus in our second paper, presented in Chapter 5. We further explain this idea and the road to this new market in Section 4.2.

4.1 Optimal bidding strategy with batteries

In our first paper, we used trading algorithms to clear local electricity markets, but in a system without batteries. However, it is important to have methods to include batteries because they have a significant impact on bidding strategies and participants' willingness to buy and sell. With batteries, prosumers are no longer forced to sell their generation at exactly the same time-step, but are more flexible to shift their demand to times when prices are more attractive.

This encouraged us to find a way to include batteries in the setting of the first paper. Therefore, we propose an optimal bidding strategy with batteries for individual sellers with surplus energy that can be used for trading algorithms. We focused on sellers with batteries because they must choose between selling at a certain time-step or storing the electricity and consuming or selling it later. In contrast, buyers must purchase electricity to satisfy their demands simultaneously. This approach also incorporates the reference price presented in Section 3.3.2.

In this section, we will introduce the methodology for including batteries for sellers and present a small example based on the Steinkjer data described in Section 3.3. Furthermore, we reflect on this model and provide suggestions for future implementations.

4.1.1 Methodology

This model uses optimization to find optimal bidding quantities and prices for each selling prosumer in each time-step. However, since competitive markets with trading algorithms are imperfect, as explored in the first paper, the outcome of the market-clearing can deviate from the optimal decision plan. For this reason, the model uses a rolling horizon where a new decision plan for the next 24-hours is used in every time-step, thus accounting for any changes in the actual trading but also including long-term planning of decisions.

Table 4.1 provides an overview of the parameters, variables, and scalars used in the model formulation of the optimal bidding strategy.

Table 4.1: Overview of parameters, variables and scalars used in the optimal bidding strategy with batteries

Parameters	
$res^{(t)}$	Available renewable generation in time-step t
$dem^{(t)}$	Demand in time-step t
$P_G^{(t)}$	Grid price in time-step t
$P_{ref}^{(t)}$	Reference price in time-step t

Variables	
$G^{(t)}$	Total grid import in time-step t
$G_{dem}^{(t)}$	Total grid import in time-step t allocated to demand
$G_{bat}^{(t)}$	Total grid import in time-step t allocated to the battery
$S^{(t)}$	State-of-Charge of the battery in time-step t
$C^{(t)}$	Battery charge in time-step t
$D^{(t)}$	Battery discharge in time-step t
$D_{dem}^{(t)}$	Battery discharge in time-step t allocated to demand
$D_Q^{(t)}$	Battery discharge in time-step t allocated to the bid
$P_b^{(t)}$	Bidding price in time-step t
$Q^{(t)}$	Bidding quantity in time-step t
$RES_{dem}^{(t)}$	Renewable generation in time-step t allocated to demand
$RES_{bat}^{(t)}$	Renewable generation in time-step t allocated to the battery
$RES_Q^{(t)}$	Renewable generation in time-step t allocated to the bid

Scalars	
η_{ch}	Charge efficiency
η_{dch}	Discharge efficiency
$C_{rate}^{(t)}$	Maximum charging rate
$D_{rate}^{(t)}$	Maximum discharging rate

This model optimizes the costs of an individual seller. The objective here is to minimize the grid import $G^{(t)}$ at the grid price $P_G^{(t)}$ minus the revenue from local trading (i.e., the quantity $Q^{(t)}$ at the bid price $P_b^{(t)}$) for all time-steps.

$$min \sum_t [P_G^{(t)} \cdot G^{(t)}] - \sum_t P_b^{(t)} \cdot Q^{(t)} \tag{4.1}$$

Because each variable can be allocated to internal consumption, demand, trade, and curtailment, they need to be divided into sub-terms. This applies to grid import, discharge, renewable generation, and demand. The following equations are balance equations representing the variables and their sub-terms.

First, the total grid import $G^{(t)}$ at each time-step is allocated either directly to the demand ($G_{dem}^{(t)}$) or to the battery ($G_{bat}^{(t)}$) to store electricity for later use, as shown in Equation (4.2).

$$G^{(t)} = G_{dem}^{(t)} + G_{bat}^{(t)} \tag{4.2}$$

Equation (4.3) determines whether the battery discharge $D^{(t)}$ is used to cover the own demand $D_{dem}^{(t)}$ or to place a bid $D_Q^{(t)}$, or a combination of both.

$$D^{(t)} = D_{dem}^{(t)} + D_Q^{(t)} \tag{4.3}$$

Furthermore, similar to the grid import, the total renewable generation $res^{(t)}$ can be consumed directly ($RES_{dem}^{(t)}$) or stored in the battery ($RES_{bat}^{(t)}$). However, unlike grid import, renewable generation can also be used to submit a bid with the quantity $RES_Q^{(t)}$. This is shown in Equation (4.4).

$$res^{(t)} = RES_{dem}^{(t)} + RES_{bat}^{(t)} + RES_Q^{(t)} \tag{4.4}$$

Equation (4.5) shows that the electricity covering the total demand $dem^{(t)}$ can come from three different source: the main grid ($G_{dem}^{(t)}$), the battery ($D_{dem}^{(t)}$) or renewable generation ($RES_{dem}^{(t)}$). Since this model only considers the seller perspective, there is no locally bought electricity to meet demand.

$$dem^{(t)} = G_{dem}^{(t)} + D_{dem}^{(t)} + RES_{dem}^{(t)} \tag{4.5}$$

For the final allocation balance, Equation (4.6) determines the source of the electricity from the bidding quantity $Q^{(t)}$ at each time-step. A seller can offer electricity from the battery ($D_Q^{(t)}$) or directly from renewable generation ($RES_Q^{(t)}$) in the LEM.

$$Q^{(t)} = D_Q^{(t)} + RES_Q^{(t)} \tag{4.6}$$

Equation (4.7) determines the state of charge $S^{(t)}$ of the battery at each time-step. The state of charge depends on the state of charge of the previous time-step and charging or discharging decisions. The charging and discharging are both subject to the battery efficiencies, η^c, and η^d.

$$S^{(t)} = S^{(t-1)} + \eta_{ch} \cdot C^{(t)} - \frac{1}{\eta_{dch}} \cdot D^{(t)} \tag{4.7}$$

The battery is constrained to physical properties, represented by an upper bound, $\overline{S}$ and lower bound $\underline{S}$ for the state of charge, as shown in Equation (4.8). In addition, they are restricted to charging and discharging rates $D^{(t)}_{rate}$ and $C^{(t)}_{rate}$ according to Equation (4.9) and (4.10).

$$\underline{S} \leq S^{(t)} \leq \overline{S} \tag{4.8}$$
$$0 \leq C^{(t)} \leq D^{(t)}_{rate} \tag{4.9}$$
$$0 \leq D^{(t)} \leq C^{(t)}_{rate} \tag{4.10}$$

Equation (4.11) sets the range of the bidding price $P^{(t)}_b$. It can range from the market reference price $P^{(t)}_{ref}$ as a lower bound up to the grid price $P^{(t)}_G$. The market reference price [1] reflects the state of the local market in terms of renewable electricity availability, demand, and wholesale prices. The grid price, in contrast, is the upper bound since buyers would not buy electricity that is more expensive than the grid price.

$$P^{(t)}_{ref} \leq P^{(t)}_b \leq P^{(t)}_G \tag{4.11}$$

Furthermore, we determine the quantity using Equation (4.12). This equation gives a relation between the bidding price and quantity since all other variables are fixed for a given time-step. In this model, the quantity decreases as prices increase. Consequently, no quantity is offered when the bidding price is equal to the grid price and the maximum quantity Q_{max} is bid at the market reference price. This relation between the bidding price and quantity increases a seller's chance of staying in the market at the time-steps of high renewable generation. In contrast, if the price were high for large quantities, other sellers might be selected for trading, leaving the seller unable to sell its renewable generation.

$$Q^{(t)} = \frac{-1}{P^{(t)}_G - P^{(t)}_{ref}} \cdot (P^{(t)}_b - P^{(t)}_G) \cdot Q_{max} \tag{4.12}$$

Finally, the model has a maximum bidding quantity, which is subject to two constraints given by Equation (4.13) and (4.14). For both constraints, the term of renewable generation assigned to the bidding quantity is identical. However, two different constraints on the battery must be considered.

[1] For a detailed explanation of the market reference price, see Section 3.3.2

First, the battery discharge must not exceed the discharging rate $D_{rate}^{(t)}$ in any time-step. Thus the first constraint of the maximum bidding quantity is given by the sum of the discharging rate and the renewable generation, as shown in Equation (4.13). Secondly, the battery cannot discharge more electricity than is available, which is the state of charge in time-step t, minus the lower bound. Hence, the maximum bidding quantity is also constrained by the sum of the available discharge and the renewable generation, as shown in Equation (4.14).

$$Q_{max} \leq D_{rate}^{(t)} + RES_Q^{(t)} \tag{4.13}$$

$$Q_{max} \leq S^{(t)} - \underline{S} + RES_Q^{(t)} \tag{4.14}$$

4.1.2 Application to Steinkjer case

To give an application example of this model, we applied this model to the Steinkjer case, which we described in Section 3.4. One household equipped with a 10 kW PV system and a 4 kWh battery is selected for this example. The battery specifications are presented in Section 5.4. To show variations in the strategy over time, we chose the first five days.

Figure 4.1 illustrates the bidding price to the grid price and market reference price, as well as the bidding quantity over the five days. The figure shows that bidding quantities only occur during the day. In addition, bidding quantities mainly occur when the battery state of charge is high or at a maximum. This indicates that the prosumer benefits more from shifting its surplus electricity to cover the demand later. When the state of charge is at its maximum, as on the first, second, or fourth day, there is no better option than to sell the quantity, as it would be curtailed otherwise. Furthermore, grid prices are highest during the day, so prosumers can earn the most by selling their surplus at these times. On the third day, there is no bidding quantity at all because no surplus electricity is generated.

Moreover, the figure also shows that the prosumers' bidding price is mostly very close to the market reference price when no quantities are bid. However, when quantities are bid, in turn, the bidding price jumps to a higher price. These jumps to higher bid prices vary in size. On the first or second day, for example, the spikes are higher than on the fifth day, on which the bid price is relatively low. Simultaneously, the bidding price on the fifth day is significantly higher than on the other days. This follows from the relation between the bidding price and quantity in Equation 4.12, where bid quantity increases as price decreases. As a result, the prosumer is willing to sell larger quantities at lower prices, increasing its chance of selling all of its quantity rather than curtailing or selling at a relatively low feed-in tariff.

