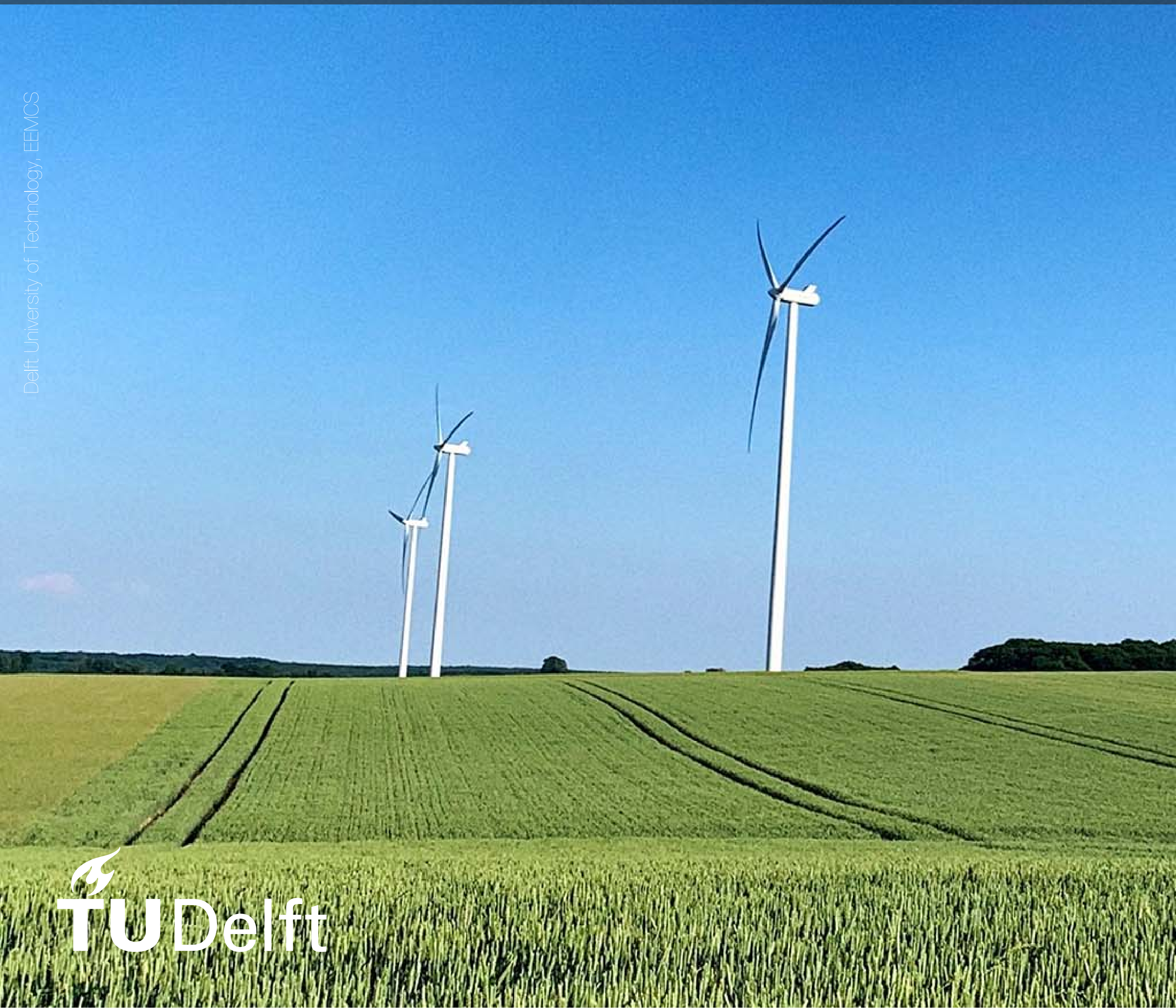
Efficiency of Peer-to-Peer Trading Coalitions in Energy Communities

MSc Computer Science - Software Technology

Ying Zhang

Delft University of Technology, EEMCS



TU Delft

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by

Ying Zhang

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Thesis committee:	Dr. V. Robu,	CWI, TU Delft supervisor
	Dr. N. Yorke-Smith,	TU Delft,
	Dr. S. Tindemans,	TU Delft,

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TU Delft

Preface

This work reports the research performed for the Master Thesis for the degree of Master of Science in Computer Science at Delft University of Technology. The majority of the work was performed during a 9 month internship at the Centrum voor Wiskunde en Informatica (CWI), Amsterdam. Currently a journal paper is also in preparation for submission. During the design and execution of the project, I got a lot of help of many people and would like to thank everyone.

First, I would like to thank my supervisor, Dr. Valentin Robu. Your guidance and advice was invaluable for forming the foundation of the research. Your feedback pushed me to further develop my skills in presenting, writing, critical thinking and more. I am also extremely grateful for the encouragement throughout the project.

I would also like to thank my colleagues at CWI for sharpening my problem solving skills and providing practical insights. I'd like to especially thank Sho Cremers, who was my office mate. I was able to bounce a lot of ideas off you and consult you regarding specific domain-specific methodologies and code optimizations.

I would like to thank my family and friends, who provided me with their endless support and interest, and when necessary proved a useful distraction to take my mind of the busy work.

Finally, to those I have met but not explicitly mentioned, I am thankful for all you've done for me and my colleagues and hope to be able to work with you again in the future.

Ying Zhang
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Abstract

Peer-to-peer trading and energy communities have garnered much attention over the last few years due to the wider spread of distributed energy resources. Much research has been performed on the mechanisms and methodologies behind their implementation and realisation. However, the efficiency and micro-structure of trading in such markets raise many important challenges. To analyse the efficiency of peer-to-peer energy markets, we consider two different popular approaches to peer-to-peer trading, i.e. centralised and decentralised and explore the economic benefits these models bring given optimal trading schedules computed by a joint schedule optimizer. In both these modes, benefits can be realised mainly due to the diversity in consumption behaviour and renewable energy generation between prosumers in an energy community. This diversity decreases quickly as more peer-to-peer energy contracts are established and more prosumers join the market, leading to significantly diminishing returns. In this work, we aim to quantify such effects using large-scale real-world data from two trials in the UK, i.e. the Low Carbon London project and the Thames Valley Vision project. We show that only a small number of peer-to-peer contracts and a fraction of the prosumers are needed to realise the majority of the Gains from Trade.

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Glossary

Subscripts and Sets

K	Set of agents in the community that participate in trade.
N	Set of agents in the community.
i	For agents.
j	For agents.

Parameters

T	Time horizon.
$\tau^b(t)$	Buying price (i.e. import tariff) at t [pence/kWh].
$\tau^s(t)$	Selling price (i.e. export tariff) at t [pence/kWh].
d	The deadline of negotiation.
k	Number of peers in the negotiation framework.

Variables

Ω_i^a	Energy contracts accepted by agent i.
Ω_i	Set of all possible energy contracts for agent i.
Ω	Set of all possible energy contracts.
Θ	Peer-to-peer oracle.
ω	Energy contract tuple (i, j, θ).
$\theta(t)$	Energy amount traded at time t decided by Θ.
θ	Energy amounts traded decided by Θ.
$\widetilde{b_i}(T)$	Accumulated bill for agent i at time T after trading.
$\widetilde{e_i^b}(t)$	Energy bought by agent i after peer-to-peer trading.
$\widetilde{e_i^s}(t)$	Energy sold by agent i after peer-to-peer trading.
$\widetilde{e_i}(t)$	Net demand for agent i after peer-to-peer trading.
$b_i(T)$	Accumulated bill for agent i at time T.
$b_K(T)$	Accumulated bill for K at time T.
$c_i^g(T)$	Generator costs for agent i over T.
$c_K^g(T)$	Generator costs for K over T.
$c_i^{bat}(T)$	Battery degradation cost for agent i over T.
$c_K^{bat}(T)$	Battery degradation cost for K over T.
$d_i(t)$	Demand for agent i.
$d_K(t)$	Aggregated demand for K.
$e_i^b(t)$	Energy imported by agent i.
$e_K^b(t)$	Energy imported by K.
$e_i^s(t)$	Energy exported by agent i.
$e_K^s(t)$	Energy exported by K.
$e_i^t(t)$	Energy traded by agent i.
$e_i(t)$	Net demand for agent i.
$g_i(t)$	Generation for agent i.
$g_K(t)$	Aggregated generation for K.
$o_i(r)$	The offer that agent i proposes in round r.
$p_i^{bat}(t)$	Battery power at time t.
rv_i	The reservation value of agent i, i.e. the minimum utility the agent will accept..
r	The round number of negotiation.
t	Time step.

u_i^{max}	The maximum utility that can be gained by agent i from trading.
$v_i(\omega)$	Value of the contract ω gained by agent i.

Acronyms

GT	Gains from Trade.
SoC	State of Charge.
DF	Depreciation Factor.
MILP	Mixed-Integer Linear Programming.
P2P	Peer-to-peer.
RES	Renewable Energy Resource.

1 Introduction

Energy systems around the world are changing. Until recently, energy systems were primarily centralised networks managed by large utility companies. However, currently, a paradigm shift is occuring. Recent years have seen many initiatives for creating *local energy communities*. These communities typically consists of 50-200 prosumers who each consume energy but also produce some energy using some renewable energy source [1]. Some notable examples of community initiatives include the REflex project [2], Community Energy Scotland [3], Low Carbon London [4], etc. Accompanied with this change, research in the organisation of such communities has become a key topic [5, 6]. However, there are still many challenges that need to be solved. There is currently no consensus on what the best organisation for such an energy community is. Most organisations can be broadly categorized into two different approaches [5, 7].

First, there are peer-to-peer (P2P) systems where prosumers trade energy with one another. Second is the formation of energy coalitions, where prosumers group together and utilize shared energy resources (e.g. community wind turbine, community battery). Energy coalitions often benefit from their collaborative nature, leading to efficient use of resources for the community. On the other hand, peer-to-peer systems benefit from their decentralised nature. They can often be privacy conserving and more secure with the support of many new supporting developments such as energy contracts and blockchain technology. Furthermore, they allow for a more strategic setting, where prosumers are incentivized to optimize individual benefits.

While decentralization provides many tangible benefits, there are still important open questions. While with enough trades peer-to-peer systems will approach similar community benefits from a social welfare perspective as the coalitional approach, each trade has some associated cost. These costs might make some trades with marginal benefits irrational. So an important question would be how many trades are required to realise most of the potential benefits from peer-to-peer energy trading in such an energy community?

Another important question would be that of prosumer participation. An energy community may be composed of up to several hundred prosumers. But do all of them need to participate in trading?

Several papers have shown that every member of a community can benefit from being involved in peer-to-peer trading [8, 9]. However, the picture is more nuanced, these papers consider only simplified models without many physical constraints and no energy storage. Besides, even if there are some marginal gains to be had, the potential costs may outweigh the benefits. For example, consider 2 prosumers, each with their own micro-generation (e.g. solar panels on the roof) and battery. In theory, peer-to-peer trading should definitely provide benefits for these consumers, and this is certainly true at least some of the time. However, say that the demands are very closely aligned, e.g. they both have a work pattern that involves not much consumption during the morning/day, and a consumption peak in the evening. Peer-to-peer trading between these two prosumers might deliver only insignificant benefits in this case. Thus, participation might not be justified by the cost of setting up such a peer-to-peer contract.

Then a question would be whether it would be possible to achieve a high percentage of the possible benefits with only the most promising fraction of prosumer participating in peer-to-peer trading?

Furthermore, even if a majority of the prosumers would participate in trading, with whom should they trade? Prosumers that can significantly benefit from each other might participate in trading together, forming so-called *trading coalitions*. However, multiple of these could form without any of them overlapping. Thus, the emergence of these trading coalitions warrants closer investigation.

Finally, the value of an energy contract is dependent on the prosumers that establish them. Prosumers value energy quantities differently depending on their own consumption and generation profile with respect to others. The diversity of a community might affect the potential gains achieved from peer-to-peer trading. Thus, the effect of diversity factors on the previous questions needs to be studied.

This paper is the first to examine these questions using a real large-scale data set from earlier trials, i.e. Thames Valley Vision and Low Carbon London.

To answer these questions, we consider two popular approaches to P2P markets. The first is a centralised approach to P2P that uses a central matching and clearing mechanism. The second is a more decentralised approach using automated negotiation.

Furthermore, we provide a novel method for performing peer-to-peer trading using large-scale data sets. Due to computational complexity, prior works often consider small communities with a few prosumers. The focus of their work often lies on the underlying methodology and strategies and they do not explore real-world data. This results in them simulating short trading windows (e.g. 1 day) with extremely large intervals (e.g. 4-6 hours).

However, a more detailed and data-driven approach is needed to provide insights into the effectiveness of peer-to-peer trading in real-world settings. Thus, we propose a framework where energy exchanges are computed using a joint schedule optimizer. This optimizer computes the trading schedule with the maximum benefits. The peer-to-peer trading mechanism then considers the redistribution of the benefits.

1.1. Research Questions

This thesis considers the effectiveness of peer-to-peer markets. In this section, we summarise the major research questions that we will answer by investigating the effectiveness of two approaches to peer-to-peer markets.

- How many peer-to-peer energy contracts need to be established to realise the majority of the potential benefits in an energy community?
- Which fraction of the energy community needs to participate in the peer-to-peer market to achieve a high percentage of the possible benefits?
- How do trading coalitions emerge from establishing peer-to-peer energy contracts and how are the benefits distributed?
- How does the composition and diversity in energy demand profiles affect the potential benefits with respect to the number of contracts or the percentage of prosumers that participate?

1.2. Thesis Structure

The remainder of the thesis work is organised as follows: In Chapter 2, we present several approaches to peer-to-peer energy communities in existing literature. Furthermore, we examine different methods for minimizing costs for a prosumer. Chapter 3 outlines the models used for prosumers, communities, and how they control their energy assets to minimize costs. Afterwards, in Chapter 4, we explain two approaches to peer-to-peer trading. Namely, a centralised model using a centralised matching and clearing mechanism, and a decentralised model using automated negotiation. Then, in Chapter 5, we discuss pre-processing used on the real-world data to ensure that generation and demand of a community is accurately reflected in the experiments. In Chapter 6, we perform a techno-economic analysis of the two approaches and the effectiveness of peer-to-peer trading in terms of the number of contracts and prosumer participation required to realise the benefits. Finally, Chapter 7 concludes the work and highlights some topics for future research.

2
Related Work

This chapter outlines the major areas of relevant research on energy communities and peer-to-peer markets. To form an idea of state-of-the-art energy and battery control systems for regulating the use and generation of renewable energy, we discuss the relevant research in section 3.1.2. To extend this towards groups of consumers connected to the local energy grid and their interactions, we explore literature related to energy communities in section 3.1.2. These topics will lay the foundation for exploring the benefits and effectiveness of peer-to-peer trading in general.

2.1. Energy/Battery Control Systems

Renewable energy systems are often complex systems, that consist of many different variables, e.g. usage of appliances, wind speeds, solar power, house isolation, etc. One key challenge for these systems is deciding how a prosumer uses generated energy to fulfil their demands and how to handle excess generation and residual demand. These decisions often are stimulated by economical motives. Effective use of peer-to-peer trading requires an efficient single prosumer model that is able to use its own generated energy. So, in this section, we examine different approaches to control algorithms.

2.1.1. Optimization-based

Optimization models are widely adopted for controlling energy systems. This often is a logical choice, since a clear objective function exists, i.e. minimising the total costs of the system over a specified time span. Popular decision variables for the objective function are the cash flow as result of energy being exported and imported. More recent works, also include the depreciation costs of the energy storage solution [10, 11].

These decisions are often constrained by many factors since they are the result of energy that is left over or required after interacting with battery storage. Common constraints consist of the state of charge not exceeding maximum capacity or dropping below minimum capacity, the total demand being met at any time point, staying with operable bounds for charging and discharging the battery, etc.

Given such a constraint model, different approaches exist for solving such a system to optimality. Couraud et al. [12] propose to use a MILP solver to find the optimal control scheme. They find that significant reduction can be found using this model, however, it does require an ample look-ahead window. This required look-ahead window limits the practical application of the technique due to the computational complexity of the problem.

An alternative approach is proposed by Riffonneau et al. [13]. They use dynamic programming instead of a MILP solver. Their results show significant gains when considering a short period. However, performance on large-scale data has not been verified. Similar to MILP, dynamic programming suffers from high computational complexity.

Motivated by the complexity, works using machine learning for real-time optimizations have been proposed by several authors [14, 15, 16].

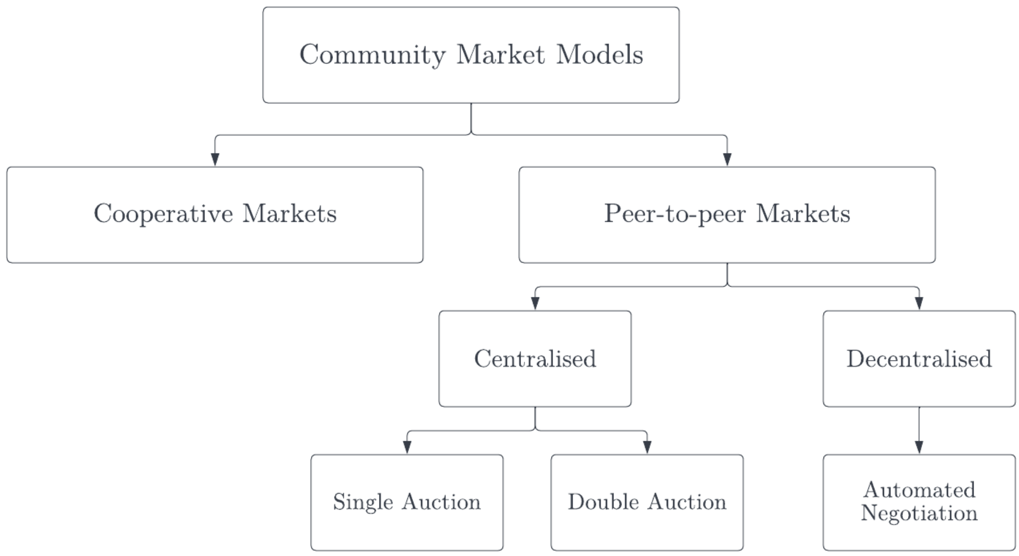


Figure 2.1: Different approaches to energy communities

2.1.2. Heuristics-based

Alternatively, to using machine learning, heuristic-based models have been proposed, which similarly attempt to minimize the overall costs. However, due to most heuristics-based models not trying to directly minimize an objective function, results are often suboptimal.

