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Comparative Analysis of Market Clearing Mechanisms for Peer-to-Peer Energy Market Based on Double Auction

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Abstract: This paper aims to develop an optimisation-based price bid generation mechanism for the sellers and buyers in a double-auction-aided peer-to-peer (P2P) energy trading market. With consumers being prosumers through the continuous adoption of distributed energy resources, P2P energy trading models offer a paradigm shift in energy market operation. Thus, it is essential to develop market models and mechanisms that can maximise the incentives for participation in the P2P energy market. In this sense, the proposed approach focuses on maximising profit at the sellers, as well as maximising cost savings at the buyers. The bids generated from the proposed approach are integrated with three different market clearing mechanisms, and the corresponding market clearing prices are compared. A numerical analysis is performed on a real-life dataset from Ausgrid to demonstrate the bids generated from sellers/buyers, as well as the associated market clearing prices throughout different months of the year. It can be observed that the market clearing prices are lower when the solar generation is higher. The statistical analysis demonstrates that all three market clearing mechanisms can achieve a consistent market clearing price within a range of 5 cents/kWh for 50% of the time when trading takes place.

Keywords: peer-to-peer energy trading; double auction; market clearing prices; optimisation; bids

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1. Introduction

The increasing uptake of renewable energy sources, particularly as a means of distributed generation, has created new opportunities and challenges in the traditional energy system paradigm [1]. Energy consumers have transformed into energy prosumers with an enhanced capacity to participate in energy transactions. In an electricity network comprising a number of prosumers, there may be scenarios where some prosumers experience energy excess while others suffer from an energy deficit. In effect, the prosumers with excess generation can play the role of sellers, whereas the prosumers with an energy deficit can be considered buyers. As a result, these prosumers can form a local or peer-to-peer (P2P) energy market so that the supply/demand balance can be achieved in a localised manner [2]. According to the International Renewable Energy Agency (IRENA), P2P energy trading is defined as a model that "creates an online marketplace where prosumers and consumers can trade electricity, without an intermediary, at their agreed price" [3].

There is a massive amount of literature on P2P energy markets, which has primarily focused on the market models, optimisation and control mechanisms, as well as pricing structures. One of the very first papers on P2P energy trading [4] highlighted different energy trading mechanisms such as bill sharing, the mid-market rate and the supply/demand ratio and evaluated them through a multi-agent simulation framework in terms of energy balance, flat power profile and self-sufficiency. An overview of the P2P energy trading concepts and challenges in the virtual and physical layers was presented in [5]. In addition, the authors elaborated on different technical approaches, such as game theory and mathematical optimisation. On the other hand, the authors in [6] categorised P2P energy markets as full, community-based and hybrid P2P mechanisms. A bilateral trading network for

representing the P2P energy market was formulated in [7], where real-time and forward markets were introduced, along with distributed price adjustment mechanisms.

A locality electricity trading system was designed in [8] which modelled the interactions between prosumers and utilities and, at the same time, optimised the operation of residential loads using a genetic algorithm through the utilisation of a transactive energy framework. A similar market model was investigated in [9], where the prosumers optimised their individual energy usage at the first stage to utilise their trading resources at the second stage best through a game theoretic analysis. The P2P energy market was modelled as a bilevel framework in [10], where distributed energy resources for a prosumer were scheduled at the lower level and the upper level managed bilateral trading among the prosumers. The interaction between prosumers and the aggregator is modelled as a non-cooperative game in [11] to investigate the impact of the aggregator's decisions on the market clearing prices. The following subsection outlines a detailed literature review of the relevant works on P2P energy trading, highlighting the considerations of the market models, optimisation problems and pricing strategies, as well as auction mechanisms.

1.1. Related Works

Existing research on P2P energy trading explores different market architectures, including centralised and decentralised models for managing the energy transactions. To avoid reliance on a central aggregator in managing energy transactions, the authors in [12] developed a decentralised bilateral energy trading framework which took into account the product differentiation, as well as the network constraints, to optimise P2P energy trading. Similarly, a bilateral energy trading model was proposed in [13] which allowed for differentiated pricing decisions with a hierarchical pricing structure and was solved using the alternating direction method of multiplier in a decentralised manner. A hierarchical P2P energy trading model was developed in [14] with community, district and grid layers which included residential, commercial and industrial users. A consensus-based P2P energy trading algorithm was developed in [15] for multiple bilateral trading in a decentralised manner while considering product differentiation. The authors in [16] considered joint trading of power and uncertainty in electricity generation and demand by maximising the utilisation of flexible loads, with the aim of achieving a greater balance in uncertain supply/demand in the local network. The authors in [17] developed a minimum cost rolling horizon optimisation model to optimise the bids from prosumers through model predictive control while considering the impact of the uncertainty of renewable energy.

A number of research papers have also focussed on the different pricing mechanisms used for P2P energy trading. The authors in [18] reviewed synchronous and asynchronous energy pricing mechanisms and categorised the interactions between energy pricing and network service pricing for different market players. The impact of grid tariff designs on P2P energy trading markets and how different P2P market mechanisms can be embedded into the wholesale electricity market were discussed in [19]. The uncertainty in renewable energy generation and variations in user preferences can bring new challenges to the optimum trading decisions due to inaccuracies in the day-ahead predictions [20]. To mitigate these challenges, a new pricing mechanism is developed in [21], comprising the uncertainty marginal price, preference marginal price and local marginal price. Given that there can be variations in the generation and demand at the prosumers, there can be deviations in the actual amount of energy that is traded. In this vein, the authors in [22] developed a penalty mechanism that considered price, quantity and the percentage deviation from the agreed amount to calculate the penalty price. A Stackelberg game theoretical model was developed in [23] to determine the optimal prices for P2P energy trading while optimising the local energy consumption at the sellers and prioritising the load preferences at the buyers.

Given that P2P energy trading among prosumers involves balancing the incentives or utilities for both sellers and buyers, there is a need to formulate optimisation problems at the seller and buyer sides which take into account the different objectives of different prosumers and any constraints imposed by the generation and/or storage achievable.

