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Trading algorithms to represent the wholesale market of energy communities in Norway and England

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A R T I C L E I N F O

Dataset link: https://github.com/LocalEnergyMarkets/

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A B S T R A C T

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

1. Introduction

Decentralized energy resources (DERs) have recently experienced a significant growth in deployment and adoption due to declining technology costs. As a result, DERs are now more affordable and becoming increasingly popular for residential buildings. This has created the opportunity to develop building-to-building energy sharing systems to efficiently use on-site wind and solar power. Local electricity markets (LEMs) concepts have provided new mechanisms and ideas to facilitate energy trading [1]. LEMs provide a platform for prosumers and consumers to trade electricity. This can reduce the peak grid imports, improve DERs utilization, and lower distribution and transmission costs [2]. For example, Lüth et al. [3] analyzed LEM benefits for end-users by estimating savings up to 31% on their electricity bill when co-optimizing local electricity trading, compared to a case with no trading. Zheng et al. [4] in another study demonstrate that Peer-to-Peer (P2P) energy and storage sharing can reduce the net costs by 34.5%. In addition to the financial benefits, LEMs can bring community engagement and play a role in the energy transition [5,6].

To further explore the potential of LEMs, it is important to reflect on how to organize LEMs, how the internal market should function, and how the price will potentially be settled between diverse players with different selling and buying price willingness. In the literature, a majority of research on LEMs focuses on centralized optimization and primarily considers power flow analyses or context specific studies. However, understanding how an internal wholesale market will determine local prices and the related trading algorithms remains a challenge [7]. To this end, this paper investigates if certain trading algorithms provide market-based results that are comparable to the community model (perfect market with centralized optimal decisions) but taking into consideration bidding options that incentivizes competition (fairer prices). Particularly, the paper focuses on these research questions:

- How fair and realistic trading algorithms are in representing an energy community that aims to maximize self-consumption (market based)? How do the trading algorithms compared to a ‘perfect market’?
- How to create different bidding simulations strategies of market participants (consumers and prosumers) around a LEM reference price?

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- What is the effect of the case study characteristics (e.g., country and number of participants) on the trading algorithm outcome?

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

The structure of the rest of the paper is as follows: Section 2 presents related literature and outline research contributions. Next, the model formulations and bidding simulations are in Section 3, while the case studies and data used are described in Section 4. Section 5 presents results and the main findings. Section 6 summarizes main conclusions of the paper.

2. Related literature

Mengelkamp and Weinhardt [8] define a LEM as "a geographically distinct and socially close community of residential prosumers and consumers that have access to a joint market platform for trading locally produced electricity among each other". Within LEMs, prosumers can take an active role in electricity trading and potentially reduce grid problems raised by utilizing distributed generation resources and benefit the system operators [1,9].

2.1. Local electricity market clearing

An important design element of LEMs is how the trading should be organized. This includes how sellers and buyers will set the market-clearing within the LEM. The literature tends to focus on two main approaches: (i) a cooperative approach where the goal is to maximize social welfare, and (ii) a non-cooperative approach where the goal is to create an efficient market that stimulates competition.

For the cooperative approach, previous literature looks at LEMs and their effect on the grid. Here, the market-clearing is usually done using a centralized optimization model. The objective function is to maximize social welfare, usually through the minimization of system costs. Consequently, this method will give the optimal result, seen from a community perspective. For example, Lüth et al. [3] investigates the role of battery storage in a LEM for a cooperative community model while [10] applies it to an industrial site. Dynge et al. [11] incorporates a power flow analysis to look at the grid impacts of cooperative trading. In [12], solar units, fuel-cell, and hydrogen storage are operated collaboratively to minimize the community's total cost. The cooperative approach is ideal for the buildings owned by organizations such as universities that can collaborate to obtain financial benefits [13].

However, it is unrealistic to assume both buyers (consumers) and sellers (prosumers) aim to lower the community energy cost. Individuals often seek to maximize their own profit. Hence, the representation of competitive markets is also an important research area. Sousa et al. [14] suggest three types of design options for competitive markets: Pooled market trading, fully decentralized markets with only bilateral trading, and hybrid markets where a market agent gathers and facilitates bilateral trading. For both the pooled and hybrid market, auctions or other market clearing mechanisms that consider bids and offers are needed to clear the market [15]. For example, k-double auctions (k-DA) are widely applied in the LEMs literature [15]. In double auction mechanisms, there are two ways of establishing trading prices: uniform or discriminatory pricing. In uniform pricing, we have one market-clearing price that applies for all winning participants. As for discriminatory pricing, also known as "pay-as-bid" pricing, each trade has one price, and there is no single market-clearing price. For both there is a price coefficient, k, that determines the balance in clearing price [16].

A central assumption to model competitive markets with auctions is the representation of bids and offers. There are two main approaches: non-strategic and strategic bidding. The non-strategic bidding approach entails randomized bids without any specific strategy, which does not necessarily implies a good representation of market behavior [17]. Strategic bidding is more realistic in a competitive market but requires game-theoretic approaches [2].

Current literature that looks at competitive markets usually includes bidding strategies or provides comparisons of no-strategy and strategic approaches. For example, Lin et al. [16] investigates two bidding strategies: the best-offer and the market-power. The first does not consider the market situation in terms of market supply or surplus energy, and participants compete for the best price. In the second strategy, participants have knowledge about market conditions, such as historical PV aor demand, and bid accordingly. Mengelkamp et al. [17] also compares two agent behaviors: a no-strategy versus an intelligent bidding approach. In the DA literature, Lin et al. [16] compares discriminatory and uniform k-DA and concludes that the first provides better market decisions. Mengelkamp et al. [17] also considers uniform k-DA but compares it to another trading mechanism known as Peer-to-Peer trading. More trading algorithms, such as Generalized Second-Price and Vickrey-Clark-Groves, have been applied to LEMs in [7]. In this study, after an initial market clearing, the bidding prices are gradually changed for both sides, sellers and buyers, to extend the trade opportunities. The work in [18] proposes a mechanism based on the Continuous Double Auction that can manage the congestion within the grid by pricing the electricity flow.

The P2P trading algorithm is based on sealed bids and offers that are matched if the buying price is higher than the selling price. There is no single market-clearing price but rather discriminatory prices for each trade that occurs. The algorithm is similar to discriminatory k-DA, but instead of sorting the bids and offers, they are paired randomly. Consequently, P2P might have a higher number of trades than k-DA as there is a possibility for advantageous matching. The randomness might also reduce market power and unfair competition. However, because of discriminatory pricing, peers might pay different prices for the same product at the same time-step [17]. Mengelkamp et al. [17] based on the early work of Blouin and Serrano [19] concluded that the P2P with intelligent bidding is the most efficient. Research in [20] presents a First-Come, First-Served based market model with discrete fixed-sized time slots throughout the day. The matching process of the orders existing in the order book is similar to P2P mechanism.

Regarding double auction mechanisms, these are evaluated based on four characteristics: individual rationality (IR), budget balance (BB), incentive compatibility (IC), and economic efficiency (EE) [16]. A trading algorithm is IR if participants do not derive negative utility from their participation. Moreover, BB implies the balance of money input and output. Furthermore, IC is given when participants have an incentive to bid their true value. Finally, the algorithm must maximize the aggregated utility of the participants to be EE [16]. However, Myerson and Satterthwaite [21] showed that a DA is not economically efficient if a mechanism is IR, BB, and IC. Nevertheless, many researchers have tried to create auction mechanisms with the highest possible efficiency. For instance, McAfee [22] proposed a mechanism that achieves an approximate optimization of a single-unit auction. Moreover, a commonly used DA mechanism is the Walrasian mechanism [23]. Unfortunately, this mechanism is not IC leading to incentives for misreporting valuations and therefore manipulating the price. Finally, Segal-Halevi et al. [24] suggested a multi-unit double auction mechanism (MUDA) that is IR, BB, and IC. It approximately optimizes the economic efficiency in sufficiently large markets. The MUDA algorithm was first applied to data from a stock exchange. The algorithm has never been applied to a LEM before, to the best of our knowledge, this is the first attempt to investigate the applicability of the algorithm in this context.