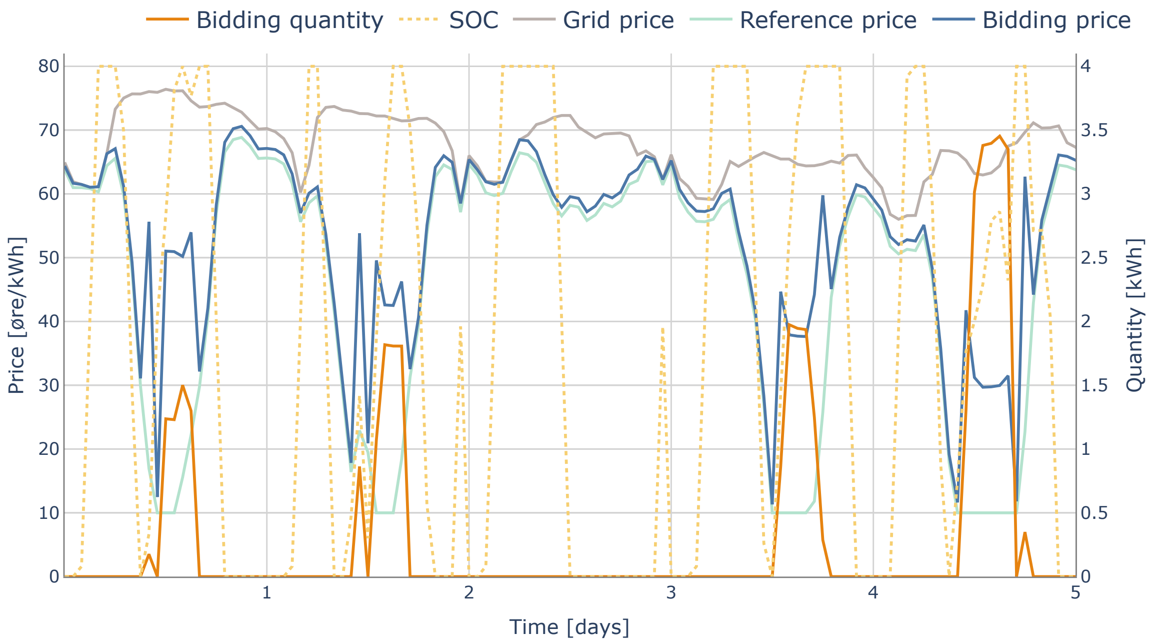


Figure 4.1: Bidding prices and quantities of the prosumer in the five-day period

The proposed model gives a potential strategy to create bidding prices and quantities for individual sellers. Clearly, there are other ways to create bidding prices and quantities for prosumers with renewable generation and battery storage. For example, the descending relation between the bidding price and quantity from Equation 4.12 could be replaced by another function that would assume different preferences and thus results in a different bidding strategy. Furthermore, stochasticity should also be considered in future implementations, as the actual generation, demand, and grid price may deviate from forecasts. Finally, advanced technologies such as machine learning can also help optimize an individual seller's bidding strategy.

4.2 Dealing with LEM surplus - The step towards a new market

Local electricity markets enable better utilization of renewable energies, but electricity surplus can still occur after the LEM clearing. Our first paper finds different amounts of surplus depending on the trading algorithm and the market configuration. Specifically, competitive markets are prone to produce surplus electricity because they are imperfect. However, cooperative markets can also generate surplus electricity when total renewable generation is higher than total demand.

Currently, there are two ways to deal with the surplus. The least economically efficient option is to curtail the electricity without receiving any money. The second, more economical option for prosumers is to sell the surplus electricity to the main grid at a relatively low feed-in tariff if the system allows it. This can currently be done in Germany and many other countries. However, the feed-in tariffs are not very beneficial for prosumers, as they only offer a low, often fixed, remuneration for their injected power. From a grid perspective, one can argue that these fixed feed-in tariffs are also not very efficient, as they do not send any price signals of the system situations. This can lead to high renewable electricity feed-in at the same time, for example, because PV systems tend to have high production peaks simultaneously, and thus potentially lead to increased system losses and violations of grid constraints.

Therefore, in the second paper of our thesis, we want to find a way to increase the value of prosumers' surplus electricity. To do this, we propose a new "Community-to-X" market, where LEMs can trade their surplus electricity with other LEMs or external players. In addition, we suggest an extension called C2X+ where DSOs can participate in the market to reduce the grid impact.

Our motivation to create this C2X market is manifold. First, the C2X market can provide financial benefits to both prosumers within LEMs and external players. Prosumers can gain increased revenue from selling their surplus energy while providing a cheaper alternative to the grid price for external players. In addition, it is unrealistic for small, individual prosumers to participate in larger markets to trade this surplus. In the C2X market, however, prosumers are aggregated into LEMs, operated by a community manager.

Other primary beneficiaries of C2X markets are DSOs. On the one hand, they can reduce grid problems through the C2X+ market, making grid investments less urgent. This also benefits prosumers and consumers, as these investment costs are often directly passed on to end-users. On the other hand, in the C2X market, prosumers are grouped into LEMs, so DSOs only need to interact with community managers and not with a large number of prosumers.

In conclusion, we believe the C2X market is a great expansion of the concept of LEMs, leading to even better utilization of renewable energy. Moreover, many market participants, such as prosumers, DSOs, and external players, can benefit from the C2X market. Chapter 5 presents our second paper and analyzes the concept of a C2X market in a German distribution grid.

Paper 2

A new marketplace for trading among plus energy neighborhoods: Community-to-X and DSO interactions

Manuscript to be submitted to an international journal

5 | A new marketplace for trading among plus energy neighborhoods: Community-to-X and DSO interactions

Abstract

Local electricity markets (LEMs) are a rising research topic as we try to facilitate a green transition in the energy system. These LEMs can be used to manage distributed energy resources (DERs) and accelerate the shift to prosumerism. However, there is still little focus on how these markets affect the physical grid and even less on how LEMs can interact with other LEMs or other market participants. Therefore, this paper addresses the following research questions: What new marketplaces will reward the surplus value of solar and wind power after internal LEM clearing? Is "Community-to-X" (C2X) a viable option for remunerating surplus energy?; What impact does LEM trading have on the grid in terms of voltage variations and system losses? What is the role of the DSO in a C2X market? We answer these questions by investigating seven energy communities connected through a low-voltage grid in Bavaria, Germany. The energy communities have different configurations in terms of size, renewable generation (PV or wind), and battery distribution. We implemented a business-as-usual model and a community-based LEM model used as a reference for the C2X market. The C2X market is a new idea where LEMs can trade their surplus energy with other market participants. We found that a C2X market with various players proved to be economically beneficial for all participants, especially for selling communities. Lastly, the extended C2X+ market can facilitate interactions between a DSO and LEMs and reduce potential grid impacts.

5.1 Introduction

As the green energy transition gains momentum and investment costs decrease, the deployment of distributed energy resources (DERs) is becoming increasingly attractive. Global installed PV capacity increased by 179 GW from 2017 to 2020 (IEA, 2022a), demonstrating the rapid expansion of DERs. This is driving the transformation from passive consumers to active prosumers.

As DERs find their way into our homes, the idea of local electricity markets (LEMs) has emerged and is becoming more relevant in research. The goal of LEMs is to optimally utilize locally generated electricity in terms of financial savings and reduced grid impacts. To achieve this, there are various configurations of LEMs, from community-based models to competitive local markets (Sousa et al., 2019). However, most research analyzes the benefits of a single LEM clearing without interactions with other players in the grid.

Surplus electricity in LEMs can occur for several reasons, but common causes are insufficient battery capacity, excessive installed capacity, or both. Moreover, imperfect markets can contribute to even more surplus after the market-clearing (Heilmann et al., 2022). However, without further connection to other participants, this surplus will be curtailed or sold at a relatively low feed-in tariff. Therefore, as the next step in this discussion, we propose a "Community-to-X" (C2X) market where communities can trade their power surpluses and deficits with other market participants. The goal of this market is to enable communities to create more economic value for their production. Furthermore, we also explore an extension of this market where the DSO can interact with participants in the distribution grid.

Based on this discussion, we address the following research questions;

- What new marketplaces will reward the surplus value of solar and wind power after internal LEM clearing? Is C2X a viable option for remunerating surplus energy?
- What impact does LEM trading have on the grid in terms of voltage variations and system losses? What is the role of the DSO in a C2X market?

We address these questions by looking at a power grid in Germany with different load and generation profiles and modeling two markets; one for local electricity trading within communities and a second C2X market for trading the plus energy neighborhood's surplus electricity. We investigate how this trading affects the economy of each market, in addition to potential grid impacts of both LEM and C2X trading. A reference case representing "business-as-usual" without any markets is used to evaluate the outcomes of the two markets.

The remaining sections of this paper are structured as follows: In section 5.2, we explore related literature and state our contributions to this research field. The methodology, including assumptions, system descriptions, and model formulations, are described in Section 5.3. Furthermore, data and relevant system information are given in Section 5.4. Section 5.5 presents the results of this study and discusses the findings. Lastly, 5.6 concludes this paper and gives remarks on potential future research.

5.2 Related Literature

As the use of DERs has increased significantly in recent years, the research of local electricity markets has gained greater importance. Mengelkamp and Weinhardt (2018) define a LEM as a group of prosumers and consumers that are geographically and socially close and have a local market for trading electricity with each other. This puts a strong emphasis on electrical proximity, as LEMs aim to prioritize the use of local DERs over long-distance energy exchange (Bjarghov et al., 2021). However, the intermittency and uncertainty of solar and wind production create opportunities to trade flexibility among participants of the LEM (Jin, Wu, and Jia, 2020).

5.2.1 LEM clearing

Over the last few years, ways for prosumers and consumers to trade electricity locally have been explored. Different approaches to local trading can be categorized into pooled (community-based) trading (e.g., Lüth et al., 2018; Moret, Pinson, and Papakonstantinou, 2020), fully decentralized (P2P) trading (e.g., Sorin, Bobo, and Pinson, 2018; Neves, Scott, and Silva, 2020) and hybrid trading (e.g., Long et al., 2017; Liu et al., 2015). In community-based markets, the community manager handles the trading centrally using a defined market-clearing mechanism to match bids and offers. In contrast, fully decentralized markets are based on bilateral contracts between actors and allow the preferences of prosumers to be considered. Finally, hybrid P2P markets combine the two previous markets. Electricity trading can take place at different layers, meaning that communities and peers can directly interact with each other at each layer. (Sousa et al., 2019; Bjarghov et al., 2021)

Many recent studies have focused on analyzing the performance of LEMs and the benefits for prosumers and consumers (i.e., Lüth et al., 2018; Dynge et al., 2021). The market design of LEMs plays a crucial role in the performance of LEMs (Okwuibe et al., 2021). The literature mainly addresses the community-based model, either in a cooperative or non-cooperative way. The cooperative approach aims to maximize benefits for society as a whole, while the non-cooperative approach seeks to create an efficient market for competition.

In cooperative market design, centralized optimization is usually chosen for market-clearing, which maximizes social welfare. This design is often used in the literature to prove a concept or investigate technical aspects of the power system. Lüth et al. (2018), for example, analyzes the role of battery storage in a LEM under perfect market assumptions and finds significant saving potential for end-users. Hashemipour, Granado, and Aghaei (2021) proposed dynamic clustering of local markets, where peers are clustered into smaller virtual LEMs based on optimal daily matching of load and renewable profiles. This reduces the computational effort and improves the efficiency of local electricity sharing.

Other studies focused more on incorporating competition, prosumers' preferences, and bidding strategies in non-cooperative models. Sorin, Bobo, and Pinson (2018), for example, introduced a fully decentralized P2P market structure using multi-bilateral economic dispatch that enables product differentiation based on individual preferences. Furthermore, Mengelkamp et al. (2018) applied a blockchain-based P2P model to a Brooklyn microgrid considering various market components.

Further studies have been conducted investigating the performance of LEMs with cooperative and non-cooperative models, which have been collected in different review papers such as Bjarghov et al. (2021), Sousa et al. (2019), Tushar et al. (2021), and Tushar et al. (2020). However, these studies primarily focus on efficient economical operation in a local market. There is little research on how LEMs can act as market participants to trade surplus energy with other participants in the distribution grid. We refer to all types of this interaction as C2X trading.

5.2.2 Inter-community trading

Previous research on interconnected plus energy neighborhoods has mainly focused on optimal power flow and congestion management.Li et al. (2020), for example, solved the coupled optimal power flow (OPF) problem by first solving microgrids locally and then finding the optimal solution for the coupled OPF with cooperative negotiation between each microgrid. Liu et al. (2020), in contrast, proposed a multi-microgrid congestion management method in the distribution grid based on non-cooperative P2P trading with game theory under normal grid operation.