From this perspective, the authors in [24] develop a mixed-integer linear programming problem to minimise the total cost to prosumers by taking into account the purchases from the electricity grid and export from distributed generation, as well as the associated investment costs. The problem of the optimal energy dispatch for multiple microgrids was studied in [25] by considering optimisation for individual microgrids at the lower level and the energy transactions between multiple microgrids and the market operator at the upper level, ensuring parallel decision making for multiple stakeholders. The authors in [26] evaluated the optimal pricing strategies for intra-microgrid and inter-microgrid P2P energy trading in a multi-microgrid scenario. A credit-rating-based energy trading strategy was proposed in [27], where the authors developed a logistic-regression-based scorecard to model the retailer characteristics and formulate the energy transaction problem as a multi-leader, multi-follower dynamic game.

P2P energy market models often involve auction mechanisms to settle the market, comprising multiple sellers and buyers. These auction mechanisms can be single-sided (involving either the seller or buyer) or double-sided (in which both sellers and buyers participate). Double auction (DA) models have been a widely used mechanism to evaluate the market clearing conditions in P2P energy trading markets, as a DA ensures enhanced fairness and decision making power for both sellers and buyers. In a double auction market, both sellers and buyers submit bids, and the auctioneer (e.g., the aggregator or the central energy management system) decides which sellers and buyers will participate and at what price the market will be cleared. Given that both sellers and buyers have equal power in determining the price, the double auction method can equalise the electricity prices among sellers and buyers. Ranking buyers and sellers in a way that maximises the utilities of both parties in DA markets can be considered rational and reasonable. The authors in [17] optimised the bids using a model-predictive-control-based cost minimisation model for a double auction market, where the bidding strategies were updated using automatic learning. Continuous bidding curves for prosumers were investigated in the double auction framework proposed by [28], where the network operator creates groups of prosumers and decides their participation based on other prosumer groups.

A social-welfare-maximising auction scheme was proposed in [29] which ensured that the total revenue of the sellers and the total cost of the buyers matched with each other, while different participants were priced differently. The authors in [30] developed a uniformly priced double auction mechanism embedded with smart contracts and implemented the method developed in Ethereum to integrate blockchain technologies. A two-stage double auction mechanism for interconnected microgrids was designed in [31], where the first stage managed auctions within the individual microgrid and the second stage considered auctions between multiple microgrids. The authors also included a fair cost distribution algorithm in the auction mechanisms developed. The authors in [32] used an iterative double auction mechanism in which participants could update their bids in an iterative manner based on the market clearing decisions made in the previous rounds.

A real-time distributed P2P energy trading strategy based on model predictive control was developed in [33], where the authors designed a continuous double-auction-based trading mechanism considering prosumers with multiple trading preference grades. A community-based P2P energy trading market for the provision of ancillary services is designed in [34], where the prosumers optimise their bidding strategies to maximise social welfare. The authors in [35] considered second-life batteries from electric vehicles in an P2P energy trading model and developed a double-auction-based trading mechanism with average pricing for market clearing that allowed prosumers to re-bid. A dynamic operating envelope was integrated with a double auction mechanism in [36], where the prosumers could not submit bids that violated the network export/import limits, thus ensuring benefits for both the prosumers and the network operators. A co-simulation framework that simulated the distribution network performance and blockchain platforms was developed in [37], which considered the impact of double-auction-based P2P energy trading in medium-voltage distribution networks.

To factor uncertainty into the trading behaviour of prosumers, a reputation index based on trading patterns and electrical distance was integrated into the P2P energy trading mechanism and an iterative double auction model was developed in [38] utilising a self-adaptation algorithm. The authors in [39] implemented a smart auction-based P2P energy trading model where the prosumers could update bids using the probability of bidding decisions and consequences through a deep learning approach. An enhanced bidding strategy was designed in [40] which used two different supply/demand ratios to determine the trading decisions and tariffs based on price quotes and excess power. Given that the buyers and sellers are prioritised as soon as a match is obtained in the double auction mechanism, the time sequence information can be further utilised to evaluate the contribution of a trading pair in network congestion, as investigated by the authors in [41]. A mechanism for determining a uniform trading price based on the correlation between the prosumer bids and the market clearing prices in an iterative manner was designed in [42].

1.2. Motivation, Contributions and Organisation

Though there has been extensive work on developing different bidding strategies, game theoretical models and optimisation algorithms and integrating them with double auction models, very few research papers have investigated the impact of different market clearing mechanisms in the context of double-auction-based P2P energy trading. It is important to investigate how optimising the prosumer bids influences the market clearing prices for different market clearing mechanisms. For effective P2P energy trading to take place, there should be appropriate consideration of suitable market clearing models. In this sense, it is highly relevant and timely to investigate the available market clearing mechanisms in terms of their effectiveness in ensuring fairness and consistency in the market clearing prices. To the best of our knowledge, there is a lack of comparative analyses among different market clearing mechanisms for P2P energy trading applications. To address this research gap, we make the following key contributions in this work:

- A quadratically constrained quadratic optimisation problem to determine the optimum seller/buyer bids is formulated to maximise the profit at the sellers and the savings at the buyers. The problem is solved simultaneously for both the amount of energy sold (purchased) and the seller (or buyer) price on the seller (or buyer) side.
- The optimised bids from the sellers and buyers are integrated with a double auction market and three different market clearing mechanisms; namely, average, trade reduction (TR) and Vickrey—Clarke—Groves (VCG) mechanisms are evaluated in comparing the market clearing prices.
- Numerical simulations are performed on the P2P energy trading model developed using a real-life solar generation and electricity demand dataset over 8 months of data during 2012–2013. The comparative analysis demonstrates a lower market clearing price for the VCG mechanism in comparison to the two other market clearing mechanisms.

This paper is organised in the following manner. The optimisation of the price bids on the seller and buyer sides is formulated in Section 2. The double auction mechanism and the associated market clearing methods for P2P energy trading are discussed in Section 3. Numerical simulation of the market clearing methods is performed in Section 4 using a real-life electricity generation and demand dataset. Finally, concluding remarks are presented in Section 5.

