TOWARDS AUCTION MECHANISMS FOR PEER-TO-PEER ENERGY TRADING IN SMART GRIDS

by

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Abstract

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The conventional energy grid is being replaced with the new emerging smart grid infrastructure. This can be attributed to the fact that it only supports unidirectional energy flow, i.e., energy is transmitted from the producer to the consumer. Smart grid addresses issues such as grid reliability, blackouts, global warming, etc, by implementing various renewable energy sources readily available for consumer use. The clean electric power can be produced from local neighbourhoods, individual houses, to large industrial businesses. Therefore, with the implementation of alternative energy sources readily available, users connected to the smart grid can purchase electric power, enabling groups and individuals to generate a profitable income. However, challenges persist attributed to user cost, and power management, resulting in active work to investigate optimization techniques between users in P2P energy trading to enhance the performance of how users trade energy among each other. Among the various energy trading mechanisms, auction-based models have demonstrated excellent performance, targetting desirable properties for P2P energy trading. In this work, we present three different auction-based models that can be utilized for practical energy trading. The prosumers (producers and consumers) of energy, play the role as sellers or buyers depending on the current supply and demand. Sellers with renewable energy sources participate to sell their excess of energy to generate a profit and satisfy the buyers' demand. We model the interaction with as single-sided and double-sided auctions, explicitly taking the dynamic nature of both the sellers and buyers into account. We further propose a profit maximization algorithm that considers power line cost, transmission capacity, and energy distribution. With theoretical analysis and simulations, we demonstrate that the proposed auctions are individually rational, truthful, computationally efficient, and budget-balanced.

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Dedicated to,

my ever-loving parents

Mr. Panki Raj & Mrs. Jeya Leela

And to my wonderful uncle and aunt

Mr. Christopher Raj & Mrs. Gulda Fancy

Declaration

I hereby declare that I have written the present thesis independently. All the quotations and sources that I used in this thesis are listed in the bibliography. I also declare that the present thesis has not been used to obtain a different or the same degree.

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Contents

List of Figures

List of Tables

List of Symbols

i – Seller.
j – Buyer.
n – Total number of sellers.
m – Total number of buyers.
S – Set of sellers.
B – Set of buyers.
$P_{(i,j)}$ – Path from sellers to buyers.
x_{cap} – Transmission capacity.
y_g – Energy flow in the path.
E_i – Generated energy from each seller.
e_i – Surplus energy.
e_k – Selling energy.
e_y – Stored energy.
Te_i – Total surplus energy from all sellers.
a_i – Ask from seller.
A – Set of ask.
d_j – Demands from buyer.
α – Set of demands.
Td_j – Total demands from all buyers.
b_j – bid from each buyer.
β – Set of bids.
W_{Si} – Welfare of the seller.
W_{Bj} – Welfare of the buyer.
P_{Si} – Reward price of seller.
P_{Bj} – Payment of buyer.
S_{gi} – Seller group.
B_{gi} – Buyer group.
S_{wi} – Winning seller.
B_{wj} – Winning buyer.
c_i – Cost of seller for generating the energy.
c_l – Line cost of sellers and buyers for using the transmission line.

List of Abbreviations

SG – Smart Grid.
P2P – Peer-To-Peer.
EV – Electric Vehicle.
ETM – Energy Trading Market.
PMA – Profit Maximization Algorithm.
CMA – Cost Minimization Algorithm.
AMA – Auction-Matching Algorithm.
PTDF – Power Transfer Distribution Factor.
CRR – Congestion Review Rights.
VCG – Vickrey Clark Groves.
ISF – Injection Shift Factor.
SBB – Strong Budget Balanced.
WBB – Weak Budget Balanced.
FPB – First Price Bid.
SPB – Second Price Bid.
SSMB – Single Seller Multiple Buyer.
MSSB – Multiple Seller Single Buyer.
SFA – Shared Facility Authority.
TEM – Transactive Energy Market .
PV – Photo Voltaic.
CDA – Continuous Double Auction.
LSE – Load Server Entities.
IoE – Internet of Energy.

Chapter 1

Introduction

There has been active research in the development of optimization techniques for peer-to-peer energy trading, owing to the recent emergence of the smart grid energy infrastructure. The smart grid updates the current energy model by utilizing a variety of technologies, e.g., automation, control systems, wireless sensors and radio-frequency (RF) communication, thus enabling an information and energy distribution network between consumers and prosumers within the grid. Additionally, the smart grid promotes users to invest in renewable energy sources to meet their electricity demands and to generate a profit by distributing any excess surplus energy to a consumer in a peer-to-peer fashion. Energy trading in a peer-to-peer manner has demonstrated to be a practical approach for both buyers and sellers to improve the performance of energy system costs. This is mainly due to providing an alternative source for users to purchase energy from one another, other than the primary grid.

Several studies such as those in [1], [2] and [3] to name few, suggested market models for grid control, electricity trading and communication. However, current models need updating as they do not adequately capture the energy trading process which results in a reduction for the seller's profit return and an increase in the buyer's purchasing costs. This can be more challenging as the grid infrastructure grows, increasing stress at the distribution level due to a surge in energy demands, requiring the need for innovative solutions and mechanisms to optimize the way users trade energy among one other. Furthermore, the outcome of optimizing the way users participate in energy trading will give incentive for society to make the necessary immediate transition into the smart grid infrastructure and address the underlying issues such as rapidly growing populations, increasing pollution and electricity demands.

The current electricity grid is outdated and will not able to satisfy the requirements for standard living within the upcoming years. It currently motivates the production of fossil fuels which significantly harms the environment due to the greenhouse gas effect [4], causing an epidemic in global warming [5]. The impact of global warming has caused temperatures to rise at an alarming rate, resulting in rising sea levels, extreme climate conditions, and environmental disasters. The planet only has a limited source of fossil fuels available for energy production which will be insufficient within the next few decades [6]. Also, electricity demands are not the same as it was 50 years ago [7].

Transmission lines are overloaded which reduces the grid reliability and results in more blackouts and brownouts. Increase in brownouts and outages will become more frequent, and a stable electrical supply will no longer be available. Our current traditional electrical system eventually will not meet the requirements of society for standard living conditions. Humanity has become highly dependent on the production of fossil fuels to meet its electricity demands. However that needs to be changed as that source is becoming scarcer by the day, paving the need for an immediate shift to satisfy future living. There are many issues with the traditional grid. It runs in a centralized fashion with one-way communication [8] and only has one central source of energy which is fed into the lines and distributed to a given destination. Another issue is the distance between the main generating source of power and consumers. Longer distances for energy distribution increases the likelihood of losses in the transmission lines, wasting an enormous amount of energy. Also, it increases the risk in line damages which affects the energy delivery to the consumers, thus reducing the grid reliability. We need to update the system that addresses these issues and utilize renewable energy sources to mitigate the effects of global warming.

1.1 Smart Grid

The smart grid is an emerging electricity grid which uniquely combines communication, storage systems, and a variety of renewable energy sources readily available for consumers and producers to trade energy in a peer-to-peer fashion [9] and sufficiently satisfies users' electricity demands.

As depicted in Fig. 1.1, the smart grid does not limit itself to only one energy generating

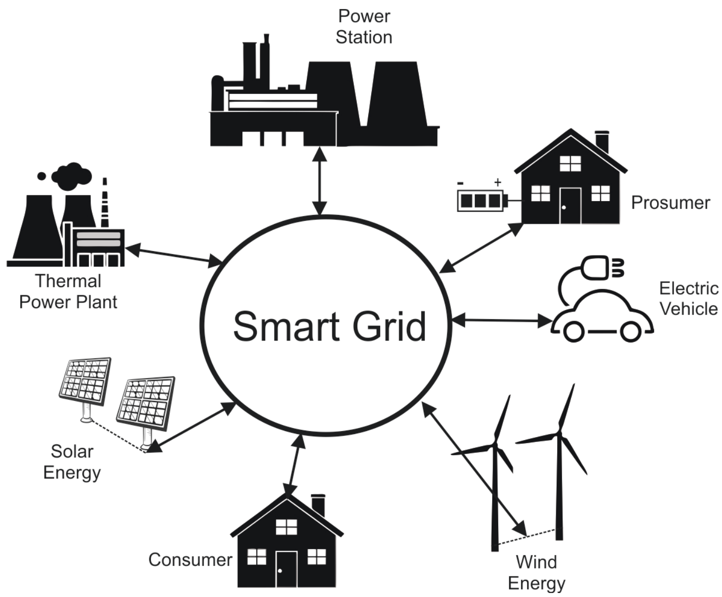

Figure 1.1: Smart grid infrastructure

source. It supports the infrastructure to distribute energy at multiple locations, thus reducing the overall stress in the transmission lines and improving the grid reliability. It further mitigates transmission line losses, since distances between consumers and producers are minimized due to the multitude of sources available at the distribution level. Users, such as homeowners, commercial, and industrial businesses, can connect to the smart grid and satisfy their energy demands by purchasing power at an alternative source or investing in green energy sources, e.g., wind, solar, hydro, geothermal, tidal. This will also address the adverse effects of global warming [10, 11, 12], by reducing gas pollution from generating clean energy at multiple sources [13]. Furthermore, with technological advancements in solar, as demonstrated in [14], where type III-V semiconductors for photovoltaic applications have reached efficiencies close to 30%, making the investment profitable for energy producers.

In addition to renewable energy sources, the smart grid employs alternative electric storage systems, such as supercapacitors, hybrid, hydrogen, and pneumatic technologies [15, 16, 17]. Alternatively, electric vehicles have demonstrated to be an effective storage system for smart grid applications. Electric cars have gained immense popularity over the past few years, and will soon surpass gas vehicle production, resulting in efficient energy storage systems. These storage systems have improved the cost performance of generating and storing energy since power is not being wasted, and have improved the energy efficiency for distribution. Therefore, since the grid enables reliable and secure energy generating sources with multiple distribution points to reduce stress and to meet the demand of all users connected to the network, the grid reliability can be improved.

1.2 Research Motivations

This work is motivated to design P2P energy trading models and optimize the way users trade energy to improve energy waste management and conservation of energy. In addition, push the reliance and popularity of clean energy production as opposed to fossil fuels and improve grid reliability by reducing the stress at the distribution level for the smart grid infrastructure. By designing energy trading models for P2P distribution, and optimizing the profit return by reducing energy bills and increasing sellers profit outcome upon energy production and distribution, users will be motivated to participate. However, there is minimal interest in users investing in energy sources. One possible solution to address the problem is to incentivize users to generate and trade electric power through the smart grid.

Unfortunately, since the process for energy trading is a relatively new technology that is only available in limited areas, the incentives for users to produce clean electric power by participating in the energy trading process requires significant attention. Therefore, this research focuses on optimizing the energy trading process, thus motivating individuals to participate in green energy production and profitable trading to enhance grid reliability. To optimize the energy trading process in a peer-to-peer fashion, it is critical to model the grid system in an effective method and to consider all underlying properties such as individual rationality, truthfulness, time complexity, fairness and budget balanced. Additionally, the mechanisms for the way of purchasing and selling energy requires significant attention.

This work focuses on modelling the energy trading models and utilizes an auction mechanism to optimize the social welfare for an energy trading market for sellers and buyers. Thus, the primary motivation of this work is to design different approaches and models for the users' to trade energy which will directly benefit by either reducing the energy bill, increasing profit return and maximizing the overall social welfare.

1.3 Research Problem

The main research problem of this work focuses on optimizing the P2P energy trading process for sellers and buyers within a smart-grid network. To address these problems, there needs to be an accurate energy trading model that considers properties and characteristics of a trading system. When designing an energy trading model the main goal is to maximize the social welfare of both the sellers and buyers. Therefore, it is critical to capture the cost of the underlying infrastructure to prepare the model for practical use. Furthermore, the model must exhibit the following properties: truthfulness, individual rationality, budget balanced, computation efficiency, and fairness. Optimal buyers or sellers can be identified using the first price bid which may not guarantee the truthfulness of the system. The main purpose of designing an auction model is to guarantee all the five properties.

Additionally, the problems of this work focus on technical issues such as, establishing a mechanism in which the buyers and sellers can purchase and sell energy from one another taking into account infrastructure variables, such as demand, grid flow, storage capacity, transmission costs, etc. Lastly, the algorithms and matching networks must be designed to optimize the social welfare of the system, i.e., match the buyers and sellers optimally.

1.4 Peer-to-peer Energy Trading

Peer-to-peer energy trading is a novel prototype [18] of power system operation which allows users to generate and trade renewable energy. Trading refers to exchanging a product and benefiting from the return. More accurately, energy trading is defined as selling a surplus of energy to a buyer that is in demand, which results in a profit return to the seller. Buyers are considered to be consumers and sellers are considered to be prosumers with respect to time. Buyers are more motivated to purchase energy from the seller since the energy was generated from a green source and is typically cheaper than the main grid. Furthermore, by producing clean energy and distributing within small networks, the transmission line stress is mitigated since the overall demand required from the main grid is reduced.

Energy trading can be performed through a seller and buyer directly. Alternatively, energy trading can be performed in a market form with the assistance of an auctioneer. This form is referred to as an energy market and consists of active sellers and buyers for energy trading and captures concepts such as consumption, generation, and storing [19].

The smart grid effectively integrates peer-to-peer energy trading. As shown from Fig. 1.2 a peer-to-peer connection is made between buyers and sellers to trade energy within the network, enabling users to purchase power from alternative sources. Peer-to-peer trading is one of the main focuses of this work. It is critical to accurately describe the function of this given application and to further optimize the way the trading is performed.

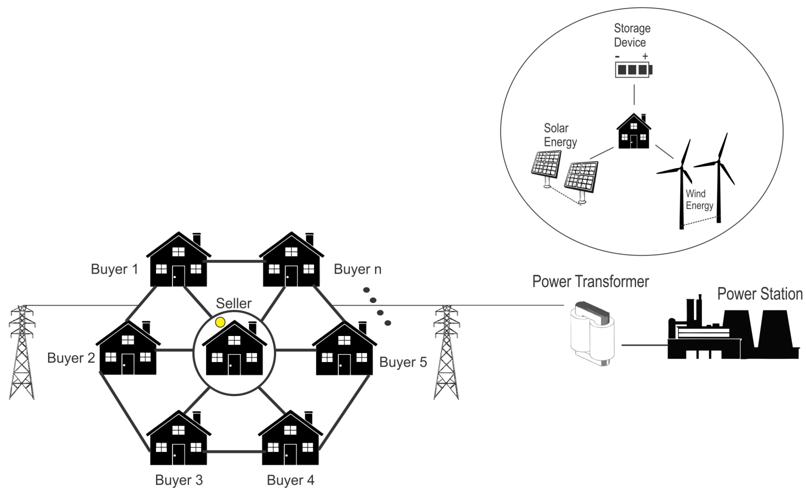

Figure 1.2: Smart grid network with peer-to-peer energy trading

There are several emerging Peer-to-Peer energy trading projects such as Vandebron, Smart Watts, Yeloha and Mosaic, SonnenCommunity, Peer Energy Cloud and TransActive Grid are emerging energy markets with a combination of software and hardware for energy trading between the sellers and buyers to trade energy. The proposed mechanism in this work is in-line with these application.

1.5 Methodology

To design an accurate model for energy trading to maximize the social welfare for sellers and buyers, it begins by considering practical elements of the network. Examples of these considerations include transmission line capacity, buyer's bid cost, seller's asking price, the distance between buyer and seller, surplus energy, etc. Next, constraints within the network need to be accounted for. For example, users cannot distribute energy which affects the transmission line resulting in line failure. Another example is sellers cannot distribute more energy than they have produced. Once the constraints and characteristics of the network are accurately modelled, optimization techniques are systematically carried out to maximize the social welfare of the network.

The methodology can be briefly summarized as follows

- Accurately model the energy trading network and mechanism.
- Implement constraints for practical scenarios.
- Optimize the solution to maximize the social welfare.

1.6 Contribution

The main contributions of this work present three different models to accurately describe the energy trading mechanism for a P2P smart grid. The first two models are applied for a single-sided auction mechanism whereas the third model was used for a double-sided auction. This section summarizes the contributions related to P2P energy trading models in detail.

1.6.1 P2P Energy Trading Models

The first model is utilized for a single seller within a P2P energy trading grid that demonstrates an alternative approach to increase the profit return of seller, which further motivates users to generate clean energy. This work also presented a profit maximization algorithm (PMA) that is specifically made for the sellers to optimize and maximize their profit return. This PMA was analysed using a normal distribution, uniform distribution and exponential distribution. In all the three distributions, simulations were performed and a comparison was made with our proposed PMA and the first price bid method and the second price bid method. As a result, the proposed mechanism outperforms the first price bid and second price bid significantly by generating an increase in profit return.

The second model demonstrates a solution for the buyer to find the optimal seller with the minimal cost, thus increasing the pay off of the buyer. A proposed cost minimization algorithm (CMA) was demonstrated to reduce the buyer's energy costs and compared with first and second price bid mechanisms. Similarly, the CMA was tested using a normal, exponential, and uniform distribution to simulate and make a comparison. Based on the simulations results, the CMA outperforms the existing methods by reducing the overall buyer's cost, demonstrating a practical approach to reduce and optimize the buyers cost.

The third model demonstrates a matching mechanism for an energy trading market (ETM), which consists of an auctioneer to match the sellers and buyers such that the social welfare of the system is maximized. A proposed auction matching algorithm (AMA) was demonstrated to effectively match the sellers and buyers.

1.7 Publications

- *Conference*:
  The 10th International Conference on Ambient Systems, Networks and Technologies (ANT).
  Title: An Auction Mechanism for Profit Maximization of Peer-to-Peer Energy Trading in Smart Grids.
  Authors: Jema Sharin Panki Raj, Abdulsalam Yassine, Salimur Choudhury.

- *Journal*:
  IEEE Transactions on Sustainable Computing.
  Title: Double-Sided Auction Mechanism for Peer-to-Peer Energy Trading Markets.
  Authors: Jema Sharin Panki Raj, Abdulsalam Yassine, Salimur Choudhury.

1.8 Thesis Outline

- Chapter 1 presents the introduction and motivation of this work. It discusses the emerging smart grid, research motivation, research problem and P2P energy trading. Additionally, the methodology is shown along with the contributions of this work.

- Chapter 2 discusses the background information on energy trading and auction mechanisms. In addition a literature overview is provided.

- Chapter 3 describes the proposed energy trading models for P2P smart grids. A discussion of the critical variables and parameters of the smart grid is also demonstrated.

- Chapter 4 demonstrates the proposed single-sided auction model 1 and 2 with results and analysis. Simulations are tested for various case studies and a comparison is made with existing mechanisms.

- Chapter 5 presents the proposed double-sided auction model for an energy trading market (ETM). An auctioneer performs the matching between the sellers and buyers in the ETM using auction matching algorithm (AMA) with respect to their bid, ask, surplus energy and the demand.

- Chapter 6 concludes the overall research work and provide future suggestions to improve the P2P energy trading in smart grids.

Chapter 2

Background and Literature Review:

2.1 Energy Trading

Energy trading is possible with emerging smart grid infrastructure since it utilizes two-communication and two-way energy transfer, necessary for traders to send and receive energy between each other [20]. Fig. 2.1 shows a simplified energy trading model which consists of a single prosumer and a single consumer connected to the smart grid. Depicting that the prosumer and consumer have the resources to transmit and receive energy. The main advantage of the smart grid is that the user can send back their surplus energy to the consumer in need or to the main electric grid, which is currently not possible using the traditional grid.

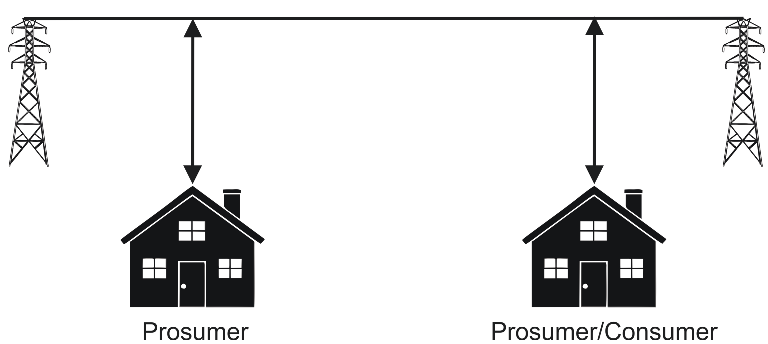

Figure 2.1: Simple energy trading infrastructure

Energy trading models and optimization techniques have been previously demonstrated and have been become an active research topic. One specific example is a model for smart factories designed in [21], to perform intelligent energy trading. The work, however, proposes a model to trade energy between the consumer and supplier in smart factories and utilizes a time limit for bidding. Meaning, the players in the network are allocated time slots to purchase energy. Once the bidding time is over, the market server decides and notifies the winner. The energy is then distributed to the winner. This is one of the many techniques in which energy trading can be performed. In the following sections, the basic variables and properties of an energy trading model will be discussed.

2.2 Auction Mechanisms

The auction-based mechanism is adopted in multiple areas and fields. Examples include but are not limited to, airport time slot allocation, cloud resource allocation, RFQ support process, baseball free-agent draft, procurement, and search advertisement [22, 23, 24, 25, 26, 27]. Auction mechanisms are used everywhere for a fair buying and selling for any product. Examples of types of auctions are English auction, Dutch auction, sealed bid auction, Vickrey auction and reverse auction, etc. Each auction differs slightly from each other according to their property. Mainly, auctions are classified into sealed bid auction and iterative auction. These auctions have demonstrated powerful use in P2P energy trading for buyers and sellers to effectively purchase and seller energy. Here, in this work, a sealed bid auction is utilized for trading the energy.

