COMPARATIVE ANALYSIS OF MARKET STRUCTURES OF P2P ENERGY TRADING IN A LOCAL ENERGY SYSTEM

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Peer-to-peer (P2P) energy trading has been recognized as an important technology to increase the local self-consumption of photovoltaics in the local energy system. Different auction mechanisms and bidding strategies haven been investigated in previous studies. However, there has been no comparatively analysis on how different market structures influence the local energy system's overall performance. This paper presents and compares two market structures, namely a centralized market and a decentralized market. Two pricing mechanisms in the centralized market and two bidding strategies in the decentralized market are developed. The results show that the centralized market leads to higher overall system self-consumption and profits. In the decentralized market, some electricity is directly sold to the grid due to unmatchable bids and asks. Bidding strategies based on the learning algorithm can achieve better performance compared to the random method.

Keywords:
P2P energy trading, local energy system, market structure, bidding strategies, Bled eConference

University of Maribor Press

DOI https://doi.org/10.18690/um.fov.6.2023.34
ISBN 978-961-286-804-8

1 Introduction

In order to reach carbon neutrality, the local energy system is undergoing a huge transformation (Salvia et al., 2021). Distributed generation resources, particularly photovoltaics (PVs) are becoming more and more popular at the demand side (B. Zhou et al., 2021). However, the large-scale penetration of PVs has a significant impact on the safe operation of the power system (Kumar et al., 2021). Therefore, to promote the self-consumption of PV within the local energy system is the focus of current research.

Peer-to-peer (P2P) energy trading has been proposed as a critical technology to increase the PV consumption in recent years (Y. Zhou et al., 2020). P2P energy trading enables direct energy trading between prosumers and consumers within the local energy system (Zhang et al., 2018). A prosumer is defined as an entity that can produce and consume electricity, such as residential households with PVs (Iazzolino et al., 2022). In the P2P energy trading, prosumers can obtain additional benefits from selling their electricity to individual consumers (Zheng, 2022). Furthermore, P2P energy trading can facilitate power balance for the power system (Soto et al., 2021).

The research on the P2P energy trading can be categorized into two main streams according to the market structure: the centralized market and the decentralized market (Muhsen et al., 2022). In the centralized market, the coordinator collects information on electricity production and consumption of all prosumers and consumers. After the trading, the coordinator allocates the payoffs of the whole system to the participants according to a predefined rule. Some rules distribute costs or profits according to each participant's contribution to the aggregate system net consumption or surplus generation (Reis et al., 2020). Some rules calculate the local market price based on the pricing mechanism, such as supply and demand ratio (SDR) (Liu et al., 2017), mid-market rate (MMR) (Long et al., 2017) and bill sharing (BS) (Y. Zhou et al., 2018). In this market, market participants are considered as price takers and they can only accept the price made by the coordinator. In the decentralized market, prosumers and consumers are able to make autonomous decisions about the amount and price of electricity to bid. These bids are submitted to a P2P trading platform and then cleared by a certain clearing approach. Different auction mechanisms, such as Discriminatory k-Double Auction (k-DA), Uniform k-

DA, Vickrey-Clark-Groves (VCG), and Trade Reduction (TR), have been proposed and compared (Lin et al., 2019). Several bidding strategies have also been introduced to investigate their influence on the conditions of the market (Yu et al., 2018). Although current studies have investigated auction mechanisms and bidding strategies, there has been no comparatively analysis on how different market structures influence the local energy system's overall performance.

This paper presents and compares two market structures, namely a centralized market and a decentralized market, with the aim of providing valuable insights into establishing a P2P energy market. Firstly, two pricing mechanisms in the centralized market and two bidding strategies in the decentralized market are developed. Secondly, a comprehensive assessment of the local energy system's overall performance including costs, profits and self-consumption, is analyzed.

2 Methodolodgy

2.1 Simulation model

We simulate a local energy market with the P2P energy trading in a local energy system. The market participants include N residential consumers or prosumers (I = 1, 2, 3, ..., N), and a coordinator. A coordinator plays a different role in different market structures. In a centralized market, they typically act as the system operator responsible for managing the system's operations. In a decentralized market, they are generally the trading platforms where electricity order matching takes place. The simulation are conducted for the day-ahead at the time interval of 1 hour (Δt = 1 h). The internal market price in the local market should lie between the electricity feed-in price and the retail electricity price. Therefore, consumers and prosumers can benefit from participating in the energy market. This can increase the local PV consumption and reduce the amount of electricity sold from the local energy system to the higher-level power grid.