2. Optimisation of the Price Bids in a P2P Energy Market

In this section, an optimum bid generation mechanism for buyers and sellers in a P2P energy market is discussed. The system model under consideration comprises L number of houses (indexed by $\ell \in [1, L]$) equipped with solar generation. At a certain time interval, the solar generation and the load demand at the ℓth house are denoted as G_ℓ and D_ℓ, respectively. Houses with excess solar generation ($G_\ell > D_\ell$) are denoted as sellers, while houses with an energy deficit ($G_\ell < D_\ell$) are denoted as buyers. The sellers aim to maximise the profit they earn from selling their excess generation. On the other hand, the buyers

try to maximise the savings they achieve by reducing their purchases from the utility. To achieve these goals, the ith seller optimises the energy sold x_i and the associated price ps_i. Similarly, the jth buyer optimises the energy purchased x_j and the associated price pb_j. The feed-in tariff and the utility rate are defined as P_f and P_u, respectively. The sellers aim to achieve a profit above the profit threshold P_{th}, and the buyers aim to obtain savings more than the savings threshold P_{sav}. These thresholds are considered for every single trading interval (i.e., 5 min, 15 min or 30 min intervals). In this paper, a real-time pricing model is considered, which varies across the different time intervals of the day. At the beginning, the sellers and buyers send their energy generation and demand information to a central energy management system, which solves two optimisation problems to determine the optimum bids for the sellers and buyers. These optimisation problem formulations are discussed in the following two subsections.

2.1. The Seller Side

The optimisation problem to maximise the profit of the sellers can be formulated as follows:

$$\max_{ps_i, x_i} \sum_i ps_i x_i \tag{1}$$

subject to:

$$x_i \geq 0 \tag{2}$$

$$x_i \leq D_i - G_i \tag{3}$$

$$\sum_i x_i \leq \sum_j G_j - D_j \tag{4}$$

$$P_f < ps_i < P_u \tag{5}$$

$$\sum_i ps_i x_i \geq P_{\text{th}} \tag{6}$$

Here, the objective function (1) aims to maximise the profit at the sellers by optimising the price and energy sell bids for each seller. The constraint in (2) denotes that the value for energy sold cannot be negative. The energy sold by each seller should be limited by the excess generation at the seller, as defined in (3). The total energy sold by all sellers cannot be more than the total energy deficit of all buyers, as specified in (4). The sell prices asked by each seller have to be in the range between the feed-in tariff and the utility rate. If the trading price is less than the feed-in tariff, the P2P energy trading will not be cost-effective for sellers. On the other hand, if the trading price is higher than the utility rate, then the buyers will prefer to purchase energy directly from the utility. The sellers in the P2P energy market aim to achieve a minimum profit P_{th} for each trading interval, which is represented by (6).

2.2. The Buyer Side

To maximise the energy cost savings at the buyers, the optimisation problem on the buyer side can be formulated as follows:

$$\max_{x_j, pb_j} \sum_j (D_j - G_j) P_u - \sum_j pb_j x_j \tag{7}$$

subject to:

$$x_j \geq 0 \tag{8}$$

$$x_j \leq D_j - G_j \tag{9}$$

$$\sum_j x_j \leq \sum_i G_i - D_i \tag{10}$$

$$P_f < pb_j < P_u \tag{11}$$

$$\sum_j (D_j - G_j) P_u - \sum_j pb_j x_j \geq P_{\text{sav}} \tag{12}$$

The objective function in (7) aims to maximise the savings achieved by the buyers through not purchasing electricity from the utility grid. The first term in (7) denotes the energy cost if the energy deficit is purchased from the utility grid. On the other hand, the second term denotes the energy cost if energy is purchased from the P2P trading market. The constraints in (8) and (9) indicate that the energy purchased cannot be negative and is limited by the energy deficit at the buyers, respectively. The total energy purchased cannot be more than the total excess generation at the sellers. The trading price has to be limited between feed-in tariff and utility rate, as specified in (11). The difference between the electricity cost for purchasing energy from the utility grid and P2P energy market should be higher than a certain minimum amount P_{sav} for each trading interval, which is incorporated in the constraint in (12).

The aforementioned optimisation problems can be categorised as quadratically constrained quadratic programming and can be solved using branch and bound methods. Once the optimum price bids and energy sell/purchase amounts are obtained at the central EMS, these outputs are forwarded to the buyers and sellers, who can verify and approve these bids for the DA process.

3. Double-Auction-Based Market Clearing

DA mechanisms enable both sellers and buyers to submit bids in the P2P energy market and obtain the market clearing decisions through joint consideration of these bids. In this paper, the central EMS is considered to be the auctioneer. The DA process begins with natural ordering, where seller bids are sorted in ascending order, while buyer bids are sorted in descending order. Then, a breakeven index is determined to be the smallest $n \in [i, j]$ for which buyer bid pb_j is greater than seller bid ps_i. Once the breakeven index is obtained, the first n sellers and buyers are selected to participate in the market, and the market clearing prices are computed based on the bids from the selected sellers and buyers. There are different market clearing mechanisms that can be adopted by the DA market. In this paper, three such mechanisms are investigated, namely average, TR and VCG mechanisms. The flowchart in Figure 1 illustrates the DA-based trading mechanisms with different market clearing strategies.

3.1. The Average Mechanism

With the average mechanism, the market clearing price is determined to be the average of the seller and buyer bids at the breakeven index n. Thus, the market clearing price for the average mechanism is defined as [43]

$$P_{\text{avg}} = \frac{ps_n + pb_n}{2} \tag{13}$$

The first n sellers will sell energy, and the first n buyers will purchase it. This scheme aims to strike a balance between the seller and buyer bids, hence promoting fairness. It offers a strong budget balance given that the auctioneer does not gain or lose in terms of monetary incentives. In this scheme, the buyers (or sellers) can benefit by reporting a smaller (or higher) bid, allowing buyers to pay less and sellers to ask for more.