2.2.1 Sealed Bid Mechanism

A sealed bid is a type of auction process in which all the players bid for the same product available in the market, and no players know the bid of other players. All players must submit their complete bid [28]. Usually, the player with the highest bid wins the auction. For example, assume that there is a product available in the market for sale and three buyers $\{B_1, B_2, B_3\}$ need that product. Each buyer will have their own valuation $\{V_1, V_2, V_3\}$ on the product. The valuation is an intrinsic relationship with the product and the buyer. Typically, a buyer will have a higher valuation for renewable energy sources as opposed to energy generated through fossil fuels. Furthermore, the buyer will submit a sealed bid $\{b_1, b_2, b_3\}$ for that product according to their valuation. No other buyers have any information of the bid of other buyers within the network. The bids are sealed and only the seller and the corresponding buyer have the information regarding the bid. Suppose that buyer B_3 submitted the highest bid b_3 and assume that buyer B_2 has the next highest bid b_2. The bids are then sorted in descending order according to their value, i.e. $\{b_3, b_2, b_1\}$. If the type of seal bid mechanism used is first price bid (FPB), the buyer j with the highest bid will win the auction and pay the submitted bid (b_j) as the payment to the seller for the market product. In this case, b_3 is paid to the seller. Alternative, in a second price bid (SPB) mechanism, the buyer with the highest bid wins and pays the second highest bid. This is summarized in Table 2.1. Therefore, B_3 still wins the auction but pays the bid b_2 as the payment for the seller. Thus, a seal bid mechanism is a practical approach when implementing an auction for P2P energy trading.

Sealed bid type	**Winning buyer's payment**
First price bid	Highest bid
Second price bid	Second highest bid

Table 2.1: Comparison of buyers' payment in first and second price bid

2.2.2 Single and Double-Sided Auction

The most commonly used auctions for product selling and buyer are the single sided auction and the double-sided auction. In a single-sided auction, all the players or buyers will be bidding on the same product from the seller [29]. Mainly, the seller does not ask for any specific price for the selling product and all the buyers play against each other by bidding on the product. Another distinction is made that it does not have to be a buyer bidding on a product. It can be a buyer that is in need of a specific product, and the sellers play among each other by trying to sell the requested product for a given price. The main point is the auction only receives variables from a single side.

Similarly, in a double-sided auction, all the buyers will submit their bid. However, the sellers also ask for a specific price, i.e., ask price, for the product they are trying to sell [30]. Therefore, additional variables are introduced in the auction. Hence, both the bid and the ask from the buyer and seller respectively. These auctions are the foundation of this work to perform energy trading, in which this work explores alternative P2P energy trading models based on single and double-sided auctions.

2.2.3 VCG

The above utilized auctions are based under the assumption that buyers and sellers are submitting their bids and ask using the Vickrey-Clarke-Groves (VCG) mechanism. This mechanism ensures that all players in the auction are acting in a truthful manner [31]. When the energy trading models are designed, this assumption that participants are acting in a truthful manner is also made in [32, 33]. VCG mechanisms assist the users to achieve an optimal solution [34] in a truthful manner. Furthermore, consider in the payment method, the winning player (the player with the highest bid) will pay the bid of the second highest player. This is referred to as "second price bid" and will not encourage the buyers to bid low or the sellers to ask high. However, VCG is always a weak budget based only if an auctioneer is introduced. Thus, the profit of the auctioneer is always zero. As a result, the seller receives whatever the buyer pays [35, 36].

Moreover, each player has their own valuation on the product. We denote the sellers' valuation as V_i and the buyers' valuation as V_j. The seller submits the ask a_i according to their valuation and the buyer submits the bid b_j according to their valuation. The utility function U is given below, where the utility of the winning seller and buyer is $U_i = a_i - V_i$, $U_j = V_j - b_j$ respectively. The utility of the losing buyer or seller = 0. When the players follow the VCG mechanism, it will not encourage any buyers to submit a low bid b_j. Because if the buyer submits a low bid, they might not win and if only two players are present, the buyer with the highest bid wins and pays only the second highest bid. Similarly, VCG will never encourage the seller to submit a high ask a_i.

2.3 Properties

A feasible auction mechanism should satisfy the properties of individual rationality, computational efficiency, truthful, fairness and budget balanced. The following properties are summarized below [37].

- **Individual rationality:** All the participating users in the auction should have a non-negative payoff. Mainly, when a seller sells a product for a specific ask price, they will not have to reduce their ask. And if a buyer bids a given value, they will not have to pay more if they win the auction [38].

- **Computational efficiency:** The auction outcome should be intractable with polynomial time complexity. Mainly, the time complexity of the system does not following an exponential relationship, in which more users prolong simulation and functionality.

- **Truthfulness:** The players in the auction do not cheat and are truthful with their values and cost when buying and selling products. It is not easy to follow truthfulness in the auction; however, monitoring certain conditions will rectify it [39].

- **Fairness:** This mechanism should be designed fair for all the users by providing equal opportunities to participate in the auction. The mechanism should be fair enough to all the buyers and sellers in submitting the asks and bids according to their valuation. No buyer or seller wins the auction in any other different ways other than following the design (treated equally). When a mechanism follows truthfulness, it naturally supports the fairness property [40].

- **Budget balanced:** If there is an auctioneer in the model, the welfare of the auctioneer should be non-negative [41].

2.4 Related Works

As previously mentioned, energy trading has become an active research topic since renewable energy sources have become a high-market demand. Additionally, motivating users to transition to renewable sources by providing incentives through optimization techniques has also been a popular topic. Also noting that energy trading is only possible through the smart grid. Here, in this section, research based on energy trading will be presented.

In [42] the authors' present the design and implementation of a modus-operand for an energy market in a smart grid neighbourhood to study and observe the effects of a practical energy trading system. Similarly, a transactive energy (TE) scheme is introduced in [43] to determine energy trading strategies among the transactive energy markets consisting of buyers and sellers. However, the work considers only photovoltaic (PV) as the renewable energy source within the market. And simulations are carried to analyze the effects of a 30-year lifespan for PV arrays to uniquely predict the system's functionality for future dates. [3] uses a distributed and centralized market scheme for an energy trading network. The goal was to provide an overview and comparison between markets by determining which benefits the local market users (prosumers and consumers) based on profit returns and further provide a connection between these two markets. The system model's objective was to minimize the energy self-consumption of prosumers. Further, the distributed market, which focuses on a peer-to-peer (P2P) exchange approach by dealing with individual buyers and sellers, was based on the continuous double auction (CDA) method whereas the centralized market focuses on the overall information of all users within the network and looks to maximize the global welfare of the system. This market was implemented using both an energy trading algorithm identifying the market equilibrium and a Vickrey-Clarke-Groves (VCG) method. Based on the results, the local markets performance was found that regardless of the market scheme, both techniques provide benefits to the users. In [44] the authors present a novel fair energy framework for energy trading among microgrid clusters. The goal was to reduce energy fluctuation, maintain balance within the infrastructure and promote local energy trading. The model uses an energy market operator (EOM) that acts as the energy allocation member. The EOM will collect data from all the buyers and arrange them based on their demands. Then, attempt to allocate each buyer to an optimal seller. In addition, the model uses a free-market approach by letting the sellers select their surplus to sell. [45] presents a customer energy trading mechanism for P2P microgrids. The authors tested various pricing mechanisms, e.g., conventional, unified, identified. It was found that unified and identified significantly reduce the energy bill of the users within the system model. However, simulations were pertained to a small-scale amount of users. [46] implemented a technique for a day ahead approach for virtual power plant owners. This allowed for accurate energy consumption predictions by taking into account weather forecasts, which causes fluctuation in energy generation for solar and wind producers.

Thus, looking to optimize the power plant owners profit income. A mixed-integer linear programming model for a single end-user is demonstrated in [47] for green energy generation and to reduce energy waste. Green energy is purchased and sold through the internet of energy (IoE), illustrating a possible technique for users to trade and sell energy. Additionally, a genetic algorithm is proposed involving a more substantial number of variables and constraints for the buyers and sellers. In [48], a P2P energy trading framework using a hierarchical approach is developed for energy markets in microgrids. The hierarchy is used for future large scale markets and consists of a top level utility grid that interfaces with a microgrid energy trader. The energy trader then communications with community energy traders. The community energy traders are split up for various neighborhoods. The hierarchy configuration is compared with regular P2P trading networks, resulting in a high performance method as the overall system costs for buyers is significantly reduced. Similarly, in [49] presented a hierarchy approach for small-scale energy trading while utilizing contract theory. The hierarchy consists of three main levels. The first and second level consist of the main macrogrid and aggregator respectively. The third level captures the entiree buyer and seller network. The authors in [50] present a P2P energy trading network that utilizes bilateral contracts. The network consists of three different agents, e.g., prosumers, suppliers and generators. This paper [51] uses a novel framework based on game theory to study the energy trading decision between the players in the energy trading model and demonstrated to be an effective approach. Therefore, we see that energy trading within the smart grid has been extensively studied. Next, we consider possible storage systems for this electric power.

The author in [52] tested the performance of the local markets using continuous double auction mechanism and a Homer optimization [53] is used to reduce the cost of the energy. Two-stage Stackelberg game [54] with different cases where energy users and shared facility authority (SFA) trade energy. The main motivation of this paper is to encourage all the energy users to participate in energy trading. Similarly, in [37] proposed a matching technique between mobile devices towards nearby cloudlets considering that the cloudlets as sellers and mobile devices as buyers. Which is similar to the pairing made in this research with sellers and buyers. The author forms two main stages of determining the winning buyer. The first stage is "Candidate-Determining and pricing," and the Second stage is "Candidate-elimination." Here the author makes matching only with one buyer to one seller where in this work matching is made with a group of buyers to the seller and a group of sellers with a buyer. Similarly, a VCG based auction-based mechanism is proposed in [55] which is designed to increase the revenue of the user. In [56], the author uses an approach to the problem by linear programming (LP) assignment. The main objective is to satisfy the seller and buyer by maximizing their revenue.

The optimization model is proposed in [57] and [58] are similar to the problem discussed in the proposed model. In this work, the constraints were designed variably for ensuring the energy transferred between the sellers and buyers are not affecting the transmission line capacity. A different approach to maximizing the seller's profit using profit maximization algorithm is proposed in this work. Furthermore, two different models with a different approach for energy trading under P2P fashion are provided. Model one suits for single user and model suits for market models. In model 1 seller have the full control for deciding the amount of energy for trading. Besides the theoretical appeal of the proposed energy trading mechanism, we consider the geographic distribution of both sellers and buyers by incorporating energy transmission costs. The proposed mechanism is based on game theory, where buyers choose the best sellers from whom to buy energy to minimize their energy bill. We also offer a centralized optimization model that reduces the system energy bill. We evaluate the performance of the proposed game by extensive simulations, where we compare its performance against the optimization model. An alternative approach to address the incentive for income was demonstrated in [59]. In which the authors disregard the profit motivation and consider the value of alternative energy sources. This is done by treating energy sources has heterogeneous products. By allowing individuals to choose by personal preferences based on the inherent attributes of the energy source. The authors in [60] provide an excellent summary into the potential of game-theoretic approach for P2P energy trading. Since game theory has the capability of optimization. In general, the game-theoretic approaches used can be eight non-cooperative or cooperative. From this work, we observe the wide interest in optimization for energy trading markets.

Auction models are also extensively used in smart grid applications. Here, the work in [61] introduces an auction model for local markets, with a proposed mechanism to assist buyers in finding the lowest cost for energy purchasing. A distributed algorithm is drafted in this paper to maximize utility efficiency. The work did not simulate using realistic energy trading model as only a set of seven buyers and sellers have been examined. In this paper [62] the author propose an algorithm that enables base stations to trade energy using a double auction framework. Here, the main contribution is to reduce non-renewable energy consumption in multi-tier cellular networks. The primary purpose of this paper [63] is to build an optimal bidding strategy for day-ahead, auction-based electricity markets. Which would improve system efficiency by preparing system functionality. In this paper [64], an agent-based model is proposed for spectrum trading and the payment is made using the first price bid method. Here, the author proposes an algorithm which controls the bidding strategies of the bidder. Different levels of risk are discussed using two different decision fusion strategies. Finally, the results analyze the environmental risk, total revenue of the bidder and the revenue of the auctioneer. In a Peer-to-Peer network, the blockchain method gives the trust for trading at each point [65, 66, 67].

An efficient iterative double-sided auction is proposed in [68] which increases the social welfare of the agents within the network. The author used double auction mechanism for allocating the resource among multiple agents and the main objective of this paper is to maximize the social welfare [69]. This framework is generic and applies to P2P overlays. Additionally, the behaviour of the energy production of renewable energy sources has received minimal consideration. This disregards practical situations in which users connected to the grid experience. Mainly, deviations in energy generation and consumption. A truthful double-sided market is designed using a greedy allocation mechanism proposed in [70] for cloud markets. In [71] the auctioneer uses a double auction mechanism to determine the winning sellers and winning buyers. The author in [20] shows the benefits of energy trading using the smart grid followed by an investigation about optimizing their benefits. Double-sided auction is always better than single-side auction since it allows both sellers and buyers to ask and bid depending on the valuation [72]. Activity rules are proposed in [73] which makes the buyers bid sincerely. A comprehensive review of various incentive approaches for energy trading is studied in [74]. Further, energy trading is investigated in a new cloud-based scenario with vehicle-to-vehicle. Efficient energy trading schemes are been reviewed. A mechanism for two-sided cloud markets is designed in [75] using a double auction mechanism. Conceptual investigation for load server entities (LSE) using double auction is studied in [76]. The risk of the low bid and high ask has been reduced using their designed mechanism. Therefore, we see the popularity in auction mechanisms utilized for the energy trading process. Next, we review work based on energy storage systems.

Alternative energy storage systems are readily available to allow users to store generated energy. The one that has received considerable interest over the past few years is electric vehicles [77]. Additionally, the authors' study the smart grid storage systems to assist in energy trading functionality. Mainly, optimization techniques have been explored to improve the cost performance of such systems. Thus, a formulation of a global scheduling problem to minimize the total cost of the all-electric vehicle performing charging and discharging during a day is performed. Similarly, [78] studies the effects that plug-in vehicles cause to decentralized grids. The effects arise from the erratic behaviour the peak demand experiences and congestion in network capability. They further demonstrated how these storage systems could be beneficial to the grid by providing alternative storage sources. This relieves balancing and congestion issues for the main grid. Since in some practical situations, the main grid itself will experience limitations others may not. The study of scheduling and optimizing problems for charging and discharging of electric vehicles (EV's) is also studied in [79]. The authors in [80] use electric vehicles to relax and reduce the level of supply and demand mismatch. This approach is referred to as vehicle to grid (V2G). The authors also present an energy trading framework used for the V2G by using the block chain and edge computing. This was done to enhance security and efficiency of the V2G energy trading framework. From recent work, we see that there has been active research to study the effects of electric vehicles used for storage systems and reduce distribution stress within smart grids. Following is a discussion of work focusing on important topics related to privacy and security.

Moreover, another issue for energy trading is security and privacy which is the essential factor in protecting participators privacy securely, studied in [81, 82]. [83] presented a P2P energy framework analysis of Blockchain, Block Lattice and Directed Acyclic Graph (the Tangle) to demonstrate the performance in comparison relative to assisting the buyers financially and securely. A secure energy trading model was designed in [84] that demonstrated how secure an energy trading microgrid is without the need of a third-party present. Security has also been an emerging research area for energy trading applications. A similar approach was proposed in [85], where the authors implemented energy trading priorities for users connected to a residential microgrid. These types of networks mainly arise in isolated communities. Where the energy production of the grid itself may be of major concern. These measures were also considered in [86]. The authors took into account that overall energy independence of a microgrid. Where the overall structure of the grid was on an island. This work allows for a useful metric to compare energy trading schemes. Moreover, the work allows individual buyers and sellers to trade energy among themselves before trading with the main grid. This was to address issues nearby homes may experience such as power outages. They also used a game-theoretic approach and compared the two analyses. Where the latter approach was found to minimize the overall electricity bills of participants. Here [87] the author presented a blockchain method for individual buyers to buy their neighbours excess photovoltaic generated power. Demonstrated in [88], the work shows a similar network with an auction mechanism where the aim is maximizing the social welfare presenting an example where two sellers and one buyer are trading energy, where the buyer fixes the price. The author gave two cases showing how the buyer receives energy from the seller. Here we see extensive work focusing on improving the security and privacy of users connected to a smart grid.

The below Table 2.2 compare the single and double-sided auction mechanisms used in various industries and the constraints used in the energy industry, additionally, this work proposes both single and double-sided auction mechanisms for energy trading models considering the major constraints such as line cost and transmission line capacity.

References	Single-sided auction	Double-sided auction	Line cost	TX Line capacity	Industry
[88, 30, 9]		✓	✓		Energy
[37]		✓			Mobile service
[58, 89, 90]			✓		Energy
[64, 91]	✓				Spectrum trading
[69, 92, 93]		✓			Resource allocation
[57]			✓		Energy
[94]		✓			Cellular network
[95]		✓			Cloud Computing
[63, 96]	✓				Energy
[97]	✓				Job scheduling
This work	✓	✓	✓	✓	Energy

Table 2.2: Comparison table

2.5 Discussion

In this chapter, a discussion on energy trading based around auction mechanisms was presented. The examination of an energy trading model with considering the line cost, and transmission line capacity was shown. Moreover, the energy trading models present in this work are built upon both a single and double side auction. In addition, these auctions are based on the seal-bid approach in which buyers have no information on other buyers and sellers have no information on other sellers in the network. Furthermore, these auctions are based upon the VCG mechanism which assumes players are participating in a truthful manner and respect the rules of the game. It was also shown the critical properties in which for a feasible auction it should be following individual rationality, computational efficiency, truthfulness, fairness and budget balanced. Lastly, it was shown the vast interest and unique approaches to related works based on energy trading and smart grid applications. Concluding the strong points of this work in a comparison table in which previous work has yet to perform.

Chapter 3

Energy Trading Models

3.1 Proposed Energy Trading Models

This section proposes the mechanisms utilized for the three energy models. In the first model, we considered a single seller with multiple buyers and analyzed how to optimize and increase the profit of the seller. Fig. 3.1 depicts the simplified diagram of this model. All the buyers participate for the same product, and no buyer has any information about any other buyers. The buyers communicate only with the seller regarding the product and the buyer submit the bid to the seller in a sealed bid fashion so that no other buyer knows about the bid. The buyer with the highest profit wins the auction. This type of energy trading model composed of a single seller with multiple buyers trading is also demonstrated in [98, 99, 100].

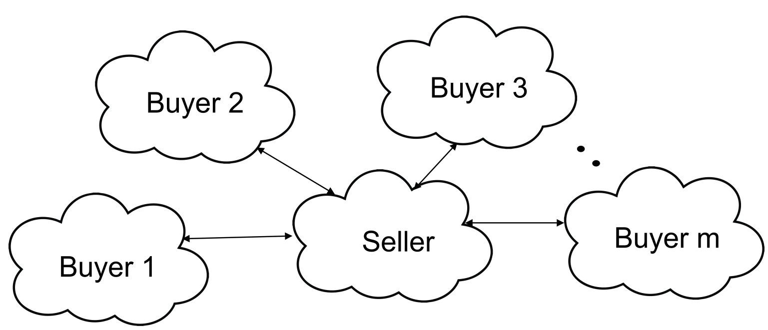

Figure 3.1: Single seller with multiple buyer energy trading model

The second model is depicted in Fig. 3.2, designed under the consideration of multiple sellers and a single buyer. It is also analyzed to determine how a buyer can obtain energy at the possible lowest cost. Additionally, sellers submit the ask and amount of energy to the buyer, and no seller knows about the other sellers' valuation or ask price. The seller communicates only with the buyer regarding the amount of product and the ask for the product. All the sellers submit their ask to the buyers in a sealed bid fashion such that no other sellers know the asks submitted by other sellers. The buyer selects the seller with the cheapest ask and selects the clean green energy with a lesser cost. Thus the seller with the least ask wins the auction.

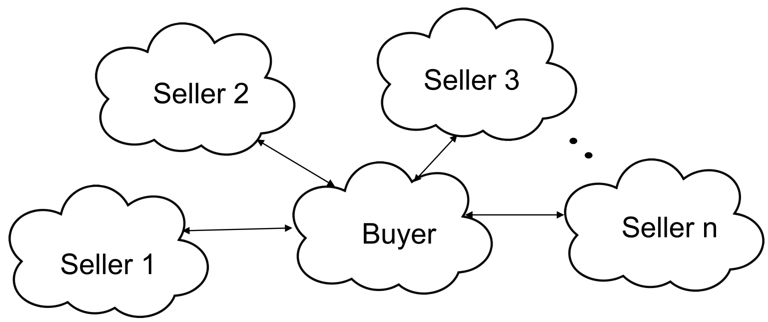

Figure 3.2: Multiple seller with single buyer energy trading model

The third model is depicted in Fig. 3.3, consisting of multiple sellers and multiple buyers. Here, an auctioneer is introduced to perform the matching between the sellers and the buyers. Sellers submit their surplus energy and the ask to the auctioneer and the buyer submits the demand and bid to the auctioneer. In addition, the buyers and sellers communicate only with the auctioneer and the role of the auctioneer is to match the sellers and buyers which optimizes the social welfare of the energy trading network. This type of network was demonstrated in [101, 102, 103, 104] for energy trading in multiple microgrids.