Heuristic-based models are based on simple `if-then` rules. These rules are predetermined and often based on intuition. A widely used idea for a heuristic control algorithm, is maximizing battery usage and, therefore, always charging the battery when possible (after satisfying regular demand) and discharging it when required [17]. These algorithms can often be further improved by taking into account future demand and forecasting prices [18].

Norbu et al. [19] noticed that, while optimization-based approaches perform better, the required look-ahead window needs to be amply large. In cases where the optimization algorithm considers short time periods, heuristic-based models outperform them significantly. They conclude that given results are comparable although slightly worse, heuristic-based models are preferred given the lower complexity.

2.2. Energy Communities

In this section, we discuss the many approaches used for modelling interactions between prosumers in an energy community. These approaches can roughly be divided into two prominent market models [7]. First, we will discuss cooperative markets, where prosumers collaborate and share their energy generation and storage. A small overview of the different mechanisms discussed is shown in figure 2.1.

Afterwards, we will examine peer-to-peer markets, where prosumers, instead of sharing, trade energy with each other.

2.2.1. Energy Cooperatives

In the cooperative model, individual prosumers are often modelled together, with shared demands and generation [20, 21]. Given the aggregate of the demands and generation, it attempts to optimize the social welfare, i.e. the combined cost savings of the community. Since the majority of the costs for prosumers come from importing energy to make up for demands from the central grid and exporting any excess, another way to look at minimizing cost is maximizing self-consumption for the community. This is why this model is also often known as collective or community self-consumption.

Due to the collaborative nature of cooperatives, the optimization process for minimizing cost often is extremely similar to approaches used for a single prosumer [19]. Often this model choice is also reflected in the physical setting as a community manager operates as an interfacing layer between all the prosumers in the community and outside producers and consumers. Moret and Pinson [22] show that the Karush-Kuhn-Tucker conditions correspond to the model where a single prosumer minimizes its own costs. This implies that both problems achieve similar optimal solutions under different assumptions. Thus, cooperatives often form a great benchmark for deciding the maximum benefits that can be extracted from an energy community.

Many recent works on energy cooperatives focus on optimizing economic and technical objectives when taking physical constraints and storage systems into account [23] and the fair redistribution of benefits [19, 24].

2.2.2. Peer-to-peer markets

Peer-to-peer markets consider prosumers that trade with each other. These types of markets tend to be more decentralised, sometimes even forgoing the need for an immediary and prosumer trading directly with one another. These markets benefit greatly from their decentralised nature, as it often stimulates transparancy and preserves privacy, however this sometimes does incur a loss in efficiency [25]. Furthermore, recent works, on using smart contracts for peer-to-peer exchanges further stimulate this effort in advancing security and perserving privacy [26].

Since prosumers trade directly with each other, these markets tend to be more strategic in nature than coalitional markets. Markets do not necessarily need to be fully peer-to-peer and may share some characteristics with cooperative models

What the best model for forming a price and deciding which prosumers need to trade is, is still an open question. In existing literature, the following three models have seen widespread use: single auction [27, 28, 29], double auction [30, 31, 32, 33, 34, 35] and automated negotiation [36, 37, 38].

Single Auction

In a single auction, only one side of the market communicates prices, either these are the sellers that underbid each other to come to the lowest acceptable price or these are the buyers that overbid each other until the highest acceptable price is reached. Then the energy agreed on energy is traded between prosumers for the set price. Generally, during an auction, consumers (i.e. buyers) submit offers to buy excess renewable energy to some central authority (e.g. aggregator, distributed system operator, etc.), who clears the bids. However, other auctions exist, for example where the seller can provide energy by shifting their own demands (i.e. demand-side flexibility) [39].

Often, these single auction markets are divided into 3 separate phases [40]. Initially, the market price is set using the auction. In the next phase, energy is exchanged. Finally, the bill is settled and the seller receives their revenue. However, due to the uncertain nature of renewable energy generation, energy might become unavailable for trade. Zepter et al. [41] propose to manage these mismatches, by anticipating these uncertainties and offering less during the initial stages.

Double Auction

Double auction is probably the most used and studied mechanism for price formation. Its defining characteristic is that both sellers and buyers offer prices. This allows sellers to communicate their willingness to accept an offer and for buyers their willingness to pay. In literature, the most common forms of double auctions are clock auctions and continuous auctions. In double clock auctions, the market is cleared at predetermined time intervals. While in continuous double auctions, there are no specified windows in which the market is cleared. Instead, a bid may be accepted and energy transactions may be completed at any time [42].

Wang et al. [42] and Deng et al. [43] show that small adjustments (e.g. two-level transactional model) to double auction mechanisms allow for the preservation of privacy while minimally impacting the potential benefits.

However, similar to a single auction mechanism, the auction is often mediated by some market operator, preventing full decentralisation of the peer-to-peer market.

Automated Negotiation

Another widely used mechanism within peer-to-peer markets is automated negotiation [44, 45]. Often this approach allows for a more decentralised market since the reliance on a central market institution decreases. In automated negotiation, prosumers are represented by autonomous agents that negotiate over several topics, e.g. price per unit, energy quantities, etc. Often, the main topic negotiation is concerned about is the price per unit [46, 47]. Etukudor et al. [48] discuss a framework where prosumers negotiate the prices for a single day ahead together with the energy quantities traded for multiple periods within the day. Another approach is discussed by Chakraborty et al. [49], who explore an energy lending scheme, where prosumers negotiate over energy quantities that they lend and the time the borrowed energy is returned.

Since peer-to-peer negotiation only considers a bilateral agreement as opposed to an auction mechanism where a market-wide price is set, an important process is also peer selection, i.e. how a prosumer decides with whom to negotiate. Concurrent negotiation approaches have been explored, where sellers negotiate with multiple sellers concurrently and vice versa [50]. However, due to computational complexity, systems favour a selection of peers before the negotiation process. A popular approach is the facilitation of peer selection by a central institution (often the platform provider) [51]. Khorasany et al. [52] propose a single peer selection approach, where prosumers select peers greedily based on maximum expected profit.

Identified Research Gaps

However, although great progress has been made by related works. There are still important remaining questions. Firstly, many peer-to-peer approaches, especially negotiation, suffer from high complexity, and generalizing it to large communities has been difficult [53]. Thus, the main contribution of earlier works often lies in their methodologies, since their experiments consider only a small simulation-based setup. Further research into how these models generalize to larger settings is required. Secondly, while peer-to-peer markets will approach the efficiency of a central market when enough contracts have been established, each contract has some associated costs. So, how many contracts are needed to realise the majority of the efficiency is still an open question.

Thirdly, these works focus on the total economic or technical benefits for either the community or an individual prosumer. However, within communities, especially those based on locality, some prosumers benefit differently from peer-to-peer trading. Efforts have been made to ensure Pareto optimality, i.e. that no prosumer is worse off in favour of another prosumer. But the benefits earned by each prosumer are not equal, since they depend on the energy consumption and generation behaviour of the prosumer compared to those of the community, e.g. a prosumer that consumes differently likely will benefit more. Thus, there is a need to investigate the effects of prosumer participation and diversity on the benefits.

We will address some of these challenges in pursuit of investigating the effectiveness of peer-to-peer trading.

3

Energy Asset Control Model

In this chapter, we outline our approach used for modelling prosumers and energy communities. First, we will describe the model that is used to reflect prosumer behaviour. This model will consider several resources within access of a prosumer in a realistic setting, such as a generator (e.g. wind turbine, PV) and a battery. The model will then use those resources to decide the optimal control behaviour that provides maximal economic benefit to the prosumer.

Besides, the control model, we also define the cost model that computes the incurred costs based on the control algorithm proposed. This cost model will consider both costs from importing and exporting energy to the central grid and depreciation costs as a result of energy assets degrading over time.

Finally, we will discuss extensions of this model toward an energy community following two different market structures, namely, a cooperative market and a peer-to-peer market.

3.1. Modelling prosumers in an energy community

In our model, prosumers are characterised by thier:

- Non-flexible energy demands
- Energy generation
- Energy storage solution (e.g. battery)

They all use a heuristic-based control algorithm that attempts to maximise the economic benefit. We first explain the underlying model in a single prosumer context. However, since these prosumers exist in a larger context, i.e. energy communities, we then extend this model to include the community.

3.1.1. Single Prosumer Model

To consider how to model a single prosumer, we need to identify their market objective. In our case, we are interested in the maximal economic benefits a prosumer can extract from interacting with their assets and the market over a specific time period. For the single prosumer model, we consider only the central power grid as an actor within the market (excluding the prosumer itself). Besides the economic benefit, a prosumer has another objective. Since we define energy demands to be non-flexible, the demand should be satisfied at all times. The demand $d_i(t)$ of a prosumer i can be satisfied by using some of the energy that was generated $g_i(t)$, discharging the battery by some amount $p_i^{bat}(t)$ that was stored at some earlier time, or by importing some power $e_i(t)$ directly from the central grid. Furthermore, since no excess energy can exist in the system at any time, the demand should be met exactly, thus, any excess should be either stored or exported to the central grid. A diagram of the power flow can be seen in figure 3.1. These constraints produce the following invariant that should always hold for a valid model:

$$e_i(t) = d_i(t) - g_i(t) - p_i^{bat}(t) \tag{3.1}$$

This invariant still allows for some flexibility from a control perspective, since only the demand and generation are inflexible from a prosumer standpoint. The prosumer can decide whether or not to buy residual demand from the grid or use battery power (if available).

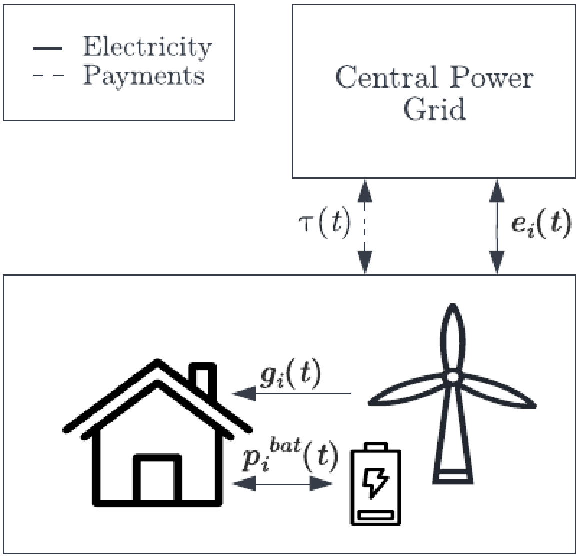


Figure 3.1: Diagram of the single prosumer model

3.1.2. Control Algorithm

To decide whether a prosumer should use the battery or interact with the grid, a control algorithm is required. The control algorithm should decide what the optimal battery usage schedule that minimizes costs is. However, the control algorithm is constrained by some physical factors, such as the battery's minimum (SoC^{min}) and maximum (SoC^{max}) capacity, charging (η^c) and discharging (η^d) efficiency, and it's maximum charge and discharge power ($p^{bat,max}$). Norbu et al. [19] found that a heuristic-based model provides close to the optimal decision when considering a flat tariff. This is due to battery usage being less expensive on average than interacting with the grid. There is also no opportunity cost of using the battery since prices for buying and selling do not fluctuate. Furthermore, a heuristic-based model proves to be less computationally expensive and less uncertain than an optimisation-based model. So in this study, we consider the heuristic-based model adapted from Norbu et al. [19]. In this model, two different regimes can be identified. We outline the strategies used in each. The first regime we consider is when there is residual demand (i.e. there is more demand than energy generated). In this case, we should attempt to discharge the battery to fulfil demands. Discharging is subjected to some constraints.

- We can never discharge more than the maximum discharge power allows: $|p^{bat}(t)| \leq p^{bat,max}$
- We can never discharge the battery below it's minimum capacity: $SoC(t) \geq SoC^{min}$

In case discharging is insufficient, the remainder of the residual will need to be bought from the central grid. We can determine the energy imported from the grid $e^b(t)$, the quantity of energy discharged from the battery $p^{bat}(t)$ and the state of charge of the battery $SoC(t)$ as follows:

$$p^{bat}(t) = \min\left(\min\left[d(t) - g(t)\right], p^{bat,max}\right), \eta^d \left[SoC(t-1) - SoC^{min}\right]\right) \tag{3.2}$$

$$SoC(t) = SoC(t-1) - \frac{p^{bat}(t)}{\eta^d} \tag{3.3}$$

$$e^b(t) = d(t) - g(t) - p^{bat}(t) \tag{3.4}$$

The second regime considers moments when there is excess generation (i.e. there is more energy generated than demand). In these cases, we will attempt to charge the battery until it is full. Any surplus after charging will be sold to the central grid. Charging is subjected to the following constraints:

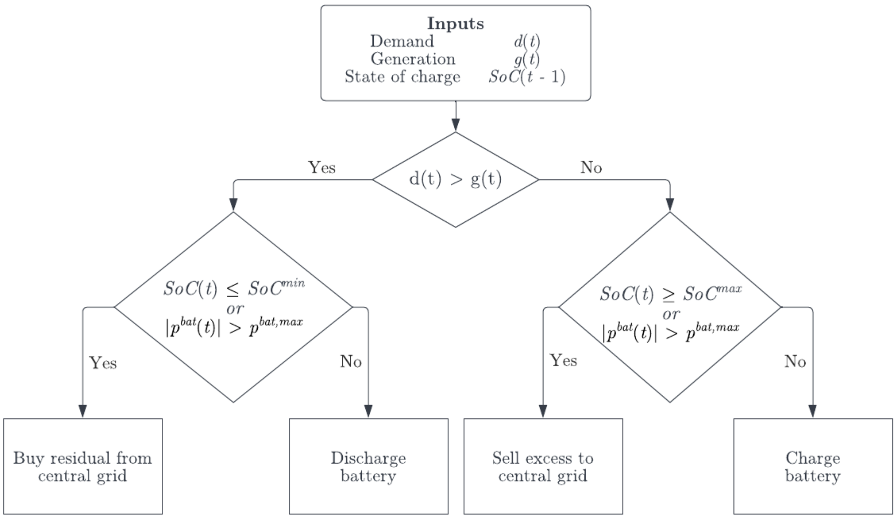


Figure 3.2: Flowchart of the heuristic-based control algorithm

- We can never charge more than the maximum charge power allows: $|p^{bat}(t)| \leq p^{bat,max}$
- We can never charge the battery beyond its maximum capacity: $SoC(t) \leq SoC^{max}$

We can determine the energy exported to the grid $e^s(t)$, the quantity of energy charged to the battery $p^{bat}(t)$ (negative) and the state of charge of the battery $SoC(t)$ as follows:

$$p^{bat}(t) = -\min\left(\min\left[g(t) - d(t)\right], p^{bat,max}\right), \frac{1}{\eta^c}\left[SoC^{max} - SoC(t-1)\right]\right) \tag{3.5}$$

$$SoC(t) = SoC(t-1) - \eta^c p^{bat}(t) \tag{3.6}$$

$$e^s(t) = g(t) - d(t) + p^{bat}(t) \tag{3.7}$$

These two regimes combined form the complete control algorithm. A flowchart outlining the algorithm is shown in figure 3.2.

Using the computed energy import from and export to the central power grid, we can compute the costs for a single prosumer.

3.1.3. Cost Computation

The cost of a prosumer can be computed as the sum of two different components, i.e. the costs and revenue from interacting with the community or the grid $c^e(T)$, and the depreciation of private energy assets $c^a(T)$, e.g. the battery and wind turbine.

$$c(T) = c^e(T) + c^a(T) \tag{3.8}$$

For a single prosumer model we only consider imports and exports to the central power grid. The costs incurred can be seen as the costs from buying energy from the grid minus the revenue gained from exporting energy to the grid. The costs depend on the quantity sold $e^s(t)$ and bought $e^b(t)$ at their respective export tariff $\tau^s(t)$ and import tariff $\tau^b(t)$. The total costs from exporting and importing energy is computed as follows:

$$c^e(T) = \sum_{t=1}^{T} e_i^b(t)\tau^b(t) - \sum_{t=1}^{T} e_i^s(t)\tau^s(t) \tag{3.9}$$

Besides the costs from exchanging energy, there are some costs associated with the use of private energy assets. Due to their use, they degrade over time, eventually leading to them being inoperable

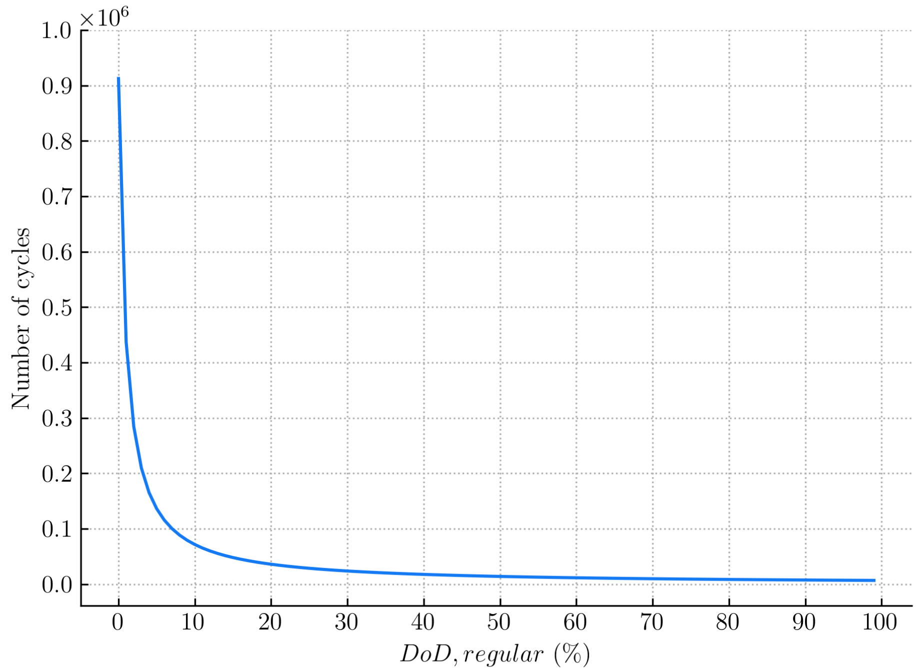


Figure 3.3: Lithium-ion battery life cycle data from Xu et al. [54]

and requiring replacement or maintenance. We quantify the degradation using depreciation based on the use and lifetime of the asset.