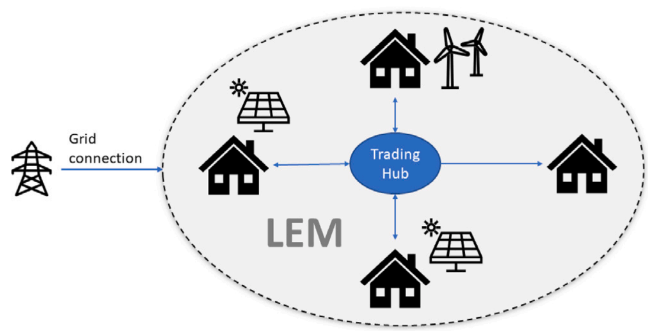

Fig. 1. Graphical illustration of the community configuration for local trading.

2.2. Contributions

As identified in the reviewed papers, there are research gaps on how to represent a wholesale market within LEMs that incentivizes trading (market based). This paper provides the following contributions:

- The comparison of the trading algorithms (MUDA and P2P), and centralized optimization . Although trading algorithms have been studied in the literature, the research on MUDA is new in the context of LEMs. P2P trading has been studied in the literature, but this is the first attempt to compare it to MUDA.
- The paper presents a new method for creating different bidding simulations for prosumers and consumers based on a reference price. We propose a new calculation of a reference price as a starting point for the bidding simulations. A similar approach was pursued by [16], but instead of using market prices from previous hours, we consider the current share of renewables in the LEM and an external grid price.
- We provide real-life examples of applying non-cooperative trading algorithms in Norway and the UK. Most studies on LEMs used centralized optimization with perfect competition. Therefore, this work contributes by applying trading algorithms on new settings and under a larger scale (200 households).
- An important finding of this paper is that the P2P algorithm leads to efficient results that are close to centralized optimization. In contrast, MUDA works less efficiently in this case, but might be not favored due to the relatively small number of participants.
- The models, codes, and data of this study are made open-source and easily accessible for replicability.

3. Methodology

Two models were developed to simulate trading within a LEM: a reference model, and a competitive model. The objective is to compare and evaluate the P2P and MUDA trading algorithms to the reference case. The latter uses centralized optimization, which gives the "perfect" solution from a system perspective. This represents a non-competitive system where a community manager handles all trades through a centralized hub. In contrast, the competitive model represents a market where participants place bids and offers in a trading hub (see Fig. 1). Social welfare is highest for the community model, but it does not account for the individuals' interests.

The LEM configuration is the same for both models and consists of consumers and prosumers connected through a trading hub. The prosumers have renewable generation (e.g. solar PV) and trade electricity with other peers. Consumers can buy from the prosumers. In both models, we assume that there are no network constraints or losses within the LEM or in the grid connection. Also, prosumers are mainly incentivized to sell surplus electricity to consumers instead of feed-in to the grid. That is, self-consumption is prioritized before local trading, and local trading is prioritized before buying from the grid, meaning the local price is assumed to be lower than the grid price.Any left over surplus is injected to the grid or curtailed.

3.1. Centralized model

The model presented in this section is based on "flexi-user"-model from [3]. The objective is to minimize the total cost for the community. However, Lüth et al. [3] only minimizes system costs, while we aim to also look at the amount of energy traded locally. Therefore, to avoid multiple optimal solutions, we have included a penalty term, P_p, to the objective function related to the total sold (exported) energy, $X^{(t,h)}$. This minimizes unnecessary trading while still giving the optimal results in terms of grid import as long as the penalty is appropriately small. Lastly, since all local trades are kept within the market, we do not consider the local trading prices (as they zero out in the summation). The objective function is in Eq. (1).

$$min \sum_{h} \sum_{t} [P_G^{(t)} \cdot G^{(t,h)}] + P_p \cdot \sum_{h} \sum_{t} [X^{(t,h)}] \tag{1}$$

The objective function is subject to several constraints, including the energy balance between supply and demand for each house. This restriction is given in Eq. (2). Here, the supply consist of local renewable production $res^{(t,h)}$, grid import $G^{(t,h)}$ and purchased (imported) electricity $I^{(t,h)}$. The demand consist of the consumed ($dem^{(t,h)}$) and sold electricity ($X^{(t,h)}$).

$$res^{(t,h)} + G^{(t,h)} + I^{(t,h)} \geq dem^{(t,h)} + X^{(t,h)} \qquad \forall t \in T, \quad \forall h \in H \tag{2}$$

Moreover, the flow of sold electricity for each participant in the market is defined in Eq. (3). Here, the total export for house h is defined as the sum of exported electricity of house h to its peers p. There is also a restriction that only allows houses that generate renewable electricity in any given time-step to export electricity in that same time-step. This restriction is defined in Eq. (4).

$$X^{(t,h)} = \sum_{p \neq h} X_P^{(t,h \to p)} \tag{3}$$

$$X^{(t,h)} = 0 \qquad \forall (t,h) | res^{(t,h)} = 0 \tag{4}$$

The purchased electricity of house h from its peers p in time-step t is calculated from the export of each peer, including a loss factor ψ, as given in Eq. (5). Furthermore, the total imported energy for each house in each time-step is then the sum of imported energy, as given in Eq. (6).

$$I_p^{(t,h \leftarrow p)} = \psi \cdot X_p^{(t,p \to h)} \qquad \forall p \neq h \tag{5}$$

$$I^{(t,h)} = \sum_{p \neq h} I_p^{(t,h \leftarrow p)} \tag{6}$$

Lastly, as the prosumers do not prioritize feed-in to the grid, the total quantity sold by all houses must equal the total quantity purchased by all houses for each time-step. We must also account for losses by including the loss factor ψ. This trading balance is given by Eq. (7).

$$\sum_{h} \psi \cdot X^{(t,h)} = \sum_{h} I^{(t,h)} \qquad \forall t \in T \tag{7}$$

In this model, loss factor is set to 1[1] to provide a fair comparison with the competitive model that does not account for losses. Table 7 in Appendix provides an overview of the variables, parameters, sets, and scalars notations.

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

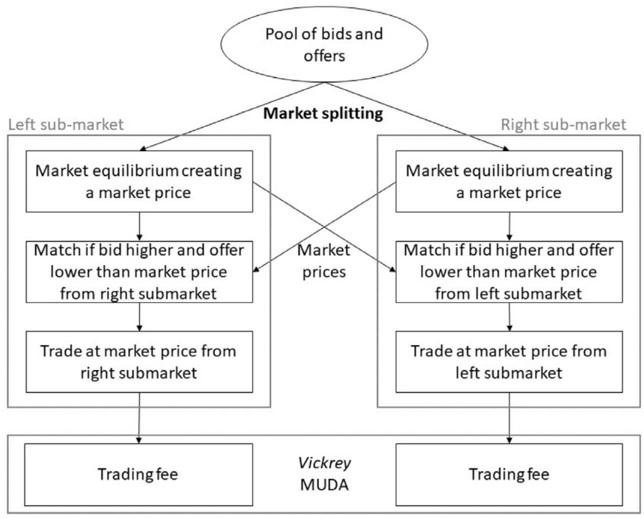

Fig. 2. Illustration of the MUDA algorithm.

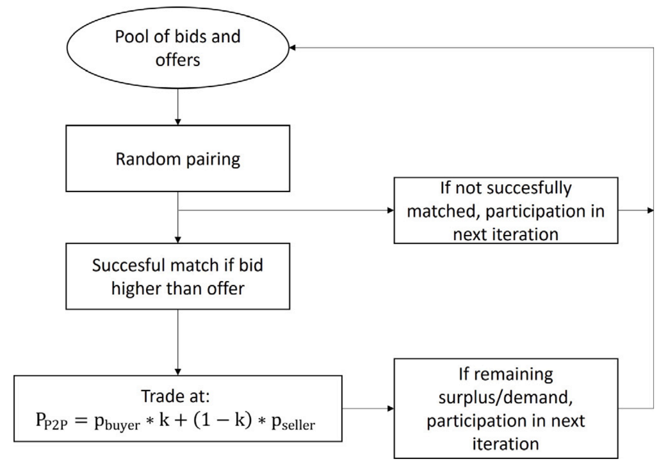

Fig. 3. Illustration of the P2P algorithm.