Some studies have also been conducted on energy trading between microgrids. Wang and Huang (2016), for instance, developed an energy trading and scheduling strategy for interconnected microgrids using an incentive mechanism based on Nash bargaining. Gregoratti and Matamoros (2014) investigated energy trading between multiple islanded (no main grid) microgrids, intending to minimize each microgrid's cost. Furthermore, Zhao et al. (2020) employed a two-layer framework for energy trading in multi-microgrids based on blockchain with continuous double auction. Here, a central node collects microgrid information (lower layer) and sends it to the trading market (higher layer).

Another approach to trade surplus energy outside a LEM is through prosumer participation in the wholesale day-ahead and intraday market. Zepter et al. (2019) developed an interface between the wholesale market and the prosumer community using a two-stage stochastic model for sequenced decision making. This idea shows how a LEM can interact with or act as an aggregator in the wholesale market and ultimately reduce the community's electricity costs.

5.2.3 Grid impacts

Zhang et al. (2018) proposed a hierarchical system structure to categorize the key elements of P2P energy trading. In this context, they emphasize the critical role of the power grid layer alongside the business, control, and ICT layer (Zhang et al., 2018). However, most studies do not adequately consider grid impacts and constraint violations of local energy sharing on the low-voltage grid (Dudjak et al., 2021; Guerrero, Chapman, and Verbič, 2018).

According to Zhang et al. (2018), LEMs can facilitate higher penetration of renewable energy in the power grid without causing any major effects on the upper levels of the grid. However, distributed generation can still cause problems in the low-voltage grid. Dudjak et al. (2021) categorizes the grid impacts into voltage variation, phase imbalance, system power peak, line congestion, cyber-attack vulnerability, and distribution system planning. In addition, this study found divergent findings for grid impacts in their review paper as current studies lead to scenario-based results.

Voltage variations are stated as the biggest challenge associated with LEMs in most research. Two main reasons are PV generation peaks leading to overvoltage and load peaks causing undervoltage (Dudjak et al., 2021). To not cause any major problems to the grid, the voltage variation should not exceed five percent (Agalgaonkar, Pal, and Jabr, 2013). Azim et al. (2019) analyzed a P2P market without considering the grid and then, in the next step, examined the grid for voltage violations. They showed that simultaneous P2P trading can cause voltage problems, leading to financial losses for the network operator. In addition, Dynge et al. (2021) compared a case with cooperative trading to a case without trading, considering power flows, voltage fluctuations, and system losses. Their results, however, indicate no significant impact on the grid when only PV systems are installed but more voltage fluctuations and system losses when batteries are added. Furthermore, Li et al. (2018) presented a LEM optimization that includes power flow equations and voltage constraints and showed that this eliminates voltage problems. Overall, research shows that power flow and grid constraints should be incorporated into LEM modeling to avoid grid problems in real-life applications.

Another way to represent grid constraints is through power loss costs or network charges that aim to send the proper signals to reduce grid problems. Guerrero, Chapman, and Verbič (2018) introduced voltage sensitivity coefficients (VSC), power transfer sensitivity factors (PTSF), and power loss (PLSF) sensitivity factors to account for impacts from P2P trading. The VSC computes voltage violations and can disable transactions. The PTSF, in turn, calculates charges for grid congestion. Lastly, the PLSF was used in combination with the VCS to calculate the costs of losses. Furthermore, Moret and Pinson (2018) proposed a method to calculate spatially and temporally varying grid tariffs based on relative transaction costs representing the flow for the lines connecting different energy communities. Moreover, there are difficulties in allocating power losses because virtual and physical transactions are different. Therefore, Di Silvestre et al. (2018) suggested the Proportional Sharing Rule (PSR) index, which provides a more precise estimation of the power losses linked to a transaction between a generator and a consumer.

5.2.4 Contributions

As indicated earlier, LEMs have played a central role in the literature, but there are still some open questions. In short, this paper closes in on some of these questions and contributes the following to the research field:

- We propose a new market design idea for trading surplus electricity after clearing a LEM. This benefits the community through additional revenue and lower electricity costs for buyers. In addition, this brings a new notion to the LEMs literature where C2X has not been explored or conceptualized.
- We expanded methods of LEM bidding strategies, using a reference price to estimate bidding prices, combined with a trading algorithm to create the C2X market.
- We provide an example of applying cooperative electricity trading in a large case study in Germany with real-life consumption data (357 households). Moreover, we include grid impacts in the analysis, which have received limited attention (at this scale) in the literature.
- We provide an example of how DSO interactions can be used to reduce overvoltage and being economically beneficial for the participating communities.

5.3 Methodology

This section presents and describes the market models used and developed in this paper. These market models are further described in Section 5.3.1. The objective of using these models is to evaluate the economic impact of LEM trading and look at how a new market for communities can increase the monetary value of electric surplus. Furthermore, we use a balanced AC power flow to analyze the system and markets from a physical perspective. Further details around this are found in Section 5.3.2. Finally, the integration between the market models and the power flow analysis is described in Section 5.3.2.

Table 5.1 provides an overview of the used sets, scalars, parameters, and variables used in this paper.

Table 5.1: Overview of sets, scalars, parameters and variables used for both the market models and power flow model.

Sets	
$t \in T$	Hours t in time horizon T
$d \in D$	Days d in time horizon D
$h, p \in C$	Houses h and peers p in community C
$b, s \in M$	Buyers b and sellers s in market M

Scalars	
ψ^{P2P}	Loss factor for local trading
P_f	Feed-in tariff
$\overline{s}/\underline{s}$	Upper/lower bounds of storage level in battery
α/β	Maximum charge/discharge rate of battery
η^c/η^d	Battery charging/discharging efficiency
S_0	Initial and final battery state of charge

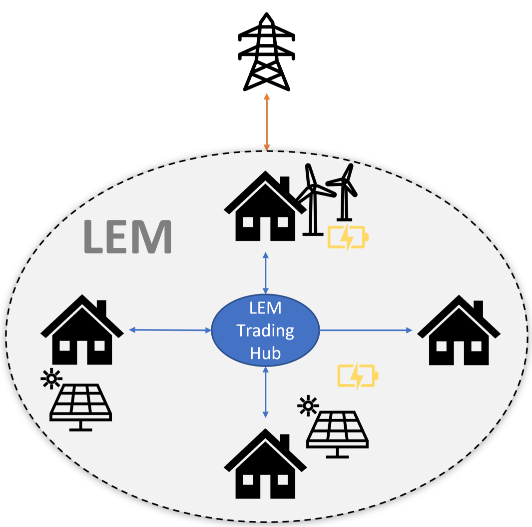
Parameters	
$dem^{(t,h)}$	Demand of house h in time-step t
$res^{(t,h)}$	Renewable energy production of house h in time-step t
$p_G^{(t)}$	Price of electricity from the grid in time-step t
$P_{ref}^{(t,C)}$	Reference price in time-step t for community C

Variables	
$G^{(t,h)}$	Grid consumption(import) of house h in time-step t
$F^{(t,h)}$	Grid feed-in of house h in time-step t
$I^{(t,h)}$	Total imported electricity of house h in time-step t
$I_p^{(t,h \leftarrow p)}$	Imported electricity of house h from peer p in time-step t
$X^{(t,h)}$	Total Exported electricity of house h in time-step t
$X_p^{(t,h \rightarrow p)}$	Exported electricity of house h to peer p in time-step t
$C^{(t,h)}$	Charge of battery of house h in time step t
$D^{(t,h)}$	Discharge of battery of house h in time step t

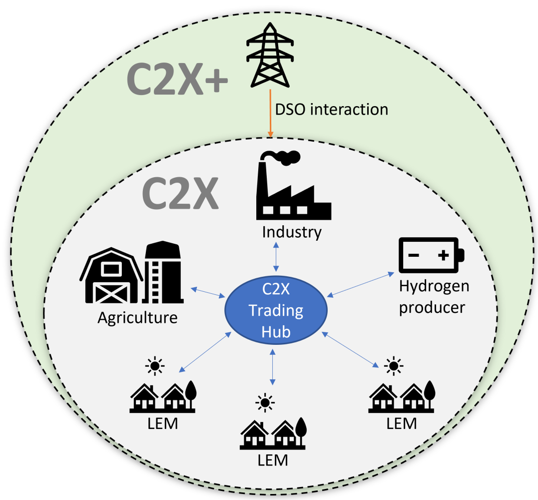
5.3.1 Market model formulation

Consider a distribution system with prosumers, consumers, and large generators, connected through a power grid with several low-voltage feeders and buses. Prosumers have a distribution of local renewable energy production (solar PV or Wind) and local batteries. The large generators have either large-scale solar PV systems or wind power production. For certain low-voltage grids, separated by low-voltage feeders, local electricity markets (LEMs) are created. These markets only consist of end-users, allowing for local electricity trading. The objective of these communities is to lower the community cost related to grid import, and thus self-consumption is prioritized within the community. The next step is to let the LEMs trade surplus between each other and other participants in a competitive market.

In this section, we will describe the three specific models used in this paper. The first is a reference model that represents a case with no market or trading possibilities, referred to as the "Business-as-usual" (BAU) model. The second model includes trading between peers in the same community, and we refer to this case as the "Local Electricity Market" (LEM) trading model. Lastly, we propose a new model, referred to as the "Community-to-X" (C2X) trading model. This model presents a new way for communities to trade and create value for their surplus electricity from the LEM clearing. In this market model, we also introduce a way for the DSO to interact in case of unwanted grid impacts through an expansion of the C2X model, which we refer to as C2X+ trading. A graphical illustration of these markets is presented in Figure 5.1.



a) LEM trading



b) C2X trading

Figure 5.1: Graphic illustration of the two main markets; LEM and C2X trading, in addition to the market expansion C2X+.

For all the models mentioned above, we disregard investment costs and do not consider the stochastic properties of either generation, prices, or load. We also do not consider battery degradation related to continuously charging and discharging the batteries. Furthermore, we assume unlimited supply from the grid. Since we run a separate power flow, we do not include losses in the market models. Hence, we set the loss factor, ψ, very close to 1[1].

Lastly, we assume the market situation is known for 24-hour periods, meaning we have multi-period optimization where we run the optimization for one day at a time. We also assume the only correlation between the 24-hour periods is the battery state of charge, and for simplicity, we set this to be fixed at 25% for both the initial and final time-step in each period. We also set boundaries on LEM trading so that export is only possible for participants with production at the same time-step.

Business-as-Usual model

The BAU model is an optimization of battery and grid import decisions where the objective is to minimize costs related to grid import for each participant. The model is based on the work by Lüth et al. (2018), but with some modifications as we do not allow trading between participants in this model. There is also an additional element in the objective function that accounts for surplus energy fed into the grid at a feed-in tariff, F. THE BAU model is only applied to households that are part of the communities in the following LEM trading model.