In this following section, we discuss the players in the network of the energy trading models.

3.2 Players

The players in the network consist of both buyers (j) and sellers (i). Each play interact differently within the system. This section explain the distinction between the players in regards to energy trading.

3.2.1 Sellers

The users who have the ability to generate energy (e) are referred to as sellers or prosumers. After consuming their energy requirements, and if they are left with any surplus energy, they can trade that surplus energy to other users in network who are currently in demand and are willing to buy the surplus energy from the seller. In return, the seller will generate a profit for trading

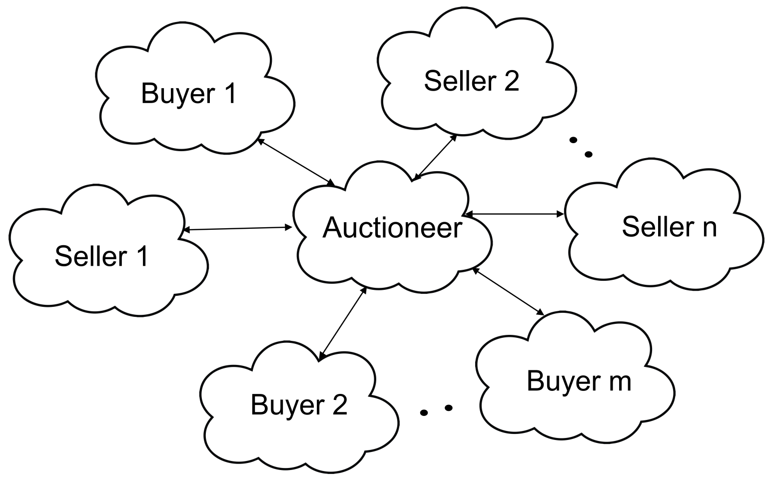

Figure 3.3: Multiple seller with multiple buyer energy trading model

and selling the energy to another user. The sellers cost is the cost required to generate a certain amount of energy. This cost includes the operating and maintenance cost for the generating device that harvests the electric power. The sellers obtain surplus energy after consuming their demands, which is the leftover generated energy or the stored energy. The surplus energy is denoted as e_i. The ask price is the price asked by the seller for their current amount of surplus energy, and it is denoted as a_i. The objective of the seller is to produce green, clean energy and consume it, so the seller does not buy energy from the grid. In addition, the seller in this work is to sell the surplus clean energy to the network and return a profit out of it. The seller is also motivated to maximize their profit return.

3.2.2 Buyers

The buyers are the users in demand and are willing to buy green energy from the sellers. Their current demand is represented as d_j. The buyers will also have a bid or cost in which they are willing to pay to purchase any energy. The bid is the offering from the buyer for their demand energy and it is denoted as b_j. The objective of the buyer is to buy clean energy from the sellers. In addition, the buyer is motivated to minimize their independent energy costs.

3.2.3 Auctioneer

The auctioneer is a third party in the network where both the sellers and buyers both submit their surplus energy, ask, demand and bid. An auctioneer is needed only when multiple sellers and multiple buyers are in the energy trading network. The main objective of the auctioneer is to match and optimize the sellers and buyers where both the sellers and buyers benefit [105]. In addition, the objective of the auctioneer is maximize the social welfare [106, 107] by matching the sellers and the buyers in an optimal method. Also, no players including the auctioneer should generate negative profits, at the worst case the pay can be zero but it should never be in negative.

3.3 Parameters

We represent the set of sellers as S and each member inside the set is denoted as i. The generated energy by the seller is denoted as E_i, after consuming their local demands, the remaining energy, i.e., surplus energy, is denoted as e_i and the ask price for the selling energy is a_i where $i \in S$.

There might be a case where the sellers will sell only apart from the surplus energy e_i since the profit may result as negative. In that case, the seller may store the remaining energy. The selling energy is denoted as e_k and the storing energy is e_y, thus $e_i = e_k + e_y$. The surplus energy is the summation of the selling energy and storing energy. When the seller sells the whole surplus energy e_i then, $e_y = 0$

In the single-sided auction models, the seller pays the line cost c_l for transporting the energy to the buyer. The line cost c_l depends on the the profit of the seller. which is calculated by the difference in the bid b_j from the buyer and the loses. The total loss of the seller is the summation of the operating cost c_i and the line cost c_l for transporting the energy to the buyer. Moreover, the seller calculates the profit for each buyer and selects the buyer with the highest profit as the winner and if the profit from all the buyer resulted in zero, then the seller stores the energy.

The set of buyers are represented as B and each buyer inside the set is denoted as j. The demand from the buyer is d_j and the bid for their demanded energy is b_j where $j \in B$. In the first two models (single-sided auction models), the buyer does not pay for the line cost c_l. The goal of the buyer is to select the seller with a minimum ask a_i and buys the clean green energy.

In the third model (double-Sided auction model), consists of multiple seller and multiple buyers. Here all the players pay the line cost c_l for using the grid's transmission line. In this model, an auctioneer is introduced to match the sellers and buyers.

3.4 Discussion

This chapter provided a general overview of the proposed energy trading models utilized in this work. The first and second model are based on single-sided auctions, which have demonstrated practical use through various domains. The first model consists of a single seller and multiple buyers, whereas the second model is for single buyer and multiple sellers. Additionally, the third model introduces an auctioneer for an energy trading network composed of multiple sellers and multiple buyers.

Following, was a discussion of the players in the network, e.g., buyers and sellers, to illustrate various restrictions and motivations when used for the energy trading models. In addition, a detailed description of the parameters used to model the energy trading process was given.

Chapter 4

Proposed Single-Sided Auction Models

In this chapter, we propose two different models based on a single-sided auction mechanism for energy prosumers and consumers. The first model, is designed for P2P energy trading that applies to a single seller and multiple buyers (SSMB). The primary motivation of this model is to maximize the profit of the seller by utilizing a proposed profit maximization algorithm (PMA). The PMA employs a unique approach to maximize the income of the seller. Similarly, the second model is designed for P2P energy trading between energy prosumers and consumers. However, it applies to multiple sellers and a single buyer (MSSB) and focuses on optimizing the buyer's purchasing costs by determining the lowest price for their energy demand from the possible various sellers. This is achieved using a proposed cost minimization algorithm (CMA).

In the first half of this chapter we discuss the initial model by illustrating the process of how communication and energy trading is performed between a single seller and multiple buyers. In addition, the proposed PMA algorithm is demonstrated using a simplified toy example. After demonstrating a toy example, simulations using a more practical scenario is carried out. The results of the simulations are then analysed using multiple types of distributions.

Similarly, in the second half we illustrate the process of how the energy and communication transfer process is performed between multiple sellers and a single buyer. Next, the proposed CMA algorithm is presented and tested using a toy example. Followed by a more practical scenario and analysed using multiple types of distributions. Lastly, we present and prove the desirable properties of an auction based mechanism.

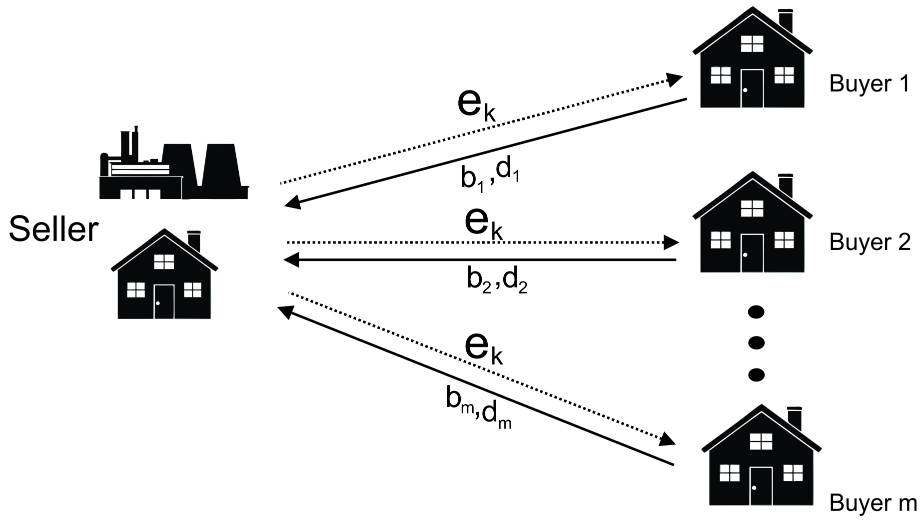

Figure 4.1: SSMB energy trading model

4.1 SSMB

The proposed initial model is depicted in Fig. 4.1 which illustrates the communication and energy flow between the seller and the buyers. All the active members in the network are considered as players. In which the buyers are looking to minimize their energy costs by purchasing at a cheaper source and the seller is looking to maximize their profit by distributing and selling a surplus of energy. The buyers have no form of communication between each other and are restricted to only communicate to the seller regarding their demand and bidding cost for the selling energy. The primary motivation of this model is for individuals or a group of energy producers that have generated a surplus of energy and would like to distribute that surplus for a given price. In addition, the primary goal of the seller is to sell the surplus energy and to maintain a non-negative profit. In such a situation the calculated profit is zero or negative, the seller will store the surplus energy instead of negative payment returns. Additionally, the model is designed in which the income of the seller depends on the amount of energy transferred to the buyer, the line cost required to use the grid's transmission lines and the seller's cost needed for generating the energy.

The basic process for P2P energy trading utilizing the proposed model is initialized with a seller who has met their own energy requirements, and currently has a surplus energy e_i, in which they are willing to distribute to a buyer for a given price. Next, the seller will invite buyers to bid to meet their own requirements. Then, the buyers will send the seller their demand d_j, and bid b_j. The seller will then respond with a selling energy e_k. The PMA is drafted to optimize and increase the overall profit return of the seller for this given process. Lastly, before proceeding, the following assumptions are made. First, the main electric grid is a buyer during peak demand. Second, the cost of the energy is cheaper to buy from the seller compared to the primary grid.

4.1.1 Network Design

The set of sellers who produce energy is denoted as $S = \{1, 2, 3..., n\}$ and a set of buyers who required energy is denoted as $B = \{1, 2, 3..., m\}$, where $i \in S$ and $j \in B$. We assume that the seller has a capacity of generating energy, and after meeting their local demands they are left with a surplus energy denoted as e_i. The energy demand of the buyers is given as d_j. The set of demands from the buyer is given as $\alpha = \{d_1, d_2, d_3, ..., d_m\}$, $d_j \in \alpha$ and d_m is the demand from the last buyer. The set of bids from the buyers to the seller is denoted by $\beta = \{b_1, b_2, b_3, ..., b_k\}$, $b_j \in \beta$ and k is the maximum number of bids. The operating cost, c_i is the cost for the seller to produce and maintain energy, e_i. The P2P power network consists of all possible paths from the seller to the buyers denoted as $p_{(i,j)} = \{p^1_{(i,j)}, p^2_{(i,j)}, p^3_{(i,j)}, ..., p^z_{(i,j)}\}$, where z is the maximum number of paths between an energy seller i and a buyer j. Each path has its own line cost and transmission capacity, denoted as c^p_l and x^p_{cap} respectively. The seller's cost consists of the transmission line cost c^p_l and energy generating cost c^p_i. The energy that is already flowing through a path is given as $y^p_{g_{(i,j)}}$ and the energy distributed by the seller to the buyer as $e_{k_{(i,j)}}$. Therefore, the transmission cost is the product of the distributed energy ($e_{k_{(i,j)}}$) and the line costs in the path (c^p_l).

When the transmission cost c^p_l and the operating cost c^p_i are greater than the buyers bid cost b_j, we will assume the seller stores their energy in a storage bank. The amount of energy stored is denoted by e_y. Where e_y is the difference between the total stored energy e_i and the distributed energy $e_{k_{(i,j)}}$. We assume the main electric grid is a buyer during peak demand and the cost of the energy is cheaper to buy from the seller compared to the main grid in this model.

4.1.2 Problem Description

In this model, the seller generates renewable energy for their local consumption and they can sell the excess of energy to buyers connected to the smart grid in a P2P fashion. The objective of the seller is to maximize their profit based on the buyers bid offerings and the line cost. The profit is expressed in Equation (4.1a).

$$\mathrm{P_r(i)} = \sum_{j=1}^{m} b_j - \Big[c_i + \sum_{P=1}^{z} \big[e^p_{k_{(i,j)}} \times c^p_l\big]\Big] \tag{4.1a}$$

$$\textbf{s.t.} \sum_{i=1}^{n}\sum_{j=1}^{m}\sum_{p=1}^{z} e^p_{k_{(i,j)}} < (x^p_{Cap} - y^p_{g_{(i,j)}}) \tag{4.1b}$$

$$\sum_{j=1}^{m}\sum_{p=1}^{z} e^p_{k_{(i,j)}} \leq e_i, \forall i \in S \tag{4.1c}$$

The line cost c^p_l in Equation (4.1a) is imposed by the electric grid company for using the infrastructure to transmit energy and it varies according to the amount of energy transferred by the seller. The energy delivered is referred to as the selling energy, $e^p_{k_{(i,j)}}$ and the bid offering from buyer j is b_j. In Equation (4.1b) we are enforcing that the selling energy, $e^p_{k_{(i,j)}}$, never exceeds the transmission line capacity, x^p_{Cap}. This ensures that no path in the system is over saturated with electric power and does not overload transmission grid, required for safety. Thus, the selling energy, $e^p_{k_{(i,j)}}$, should always be less than the difference between the total amount of transmission line capacity and the current amount of electricity flowing in the line, $y^p_{g_{(i,j)}}$. This relationship is expressed by the following formula, $x^p_{Cap} > (y^p_{g_{(i,j)}} + e^p_{k_{(i,j)}})$. In Equation (4.1c) we ensure that the seller cannot distribute more than the total stored energy, e_i.

When the energy is sold to the grid, we assume the seller does not need to consider the line cost, since the main grid will cover this expense, thus the line cost c^p_l is zero. In addition, the seller does not need to consider selecting the cheapest path since the transmission costs will be zero. In the below section we will see the designed PMA algorithm to solve the above mentioned problem.

4.1.3 Profit Maximization Algorithm

Input: Buyers demand d_j, Buyers bidding cost b_j, Transmission line capacity x^p_{Cap}, Grid flow y^p_g, Operating cost c_i, and Maximum stored energy e_i.

Output: Selling energy $e^p_{k_{(i,j)}}$, and Profit $\mathrm{P_r}$(i).

Stage:1 Determining the selling energy, e^p_k

Sort d_j in ascending order

foreach $d_j \in \alpha$ **do**

  if $(min(d_j) < e_i)$ **then**

    $\min(d_j) = e^p_k$;

  else

    $e_i = e^p_k$;

  end

end

Stage:2 Determining the winning buyer

foreach $b_j \in \beta$ **do**

  Calculate $P_r(i)$
  Sort profit in descending order
  Select the maximum $P_r(i)$, j

  if $(P_r(i) > 0)$ **then**

    Check constraints for j

    if $(e^p_k < (x^p_{Cap} + y^p_g))$ **then**

      Sell the energy to the buyer j

    else

      Eliminate that buyer j

      Repeat for j-1

    end

  else

    Store the energy

  end

end

Stage:3 Payment

The winning buyer will be paying b_j to the seller.

Payment $= \sum_{(j=1)}^{m} b_j$

end

Algorithm 1: Profit Maximization Algorithm(PMA)

4.1.4 Proposed Algorithm

Initially, the seller who has a surplus of energy, will invite the buyers in the network to send their required demand and participate in an auction. The auction is initialized by a set of buyers, B, with a set of bids, β. Where $b_j = \{b_1, b_2, b_3, ..., b_k\}$ and $b_j \in \beta$ where $b_j > 0$. The outputs of the PMA are the selling energy $e^p_{k_{(i,j)}}$ and the profit of the seller $P_r(i)$. In stage 1, after the seller receives all demands, they will select the minimum demand as their selling energy e_k. The minimum demand is determined by arranging all recieved demands in ascending order and selecting the smallest amount. Alternatively, if the buyers all have demands above the maximum available surplus energy of the seller, the seller will set their selling energy e_k as their total surplus $e_i = e_k$. Next, the seller will present their selling energy e_k to the network. The buyers who are interested in the amount of energy e_k, will then submit their bid b_j using a sealed-bid mechanism [108] to the seller. In a sealed-bid mechanism the buyer with the highest bid wins but in this design, due to line cost c_l, the buyer which has the maximum corresponding $P_r(i)$ wins. The bid β will be from the buyers according to their evaluation on the amount of energy $e^p_{k_{(i.j)}}$. The evaluation of the buyers is given by $v_j = \{v_1, v_2, ..., v_m\}$. Recall that buyers have no information of the bids submitted by other buyers in the network and only communicate with the seller.

Furthermore, in stage 2 the seller i will calculate the individual profits corresponding to each buyer j after receiving the bids. This is done using Equation (4.1a), in which the total profit is determined from the bid from the buyer minus the transmission line cost and seller cost. The buyers that resulted in a positive profit continue further and the others buyers are eliminated from the list. Thus, the remaining buyers profits are sorted in ascending order. Then, the seller will check the constraints for the buyer with the maximum profit using Equation (4.1b). If the buyer meets all constraints they can win the auction and if their demand is met, they will be removed from the list. However, the seller can decide whether or not to sell the energy, enabled by the reverse auction mechanism [109]. Alternatively, if the buyer does not meet the constraints, then the buyer is eliminated and the next buyer with the highest profit is considered. Stage 2 continues until the energy e_k is sold or none of the buyers meet the constraints.

Assuming the buyer does meet the constraints, stage 3 occurs. Stage 3 is the payment process and the buyer j pays their submitted bid b_j to the seller and is awarded the selling energy e_k.

The buyers that lost will receive nothing in return. If the profit is maximum for a particular buyer j, then the payoff P_f of that buyer is the difference of the evaluation v_j and the bid offering b_j. The buyers $-j$ receive a payoff of 0. If the bid offering is equal to the maximum profit P_r, the buyer will pay the cost equal to the bid offered. Otherwise, the payoff will be zero and they do not receive the energy. The payoff function of the buyer is given below

$$P_f = \begin{cases} v_j - b_j, & \text{if buyer j won} \\ 0, & \text{otherwise} \end{cases}$$

If the winning buyer's j energy demand has been met after the award process, they will be eliminated from the buyer list B. If the seller has a remaining e_i, the PMA repeats back to stage 1 until the surplus energy of the seller is sold or the profit becomes negative. For each iteration the seller i will continue to set the minimum demand as their selling energy $e^p_{k_{(i,j)}}$. Where the minimum demand is chosen from the set $\alpha = \{b_1, b_2, b_3, ..., b_m\}$, $b_d \in \alpha$. In the case when $b_j < (c^p_i + c^p_l)$ the profit is negative and the seller will store their surplus energy in storage bank. The summation of all the bids from all the winning buyers is the total seller's reward, $\sum_{j=1}^{m} b_j$.

This proposed PMA is designed fair enough for all the buyers to present their bid offer and considers all players equally. This ensures that buyers with the minimum demand can compete with other buyers that require a large demand of energy. The profit of the seller depends on the bid from the buyers b_j and the losses due to transmission cost c^p_l and operating cost c^p_i. The seller cannot change the operating cost but can reduce the transmission cost by selling their energy to a nearby buyer in the network to further maximize their profit. This will increase the payoff of the seller.

Shown in Fig. 4.2 is an illustration of how the buyers and seller would communicate between each other. The working procedure consists of a seller who lets the network know they have energy for sale. Next, the seller receives the required demands from the buyers. Then, the seller selects the selling energy as the minimum demand, and displays the amount to the network. The buyers will then send their demands and bid offerings for that amount of energy.

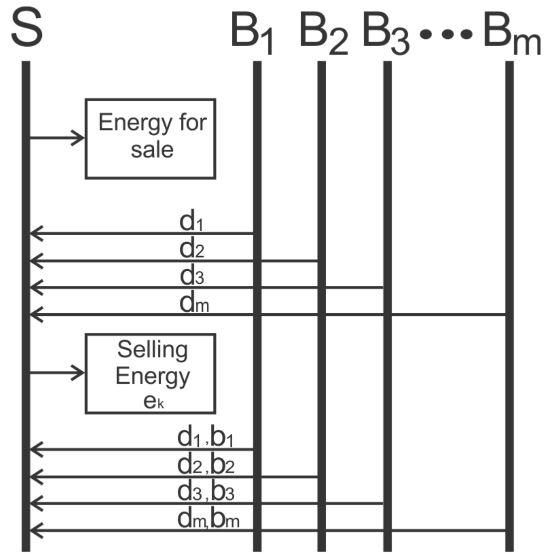

Figure 4.2: PMA working procedure

4.1.5 Numerical Results

In this section, we analyze the proposed system model and PMA using a multitude of case studies. For the first case study, a toy network is tested, composed of one seller and five buyers to explain the working procedures in detail. The seller is assumed to be a small factory able to generate their own energy requirements. This is illustrated in Fig. 4.3, in which the seller is denoted as S and the buyers are denoted as B_1, B_2, B_3, B_4, B_5. The path between the seller and buyers are denoted as P_1, P_2, P_3, P_4, P_5. For the remaining case studies, the number of buyers is significantly increased and the changes are observed. The results from the case studies are compared when using the proposed PMA and a first price bid method (FPB).