3.2. Trading algorithms - P2P and MUDA

MUDA and P2P algorithms simulate competitive behavior (trading) in the LEM. The fundamentals and descriptions of these algorithms are available in the PyMarket documentation [25]. As in the centralized optimization model, we assume a prioritization of self-consumption over trading. That is, prosumers consume their own electricity before placing an offer to the trading hub and selling their surplus energy. In case of a power deficit, consumers submit a bid to buy electricity. Then, the trading algorithms is implemented to clear the market for the whole period, one time-step at a time.

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

3.2.1. Multiple-unit double auction (MUDA) trading algorithm

Segal-Halevi et al. [24] introduced the MUDA algorithm aiming to create an economically efficient (EE) trading algorithm that is at the same time individually rational (IR), budget balanced (BB), and incentive compatible (IC).

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

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

With MUDA, participants cannot manipulate the price through strategic reporting since bids and offers are traded at an exogenously determined market price. Consequently, they only have an incentive to submit their true value, and therefore, the trading algorithm fulfills the IC requirement. Moreover, the agents do not lose through their participation, so the algorithm is IR. Furthermore, the "Vickrey"-MUDA is weakly budget balanced as the market-maker can make profits through trading fees but never losses. Finally, MUDA approximately optimizes the economic efficiency in sufficiently large markets [24]. However, it has not been applied to local electricity trading so far. Fig. 2 presents a simplified illustration of the MUDA algorithm.

3.2.2. Peer-to-peer (P2P) trading algorithm

The P2P algorithm is based on the work by Blouin and Serrano [19] and has previously been implemented for LEMs by Mengelkamp et al. [17]. Similarly to MUDA, the P2P trading algorithm works by peers submitting bids and offers into a central trading hub. These bids are then randomly paired and matched if the bidding price is higher than the offer price.

The trading price for each match is determined by Eq. (8), and thus depends on the price coefficient, k. If $k = 1$ all profit goes to seller, if $k = 0$ all profit goes to buyer. For this paper, we use a price coefficient of 0.5.

$$p_{p2p}^{(t)} = p_b^{(t)} \cdot k + (1 - k) \cdot p_s^{(t)} \qquad k \in [0, 1] \tag{8}$$

Since all bids might not be matched in the first run, the algorithm does several iterations, as illustrated in Fig. 3. This means that if a peer's bid or offer is not matched in the first iteration, or not all quantity is traded, they will participate in the next iteration. These iterations will go on until all unmatched participants either trade all their quantity or no available pairs are left in the trading hub.

An important characteristic of this algorithm, and possibly a drawback, is the price and quantity variations. Since all peers submit different bids and offers, trades have different prices according to (8) instead of one market price. Therefore, peers can end up with largely different prices for the same quantities in the same time-step. This means the algorithm can be perceived as unfair to some participants. However, the P2P trading algorithm does not provide incentives to manipulate bids and offers. Buyers try to bid as low as possible, but they must not bid too low to find a trading partner. Sellers try to drive the price up, but they need an even higher buying price. So their offer should also not be too high.

3.2.3. Reference price

The reference price reflects the situation of the local market in terms of renewable electricity availability, demand, and wholesale prices. Assuming that participants have a high level of information about the market, the reference price therefore also reflects the price a participant is willing to bid.

Fig. 4. Distribution of random bids and offers for the skewed normal distribution.

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

The proposed Eq. (9) follows the described principles. In addition, a lower bound P_{low} is added in Eq. (10) to avoid low offering prices that might not be realistic.

$$P_{ref}^{(t)} = (1 - \frac{\sum_h res^{(t,h)}}{\sum_h dem^{(t,h)}}) \cdot P_G^{(t)} \tag{9}$$

$$P_{ref}^{(t)} \geq P_{low} \tag{10}$$

3.2.4. Bidding simulations

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

We generate two sets of random numbers according to Eq. (11), one for bids (with positive λ) and one for offers (with negative λ). T_0 and T_1 are independent random numbers following a standard normal distribution. λ, σ, and μ are the parameters of the skewed normal distribution. If λ is set to zero, the resulting random numbers follow a normal distribution with the mean of μ and standard deviation of σ. Consequently, λ is the parameter determining the skewness of the distribution, as well as the expected value of the generated numbers, as shown in (12).

$$S^{(t)} = \mu + \sigma \cdot (\frac{\lambda}{\sqrt{1+\lambda^2}} \cdot |(T_0)| + T_1 \cdot \sqrt{1 - (\frac{\lambda}{\sqrt{1+\lambda^2}})^2}) \tag{11}$$

$$E[Y] = \mu + \sqrt{\frac{2}{\pi}} \sigma \frac{\lambda}{\sqrt{1+\lambda^2}} \tag{12}$$

The μ and σ are set to the reference price ($P_{ref}^{(t)}$) and 15% of the reference price, respectively. The λ that should not be unrealistically large but still reflect the effect of higher bids and lower offers is set to 0.25. Finally, Fig. 4 illustrates the skewed normal distribution for 1000 randomly generated bids and offers with the selected parameters.

4. Case studies and data

To analyze the MUDA and P2P trading algorithms and determine their efficiency, we examined a case from Norway and the UK. The cases differ in the number of houses, the distribution of renewable energy generation among the houses, and the solar radiation. Note that in a real-life implementation, these algorithms should be implemented very close to real-time. Solar surplus will be feed-in to the grid even without the existence of a LEM, hence a settlement process will be straightforward to do for the cases presented. Otherwise, research in [26] describes settlement mechanisms to handle the deviation of actual energy consumption or production from the auctions.

Table 1
Steinkjer case — Distribution of renewable generation units among the 54 households in the community.

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

4.1. Steinkjer case

In the Steinkjer case, the trading algorithms are applied in a neighborhood in Steinkjer, Norway. The data is based on Dynge et al. [11] but has been adjusted, i.e. with newly added small wind turbines, more PV systems, and battery storage were removed. This increases the overall generation of renewable energy and contributes to a more variable generation profile.

The load profiles are real consumption data collected from a smart grid project in Steinkjer. The data set includes 54 households connected through a distribution network connected to the main grid. The load profiles has a time granularity of 15 min and was retrieved over a period of 20 days from mid-June to early July. However, to match the time granularity of renewable energy generation and grid prices (hourly), the load profiles were aggregated into an hourly demand. Furthermore, the average household consumption during this period is comparatively high at 1147 kWh.

The grid price consists of the fluctuating wholesale market price and the annually constant grid tariff. The wholesale market price was retrieved from NordPool's historical data [27]. Here, we have selected 20 days that are consistent with the consumption data but from 2019. Furthermore, we have used the 2019 private household grid tariff from the DSO in Steinkjer, which is 0.42 NOK/kWh [28].

Moreover, we extracted generation profiles for wind and PV from renewables.ninja [29,30], which provides meteorological PV and wind data from the NASA MERRA-2 database [31]. Here, we selected 20 days in summer of 2019. In total, we have equipped 35 households with PV systems of varying capacities and a panel tilt of 45°. Additionally, we have equipped ten households with wind turbines of the Siemens SWT 2.3 82 model. Although the turbine model originally had a higher capacity and hub height, the data is realistic at the house level as we scaled down the capacity to 2.3 kW, see a similar approach in [32]. Table 1 summarizes distribution of renewable energy generation for the 54 households.

4.2. London case

The second case investigates the trading algorithm in a community of 200 households in London, United Kingdom. The load profiles are based on the consumption data from the low Carbon London project that took place from 2011 to 2014 [33]. All data sets have a half-hour time resolution and are taken from a 20 day period from mid June to early July. The grid prices for the London case were created in two steps. First, wholesale electricity prices were retrieved from [34]. Second, the network charges have to be taken into account to obtain the actual grid prices. Therefore, similar to [35], wholesale prices were scaled up to reach an average price of 15 pence/kWh.