The objective function, given in Equation (5.1), minimizes system costs for each time-step t and each house h. Here we define costs as grid import, $G^{(t,h)}$, multiplied with the electricity price $P_G^{(t)}$. Income is defined as grid feed-in $F^{(t)}$ multiplied with a fixed feed-in tariff P_f.

$$min \sum_h \sum_t [P_G^{(t)} \cdot G^{(t,h)} - P_f \cdot F^{(t,h)}] \tag{5.1}$$

Among all houses $h \in H$, we need to obtain an energy balance so supply equals demand for each time-step $t \in T$. In this case, supply is the local renewable generation, $res^{(t,h)}$, grid import $G^{(t,h)}$, and battery discharge $D^{(t,h)}$, while demand consists of the households' electricity demand $dem^{(t,h)}$, grid feed-in $F^{(t,h)}$ and battery charge $C^{(t,h)}$. The energy balance is given in Equation (5.2).

$$res^{(t,h)} + G^{(t,h)} + D^{(t,h)} = dem^{(t,h)} + F^{(t,h)} + C^{(t,h)} \qquad \forall t \in T, \quad \forall h \in H \tag{5.2}$$

The batteries in the system are bound to physical characteristics, represented by an upper bound $\overline{s}$ and lower bound $\underline{s}$ for state of charge, as shown in Equation (5.3). Furthermore, they are also limited to charging and discharging rates α and β according to Equation (5.4) and (5.5).

$$\underline{s} \leq S^{(t,h)} \leq \overline{s} \tag{5.3}$$

$$0 \leq C^{(t,h)} \leq \alpha \tag{5.4}$$

$$0 \leq D^{(t,h)} \leq \beta \tag{5.5}$$

[1]The loss factor is included in the centralized models to avoid arbitrage and excessive trading of electricity. It should therefore be set very close to 1 (i.e., 0.999)

The state of charge for each battery is determined by Equation (5.6). Here, the state of charge in each time-step is determined by the previous time-step and the charging/discharging decisions. The charging and discharging are subject to the battery charging/discharging efficiencies η^c and η^d. Lastly, since we deal with multi-period optimization but do not consider any direct interconnection between the periods, we have a fixed initial and final state of charge, S_0. This gives us Equation (5.7) and (5.8) for the initial and final state of charge.

$$S^{(t,h)} = S^{(t-1,h)} + \eta^c \cdot C^{(t,h)} - (1/\eta^d) \cdot D^{(t,h)} \tag{5.6}$$

$$S^{(t,h)} = S_0 + \eta^c \cdot C^{(t,h)} - (1/\eta^d) \cdot D^{(t,h)} \qquad \forall t = 1 \tag{5.7}$$

$$S^{(t,h)} = S_0 \qquad \forall t = Nt \tag{5.8}$$

LEM trading model

Similarly to the BAU model, this model is also an optimization model based on the work by Lüth et al. (2018), but in contrast, we now include trading between peers within the same LEM. Thus, the objective function is the same as in the reference model, given in Equation (5.1). Since all local trading stays within the LEM, we do not include trading prices in the objective function as the income and cost of this trading cancel each other out. The battery constraints are also the same as in the BAU case and are given in Equations (5.3) to (5.8).

Since we now include trading, the model has several more constraints. Because all trading stays within each LEM, the total export of each house h is the sum of the export of house h to its peer p, according to Equation (5.9). Additionally, the export is constrained so that only houses with res generation in time-step t can export electricity, as given by Equation (5.10).

$$X^{(t,h)} = \sum_{p \neq h} X_P^{(t,h \to p)} \tag{5.9}$$

$$X^{(t,h)} = 0 \qquad \forall (t,h) | res^{(t,h)} = 0 \tag{5.10}$$

Furthermore, the import of house h from peer p is given as the export of each peer p to house h, including a loss factor ψ. This relation is given in Equation (5.11). Additionally, the total imported electricity of house h is given as the sum of imported electricity of house h from all its peers p, as given in Equation (5.12).

$$I_p^{(t,h \leftarrow p)} = \psi^{P2P} \cdot X_p^{(t,p \to h)} \qquad \forall p \neq h \tag{5.11}$$

$$I^{(t,h)} = \sum_{p \neq h} I_p^{(t,h \leftarrow p)} \tag{5.12}$$

As all traded quantities for each house stay within the LEM, the relationship between total traded quantities $X^{(t,h)}$ and $I^{(t,h)}$ is given by Equation (5.13).

$$\sum_{h}[\psi^{P2P} \cdot X^{(t,h)}] = \sum_{h} I^{(t,h)} \qquad \forall t \in T \tag{5.13}$$

The energy balance is similar to the one in the BAU model, but we now also include decision variables for total trading import $I^{(t,h)}$ and export $X^{(t,h)}$. The full energy balance constraint is shown in Equation (5.14).

$$\begin{aligned} &res^{(t,h)} + G^{(t,h)} + D^{(t,h)} + I^{(t,h)} = \\ &dem^{(t,h)} + F^{(t,h)} + C^{(t,h)} + X^{(t,h)} \qquad \forall t \in T, \quad \forall h \in H \end{aligned} \tag{5.14}$$

C2X trading model

In the C2X trading model, we aim to take advantage of the surplus electricity in each community which would otherwise be sold at a relatively low feed-in tariff to the grid. To do this, we propose a competitive market where the communities and other participants (i.e., industry, agriculture, or hydrogen producers) can sell and buy electricity from each other. Furthermore, we assume the participants within the LEMs will not change their decisions based on the outcome of the c2X market, i.e., the LEM clearing is not affected by the expected outcome of the C2X trading.

For the C2X market, we use a trading algorithm to clear the market. Based on findings by Heilmann et al. (2022), we chose to use the P2P trading algorithm to allow for a competitive market with relatively few participants. The P2P algorithm pairs random players in the market and allows them to trade if the buyer's price is higher than the seller's price. When buyers and sellers are successfully matched, they trade at a price midway between their bid and offer. If either player still has a quantity left to buy or sell after the first round they move on to the next iteration of the algorithm. This continues until there are no more possible pairings left either because all quantity is successfully traded or all remaining offers are higher than all remaining bids, so that no more matches can be made. Further descriptions of the algorithm can also be found in the Pymarket documentation (Kiedanski, Kofman, and Horta, 2022).

To use the P2P trading algorithm, we also need bids and offers for all buyers b and sellers s in market M. For external players, we find prices based on assumed preferences, while for the communities, we use a reference price to reflect each community's preference to sell or buy. The idea behind this reference price was first introduced in Heilmann et al. (2022). In this model, we use the same concept but with some modifications.

Each community C has its local reference price based on the available surplus in the given community. Since all surplus is fed into the grid, the sum of the feed-in

$F^{(t,h)}$ for all houses h in community C equals the surplus of each community C. The reference price $P_{ref}^{(t,C)}$ is then calculated for each community by using Equation (5.15).

Because the communities can sell surplus to the grid at a given grid tariff we assume they will never bid lower than this tariff. Hence, we use the feed-in tariff as a lower bound, as shown in Equation (5.16).

$$P_{ref}^{(t,C)} = (1 - \frac{\sum_h F^{(t,h)}}{\sum_h dem^{(t,h)}}) \cdot P_G^{(t)} \tag{5.15}$$

$$P_{ref}^{(t,C)} \geq P_f \tag{5.16}$$

C2X+ trading model

To further expand the idea of the C2X market, we also introduce a variant of the market referred to as the C2X+ market. By centralized management of DERs through LEMs, We propose a way for the DSO to interact with the community managers of LEMs in case of potential grid problems caused by specific buses within communities.

Here, the DSO can observe the participants in the market and choose to interfere with targeted communities to buy flexibility as needed. This means the DSO can purchase services from communities before the C2X clearing. This service can, for example, be to curtail surplus energy to avoid overvoltage.

The principle of this market is that the DSO needs to estimate volumes at one or several buses that will reduce or remove the problems they are aiming at. We assume DSOs already have forecasting methods to obtain such volumes. In this paper, we run power flow calculations in PandaPower to estimate volumes as needed.

The DSO will then enter the market to buy this quantity at a given price. For the interaction to make sense, seen from a community perspective, this price needs to be at least higher than the feed-in tariff but preferably around or higher than the market prices of C2X for the community to benefit from this interaction. Hence, we assume the average C2X market price to be a good starting point for this DSO interaction.

5.3.2 Power flow analysis

The last part of the system analysis includes a power flow calculation that uses the resulting injected power in each bus from the market models. Here we want to evaluate steady-state grid impacts such as bus voltage and system losses. This allows us to consider not only the economic effects of these markets but also the potential physical consequences.

In addition to the grid topology, the active and reactive power injected into each grid node are required to run a power flow calculation for a single time-step. The active power can be directly estimated according to the market, assuming no generation unit does active voltage control[2]. The estimation of active power is discussed in more detail in section 5.3.2. The reactive power is estimated based on the power factor of the consumers in the system and households electrical consumption, given in Equation (5.17).

$$Q^{(t,h)} = dem^{(t,h)} * \sqrt{\frac{1}{PF^2} - 1} \tag{5.17}$$

Lastly, we're also interested in the losses in the system. Therefore, we consider line and transformer losses, and assume other losses are insignificant in the scope of this paper. Thus, the total losses P^{tot}_{loss}, considered in this system, are defined by Equation (5.18). Detailed descriptions on how these are calculated can be found in the PandaPower documentation (Thurner et al., 2018).

$$P^{tot}_{loss} = P^{line}_{loss} + P^{transformer}_{loss} \tag{5.18}$$

To run a balanced AC power flow, we use PandaPower, an open-source tool for power flow calculations. The standard method, and the one used in this paper for running the calculations, is the Newton Raphson (NR) solver. This is an iterative solver that needs initial starting conditions. In this paper, we use a flat start, meaning we set all voltage angles to 0, and the voltage for PQ-buses to 1.0 per unit (p.u.). The same applies to the slack bus. For further details on PandaPower and the NR solver, we refer to the PandaPower documentation (Thurner et al., 2018).

Integrating the market results into power flow calculations

To run the power flow, we need to find the injected active power in each bus. Generally, this is defined as load (into node) minus generation (out of node), as shown in Equation (5.19).

$$P_{net} = P_{load} - P_{generation} \tag{5.19}$$

For the BAU case, the energy balance depends on whether or not the participant has batteries. Equation (5.20) shows the general formulation for participants with batteries, while for those without the charging C and discharging D will be zero.

$$E^{BAU}_{net} = dem^{(t,h)} + C^{(t,h)} - res^{(t,h)} - D^{(t,h)} \tag{5.20}$$

For the LEM trading model there are also trading opportunities and the energy balance changes according to this. The balance is now calculated from Equation (5.21), which depends on the trading and grid import/feed-in decision. As there are no additional batteries or flexibility included in the C2X trading model, the power

[2]This is a decent assumption for the small-scale DERs connected to the distribution grids.

flow will be the same as in the LEM trading model. Hence we use the same power flow calculations for both models.

$$E_{net}^{LEM} = G^{(t,h)} + I^{(t,h)} - F^{(t,h)} - X^{(t,h)} \tag{5.21}$$

Because the energy balances are given as energy E in kWh per 15 minutes, we need to convert this into (injected) power, P_{inj}, in MW, by using Equation (5.22).

$$P_{inj} = E \cdot 4/1000 \tag{5.22}$$

5.4 Data and system description

This section gives an overview of the data used for the different cases. The data set is based on grid data from a synthetic low and medium voltage distribution grid in Germany.

5.4.1 Grid data

The synthetic grid was created with ding0 (2021). Ding0 is a python package that generates different synthetic medium and low voltage distribution grid topologies based on open data. For this study, we have chosen the grid with the ID “2702”. This grid fulfills our requirements in terms of size and number of generators. According to the x and y coordinates of the synthetic grid, it is located in Königsbrunn, a small town in southern Bavaria. It comprises 1158 buses, 363 of which are connected to a load, and 121 are equipped with a generator. Both generation units and loads can occur on a bus. In addition, the network contains 17 (low voltage) feeders that determine the allocation of the neighborhoods. Communities were formed at feeders with more than five buses so that all buses in a community are connected to the same feeder. We created seven communities with a number of buses ranging from six to 77. There are also 17 transformers in the system. To model these, we use the standard types provided by PandaPower. There are also some transformers in the Ding0 system not included in these standards. For these, we choose the standard types with a higher capacity. In addition, we assume a fixed power factor of 0.9 lag, following the assumptions of Stetz et al. (2011). Figure 5.2 provides the sketch of the distribution grid and shows the location of the low-voltage solar and wind communities.