Simulation Setting

The algorithm was tested and simulated using MATLAB to obtain a solution for the following case studies. In the toy example, the seller has 100 kWh of surplus energy and the demand from the buyers ranges from [20-50] kWh. The operating cost of the seller is 1.2 cents per kWh and the assumed transmission capacity is 1000 kWh for all possible paths within the network. It is assumed that three of the buyers have one path to reach the seller and the other two buyers have two paths. The line cost ranges from [0.9 - 1.6] cents per kWh. The average grid flow throughout all possible paths is assumed to be 200 kWh. The buyers' offer ranges from [7-14] cents/kWh

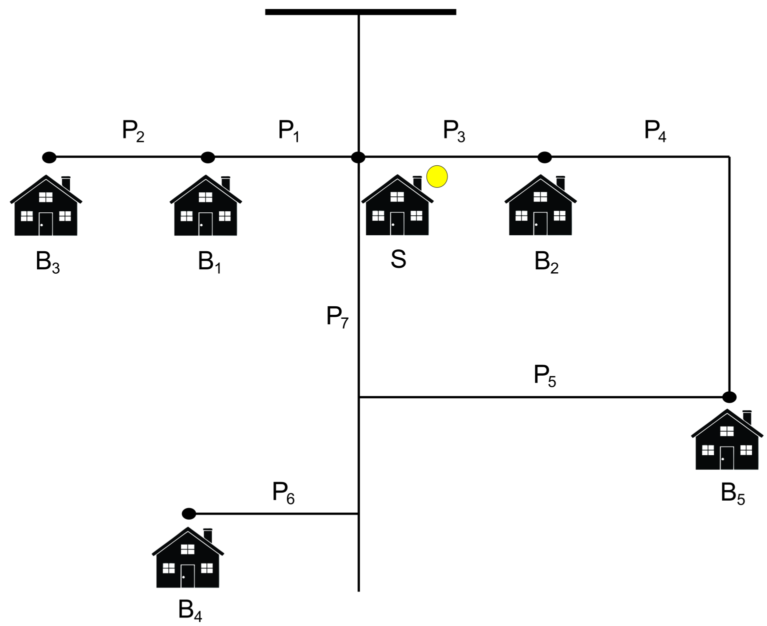

Figure 4.3: Schematic test diagram showing the paths between the sellers and the buyers

[110] in each iteration. We further consider the main electric grid as a seller with a higher sell cost compared to the seller. The ranges set are for simulation purposes only. We initialize the simulation with a set of buyer's demand. For latter case studies the number of buyers is increased from 20, 40, 60, 80, 100, and 300. In all cases, the seller has 5000 kWh of surplus energy and the demand from the buyers ranges from [40-1500] kWh. In the 300 case, the demands and line costs are generated using three different types of distributions.

Simulation Results

Using the FPB method the seller receives bid offerings from all buyers for their surplus energy $e_i = 100$ kWh. The seller then calculates the profit $\mathrm{P_r}$ for each buyer using Equation (4.1a). The highest profit calculated was 180 cents for the demand of 50 kWh from buyer 5. The seller then distributes this 50 kWh surplus energy to buyer 5. Similarly, the seller distributes 20 kWh and 30 kWh to buyer one and two respectively. All surplus energy distributed generates a net profit of 330 cents.

Using the PMA the seller selects the minimum demand from the set of buyers $min(d_j) =$ 20kWh. Therefore, the selling energy $e_{k_{(i,j)}}$ is set to 20kWh. The seller then receives bid offerings b_j for this selling energy and calculates the profit using Equation (4.1a) for each buyer. Next,

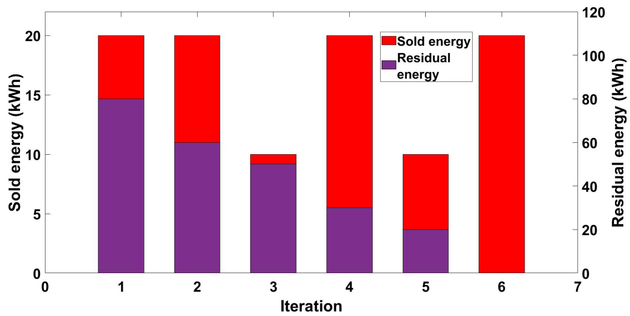

Figure 4.4: Sold and residual energy of the seller for each iteration from the proposed auction mechainsm

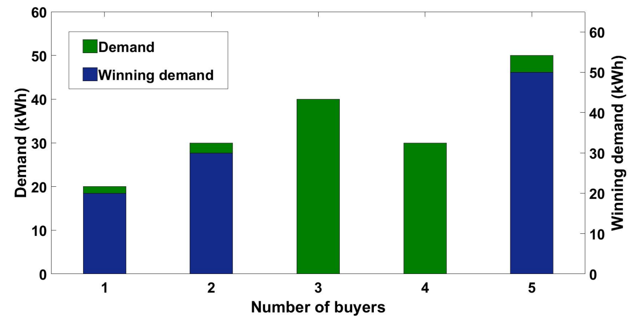

Figure 4.5: Demand and winning demand for each buyer from proposed auction mechanism

the seller distributes the energy to the buyer with the highest calculated profit if the constraints are met. In the first iteration, the highest profit calculated was from buyer 5 with a value of 250 cents and the constraints were met. Thus, the 20 kWh is received by buyer 5. In each iteration, the seller continues to select the minimum demand as the selling energy and repeats the same procedure until the seller is left with no surplus energy remaining or the profit result is negative. The simulation took six iterations for this case study to distribute the 100 kWh of surplus energy, generating a total net profit of 350 cents.

Fig. 4.4 represents the sold and residual energy of the seller from the proposed algorithm. In each iteration, the seller distributes 20 kWh, 20 kWh, 10 kWh, 20 kWh, 10 kWh and 20 kWh respectively. Fig. 4.5 represents the demand of each buyer and how much energy each received from the seller. Buyer 1, 2, and 5 all receive their required energy demands. Due to the line costs and the minimal surplus of energy, buyer 3 and 4 do not acquire any energy.

We now make a comparison between FPB and PMA. Recall, that in the FPB the seller selects the maximum bid without initializing their selling energy as the minimum demand presented from the set buyers, β. In our proposed system model, the iteration count takes longer to compute the optimal buyer but generates a larger profit. Fig. 4.6 displays the profit generated by the seller after each iteration using the PMA. The total profit of the seller is the summation from each profit generated after each iteration, resulting in a total net profit of 350 cents. Fig. 4.7 depicts the difference in the profits of the seller between the FPB and the proposed auction mechanism. From the results, it is concluded that the profit from our proposed algorithm significantly out performs the existing FPB method.

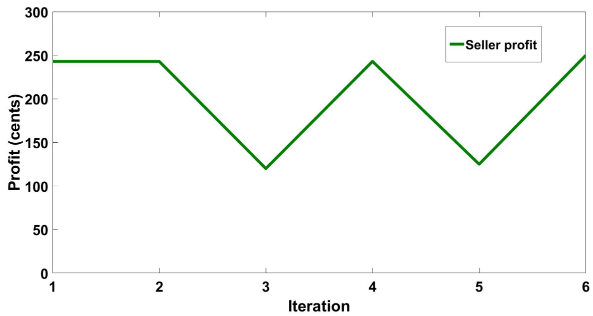

Figure 4.6: Profit generated by the seller in each iteration from the proposed auction mechanism

Figure 4.7: Comparing the profits from the seller in first price bid with the proposed auction mechanism

Next, the PMA and the FPB are applied and tested in a more practical scenario where there is a total of 20 buyers with a demand ranging from [100-800] kWh with a line cost of [5-50] cents. The seller surplus energy e_i is 5000 kWh. Fig. 4.8 represents the demand from the 20 buyers as well as the winning buyers using FPB method. It is observed that only 2 buyers attain a winning demand compared to all 40 buyers with a profit of 11500 cents.

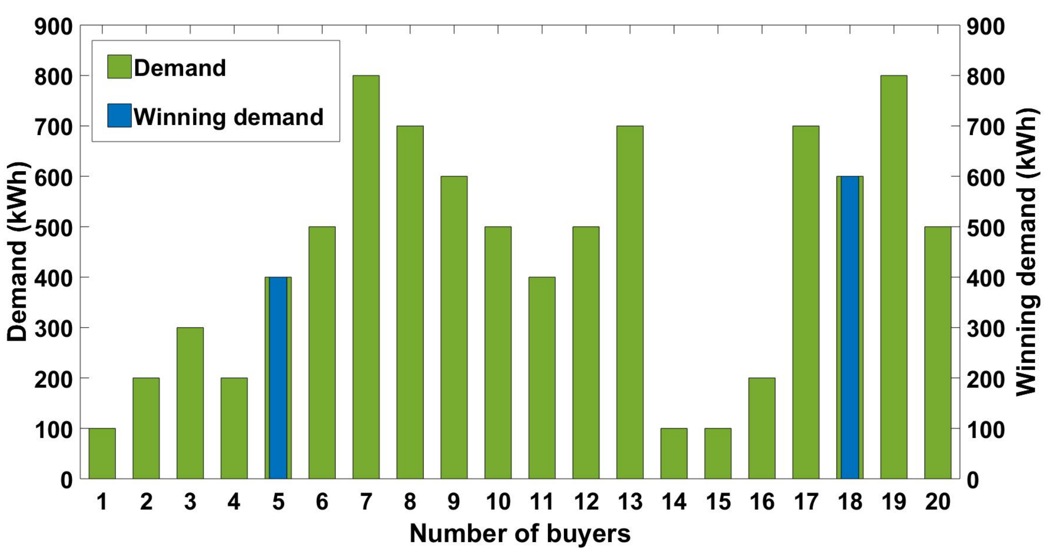

Figure 4.8: Demand and winning demand energy for each buyer from the first price bid method

Fig. 4.9 displays the demand from all 20 buyers and the winning demand using PMA. It is observed that a significant amount of buyers attain a winning demand, and most importantly, there is a large increase in the generated profit for the seller with a total net of 14750 cents.

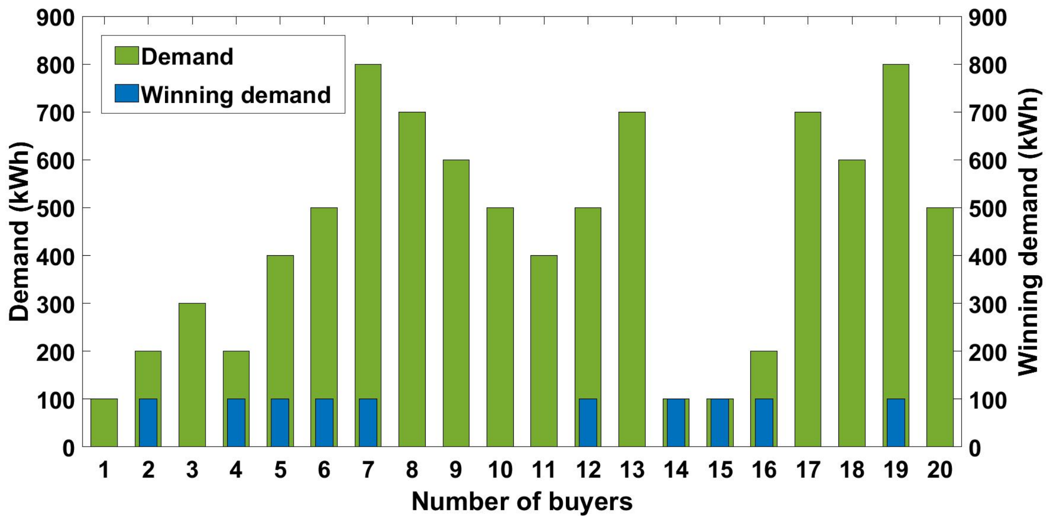

Figure 4.9: Demand and winning demand energy for each buyer from the proposed auction mechanism

Comparing the profit of the seller with the two methods (FPB and PMA) is shown in Fig. 4.10 for 20 buyers. It is observed that the seller generates more profit using the PMA approach than the FPB method. Demonstrating effective performance for P2P energy trading.

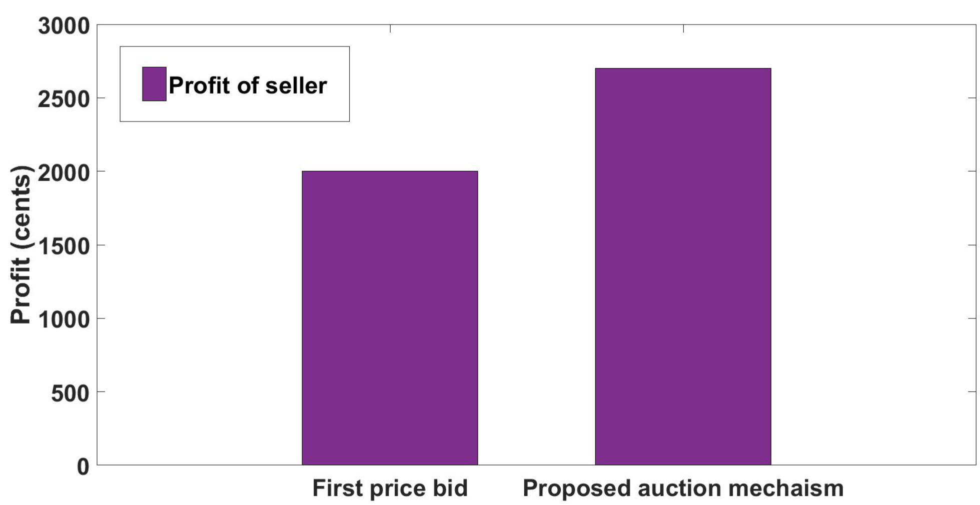

Figure 4.10: Comparing seller's net profit using first price bid with the proposed auction mechanism

Furthermore, we increase the number of buyers from 20 to 100 in steps of 20 with demands [500-3000] kWh and the line cost are [7-12] cents. The surplus energy is 5000 kWh. The profit variations from both FTB and PMA methods are shown in Fig. 4.11. Similarly, it is assured that the PMA outperforms the first price bid.

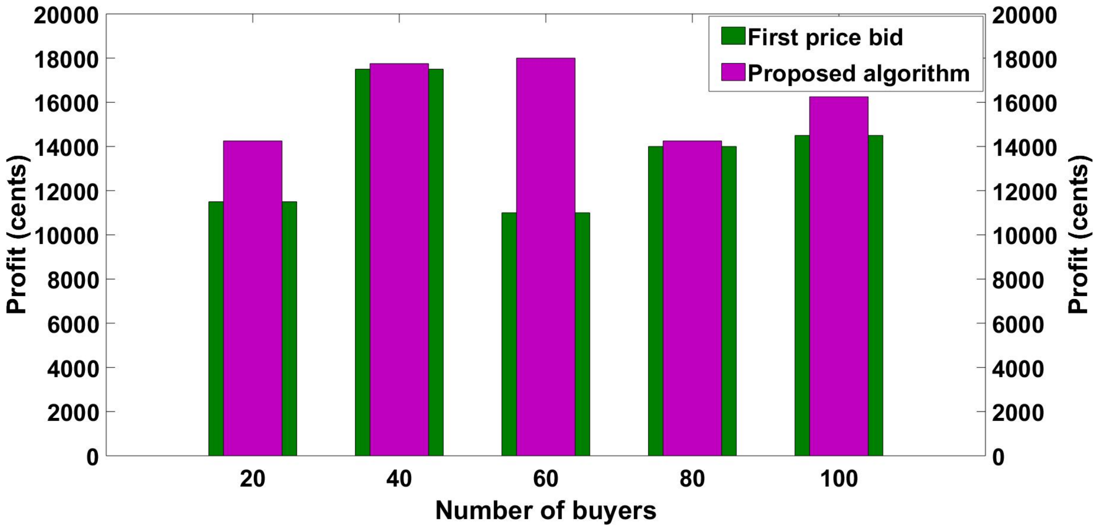

Figure 4.11: Comparing the profits from the seller in first price bid with the proposed auction mechanism

We now analyze the simulation results in more detail. For explanation purposes we will study the case of 40 buyers in different scenarios. For example, it is possible that all buyers may have the same bid offering to the seller. In addition, it may be possible that the line costs are the same as well. Therefore, we can study these cases in more detail. In the first scenario, suppose all 40 buyers have a bid of 6000 cents for a demand of 500 kWh and the line costs vary from [7-10] cents/kWh. For the second scenario, assume the line costs are 8 cents/kWh for all 40 buyers and the bid ranges from [5000-6750] cents. In the third scenario, we assume all bids are the same and the distances between the seller and all 40 buyers are the same. As shown from Table 4.1, when using the FPB and the proposed mechanism, the profit of the seller is larger in comparison for the first two cases. However, in the the third case, the profit of the seller is same using both mechanisms. Although, in the proposed mechanism, more buyers are winning the auction. Finally, we express the simulations results from above when the buyers have a different bid and line cost. Observing that the seller generated 17500 cents using FPB and 17750 cents using the PMA. From these results we further conclude that even under various scenarios the PMA outperforms the FPB method.

Fig. 4.12 displays the profit generated during 24 hours for the proposed mechanism, with an

40 buyers		
	First price bid	Proposed mechanism
Same bid	15000	15500
Same line cost	17000	18970
Same bid and line cost	14000	14000
Different bid and line cost	17500	17750

Table 4.1: Profit of the seller

increased amount of buyers in the network. Each time slot corresponds to a two hour period. The profit maxed at t9 which corresponds to the peak demand time during the day, where as t2 corresponds to a reduced demand. During the peak time region the grid is a buyer and we can assume sellers can achieve higher profit returns by selling their surplus energy to the grid directly. The results overall demonstrate that the profit is always larger using the PMA compared to the FPB method. It is further demonstrated that the optimal time to sell energy is during peak time.

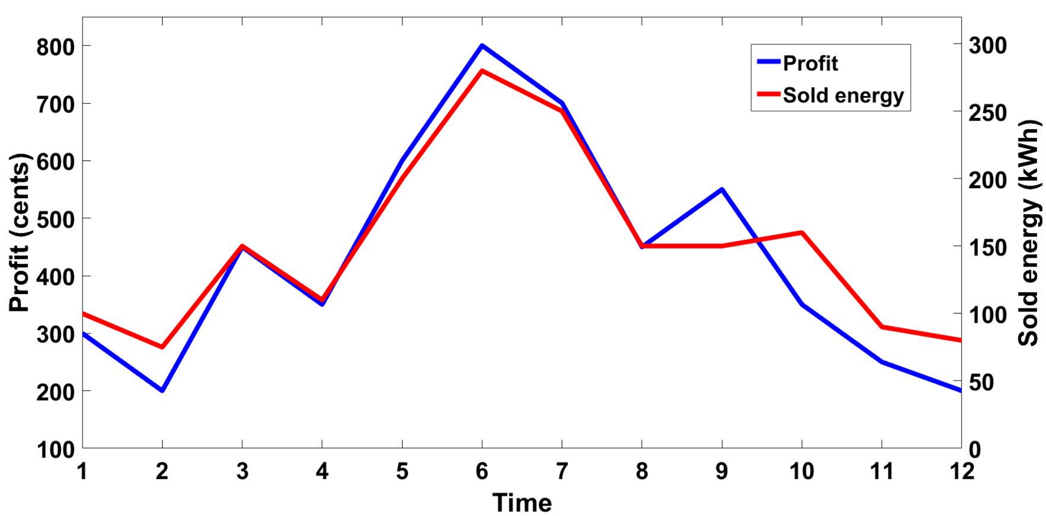

Figure 4.12: Profit generated by the seller at different time slot in a day

Fig. 4.13 shows the profit generated by the seller in all three methods: FPB, SPB and the proposed mechanism. All methods are analysed using different distributions, normal, exponential and uniform. As shown from the results, the proposed mechanism outperforms the FPB and SPB method, in which the sellers profit is maximum for all three cases. However, recall that the SPB method is the most truthful and is similar to the FPB method as it only varies in the payment. The winning buyer will pay the second most winning buyer's bid, which will increase the payoff of the buyer since the winning buyer pays a decreased bid price. In addition, this will decrease the seller's profit.

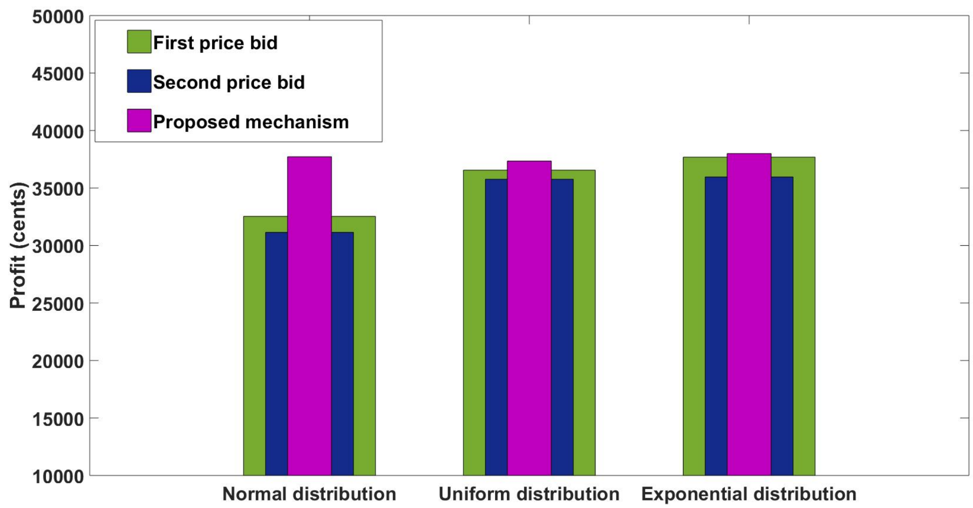

Figure 4.13: Comparing profit generated by the seller with 300 buyers using first price bid, second price bid and proposed mechanism for a normal, exponential and uniform distribution

Fig. 4.14 shows the total bid from all 300 buyers using a normal, uniform and exponential distributions. In addition, the figure also shows the winning bid of the buyers. We observe that the normal distribution has the highest total and winning bid cost.