3.2. The Trade Reduction Mechanism

With the TR mechanism, the first $n-1$ sellers and buyers participate in the trading. The sellers receive the highest sell bid, ps_n, at the breakeven index, and the buyers pay the lowest buying price pb_n, where the difference between ps_n and pb_n is maintained by the auctioneer. Thus, the market clearing price in the TR mechanism is given by [43]

$$P_{\text{TR}} = \begin{cases} ps_n & \forall \text{seller} \in [1, n-1] \\ pb_n & \forall \text{buyer} \in [1, n-1] \end{cases} \tag{14}$$

In this mechanism, the first $n-1$ sellers and buyers participate in the trading. The sellers receive more than what they asked for given that $ps_n > ps_{n-1}$. On the other hand, buyers pay less than what they offered because $pb_n < pbn-1$. This mechanism is less efficient in comparison to the average mechanism given that the n^{th} seller and buyer do not trade even if $pb_n > ps_n$.

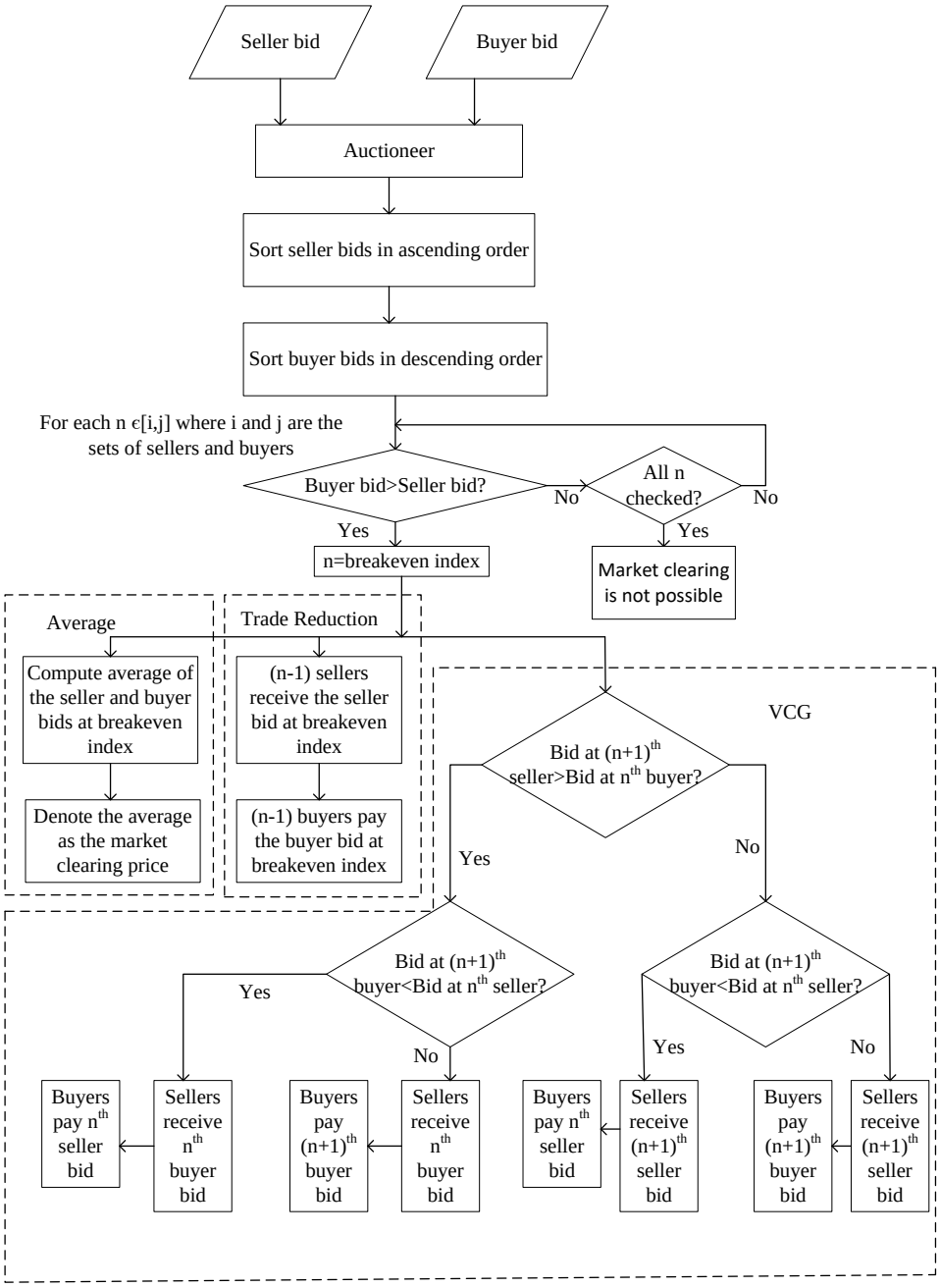


Figure 1. Double-auction-based P2P energy trading with three different market clearing mechanisms.

3.3. The Vickrey–Clarke–Groves (VCG) Mechanism

In the VCG mechanism, there can be four different cases, and the market clearing price for sellers and buyers are computed accordingly:

1. If $ps_{n+1} > pb_n$ and $pb_{n+1} < ps_n$, then the market clearing price is represented by [44]

$$P_{\text{VCG}} = \begin{cases} pb_n & \forall \text{seller} \in [1, n] \\ ps_n & \forall \text{buyer} \in [1, n] \end{cases} \quad (15)$$

2. If $ps_{n+1} < pb_n$ and $pb_{n+1} < ps_n$, then the market clearing price is represented by [44]

$$P_{\text{VCG}} = \begin{cases} ps_{n+1} & \forall \text{seller} \in [1, n] \\ ps_n & \forall \text{buyer} \in [1, n] \end{cases} \quad (16)$$

3. If $ps_{n+1} > pb_n$ and $pb_{n+1} > ps_n$, then the market clearing price is denoted by [44]

$$P_{\text{VCG}} = \begin{cases} pb_n & \forall \text{seller} \in [1, n] \\ pb_{n+1} & \forall \text{buyer} \in [1, n] \end{cases} \quad (17)$$

4. If $ps_{n+1} < pb_n$ and $pb_{n+1} > ps_n$, then the market clearing price is denoted by [44]

$$P_{\text{VCG}} = \begin{cases} ps_{n+1} & \forall \text{seller} \in [1, n] \\ pb_{n+1} & \forall \text{buyer} \in [1, n] \end{cases} \quad (18)$$

In this scheme, the difference between the market clearing prices of the sellers and buyers is paid by the auctioneer; thus, a balanced budget cannot be achieved. Since the market clearing prices of the sellers and buyers are determined by each other's bids, the sellers and buyers cannot provide misleading bids without losing their incentives.