2.2 Centralized market

In the centralized market, the information about the requested electricity from consumers and the available surplus PV generation from prosumers is transmitted to the coordinator. The coordinator calculates the total electricity demand and electricity surplus of the local energy system. Then the coordinator trades with the grid to balance local supply and demand. After the trading, the coordinator decides how to distribute the system profits according to a predefined rule. This paper compares two rules: the costs and profits distribution rule, and the internal pricing mechanism.

2.2.1 Costs and profits distribution rule

The costs and profits distribution rule represents a fair mechanism to directly distribute the system costs and profits. Different rules have been proposed to achieve fairness in the distribution. Allocation based on the amount of each participant's electricity consumption and electricity injected is the most basic rule. The costs and profits of participants are calculated by Eq. (1).

$$\textit{Costs and profits distribution} = \begin{cases} PE_{i,t} \cdot f_{in},\ \textit{if}\ NC_{i,t} \geq 0 \\ SE_{i,t}^{local} \cdot f_{market} + SE_{i,t}^{grid} \cdot f_{out},\ \textit{if}\ NC_{i,t} < 0 \end{cases} \tag{1}$$

$NC_{i,t}$ is the net consumption of the paticipant *i* at time *t* [kWh]. If $NC_{i,t} \geq 0$, the paticipant *i* is a buyer; otherwise the paticipant *i* is a seller. f_{in} is the retail electricity price from the grid [$/kWh]. f_{market} is the internal market price [$/kWh]. f_{out} is the electricity feed-in price [$/kWh]. $PE_{i,t}$ is the purchased electricity of the paticipant *i* at time *t* [kWh]. $SE_{i,t}^{local}$ is the locally sold electricity of the paticipant *i* at time *t* [kWh]. $SE_{i,t}^{grid}$ is the sold electricity into the grid of the paticipant *i* at time *t* [kWh]. If $\sum NC_{i,t} < 0$, the system sells the surplus electricity to the grid, and the sold electricity is distributed among sellers according to the proportion of thier contribution to the system's net comsuption; otherwise, no surplus electricity is sold to the grid.

2.2.2 Internal pricing mechanism

As the costs and profits distribution rule are unable to reflect real-time electricity prices in the current trading market, various internal pricing mechanisms are proposed. Supply and demand ratio (SDR), mid-market rate (MMR) and bill sharing (BS) are three typical pricing mechanisms. Taking the SDR mechanism as an example, an internal pricing model for energy sharing is established, where the internal price is defined as a segmented function of the energy supply-demand ratio within the market. Specifically, the supply-demand relationship in the P2P energy market can be represented by the total surplus and demand electricity at each time interval. The supply-demand ratio of electricity is defined by Eq. (2).

$$SDR_t = \frac{\sum_{i \in N_S} SE_{i,t}}{\sum_{i \in N_B} PE_{i,t}} \tag{2}$$

SDR_t is the supply-demand ratio at time *t*. $SE_{i,t}$ is the sold electricity of the paticipant *i* at time *t* [kWh]. $PE_{i,t}$ is the purchased electricity of the paticipant *i* at time *t* [kWh]. N_S and N_B are the collection of sellers and buyers.

Typically, there is an inverse proportion relationship between the price and the supply-demand ratio. Therefore, the selling and purchasing prices within the market are calculated by Eq. (3) and Eq. (4), respectively.

$$p_{sell,t} = \begin{cases} \dfrac{f_{out} \cdot f_{in}}{(f_{in} - f_{out}) \cdot SDR_t + f_{out}}, & 0 \le SDR_t < 1 \\ f_{out} & , SDR_t > 1 \end{cases} \tag{3}$$

$$p_{buy,t} = \begin{cases} p_{sell,t} \cdot SDR_t + f_{in}(1 - SDR_t), & 0 \le SDR_t < 1 \\ f_{out} & , SDR_t > 1 \end{cases} \tag{4}$$

$p_{sell,t}$ and $p_{buy,t}$ is the selling and purchasing prices within the market at time *t* [$/kWh].

2.3 Decentralized market

In the decentralized market, P2P energy trading allows consumers and prosumers to directly buy and sell PV resources using a blockchain-based platform. Consumers and prosumers can submit their own electricity bidding to the trading platform, and the platform settles orders through a specific clearing algorithm. In this paper, the periodic double auction market that leads to a single clearing price for every trading period is implemented (Zade et al., 2022). During the trading period, participants submit bids or asks according to their roles of buyers or sellers. Once all bids and asks have been received, they are collected in an order book. At clearing time, bids are sorted in descending order and asks are sorted in ascending order by price. All bids where the buy price exceeds or equals the ask price are matched. At the end, the clearing prices are calculated based on the uniform price calculation method. Different bidding strategies have been proposed to test the feasibility of implementing a P2P trading market. This paper compares two bidding strategies: random bidding strategies and learning algorithm based bidding strategies.