5.4.2 Community data

All input data were available in or converted to a time granularity of 15 min to increase the level of accuracy of the analysis. In addition, demand profiles, solar and wind profiles, and grid prices were retrieved for the period from April to June

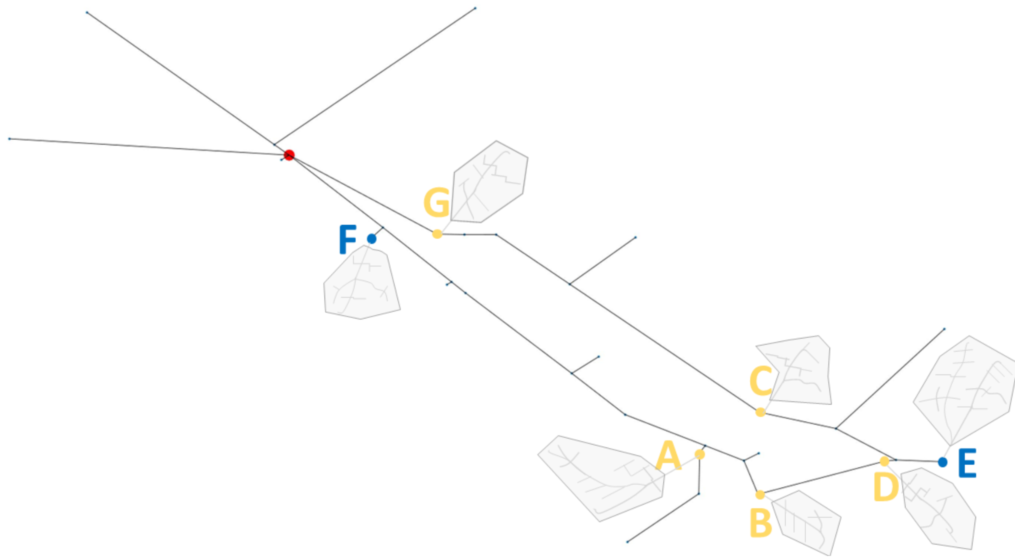


Figure 5.2: Sketch of the distribution grid including the location of the communities

2019. These months have a good mix of solar and wind generation, so variations in community energy surplus are expected.

The data set contains demand profiles for 357 households, five agricultural plants, and one industrial plant. This configuration depends on the grid topology that Ding0 has generated. As part of the work of Beyertt et al. (2020), they published smart meter data for 200 households across Germany with different demographic characteristics. To cover all 357 households, duplicates with a certain degree of randomness were created in addition to the original data set. To do so, a lower and an upper bound, per time-step, were estimated according to the standard deviation over all available household profiles. Then, new random profiles were generated by adding a random vector, between lower and upper bounds, to an arbitrary household profile. Furthermore, five demand profiles of agricultural plants were generated using the standard load profiles from BDEW (2017). These daily load profiles for a certain period of a year were combined to a demand profile for April to June. Lastly, one demand profile from 2017 was used for the industrial plant Braeuer, 2020.

The production time series for PV and wind energy production were retrieved from renewables.ninja Pfenninger and Staffell, 2016; Staffell and Pfenninger, 2016. This website obtains meteorological data from the NASA MERRA-2 database from 2019 Rienecker et al., 2011. Unfortunately, renewables.ninja only provides time series with hourly resolution. Therefore, we divided the hourly production by four to convert it into a time granularity of 15 min. Furthermore, we equipped the households with wind turbines of the Siemens SWT 2.3 82 model. Although the turbine model originally had a higher capacity and hub height, the data is realistic at the house level as we scaled down the capacity to 2.3 kW, see a similar approach in Crespo del Granado, Wallace, and Pang, 2014.

For batteries, we distributed SonnenBatterie units among the communities. The batteries have a capacity of 4 kWh and a one-way efficiency of 98%. In addition, the connection of the batteries to 2.5 kW inverters with a maximum efficiency of 96% leads to a (dis-) charging time of 100 min GmbH, 2022. Table 5.2 gives an overview of the community configurations.

Table 5.2: Overview of the community configurations

	Community						
	A	**B**	**C**	**D**	**E**	**F**	**G**
Households	13	31	51	77	5	27	29
2 kW PV	4	3	1	5	-	-	3
4 kW PV	3	3	2	6	-	-	4
6 kW PV	1	2	2	4	-	-	1
8 kW PV	-	2	1	1	-	-	1
10 kW PV	-	-	2	1	-	-	-
2 kW wind	-	-	-	-	3	6	-
Batteries	2	3	4	4	1	1	2

Electricity prices consist of the German wholesale market price, transmission and distribution network charges, and various taxes & levies. The market prices were obtained from the "Energy-Charts" website provided by Fraunhofer ISE (2019). Taxes & levies are uniform throughout Germany and taken from BMWK (2022c). Transmission and distribution network charges depend on location. In Königsbrunn, LEW is the responsible DSO and charges 6.34 ct/kWh, including transmission and distribution network charges. Furthermore, Germany has a feed-in tariff for injecting renewable energy into the main grid, which changes monthly. For simplification, we have used the feed-in tariff from May (10.95 ct/kWh), which is also the average of the months April, May, and June Solarenergie Förderverein Deutschland e.V., 2022.

5.4.3 C2X data

In the C2X trading model, communities can trade their surplus energy with other market participants after clearing the local market internally in the LEM trading model. The P2P trading algorithm used for the C2X clearing requires buying bids and selling offers of the participants to match them. In this paper, we establish bids and offers to reflect each participant's willingness to pay as realistically as possible but with some simplifications.

The bids and offers of the communities were created using a reference price based on Heilmann et al. (2022). The reference price reflects the situation in a community's market with regard to surplus electricity that can be sold to other participants.

Accordingly, the reference price is low when the surplus electricity is high and vice versa. The reference price was applied to each community individually and is used for the communities' bids and offers.

The quantities a community is willing to sell or buy results from the "Community Only" clearing. The resulting surplus energy is the quantity the communities offer to the other participants. The community's demand equals the grid import from the LEM clearing, trying to reduce it and avoid higher grid prices.

In addition, we included external participants in the C2X who only buy electricity from the offering communities. We included one industrial plant and five agricultural farms with the demand described above, as they are already part of the grid. The bid price for the industrial plant was calculated by scaling the grid prices to the average electricity price for industry in 2019 of 18.43 ct/kWh BDEW, 2022. For agricultural farms, a fixed price of 23 ct/kWh was assumed, slightly below the average grid price.

We also included a hydrogen producer and a supplier with unlimited demand. For the hydrogen producer, we also set a constant price. We chose a relatively low price of 15 ct/kWh because hydrogen production is not economically viable at higher electricity costs. Lastly, we chose the supplier's bid price always to be 80% of the grid price.

5.5 Results and discussion

In this chapter, we first present and analyze the main points of interest regarding the LEM trading model compared to the BAU case. Furthermore, we use a power flow analysis to evaluate the grid impact of the LEM trading. We also look at what economic benefit the C2X market has on the participating communities. Lastly, we evaluate the effect of the DSO entering the C2X market to create incentives to reduce grid impacts.

To analyze the results of the market models, we use several key performance indicators (KPIs). Table 5.3 explains the overall and C2X specific KPIs used in this paper. The goal of using these KPIs is to look at the efficiency and potential effects for end-users participating in the different markets. The KPIs for the BAU case are based on all participants in the communities in the LEM model but do not consider any other players in the system, such as other houses, industry, and agriculture.

5.5.1 Local electricity market trading

Market results

First, we look at the operational decisions for the LEM trading model compared to the BAU case. In the LEM trading model, households can trade locally within the community using centralized optimization. Consequently, surplus electricity of households can be traded to neighbors to increase the self-coverage of a community.

Table 5.3: Definition of general KPIs for each community in the market.

General KPIs	
Cost [EUR]	Total cost for covering demand over the whole period
Income [EUR]	Total income for selling surplus over the whole period
System cost [EUR]	Total overall cost for communities minus income from purchases and sales of energy
Price [ct/kWh]	Average electricity grid price for covering demand, excluding income of selling surplus electricity
Unit cost [ct/kWh]	Average cost of electricity, including income of selling electricity locally and to the grid
Self-coverage [%]	Percentage of demand covered by local production
Grid import [kWh]	Total imported electricity from the grid
Feed-in [kWh]	Total surplus electricity sold to the grid
Traded el. [kWh]	Amount of electricity traded among peers within a LEM

C2X Specific KPIs	
Sold el. [kWh]	Electricity sold in the C2X market
Res. surplus [kWh]	Resulting surplus after trading in the C2X market
Sell price [ct/kWh]	Average price per unit of sold energy
Income C2X [EUR]	Total income of sold energy in the C2X market
Bought el. [kWh]	Electricity bought in the C2X market
Res. deficit [kWh]	Resulting deficit after trading in the C2X market
Buy price [ct/kWh]	Average price per unit of bought energy
Cost C2X [EUR]	Total costs of bought energy in the C2X market

However, in times of electricity deficits, consumers and prosumers might still need to purchase electricity from the main grid. In the BAU case, there is no trading, and self-generated electricity can only be used by the prosumers producing it.

Table 5.4 presents the operational KPIs for the LEM trading model and BAU case. As expected, the communities facilitate more efficient use of the locally produced energy. The considerable amount of energy traded leads to a significant increase in community self-coverage. However, even after local trading, the communities still have a large surplus. In particular, high electricity surpluses occur in communities with PV systems, such as communities A, B, and G. This is most likely due to the high generation peaks during the day, which cannot be fully traded or stored because of the limited availability of batteries.

Table 5.4: KPIs related to operational decisions of the LEM model and BAU case

KPI	**BAU**	**A**	**B**	**C**	**D**	**E**	**F**	**G**
Traded el. [kWh]	0	2 503	9 903	15 669	21 856	560	2 463	5 485
Grid import [kWh]	15 4830	4189	12 393	26 791	44 085	130	10 092	7108
Feed-in [kWh]	78 005	5 725	6 700	3 080	4 238	1 031	65	6 997
Self-coverage [%]	14	55	50	40	38	88	27	53

Table 5.5 shows an overview of the economic-related KPIs. Here, we observe a significant reduction in average electricity prices and costs per kWh for all communities compared to the BAU case. For Community E, we even see a negative unit cost. Supported by the high level of self-consumption, the community imports very little electricity from the grid and has an income higher than their costs. We also see, as expected, that the system costs decrease when implementing LEM trading for the communities. This is because the imported electricity is lower, reducing the costs related to grid import.

Table 5.5: KPIs related to economic impacts of the LEM model and BAU case

KPI	**BAU**	**A**	**B**	**C**	**D**	**E**	**F**	**G**
Income[EUR]	8542	627	734	337	464	113	7	766
Cost[EUR]	40 321	1089	3241	7012	11 566	33	2619	1860
System cost [EUR]	31 779	463	2508	6675	1 1102	-80	2611	1094
Price [ct/kWh]	22.4	11.7	13.0	15.7	16.2	3.1	18.8	12.3
Unit cost [ct/kWh]	17.6	5.0	10.1	15.0	15.5	-7.7	18.8	7.2

As we can see from these results, the LEM trading enables better utilization of the resources within the system and increases the participants' economic benefit. There is, however, still a substantial amount of surplus electricity in the communities.