In our model, we consider two assets that depreciate significantly, namely the wind turbine and the battery. The total depreciation costs is given by:

$$c^a(T) = c^g(T) + c^{bat}(T) \tag{3.10}$$

The depreciation cost for a wind turbine is calculated as follows:

$$c_i^g(T) = \frac{\max_t g_i(t) \cdot c_{kW}^g}{\lambda^{bat}} \tag{3.11}$$

where c_{kW}^g is the cost per rated kW and λ is the lifetime of the wind turbine. The rating of the wind turbine is decided as the maximum power generated at any time step.

Accounting for Battery Degradation in The Discharging Model

The picture is slightly different for the battery since the degradation is highly dependent on the use pattern. Frequent charging and discharging, especially when the depth of discharge is deep, will accelerate degradation significantly. Manufacturers of batteries often specify a battery cycle life on a provided datasheet. This cycle life specifies the expected number of charge/discharge cycles per depth of discharge that can undergo before the performance drops below operable levels. In this study, we use the lithium-ion battery cycle life data specified by Xu et al. [54] (see figure 3.3).

However, test settings in which these batteries have been rated are often not reflective of real applications. In test settings, the common measure is the number of regular full cycles. Full cycles are phases where the battery is discharged and charged at the same depth. Half cycles consider either only a discharging or a charging phase.

Regular cycles consist of a discharge from a 100% SoC to a specific state of charge below it and then a charge back to 100% SoC. E.g. for a DoD of 40%, you would start at 100% SoC, discharge to 60% SoC and then charge back to 100% SoC. Irregular cycles would start at SoC besides 100%.

However, in actual use cases, half-cycles and irregular cycles are very common. Since irregular cycles strain the battery differently, the impact on the lifespan differs significantly. To factor in these effects, we adopt the modified rainflow counting algorithm proposed by Norbu et al. [19]. The rainflow counting

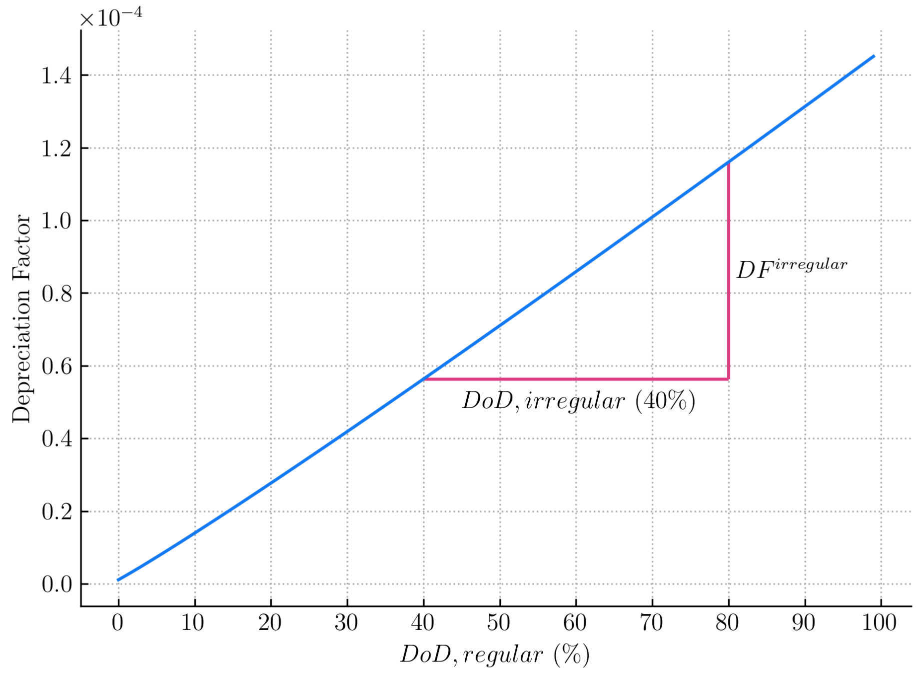


Figure 3.4: Depreciation factor for regular cycles with an example of an irregular cycle starting at 60% SoC and ending at 20% SoC. (Data is based on the lithium-ion life cycle data from Xu et al. [54])

algorithm receives the state of charge over the usage period and outputs the number of cycles that have a particular starting and ending state of charge. Using that we can categorize them into regular or irregular cycles and full or half cycles. For regular cycles, we use the provided cycle life to compute the depreciation as follows:

$$DF^{regular} = \sum_{DoD=0\%}^{DoD=100\%} \frac{n^{DoD,regular}}{N_{cycles}^{DoD,max}} \tag{3.12}$$

where $n^{DoD,regular}$ is the number of regular cycles at the specific DoD value during the evaluation period, and $N_{cycles}^{DoD,max}$ represents the cycle life reported by the manufacturer.

For all the irregular cycles J during the evaluation period, we compute the deprecation factor as follows:

$$DF^{irregular} = \sum_{j \in J} n_j \cdot \left| \frac{1}{N_{cycles}^{DoD^{eq}(SoC^{Start}),max}} - \frac{1}{N_{cycles}^{DoD^{eq}(SoC^{End}),max}} \right| \tag{3.13}$$

where SoC^{Start} and SoC^{End} are the starting and ending state of charges respectively for the irregular cycle j, n_j represents the number of irregular cycles, and $N^{DoD^{eq}(SoC^{Start}),max}$ corresponds to the maximum number of cycles for $DoD^{eq}(SoC^{Start})$, i.e. a depth of discharge equivalent to a cycle starting at 100% SoC and ending at SoC_j^{Start}. It can be computed using:

$$DoD^{eq}(SoC^{Start}) = 100 - \left(\frac{SoC^{Start}}{SoC^{max}} \cdot 100 \right) \tag{3.14}$$

We compute $N^{DoD^{eq}(SoC^{Start}),max}$ using a similar notion.

For example, the depreciation factor of a cycle starting at 60% SoC and ending at 20% SoC, would be the absolute difference between the depreciation factor for a regular cycle with a DoD of 40% and the factor for a regular cycle with a DoD of 80% (see figure 3.4).

Using this depreciation factor, we can compute the yearly degradation cost as follows:

$$c_i^{bat}(T) = \frac{SoC^{max} \cdot c_{kWh}^{bat}}{\max\left(DF, \lambda^{bat}\right)} \tag{3.15}$$

where c^{bat}_{kWh} is the battery cost per kWh and λ^{bat} is the maximum lifetime of the battery.

3.1.4. Community Energy Model

This single prosumer model can be easily extended to support the interaction between prosumers within a community. Not all prosumers need to necessarily participate. We denote the set of prosumers that do participate in trading energy as the trading coalition $K \subseteq N$. The single prosumer model needs to be extended to consider this subset of prosumers and compute their costs. In this study, we consider two extensions. First, we look at the simple extension of the single prosumer model towards a coalitional model. In this cooperative model, prosumers can freely use each other's assets and they collaborate to achieve maximal social welfare. This model is important to consider since social welfare is optimized and can therefore form a baseline for the optimal benefits a community can gain from trading. Furthermore, the control of the whole community can provide important insights into finding optimal P2P contracts. Second, we consider the peer-to-peer model, where instead prosumers exchange quantities of energy for some price. This price is negotiated by the specified peer-to-peer mechanism.

Cooperative Model

In a cooperative model, we consider a trading coalition K, where each prosumer $i \in K$ has their own energy assets. However, they can use other prosumers' assets if necessary. Each prosumer i within the community also has their own demand profile $d_i(t)$ and generation profile $g_i(t)$. The key intuition for computing the costs is that this cooperative model does not differ a lot from the single prosumer model. Since prosumer share their assets and their demands can be satisfied by anyone's generation, we can reduce the coalition to a single prosumer with the aggregated demands, generation and storage of the individual prosumers. We can create aggregate representations for the three characteristics of a prosumer for the coalition. First, we compute the combined demand profile as the sum of the loads at each time point, i.e.:

$$d_K(t) = \sum_{i \in K} d_i(t) \qquad \forall t \in [0, T] \tag{3.16}$$

Second, we compute the generation profile for the coalition as follows:

$$g_K(t) = \sum_{i \in K} g_i(t) \qquad \forall t \in [0, T] \tag{3.17}$$

Finally, we can compute the combined capacity of the batteries as follows:

$$SoC_K = \sum_{i \in K} SoC_i \tag{3.18}$$

Using these, we can compute the combined costs of the coalition using a similar approach as the single prosumer model.

Peer-to-Peer Model

For the peer-to-peer model, prosumers trade energy quantities with each other. It is common for these trades to be recorded in energy contracts, detailing the relevant information of the trade. We formally define an energy contract as a triplet $\omega = (i, j, \theta(t))$, where i and j are the prosumers participating in the trade and θ are the energy quantities traded from i to j (note that the quantities can be negative if energy is traded from j to i). The contracted space containing all possible contracts is denoted by Ω.

We consider these contracts from a social welfare perspective and identify the value of such a contract as the savings it can provide to the combined bill of the prosumers involved in the contract. The value of such a contract is denoted as $v(\omega)$. How this value is distributed amongst the prosumers is decided by the peer-to-peer mechanism. Similarly, the mechanism decides which contracts are accepted and which are rejected. Accepted contracts are realised and energy is exchanged accordingly. The set of accepted contracts is denoted by Ω^{accept}.

The contracts that a prosumer accepts change the energy they have available at a particular time step. However, demands still need to be satisfied for each prosumer so any residual demands need to be satisfied by importing energy from the grid (or discharging the battery). Similarly, excess energy still needs to be exported to the grid (or used to charge the battery). To compute how much residual demand or excess generation is left, we first compute the total energy quantity traded $e^t(t)$ by a prosumer i for each time step as follows:

$$e_i^t(t) = \sum_{(i,j,\theta)\in\Omega_i^a} \theta(t) - \sum_{(j,i,\theta)\in\Omega_i^a} \theta(t), \qquad \forall j \in K \tag{3.19}$$

The total amount of energy remaining that should be sold or bought from the grid is given by:

$$e_i(t) = g_i(t) - d_i(t) - e_i^t(t) \tag{3.20}$$

We can use this energy instead of the generation and demand profiles in the battery control algorithm to compute the energy that needs to be sold $e^s(t)$ to and bought $e^b(t)$ from the grid using the method outlined in section 3.1.2.

Using these values we can compute the costs from interacting with the community or the grid $c_i^e(T)$ for a single prosumer i as follows:

$$c_i^e(T) = \sum_{t=1}^{T} e_i^b(t)\tau^b(t) - \sum_{t=1}^{T} e_i^s(t)\tau^s(t) - \sum_{\omega\in\Omega_i^a} v_i(\omega) \tag{3.21}$$

where Ω_i^a are the accepted contracts involving prosumer i and $v_i(\omega)$ is the value attributed to i by the peer-to-peer mechanism. Note that for a single contract $v_i(\omega) + v_j(\omega) = v(\omega)$.

Costs as results from the degradation of assets $c_i^a(T)$ remain the same as in the single prosumer model since assets are still individually owned. Total costs for a single prosumer are then given using:

$$c_i(T) = c_i^e(T) + c_i^a(T) \tag{3.22}$$

The costs for the trading coalition K is equal to the sum of the costs for the prosumers that are part of the coalition:

$$c_K(T) = \sum_{i\in K} c_i(T) \tag{3.23}$$

4

Peer-to-Peer Trading Models for Energy Communities

In this chapter, we will consider two different peer-to-peer market models that will be used to evaluate the efficiency of peer-to-peer electricity markets.

One of the models is a centralised market approach where a central market institution decides on the energy contracts, the involved prosumers and the distribution of benefits. The other model considers a more decentralised approach, where prosumers negotiate over the acceptance of contracts and the distribution of the benefits. To ensure that the evaluation reflects a realistic market setting, we perform a data-driven analysis using a large-scale real-world data set.

Both of these models will prove to provide significant benefits to the energy community, to quantify these benefits, we begin this chapter by formally defining these benefits. Furthermore, before introducing both models, we outline how we tackled the high complexity of peer-to-peer trading using a joint schedule optimizer. This optimizer plays a key role in both models by reducing the computational complexity of the exchanges by computing optimal peer-to-peer energy contracts.

4.1. Gains from Trade in Energy Trading

Due to the diversity of demand and energy profiles and the increased availability of energy storage, trading coalitions are more efficient and flexible than individual prosumers. This leads to a decreasing reliance on the grid. Since one of the major components of the costs is the interaction with the central energy grid, trading energy leads to significant savings in the total costs. These savings are called the 'Gains from Trade' (GT).

For both models, we can compute the Gains from Trade as follows:

$$GT_K(T) = \sum_{i \in K} b_i(T) - b_K(T) \tag{4.1}$$

We note that this value is at least zero since in the worst case everyone would exclusively use their individual assets. This would mean that the community's costs would be equal to the sum of individual costs, i.e. $\sum_{i \in N} b_i(T) - b_K(T)$

For the peer-to-peer setting, we identify an alternative computation, i.e.:

$$GT_K(T) = \sum_{\omega \in \Omega^{accept}} v(\omega) \tag{4.2}$$

Since the savings from peer-to-peer trading are effectively the combination of the savings of all established peer-to-peer contracts.

4.2. Joint Schedule Optimizer

The goal of peer-to-peer trading is to maximise the gain from trades. However, there are two major challenges that make computing these for realistically sized communities difficult.

The first problem is the computational costs, since every prosumer has different demand and generation profiles, and the quantities of energy that can be exchanged during each period can range between many different values, the contract space becomes infeasibly large.

The second problem is that these gains need to be distributed among the prosumers that participate in trade. To address the computational complexity of the energy exchange, we propose a novel method that uses a joint schedule optimizer to compute the optimal energy schedule, i.e. the energy quantities that should be exchanged to create a peer-to-peer energy contract with maximal GT. This optimizer behaves similar to an oracle that is used to solve algorithmic problems.

Furthermore, this method provides several other advantages over the energy quantities being optimized during the peer-to-peer mechanism. Since only the joint schedule optimizer requires information about the demand and generation profiles, and only the combined schedule is broadcasted to the prosumers, privacy is conserved.

A key insight for designing this optimizer is that coalitional modelling will lead to a solution that maximizes optimal welfare together with the minimum energy quantity exchanged with the grid, and the battery SoC during the operation window. Using these factors, we can extrapolate the demand, generation and battery usage of the individual prosumers. Since a peer-to-peer trade only involves two prosumers, this extrapolation can be computed with reasonable complexity.

To get the optimal social welfare found by the coalitional model, it suffices to satisfy the following constraints. The combined net demand at each time step for two agents should be equal to the net demand of a coalition of two agents, i.e.:

$$e_{\{i,j\}}(t) = e_i(t) + e_j(t) \tag{4.3}$$

This constraint ensures that the costs of exchanging energy with the grid are equal. The net demand is analogous to the residual demand and excess generation, however, it combines the two into a single value, where a positive value denotes residual demand and a negative value excess generation.

To ensure that the depreciation costs of the assets are equivalent, we need to ensure that battery usage remains the same over both cases, i.e.:

$$SoC_{\{i,j\}}(t) = SoC_i(t) + SoC_j(t) \tag{4.4}$$

If both of these constraints are satisfied, we ensure that the system of two prosumers behaves as a coalition, and thus has the same costs. To compute the schedule that ensures that both these constraints are satisfied, we propose a few different methods, that have slightly different goals.

4.2.1. Method 1: Balancing loads

Instead of trying different methods to compute the individual net demands, we can consider a simple balanced load scheme. This scheme attempts to balance the loads and SoC after the trading process. However, since different prosumers have different battery capacities and different generation capacities, we balance the loads accordingly.

This means the contract will contain exchanges leading to the following net demands for the prosumers:

$$e_i(t) = e_j(t) = \frac{e_{\{i,j\}}(t)}{2} \tag{4.5}$$

Furthermore, the SoC should also be balanced:

$$\frac{SoC_i(t)}{SoC_i^{max}} = \frac{SoC_j(t)}{SoC_i^{max}} = \frac{SoC_{ij}(t)}{SoC_{ij}^{max}} \tag{4.6}$$

This provides us with targets for the net demand and SoC for each of the prosumers. To find the energy quantities we do the following:

1. Compute the net demand and the SoC for either prosumer for each time step using the algorithm outlined in section Section 3.1.2.
2. Compute the net demand for a coalition containing the two prosumers for each time step using the algorithm outlined in Section 3.1.4.
3. Apply equations 4.5 and 4.6 to find the targets.

4. Compute the differences between the sum of the target net demand and SoC and the sum of computed net demand and SoC.

An example of how this method applies to demand profiles is shown in figure 4.1. The energy is transferred in such a way that the final residual demand profiles have similar loads at each timestep.

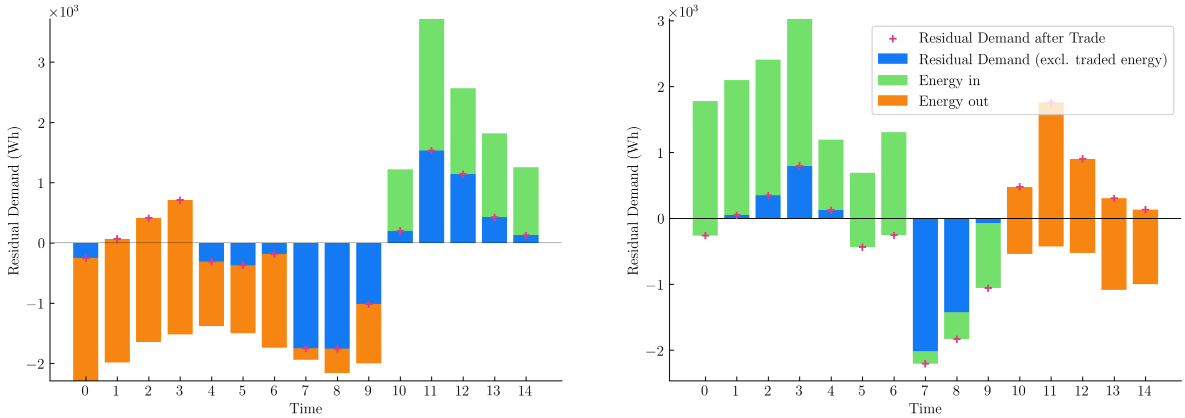


Figure 4.1: Example of the joint schedule optimizer balancing loads

While this approach is easy to understand and very tractable, it has some noticeable downsides. First, due to both prosumers receiving some amount of the SoC and net demand, often more energy is exchanged than minimally required. Furthermore, the diversity of the two prosumers is not preserved for future trading, since both will receive similar profiles after the balancing. So we also propose another method to potentially solve these problems.