2.3.1 Random bidding strategies

During the trading period, each consumer or prosumer bids with a random buy or sell price without any strategic foresight. This means that it does not take into account historical or retail electricity costs on the market. Participants randomly bid in a certain price interval. Prosumers are unwilling to accept a price below the electricity feed-in price, while consumers are unwilling to pay a price above the retail electricity price. Therefore, the upper price limit is set to the retail electricity price, and the lower price limit is set to the electricity feed-in price. Bid and ask prices are randomly sampled from a uniform distribution between f_{out} and f_{in}.

2.3.2 Learning algorithm based bidding strategies

In a real-world setting, consumers and prosumers are capable of learning from past decision-making experiences, which reflects their intelligent characteristics. Based on the income they earn as prosumers and the costs that incur to them consumers, they adjust their propensities to place specific orders. Different reinforcement learning algorithms have been proposed to simulate the learning ability of participants, such as Roth-Erev (RE) algorithm (Nicolaisen et al., 2001) and Q-learning algorithm (Chiu et al., 2022). This paper takes the RE algorithm as an example to illustrate the performance of reinforcement learning algorithms (Mengelkamp et al., 2017). The basic idea of the algorithm is to give priority to previous successful decisions and to learn from recent experiences.

Firstly, participants determine their own set of bidding strategies. In this paper, the market price range is discretized into an integer number of bid strategies according to its upper and lower bounds. Therefore, the set $S = \{ f_{out}, \dots, f_{in} \}$ represents all possible bidding strategies of the participants. In the beginning, the participants have the same initial propensities for each strategy.

Secondly, as the P2P energy trading clears, participants update their own propensities for each strategy, as shown in Eq. (5).

$$pr_{i,j,t+1} = (1-\lambda) \cdot pr_{i,j,t} + \begin{cases} R_t(s_t) \cdot (1-\varepsilon), j = s_t \\ pr_{i,j,t} \cdot \dfrac{\varepsilon}{|S|-1}, otherwise \end{cases} \tag{5}$$

$pr_{i,j,t}$ represents the propensity of the participant *i* for each strategy *j* at time *t*. The parameter $\lambda \in [0,1]$ represents the participant's memory factor. The higher the value of λ is, the faster the participant forgets the past decision results. The parameter $\varepsilon \in [0,1]$ represents the participant's learning speed. As the value of ε decreases, the importance of the previous action in future decisions increases for the participant. $R_t(s_t)$ is the achieved income or the saved costs of the participant when its chosen strategy is *s* at time *t*. For prosumers and consumers, $R_t(s_t)$ is calculated by Eq. (6) and Eq. (7).

$$R_{prosumer,t}(s_t) = SE_{i,t}^{local} \cdot f_{market} + SE_{i,t}^{grid} \cdot f_{out} \tag{6}$$

$$R_{consumer,t}(s_t) = PE_{i,t} \cdot (f_{in} - f_{market}) \tag{7}$$

Finally, the probabilities with which the participant *i* chooses strategy *j* are then derived from these propensities at time $t+1$, as shown in Eq. (8). The roulette method is employed to select the final bid strategy.

$$prob_{i,j,t+1} = \frac{pr_{i,j,t+1}}{\sum_{j=1}^{S} pr_{i,j,t+1}} \tag{8}$$

3 Case study description

This study targets a hypothetical local energy system of 100 residential homes. In order to reflect the diversity of the houses, the size of the house is randomly sampled from 1,000 to 4,000 square feet. Figure 1 presents the hourly base load and PV generation profiles of a 2,546 square feet house during a summer month, which are obtained from (Lin et al., 2019). The load and PV generation profile of each house in the system is determined by scaling the base load and PV generation profile proportionally to the previously generated house size. The retail electricity price is $0.123/kWh and the electricity feed-in price is $0.033/kWh. For the system, two PV penetration levels are tested (40% and 60%) with two market structures (the centralized market with the distribution rule and SDR pricing mechanism, and the decentralized market with random and learning algorithm based bidding strategies).