Table 4.2 shows the computation time for 20 - 300 buyers. Observing that as the buyers increase from 20 - 300, the time increases from 1.3 to 3.4 ms which is bounded. As a result, the time complexity does increase with an increase number of buyers and the optimal solution is computed in limited time.

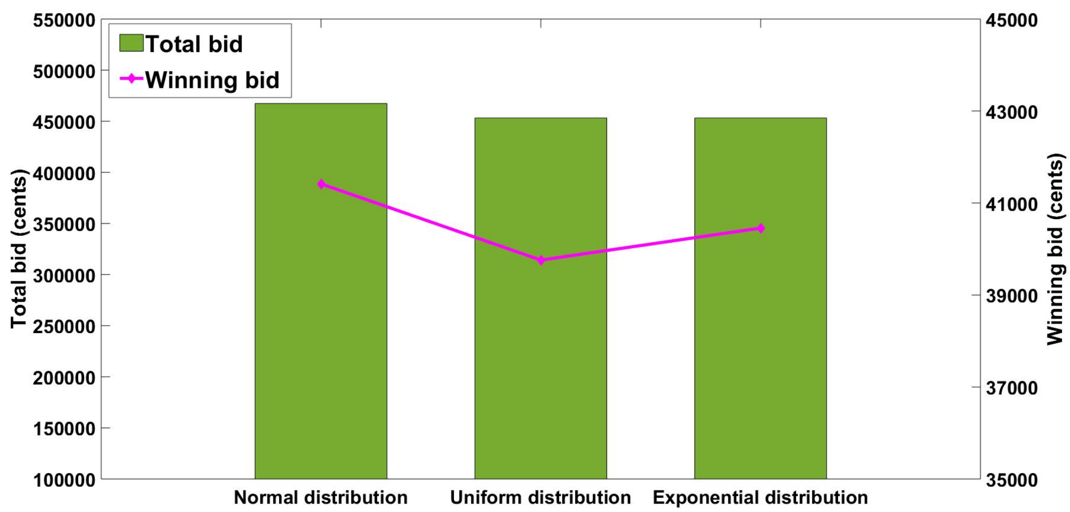

Figure 4.14: Comparing the total bid with the winning bid for 300 buyers using the proposed mechanism at normal, exponential and uniform distribution

Time Requirement						
Number of buyers	20	40	60	80	100	300
Time (ms)	2.3	2.78	2.91	3.02	3.06	3.47

Table 4.2: SSMB Time Complexity

High Demand - Buyers

In this proposed model, the seller selects the minimum demand as the selling energy in each iteration. This may in fact look as if we are giving importance to the buyer with minimum demand. However this is not the case. By selecting the minimum demand, we allow the seller to consider all buyers within the network, resulting in a fair game. In addition, it considers all possible cases for the seller to maximize their profit return.

Sellers' Cost

We used 1.2 cents per kWh as the sellers cost and the line cost ranges from [0.9 - 1.6] cents per kWh for the simulation purpose. The sellers cost c_i for different renewable sources in Table 4.3 is from [111] and the average distribution cost is 1.072 cents per kWh from Hydro - Thunder Bay, ON, Canada.

Renewable Energy Cost		
Sources		Cost in cents per kWh
Solar	Thermal	12-18
Geothermal	Electricity	2 - 10
	Heat	0.5 - 5.0
Biomass	Electricity	5 - 15
	Heat	1 - 5
Wind	Onshore	3-5
	Offshore	6-10
Hydro	Large scale	2 - 8
	Small scale	4-10

Table 4.3: Renewable energy cost in cents per kWh

4.2 MSSB

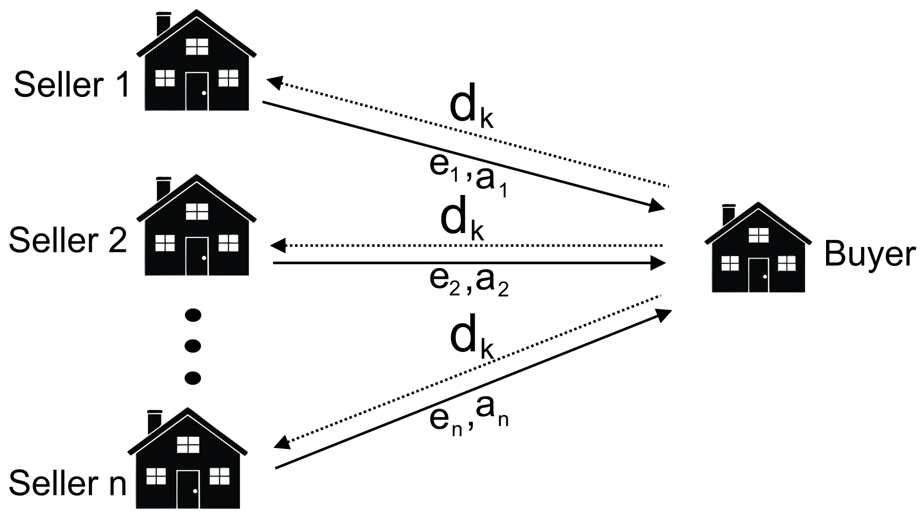

Figure 4.15: MSSB energy trading model

In this section, the model describing the P2P energy trading process for multiple sellers and a single buyer is presented. Fig. 4.2 illustrates the communication flow and energy transfer between the sellers and buyer. Recognizing the no sellers communicate with each other and only communicate with the buyer. The primary motivation for the development of this model is to reduce and minimize the buyer's energy system costs by utilizing a proposed cost minimization algorithm (CMA). The network design and problem description of the proposed model us discussed in detail with an in depth discussion on the CMA mechanism. Numerical results and simulations are performed to test and compare the CMA against the first and second price bid mechanisms.

4.2.1 Network Design

The set of sellers in the network is represented as $S = \{1, 2, 3.., n\}$ where $i \in S$ and contain a surplus energy $E = \{e_1, e_2..., e_n\}$, where $e_i \in E$. Each seller has a ask price which is denoted as $A = \{a_1, a_2..., a_n\}$ where $a_i \in A$. The ask of the seller depends on the line cost c_l and the seller's cost c_i which includes generating and operating cost. Buyers are represented as $B = \{1, 2, 3.., m\}$ where $j \in B$. However, in this model, there is only one buyer $j = 1$. The demand of the buyer is represented as d_j with a valuation of V_j. The paths between the sellers and buyers are denoted as $p_{(i,j)} = \{p^1_{(i,j)}, p^2_{(i,j)}, p^3_{(i,j)}.., p^z_{(i,j)}\}$.

Each path has its own line cost c_l, and transmission capacity x^p_{cap} and. Additionally, the energy that is currently flowing through the path is denoted as $y^p_{g_{(i,j)}}$.

4.2.2 Problem Description

The buyer's objective is to minimize the cost based on the sellers ask a_i offerings. Here, the seller is only paying the line cost when selling the surplus energy e_i to the buyer. The buyer's goal is to find the cheapest cost compared to all the sellers in the network. The purchasing cost $\mathrm{C_{ost}}$ of the buyer is expressed in Equation (4.1a).

$$\mathrm{C_{ost}(j)} = \sum_{i=1}^{n} a_i \tag{4.2a}$$

$$\textbf{s.t.} \sum_{i=1}^{n}\sum_{j=1}^{m}\sum_{p=1}^{z} d^p_{j_{(i,j)}} < (x^p_{Cap} - y^p_{g_{(j,i)}}) \tag{4.2b}$$

$$\sum_{j=1}^{m}\sum_{p=1}^{z} d^p_{j_{(i,j)}} \leq D_j, \forall j \in B \tag{4.2c}$$

Equation (4.2a) represents the total cost of the buyer which is given as the summation of all the winning sellers ask a_i. The constraint given in Equation (4.2b), ensures that the demand energy, $d^p_{j_{(i,j)}}$, never exceeds the transmission line capacity, x^p_{Cap}. This is needed to ensure the safety of the transmission grid in which the demand energy $d^p_{j_{(i,j)}}$, should always be less than the difference between the total amount of transmission line capacity x^p_{Cap}, and the current amount of electricity flowing in the line, $y^p_{g_{(i,j)}}$. The constraint given in Equation (4.2c), ensures that the buyer cannot purchases energy from a seller more than the total demand D_j. In the following part, the proposed CMA is presented showing showing the working procedure of the mechanism.

4.2.3 Cost Minimization Algorithm

Input: Surplus energy e_i, Sellers ask a_i, Transmission line capacity x^p_{Cap}, Grid flow y^p_g, Seller cost c_i and total demand Td_j.

Output: Selling energy e_k, Instant demand d_j and Buyer's cost $\mathrm{C_{ost}(j)}$.

Stage:1 Determining the instant demand d_j

Sort e_i in ascending order **foreach** $e_i \in E$ **do**

    if $(min(e_i) < Td_j)$ **then**
        $\min(e_i) = d_j$
    else
        $Td_j = d_j$
    end

end

Stage:2 Determining the selling energy

if $e_i > d_j$ **then**
    $e_k = d_j$
else
    $e_i = d_j$
end

Stage:3 Determining the winning seller

foreach $a_i \in A$ **do**
    Sort i in ascending order w.r.t a_i
    if $(\mathrm{C_{ost}(j)} \leq V_j)$ **then**
        Check constraints for i
        if $(d^p_j < (x^p_{Cap} + y^p_g))$ **then**
            Buy it from the seller, i
        else
            eliminate that seller i
            Repeat for i+1
        end
        repeat till $Td_j = 0$
    else
        Buy energy from the grid
    end
end

end

Algorithm 2: Cost Minimization Algorithm(CMA)

4.2.4 Proposed Algorithm

A simplified illustration of the CMA algorithm in working progress can be seen below in Fig. 4.16. The CMA initializes after the buyer indicates to the sellers that they are in need of energy demand. In the first stage, the buyer receives responses from the sellers indicating their current surplus energy e_i. The buyer will then sort this information in ascending order and select the minimum demand denoted as instant energy d_j. This process in critical to ensure fairness within the network. Alternatively, if the buyer receives demands above or equal to their total demand, they will set their total demand as d_j. This stage is the essential part for the buyer to determine the instant demand d_j. The second stage initializes with the buyer lets the sellers aware of the instant demand d_j. The sellers determine the amount of selling energy e_k by comparing it with the instant demand d_j. If the surplus energy e_i is greater than the received d_j, then the seller will set their selling energy e_k as d_j. Alternatively, the seller will set their surplus e_i as d_j. The sellers will respond back to buyer with the selling energy e_k or e_i depending on the previous condition. Additionally, the seller will respond with the ask a_i which depends on their line cost c_l to reach the buyer and the seller cost c_i for generating and operating purposes. This is the essential stage for the sellers to determine their selling energy. In the next stage, the buyer determines the winning seller. This is accomplished by sorting the ask a_i in ascending order according to their seller. Then, the buyer will select the seller with the minimum ask and check the constraint given in Equation (4.2b). If the constraint is met, the seller wins the auction and the energy is transmitted to the buyer. If the winning seller has their surplus energy completed depleted in this process, they are removed from the list. If however, the constraint was not met, the seller is removed from the set S. This process will repeat until the total demand of the buyer is zero. Alternatively, if the calculated cost is greater than the buyers valuation, the buyer will purchase their energy directly from the grid. The payment of the buyer is equal to the bid b_j the buyer offered.

4.2.5 Numerical Results

In this section, we perform a similar analysis and simulations using a toy example with one buyer and four sellers to test the performance of CMA. We assume the sellers are small factories able to generate their energy requirements. For the remaining case studies, the number of sellers is significantly increased and the changes are observed in the simulations results. We

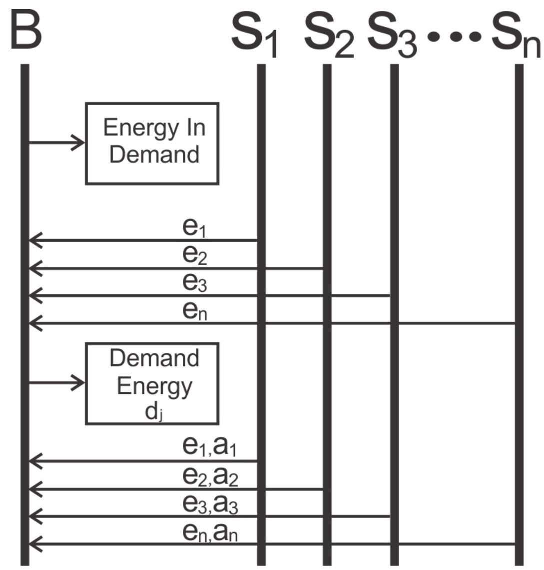

Figure 4.16: CMA working procedure

also consider various ideal scenarios for a randomly chosen case study to observe the end effects. In addition, the CMA is compared with a the first and second price bid mechanisms to evaluate the performance of the proposed mechanism.

Simulation Setting

The CMA algorithm was tested and simulated using MATLAB to obtain a solution for the case studies. In the toy example the buyer has an energy demand of 60 kWh and the surplus energy from the sellers ranges from [20-80] kWh. The operating cost of the seller is 1.2 cents per kWh and the line cost ranges from [0.9 - 1.6] cents per kWh. The assumed transmission capacity is 1000 kWh for all possible paths within the network. It is assumed that sellers have one path to reach the seller and the other two buyers have two paths. The average grid flow throughout all possible paths is assumed to be 200 kWh. The sellers' offer ranges from [7-14] cents/kWh [110] in each iteration. We further consider the main electric grid as a seller with a higher sell cost compared to the seller. The ranges set are for simulation purposes only. We initialize the simulation with a set of seller's surplus energy. For latter case studies the number of sellers is increased from 20, 40, 60, 80, 100, and 300. In all cases, the seller has 5000 kWh of surplus energy and the demand from the buyers ranges from [40-1500] kWh. In the 300 case, the demands and line costs are generated using three different types of distributions.

Simulation Result

The simulations results from the toy example depicting the surplus and sold energy with respect to each seller is shown in Fig. 4.17. From here, we observe that both seller 1 and seller 2 were able to completely distribute and sell their energy to the buyer. Most importantly, we observe that the seller with lowest amount of surplus was also still able to play and win the auction. Furthermore, we now make a comparison using the CMA with the first and second price bid mechanism. As shown from Fig. 4.18 we observe that the buyer's cost is significantly more using the second price bid mechanism. We also observe that the buyer achieves reduced energy costs when utilizing the proposed CMA.

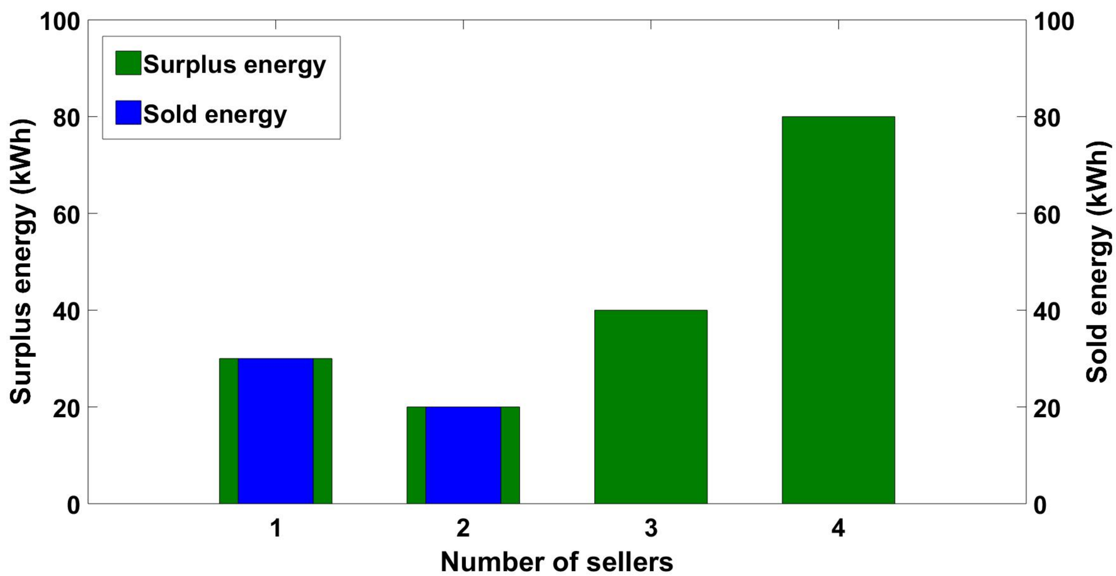

Figure 4.17: Toy Example: Surplus and sold energy for each seller when using the proposed mechanism

Next, we now investigate a more practical case study. Thus, the number of sellers is increased from 4 to 20. Fig. 4.19 displays the sold and surplus energy of all 20 buyers when employing the FPB mechanism. Observing that only four of the twenty buyers were able to sell their energy to buyer. Comparing these results with the results from Fig. 4.20, which depicts the sold and surplus energy of the sellers when using the CMA mechanism. We observe that an increase in amount of buyers were able to obtain a profit and distribute energy to the buyer. Here, a total of seven buyers were able to obtain profit as compared to four. From these results, it is expected

Figure 4.18: Comparing buyer's energy cost from 4 sellers using first price bid, second price bid and proposed mechanism

that the buyer's cost are significantly reduced since the CMA optimizes the P2P energy trading process in a more effective manner. This observation is clearly presented in Fig. 4.21. Observing that the CMA outperforms the first and second price bid mechanisms by reducing the buyer's cost significantly.

We continue the process of increasing the number of sellers form 20 to 100 in steps of 20 and compare the simulation results of the various mechanisms. Shown in Fig. 4.22. displays the buyer's cost when the network contains 20 to 100 buyers and the CMA, first and second price mechanisms are employed. The results display that no matter the number of sellers in the network, the buyer obtains a optimized and reduced energy cost when the CMA is utilized. Demonstrating effective performance for a practical P2P energy trading process.

We now study extreme scenarios in the network when there is a total number of 60 sellers. For the first and second scenario, we assume that the unit price and line cost is the same respectively. The third scenario assumes both the unit price and line costs are the same. When the line costs are the same we can assume that all sellers are located at equivalent distances to the buyer. The last scenario, which is when the sellers have different unit prices and line costs is used from the previous results to compare with the above scenarios. Shown in Table 4.4, depicts the

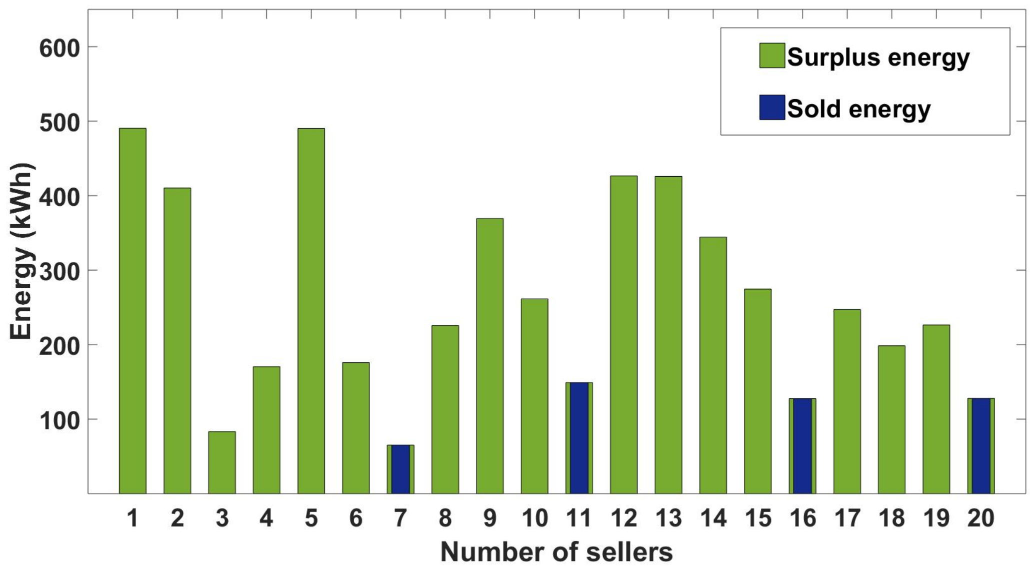

Figure 4.19: Surplus and sold energy for each seller using the first price bid method