4.2.2. Method 2: Minimizing Energy Quantities

This method attempts to exchange the minimum energy required by exploiting some heuristics from the battery control algorithm. However, a drawback of this method is that it is less applicable to other control algorithms compared to method 1. We observe that due to the control algorithm outlined in Section 3.1.2 there are two distinct regimes. Either there is no residual demand and some SoC or there is no SoC and some residual demand. Using prior knowledge that either of these needs to be true, we can optimize the residual demand separately from the SoC.

Initially, we optimize the residual demand by compensating the residual demands with any excess generation available. However, we do ensure that the prosumer with excess generation does not end up with any residual demand. This would also result in no energy being traded unless one prosumer has excess generation and the other has residual demand. Without loss of generality take that prosumer i has excess generation and prosumer j has residual demand. Then, the energy transferred $e_{ij}^{t_e}(t)$ from i to j during this step will be:

$$e_{ij}^{t_e}(t) = \min\left(g_i(t) - d_i(t), d_j(t) - g_i(t)\right) \tag{4.7}$$

Now, to ensure that the the SoC of both prosumers line up with the expected value. We first compute the expected combined SoC_{ij} using the cooperative model (see section 3.1.2). In case the combined expected SoC_{ij} is equal to the sum of the individual SoC's, no trading is required to compensate. However, in case it is less, it can only be the result of one of the individual batteries exceeding their maximum capacity. To adjust for this, the excess is traded to the other prosumer and used to charge their batteries instead. Without loss of generality, suppose that prosumer i battery is at maximum capacity. Then, the energy transferred $e_{ij}^{t_b}(t)$ to correct for the SoC from i to j is:

$$e_{ij}^{t_b}(t) = \eta_c\left(SoC_{ij} - SoC_j - SoC_i\right) \tag{4.8}$$

We provide an example of the demand profiles after applying this method in Figure 4.2. We see two prosumer that trade with one another by exchanging the minimal amount of energy. Notably, during timesteps $t = 4, 5, 6$, it seems that more energy is traded than necessary, however, this is due to the battery exceeding capacity for the left prosumer.

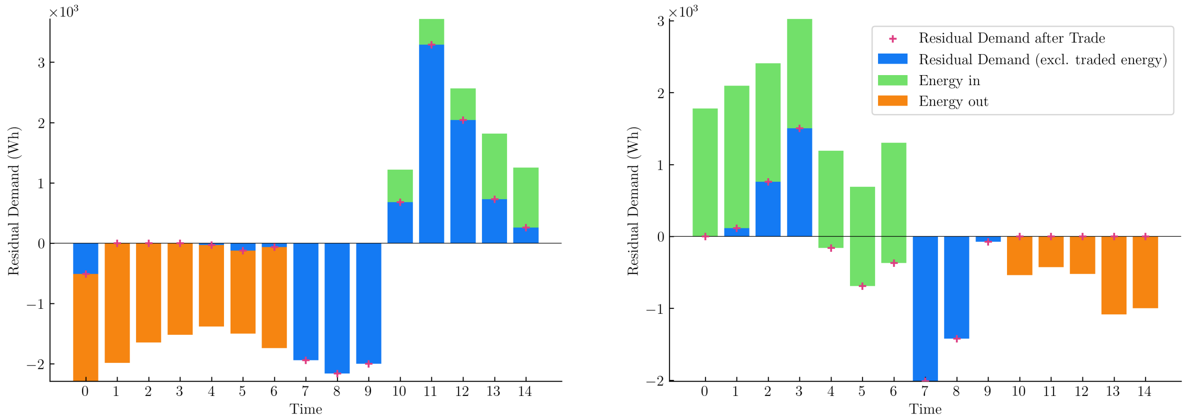


Figure 4.2: Example of the joint schedule optimizer minimizing energy quantities

Minimizing the energy quantities traded has some major advantages to method 1, as it preserves the diversity of the prosumers better. While some diversity is lost, due to trading towards a system where no external energy is needed, only the minimal amount is traded. Besides, in a real application, attempting to minimise the trading amount helps to prevent overloading the logistics system and reduces overhead costs.

4.2.3. Comparison of Schedule Optimizer Algorithms

While both methods deliver an optimal schedule given the specified constraints, there are some key differences between them. Method 1 allows for quick computation and accurate results, while method 2 preserves the diversity and minimizes the energy quantities. Both methods also have different impacts on future trades, since the resulting profiles after trading differ significantly. However, since the sum of profiles equals the optimal schedule specified by the coalition, the value of both contracts is equivalent. Making both methods appropriate for analyzing the effects of peer-to-peer trading on social welfare. In the remainder of the study, we mainly use method 2, as the computational advantage provided by method 1 does not outweigh the diversity and smaller trade quantities of method 2.

Using this method, we can implement the joint schedule optimizer. This optimizer allows us to record the optimal trading schedule and its value, but does not provide us any direction on how to distribute the gains from the contract nor whether the contract should be accepted by either prosumer. These two factors will be handled by the peer-to-peer trading mechanism. In this study, we consider two models, centralised matching and clearing and peer-to-peer negotiation.

4.3. Centralised Matching and Clearing

The centralised matching and clearing mechanism is a centralised mechanism, where the market is cleared by accepting contracts in order of maximal Gains from Trade. To find which contracts have the highest Gains from Trade, we compute a subset of the contract space given by the joint schedule optimizer for all the potential pairs of prosumers. This ensures that for each pair, we only consider the most efficient contract. These contracts are then sorted in order of decreasing gains, and the highest value contract is accepted by the market. Gains from the contract are equally split between the two prosumers.

After such a contract is accepted, contracts involving the prosumers of the accepted prosumer need to be recomputed, as their energy profiles change. Hence, only a single contract is accepted before (partially) recomputing the contract space. For a visual overview of the process, see Figure 4.3.

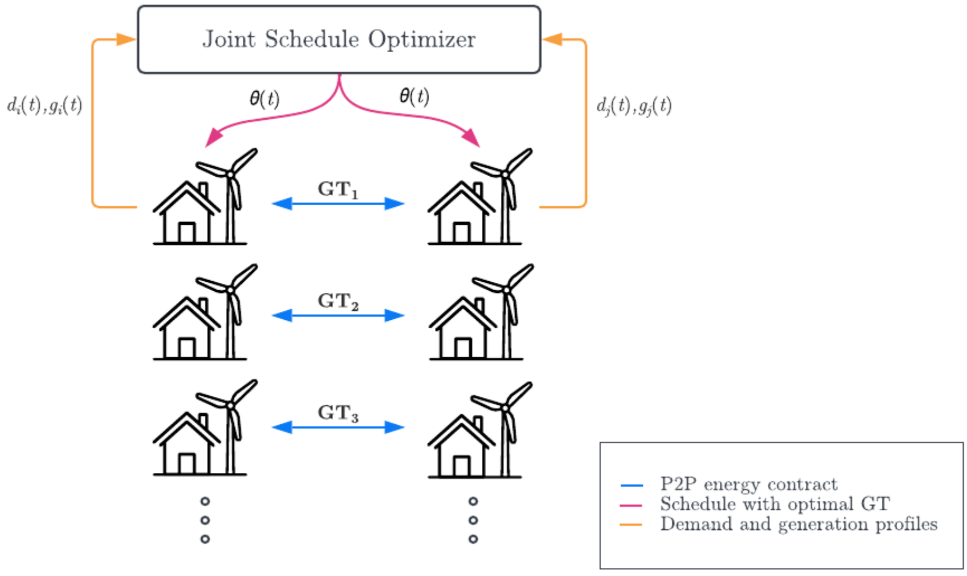


Figure 4.3: Centralised matching and clearing, note that contracts are matched in order of decreasing Gains from Trade, i.e. $GT_1 \geq GT_2 \geq GT_3 \geq ...$

We can define a single round of accepting a contract as follows:

1. Compute the contract space given the prosumers' net demands profiles $\widetilde{e_i}(t)$
2. Sort the contracts space in descending order by Gains from Trade
3. Accept the contract with the highest Gains from Trade
4. Split the gains equally between the two prosumers

This process continues until no more trades can be made, or the gains of trade drop below a specified threshold. Since the method accepts contracts in order of most gains, subsequently accepted contracts will have less or equal value, eventually leading to very small gains.

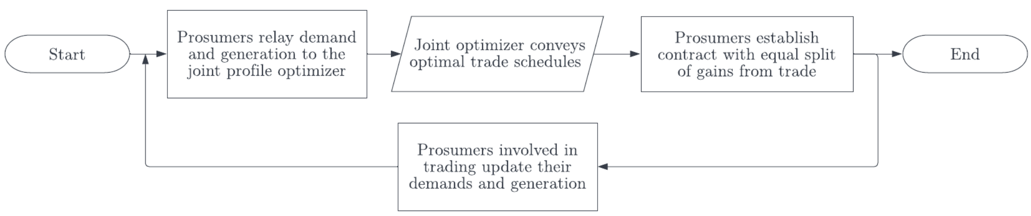


Figure 4.4: Flow diagram for centralised matching and clearing

4.4. Peer-to-Peer Negotiation Framework

Negotiating peer-to-peer contracts has proven complex [49, 48, 52], with earlier works often limiting the negotiation domain to a small number of time steps and quantities. Our framework consists of two main steps, i.e. peer selection and negotiation. During the peer selection step, we select a number of prosumers based on the highest possible savings. Finally, during negotiation, the distribution of the gains is decided. These steps are then iterated over until no more new contracts can be established or a specified deadline has been reached. While earlier works have considered multi-issue negotiation, resulting in an extremely large negotiation space, we instead consider a scheme where we use a joint profile optimizer, that computes the optimal energy exchange schedule. Prosumers, therefore, do not

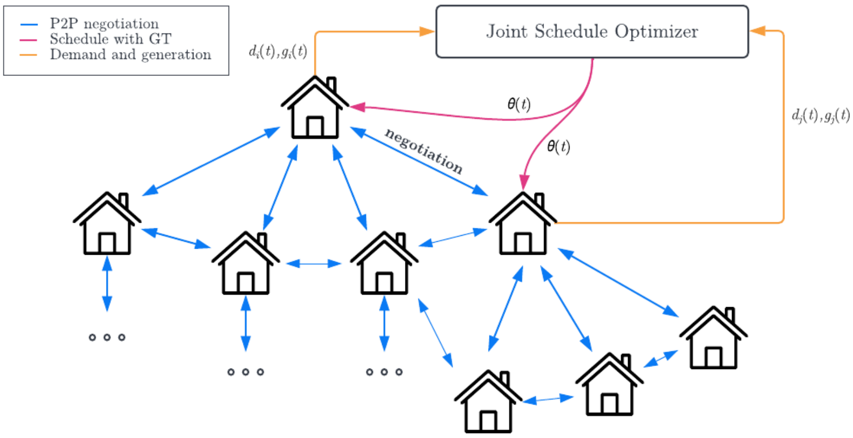


Figure 4.5: Decentralised P2P negotiation between several prosumers, note that interaction between the joint profile optimizer and prosumers happens for each negotiation, however, only one example is shown.

need to negotiate over how much energy needs to be exchanged at each time step, since the best strategy is to follow the schedule prescribed by the profile optimizer. The schedule will lead to joint Gains from Trade, but will not provide the gains for each prosumer. Thus, prosumers will need to negotiate over the redistribution of the Gains from Trade. The introduction of a joint profile optimizer enables a reduction of complexity. This allows us to consider longer more granular trading periods. Furthermore, its introduction also maintains privacy, as prosumers only need to know how much energy needs to be traded at each time step.

4.4.1. Negotiation

The negotiation protocol is based on the concurrent alternating offers protocol. It consists of two phases: A offer phase and a commit phase. In the offer phase, agents keep exchanging offers until at least one is accepted. While in the commit phase, a single most promising offer is accepted by the market.

Offer phase

The bidding phase consists of multiple rounds. During each round, every agent provides an offer to multiple different agents. Note that the offer is the same for each partner and it is not possible to provide different offers in a single round. Furthermore, the offer made should depend only on the value of the contract and cannot include any details about the contract itself. The receiving agent then can accept or reject the offer. In case the offer is accepted, it is made public and will be considered for approval by the market. Otherwise, the bidding agent will create another offer during the next round.

Algorithm 1 Offer exchange phase

Input: Contract space Ω, sets of potential trading partners P_i for each agent $i \in N$, agent strategy s_i for each agent i
Output: Set of accepted offers and contracts (can be more than one)

```
r ← 0
Ω^a ← ∅
O^a ← ∅
while r < deadline AND Ω^a = ∅ do
    for all i ∈ N do
        for all j ∈ P_i do
            select ω = (i, j, θ) ∈ Ω                    ▷ Precomputed by the profile optimizer
            make-offer_{i→j}(r, v_i(ω), s_i)
        end for
    end for
    for all o ∈ receive-offers_i(r) do
        if accept-offer_i(r, o, s_i) then
            select ω = (i, j, θ) ∈ Ω                    ▷ Find the contract belonging to the offer
            Ω^a ← Ω^a ∪ {ω}
            O^a ← O^a ∪ {o}
        end if
    end for
    r ← r + 1
end while
return Ω^a, O^a
```

Commit phase

In the commit phase, the market looks at all the public offers and approves the one with the highest gains of trade. All other offers are then rejected, to prevent large regret, as some players in the market have changed, which might lead to a better deal. After accepting the offer, the payments are settled and energy is exchanged. After the energy exchange, the contract space should be updated.

Algorithm 2 Commit phase

Input: Contract space Ω, all prosumers $i \in N$, set of all accepted contracts Ω^a and offers O^a in the offer phase
Output: Accepted contract ω^a and new contract space Ω'

```
Sort (ω, o) ∈ Ω^a × O^a on v_i(ω) in descending order
ω^a, o^a ← Ω^a × O^a.pop()                              ▷ The contract with the most value
(i, j, θ) = ω^a
î ← update-profiles(i, θ)
ĵ ← update-profiles(j, θ)
exchange-payment_{i→j}(o^a)
Ω' ← Ω
for all ω = (i, k, θ) ∈ Ω do          ▷ Contracts including agents in ω^a should be updated
    Compute ω' using the profile optimizer
    Ω' ← Ω' \ {ω} ∪ {ω'}
end for
return ω^a , Ω'
```

4.4.2. Peer selection

During the peer selection process, the mechanism selects for each prosumer a subset of prosumers to trade with. The peers of a prosumer are sorted based on the potential gains and the k peers with the highest potential gain are selected as peers. The prosumer is able to negotiate with each peer concurrently. This method might lead to asymmetric negotiation, as it is not guaranteed that for each peer in the top k the original prosumer is also in their top k.

Algorithm 3 Peer selection algorithm for agent i

Input: Set of all possible energy contracts Ω_i, number of desired trading partners k
Output: List of the top-k trading partners
Sort $\omega \in \Omega_i$ on $v_i(\omega)$ in descending order
return $\Omega_i[1..k]$

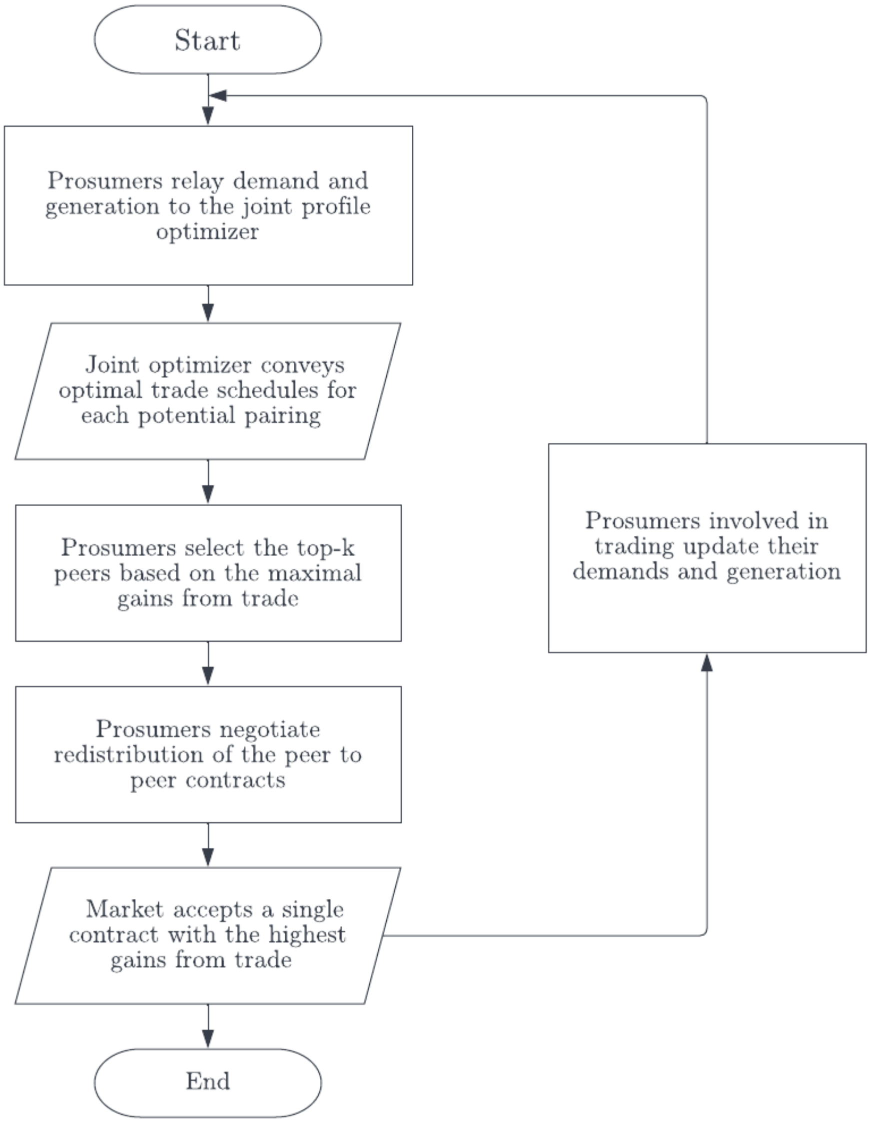


Figure 4.6: Flow diagram for peer-to-peer negotiation

4.4.3. Agent strategies

The negotiation strategy dictates the offer and acceptance behaviour of an agent. For this work, we have chosen to only consider a single negotiation strategy since the main focus of the work is to investigate the effectiveness peer to peer trading markets and their total benefits. Different negotiation strategies affect how the gains inside a trading coalition are distributed and also can impact the formation of the trading coalition. But, it would not significantly affect the total benefits of peer-to-peer trading. The chosen negotiation strategy was a linear concession strategy.