The consumption data includes house types with different demand patterns in terms of demographics, social factors, population, and

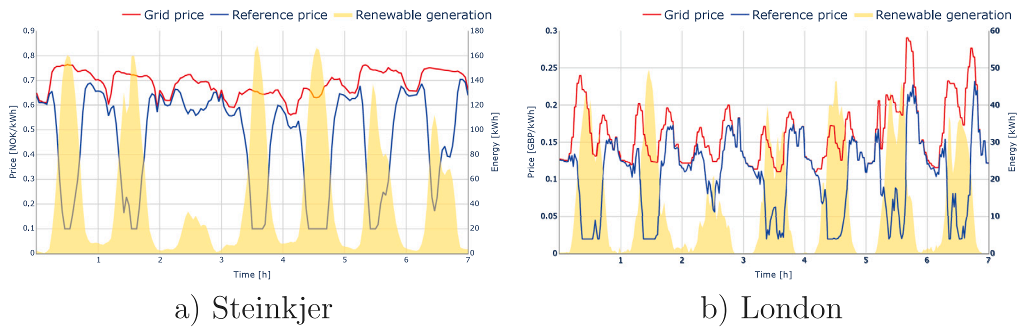

Fig. 5. Reference price in the communities compared to grid price and renewable generation.

Table 2
London case — Distribution of renewable generation units among the 200 households in the community.

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

consumption behavior. This data set comprises 164 affluent and 78 comfortable houses.

Solar generation profiles were calculated based on solar irradiation, and temperature data in London from 2013 [36,37] for different capacities with an efficiency of 21% and a panel tilt of 35°. Similar to [35], many new profiles are generated by adding random vectors to the original one to increase the diversity of the solar generation in the community. Wind data was derived from wind speed data from an area near London. The generation profile was then calculated by fitting a curve to the power-to-wind-speed profile of a 2.3 kW turbine (similar to [3]). Table 2 summarizes distribution of renewable energy generation among the 200 households.

4.3. Bidding simulation and implementation

As described in Section 3.2.4, the application of the trading algorithms requires bids and offers. For this purpose, we developed a reference price according to Eq. (9) and then generated the bids and offers randomly around the reference price using the skewed normal bidding simulation. Fig. 5 illustrates the reference price for both cases in the first week. As expected, the reference price depends strongly on the share of renewable generation. This leads to high variations of the reference price, both over time and in the two cases. In times of low renewable generation, especially at night, the reference price converges towards the grid price. But in times of high local generation, the reference price is close to or equal to the lower bound. The chosen lower bounds, P_{low}, are 10 NOK/kWh for the Steinkjer case and 0.25 GBP/kWh for the London case.

In the next step, we generated 1000 bids and offers based on the reference price using the bidding simulations. Fig. 6 presents the generated bids and offers for the first three days for both cases. The Figure illustrates the desired effect of the bidding simulation, i.e., the bids (blue dots) tend to be slightly higher than the offers (red dots).

5. Results and analysis

To analyze the algorithms MUDA and P2P, the centralized optimization model is used as a reference approach as it provides optimal results for local trading from a community perspective.

The trading algorithms are compared based on various Key Performance Indicators (KPIs), see Table 3. The KPIs provide relevant information to determine the efficiency of a particular trading algorithm.

5.1. Steinkjer case

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

5.1.1. Community model - Centralized optimization

The centralized optimization results in total system costs of 27 037 NOK, which is the cheapest solution for supplying households with the electricity they demand. With the given generation of renewable energy, the community can cover 36.1% of its consumption by itself. Participants prioritize self-generated electricity over trading, but 2506 kWh is still traded locally between the households. It reduces the dependency of the community members on the main grid, and as [38] states, it can be considered a complementary approach towards energy efficiency, sustainability, and net zero emissions by 2050. The rest, a share of 63.9%, is also imported from the main grid. Since centralized optimization represents the optimal solution, we can see that 2.7% curtailment (or grid feed-in) of the generation is unavoidable.

Fig. 7 shows the grid import, self-consumption, and curtailment of the community in the first week. During the day, there are high shares of self-consumption, while at night, the electricity grid almost exclusively covers the electricity demand. An exception appears in day three when there was a lower renewable energy generation.

Since the optimization aims to cover the demand of all households as cheaply as possible, and there are no local trading losses, all the local production will be shared among the households in the community. As there is no storage in the system, there will be curtailment if the renewable generation exceeds demand at any time-step. This is the case on the fourth, fifth and sixth day in Fig. 7. Moreover, the figure illustrates the optimal traded energy in the first week. Peaks in the energy traded occur during the day when the local generation, and thus self-consumption, is high. At these times, the prosumers' electricity generation exceeds their demand, so they share their surplus with other peers. Furthermore, no energy trading takes place on the third day. This is because the prosumers' own generation does not exceed their demand, hence they cannot offer surplus energy for trading.

5.1.2. Competitive model - Trading algorithms

Here we compare and analyze the MUDA and P2P trading algorithms. Table 4 presents the KPIs. The results of the P2P algorithm are relatively close to the solution of centralized optimization. The KPIs of the MUDA algorithm, in contrast, have a significantly greater gap to the centralized optimization. The traded energy using MUDA is lower compared to using P2P. This results in higher curtailment with MUDA as less electricity is distributed between the households. Consequently, MUDA gives a lower self-consumption, and more electricity is imported from the main grid. Also, a higher grid import results in higher system costs with MUDA.

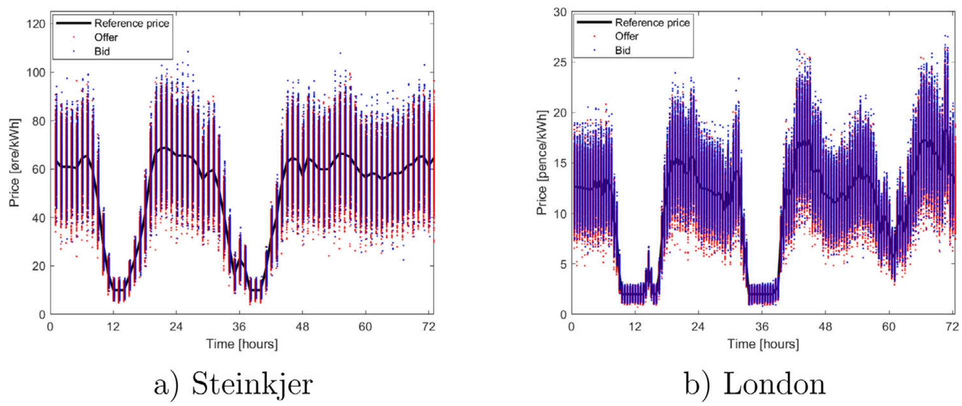

Fig. 6. Sample from the first 72 h of calculated bids and offers from the skewed normal distribution.

Table 3
Definition of KPIs used in this paper.

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

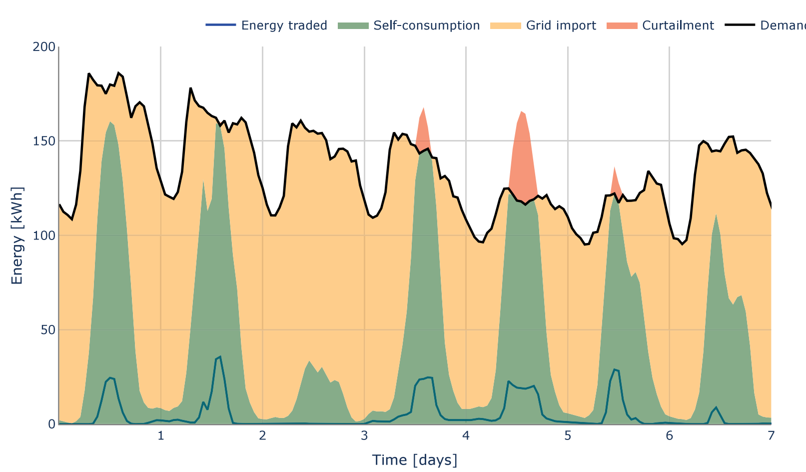

Fig. 7. Steinkjer case — Grid import, energy traded, self-consumption, curtailment (or grid feed-in) and demand for the first seven days of the centralized model.