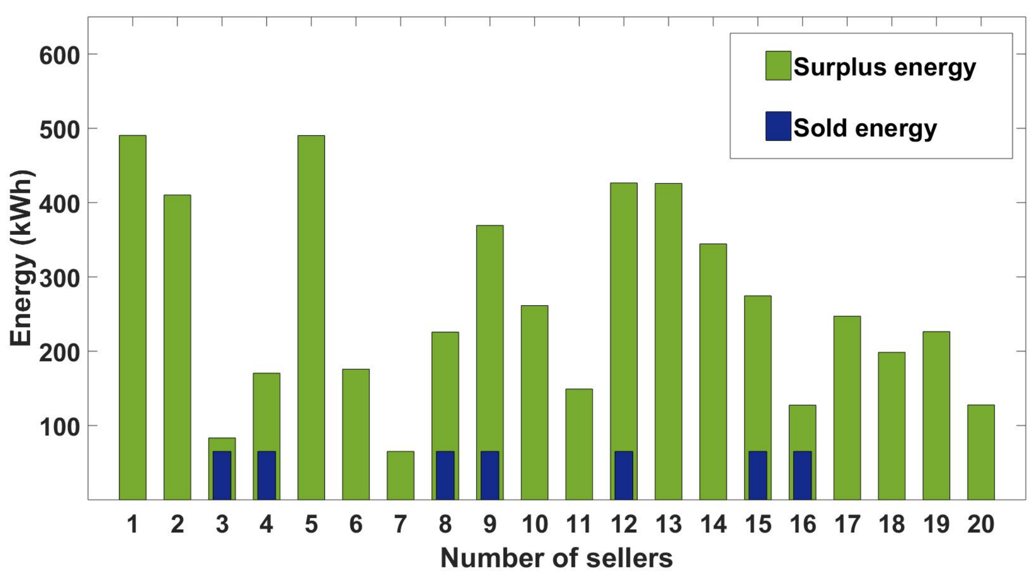

Figure 4.20: Surplus and sold energy for each seller using the proposed mechanism

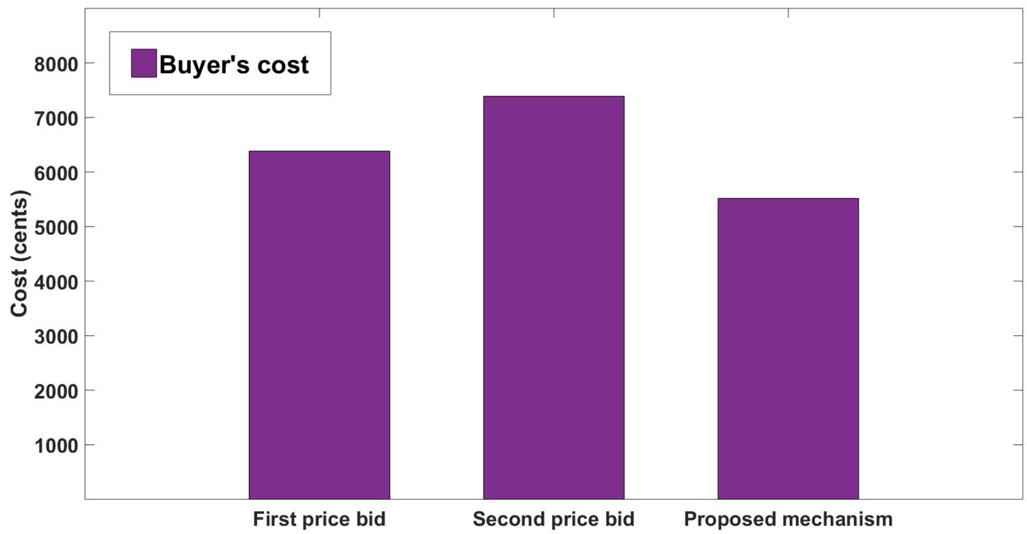

Figure 4.21: Comparing buyer's energy cost from 20 sellers using first price bid, second price bid and proposed mechanism

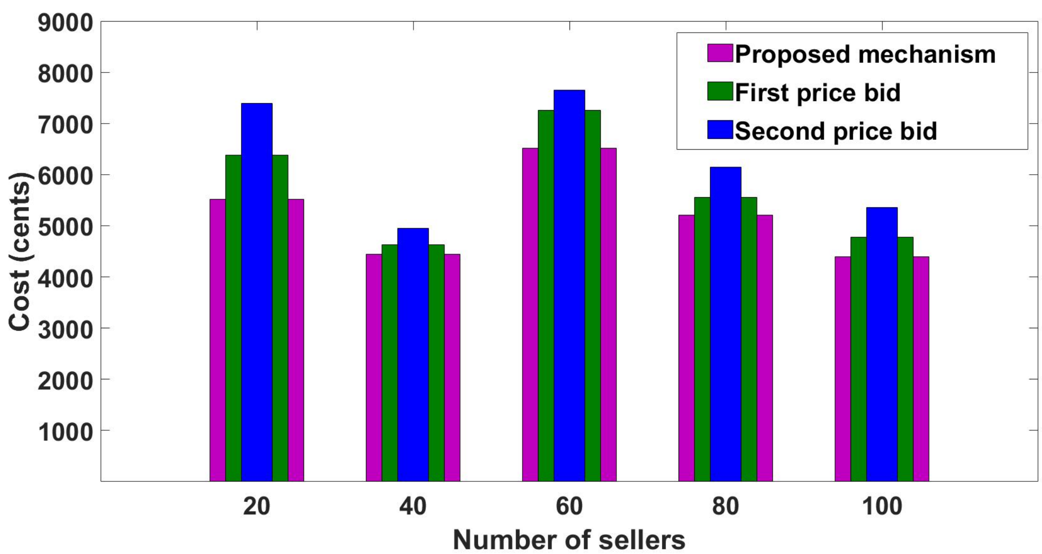

Figure 4.22: Comparing buyer's energy cost from various number of sellers using first price bid, second price bid and proposed auction mechanism

buyer's energy costs for all scenarios. We observe that even under extreme cases, the proposed mechanism continues to outperform the first and second price mechanisms.

60 sellers			
	First price bid	Second price bid	Proposed mechanism
Same unit price	6904	7230	6595
Same line cost	7350	7888	6611
Same unit price and line cost	7000	7430	7000
Different unit price and line cost	7255	7646	6518

Table 4.4: Analysing 60 sellers at different scenarios

Furthermore, the simulations are performed testing 300 sellers when distributed using a normal, uniform, and exponential function. Shown in Fig. 4.23 depicts the buyer's energy cost for each mechanism and distribution function. Observing that when using the CMA for a normal distribution, the buyer's energy costs are minimal. Additionally, using a uniform distribution and the second price bid mechanism, the buyer obtains the highest energy costs. Nonetheless, the CMA outperforms the alternative mechanisms when the sellers are distributed using various functions.

Shown in Fig. 4.24 illustrates the comparison with the total ask and the winning ask while using the proposed mechanism. As shown, the exponential distribution attains the highest winning ask in comparison with the normal and uniform distributions. Lastly, the time complexity curve is analyzed by determining the computation time for all simulated case studies, which is shown in Table 4.5. Observing that the time does not increase when their is an increase in the seller count, thus, the curve is bounded.

Table 4.5 shows the time complexity of the MSSB simulations. Observing as the sellers increase from 20 - 300, the time increases from 1.26 - 2.8 ms. As a result, the time complexity is bounded and the optimal solution is computed in limited time.

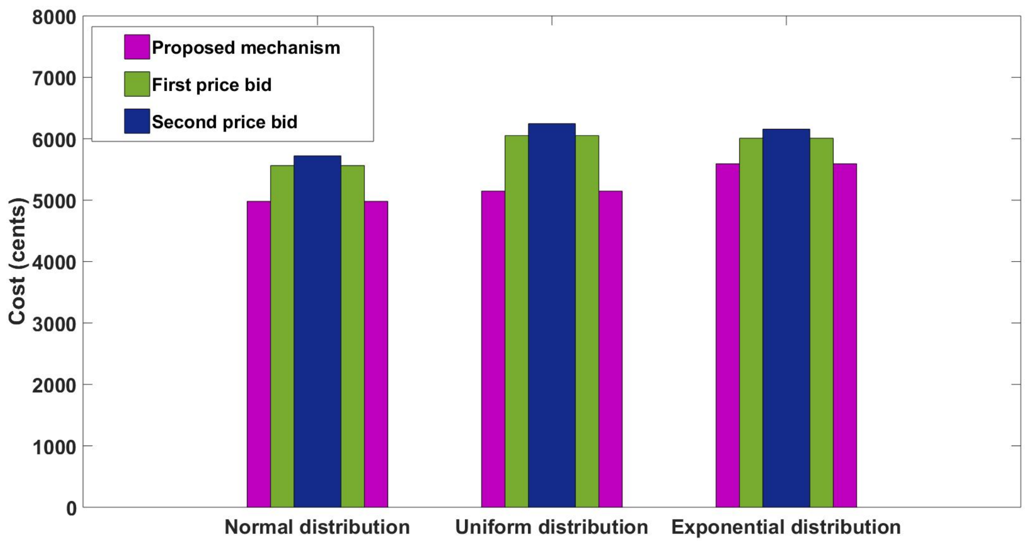

Figure 4.23: Comparing the cost of the buyer with 300 sellers using first price bid, second price bid and proposed mechanism at normal, uniform and exponential distribution

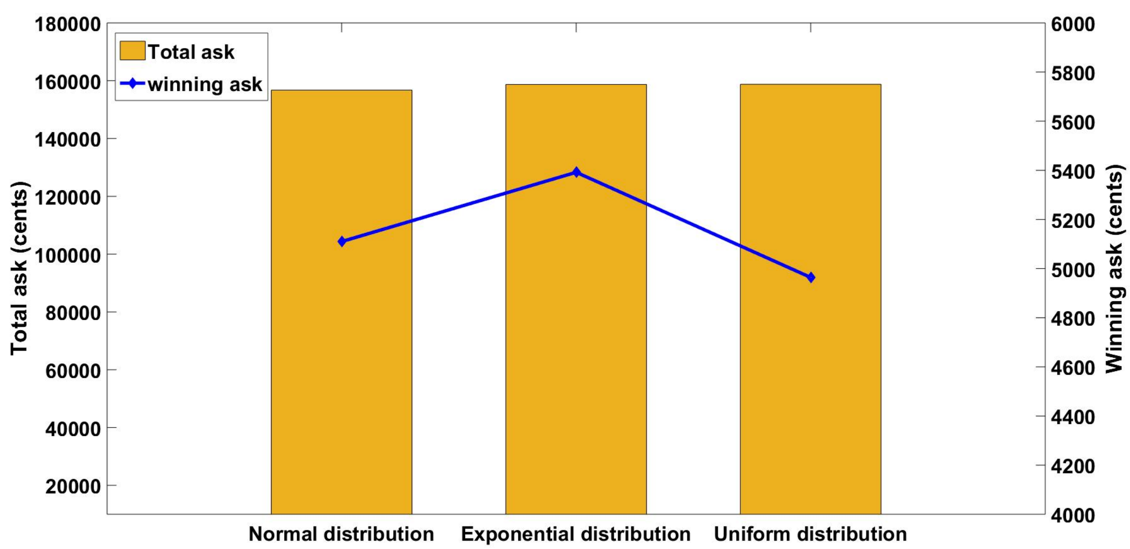

Figure 4.24: Comparing the total ask with the winning ask for 300 sellers using the proposed mechanism for normal, uniform and exponential distribution

Time Requirement						
Number of sellers	20	40	60	80	100	300
Time (ms)	2.334	2.876	3.003	3.12	3.63	3.47

Table 4.5: MSSB Time Complexity

4.3 Proof of Desirable Properties

This section presents the mathematical and descriptive proofs for the desirable properties of both the CMA and PMA. Recall, the properties from Chapter 2 that describe an effective system are individually rational, truthfulness, fairness, and computational efficiency.

Property 1. Individually rational

PMA is individually rational

Proof: In PMA there are two conditions needed for the buyer to win the auction.

- $\forall\, b_j \in \beta$ the bid submitted by the buyer should generate a maximum profit.
- The energy transferred to the buyer should always follow the constraints from Equation (4.1b).

If any buyer satisfies these two conditions then that particular buyer j will be winning the auction and pays the bid b_j the buyer j submitted. The buyers $-j$ lose the auction and does not pay anything. Which clearly states that no single buyer loses profit by participating in the auction and do not generate a negative payoff.

The seller sells the energy only when the bid b_j from buyer j generates a positive profit. If the profit is not positive, the seller is not selling the energy to that buyer. This ensures the seller payoff is always positive when participating in the auction. Both the seller and buyer do not lose anything in the PMA which proves the designed algorithm is individually rational to all the players.

CMA is individually rational

Proof: In the CMA there are three conditions required for the seller to win the auction.

- $\forall\, a_i \in A$ the ask submitted to the buyer should be the minimum cost from all sellers.
- The foremost condition is the ask should be greater or equal to the buyer's valuation ($a_i \geq V_j$)
- The transferring energy should always follows the constraint in Equation (4.2b).

If any seller cleared these three stages then that particular seller i will be winning the auction and sells the energy to the buyer. In return, the buyer pays the ask a_i as the payment to the seller. The rest of the sellers $-i$ lose the auction and do not sell anything to the buyer. Furthermore, the losing sellers $-i$ do not generate any positive or negative profit. If the $\mathrm{C}_{\mathrm{ost}} > V_j$ then the buyer will not purchase the energy from the seller. This ensures that the buyer is not paying more than the valuation and the seller is not receiving anything less than the ask. Moreover, this algorithm makes sure that the payoff of all the users remains zero or positive and no one loses anything by participating in the auction. This proves the designed algorithms, PMA and CMA, which use a single-sided auction mechanism are individually rational and no users lose anything by participating in the proposed auction mechanism.

Property 2. Computational efficiency

PMA is computationally efficient

Proof: The PMA algorithm initiates with sorting the demands in ascending order. Finding the minimum demand takes $O(n \; log \; n)$ of time complexity. Next, a FOR loop is used to check all the demands d_j, which have a time complexity of $O(m)$. Next, assigning the minimum demand as the selling energy ($min(d_j) = e_i$) can be obtained in $O(1)$ time. The total time complexity of stage 1 is $O(nm \; log \; n)$. Stage 2 initiates with calculating the profit using the bids b_j from all the buyers. This requires a FOR loop with time complexity of $O(n)$, followed by sorting the profits of the buyer with time complexity $O(m \; log \; m)$. Checking the constraints can be obtained in $O(1)$ time. The total time complexity of stage 2 is $O(m \; log \; m)$. Therefore, the computational complexity of PMA is bounded by $O(m \; log \; m + nm \; log \; n)$ Table 4.2 shows that the computational efficiency of PMA which is bounded by a limited time.

CMA is computationally efficient

Proof:

The CMA algorithm initiates with sorting the surplus energies e_i from the seller in ascending order. Finding the minimum demand takes $O(n\ log\ n)$ of time complexity. Next, a FOR loop is used to check all the demands d_j, which have a time complexity of $O(m)$. Lastly, assigning the minimum surplus energy as the demand ($min(e_i) = d_j$) can be obtained in $O(1)$ time. The total time complexity of stage 1 is $O(nm\ log\ n)$. In stage 2 we are checking the condition using an IF statement which requires time $O(1)$. Stage 3 Checking the constraints can be obtained in $O(1)$ time. The total time complexity of stage 2 is $O(m\ log\ m)$. Therefore, the computational complexity of CMA is bounded by $O(m\ log\ m + nm\ log\ n)$. Table 4.5 shows that the computational efficiency of CMA which is bounded by a limited time.

Property 3. Truthfulness

PMA is truthful

Proof: We assume that the buyers follow VCG mechanism for submitting the bids which ensures truthfulness in the mechanism.

- If any buyer j submits a low bid, the buyer j cannot generate additional profit to the seller and will not get a chance for winning the auction. Thus, even if any buyer cheats, this proposed mechanism will never let the cheating buyers to win.
- In this mechanism the seller does not have any ask price, so there is no possible way for the seller to cheat.

Concluding that buyer and seller cannot cheat using the algorithm. This demonstrates truthfulness exists in the proposed mechanism.

CMA is truthful

Proof: We assume that the sellers follows the VCG mechanism for submitting the asks to the buyer, which ensures truthfulness in the mechanism.

- The only possibility of the seller with the high ask to win the auction is only when the cost of the seller c_i is greater than or equal to the valuation of the buyer V_j. If any seller i submits a high ask to the buyer, and if the seller's i ask a_i is the lowest ask compared to all the sellers $-i$, then the seller i will win the auction unless the ask is greater than the valuation which will not increase the buyer's cost since it is less than the sellers cost.
- In this mechanism the buyer does not have any bid price, therefore there is no possible ways for the buyer to cheat in this mechanism.

Concluding that the buyer and seller cannot cheat using the algorithm. This shows truthfulness exists in the proposed mechanism.

Property 4. Fairness

PMA is fair

Proof: All buyers can bid for their energy demand. Even the buyer with lowest demand can participate in this auction mechanism. When the seller selects the more significant bid following the first price bid mechanism, the seller might have a better chance of losing the buyer with a lower bid, but this algorithm ensures the possibility of winning the buyer with the lower bid.

CMA is fair

Proof: All sellers can send the ask price for their surplus energy according to their generating and line cost. Even the seller with lowest surplus energy can participate in this auction. When the buyer selects the highest ask by following the first price bid mechanism, the seller is more likely of losing the buyer with a lower bid, however this algorithm ensures the possibility of the winning of the buyer with the lower bid.

4.4 Discussion

This chapter demonstrated two different model based on a single-sided auction mechanism for P2P energy trading in the smart grid. The initial model was targeted for multiple buyers and a single seller. The network design and problem description of the model were presented. In addition, the constraints and profit formulation was also demonstrated. As a result, the seller was able to optimize their profit return when using the proposed PMA mechanism. Extensive simulations were tested to ensure the validity of the mechanism. In addition, alternative distribution functions were tested when employing the buyers. The PMA was compared with the existing FPB method and as a result the PMA continually outperformed in all aspects. The critical properties to ensure effectiveness in the mechanism was also demonstrated through proof analysis, resulting in a fair, efficient, truthful and rational mechanism. Demonstrating a useful auction approach for practical energy trading.

The second part of the chapter presented an alternative approach in P2P energy trading concerning the buyer's perspective. In which a model for a single buyer and multiple sellers was presented, demonstrating both the network design and problem descriptions. The formulations for the constraints were stated and the total energy cost of the buyer as well. The model was tested using a proposed CMA mechanism, in which motivation was to minimize the buyer's energy cost. The CMA was tested and compared with the first and second price bid mechanisms. As a result, the CMA outperformed the existing methods in all manners. The CMA was also resulted in a fair, efficient, truthful and rational mechanism.

Chapter 5

Proposed Double - Sided Auction

In this chapter, a proposed system model is demonstrated for a P2P energy trading market (ETM) composed of multiple buyers, sellers, and an auctioneer. The sellers are individuals in the ETM that have generated a surplus of energy by use of renewable energy sources and are looking to distribute the excess power for a profit. Similarly, the buyers are individuals in the ETM who are seeking to meet their energy demand requirements at a lower profit. The buyers and sellers are both dynamic players with an active response between them by interacting and negotiating their cost for their excess energy and the demands. The auctioneer is introduced in the network for performing all interactions and negotiations. The auctioneer's primary function is used for matching the sellers with the optimal buyers for maximizing the overall profit return within the ETM. Moreover, multiple sellers with individual ask prices are used in this model which the auctioneer uses for the optimization. The chapter begins with a detailed representation of the ETM. Next, the market model is presented for all members of the ETM. The auction-matching algorithm (ATM) is then demonstrated with simulation results and analysis. Further conclusions are then presented.

5.1 Energy Trading Market

As depicted in Fig. 5.1, the ETM consists of an auctioneer and a set of sellers and buyers. The sellers and buyers in the ETM are active players with continuous communication with the auctioneer. The market runs in a decentralized platform with bi-directional communication. As a result, energy and communication flow is transmitted via seller to auctioneer and buyer to auctioneer. Thus, the energy is traded in a P2P fashion [9].It is further considered that the

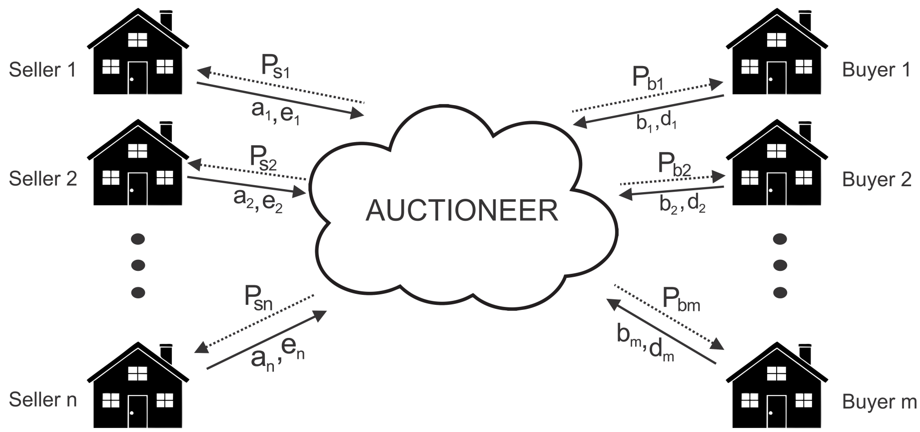

Figure 5.1: Energy trading model for double-sided auction

losses are minimal within the distribution feeders [112]. The auctioneer is the primary function of the ETM and controls and operates the entire network. Nothing that the buyers and seller do not communication directly. The sellers will communicate with the auctioneer regarding their current surplus energy, and the buyer interacts with the auctioneer regarding their current energy requirement and bid offering. With this given information, the auctioneer has to match the buyers with the sellers concerning system efficiency, truthfulness, and budget balance. In addition, the auctioneer's motivation is to optimize the social welfare within the P2P ETM.