In the first round, the agent proposes an offer that is equal to the maximum utility u_i^{max} that can be gained from trading with all partners combined. This represents the market power of the agent. The agent also defines a reservation value rv_i, which is the minimum utility the agent will accept. The bid in consequent rounds is determined as a linear function of the round number r that decays to the minimum utility when the deadline d is reached. This function is defined as:

$$o_i(r) = rv_i + (u_i^{max} - rv_i) \cdot (1 - \frac{r}{d}) \tag{4.9}$$

The agent will accept a bid if a received bid has a value higher or equal to its last bid.

5

Pre-processing Generation and Demand Data

Before we can examine the experimental results, the data needs to be pre-processed in such a way that it is reflective of the real world and usable within the proposed framework. In this chapter, we outline some of the pre-processing steps used. First, we discuss how we extracted generation profiles from the gathered weather data. Second, we decide how to optimally allocate batteries to prosumers. Finally, we apply popular demand profiling techniques to find unique demand profiles, so we can create realistic scenarios sampled from a large community.

5.1. Wind Power Modelling

The weather data has been sourced from the time period when the trials were performed. However, while wind speed data is easily accessible, no data has been published in regards to the wind power generated by each household during that time period. So, in this section, we explain how we modelled the wind power from the available wind speed data.

5.1.1. Wind speed to power conversion

While weather data is widely available for many regions around the world, the energy generated by wind turbines is not often published. To obtain the energy from the wind data, we use the power curve based on the data sheet of a typical community wind turbine inspired by methods from Norbu et al. [19], Früh [55] and Andoni et al. [56].

The wind data from the UK Met Office Integrated Data Archive System (MIDAS) is provided as hourly mean wind speed measured at an anemometer with a nominal height of 26m above ground. These wind speeds have been converted to the wind speeds at wind turbine hub height (e.g. 50m for Enercon E-33) using a logarithmic shear profile:

$$v^h(t) = v^a(t)\frac{\log(Z^h) - \log(Ra)}{\log(Z^a) - \log(Ra)} \tag{5.1}$$

where $v^h(t)$ is the wind speed at hub height, $v^a(t)$ refers to the wind speed at anemometer height, Z^h and Z^a refers to the hub height and anemometer height respectively and RA denotes the surface roughness. In our study, we use $Z^h = 50m$, $Z^a = 26m$ and $Ra = 0.03m$ (as adopted by Norbu et al. [19]) to compute the wind speed at hub height.

Given this wind speed, we can calculate the wind power produced by a wind turbine using the data sheet of a typical wind turbine. In this study, we consider the Enercon E-33 [57]. Based on the methods from earlier works by Norbu et al. [19], Andoni et al. [56], who found that the power curve is well approximated using a sigmoid function. We fit a sigmoid curve to the values provided by the data sheet and find the following sigmoid:

$$g(t) = \frac{1}{1 + e^{-a(v(t)-b)}} \tag{5.2}$$

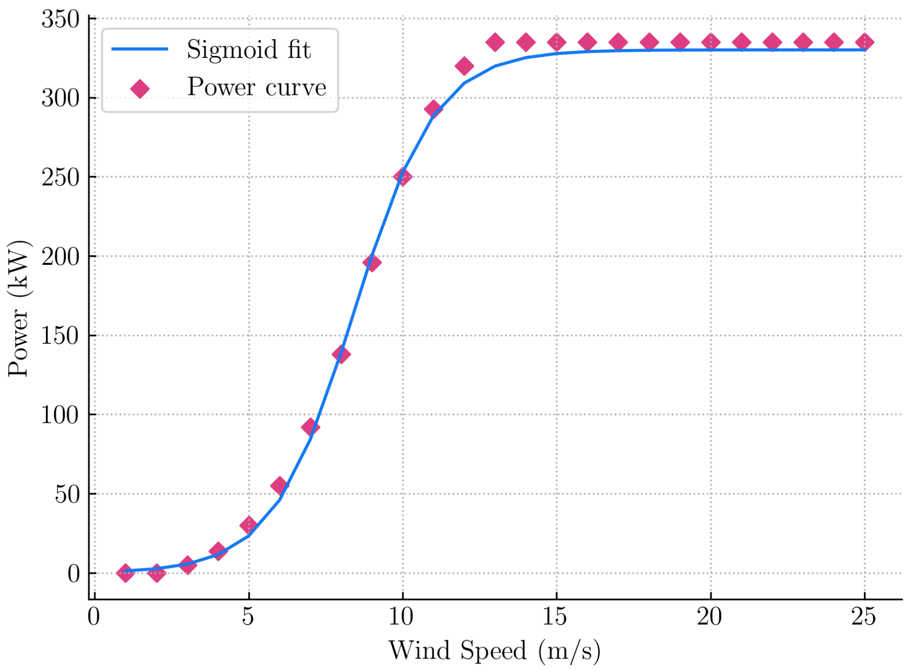


Figure 5.1: Sigmoid fit of the Enercon E-33 power curve

where $v(t)$ is the wind speed at hub height at time t obtained by equation (5.1), and $a == 0.7526s/m$ and $b = 8.424m/s$ as found by fitting the power curve. This provides us with an easily computable and quite accurate estimation of the wind power produced by a wind turbine. The fit is shown in figure 5.1.

5.1.2. Wind turbine share

A whole wind turbine is often too expensive and excessive for a single prosumer to own. So often prosumers in a community share the costs and the energy generated by a wind turbine. To find the share that a prosumer should use, we perform a parameter sweep of the typical share range for each prosumer. The goal here is to minimize the total bill given no battery storage. Intuitively, the share should not be too small or too large. The costs should be decreasing initially since energy generated by the wind turbine is cheaper to cover demands than the import costs from the grid. However, after the demands are covered, increasing the share will only increase depreciation costs unless the export tariff is sufficiently high. In case the export tariff is higher than the price per kWh generated by the wind turbine, this would effectively mean that buying wind turbines would be an effective investment. However, in the current climate export tariffs are very low, thus a too large share would often increase costs.

To illustrate the optimization process, we show how the power share influences the costs in figure 5.2 for a typical prosumer with an annual demand of 1838 kWh.

5.2. Battery sizing

To further improve the efficiency of renewable energy, many prosumers also acquire a battery system. We determine the optimal battery size using a similar approach to the method outlined in section 5.1.2. However, since prosumers often first purchase a wind turbine share or solar panels, with battery systems being less popular, we assume that the wind turbine share is already optimized without a battery. Using this optimal wind turbine share, we use a parameter sweep to find the optimal battery capacity.

An example of the optimization process for a prosumer with an annual demand of 1838 kWh is shown in figure 5.3.

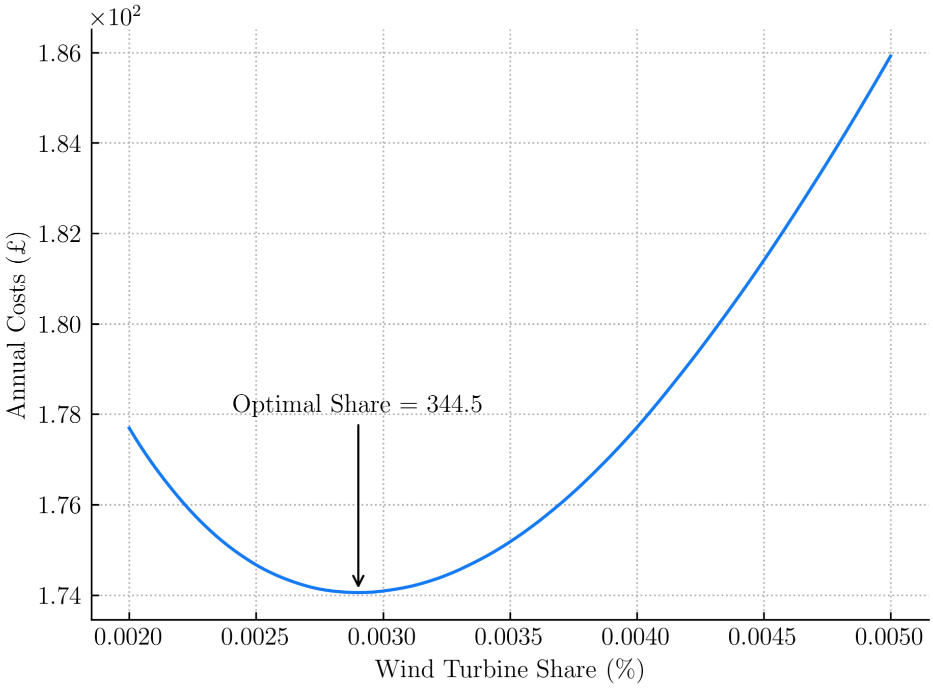


Figure 5.2: Economical optimization of wind turbine share for a prosumer with an annual demand of 1838 kWh

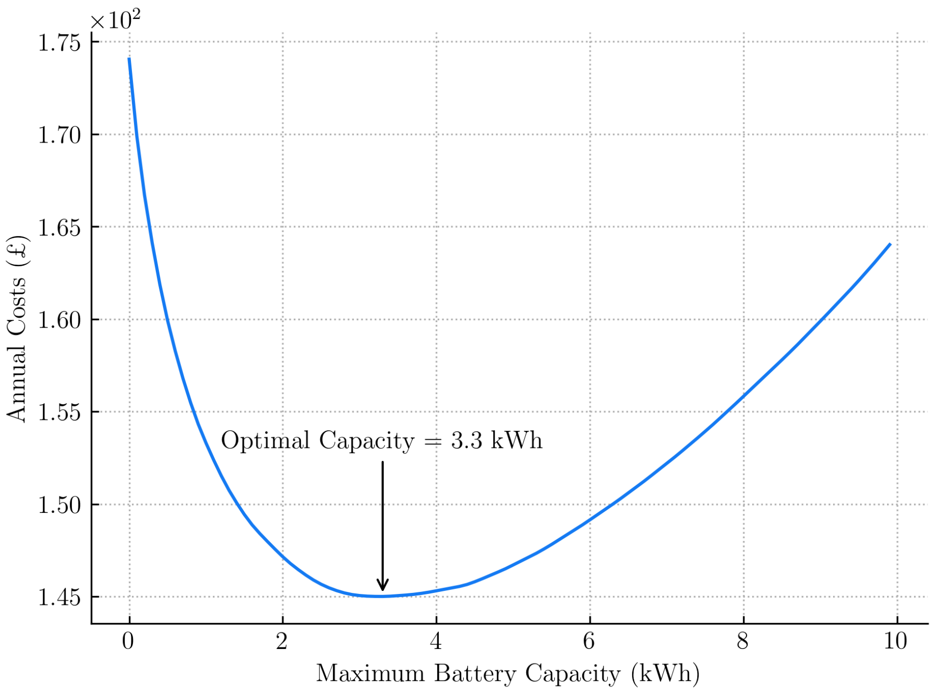


Figure 5.3: Economical optimization of maximum battery capacity for a prosumer with an annual demand of 1838 kWh

5.3. Prosumer clustering

In our experimental results (for more details see Chapter 6, we study a large dataset from the Low Carbon London Trial, which consists of over 5500 households. However, many realistically sized communities consist of only about 50-200 communities [1]. So, in many cases instead of considering a community of over 5500 prosumers, we instead create experimental scenarios with realistic diversity

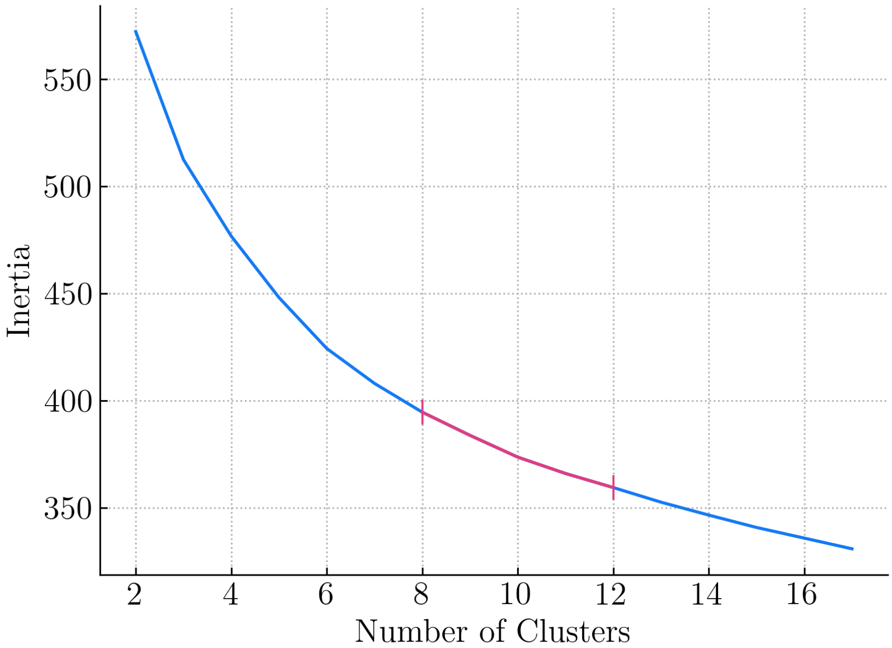


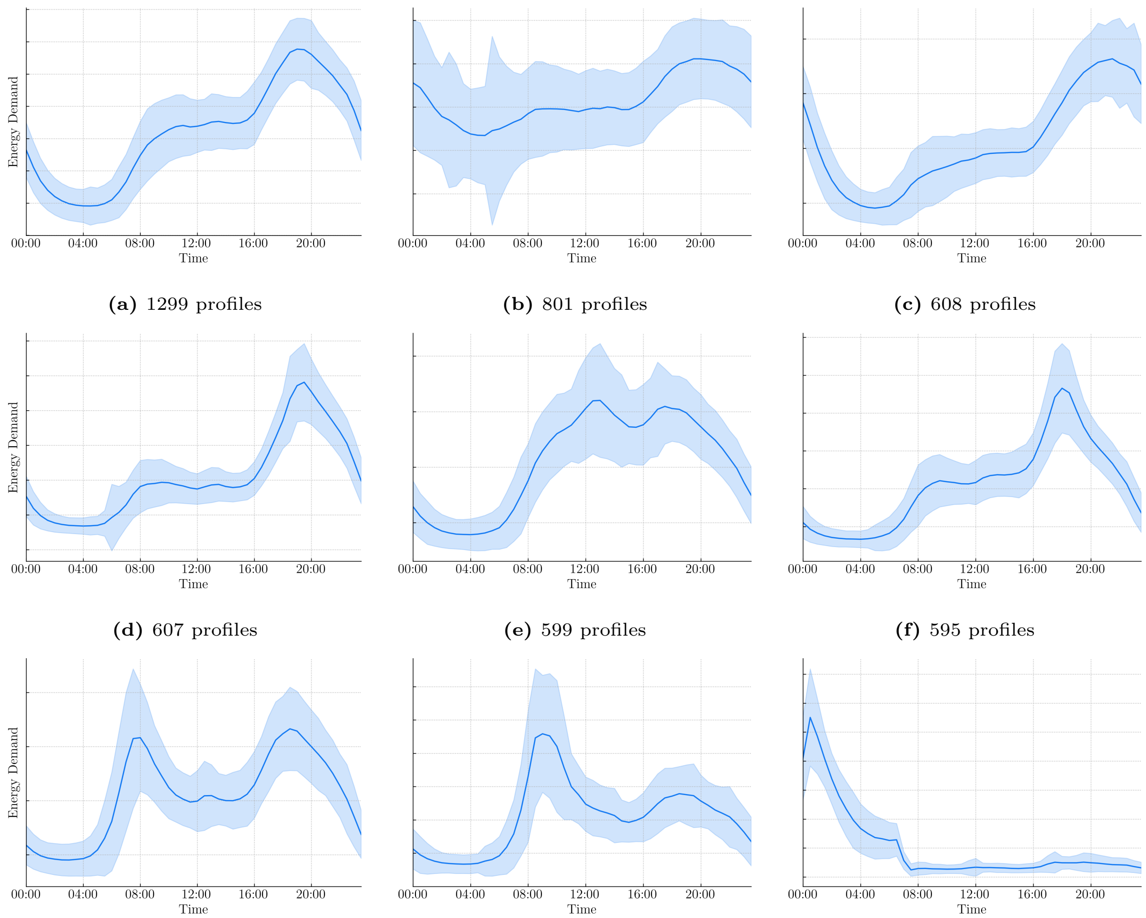
Figure 5.4: Elbow plot of k-means clustering on daily average demand profiles

and sizes closely fitting the distribution in the large-scale dataset. To ensure that the distributions are preserved, we apply stratified sampling. A widely used method for identifying strata in energy demand modelling is clustering on energy demand profiles [58, 59]. The data to be clustered consists originally of 48 half hours for 365 days, creating a demand profile with $365 \cdot 48 = 17520$ points. However, due to the high dimensionality of this data, clustering directly on the profiles suffers from the curse of dimensionality [60]. So, instead, we reduce the number of points to consider by reducing the demand profile to a recognizable consumption pattern. Categorizing consumption patterns is often done using daily average data from the winter months by utility companies and other studies [61, 62]. We apply a similar approach. However, since prosumers display different consumption patterns during weekends and holidays, we filter out these days. Then from the remaining days, we average data from the months of December to March. Each prosumer is then represented by a 48-dimensional vector representing the average 48 half hours of their typical daily energy demand. Since, we are mostly interested in the consumption pattern, not necessarily the consumption quantity, we normalize these demand vectors such that the sum of the demand is equal to 1, i.e. we use the $L1$-norm. These vectors are then clustered using K-means clustering. To find the number of clusters, we use the elbow method and silhouette method.

First, we perform the elbow method to identify a range of reasonable cluster numbers. Looking at the elbow graph, we find no strong inflection point. So, identifying a K from just the elbow method is difficult. Instead we identify a range of k values, i.e. 8-12 in which the inflection point could be situated (see figure 5.4).