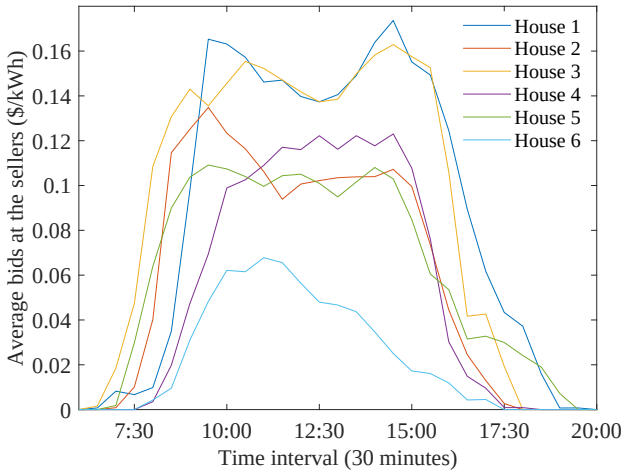
4. Results of the Comparative Analysis and Discussion

In this section, a comparative analysis was performed across three different market clearing mechanisms, namely the average, TR and VCG mechanisms, for a group of six residential users integrated with rooftop solar panels. The generation and demand profiles of these houses were obtained from the Ausgrid solar home electricity dataset from 1 July 2012 to 30 June 2013. The dataset contains solar generation and electricity demand information for 300 households across different postcodes in New South Wales, Australia. Many of these houses are equipped with a controlled load for hot water systems. The data are available for every 30 min interval for one year. The dataset also includes information about the postcodes and solar generation capacities of the installations. The dataset has been widely used in different research papers on P2P energy trading, particularly due to its relevance to the geographical context of the Southern Hemisphere [45–47]. However, it should be noted that the proposed methods can be similarly applied to other datasets, and an equivalent performance can be expected for other geographical conditions. The households selected from this dataset have solar panel generation capacities of 3.78 kWh, 1.62 kWh, 1 kWh, 1 kWh, 1 kWh and 2 kWh, respectively. Note that the analysis was performed over the months July 2012–September 2012 and February 2013–June 2013. This was due to the unavailability of some user data during October 2012–January 2013. The utility rate and feed-in tariff are considered 40 cents/kWh and 10 cents/kWh, respectively. The profit and savings thresholds are assumed to be 0.5 cents and 1 cent for every half-hour interval. The generation and demand data for the aforementioned six houses are integrated with the optimum energy trading algorithms to compute the bids to maximise the seller profits and buyer savings. Then, the bids generated are forwarded to the double-auction-based market clearing mechanisms, and the market clearing prices obtained through the average, TR and VCG mechanisms are compared.

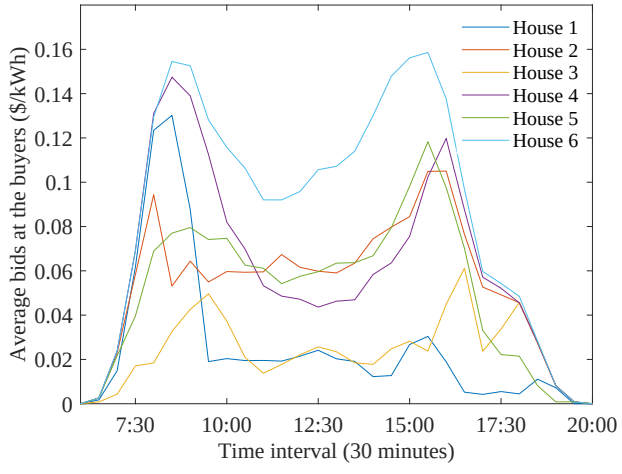
4.1. Bidding Patterns of the Sellers and Buyers

Figure 2a,b represent the optimum bids generated for buyers and sellers by solving the optimisation problem in Section 2 and then averaging the bids over all the days in the 8 months considered in this study. Since the same prosumer can be a seller or a buyer at different time intervals, the same set of houses is present in both figures. However, it is worth noting that the same house cannot be a seller and a buyer at the same time. It can be observed that the bids at the sellers are limited between 0 and 16.5 cents/kWh, whereas for buyers, the bids are between 0 and 15.5 cents/kWh. Note that in some cases, the average bids are less than the feed-in tariff. This is because of averaging over 242 days, on some

of which the prosumer did not bid as a seller/buyer, resulting into zero bid values for the seller/buyer. On average, House 1 submits the highest bid as a seller, while House 6 submits the highest bid as a buyer. As sellers, Houses 1 and 3 submit higher bids in the morning and late afternoon compared to midday, when the solar generation is expected to be higher for all houses. This is because the sellers can sell higher excess generation at a lower price and achieve the same profit threshold. On the other hand, the remaining sellers have a higher average bid at midday. This indicates that these sellers participate in bidding mostly during the midday period. The buyers also bid for a higher price during the morning and late afternoon, when they have a greater energy deficit. However, House 3 bids the lowest as a buyer, which may be due to its smaller energy deficit. As a buyer, House 1 bids the highest during the morning, indicating a significant energy deficit during this period.