Table 4
Steinkjer case — Comparison of KPIs for centralized, MUDA and P2P for the skewed normal bidding simulation.

KPI	Centralized	MUDA	P2P
System cost [NOK]	27 037	28 091	27 229
Grid import [kWh] (%)	39 553 (63.9)	41 073 (66.3)	39 829 (64.3)
Self-consumption [kWh] (%)	22 388 (36.1)	20 868 (33.7)	22 112 (35.7)
Curtailment [kWh] (%)	615 (2.7)	2135 (9.3)	891 (3.8)
Energy traded [kWh]	2506	986	2230

Figs. 8 and 9 examine the driving factors behind the KPIs in more detail. They show the grid import, self-consumption, curtailment and energy traded in relation to the community demand in the first week using MUDA and P2P.

With centralized optimization, we can observe unavoidable curtailment only on the fourth, fifth and sixth day. With MUDA, in contrast, curtailment occurs every day except the third day when there is no energy trading, as indicated in Fig. 8. Furthermore, we can observe that grid import and curtailment occur at the same time-steps. This means that MUDA fails to match a significant number of bids and offers. As a result, households have to import more expensive electricity from the grid, and locally produced electricity has to be unnecessarily curtailed.

Fig. 9 shows that using the P2P algorithm results in more traded energy than MUDA. Therefore, the community's self-consumption is significantly higher, and curtailment is reduced. However, we can still observe that P2P does not match all bids and offers, resulting in more curtailment than the centralized optimization. For example, on the second day, there are grid imports and curtailment, which means that available renewable electricity could not be used because the bids and offers were not successfully matched.

Fig. 10 illustrates the average prices of the trades in each time-step for both MUDA and P2P. Here, we can observe two different effects caused by the different characteristics of the algorithms. First, the average price of the MUDA algorithm is higher than the P2P average price and the reference price in most time steps, especially when the reference price is high. This is supported by the calculation of the average prices of all trades. For MUDA, the average price of all transactions is 0.31 NOK/kWh. In contrast, the average price when using P2P is 0.23 NOK/kWh. However, it can also be seen that the average prices of the MUDA algorithm never exceed the grid prices. Secondly, we can

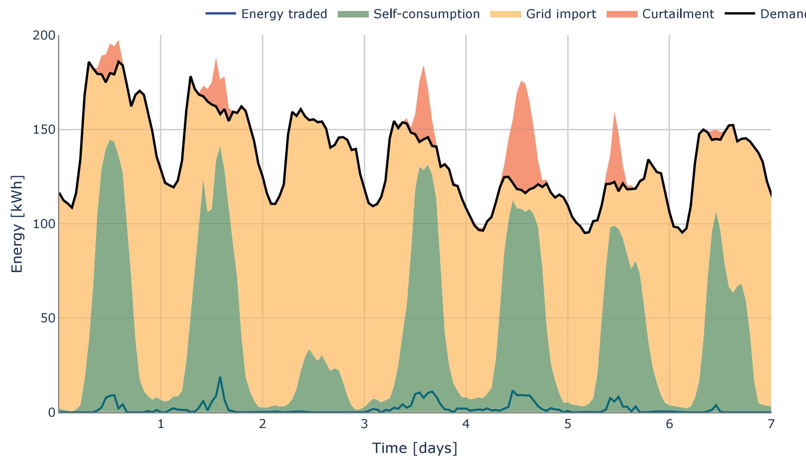

Fig. 8. Steinkjer case — Grid import, energy traded, self-consumption, curtailment (or grid feed in) and demand for the first seven days when using the MUDA algorithm.

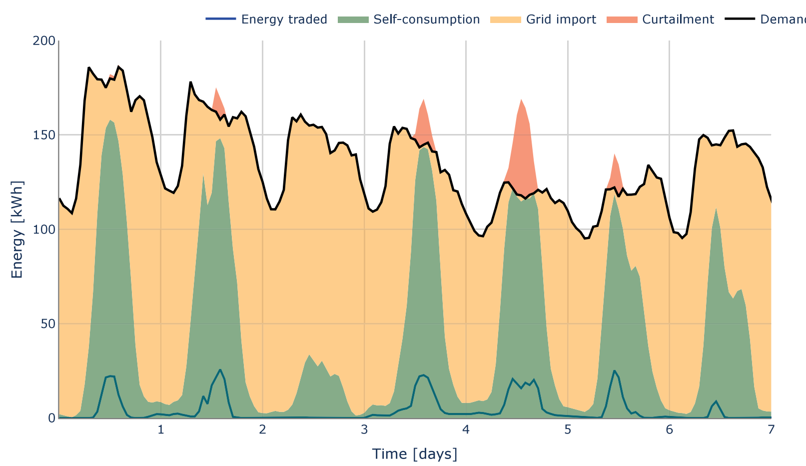

Fig. 9. Steinkjer case — Grid import, energy traded, self-consumption, curtailment (or grid feed in) and demand for the first seven days when using the P2P algorithm.

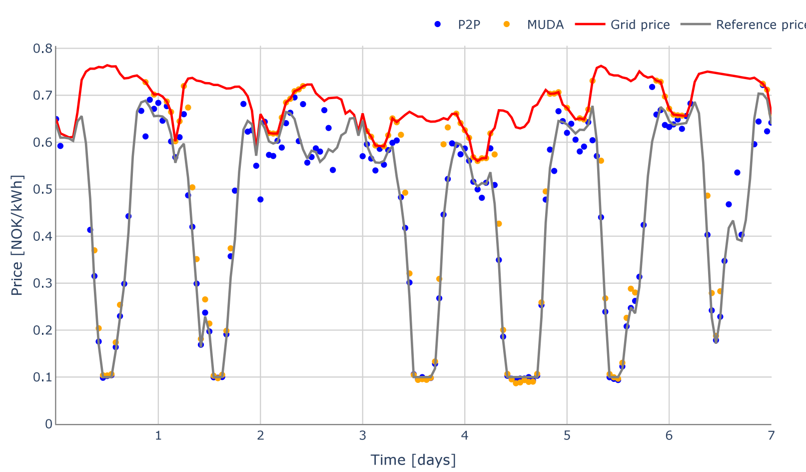

Fig. 10. Steinkjer case — Average Prices for each time-step in addition to grid price and reference price for the first week of the simulation.

observe more fluctuating average prices for P2P, particularly at high reference prices. In contrast, in times of high generation, the average prices converge to the reference prices when using P2P.

5.2. London case

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

5.2.1. Community model - Centralized optimization

Compared to the Steinkjer case, we observe significant differences in the results of the London case. A central difference is the higher

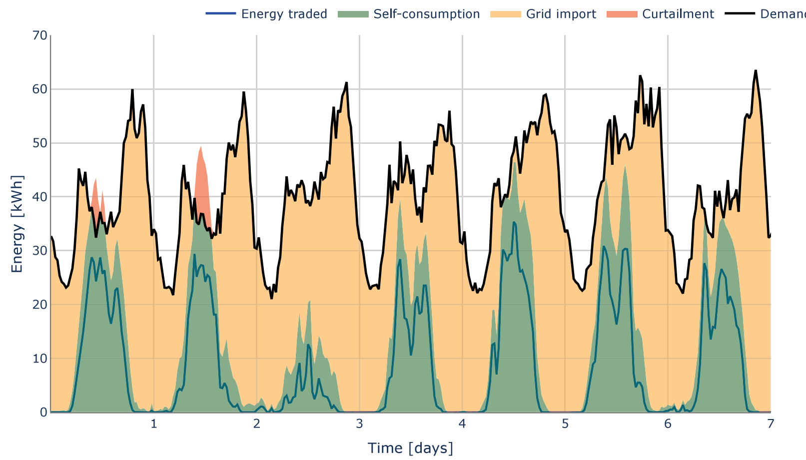

Fig. 11. London case — Grid import, energy traded, self-consumption, curtailment (or grid feed-in) and demand for the first seven days of the centralized model.

traded energy in the London case. At 8193 kWh, the traded energy is more than three times higher than in the Steinkjer case. This is because electricity generation of the prosumers is higher and the average demand per household is lower. Consequently, there is more surplus electricity that can be traded to other households in the community. Accordingly, Fig. 11 reveals that high shares of self-consumption are covered by traded energy. Furthermore, if the surplus electricity is optimally distributed, curtailment can be kept at a low level of 4.3% of the total electricity generated.