Power flow analysis

Moving on, we evaluate the grid impacts of the LEM trading. As described in Section 5.3, we use the market results to find the injected power in each bus and then run a power flow to take a closer look at the physical aspects of the model. For this part of the result, we look closer at the second week in April to show the details in voltage and loss in the given period.

Figure 5.3 shows the system losses for seven days in April for both the LEM trading and the difference between the losses in the LEM model and the BAU case. Firstly, we should expect slight loss variations due to changes in the storage and export/import decisions between the cases. However, the red line in the figure presents the difference in system losses between the cases and shows that the difference is insignificant. In general, we observe that the losses are closely related to the time-steps where we have high production from the PV systems in the middle of the day.

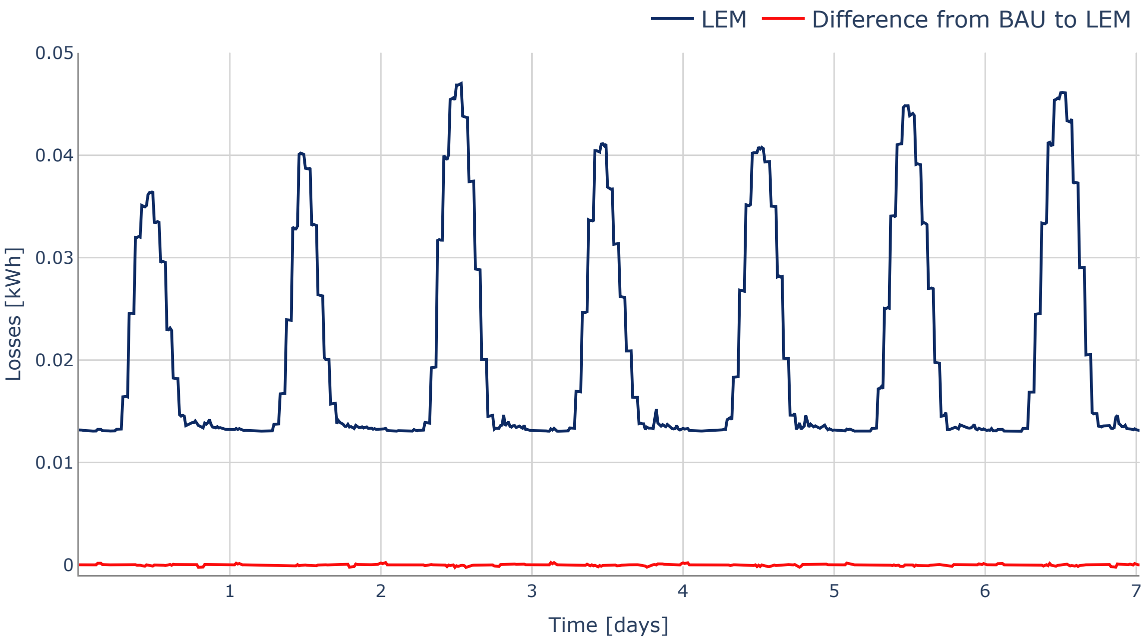


Figure 5.3: Total system losses from LEM trading and the difference to BAU for seven days in April

Figure 5.4 shows the maximum and minimum bus voltage in the system for seven days in April for all buses. From the figure, we see that the maximum voltage in this period deviates from the nominal voltage by over five percent p.u. on days three and seven. This indicates that there might be some issues with high production and the system is already on edge in terms of overvoltage. However, the highest voltage peaks come from a bus with a large PV generator and are therefore not an issue created by the LEM trading. For buses within the LEMs, the highest voltage in this period is 1.3%. The minimum voltage in the system for this period is well within 2.6% of the nominal voltage; thus, we will focus on the problems with potential overvoltage moving on in this paper.

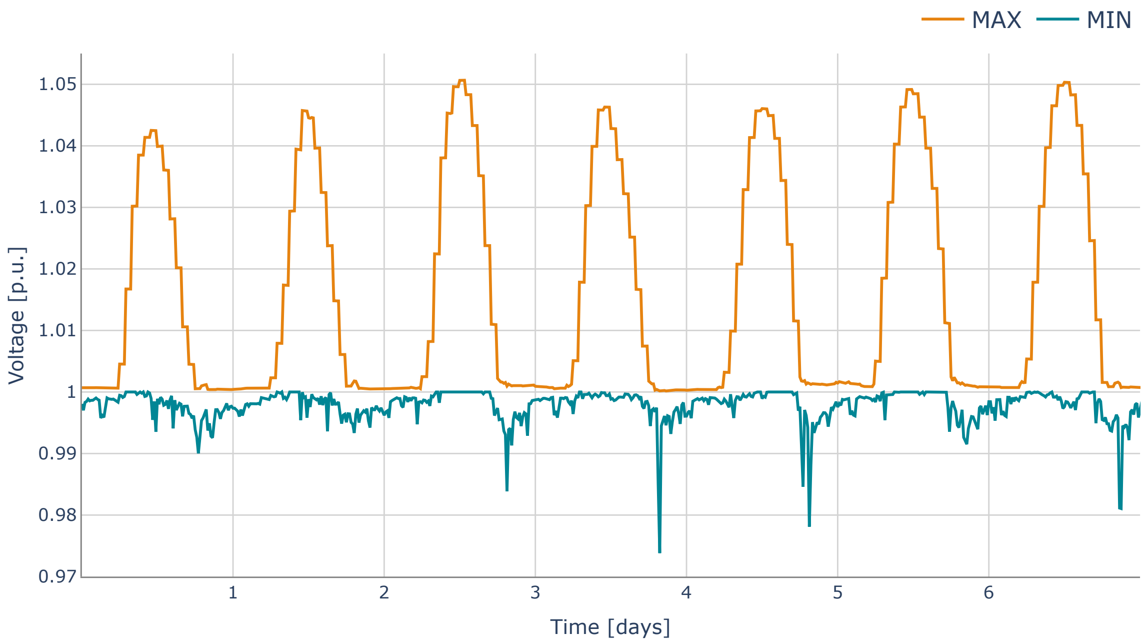


Figure 5.4: Minimum and maximum voltage of all buses in the system for seven days in April

From these results, we have observed that LEM trading generally does not affect the grid significantly, neither in terms of system losses nor voltage problems, compared to the BAU case. This supports the findings in Dynge et al. (2021).

5.5.2 Community-to-X (C2X) trading

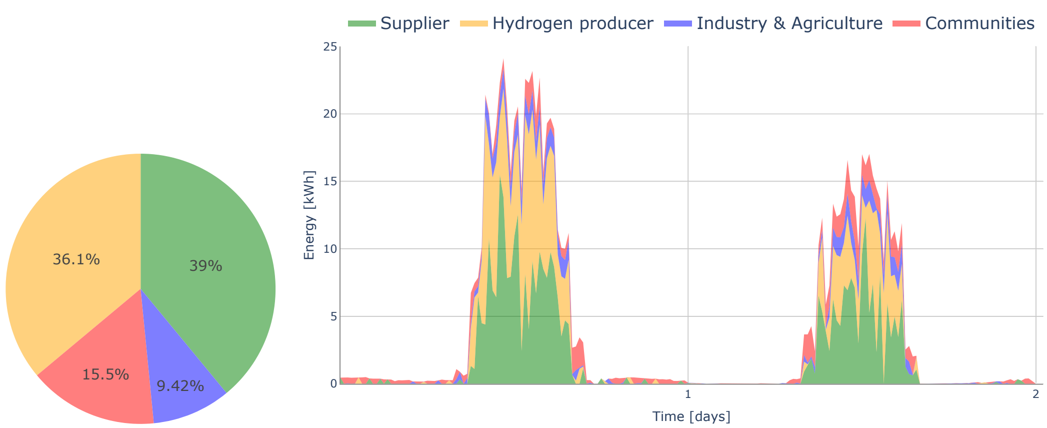
In the C2X model, we take one step further from LEM trading and allow communities and other external players to trade with each other. For this section, we use the LEM model results as a reference case to evaluate the economic impacts of this market on the participating communities. For a full comparison of the KPIs for all communities across the LEM and C2X model, see Tables B.1 to B.4 in Appendix B.

Table 5.6 shows the KPIs specific to the C2X market. Here, we observe that all communities sell and buy in this market. There are, however, large differences in sold and bought electricity between the communities. For example, communities A, B, and C sell large quantities but only buy relatively small quantities. In contrast, Community F sells much less than it buys. As we can see from the resulting surplus and deficit, the communities can sell almost all their surplus. However, there is still a large deficit in the market.

The reason we are left with surplus electricity is due to imperfect market trading. In times of low production, the communities' reference prices are relatively high. Consequently, the offers can exceed the bids of all the other players in the C2X market, making pairing impossible due to the characteristics of the P2P algorithm.

This indicates that the communities' selling prices are not fully optimal in terms of selling quantities in this specific market. However, this only happens in a few time-steps at prices close to the grid price and may be a biased result since we assumed lower prices for external agents.

Figure 5.5a) shows that 16% of the available surplus in the market is bought by communities, while external players buy 84%. Specifically, the hydrogen producer and supplier with endless demand obtain large shares of the bought quantity of surplus electricity, as they buy all selling quantities of a community if matched successfully. In addition, we have five communities equipped with PV, which means that these communities often have a surplus of energy at the same time, so they do not buy electricity in these time-steps. However, Figure 5.5b) illustrates the bought surplus quantities at each time-step for the first two days. Here, we observe that during periods with a low surplus, there are mainly communities selected for trading. This is due to the high reference price of selling and buying communities, so only matches between these communities are possible.



a) total b) first two days

Figure 5.5: Quantity bought by each participant group at each time-step in the first two days and in total over the entire period

In Table 5.6, we can also observe that the average selling prices for the communities are lower than the buying prices. The reason for this is the characteristics of the reference price. When communities have a deficit, there is no surplus, and the reference price equals the grid price. Consequently, when a community buys electricity, it always bids a high price. Since the trading prices are midway between the bids and offers, the high reference prices lead to higher average buying prices for the communities compared to external players.

Table 5.6: KPIs specific for the C2X market

KPI	A	B	C	D	E	F	G
Sold el. [kWh]	5724	6686	2975	4115	1031	65	6992
Res. surplus [kWh]	0.6	14.4	105.1	123.1	0.3	0.4	4.7
Selling price [ct/kWh]	15.2	15.2	15.9	15.6	16.7	18.2	15.0
Income C2X [EUR]	868	1016	472	6426	172	12	1052
Buy el. [kWh]	63	132	452	625	46	2865	92
Res. deficit [kWh]	4125	12 261	26 339	43 459	84	7227	7016
Buying price [ct/kWh]	18.5	19.1	19.4	19.4	18.7	18.9	18.8
Cost C2X [EUR]	12	25	88	121	9	542	17

Figure 5.6 shows the relation between surplus and deficit after the LEM trading and the quantities bought and sold in the C2X market for five days. The surplus of the LEM trading is close to the sold quantities in the C2X market and is therefore not included in the plot.