5.2 Market Members Modeling

The market is formed by the number of active sellers and buyers. The sellers are the individuals who generate energy from a type of renewable source, and upon meeting their local demands, seek to distribute their excess energy e_i for a price in the EMT to generate a profit. The set of sellers are denoted as $S = \{1, 2, 3..., n\}$ where $i \in S$. The sellers cost, c_i is the cost for the seller to generate and maintain their energy, e_i. The summation of the operating cost c_o and generating cost c_g is the total cost c_i of each seller.

$$c_i = c_o + c_g \tag{5.1}$$

The generating cost c_g is a quadrative convex function [88] with predetermined constants. The operating cost c_o is the cost of maintaining and operating the power generating device. All the buyers and sellers in the ETM are required to pay the line cost c_l when using the infrastructure supplied by the central grid for transferring and receiving energy. The surplus energy from the seller can be transferred to many buyers and the subset is formed $e_i = \sum_{j=1}^{m} d_j$. Each seller has a individual ask price according to the cost function of the surplus energy. The ask is denoted as $A = \{a_1, a_2, a_3 ..., a_n\}$ where $a_i \in A$. The sellers receive a reward P_{si} for generating and selling their surplus energy, and the auctioneer chooses that reward price. The welfare of the seller is given by

$$W_{Si} = P_{si} - \Big[c_i + \sum_{j=1}^{m} [e_i * c_l]\Big], \tag{5.2}$$

where P_{Si} is the reward received by each seller, c_i and c_l are the seller cost and line cost and e_i is surplus energy. Equation (5.2) is the total welfare of each seller, and each sellers' goal is to maximize their welfare.

Buyers are the players who are willing to buy their energy demands from the sellers in the ETM. The set of buyers are denoted as $B = \{1, 2, 3..., m\}$ where $j \in B$ with their demand is given $\alpha = \{d_1, d_2, d_3, ..., d_m\}$, $d_j \in \alpha$. The bid for their required energy demand is denoted as $\beta = \{b_1, b_2, b_3, ..., b_m\}$, $b_j \in \beta$. For using the transmission lines from the central grid, each buyer needs to pay the line cost c_l according to their demand and load on the line. Furthermore, each buyer has their own valuation on the energy which represents their satisfaction level from the available energy sources from the market and the valuation function should be a non-decreasing function [113]. Thus, the valuation is denoted by $V = \{V_1, V_2, V_3, ..., V_m\}$, $V_j \in V$ and the equation for valuation of each buyer is from [88] shown in Equation (5.3) considering ξ_j and ϖ_j as predetermined constants

$$v_j = \xi_j d_j - \varpi_j d_j^2, \forall j \in B \tag{5.3}$$

The demand of the buyer is met with the summation of all the received energy from the buyers $d_j = \sum_{i=1}^{n} e_i$. The buyers pay the payment P_{bj} for buying the surplus energy to the seller and the payment price P_{Bj} is chosen by the auctioneer. Shown below in Equation (5.4) represents the welfare of the buyer.

$$W_{Bj} = V_j - \Big[P_{bj} + \sum_{i=1}^{n} [d_j * c_l]\Big]. \tag{5.4}$$

Where V_j is the valuation, P_{bj} is the payment, d_j and c_i are the demand and operating costs receptively. The primary motivation all players is to maximize their welfare, and the goal of this market is to maximize the total social welfare. Therefore, we want to maximize the following equation.

$$max \sum_{i=1}^{n} \sum_{j=1}^{m} (W_{Si} + W_{Bj}) \tag{5.5}$$

Where n and m are the total number of the sellers and the buyers. This convex problem is solved by having a third party called an auctioneer, which is placed between the buyers and the sellers. The auctioneer follows an auction mechanism to decide the winner.

5.2.1 Auction Process

The double-sided auction is considered as a game with sellers and buyers as players following the bid and ask from the individual player's valuation. The valuation of the individual players are not known by the auctioneer [114]. The auctioneer matches the buyer with the seller according to the ask and bid from the seller and buyer. The auction is initialized only when the asks are greater than the bid ($a_i < b_j$) and there will be no auction when ($a_i > b_j$) or ($a_i = b_j$), thus a VCG mechanism exists in this auction. In a VCG mechanism, if the bid is equal or lesser than the ask, then no trade takes place between the seller and buyer. Furthermore, each seller sends their excess energy e_i to the auctioneer, and at the same time, each buyer sends their demand d_j to the auctioneer. The role of the auctioneer is to match the buyers with the sellers following properties and conditions.

5.2.2 Price and Line Cost

The auctioneer calculates the price λ after collecting all bids and demands, (b_j, b_d) from the buyer and all the surplus energy and ask price, (e_i, a_i) from the sellers. Where n and m are the total number of seller sand the total number of the buyers in the network respectively. The price λ is calculated based on the double auction process with an average mechanism, given by the following expression.

$$\lambda = \frac{\sum_{i=1}^{n} \frac{a_i}{e_i} + \sum_{j=1}^{m} \frac{b_j}{d_j}}{n+m} \tag{5.6}$$

where a_i, b_j, e_i, d_j are the ask, bid, surplus energy, and demand respectively. The price λ is calculated at a particular instant in time within the EMT. When using the grid for transporting and receiving energy, sellers and buyers need to pay the line cost c_l. The line cost varies and depends on the amount of energy being transported from seller to buyer. The line cost expressed from [88] is shown in Equation (5.7).

$$c_l = \sum_{p=1}^{z} \frac{PTDF_{ij} * nl}{y_g} \tag{5.7}$$

where z and nl is the total number of paths and lines respectively, y_g is the energy flowing on the particular path and $PTDF_{ij}$ (Power Transfer Distribution Factor) is a linear approximation of the distribution factor in a CRR (Congestion Review Rights) model [115] which indicates the fraction of transferred power between the seller i and the buyer j. $PTDF_{ij}$ for single line l by Υ is shown in Equation (5.8) [88]

$$\Upsilon_l^{\varpi} = \Upsilon_l^i - \Upsilon_l^j. \tag{5.8}$$

Where $\varpi = \{i, j, t\}$ is the transferred t unit of energy from the seller i to buyer j. The injection shift factor (ISF) in the line l is given by Υ_l^i and Υ_l^j for bus i and j.

5.2.3 Fair Price Range

The fair price range is calculated to determine the price which can benefit both the buyer and seller from the low bid and high ask respectively. This calculation ensures no buyers have bids that are too low and additionally, no sellers have asks too high. The auctioneer can use the below method to calculate the fair range for the buyers and sellers in an auction. Any buyer that bids lesser than the price range is a loss for the seller and any seller who asks higher than the price range is a loss to the buyer. Therefore, it is necessary to determine an optimal range where both the buyers and sellers can agree on a price. This equation will help in determining the price range needed to benefit both parties, thus, no buyers and sellers will face any losses. There are multiple factors which make it hard to determine the fair ask price for sellers, as each of them has various alternative generating costs due to the different energy generating devices, such as Solar, Hydro, Wind, etc. Hence, we can only fix a range and not the actual cost, leading to the following expression

$$\lambda_{min} \leq \lambda \leq \lambda_{max}. \tag{5.9}$$

Where λ_{min} is the average of all buyers bids lesser than the λ and λ_{max} is the average of all the sellers asks greater than λ. Denoted as

$$\lambda_{min} \leq \frac{b_j}{d_j}$$

and

$$\lambda_{max} \geq \frac{a_i}{e_i}$$

.

According to this method, the buyer's bid cannot be lesser than λ_{min} and the seller's ask cannot be higher than the λ_{max}. All the buyers with bids below the λ_{min} and the sellers with ask greater than λ_{min} will be removed from the auction and cannot participate in the auction. The calculation of λ_{min} and λ_{max} are demonstrated below to calculate the fair price range.

5.2.4 Assumption and Preconditions

The following assumptions and preconditions for the ETM are presented before continuing further.

- The losses are less while trading energy.
- The buyer receives the amount of energy the seller sends.
- The auctioneer has all required information of the network.
- No interaction between the sellers and buyers.
- No interaction between the seller i with other sellers $-i$ and buyer j with other buyers $-j$.
- If $(\frac{a_i}{e_i} > \lambda_{max}, \forall i)$ or $(\frac{b_j}{d_j} > \lambda_{min}, \forall j)$, then i or j are eliminated from the market.

In the following section the auction matching mechanism is proposed discussing the critical stages of the process.

5.3 Auction-Matching Algorithm

Stage:1 Matching

Input Buyers demand d_j, Buyers bid b_j,Surplus energy e_i, Sellers ask a_i .
Output Seller group S_g^i, Buyers group B_g^j .
foreach $i \in S$ *and* $j \in B$ **do**
  if $(\frac{a_i}{e_i} < \frac{b_j}{d_j})$ **then**
    Form seller group and buyer group.
    $j \in S_g^i$
    $i \in B_g^i$
  else
    $j \notin i$, $i \notin j$
  end
end

Stage:2 Determining the winning buyers and sellers

Input Seller group S_g^i, Buyers group B_g^j, Total Demand Td_j and Total energy Te_i .
Output Winning seller S_w^i, Winning buyers B_w^j .
foreach $a_i \in A$ *and* $d_j \in \alpha$ **do**
  sort i, a_i in ascending order
  sort j, d_j in descending order
  if $(Te_i < Td_j)$ **then**
    if $(e_i = d_j)$ **then**
      buyer j won energy from seller i
    else
      $\forall d_j \subset S_g^i \neq e_i$
      Select the buyer with maximum demand
    end
    continue the process till $e_i = 0$
  else
    if $(d_j = e_i)$ **then**
      seller i is selected for buyer j
    else
      $\forall e_i \subset B_g^j \neq d_j$
      Select the seller with minimum ask
    end
    continue the process till $d_j = 0$.
  end
end

Algorithm 3: Auction-Matching Algorithm (AMA)

5.4 Energy Allocation

Energy allocation using greedy method, in which a seller with the minimum ask is given priority to buyers with equal or the highest demand compared to the sellers, and buyer with the highest demand is preferred first to the sellers with an equal surplus energy or lesser ask. The auctioneer determines the matching between the buyers and the sellers following the conditions. The matching is achieved by changing orders with preference structures and optimizing the social welfare [116]. As the auctioneer does not see the buyer's valuation and seller's cost of generating the energy, the auctioneer can only fix some conditions for the seller's ask, and the buyer's bid when it is not too big or too low compared to the market value. Besides, the auctioneer wants to make sure that no buyer pays more than the bid and no seller receives less than the ask.

5.4.1 Matching

Matching condition checks the unit price of the sellers and buyers and forms a group where sellers ask is higher than the buyer's bid shown in Equation (5.10).

$$\frac{a_i}{e_i} < \frac{b_j}{d_j}. \tag{5.10}$$

Condition, ensures that no seller receives the reward lesser than the ask ($P_{Si} \not< a_i$). Therefore, it would be optimal for the auctioneer to pick any one value between the ask a_i and bid b_j as the reward P_{Si} and payment P_{Bj} to the seller and buyer. It also assures that the auctioneer's welfare has also remained positive.

An example is shown below for a further understanding of the proposed matching concept. Let us consider 5 sellers {S1, S2, S3, S4, S5} and 5 buyers {B1, B2, B3, B4, B5} in the ETM. Each seller has an ask a_i and surplus energy e_i similarly, each buyer has a demand d_j and bid b_j. The seller and buyer group is denoted as S_g^i and B_g^i. The buyers B1, B2 and B3 satisfies the Equation (5.10) for S1, and these three buyers forms a group under the seller S1 as $S_g^1 =$ {B1, B2, B3} likewise, each sellers will have an individual group $\{S_g^1, S_g^2, S_g^3, S_g^4, S_g^5\}$ with the buyers who all satisfies the Equation (5.10) for the individual sellers. The sellers S3, S4, S8 and S9 fits the Equation (5.10) to B5. Moreover, these 4 sellers form a group with the buyer B5 as $B_g^5 =$ {S3, S4, S8, S9}. Similarly, each buyer will have an individual group $\{B_g^1, B_g^2, B_g^3, B_g^4, B_g^5\}$ with the sellers who all obey the Equation (5.10) for the individual buyers.

5.4.2 Condition

let us assume the cost of sellers and buyers are equal, thus

$$c_l + b_j = c_l + a_i$$

Now since both the sellers and buyers need to pay the line cost, we can eliminate the line cost from the previous equation, hence

$$b_j = a_i$$

$$b_j \to v_j,\ a_i \to c_i.$$

The bid of the buyer depends on the buyer's valuation but the ask of the seller depends on the generating and operating cost. Therefore, the valuation of the buyer can never be equal to the generating cost. This is the reason why we are checking if the bid is higher than the ask in the above condition to make it fair for both buyer and seller. Therefore, the buyers bid cannot be equal to the sellers ask price.

$$b_j \neq a_i.$$

The main reason we match the buyers with the higher bid to the sellers with the lesser ask as in Equation (5.10), is to always ensure that the social welfare of the market Is increased. This is because social welfare depends on each player, which will increase the profit of the sellers and reduce the cost of the buyer. Thus the social welfare is increased

5.4.3 Selecting the Winning Buyer and Seller

Winning sellers and winning buyers are determined under two various scenarios. In scenario 1, the total surplus energy of the seller is lesser than the total demand of the buyer in the EMT ($Te_i < Td_j$) and in scenario 2, the total demand of the buyers is lesser than the total surplus energy of the seller ($Td_j < Te_i$) in ETM.

Scenario 1 ($Te_i < Td_j$)

Under this scenario, the total surplus energy is lesser than the total demand ($Te_i < Td_j$) in the ETM. Therefore, all the sellers in the market will be cleared easily leaving some buyers without meeting the demand.

1. Sellers with the minimum ask are preferred first.
2. Buyers with equal demand ($d_j = e_i$) to the seller's surplus energy are cleared first.
3. $\forall d_j \subset S_g^i \neq e_i$

If no buyer's demand is equal to the seller surplus energy ($d_j \neq e_i$) then the buyer with highest demand in the group S_g^i are cleared first. In the previous section, each seller has a group S_g^i of eligible buyers under them. After sorting the sellers in ascending order concerning the ask a_i, check if any buyers demand is equal to the surplus energy ($d_j = e_i$) and if the condition is met, the seller and buyer won the auction. If no demand is the same as the surplus energy ($d_j \neq e_i$), then the buyer with the highest demand from the seller group S_g^i can win the seller's surplus energy. Repeat the same two process until the seller has no surplus energy left. Follow the same procedure for all the sellers in the market clearing the sellers with minimum demand apex.

Scenario 2 ($Td_j < Te_i$)

In this scenario, the total demand is lesser than the total surplus energy ($Td_j < Te_i$) in the ETM. Therefore, the buyers are preferred first and all buyers easily can meet the demand leaving some sellers without selling the surplus energy.

1. Buyers with higher demand are cleared first.
2. Sellers with equal ask or minimum ask are preferred first.

From the grouping section, each buyer has a group B_g^i of sellers under them. After sorting the buyer with the highest demand, check if any seller from the corresponding group of the buyer has the same surplus energy as the buyer demand ($e_i = d_j$) and if the condition is met, the buyer and seller won the auction. If no surplus energy is equal to the demand ($e_i \neq d_j$), then the seller with minimum ask is cleared first. Repeat the same two procedures until the buyer's demand met. Follow the same for all the buyers in descending order clearing the buyers with maximum demand at the apex.

Payment and Reward

We assume each seller and buyer follow VCG mechanism for payment which ensures the truthfulness among the players. The buyer pays the payment P_{Bj} for buying the demanded energy, and the seller receives the reward P_{Si} for selling the surplus energy. The auctioneer is the one who selects the price for payment and reward. The buyer payment should never be greater than the bid b_j, and the seller reward is never lesser than the ask a_i which is the essential condition for the design to follow the properties of individual rationality, truthfulness, budget-balanced and fairness.

There are two types of payment methods that can be used for this model:

- 1. *Random value*: In this method, the auctioneer picks a random value between the bid b_j and ask a_i of the winning buyer and seller. For example, consider that the winning buyer has a bid b_j of 20 cents, and the winning sellers has a ask a_i of 10 cents. The auctioneer will now select any value between from 11 cents to 19 cents. Then, this will be payment of the buyer and the reward of the seller.

- 2. *Second price bid*: In this method, the auctioneer selects the second highest bid as the winning buyer's payment for the reward of the seller.

Further, two types of incomes are available for the auctioneer, the first method makes "no income" or "zero income" for the auctioneer which follows a strong budget balanced (SBB) property, and the next method, "makes income" or "positive income" to the auctioneer which follows weak budget balanced (WBB) property. The auctioneer should generate revenue for matching the sellers and the buyers which will motivate the auctioneer to do the role. In the first income method, the auctioneer can pick any value in-between the a_i and b_j as the reward P_{Si} and payment P_{Bj} to the seller and buyer after matching the buyer with the seller. Equation (5.11) will return nothing to the auctioneer. Still, the system remains budget-balanced since no participators including the auctioneer pay-off are in negative range.

$$b_j > P_{Bj} = P_{Si} \geq a_i \tag{5.11}$$

The matching is established with the ask of the sellers is lesser than the buyer's bid ($a_i < b_j$). So, if the auctioneer makes the whole bid b_j as the payment P_{Bj} from the buyer and pays it s the reward P_{Si} to the seller, then the auctioneer will generate zero income. The income of the auctioneer is the difference between the payment and the reward, given by Equation (5.12).

$$AuctioneerRevenue = P_{Bj} - P_{Si} \tag{5.12}$$

To generate positive income, the auctioneer should equate the payment to the bid and equate the reward to the ask as shown in Equation (5.13) so, the difference between the payment and reward will be the income of the auctioneer.

$$b_j = P_{Bj}, a_i = P_{Si} \tag{5.13}$$

Equation (5.13) ensures that the auctioneer welfare is also increased and the system follows the property budget-balance since no participators including the auctioneer lose anything. Thus, the VCG mechanism optimizes the social welfare with truthfulness, and allows the buyer to submit a true value. If the buyer does not provide a real value, the buyer will not get anything in return.

These are the procedure that are designed for the auctioneer follow.

5.5 Numerical Results

For the following simulation, we consider fifteen users in total, with seven buyers and eight sellers. The bid and the ask are of true valuation and true cost [9]. The below table shows the number of sellers, i and buyers, j with their surplus energy e_i, ask a_i, demand d_j, and bid b_j.

Sellers and Buyers List					
Sellers, i	Selling energy, e_i	ask, a_i	Buyers, j	demand, d_j	bid, b_j
1	10	80	1	20	300
2	20	240	2	40	220
3	30	330	3	70	1050
4	50	550	4	10	60
5	10	90	5	10	100
6	60	780	6	20	300
7	60	720	7	40	480
			8	30	450

Table 5.1: An illustrative example for model 2

5.5.1 Simulation Setting

The algorithm was tested and simulated using C-programming. The surplus energy of the seller ranges from [10-60] kWh, and the ask for the surplus energy ranges from [80-780] cents. It shows each seller has the ask range [7-14] cents per kilowatt [110]. The demand from the buyer ranges from [10-70] kWh and bids for the demanded energy range from [60-1050] cents.

Which shows each buyer's valuation of energy ranges from [6-18] cents. A walk-through example is shown below explaining the working of the algorithm.

5.5.2 Simulation Result

Eligibility

The first thing to do is to check all the sellers and buyers that are eligible for the auction. This step calculates λ, λ_{min} and λ_{max}. The calculated values are $\lambda = 11.5$ cents, $\lambda_{min} = 7.16$ cents and $\lambda_{max} = 12.3$ cents from Equation (5.5). λ_{min} is the average of bids from buyer whose bids are lesser than λ and λ_{max} is the average of asks from seller whose asks are greater than λ. The sellers with ask above the λ_{max} and the buyers with bid lesser than λ_{min} are automatically eliminated from the auction. Thus, seller {S6}, buyer {B2 and B4} are excluded from the auction. Sellers:{S1, S2, S3, S4, S5, S7} and buyers:{B1, B3, B5, B6, B7, B8} are only allowed in the auction.

Grouping

This is the first stage the auctioneer does after receiving all the surplus energy e_i and ask a_i from the seller and all the demand d_j and bid $b)j$.

- Seller 1 has $e_i = 10$ kWh with $a_i = 80$ cents which results with a unit price of 8 cents. According to the algorithm, all the buyers greater than the unit price of 8 cents are in the group of seller 1. Thus, buyers {B1, B3, B5, B6, B7, B8} Are grouped with the seller 1 with the demand of {20, 70, 10, 20, 40, 30}. Similarly, all the buyers with a higher bid than the sellers ask are present in each seller's group.

- Seller 2 has $e_i = 20$ kWh with $a_i = 240$ cents is grouped with buyers {B1, B3, B6, B8} with the demand of {20, 70, 20, 30} kWh.

- Seller 3 has $e_i = 30$ kWh with $a_i = 330$ cents is grouped with buyers {B1, B3, B6, B7, B8} with the demand of {20, 70, 20, 40, 30} kWh.

- Seller 4 has $e_i = 50$ kWh with $a_i = 550$ cents is grouped with buyers {B1, B3, B6, B7, B8} with the demand of {20, 70, 20, 40, 30} kWh.

- Seller 5 has $e_i = 10$ kWh with $a_i = 90$ cents is grouped with buyers {B1, B3, B5, B6, B7, B8} with the demand of {20, 70, 10, 20, 40, 30} kWh.

- Seller 7 has $e_i = 60$ kWh with $a_i = 720$ cents is grouped with buyers {B1, B3, B6, B8}with the demand of {20, 70, 20, 30} kWh.

Winning Buyers and Sellers

Now, here the auctioneer follows two conditions to make the auction process fair and value.
1. Sellers with lesser asks are given first priority.
2. Buyers with higher demands are cleared first.