Moreover, Fig. 11 also shows similar effects as in the Steinkjer case in terms of self-consumption and grid import. During the day, we observe a high share of self-consumption due to the higher solar irradiation. In contrast, at night, the electricity supply is mainly covered by grid imports. The centralized optimization in the London case results in a self-consumption of 34.7% and grid import of 65.3%, very similar to the Steinkjer case. Finally, the system costs amount to 3844 GBP, representing the cheapest solution for the community.

5.2.2. Competitive model - Trading algorithms

In this section we analyze the MUDA and P2P trading algorithm for the London case. Table 5 shows the KPIs of the trading algorithm compared to centralized optimization for the London case. Similar to the Steinkjer case, the KPIs of P2P are much closer to centralized optimization relative to MUDA. Accordingly, the use of P2P also leads to a relatively high self-consumption (32.3%) and thus a low grid import (67.7%). Using MUDA, in contrast, leads to a significant decrease in self-consumption (24.9%) and an increase in grid import (75.1%). As a result, the system costs for MUDA (4423 GBP) are considerably higher than for P2P (3981 GBP). However, with both trading algorithms, there is a substantial increase in curtailment. When using P2P, 10.8% of the generated electricity is curtailed, and with MUDA the curtailment increases to 31.3%. This is most likely due to the different characteristics of the London case, where more surplus energy is generated, and more local trading is required to achieve the optimal solution. As a result, we can see large quantities of traded energy but also more curtailment due to unsuccessful trading attempts.

Looking at Figs. 12 and 13, we observe similar effects as in the Steinkjer case. However, due to the characteristics of the London case and the increased energy surplus, the impacts of the trading algorithms are even stronger. Fig. 12 shows high grid imports and curtailment occurring in the same time-steps when using MUDA. Simultaneously, the self-consumption is significantly lower with MUDA compared to centralized optimization. This means that a large amount of locally generated electricity is curtailed unnecessarily, and costly electricity has to be supplied from the main grid.

Table 5
London case — Comparison of KPIs for centralized, MUDA and P2P for the skewed normal bidding simulation.

KPI	Centralized	MUDA	P2P
System cost [GBP]	3844	4423	3981
Grid import [kWh] (%)	25 063 (65.3)	28 817 (75.1)	25 970 (67.7)
Self-consumption [kWh] (%)	13 295 (34.7)	9542 (24.9)	12 389 (32.3)
Curtail/grid feed in [kWh] (%)	596 (4.3)	4350 (31.3)	1503 (10.8)
Energy traded [kWh]	8193	4439	7286

Fig. 13 displays that grid import and curtailment also occur in the same time step when using P2P. However, this happens less frequently and to a smaller extent. Consequently, self-consumption is significantly higher with P2P when renewable generation is high, leading to almost complete self-sufficiency in some time-steps.

Fig. 14 illustrates the average prices of trades in the first week relative to the reference price and grid price. As in the Steinkjer case, when MUDA is used, the average prices are mostly higher than the reference prices and the P2P average prices, especially in time steps with low renewable generation. Again, the average price for all transactions when using MUDA is higher (0.050 GBP/kWh) than P2P (0.049 GBP/kWh). Nevertheless, the average prices of MUDA and P2P are much closer in the London case compared to the Steinkjer case. Furthermore, we also observe the effect of fluctuating P2P average prices.

5.3. Comparison of the trading algorithms

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

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

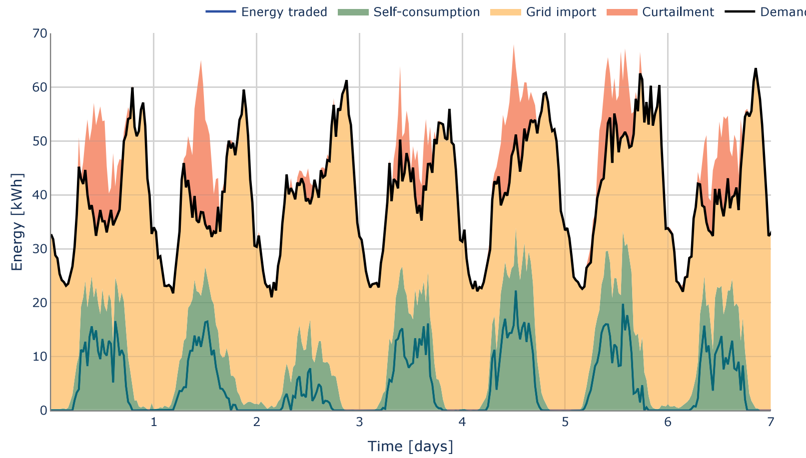

Fig. 12. London case — Grid import, energy traded, self-consumption, curtailment (or grid feed in) and demand for the first seven days when using the MUDA algorithm.

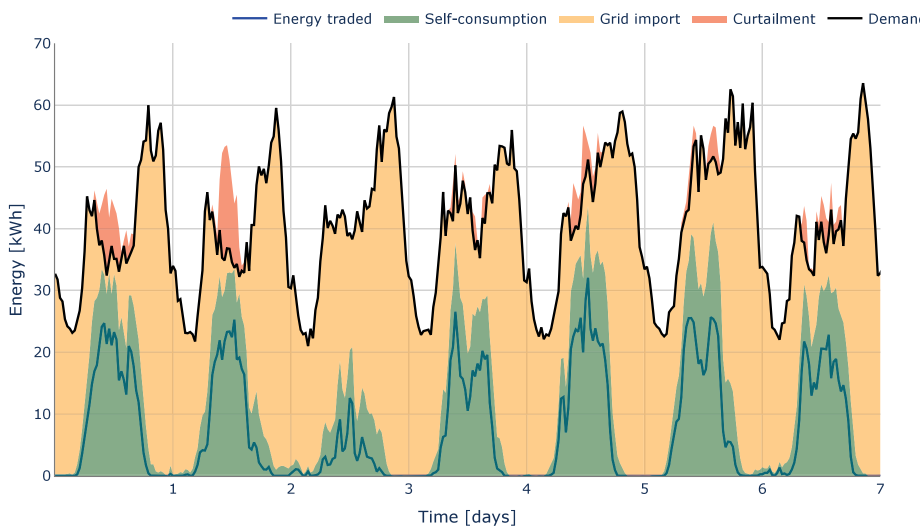

Fig. 13. London case — Grid import, energy traded, self-consumption, curtailment (or grid feed-in) and demand for the first seven days when using the P2P algorithm.