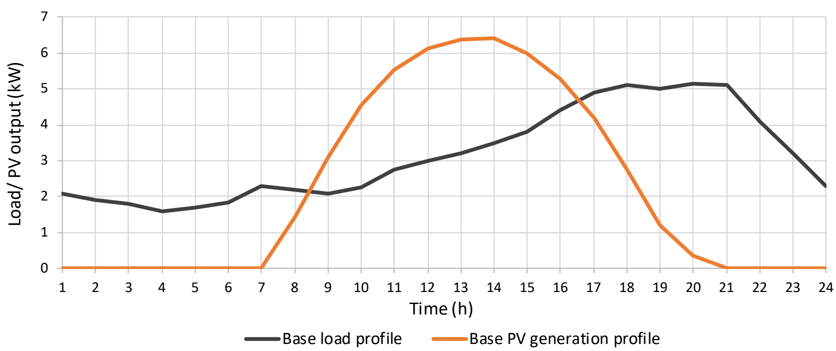

Figure 1: A 24h base load and PV generation profile

4 Simulation results

4.1 Case I: 40% PV penetration

The 24h load and PV generation profiles of the local energy system with 60 consumers and 40 prosumers are illustrated in Figure 2. It should be noted that the load profile for the 60 consumers is superimposed on the aggregate load profile for the 40 prosumers. By combining these two profiles, the total load of the system can be determined. As a result of the 40% ratio of prosumers to consumers, the total prosumer load is lower than the total consumer load. Between approximately 8:30

am and 16:30 pm, prosumers in the system generate surplus PV energy that can be exchanged with their neighbors.

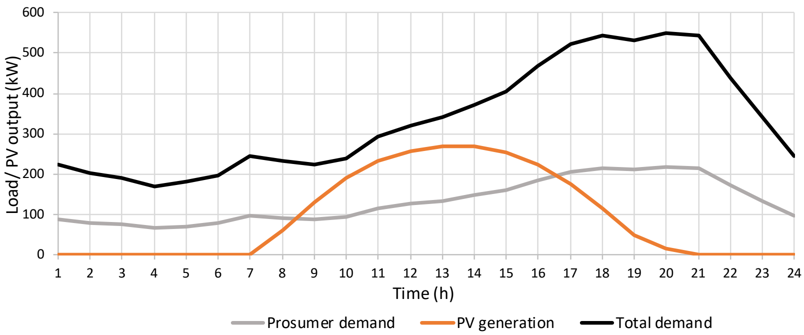

Figure 2: System supply vs demand at 40% PV penetration

Some key performance evaluation indicators regarding the overall performance of the system under different market structures are analyzed in Table 2. The centralized market achieved 100% local PV self-consumption, while in the decentralized market, some prosumers have to sell electricity directly to the grid due to the failure of some bidding orders. This leads to lower self-consumption in the decentralized market. In both pricing rules of the centralized market, the same total system profits are achieved. However, the benefits obtained by different consumers and consumers vary. Consumers earned revenue by selling electricity to consumers and the grid, while consumers saved costs through the P2P energy trading. Under the distribution rule, consumers could not benefit from energy trading. The SDR mechanism appears to be a fair mechanism that can benefit both consumers and consumers. In the decentralized market, bid strategies based on the learning algorithm achieves higher system self-consumption and total profits. However, the cost savings obtained by consumers actually decrease. As shown in Figure 3, this is due to the higher clearing prices resulting from the learning algorithm. The increase of the average percentage traded through the learning algorithm is not significant compared to the random algorithm. This is because the key to achieving higher self-consumption lies in the bidding of a small number of prosumers.

Table 1: The system performance of different market structures at 40% PV penetration

	Self-consumption	Profits ($)			Average Percentage traded
		Consumer	Prosumer	Total	
Centralized – Distribution rule	100%	0	95.29	95.29	/
Centralized – SDR mechanism	100%	56.46	38.83	95.29	/
Decentralized – Random bidding	64.79%	16.72	45.02	61.74	46%
Decentralized – Learning algorithm	92.32%	10.06	77.91	87.97	48%

From Figure 3, it can be seen that in the centralized market, the internal selling price and buying price determined by the SDR mechanism are highly correlated with the power supply-demand ratio. The greater the supply-demand ratio is, the lower the internal price is. In the decentralized market, the clearing price obtained through the learning algorithm gradually increases because it is a seller's market and the electricity cannot fully meet the needs of all consumers.