Matching the buyers with the sellers, at first the auctioneer looks if any buyer's demand is equal to the sellers surplus energy $d_j = e_i$ inside the first seller group. If so, then the seller can sell the surplus energy to the buyer with the same amount of demand. If not, the auctioneer selects the buyer with the higher demand to the seller. Finally, still, the seller is left with surplus energy, the next highest top demand buyer is chosen. After the sorting the sellers in ascending order the priority (sellers are cleared in this order) is given in the order of {S1, S5, S3, S4, S2, S6 } Following the algorithm the market clearing mechanism takes place.

- Seller 1: Buyer 5 wins 10 kWh with the condition $d_j = b_j$ since seller 1 surplus energy and buyer 3 demands are equal.

- Seller 5: The buyer with highest demand is selected. Buyer 3 wins 10 kWh and left with 60 kWh demand.

- Seller 3: Buyer 8 wins 30 kWh.

- Seller 4: Buyer 3 wins 50 kWh and left with 10 kWh demand.

- Seller 2: Buyer 1 wins 20 kWh.

- Seller 7: Buyer 6 and buyer 7 wins 20 and 40 kWh.

Payment

The auctioneer selects the price P_{Si} and P_{Bj} from the winning seller and buyer. Following Eq.(5.10) using random value method.

- S1:{B5} Buyer 5 pays 90 cents to seller 1 $P_{S1} = P_{B5}$
- S2:{B1} Buyer 1 pays 270 cents to seller 2 $P_{S1} = P_{B5}$
- S3:{B8} Buyer 8 pays 390 cents to seller 3 $P_{S1} = P_{B5}$
- S4:{B3} Buyer 3 pays 600 cents to seller 4 $P_{S1} = P_{B5}$
- S5:{B3} Buyer 3 pays 140 to seller 5 $P_{S1} = P_{B5}$
- S7:{B6, B7} Buyer 6 and 7 pays 290 and 460 cents to seller 7 $P_{S1} = P_{B5}$

Since buyer 3 wins partial demand from seller 4 and partial demand from seller 5, buyer 3 only partially for both the sellers. Below are the following summary results from this case study.

- Total welfare of sellers = 2240
- Total ask of the seller = 2010
- Total buyers bid = 2680
- Total welfare of the buyer = 2680 - 2240 = 440

For this illustrated example, all the eligible sellers sold their total energy of 180 kWh, but buyer 3 left with 10 kWh demand and the rest of all the qualified buyers met their demand of 180 kWh. Fig. 5.2 illustrates the ask price and reward of each seller from the example. As depicted, all but a single seller successfully generated a positive profit. In addition, even the sellers with a reduced surplus were able to participate and win in the auction. Thus, proving fairness. Furthermore, from displayed in Fig. 5.3, which shows the buyers bid and payment, we see that the buyer were able to pay less than their required bid. Further allowing all players to participate in the auction.

Fig. 5.4 displays the results of how each buyer and seller were assigned. Observing that dual assignment is possible, seller 4 and 5 distributes their surplus to the buyer 3. Similarly, buyer 6 and 7 receives energy from seller 7.

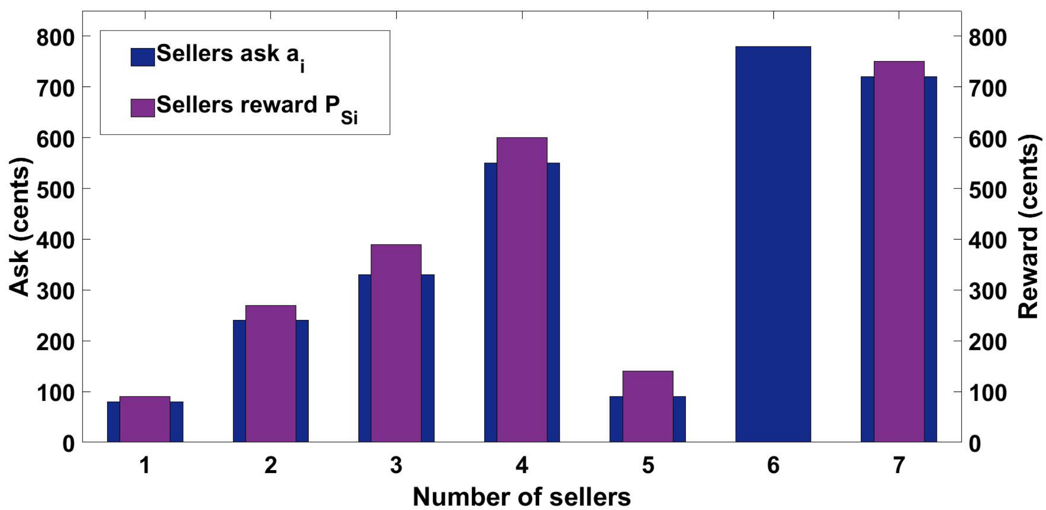

Figure 5.2: Comparing the ask a_i and reward P_{Si} for the participated sellers

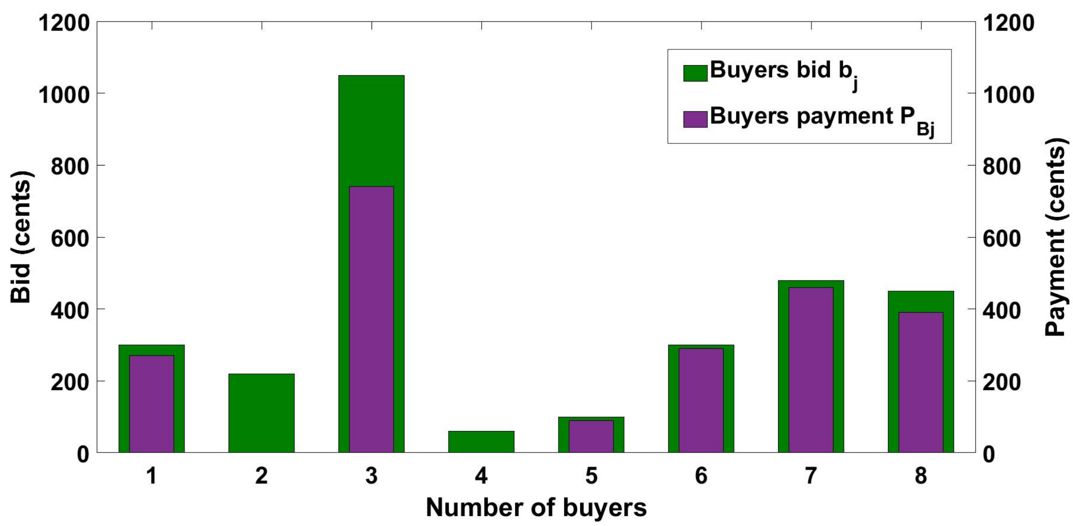

Figure 5.3: Comparing the bid b_j and payment P_{Bj} for the participated buyers

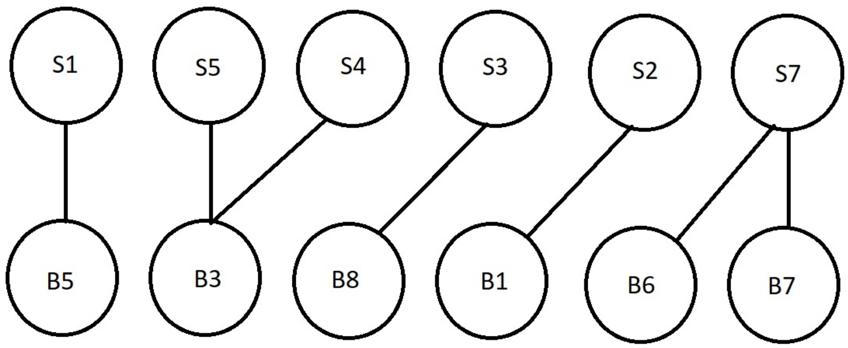

Figure 5.4: Matched winning sellers and buyers

Next, the amount of sellers and buyers are increased to 25, 50 and 75 and the simulation is performed. Fig. 5.5 illustrates the total ask and reward for all winning sellers using the AMA algorithm. As clearly shown, the winning sellers receive more than their ask price, encouraging all prosumers to generate clean energy and utilize it in profitable manner.

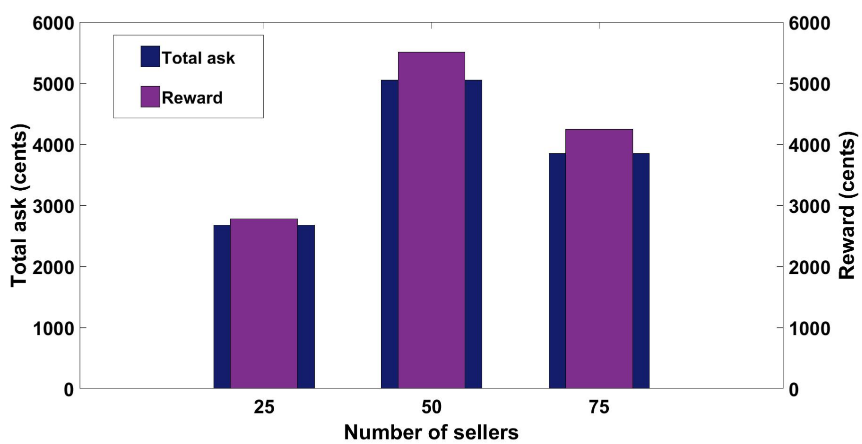

Figure 5.5: Comparing the total ask of all winning sellers with the total reward of all winning sellers

Fig. 5.6 shows the total bid and payment of the winning buyers. As shown, no buyers pays more than their bid and the overall payment is less than their submitted bid. Thus, the AMA algorithm encourages the buyers to buy clean energy from the prosumers as their cost is reduced.

We now observe the social welfare of the network as shown Fig. 5.7. As depicted, the payment and reward is always maintained between the total ask and total bid from all winning users. This is ensured from the matching used in Eq.5.10. Which matches only the buyer with the higher

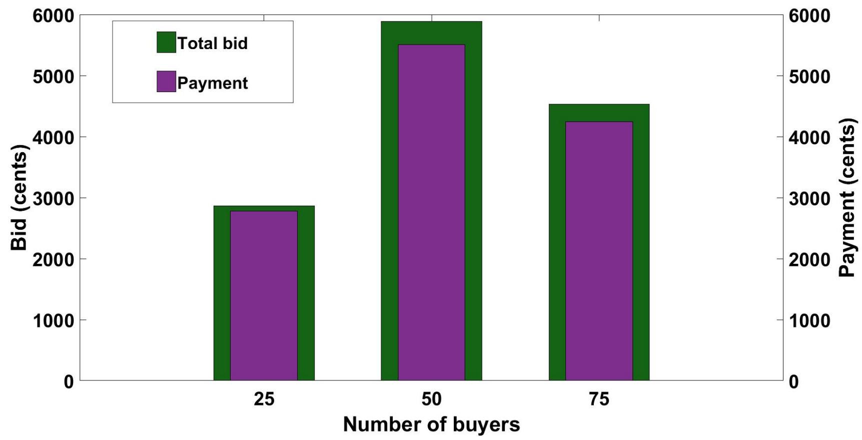

Figure 5.6: Comparing the total bid from all winning buyers with the total payment from all the winning buyers

bid to the seller with lesser ask, e.g., ($b_j > a_i$). This balances the energy trading market and both the prosumers and consumers increases their welfare. As a result, the social welfare of the market is maintained

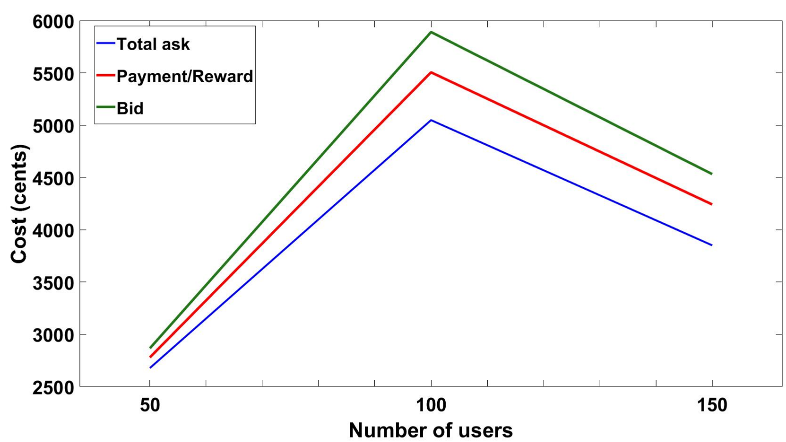

Figure 5.7: Comparing the total sytem cost

Next, the amount of sellers and buyers were increased to 500 and the simulations were performed. This was done using a uniform distribution. The results of the uniform distribution are shown in Fig. 5.8. Observing how each seller and buyer are matched.

Table 5.2 summarizes the computation time for 50 - 1000 users. Observing that as the users increase from 50 - 1000, the time increases from 8.1 - 61 ms. With the optimal solution computed

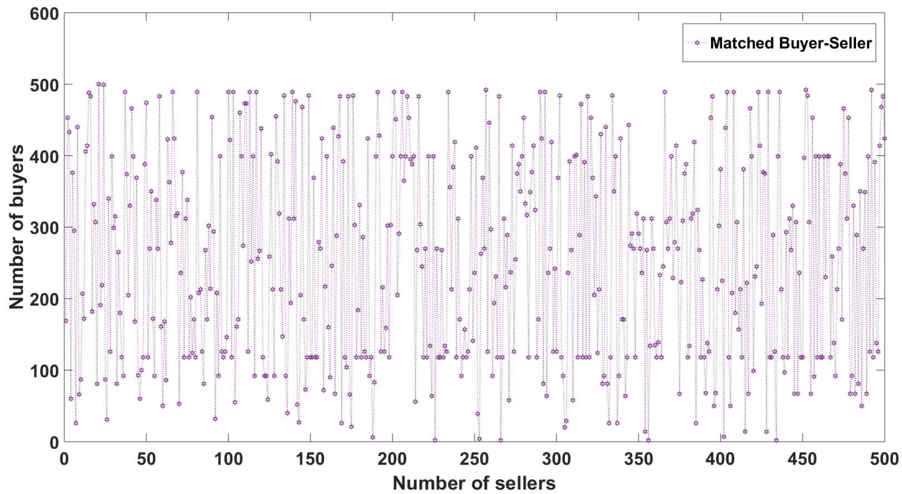

Figure 5.8: Matched sellers and buyers using uniform distribution

in a limited amount of time.

Time Requirement				
Number of users	50	100	150	1000
Time (ms)	1.502	6.747	16.172	92.47

Table 5.2: Time Complexity

5.6 Proof of Desirable Properties

This section proves the properties of budget balance, truthfulness, computational efficiency, and system efficiency in the proposed algorithm.

Property 1. ***AMA is individually rational***

Proof: In proposed algorithm, the auctioneer follows the condition ($\frac{a_i}{e_i} < \frac{b_j}{d_j}$) to match the buyers with sellers, which allows the sellers to group only with the buyers having a higher bid than the seller's ask. This assures that no seller receives the reward lesser than the ask. Equation (5.8) indirectly mentions $a_i < b_j$ the ask of the seller is always lesser than the bid of the buyer. Thus, the losing seller does not receive any reward and the losing buyer is not charged any payment. Similarly, the auctioneer picks the reward and payment to the seller and buyer using the condition ($b_j > P_{Bj} = P_{Si} \geq a_i$) which assures no buyer pays the payment more than the bid. As seen from the case study, the proposed algorithm never charges a payment higher than the individual buyer's bid while each seller receives the reward equal or higher than the ask. The clarification mentioned earlier proves the algorithm is individually rational to both sellers and buyers. Auctioneer payoff is zero which is non-negative and non- positive, and this further proves no participators including the auctioneer lose anything using this mechanism.

Property 2. ***AMA is computationally efficient***

Proof: The AMA algorithm starts with matching the sellers and buyers based on the condition in Equation (5.10) which requires computational time of $O(n)$. Next. in stage 2, the for loop is initiated with time complexity of $O(n)$ followed by sorting the sellers and buyers in arranging and descending order requires $O(n \ log \ n)$ and $O(m \ log \ m)$ respectively. The IF statement in the algorithm used to check the condition uses $O(1)$ computational time. The input of stage 2 is the output from stage 1, satisfies $|S_w| \leq |S| \leq m$ with the time complexity of $O(m^2)$. The total time complexity of this mechanism is polynomial in the order of $O(m^2 + mn \ log \ n)$. Table 5.2 shows that the computational efficiency of AMA, where the solution is obtained in a limited time.

Property 3. ***AMA is budget-balanced***

Proof: After determining the winning sellers and buyers, the auctioneer selects the reward P_{Si} and payment P_{Bj} to the seller and buyer using the condition $(b_j > P_{Bj} = P_{Si} \geq a_i)$. There is no shortage by the auctioneer, and the payment paid by the buyer is equal to the reward received by the seller.

$$\sum_{j \in B_w^j} P_{Bj} - \sum_{i \in S_w^i} P_{Si}$$

$$(P_{Bj} - P_{Si}) = 0 \ \ \forall B_w^j \ , S_w^i \tag{5.14}$$

Which further shows the proposed mechanism is strongly budget balanced, since the payoff of the auctioneer is zero and proves no participating players lose using the proposed mechanism.

Property 4. ***AMA is truthful***

Proof: We assume both the sellers and buyers follow the VCG mechanism in submitting the ask and bid to the auctioneer.

Lemma 1 Algorithm is truthful to the seller.

- If any greedy seller submits a high ask that will be out of the range λ to λ_{max} and automatically that seller is eliminated from trading.

- Assume that any seller with the higher ask participated in the auction, then before they are matched with any buyer, the auctioneer follows an condition $a_i < b_j$ for matching the seller with the buyer. Ensuring that the seller with the highest ask cannot be matched with any buyer unless if any buyer's bid is greater than the ask of the seller.

- At various time the seller cost c_i may be higher for generating the energy. Considering that the buyer needs to pay too much of the cost to buy that energy from the seller with a higher generating cost and the system efficiency decreases by the buyer who pays more to buy the energy. Thus, the auctioneer eliminates the seller from the auction.

Therefore, whatever the case for the seller to submit a high ask $\forall a_i \in A$ it is been shown clearly the seller with the high ask is eliminated from the auction or not matched with any buyers.

Lemma 2 The algorithm is truthful to the buyer.
Buyer's bid b_j will be matched with the seller under the major condition in Equation (5.8).

- If any buyer j submits a low bid b_j, then the buyer j cannot be matched with any seller unless the ask of any seller is lesser than the bid $(a_i < b_j)$.

- If no sellers ask a_i is lesser than the bid b_j of buyer j, $(a_i \nless b_j)$ then the buyer j is not matched with any seller i.

This assures no buyer with a low bid is matched with any seller and wins the auction. This further proves that AMA is truthful for both sellers and buyers in the auction.

Property 5. *AMA is fair*

Proof: This mechanism is designed fair for both the sellers and buyers to submit the ask a_i and bid b_j from the individual valuation. All players have an equal opportunity to submit the bid and ask. The matching is made only with the highest bid from the buyer to the seller with a low ask.

5.7 Discussion

This chapter demonstrated a double-sided auction mechanism for a P2P ETM market. The market consist of multiple sellers, multiple buyers and an auctioneer. The sellers are considered as small factories or individual with a surplus of energy. The buyers are players in the network looking for clean alternative energy sources to meet their demand. It was shown that the auctioneer effectively matches the sellers and buyers to optimize the social welfare of the ETM. The model is suitable for market subscribers. Here, we proposed a mechanism which is strongly budget balanced i.e., no participators payoff is in negative. The results show, that the auctioneer does not recieve any profit. In future we can design a different payment method in which the payment of the buyer is not equal with the seller reward ($P_{Bj} \neq P_{Si}$) and the auctioneer can make profit in return for matching the sellers with the buyers.

Chapter 6

Conclusion and Future Work

6.1 Conclusion

This research demonstrated three P2P energy trading models for the emerging smart grid infrastructure to address the issue of reducing stress at the distribution level. The first two models are based upon a single-sided auction mechanism, which are used to optimize the seller and the buyers' energy costs through a proposed PMA and CMA mechanisms respectively. The PMA is used to maximize the profit return of the seller when seeking to distribute surplus energy to a buyers in the network. It was demonstrated through the simulations results that the seller was able to maximize their profit and was compared with exiting mechanisms in which the PMA outperformed. Similarly, the CMA was simulated and compared with alternative approaches and it was shown that the proposed mechanism outperformed in all manners with regards to reducing the buyers energy costs. It was also shown through proof and analysis that both models exhibit the desirable properties of individual rationality, computational efficiency, truthful, fairness and budget balanced. A last model was based on a double-sided auction which introduced an auctioneer to optimize the social welfare of an ETM by matching buyers and sellers such that the resultant energy cost would be minimized for each player. A proposed AMA was demonstrated and simulated to evaluate the performance of the system model. It was also shown through proof that the model exhibits the desirable properties of individual rationality, computational efficiency, truthful, fairness and budget balanced. This research resulted in effective and practical auction-based models to incentive and motivate users to invest and participate in P2P energy trading.

6.2 Future Work

Future work would investigate and explore alternative pricing schemes for the double-side auction which would enable the auctioneer to obtain a profit return. Additionally, various and diverse settings of the ETM market would also be explored. This work focused mainly on designing the P2P energy trading models for static scenarios. Future work would focus on the dynamic properties of the smart grid network to consider the minimum path at all instances in time. An example would be to design algorithms that dynamically select the shortest/least cost path between the source and destination. In addition, we would like to design the models that take into consideration of the season. This can capture the dynamic variations of the supply and load of the smart grid network.

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