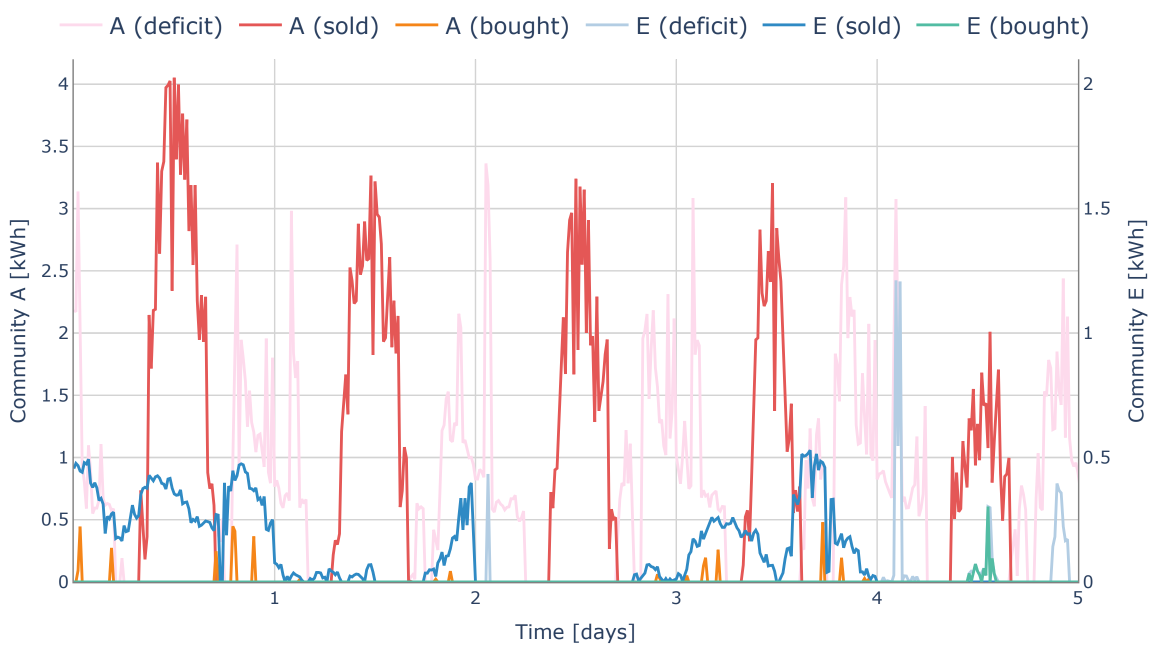


Figure 5.6: Relation between surplus and deficit in the LEM market, and traded quantities in the C2X market for Community A and E

As the LEM trading market is modeled, one community will never have both surplus and deficit in the same time-step, meaning they will either sell or buy in the C2X market at each time-step. Here, we can see that the two communities occasionally have surplus and deficits at different times. This enables them to utilize the C2X market and exchange electricity when it benefits both parties. For example, at the beginning of the first day, when Community A has a deficit, and Community E has a surplus, they trade at a price that is beneficial for both of them compared to the alternatives of grid import and feed-in.

Table 5.7 presents the KPIs related to the economic situation of each community after participating in the C2X market. As expected, we see that both the price and unit cost decrease for all participants when participating in this market. Because buying prices are lower than the grid import price and selling prices are higher than the feed-in tariff, this market will economically benefit all participants.

Table 5.7: General KPIs for the C2X market results

KPI	**A**	**B**	**C**	**D**	**E**	**F**	**G**
Price [ct/kWh]	11.7	13.0	15.7	16.1	2.9	17.5	12.3
Unit cost [ct/kWh]	2.3	8.9	14.6	15.2	-13.7	17.4	5.3
System cost [EUR]	216	2215	6499	10870	-143	2423	801
LEM system cost [EUR]	462.6	2507.8	6674.9	11101.5	-80.3	2611.4	1094.0
Difference [EUR]	246.2	292.7	175.8	231.6	-62.1	188.8	292.7
Difference[%]	53 %	12 %	3 %	2 %	77 %	7 %	27 %

Figure 5.7 shows the price and unit cost changes between the LEM and C2X markets for all communities. Here, we see that both decrease in the C2X market. However, the price change is only between 0.3 and 8.7%, while the unit cost has a greater range with decreases of 2.1 to 77.3%. The change in unit cost is largest for the communities that have sold large quantities. This is because the price is only affected by the amount of grid imports, while the unit cost also considers income. Consequently, the high amounts of sold electricity in this market have a greater impact on the overall savings. However, the communities in this market generally sells much more than they buy, thus this might not be the case for all C2X markets.

So far, we have observed operational decisions and key economic impacts of participating in the C2X market. As we can see from these results, the C2X market reduces the overall electricity costs for participating communities. This is reflected in lower system costs for each community and reduced unit cost per kWh for prosumers.

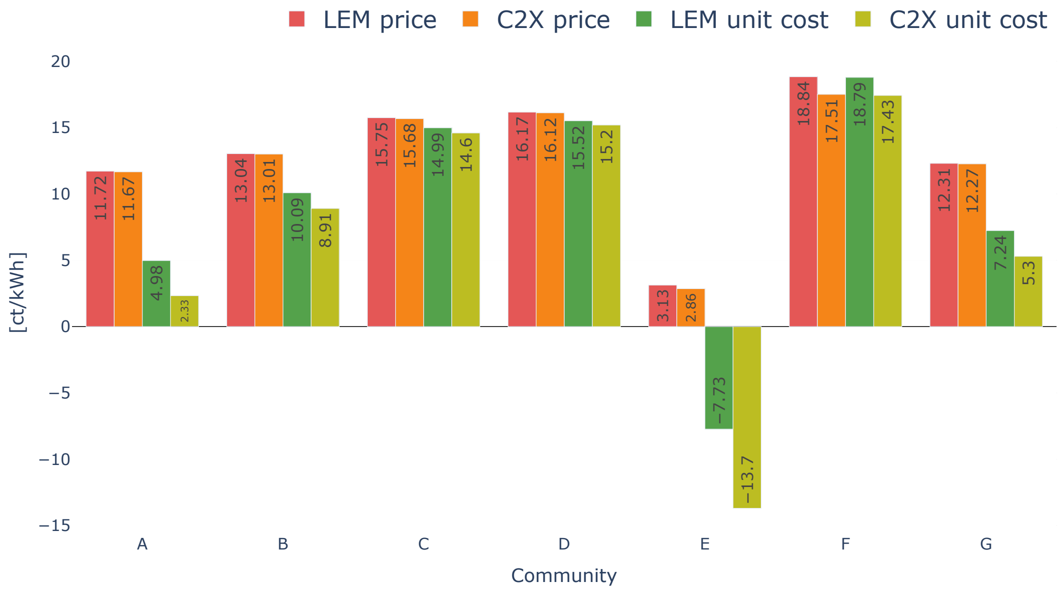


Figure 5.7: Price and unit cost in both LEM and C2X, for all communities in the system.

C2X+

Even if the results from the LEM trading indicate that there are no critical grid issues related to the operation of LEMs and their local trading, this might not always be the case. For different configurations of LEMs, or in the case of a future scenario with increased penetration of local renewable production, we might experience bigger issues. To further investigate this C2X+ market, we use a future scenario where we consider the same system as before, but with an increase in capacity of both wind and PV units for certain prosumers.

Figure 5.8 shows the voltage magnitude of bus 195 in the original system and the future scenario. Here, the maximum voltage triples in times of high PV generation. It is worth mentioning that the voltage is still not critical in terms of grid issues, but can be useful as an example of how this market could work.

Looking at a selected bus with a high voltage magnitude for a given time-step we can estimate how much a decrease in feed-in power will affect the voltage magnitude in that bus. Here, the chosen bus (195) is located within Community A and has high voltages during the daytime due to high PV production. In time-step 48 (12:00), a surplus of 2.87 kWh is exported to the grid for the fixed feed-in tariff. By reducing the injected active power of this bus by 2.87 kWh, we can reduce the voltage magnitude from 1.8% overvoltage to 1.1%.

Now, we assume the DSO wants to buy curtailment of all surplus for this bus in time-steps with voltages exceeding 1.1% p.u. This happens in 205 time-steps of the three-month period and results in a total curtailed quantity of 478.5 kWh. Based on the assumptions stated previously, we take a basis in the average market selling price

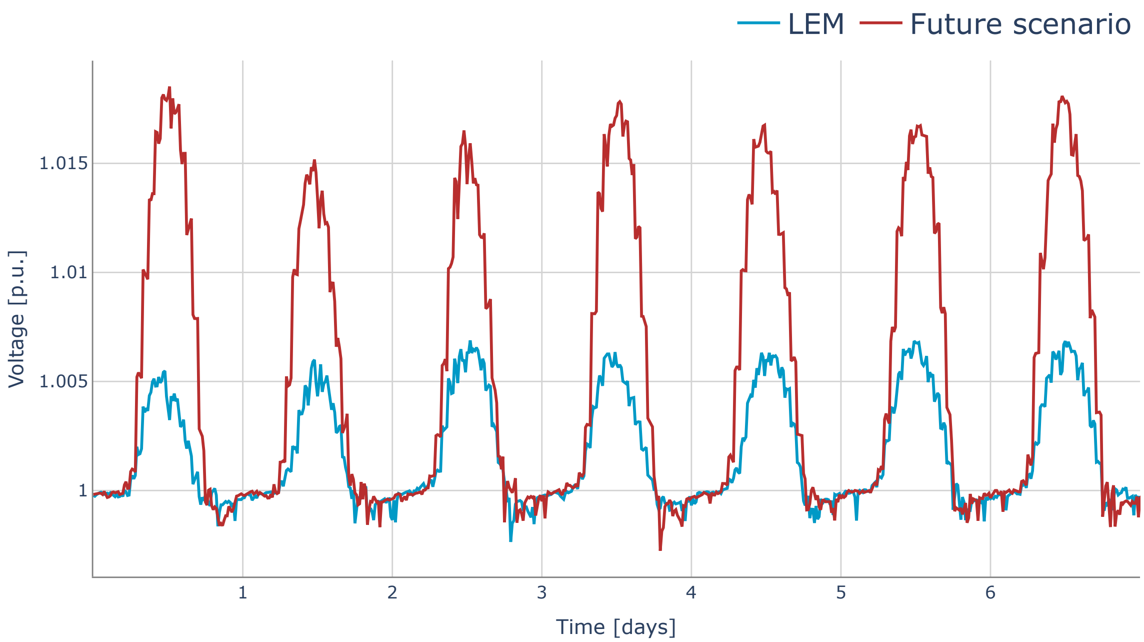


Figure 5.8: Voltage magnitude for bus 195 in the original case and a future scenario for the seven days in April.

for all communities as the DSO interaction price. This price is at 16.0 cent/kWh for C2X market-clearing. Community A will then receive 76.6 EUR for trading with the DSO.

The idea behind this market is not that the LEMs are the problem in themselves regarding grid impacts but rather that LEMs can be a good way for the DSO to interact and manage challenges related to an increasing share of DERs. Additionally, participating communities can earn from this interaction. How much they earn depends on the market prices and should be further analyzed. We can also assume that these payments will, directly or indirectly, be paid by end-users in the same way the cost of grid expansions would. In any case, we consider this a possible solution where the DSO can avoid time and resource-intensive grid expansions, which will eventually also be paid by the end-users.

5.6 Conclusion

In this paper, we investigated the impacts of different market models using real-life data applied to a synthetic low-voltage grid in Bavaria, Germany. We looked at the physical and economic impacts of LEM trading compared to a reference case without any market. Additionally, we proposed and evaluated a new market (C2X) for community surplus trading and DSO interactions and analyzed how this market can benefit the participants.

For the first part, we concluded that LEM trading is a great opportunity for efficient use of DERs and cost-saving for its participants, seen from a social welfare perspective. Furthermore, the finding in this paper support previous studies in that LEM trading itself does not cause critical grid impacts, compared to a case with the same units just without trading.