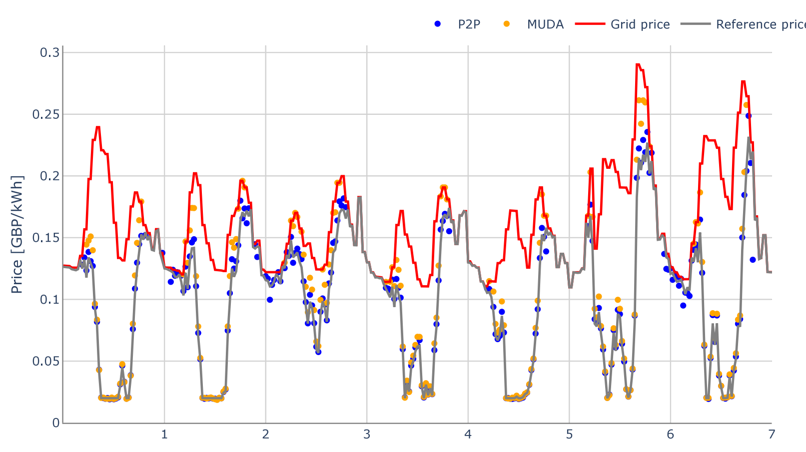

Fig. 14. London case — Average Prices for each time-step in addition to grid price and reference price for the first week of the simulation.

buy electricity from the grid, and local generation would have to be curtailed.

Compared to the result of MUDA, the use of P2P leads to significantly more trading. The P2P algorithm allows multiple iterations of random matching of bids and offers. Therefore, there is a higher probability of a bid finding an offer to trade with. However, the results show strong fluctuations in the average prices. This is because bids and offers are traded at the price midway between them, and therefore the

Table 6
Difference to centralized optimization in percentage.

KPIs	Steinkjer			London		
	Cent.	MUDA	P2P	Cent.	MUDA	P2P
System cost	27 037	+3.9	+0.7	3845	+15.0	+3.6
Grid import	39 553	−6.8	−1.2	25 063	−28.2	−6.8
Self-consumption	22 388	+3.8	+0.7	13 295	+15.0	+3.6
Curtail/grid feed in	615	+247.4	+44.9	596	+630.0	+152.2
Energy traded	2506	−60.7	−11.0	8193	−45.8	−11.1

trading prices of simultaneous trades from different peers vary. These average price fluctuations are smaller when renewable generation is high and more bids and offers are submitted. It indicates that average prices converge towards the reference price when the number of bids and offers is higher. In times of low generation, the number of offers is limited, and only a few trades determine the average prices leading to stronger fluctuations in the average prices. Comparing the two cases confirms this, as the effect is much stronger in the Steinkjer case, where there are fewer households and, thus, fewer bids and offers.

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

To compare the performance of the trading algorithms between the Steinkjer and London cases, we calculated the percentage gap to centralized optimization for MUDA and P2P, as shown in Table 6. This again shows that both trading algorithms perform less effectively in the London case, as more energy has to be traded, which is described in Section 5.2.

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

6. Conclusion

This paper studied the market efficiency of two trading algorithms in LEMs or energy communities. We looked at how to represent local electricity trading in a LEM using the MUDA and P2P trading algorithms. Based on real-case data from Norway and England, we simulated trading in a LEM for both algorithms vis-a-vis to a reference case (centralized optimization). The model for the reference case was based on an optimization model that minimizes total cost [3].[2] The two trading algorithms take bids and offers from energy users and simulate matching decisions to pair buyers (consumers) and sellers (prosumers), hence resembling some market behavior. To construct the behavior of bids and offers, we developed a community reference price from which a willing to sell or to buy price behavior follows a normal distribution. However, note that the main purpose of this analysis is on how trading algorithms represent the potential market behavior of a community by showing the potential price formation in an internal wholesale market. Estimating and gaining insights on that gives a better understanding on the creation of a LEM within an energy community.

Results and analyses indicate that P2P has a better trading efficiency compared to MUDA. This is reflected in less curtailment (or grid feed-in) and more traded electricity when using P2P. However, P2P is sometimes unfair as random pairing can lead to large difference in trading prices for the same product. In addition, the "Vickrey"-MUDA results in higher average prices due to trading fees. In the London case, the trading algorithms have lower efficiencies as more electricity trading occurs. This implies that curtailment (or grid feed in) increases when a higher energy surplus is up for trading. However, when comparing the two cases, MUDA reduces the gap (compared to the centralized optimization) in the London case, indicating that MUDA works better with a larger number of participants. Yet, the Market Allocation Efficiency, according to the definition of paper [26], is lower for the MUDA algorithm than P2P. This is also the case in this paper results.

In short, the P2P performs well in representing a wholesale market behavior as there is much electricity trading and less curtailment. MUDA seems fairer than P2P but has lower market efficiency. MUDA performs well in larger communities if trading fees are adequately used. The results indicate that trading fees in the "Vickrey" MUDA can lead to higher prices that may even exceed the grid prices, resulting in fewer matches of bids and offers. Therefore, further research should consider other MUDA variants, such as the "Lottery" MUDA, where bids and offers are randomly selected without trading fees, may be more suitable for LEMs.

An important point for further research will be to consider flexibility from the participants. Batteries, such as electric vehicles, can allow for a more dynamic and strategic trading process. In addition, demand response can be included to analyze the price responsiveness of participants. Further research might also consider to coordinate interests between the energy community and other actors (e.g. DSOs, aggregators, etc.) [39].

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

We have shared the links to the codes and cited the data used in the paper. Available at: https://github.com/LocalEnergyMarkets/

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Appendix. Notations declaration

See Table 7.

[2] For further information, please refer to https://github.com/LocalEnergyMarkets/LocalCommunity.

Table 7
Overview of sets, scalars, parameters and variables used in this paper.

Sets	
$t \in T$	Hours t in time horizon T
$h, p \in H$	Houses h and peers p in community H
$b, s \in H$	Buyers b and sellers s in community H
Scalars	
P_p	Export penalty term
ψ	Loss factor for local trading
P_{low}	Lower bound for reference price
Parameters	
$dem^{(t,h)}$	Demand of house h in time-step t
$res^{(t,h)}$	Renewable energy production of house h in time-step t
$p_G^{(t)}$	Price of electricity from the grid in time-step t
$P_{ref}^{(t)}$	Reference price in time-step t
$S^{(t)}$	Bids and offers from the skewed normal distribution in time-step t
T_0	Set of random number following a normal distribution
T_1	Set of random number following a normal distribution
λ	Skewness factor of normal distribution
σ	Standard deviation of normal distribution
μ	Mean value of normal distribution
Variables	
$G^{(t,h)}$	Grid consumption of house h in time-step t
$I^{(t,h)}$	Total imported electricity of house h in time-step t
$I_p^{(t,h \leftarrow p)}$	Imported electricity of house h from peer p in time-step t
$X^{(t,h)}$	Total exported electricity of house h in time-step t
$X_p^{(t,h \rightarrow p)}$	Exported electricity of house h to peer p in time-step t
$p_{p2p}^{(t)}$	Local p2p trading price for a given trade in time-step t
E	Expected value

References

[1] Matthias Maldet, Frida Huglen Revheim, Daniel Schwabeneder, Georg Lettner, Pedro Crespo del Granado, Aziz Saif, Markus Löschenbrand, Shafi Khadem, Trends in local electricity market design: Regulatory barriers and the role of grid tariffs, J. Cleaner Prod. (ISSN: 0959-6526) 358 (2022) 131805.

[2] Sigurd Bjarghov, Markus Löschenbrand, AUN Ibn Saif, Raquel Alonso Pedrero, Christian Pfeiffer, Shafiuzzaman K Khadem, Marion Rabelhofer, Frida Revheim, Hossein Farahmand, Developments and challenges in local electricity markets: A comprehensive review, IEEE Access 9 (2021) 58910–58943.

[3] Alexandra Lüth, Jan Martin Zepter, Pedro Crespo del Granado, Ruud Egging, Local electricity market designs for peer-to-peer trading: The role of battery flexibility, Appl. Energy 229 (2018) 1233–1243.

[4] Siqian Zheng, Gongsheng Huang, Alvin C.K. Lai, Techno-economic performance analysis of synergistic energy sharing strategies for grid-connected prosumers with distributed battery storages, Renew. Energy (ISSN: 0960-1481) 178 (2021) 1261–1278.

[5] A. Pacheco, J. Monteiro, J. Santos, C. Sequeira, J. Nunes, Energy transition process and community engagement on geographic islands: The case of Culatra Island (Ria Formosa, Portugal), Renew. Energy (ISSN: 0960-1481) 184 (2022) 700–711.