(**a**) Seller bids



(**b**) Buyer bids

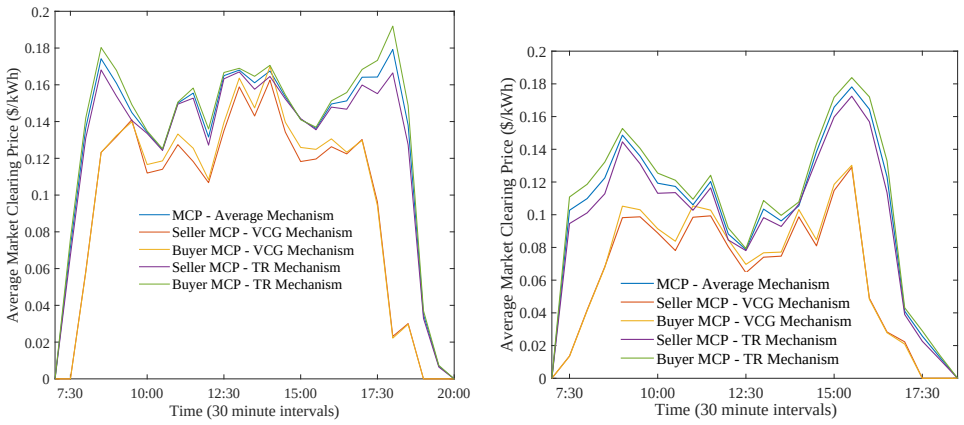
Figure 2. Seller and buyer bids averaged over different months.

4.2. Seasonal Trends in Market Clearing Prices

Figure 3a–d show the average market clearing prices across the different time intervals of the day during the months of February, April, July and September when the average, VCG and TR mechanisms are used. In Australia, the summer months include September to March, while the winter months are April to August. There are five different market clearing prices given that with the TR and VCG mechanisms, the market clearing price is different for sellers and buyers. The prices are averaged over all the days in a specific month to obtain the average market clearing prices. It can be observed that in the winter months,

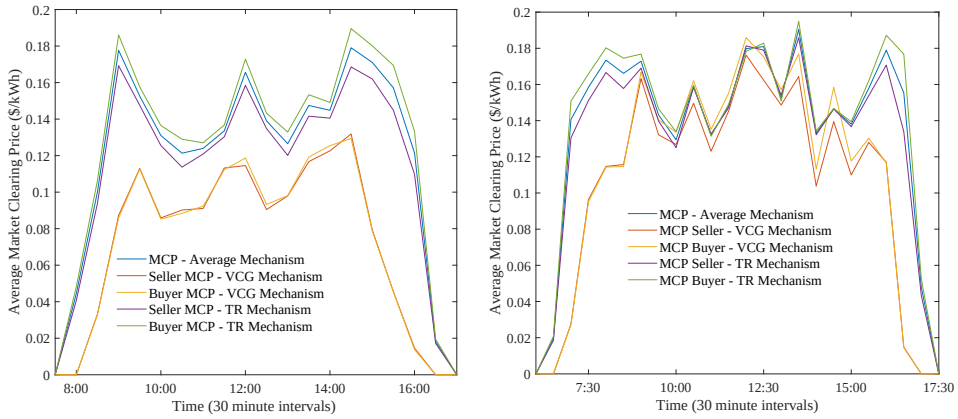
the market clearing stops by 5:30 p.m., whereas in summer, the market clearing continues until 8:00 p.m. due to the extended daytime during summer. The month of September shows an exception, which may be due to the fact that daylight has not increased at the beginning of spring. In all cases, the market clearing price for the average mechanism lies between the market clearing prices for sellers and buyers in the TR mechanism. The VCG mechanism leads to a lower market clearing price in all cases unless there is high penetration of solar generation, as observed for the month of September. In this case, the VCG mechanism has a lower market clearing price compared to that of the other mechanisms during early morning and late afternoon periods. This is because in the VCG mechanism, buyers pay less than the price they bid, and the central auctioneer has to balance the difference between what the buyers pay and what the sellers receive. It can also be noted that the difference between the buyer and seller market clearing prices is higher in July for the TR mechanism, whereas the difference is minimal for the VCG mechanism. On the other hand, in February, the VCG mechanism experiences the highest difference between the seller and buyer market clearing prices, while this difference is smaller for the TR mechanism.

Figure 4 illustrates the average market clearing prices for different months across the average, TR and VCG mechanisms. The market clearing prices are averaged over all samples and all time intervals in a certain month. Only the months from February to September are considered, for which generation and demand data are available for all of the houses. It can be noted that the average market clearing prices lie in a range between 3 cents/kWh and 7.5 cents/kWh for the various schemes. The overall trend for the average and TR mechanisms incorporates a higher market clearing price in the summer months, which gradually decreases during the winter months. For the VCG mechanism, a specific pattern cannot be observed. However, it is worth noting that the VCG mechanism has a lower market clearing price, similar to what was observed in Figure 3. Also, there is a greater difference between the market clearing prices for sellers and buyers in the VCG mechanism in comparison to the TR mechanism.



(**a**) February (**b**) April

Figure 3. *Cont.*



(**c**) July (**d**) September

Figure 3. Market clearing prices for the average, VCG and TR mechanisms averaged over different days in a certain month.

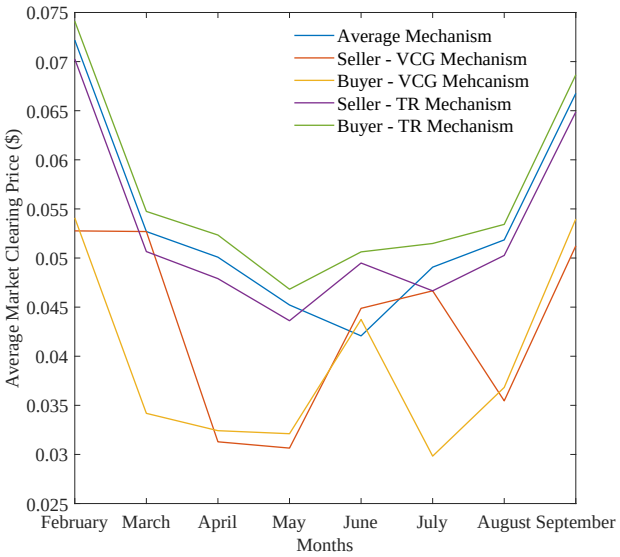
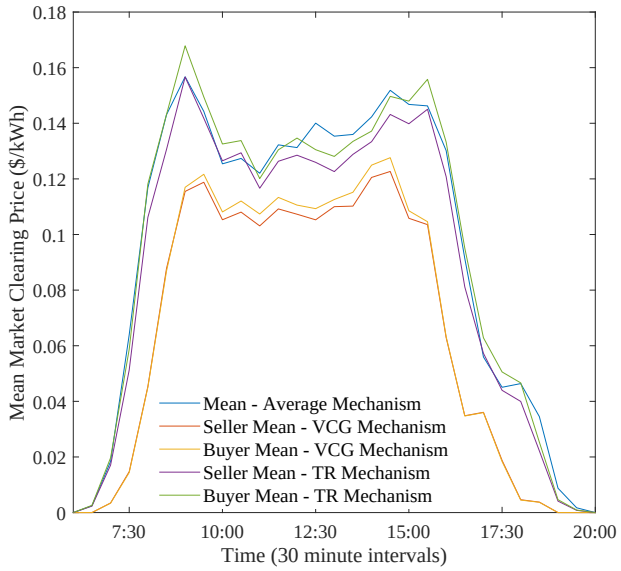