Using the identified k-values, we apply the silhouette method to identify the best k-value. We look at the silhouette plots and 2d visualisation plots using PCA and T-SNE to identify which k separates the clusters the best (see figure 5.5). What we find is that none of the k-values is able to perfectly separate the plots, with there being a lot of overlap. K-means struggles with clustering unbalanced classes, and based on previous works, a community predominantly consists of 'evening peak' prosumers, i.e. prosumers who consume a lot during the evening, less during the day and very little during the night. With many other consumption patterns being variations on the 'evening peak' prosumer. This likely results in a lot of overlap from the classes, as they could all be derived from the evening peak prosumers. Furthermore, reducing the dimensionality from 48 to 2 results in a lot of cluttering in the 2d plots even given the use of PCA or T-SNE. However, from these identified plots, we find the most appropriate k to be 9. Since more clusters lead to a lot of overlap and a few clusters have a silhouette score far below average. $k = 8$ would have been possible as well, however, it contains one class that is disproportionately below average compared to the other clusters.

A better intuition about the found clusters can be formed by looking at the demand profiles of the clusters found.



(a) 1299 profiles **(b)** 801 profiles **(c)** 608 profiles

(d) 607 profiles **(e)** 599 profiles **(f)** 595 profiles

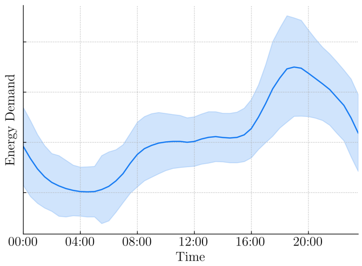
(g) 526 profiles **(h)** 169 profiles **(i)** 47 profiles

Figure 5.6: Average daily demands for different consumer profile clusters. Error bars represent the standard deviation of the demand profiles within the cluster.

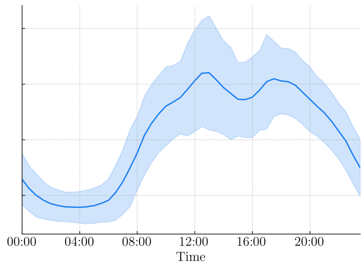
Looking at the 9 identified clusters, we can clearly see the bias K-means exerts on the evening peak consumption pattern. However, there are slight differences in where the evening peak is located (i.e. a shift a few hours) or the amplitude of the peak. We, further, clean up the data by combining these evening peak prosumers in a single group. This finally results in the 5 clusters, we use for the remainder of the study, these are shown in figure 5.7

Analogous to earlier works, we find that the majority of these profiles follow an evening peak pattern, where a noticeable peak in consumption can be observed during the early evening, often as a result of prosumers coming home from work. Figure 5.7b shows another much occurring pattern, where energy demands stay consistent throughout the day while still being low during the night. Since this is likely an effect of prosumers working from home and therefore using energy throughout the day, we call this group 'work from home'. The final large group consists of prosumers that consume large quantities of energy during the morning and evening, likely pertaining to users that have a similar lifestyle to the 'Evening peak' group, but also use a lot of energy in the mornings. The remaining two clusters do not have this peak consumption during the evening but at different moments during the day. The 'morning peak' group consumes the majority of energy during the early mornings, while the 'night owl' group consumes the majority of their energy overnight.

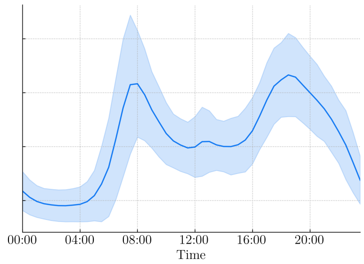
Figure 5.5: Silhouette plots for $k \in (8, 12)$



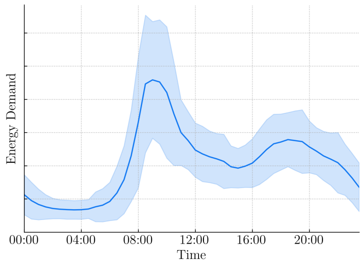
(a) Evening peak (3910 profiles)



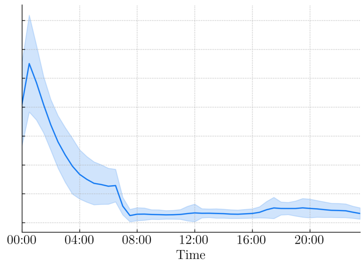
(b) Work from home (599 profiles)



(c) Morning + Evening peak (526 profiles)



(d) Morning peak (169 profiles)



(e) Night Owl (47 profiles)

Figure 5.7: Average daily demands for different consumer profile clusters. Error bars represent the standard deviation of the demand profiles within the cluster.

6

Experimental Results using Large-Scale Data

Peer to peer trading allows for energy communities to improve social welfare due to the Gains from Trade. To assess the extent and efficiency of peer-to-peer trading has, we consider two different experimental scenarios based on real-world large-scale data sets. The first scenario considers the Thames Valley Vision trial, where we compare the methods in a decently sized community, which is commonly seen in real-world settings [63]. The second scenario considers a much larger set of prosumers in the Low Carbon London trial. Here we can see, whether the results hold up in larger settings as well as the effect that different compositions of a smaller community may have on the effectiveness of trading. In both scenarios, we model the energy assets of a prosumer as follows:

- Each prosumer has access to a lithium-ion battery. The price of the battery was fixed to £150/kWh and its lifetime to 20 years. The battery life cycle data was obtained from [54]. For each prosumer, the battery capacity was computed by minimizing the bill in isolation. The choice for a lithium-ion battery was made due to its techno-economical viability over other alternatives such as lead acid [64].
- Each prosumer has access to a share of a wind turbine, where the share was computed by minimizing the yearly bill given no access to any storage. The price of the wind turbine was set to £1072/kWh and its lifetime to 20 years. The wind speed to power curve has been interpolated using data for a typical community wind turbine (i.e. Enercon E-33).

Furthermore, both scenarios consider a flat import tariff of 16p/kWh and an export tariff of 0p/kWh. We consider the simulation of these energy communities for a 1 year period with 30-minute granularity, resulting in $365 * 48 = 17520$ time steps.

The two data sets we consider, i.e. Thames Valley Vision and Low Carbon London have been sourced from two different trials performed in the UK and have some slightly different characteristics:

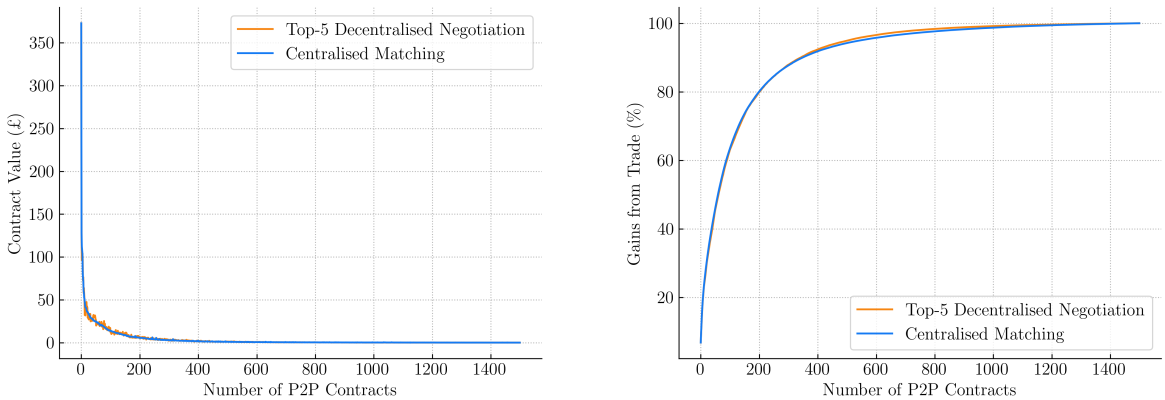
- **Thames Valley Vision**: Data from the Thames Valley Vision project has been used for the first scenario. The dataset consists of half-hourly demand data for 220 UK households in the Bracknell area. From these 220 households, we consider only the 200 domestic unrestricted consumers. The project's aim was to evaluate the viability of a variety of smart grid solutions in a low-voltage network, such as demand-side response.
- **Low Carbon London**: The Low Carbon London trial was held between November 2011 and February 2014. During these 2.5 years, energy consumption readings were taken half hourly for a total of 5567 households. Careful consideration ensured that the consumers in the trial represented a balanced sample of the Greater London population. The published data was part of a larger project attempting to investigate the impact of low carbon technologies and facilitate the development of viable solutions for a Distributed System Operator to support the transition to low carbon emission.

6.1. Scenario 1: Results using Thames Valley Vision Project Data

First, we define a scenario based on the Thames Valley Vision trial held in the Thames Valley area in the UK. The data set consists of the demand profiles of 200 households with weather data being retrieved from the UK Meteo Office [65]. This scenario is used to assess the value of peer-to-peer contracts at different points during the trading process. Using both of the proposed peer-to-peer frameworks, we assess the marginal value and determine the number of contracts required to realise the majority of the potential gains. Furthermore, we look at the effect of agent participation on the gains of trade and how trading coalitions emerge from prosumers participating in the peer-to-peer market.

6.1.1. Marginal gains from peer-to-peer contracts

Intuitively, contracts established early in the trading process are more valuable since prosumers still have many periods of large residual demand and excess generation. However, as the trading progress and more contracts are accepted, the residual demands are compensated by earlier accepted contracts. This would logically result in the value of consequent contracts decreasing. We observe that the marginal value of a contract indeed drops drastically even when only a small number of contracts have already been established.



(a) Value of a single contract

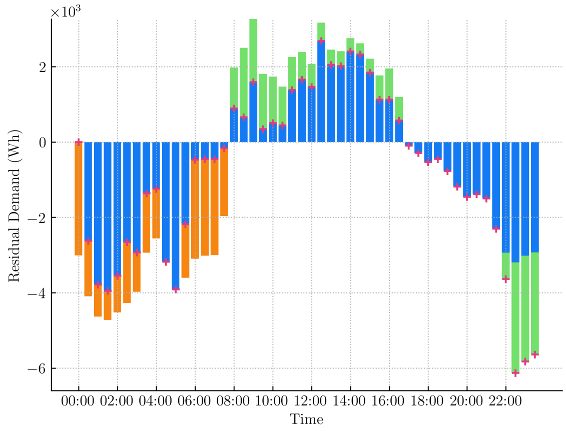
(b) Percentage realised of the potential Gains from Trade

Figure 6.1: Convergence of the marginal gains of P2P energy contracts for the Thames Valley Vision data set

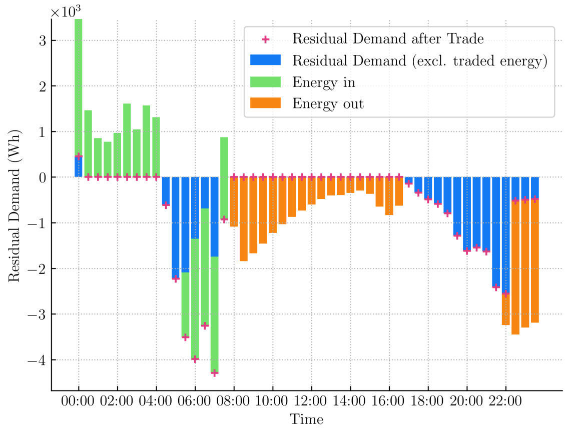
Figure 6.1a shows how the value of the n^{th} accepted contract as more contracts are accepted. The initial contract shows a significant contribution towards reducing the total costs of the prosumers involved in trading. But contracts accepted after the first 400 almost have a very marginal value. Using the theoretical optimal Gains from Trade found by a coalitional model, we can find the contribution of the contracts towards the total potential Gains from Trade. Figure 6.1b shows the total gains as a percentage of the potential gains achieved after a number of peer-to-peer contracts are accepted by the market. Surprisingly, we see that almost all the potential gains are already realised after only 1000 contracts have been established, as opposed to a total of $200C2 = 19900$ different pairings a community of 200 prosumers has.

Notably, both peer-to-peer mechanisms show similar convergent behaviour, showing that the observed effect is independent of the mechanism used. A small difference between both models is that the value of a single contract fluctuates more for the top-5 decentralised negotiation framework than for the centralised matching and clearing model. This is a consequence of the highest value contract not being accepted by the market, but another lower value contract achieving a quicker consensus. However, the general trend for both models is similar.

Further investigation into the contracts that are established shows that the observed value of contracts is primarily caused by the different alignment of periods of residual demand and excess generation for different prosumers. We showcase the effect of the first established peer-to-peer contract on the net demand of both prosumers for a single day to illustrate the gains from misaligned profiles in figure 6.2.



(a) Evening Peak Prosumer



(b) Night Owl Prosumer

Figure 6.2: Example of the effect of an established contract on the residual demands of the involved prosumers

This contract happens to be between two very prosumers with very different consumption behaviour. The residual demand profile shown in figure 6.2a exerts the behaviour of an evening peak prosumer and the profile shown in figure 6.2b that of a night owl. We see that during the night hours (i.e. 0:00-8:00) the night owl initially has high residual demands, while the evening peak prosumers have a lot of excess generation. However, after the energy is exchanged from the energy contract, the majority of the deficit is compensated. Similarly, during the day period, the evening peak prosumer experiences an energy deficit and receives energy from the night owl prosumer.

After this trade, both prosumers have less extreme periods of residual demand and excess generation, i.e. the residual demand curve has flattened. This will result in lower costs from importing energy from the central power grid and therefore explains the Gains from Trade. This also confirms our suspicions as to why the later contracts are less valuable since the residual demands have been compensated already, making it harder to match periods of residual demands with excess generation and lowering the effect of exchanging energy during those periods.

6.1.2. Prosumer Participation

Energy communities typically consist of about 50-200 households, however, the prospective gains from joining a peer-to-peer market for a single prosumer can differ drastically. Prosumers that have energy demands during periods when energy is scarce and have excess generation when energy is plentiful on the market stand less to gain from participating in peer-to-peer trading. Sometimes, these potential gains might be insufficient due to the overhead and potential fees of joining such a peer-to-peer market. So, even for a small community, many prosumers might not necessarily need to participate.

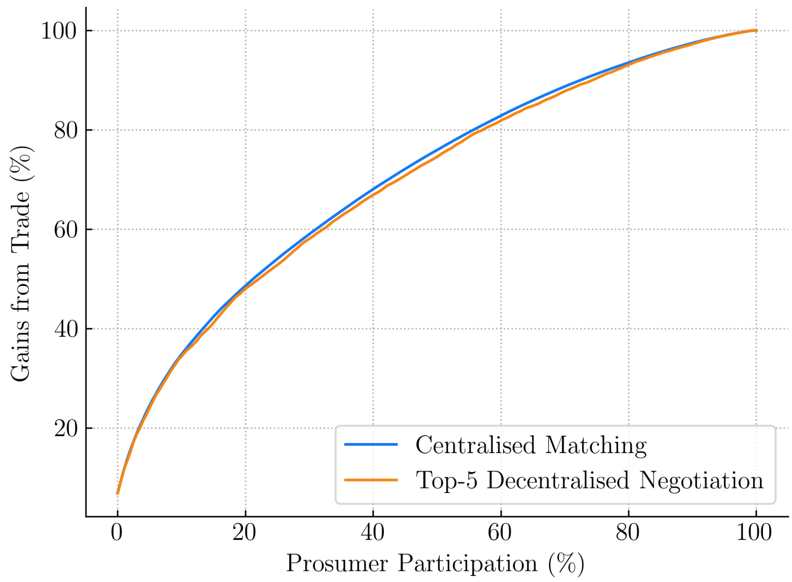


Figure 6.3: Convergence of the Gains from Trade as a function of prosumer participation

Figure 6.3 shows the total Gains from Trade of the community based on how many prosumers participate in the peer-to-peer market. A 100% of the Gains from Trade can only be realised when all prosumers participate in trades. This shows that there is always some incentive for a prosumer to join peer-to-peer trading. However, while there is some value for some prosumers, the majority of the gains can be realised even when only 60% of the community takes part. But for the final 5% of the benefits, a little under 20% of the community needs to join. Whether trading would ultimately be meritous depends on the exact costs.

To investigate, why the marginal contribution of some of the prosumers is so small, we look at the contract values for a prosumer before any contracts are established. These values indicate the bilateral gains a prosumer can achieve with any potential trading partner and can hint at whether their participation would be beneficial.

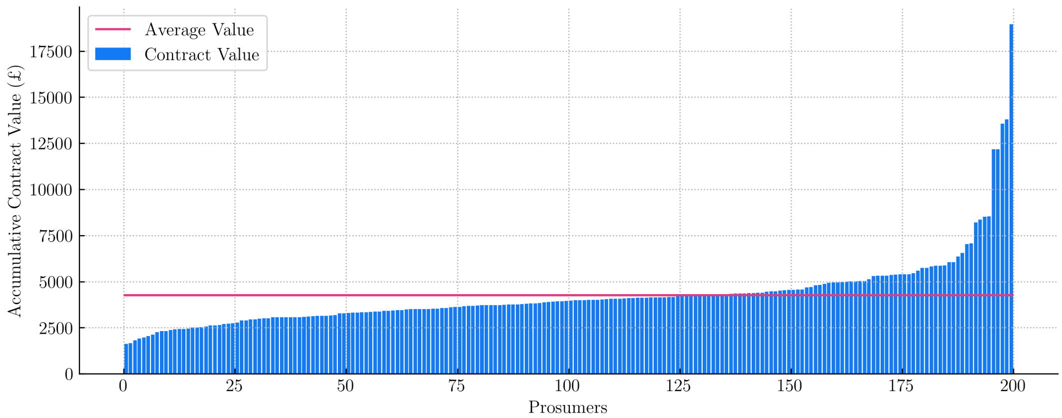
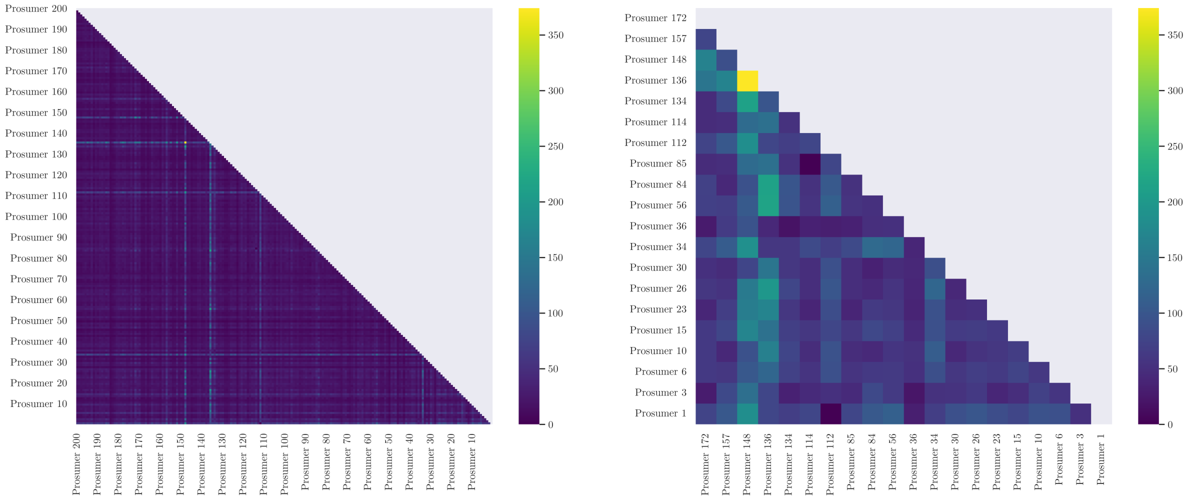


Figure 6.4: Cumulative value of all P2P contracts for each prosumer sorted by total

Figure 6.4 shows the cumulative value of all the potential contracts a prosumer can establish before any are accepted ordered by value. The majority of the prosumers fall below the average, but there are a few outliers that have significant benefits for participating in trading. The small fraction of prosumers that stand to gain significantly from peer-to-peer trading explains why the majority of the Gains from Trade can be realised with relatively few prosumers participating. However, since these outliers have such high values, it is likely that the other prosumers have inflated cumulative values, due to them having contracts with the outliers.