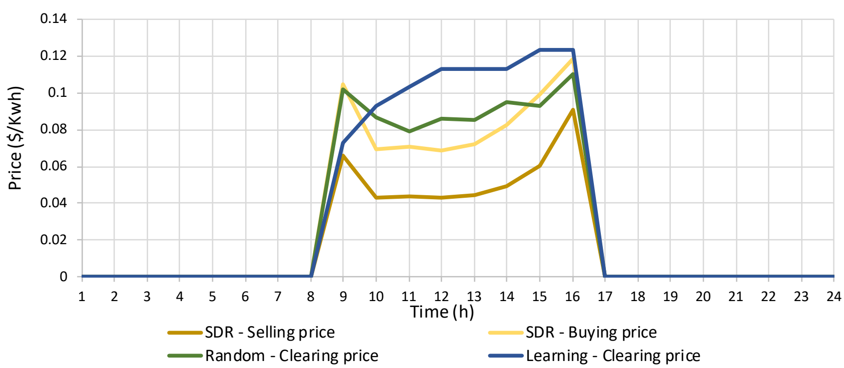

Figure 3: Internal market price of different market structures at 40% PV penetration

4.2 Case II: 60% PV penetration

Figure 4 displays the load and PV generation profiles for the system at 60% PV penetration. Even after meeting the electricity demand of the system, there is an excess of PV output from the system between approximately 9:30 am and 14:30 pm due to a higher penetration of PV.

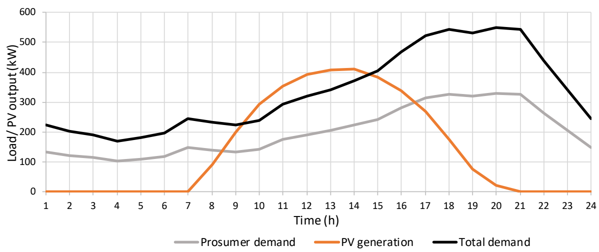

Figure 4: System supply vs demand at 60% PV penetration

According to Table 2, the centralized market can only achieve an ideal 75.43% local energy consumption. Higher total system profits are achieved at a 60% PV penetration rate compared to a 40% PV penetration rate. The conclusions drawn from Table 2 are similar to those in Table 1, where the centralized market leads to higher self-consumption and total profits compared to the decentralized market. In the decentralized market, bid strategies based on the learning algorithm can achieve better performance than the random method.

In Figure 6, due to the surplus of electricity caused by PV generation being greater than consumers demand at noon, the internal electricity price in the centralized market equals the electricity feed-in price. Similarly, in the decentralized market, the clearing price resulting from bid strategies based on the learning algorithm first decreases and then increases, which is also a response to the surplus of electricity resources.

Table 2: The system performance of different market structures at 60% PV penetration

	Self-consumption	Profits ($)			Average Percentage traded
		Consumer	Prosumer	Total	
Centralized – Distribution rule	75.43%	0	118.68	118.68	/
Centralized – SDR mechanism	75.43%	41.77	76.91	118.68	/
Decentralized – Random bidding	42.31%	23.91	59.71	83.62	46%
Decentralized – Learning algorithm	43.64%	24.54	73.96	98.50	42%

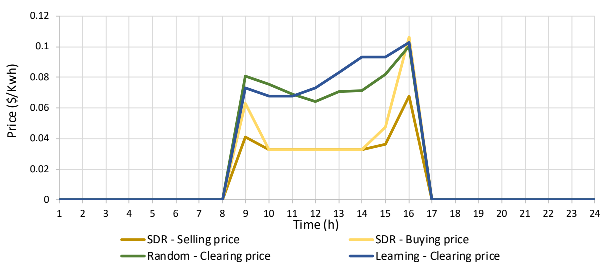

Figure 5: Internal market price of different market structures at 60% PV penetration

5 Conclusions

P2P energy trading plays a significant role in increasing the self-consumption of the local energy system. It can also involve consumers and prosumers in the local energy market. In different market structures, namely centralized and decentralized markets, P2P energy trading provides great economic advantages to market participants to encourage their involvement. The centralized market-based approach seems to have greater advantages as it leads to higher overall system self-consumption and profits. However, participants in the centralized market are considered as price takers and may not be fully incentivized to participate the market actively. Otherwise, participants can make decisions and bid in the decentralized market. Bid strategies based on the learning algorithm in the decentralized market show better performance compared to the random method, but this relies on participants learning from their bidding history. Overall, this study provide insights for evaluating the impact of different P2P energy trading market structures on the performance of the local energy system.

Acknowledgements

The authors gratefully acknowledge the support of the National Natural Science Foundation of China (No. 51978601 and No. 52161135202).

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