Figure 4. Average market clearing prices across different months for the average, TR and VCG mechanisms.

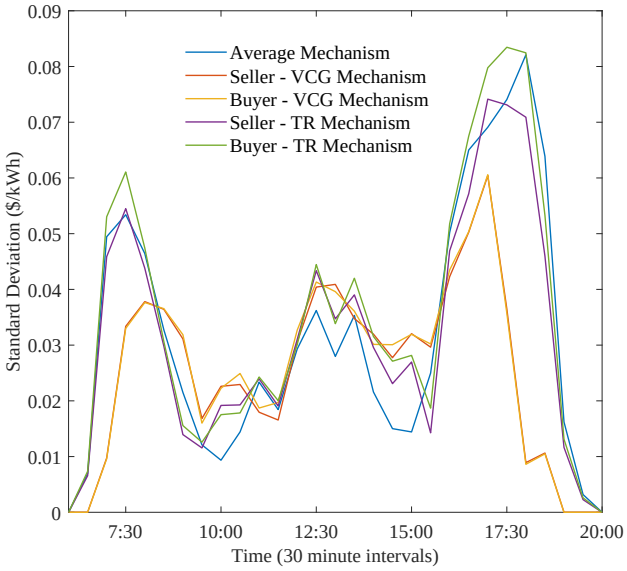
4.3. Statistical Analysis of the Market Clearing Prices

Figure 5a,b represent the mean and standard deviation of the market clearing prices on different days of the different months considered in the analysis for the average, TR and VCG mechanisms. The mean market clearing price demonstrates a similar trend as in Figure 3. That is, the market clearing prices for the VCG mechanism are lower than those of the average and TR mechanisms. However, the average mechanism has a slightly higher market clearing price in comparison to the TR mechanism during 1–4 p.m., which was not observed in Figure 3. On average, the highest daily market clearing prices attained by the average and TR mechanisms are 15.5 cents/kWh and 17 cents/kWh, occurring at 9 a.m. On the other hand, the highest daily market clearing price for the VCG mechanism is 13 cents/kWh, occurring at 3 p.m. From Figure 5b, it can be observed that the highest standard deviation in the market clearing prices occurs during the early morning and late afternoon periods, when the solar generation in different houses has a higher variation. The highest standard deviation is 8.3 cents/kWh, which occurs for the TR mechanism at 5.30 p.m. The VCG mechanism has a lower standard deviation compared with the average and TR mechanisms during the early morning and late afternoon periods. The

VCG mechanism has a similar trend to that in the TR mechanism at midday, which is slightly greater than that for the average mechanism.



(**a**) Mean



(**b**) Standard deviation

Figure 5. Mean and standard deviation of the market clearing prices for the average, TR and VCG mechanisms.

Figure 6 presents a box–whisker plot for the daily average market clearing prices across the average, TR and VCG mechanisms. The market clearing prices for each day in each month were averaged, and then only those days on which the market clearing prices for all mechanisms were non-zero were selected. This resulted in 151 samples, which were used to generate the box–whisker plot. The bottom and top edges of the boxes indicate the 25th and 75th percentiles of the data, respectively. The whiskers represent the minimum and maximum market clearing prices for each mechanism. The median of the data is represented by the line in the middle of each box, while any outliers are represented by circles. It can be observed that the VCG mechanism has more outliers in comparison to the other mechanisms, but these are still less than 5% of the samples. The median daily average market clearing prices for the average, VCG and TR mechanisms can be

observed as 14.5 cents/kWh, 10 cents/kWh (11 cents/kWh for buyers) and 14 cents/kWh (15 cents/kWh for buyers). As seen from the figure, the VCG mechanism has greater variation in the market clearing prices across different samples. However, for all mechanisms, the difference between the 25th and 75th percentiles (i.e., the width of the box) is consistent and is approximately 4 cents/kWh.

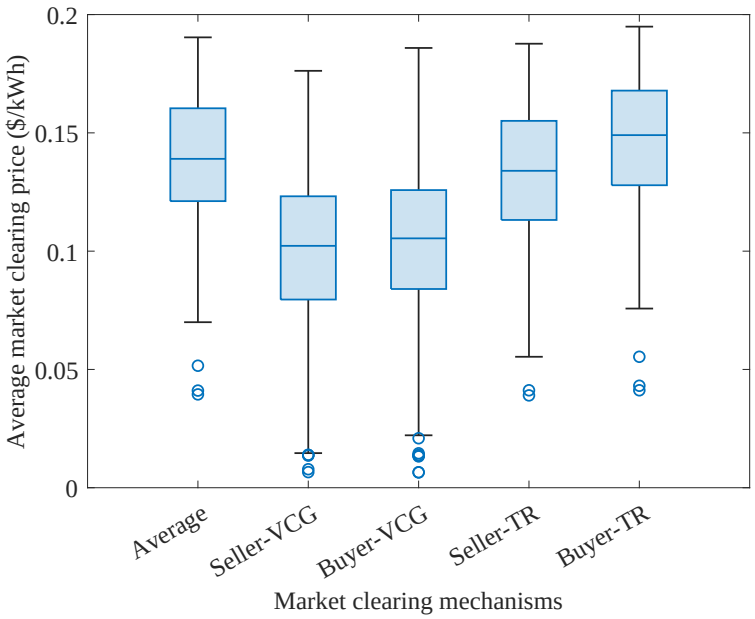


Figure 6. Box–whisker plot for average (daily) market clearing prices for average, TR and VCG mechanisms. The blue circles denote the outliers.