(a) All prosumers

(b) Top 10% with the highest cumulative value

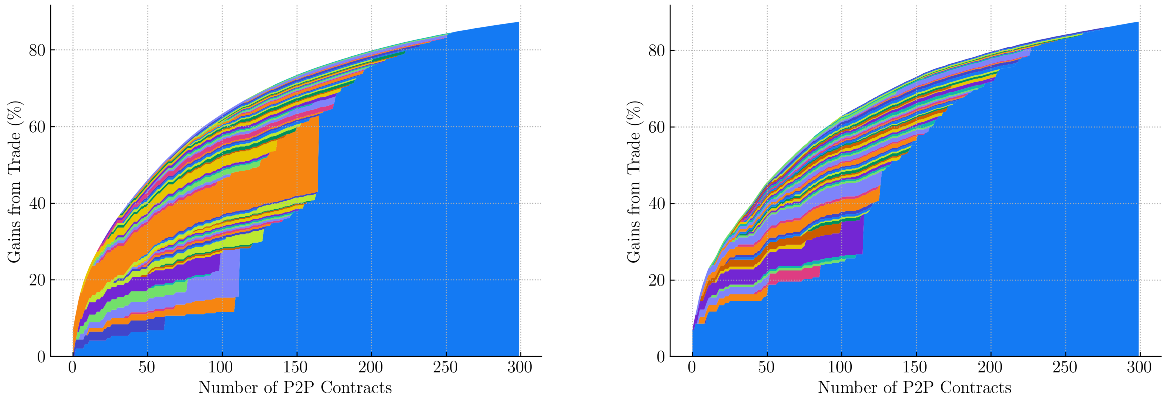
Figure 6.5: Gains from Trade for P2P contracts, prosumer numbers represent the internal labelling of the prosumers

We can also observe this in Figure 6.5. Only a few prosumers contribute to each prosumer's cumulative value. However, as more contracts are established, their potential greatly diminishes, leading to the diminishing returns we see at higher prosumer participation percentages. Notably, even looking at the top 10% most promising prosumers in figure 6.5b, we find that even here, there are some prosumers that stand out significantly from the others. However, differences between prosumers are less noticeable and everyone seems to be able to contribute sufficiently to warrant their participation.

6.1.3. Emergence of Trading Coalitions

Before any P2P contracts are established, prosumers effectively behave similarly as they would in isolation. However, the introduction of the peer-to-peer market allows for collaboration and a potential reduction in overall costs. This collaboration leads to the formation of trading coalitions consisting of prosumers that have contracts with one another. Eventually, after continuing to establish contracts, these smaller trading coalitions will converge to the grand coalition consisting of every prosumer in the community. However, before their merger into the grand coalition, the trading coalitions are able to extract some of the Gains from Trade, without interaction with other coalitions. Examining how these trading coalitions emerge can provide valuable insights into how the gains are distributed and how different mechanisms influence the Gains from Trade for the small trading coalitions.

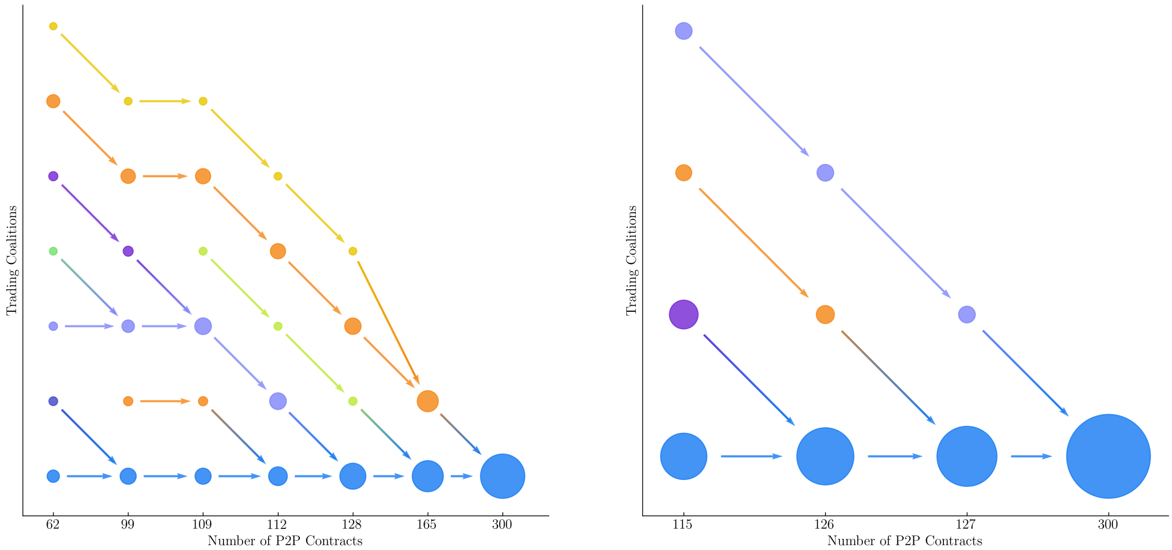
Formally, a trading coalition represents the prosumers that have an agreed contract with each other either directly, or is indirectly connected by another prosumer, e.g. prosumer i has a contract with prosumer j and prosumer i has a contract with prosumer k, then the trading coalition would be $\{i, j, k\}$, even though j, k do not have an agreed contract.



(a) Centralised matching and clearing

(b) Top-5 decentralised negotiation

Figure 6.6: Gains per energy trading coalition as a function of the number of P2P contracts between prosumers



(a) Centralised matching and clearing

(b) Top-5 decentralised negotiation

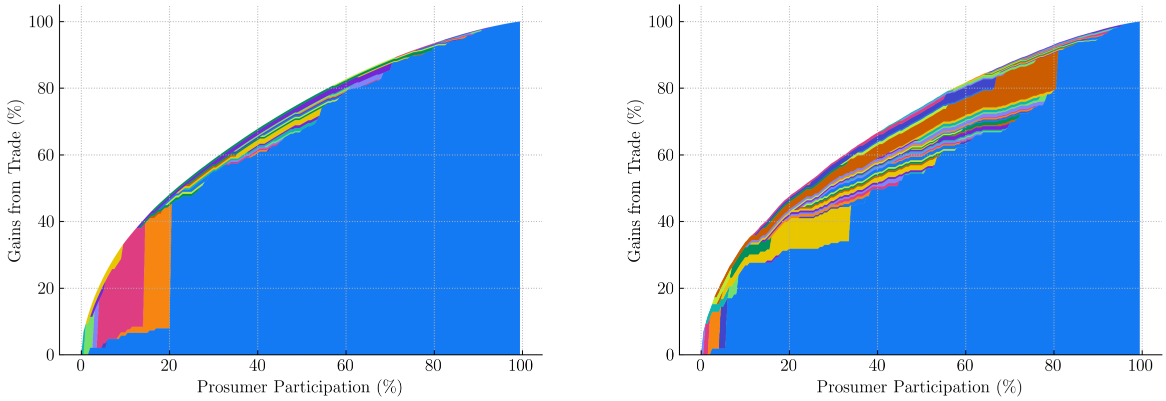
Figure 6.7: Merging of different energy trading coalitions based on the number of P2P contracts established. The area of the bubbles represents the total Gains from Trade the trading coalition achieves. Only time steps where coalitions that contribute at least 3% of the Gains from Trade are merged are shown and only the coalitions that contribute at least 2% to the Gains from Trade are shown

Figure 6.6 shows the gains of trade for each trading coalition, where the x-axis represents the number of contracts accepted. Different colours represent different trading coalitions. Initially, we see that there are many small coalitions, but eventually, all prosumers are included within the same trading coalition, i.e. forming the grand coalition. Here we can see clear differences between the dynamics experienced, by the centralised matching and clearing approach as opposed to the decentralised negotiation approach. The centralised matching approach creates a larger trading coalition before merging them together into the grand coalition, while for decentralised negotiation trading coalitions stay relatively small.

A clearer overview of how these coalitions are merged together is shown in figure 6.7. Here, we show the trading coalitions that contribute significantly to the Gains from Trade and how they are merged together. Centralised matching more clearly displays behaviour that leads to the creation of more noteworthy trading coalitions.

Centralised matching and clearing prefers contracts between smaller trading coalitions than merging them into a single large coalition. Furthermore, trading coalitions start to merge into the grand coalition only when the majority of the Gains from Trade have already been realised. Our earlier insights in early energy contracts retrieving their value from drastic differences in alignment also apply here. Since smaller trading coalitions have more periods of residual demand and excess energy, a collaboration between them leads to higher gains than collaboration with the larger coalitions, since the majority of the gains have already been extracted. Since the centralised mechanism prefers to accept contracts with higher gains, the early contracts will lead to the smaller coalitions merging. Finally, after those gains have been achieved, minute differences have compounded enough to be valuable to be considered.

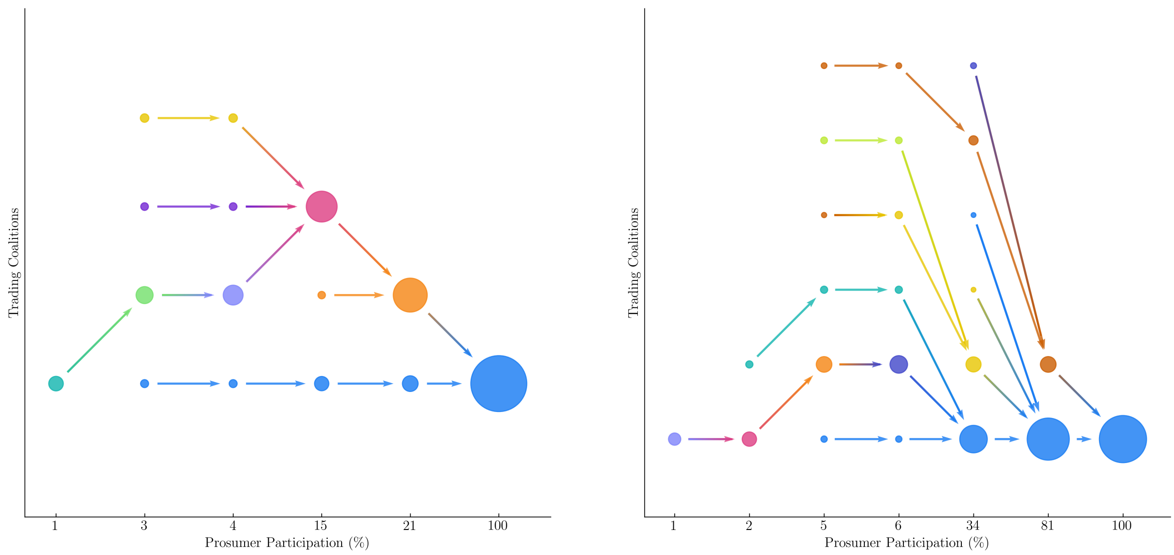
While a similar effect can be observed for top-5 decentralised negotiation, i.e. many small trading coalitions form, they tend to not grow larger but merge into the largest coalition instead. Since negotiation is based on consensus, an important factor to consider is the market power of a coalition. Small coalitions are quite diverse and have a lot of potential for establishing contracts, while for larger coalitions this diversity has mostly already been utilised and they have less to offer. This asymmetry in market power leads to small trading coalitions establishing contracts with larger coalitions in which the small coalitions lay claim to a larger fraction of the benefits. Besides, contracts between small coalitions take longer to form since they both demand higher compensation and, therefore, happen less often.



(a) Centralised matching and clearing

(b) Top-5 decentralised negotiation

Figure 6.8: Gains per trading coalition as a function of prosumers that participate in trading



(a) Centralised matching and clearing

(b) Top-5 decentralised negotiation

Figure 6.9: Merging of different energy trading coalitions based on the percentage of prosumers that participate in trade. The area of the bubbles represents the total Gains from Trade the trading coalition achieves. Only time steps where coalitions that contribute at least 5% of the Gains from Trade are merged are shown and only the coalitions that contribute at least 1% to the Gains from Trade are shown

Surprisingly, we observe a different process when considering prosumer participation in trading. Instead of accepting contracts, here we look at how trading coalitions would form when adding the prosumer with the most promising returns from trading to the market. We observe in Figure 6.8 that for centralised matching and clearing less noteworthy trading coalitions form than for decentralised negotiation.

In Figure 6.9, we show the trading coalitions with significant contributions to the gains from trading and their merging process. We can also see for centralised matching that there are a small number of significantly sized trading coalitions and that they tend to merge into the largest coalition. Yet, the merging process for decentralised negotiation involves a lot more groups. For centralised matching and clearing the most diverse prosumers initially form trading coalitions. Thus initially we have a few coalitions that have a major share of the gains. Since consequent prosumers that join the market will gravitate towards the profiles that differ the most from their own, this will lead to these coalitions growing significantly until their gains are extracted. Decentralised negotiation differs since here it is unlikely that very diverse prsumers will form a trading coalition together due to both of them having a high market power. They are more likely to form a coalition with a prosumer with low market power and lay claim to the majority of the gains.

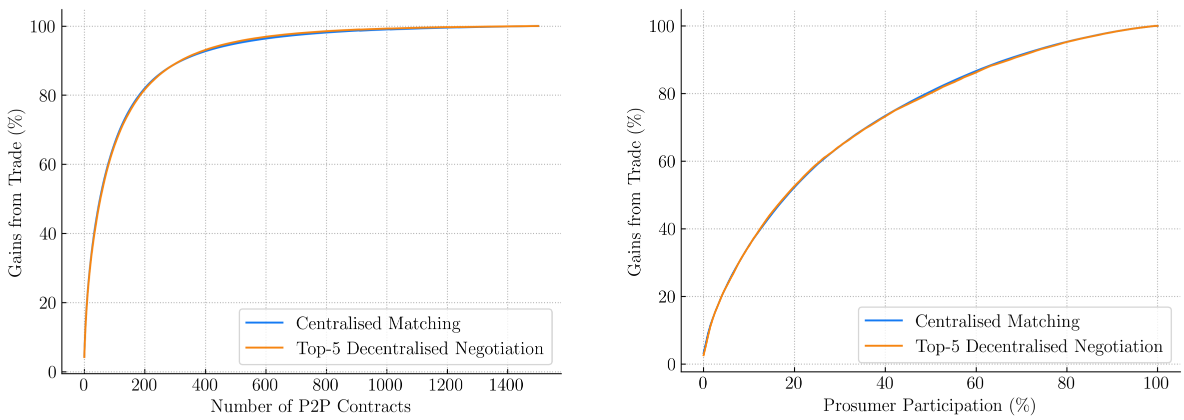
6.2. Scenario 2: Results using Low Carbon London Project Data

Results for the Thames Valley Vision trial data set indicate that peer-to-peer trading is very effective at realising the Gains from Trade, even when considering only a small number of contracts and a fraction of the community. However, whether these observations are particular to the examined community or apply to a more general market still needs to be studied. Furthermore, the value of the contracts is highly dependent on the prosumers that establish them. Prosumers value energy quantities differently depending on their own consumption and generation profile with respect to others'. The diversity of a community might affect the potential gains achieved from peer-to-peer trading. Thus, the effect of diversity factors on the community needs to be examined.

In this second scenario, we consider a larger dataset with about 5567 households retrieved from the Low Carbon London trial [4]. This dataset provides a larger and more representative set of households for the London region. However, since realistically sized communities behind a substation often are smaller sized, e.g. around 50-200 [1], instead of considering the whole community, we create experimental scenarios with realistic diversity and sizes closely fitting the distributions in the large data set.

6.2.1. Convergence of the Gains from Trade

From the 5567 households, we consider a representative community that mirrors the distribution in the larger data set. We examine how both the Gains from Trade converges as functions of the number of established P2P contracts and the percentage of prosumer participation. We see that for a community with a realistic distribution, similar convergence as the Thames Valley Vision data set is observed. In Figure 6.10a, we show how the gains converge for 20 different communities. Interestingly, the deviations observed between different communities are extremely marginal, i.e. the communities with very similar compositions show similar convergent behaviour.



(a) Bilateral trade contracts

(b) Community size

Figure 6.10: Convergence of the Gains from Trade (as percentage of the gains achieved by an energy community)

Notably, we find that the gains converge faster compared to the Thames Valley Vision dataset. This observed result originates from the diversity in this dataset being slightly lower, with the majority of the profiles exerting the evening peak prosumer behaviour. However, the overall trend follows a similar pattern, with contract values diminishing extremely quickly when a large number of contracts have already been established and the marginal value of the least promising prosumers being relatively low.