[6] Lin Herenčić, Mislav Kirac, Hrvoje Keko, Igor Kuzle, Ivan Rajšl, Automated energy sharing in MV and LV distribution grids within an energy community: A case for Croatian city of Križevci with a hybrid renewable system, Renew. Energy (ISSN: 0960-1481) 191 (2022) 176–194.

[7] Simona-Vasilica Oprea, Adela Bâra, Devising a trading mechanism with a joint price adjustment for local electricity markets using blockchain. Insights for policy makers, Energy Policy (ISSN: 0301-4215) 152 (2021) 112237.

[8] Esther Mengelkamp, Christof Weinhardt, Clustering household preferences in local electricity markets, in: Proceedings of the Ninth International Conference on Future Energy Systems, 2018, pp. 538–543.

[9] Andrea Paladin, Ridoy Das, Yue Wang, Zunaib Ali, Richard Kotter, Ghanim Putrus, Roberto Turri, Micro market based optimisation framework for decentralised management of distributed flexibility assets, Renew. Energy (ISSN: 0960-1481) 163 (2021) 1595–1611.

[10] Guro Sæther, Pedro Crespo del Granado, Salman Zaferanlouei, Peer-to-peer electricity trading in an industrial site: Value of buildings flexibility on peak load reduction, Energy Build. 236 (2021) 110737.

[11] Marthe Fogstad Dynge, Pedro Crespo del Granado, Naser Hashemipour, Magnus Korpås, Impact of local electricity markets and peer-to-peer trading on low-voltage grid operations, Appl. Energy 301 (2021) 117404.

[12] Hasan Mehrjerdi, Peer-to-peer home energy management incorporating hydrogen storage system and solar generating units, Renew. Energy (ISSN: 0960-1481) 156 (2020) 183–192.

[13] Catalina Alexandra Sima, Claudia Laurenta Popescu, Mihai Octavian Popescu, Mariacristina Roscia, George Seritan, Cornel Panait, Techno-economic assessment of university energy communities with on/off microgrid, Renew. Energy (ISSN: 0960-1481) 193 (2022) 538–553.

[14] Tiago Sousa, Tiago Soares, Pierre Pinson, Fabio Moret, Thomas Baroche, Etienne Sorin, Peer-to-peer and community-based markets: A comprehensive review, Renew. Sustain. Energy Rev. 104 (2019) 367–378.

[15] Shuang Xu, Yong Zhao, Yuanzheng Li, Yue Zhou, An iterative uniform-price auction mechanism for peer-to-peer energy trading in a community microgrid, Appl. Energy 298 (2021) 117088.

[16] Jason Lin, Manisa Pipattanasomporn, Saifur Rahman, Comparative analysis of auction mechanisms and bidding strategies for P2P solar transactive energy markets, Appl. Energy 255 (2019) 113687.

[17] Esther Mengelkamp, Philipp Staudt, Johannes Garttner, Christof Weinhardt, Trading on local energy markets: A comparison of market designs and bidding strategies, in: 2017 14th International Conference on the European Energy Market (EEM), IEEE, 2017, pp. 1–6.

[18] Vytelingum. P, Ramchurn. S, Voice. T, Rogers. A, Jennings. N, Trading agents for the smart electricity grid, in: The Ninth International Conference on Autonomous Agents and Multiagent Systems (AAMAS 2010), Toronto, Canada., 2010, pp. 897–904.

[19] Max R. Blouin, Roberto Serrano, A decentralized market with common values uncertainty: Non-steady states, Rev. Econom. Stud. 68 (2) (2001) 323–346.

[20] Dejan Ilic, Per Goncalves Da Silva, Stamatis Karnouskos, Martin Griesemer, An energy market for trading electricity in smart grid neighbourhoods, in: 2012 6th IEEE International Conference on Digital Ecosystems and Technologies (DEST), 2012, pp. 1–6, http://dx.doi.org/10.1109/DEST.2012.6227918.

[21] Roger B. Myerson, Mark A. Satterthwaite, Efficient mechanisms for bilateral trading, J. Econom. Theory 29 (2) (1983) 265–281.

[22] R. Preston McAfee, A dominant strategy double auction, J. Econom. Theory 56 (2) (1992) 434–450.

[23] Aldo Rustichini, Mark A. Satterthwaite, Steven R. Williams, Convergence to efficiency in a simple market with incomplete information, Econometrica (1994) 1041–1063.

[24] Erel Segal-Halevi, Avinatan Hassidim, Yonatan Aumann, Muda: A truthful multi-unit double-auction mechanism, in: Proceedings of the AAAI Conference on Artificial Intelligence, Vol. 32, 2018, 1.

[25] Diego Kiedanski, Daniel Kofman, José Horta, Pymarket documentation, 2022, URL: https://pymarket.readthedocs.io/en/latest/index.html/ (visited on 05/30/2022).

[26] Simona-Vasilica Oprea, Adela Bâra, Vlad Diaconita, A motivational local trading framework with 2-round auctioning and settlement rules embedded in smart contracts for a small citizen energy community, Renew. Energy (ISSN: 0960-1481) 193 (2022) 225–239.

[27] NordPool, Historical market data, 2022, URL: https://www.nordpoolgroup.com/historical-market-data/ (visited on 03/07/2022).

[28] A.S. Tensio, Nettleiepriser privat gjeldende fra 1. januar 2019, 2022, URL: https://ts.tensio.no/kunde/nettleie-priser-og-avtaler/2019-nettleie-privat (visited on 03/07/2022).

[29] Stefan Pfenninger, Iain Staffell, Long-term patterns of European PV output using 30 years of validated hourly reanalysis and satellite data, Energy 114 (2016) 1251–1265.

[30] Iain Staffell, Stefan Pfenninger, Using bias-corrected reanalysis to simulate current and future wind power output, Energy 114 (2016) 1224–1239.

[31] Michele M Rienecker, Max J Suarez, Ronald Gelaro, Ricardo Todling, Julio Bacmeister, Emily Liu, Michael G Bosilovich, Siegfried D Schubert, Lawrence Takacs, Gi-Kong Kim, et al., MERRA: Nasa's modern-era retrospective analysis for research and applications, J. Clim. 24 (14) (2011) 3624–3648.

[32] Pedro Crespo Del Granado, Stein W. Wallace, Zhan Pang, The value of electricity storage in domestic homes: a smart grid perspective, Energy Syst. 5 (2) (2014) 211–232.

[33] U.K. Power Networks, Smartmeter energy consumption data in London households, 2022, URL: https://data.london.gov.uk/dataset/smartmeter-energy-use-data-in-london-households (visited on 03/07/2022).

[34] ENTSO-E, Transparency platform, 2022, URL: https://transparency.entsoe.eu/ (visited on 03/07/2022).

[35] Naser Hashemipour, Pedro Crespo del Granado, Jamshid Aghaei, Dynamic allocation of peer-to-peer clusters in virtual local electricity markets: A marketplace for EV flexibility, Energy 236 (2021) 121428.

[36] SoDa. Solar radiation data, Helioclim-3 archives, 2022, URL: https://www.soda-pro.com/web-services/radiation/helioclim-3-archives-for-free (visited on 03/07/2022).

[37] Goddard Earth Sciences Data, Information Services Center (GES DISC), Global modeling and assimilation office (GMAO)(2015), MERRA-2 tavg1_2d_slv_Nx: 2d, 1-hourly, time-averaged, single-level, assimilation, single-level diagnostics V5. 12.4, 2015.

[38] Mircea Stefan Simoiu, Ioana Fagarasan, Stéphane Ploix, Vasile Calofir, Modeling the energy community members' willingness to change their behaviour with multi-agent systems: A stochastic approach, Renew. Energy (ISSN: 0960-1481) 194 (2022) 1233–1246.

[39] Vladimir Z. Gjorgievski, Snezana Cundeva, George E. Georghiou, Social arrangements, technical designs and impacts of energy communities: A review, Renew. Energy (ISSN: 0960-1481) 169 (2021) 1138–1156.