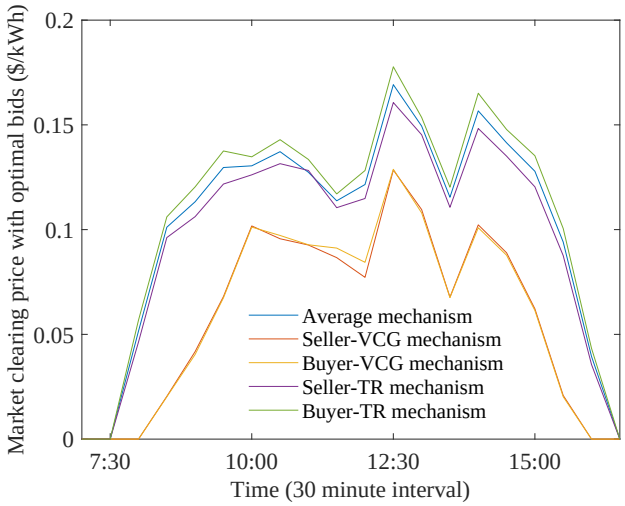
4.4. Comparison of the Different Market Clearing Prices

As can be observed from Figures 3, 5 and 6, there is a relative pattern in the market clearing prices for the different mechanisms. The market clearing price for the average mechanism lies between that of the seller and buyer market clearing prices of the TR mechanism. This is expected from (13) and (14), which show that the market clearing price for the average mechanism is equivalent to the arithmetic mean of the seller and buyer market clearing prices in the TR mechanism. The VCG mechanism results in a lower market clearing price in most cases given that the market clearing price for buyers (either ps_n or pb_{n+1}) is lower than the market clearing price (pb_n) in the TR mechanism. It is worth noting that there is a smaller difference between the buyer and seller market clearing prices in the VCG mechanism in comparison to the TR mechanism. This is because in the VCG mechanism, sellers and buyers determine each other's market clearing prices and hence enable the maximum social welfare. Another benefit of the VCG mechanism is that the market clearing price varies less over the course of the day, while the other mechanisms exhibit higher market clearing prices during periods of low solar generation. The VCG mechanism has a lower standard deviation in comparison to that of the other mechanisms, which may lead to less market volatility.

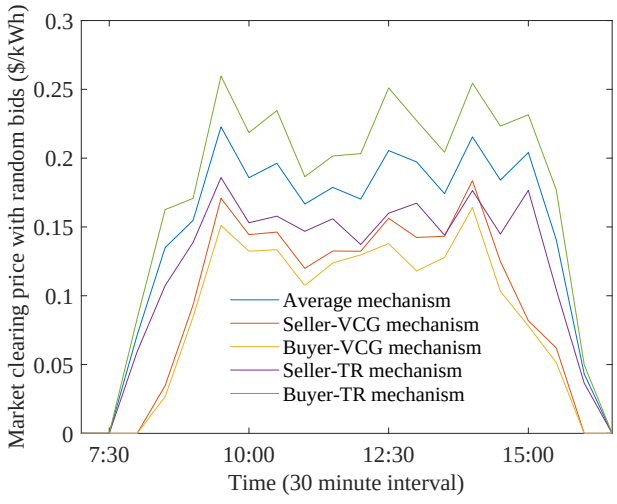
4.5. Comparison with Random Bidding

In this section, a comparison of the market clearing prices is demonstrated between scenarios in which the optimal bids are used and scenarios in which randomly generated bids are used. Many existing research papers have considered randomly generated bids in the DA process [43,48]. These bids are often generated as uniformly distributed random numbers between the feed-in tariff and the utility rate. Figure 7a,b illustrate the market clearing prices for the optimally and randomly generated bids, respectively. These bids were generated for the 30 days of the month of June, and the market clearing prices for the three mechanisms were computed accordingly. The market clearing prices were then

averaged over the number of days and plotted in this figure. It can be observed that the market clearing prices with randomly generated bids are higher for all the market clearing mechanisms in comparison to those of the optimally generated bids. Moreover, there is greater variation between the buyer and seller market clearing prices in the TR and VCG mechanisms when using random bids. Similarly to the optimally generated bids, the random bid scenario exhibits a lower market clearing price for the VCG mechanism. In addition, the market clearing prices for the average mechanism lie between the seller and buyer market clearing prices in the trade reduction mechanism. A clear difference that can be observed between the use of optimally and randomly generated bids is that the market clearing prices are more stable during stable solar generation periods when using optimally generated bids, while the market clearing prices are more volatile when using randomly generated bids.



(**a**) Optimal bids



(**b**) Random bids

Figure 7. Mean market clearing prices for average, TR and VCG mechanisms with optimally and randomly generated bids.

5. Conclusions

This paper investigates a double-auction-aided P2P energy trading mechanism where the energy sold/purchased and the seller/buyer prices are optimised to maximise the profit and cost savings for the seller and buyer, respectively. Based on the optimum price bids generated at the sellers and buyers, three different market clearing strategies, namely the

average, TR and VCG mechanisms, are evaluated and compared. The developed method is evaluated for a real-life energy generation and demand dataset, and the market clearing prices obtained for the three market clearing mechanisms are compared. The numerical results demonstrate that the VCG mechanism leads to a lower market clearing price compared with that of the other market clearing mechanisms across different months of the year. Moreover, the market clearing prices decrease during periods of higher solar generation given that the participants aim for specific profit and savings thresholds. Future work will focus on developing a predictive model for market clearing prices based on user bids and, in effect, influencing user strategies to maximise their utilities in a double auction market.

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