However, from the LEM trading, there can still be an electricity surplus, which should be used as efficiently as possible. Our results show that participation in the C2X market benefits all players, but significant variations occur between the communities in terms of total savings and quantities bought and sold. Generally, the communities with a high surplus can sell most of it, thus increasing their revenue and lowering system costs significantly. In contrast, communities with higher deficits are not able to cover their demand in this market. The primary reason for this is that external players with high demand buy significant quantities if selected, thus increasing the competition for buying surplus. This indicates that the C2X market (with the given configurations) is only of great benefit to selling communities.

Furthermore, we conclude that the C2X+ market with DSO interactions economically benefits targeted communities and values their curtailed surplus. The C2X+ market can also contribute as an alternative to time- and resource-intensive grid upgrades. So even if the DSO interactions eventually end up being paid for by end-users, we believe society as a whole can benefit from using these interactions where possible instead of grid upgrades. We would also like to propose that other players, such as balance responsible parties, can also enter this market to buy flexibility in addition to the DSO.

Although the results in this paper are limited to the system used, we demonstrate the concept of the markets and find that the overall economic benefits of participating in LEM and C2X trading are substantial. Furthermore, to fully utilize the potential of the C2X market, it is important to include players with different surplus and deficit profiles.

To point out potential opportunities for future research concerning this paper, we would like to propose the following as starting points:

- Closing the loop between the LEM trading and C2X trading, as this study does not consider any strategy for trading between the markets. However, this can be an important factor as the decisions in both markets will be affected by each other.

- Testing the findings of this paper with different data. For example, by using grids in other parts of Germany, or the world, as the robustness of the grid will vary and thus affect the results. Lastly, because this paper is limited to the data used, it can be useful to consider other participants for both the LEM and C2X trading models.

- Using a different trading algorithm than P2P, as it can be perceived as unfair and bids and offers are matched completely randomly.

- Conduct a cost-benefit analysis for the DSO interactions. This can be used to investigate the actual benefit of the C2X+ market compared to potential grid expansions.
- Using dynamic and smart bidding for all participants. As this paper focuses on proving the concept, additional research, including a deeper understanding of each participants bidding strategy, can be useful for a greater understanding of the C2X markets. This can, for example, be done through machine learning.

6 | Concluding remarks

LEMs have become an increasingly interesting topic in research over the last decade as a way to manage and efficiently use DERs. In this thesis, we aimed to contribute with new perspectives and bring new ideas to expand the current notions of how these LEMs operate, both internally and externally. In short, we looked at how different trading algorithms affect the market-clearing of these communities and proposed a new way to increase the value of renewable energy surplus after the clearing. We did this by authoring two papers:

In the first paper, presented in Chapter 3, we took a closer look at the internal market-clearing of LEMs. The purpose of this paper was to investigate the efficiency of two trading algorithms: MUDA and P2P. These algorithms were applied to two different LEMs to compare the efficiency of different system configurations. We discovered that the P2P trading algorithm is more successful in terms of trading with relatively few (<200) participants, while MUDA can provide fairness to a market. Lastly, we also discovered that using trading algorithms instead of centralized optimization often results in a significant amount of surplus electricity after the market clearing because these types of markets are not perfect.

We recognize batteries as an essential part of the transition to an energy system with volatile renewable energy sources because they offer much-needed flexibility to the system. However, we did not include batteries in the first paper. Furthermore, methods to integrate charging and discharging decisions into a market with bids and offers are not fully explored. Hence, as a transition and expansion from the first paper, we proposed how this can be done for future work.

As mentioned, the first paper revealed that surplus electricity is likely to occur in LEMs. Depending on the system and local regulations, this surplus will either be sold at a feed-in tariff or curtailed. This was the starting point for the second paper, presented in Chapter 5, where we researched more efficient ways to use this surplus in terms of financial gains and grid impacts. For the first part of this paper, we analyzed how establishing LEMs in a distribution grid affects both the economy of participants and the grid as a whole. Our conclusion supports previous studies in that LEMs reduce the system costs for participants and contribute to more efficient use of resources. Furthermore, we found that LEMs themselves are not responsible for major grid impacts but can be a good way of centralizing and managing DERs under one community manager.

For the central part of the second paper, we looked at how the previously mentioned surplus can be managed. We proposed an innovative new marketplace where several communities and external players can trade. This market aims to trade surplus and to facilitate communities with different generation and load characteristics to complement each other. The results show that all participants benefit from this market in terms of financial gains. However, due to the system characteristics, selling was more beneficial than buying as there was more competition for buying.

In the second paper, We also gave an example of how the DSO can use this market to monitor the trading and potentially intervene whenever needed to buy curtailment. We also argue that the C2X+ market can be a potential alternative to grid expansions in cases where smaller adjustments in production are needed to keep the grid operating efficiently. We also suggested that this market can be used by other participants than suggested in this paper, such as balance responsible parties that want to buy flexibility. In short, we think this is an exciting new marketplace that can provide alternatives to the conventional thinking of how LEMs should operate.

As we have discovered throughout this thesis, research on the design of LEMs is generally covered by the current literature, with some exceptions, such as the analysis and application of trading algorithms. However, we believe our most important contribution is the new idea of how LEMs can be integrated into the bigger system. This is very important moving forward as the LEMs will become a part of the system and not just stand-alone.

Lastly, we are aware that our results are affected by assumptions and simplifications. For example, we based the market reference price on the assumption that prosumers and communities have more or less perfect information. Additionally, the prices for external actors in C2X are based on assumptions of their preference and do not reflect the market conditions. Furthermore, we used fixed demand and renewable generation without including uncertainty. However, we still trust that this research provides a good starting point for further work. Some suggestions for expansions and new addition to our work is presented in Section 6.1.

6.1 Suggestions for future work

As the final part of concluding our work in this thesis, we will give a few suggestions for how this work can be expanded or used as a starting point for other interesting studies:

- We identified that incorporating batteries into bidding strategies is an under-explored area. However, we suggested a method to create bidding quantities and prices for prosumers with battery storage. This, or further developments of the method, can be used to create bidding strategies for trading algorithms.

- We developed a new C2X market based on the outcome of LEM trading without considering any strategy between these markets. However, decisions in both markets will influence each other, so the loop between LEM-clearing and the C2X market should be closed in future work.

- The models used in this thesis can be tested in other settings. On the one hand, this shows how the trading algorithms perform under different configurations. On the other hand, it indicates to what extent the results of C2X are based on the market characteristics. Furthermore, we have not identified any major grid problems in the LEM trading model. Other grid configurations may have a more significant impact, making integrating the C2X+ market more relevant.

- We disregarded investment costs for prosumers and the DSO. Therefore, we suggest including investment costs in future implementations or conducting a cost-benefit analysis to get a full picture of the actual benefits of the C2X-market.

- We suggest including smart bidding strategies involving, for example, game theory or machine learning to strengthen the assumptions of bids and offers in the markets. Furthermore, stochastic properties for price and production developments should also be considered to get a complete picture of how the market participants behave long-term.

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A | Additional material - Paper 1

Uniform distribution results

Table A.1 and Table A.2 illustrate the results when using the bidding simulation with uniform distribution. They show that the uniform distribution leads to less efficient market results compared to the skewed normal distribution, which is reflected in an increase in grid imports and higher system costs.

Table A.1: Steinkjer case - Comparison of KPIs for centralized, MUDA and P2P for the uniform bidding simulation

KPI	**Cent.**	**MUDA**	**P2P**
System cost [NOK]	27 037	28 176	27 334
Grid import [kWh] (%)	39 553 (63.9)	41 200	39 980
Self-consumption [kWh] (%)	22 388 (36.1)	20 741(33.5)	21 961(35.5)
Curtailment [kWh] (%)	615 (2.7)	2 262(9.8)	1 042(4.5)
Energy traded [kWh]	2 506	859	2 079

Table A.2: London case - Comparison of KPIs for centralized, MUDA and P2P for the uniform bidding simulation

KPI	**Cent.**	**MUDA**	**P2P**
System cost [GBP]	3 844	4 524	4 082
Grid import [kWh] (%)	25 063 (65.3)	29 482	26 621
Self-consumption [kWh] (%)	13 295 (34.7)	8 876(23.1)	11 737(30.6)
Curtailment [kWh] (%)	596 (4.3)	5 015(36.1)	2 154(15.5)
Energy traded [kWh]	8 193	3 774	6 635

B | Additional material - Paper 2

Full comparison of market results

Tables B.1 to B.4 provide a full comparison of the changes in KPIs between the LEM to the C2X clearing for all communities. Additionally, changes in percentage, using the LEM trading model results as a reference, are also added to the tables.

Table B.1: Comparison of system KPIs between LEM trading model and C2X trading model, for Community A and B

	Community A		*Community B*	
KPI	**LEM (ref)**	**C2X**	**LEM (ref)**	**C2X**
Price [ct/kWh]	11.7	11.7 (-0.4%)	13.0	13.0 (-0.3%)
unit Cost [ct/kWh]	5.0	2.3 (-53.2%)	10.1	8.9 (-11.7%)
Income [EUR]	626.84	868.50 (+38.6%)	733.65	1017.54 (+38.7%)
Cost [EUR]	1089.42	1084.83 (-0.4%)	3241.41	3232.62 (-0.3%)
System cost [EUR]	462.58	216.34 (-53.2%)	2507.76	2215.08 (-11.7%)
Benefit [EUR]	-	246.24	-	292.68

Table B.2: Comparison of system KPIs between LEM trading model and C2X trading model, for Community C and D

	Community C		*Community D*	
KPI	**LEM (ref)**	**C2X**	**LEM (ref)**	**C2X**
Price [ct/kWh]	15.7	15.7 (-0.4%)	16.2	16.1 (-0.3 %)
unit Cost [ct/kWh]	15.0	14.6 (-2.6 %)	15.5	15.2 (-2.1 %)
Income [EUR]	337.23	483.84 (+43.5%)	464.11	655.68 (+41.3 %)
Cost [EUR]	7012.17	6983.02 (-0.4 %)	11565.64	11525.60 (-0.3 %)
System cost [EUR]	6674.95	6499.18 (-2.6 %)	11101.53	10869.93 (-2.1 %)
Benefit [EUR]	-	175.76	-	231.61

Table B.3: Comparison of system KPIs between LEM trading model and C2X trading model, for Community E and F

	Community E		*Community F*	
KPI	**LEM (ref)**	**C2X**	**LEM (ref)**	**C2X**
Price [ct/kWh]	3.1	2.9 (-8.7 %)	18.8	17.5 (-7.0 %)
unit Cost [ct/kWh]	-7.7	-13.7 (-77.3 %)	18.8	17.4 (-7.2 %)
Income [EUR]	112.88	172.18 (+52.5 %)	7.16	11.87 (+65.8 %)
Cost [EUR]	32.54	29.70 (-8.7 %)	2618.53	2434.41 (-7.0 %)
System cost [EUR]	-80.34	-142.47 (-77.3%)	2611.37	2422.53 (-7.2 %)
Benefit [EUR]	-	62.13	-	188.83

Table B.4: Comparison of system KPIs between LEM trading model and C2X trading model, for Community G

	Community G	
KPI	**LEM (ref)**	**C2X**
Price [ct/kWh]	12.3	12.3 (-0.4 %)
unit Cost [ct/kWh]	7.2	5.3 (-26.8 %)
Income [EUR]	766.17	1052.30 (+37.3 %)
Cost [EUR]	1860.15	1853.56 (-0.4 %)
System cost [EUR]	1093.98	801.27 (-26.8 %)
Benefit [EUR]	-	292.71

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Expanding the notions of local electricity markets

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