6.2.2. Influence of community diversity

In communities that mirror the real-world dataset, we observe very similar effects. However, as we noted for the Thames Valley Vision data set, the majority of the Gains from Trade are caused by the diversity in demand profiles. Consumption behaviour for prosumers might differ around the world and a notable shift in demand profiles may be observed in the future, e.g. caused by the major adoption of working remotely due to the covid-19 pandemic. This leads to changes in diversity observed within a community. To investigate the effects different compositions have on the gains and efficiency of peer-to-peer trading, we adopt the concept of diversity factor to objectively measure the diversity of a community and use it to see how the convergence and Gains from Trade vary for different compositions.

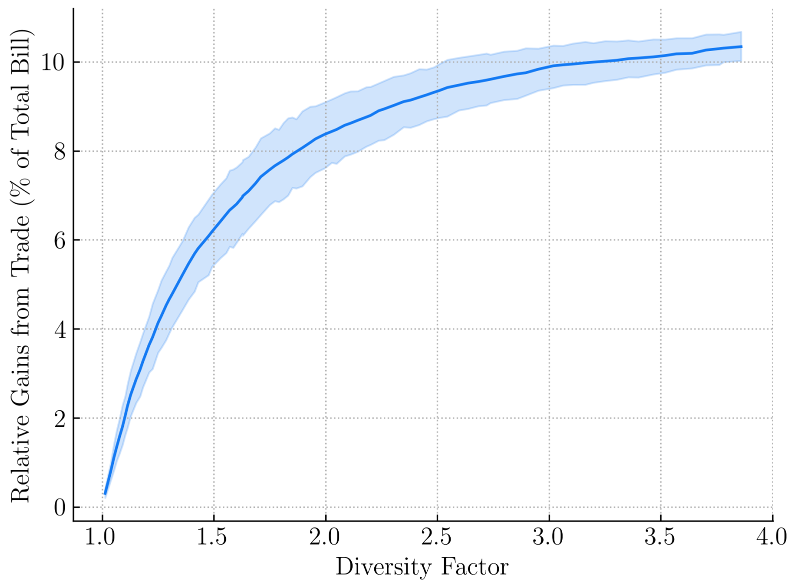
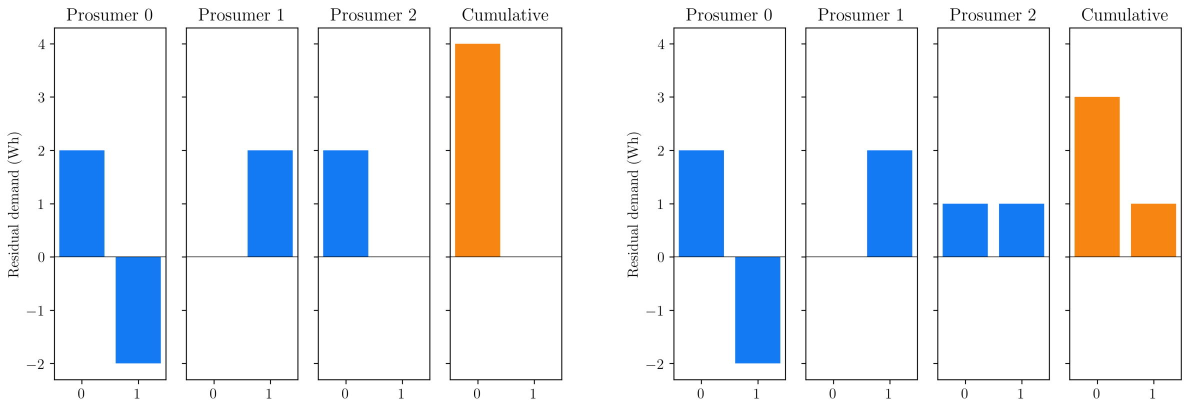


Figure 6.11: Influence of diversity factor of the energy community on total Gains from Trade

Figure 6.11 shows the Gains from Trade as a percentage of the total bill compared to the diversity factor. Multiple (i.e. 15) different communities have been generated for several (i.e. 100) diversity values. We observe that the Gains from Trade increase with diversity. However, noticeably, we find that initially the curve is extremely steep, with the effects of diversity having a significant impact on low diversity factors. However, for higher diversity factors, we find that the gains increase marginally. These diminishing returns can be attributed to the fact that for low diversity communities many periods of residual demand exists which can be compensated easily by slightly increasing diversity. However, for a high diversity community, adding a prosumer with a different consumption profile might not necessarily lead to significant improvements since the residual demand might not align with excess generation. Furthermore, residual demand periods are less extreme, requiring less energy to fulfil them and therefore reducing the potential gains to be had. We can easily illustrate this effect using a small community of 3 prosumers with 2 demand periods.

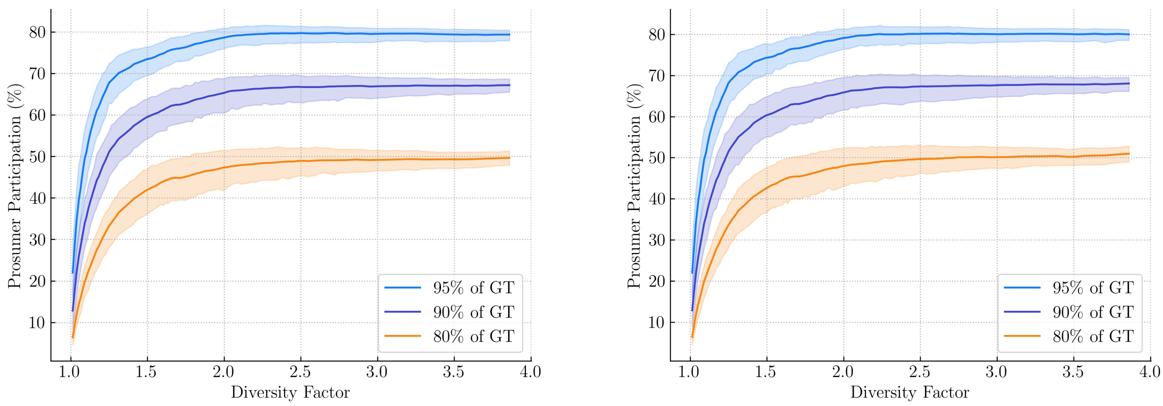


(a) Example community with diversity factor of $\frac{2+2+2}{4} = 1.5$ **(b)** Example community with diversity factor of $\frac{2+2+1}{3} = 1.\overline{6}$

Figure 6.12: Example of increased diversity factor having a negligible effect on gains

The community shown in Figure 6.12a has a diversity factor of 1.5. The cumulative residual demand of the community is 4 Wh. Increasing the diversity of the community by substituting Prosumer 2 with a different prosumer results in the community shown in Figure 6.12b. This second community has a diversity factor of $1.\overline{6}$. Conversely, we can intuitively derive this from the cumulative residual demand, since it is more equally distributed over the different periods. However, the total residual demand still comes to 4 Wh. For a flat tariff, this would mean that both communities would pay the same cost for importing energy from the grid. The total costs have not changed, while diversity has increased. This is due to the first community already fully utilising the excess generation for satisfying residual demands. If we would consider a dynamic tariff, this could even result in an increase in costs if the second time period experiences a higher tariff. Thus, increasing diversity does not always decrease costs. However, the trend shown in Figure 6.11 does motivate that generally an increase in diversity is beneficial to the community.

Another important factor to consider is whether the diversity significantly impacts the fraction of the community that should participate in trading. Intuitively, a non-diverse community would require fewer prosumers trading since prosumers that do not differ a lot from others have a small incentive to participate.



(a) Centralised matching and clearing **(b)** Top-5 decentralised negotiation

Figure 6.13: Influence of diversity factor of the energy community on the prosumer participation required for achieving the majority of the Gains from Trade

Figure 6.13 shows the prosumer participation required for different fractions of the Gains from Trade. We observe that for low diversity communities the prosumer participation required to realise the majority of the gains indeed is a lot less than for more diverse communities. Surprisingly, the threshold does not grow significantly for diverse communities. Almost all communities with a diversity factor higher than 2.5 require about 50% prosumer participation for about 80% of the Gains from Trade. Furthermore, these thresholds seem to be independent of the peer-to-peer mechanism used, since we observe similar trends for centralised matching and clearing and decentralised negotiation.

6.3. Discussion

Our observations show that peer-to-peer markets are very effective in realising the potential Gains from Trade. Typically, in peer-to-peer trading, exchanges are recorded in energy contracts detailing the relevant trade information, such as energy quantities, involved participants and time of trade. However, the computation of these contracts has an apparent cost. Furthermore, there might be costs associated with logistics and interaction with the local grid [66]. Thus, there is a need to minimize the number of contracts required. Fortunately, we find that even for a decently sized community, not a lot of contracts are required to achieve a majority of the gains. This is due to the bulk of the gains being attributed to the differences in the alignment of residual demand and excess generation periods. Initial contracts are able to exploit these differences significantly to generate considerable gains. However, consequent contracts are less beneficial since the majority of the residual demand has already been compensated.

This effect also is apparent when attempting to identify prosumers that stand to gain substantially from participating in trade. Intuitively, prosumers that align with the majority of prosumers stand to gain less since excess generation during their periods of residual demand is scarce. We observe that only a small fraction of the prosumers drive the Gains from Trade in a community. We are able to achieve a large majority of the Gains from Trade with a fraction of the prosumers.

Interestingly, both observations apply independently of the underlying peer-to-peer mechanism. Further investigations into how the gains are distributed by the peer-to-peer mechanisms between trading coalitions that emerge during the trading process show that while the process the gains are achieved differs slightly, the overall gains develop similarly. This is due to in both cases optimal exchanges having similar effects on the cumulative residual demand profile of the community. These investigations also bring different nuances of the two considered peer-to-peer mechanisms to light. Centralised matching prefers to group diverse agents, while decentralised negotiation achieves similar results by merging diverse agents into the majority. These nuances are the result of centralised matching and clearing prioritising gains, while negotiation prioritising market power.

Finally, we also show that the diversity of the community has a significant impact on low diversity communities since the effects of a diverse prosumer satisfying residual demands are more noticeable. However, for high diversity communities, this effect becomes less prevalent due to the majority of the existing excess generation periods already compensating for the residual demands.

7

Conclusion

In this paper, we examine the efficiency of peer-to-peer markets (compared to coalitional markets) in terms of contracts established and market participation using large-scale data from several trials in the UK. We study this, by using 2 models grounded in earlier research, each respectively representing centralised and decentralised markets. Furthermore, to ensure that the results are representative, we develop a new framework that uses a joint profile optimizer to allow for simulating large-scale peer-to-peer processes. Results show that peer-to-peer markets are very effective at realising potential gains. This efficiency is irrespective of the underlying peer-to-peer model, as both the centralised model and the decentralised model exhibit similar behaviours regarding the number of energy contracts required and minimum prosumer participation. However, they do display significantly different behaviours when considering the emergence of trading coalitions. We provide the following answers to the relevant research questions proposed in chapter 1.

How many peer-to-peer energy contracts need to be established to realise the majority of the potential benefits in an energy community?
Only a small fraction of the contracts are required to realise the majority of the Gains from Trade. Contracts being accepted after many contracts have already been established show significantly diminishing returns. In a typical community of 200 prosumers, with a potential of $200C2 = 19900$ different pairings, only about 200 energy contracts (i.e. 1%) are required to extract about 80% of the Gains from Trade. The number of contracts grows quicker when trying to extract larger percentages. A little less than 400 (i.e. 2%) energy contracts are required to realise 90% of the Gains from Trade and about 1000 (i.e. 5%) energy contracts are required to realise over 99% of the Gains from Trade. However, even though significantly more contracts are required when more Gains from Trade are being realised, the overall number of contracts is still a small fraction of the total possible contracts. This is due to the periods of residual demand and excess generation slowly disappearing when more energy contracts are accepted. Since a major contributor to the value of a contract is the alignment of the excess generation periods of a prosumer with another's residual demand period, the value of an energy contract diminishes quickly when they start disappearing. Where we can see that energy contracts established after the first 400 have a value less than 0.1% of the first accepted contract.

Which fraction of the energy community needs to participate in the peer-to-peer market to achieve a high percentage of the possible benefits?
Only the most promising fraction of the community needs to participate in trading to realise the majority of the gains, with about 80% of the benefits being achievable with about 50% prosumer participation. However, for achieving a higher percentage, relatively more prosumers are required. We require around 70% for 90% of the Gains from Trade and over 80% for 95%. These diminishing returns are a result of prosumers with non-diverse profiles contributing little to reducing the overall costs.

How do trading coalitions emerge from establishing peer-to-peer energy contracts and how are the benefits distributed?
Trading dynamics differ significantly depending on the underlying peer-to-peer trading mechanism. The centralised approach will maximise the value of the accepted contract. This leads prosumers with very

different demand profiles to be more likely to trade with each other, i.e. high diversity prosumers trade early. Trading coalitions that form will consist of a small number of relatively diverse prosumers. During the initial stages of the trading process, this will result in many small trading coalitions. However, after the most diverse agents have traded with one another, they will eventually merge into the grand coalition. However, decentralised negotiation shows different dynamics since accepted contracts are highly dependent on the market power of the prosumers. High diversity prosumers lay claim to larger shares of the contract's value. Thus, they are more likely to create contracts with low diversity prosumers since low diversity often results in lower market power. This leads to a single low-diversity community growing quickly and eventually becoming the grand coalition.

How does the composition and diversity of an energy community affect the potential benefits based on the number of contracts or the percentage of prosumers that participate? The value of energy contracts is highly dependent on the prosumers that establish them. The difference of demand and generation profiles of prosumers often is a deciding factor in realising any benefits peer-to-peer trading has to offer. Therefore, an increase in diversity leads to higher potential benefits. However, this is accompanied by a decrease in efficiency since more contracts and prosumer participation is required to realise these gains. Fortunately, the number of contracts that are required stays within a reasonable bound even for very diverse communities. Furthermore, we observe that the effects of increasing diversity diminish significantly for an already decently diverse community. For the Low Carbon London trial, 80% of the Gains from Trade can be achieved with only 50% prosumer participation with a diversity factor over 2.0. For diversity values between 1.0 and 2.0, the participation required ranges between 8% to 50%. Similar observations can be made for 90% and 95% of the Gains from Trade, requiring about 68% and 80% respectively.

7.1. Future Work

Currently, peer-to-peer markets are a popular topic in research, their focus is mainly on the mechanisms and methodologies behind implementation and realisation. However, future investigations into the effectiveness and exploration of the benefits of peer-to-peer markets are required to motivate their deployment. This work takes a big first step into exploring this space, however, many directions for future work are still left unexplored. We identify the following potential streams of future research.

7.1.1. Exploration of different data sets

In this paper, we consider large-scale data from the UK region. However, other regions, including the Netherlands (e.g. GridFriends project [67]), around the world might evaluate peer-to-peer trading differently, due to different consumption habits and sources of renewable energy. For example, some interesting concepts to explore are:

- **Examine peer-to-peer markets in different regions around the world**: Different energy markets around the world have different nuances regarding the use of electricity. While many first-world countries have consistent work-life balance schedules. In regions like China or India, working hours deviate significantly, which leads to different consumption behaviours. Furthermore, some regions around the world regularly experience periods of electricity deficits, leading to schemes like load-shedding where energy consumption effectively falls to zero. Investigation of these types of regions shows whether peer-to-peer trading might be equally effective given different circumstances.
- **Examine different sources of renewable energy**: This work mostly considers wind energy, which is widely available in the UK. However, for many regions around the world, wind energy is not the most effective source of renewable energy. For example in the sub-Saharan desert, solar power might prove more efficient. Having access to more or less renewable energy could drastically influence the capabilities of peer-to-peer trading and the use of battery energy storage systems.

7.1.2. Computational- and logistics costs

We have observed that the value of more peer-to-peer contracts diminishes quickly the more contracts have been established. Consequently, the costs of computing and upholding these contracts may outweigh the benefits it provides. However, the point at which this happens is still unclear. To effectively discern which contracts are beneficial, future work may include some of these costs. Examples of costs that might be considered are:

- **Costs from computing contracts**: The computation of contracts costs some amount of energy since there is a system that needs to run optimisations and compute the contracts and systems that need to record and keep track of the contracts. Servers that are typically used for these purposes come with significant expenses.
- **Fees for organisations regulating the market**: Often the deployment of peer-to-peer energy systems is accompanied by significant costs which are shouldered by a company or an organisation. Recuperation of these costs often takes the form of fees for the usage of the system.
- **Logistics costs for using the local energy grid**: Energy transported over the local energy network incurs costs from deciding how to transport the energy to the upkeep required for the network to keep functioning.

7.1.3. Physical constraints for energy exchanges

Some physical constraints are considered within the current work, mostly regarding the use of the battery energy system and wind turbine. However, for peer-to-peer trading, many other physical constraints need consideration, especially constraints considering the local energy grid. Some of the most important constraints that may be considered are:

- **Import and export capacities**: Specific network connection points have a maximum capacity, i.e. a maximum amount of kWh that can be exported or imported at any time. Peer-to-peer trading generally increases the energy quantities exchanged and the number of participants. Given constraints to the total amount that can be exchanged in a particular time interval, peer-to-peer trading might reduce in efficiency. It also will increase computational complexity as there is more need to predict future demand to circumvent these network capacity constraints.
- **Line congestion**: Peer-to-peer markets exchange significant quantities of energy, however, the network architecture supports only a certain quantity of energy. This might result in some trades being physically impossible and would further reduce the opportunities for creating peer-to-peer contracts.
- **Network topology**: Network topology might play an important role in deciding which exchanges are optimal for the community. Since energy quantities traded over large distances may lead to more line congestion and a higher loss of transported energy. Considering, the topology of prosumers might give priority to trades involving well-connected prosumers.

7.1.4. Dynamic Time-of-Use tariffs

The current model considers a flat tariff pricing scheme for importing and exporting energy from the central grid. However, there are some companies (e.g. octopus energy [68]) currently that offer dynamic pricing on importing and exporting energy. Using dynamic time-of-use tariffs will result in comparatively different results, as it will have a significant effect on the effectiveness of trading energy at certain time points depending on the market price. Furthermore, the battery control algorithm and joint schedule optimizer need to be adjusted to keep the varying market prices into account since storing energy is not always the most effective choice if export prices are high. Furthermore, it may also be more cost-efficient to import energy when prices are low.

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