Article

Developing an Appropriate Energy Trading Algorithm and Techno-Economic Analysis between Peer-to-Peer within a Partly Independent Microgrid

Fahim Muntasir [1], Anusheel Chapagain[1], Kishan Maharjan[1], Mirza Jabbar Aziz Baig[1*], Mohsin Jamil[1*], Ashraf Ali Khan[1*]

1. Department of Electrical and Computer Engineering, Faculty of Engineering and Applied Science, Memorial University of Newfoundland (MUN), St. John's, NL, A1C 5S7, Canada

Abstract: The intimidating surge in the procurement of Distributed Energy Resources (DER) has increased the number of prosumers, creating a new possibility of local energy trading across the community. This project aims to formulate the peer-to-peer energy (P2P) sharing model to encourage the DERs to share the surplus energy among the consumers. An effective pricing method is developed based on the supply-demand ratio (SDR) with the importance of self-optimization allows the prosumers to maximize their energy sharing and profits. And to implement this pricing method, a simplified dynamic matchmaking algorithm has been deployed to introduce Outstanding Prosumer to interact with existing consumers to increase the efficiency and profitability of the trade network. On the other side, consumers also benefit from this model as they can pick the most economical energy supplier instead of relying on the utility grid. The prosumer with high excess energy and the consumer with the highest energy demand will be prioritized to maintain the SDR ratio to one or greater than one. Here, all the above-stated features of the peer-to-peer energy trading have been demonstrated with some calculations to back up some tangible results. Finally, a case study is simulated among the residents of Dhaka, Bangladesh, to demonstrate how the peers can be profited by participating in the trading at a given time. Comparing the results with and without P2P trading, there has been a 17.54% of reduction on an electric bill on a typical day of July and 49.53% of reduction in the interaction with the grid.

Keywords: Peer-to-peer energy trading, Supply-demand ratio, microgrid, pricing model, matchmaking algorithm, self-optimization

---

1. Introduction

This project aims to develop a peer-to-peer (P2P) for the prosumers (those who consume and produce energy) to trade locally and get ownership of locally generated renewable energy. With a third-party regulator, one can securely make a transaction with another peer connected to the microgrid to facilitate energy mobility without needing a central authority. This will subsequently facilitate eliminating the upfront cost of running the centralized energy trading administration and lowering the transaction cost. Furthermore, an intelligent algorithm has been developed to declare the energy price according to the hourly updated generation, consumption, excess energy, and SDR so that the prosumers will be extra motivated to self-optimize their consumption to take part in the trading. Thus, this project is an optimal solution for motivating the resident and other organizational groups to use green energy, facilitating decarbonization and sustainable energy culture.

Globalization is bringing technological change to every major infrastructure in the world as it continues to grow and affect every aspect of life. P2P energy trading technology has shown the possibility of shifting the idea of the current centralized energy market into a decentralized system. With the high upfront cost and long breakeven period, residential people are still reluctant to purchase green energy resources privately, which is the main reason why different renewable sources aren't easily deployable. Therefore, the P2P energy trading platform will attract the different prosumers to participate in energy trading and allow them to treat their private energy as a stock in the trading market. Furthermore, the emergence of block-chain technology has raised this energy trading mechanism to the next level, which acts as a decentralized, immutable ledger that allows the privacy and security of digital information[1]. Baig et al. [2] illustrated a P2P model using block-chain technology. The proposed model performs energy trading via an IoT-based platform. The financial transaction is done as per the negotiations between the peers. Here the exchange of electricity was done between two peers only. A hardware prototype was being built to demonstrate the trading practically. Alhasnawi et al. [3] studied on a multi-agent system to control the P2P of Networked Renewable Energy Resources based on IoT and this control is fully distributed containing two control layers. AlSkaif et al. [4] proposed two strategies to determine the trading preferences of two households participating in P2P energy trading. One of the strategies focuses on the excess power generation and consumption balance between prosumers and consumers. The second one is based on the distance between two peers. They gathered data from a residential area in the Netherlands and performed a simulation. The simulation results showed that the peers participating in the P2P scheme had less interaction with the utility grid. In contrast, the amount of energy was traded significantly higher when the trading was done based on distance. The paper also noticed the P2P among peers when electric heating is turned on in residential homes. It reveals that electric heating reduces the energy exchange between two peers. However, implementing P2P energy trading in real time is associated with several challenges.

Installation of Distributed generations (DGs) has its benefits as it enables consumers and prosumers to share energy which helps reduce dependency on the utility grid, lowers electricity bills, and promotes the utilization of electricity of prosumers to the utility grid[5]. As per [6], autonomous energy trading is based on policies and protocols for matching and sharing energy, but these methods lack a pricing mechanism without which it is difficult to facilitate the sharing with demand response. The pricing problem between retailers and consumers of electricity has attracted much research. Carrion et al. have proposed bi-level stochastic programming to decide the pricing that will be available for consumers[7]. As per [8], a Stackelberg game model was demonstrated between the interaction of prosumers and consumers by optimizing the day-ahead hourly prices. By the implementation of Demand Response (DR) which is a Demand Side Management(DSM) technique, prosumers who are participating in the P2P trading can optimize their energy consumption pattern by shifting their load from peak hour to off-peak hour minimizing their electricity cost and selling out more energy to other peers [9]. A survey by Abdella et al. has presented a review of existing demand response optimization models, power routing devices, and power routing algorithms and identified some challenges revolving around P2P energy trading [10]. Energy traders implement various pricing strategies, such as Real Time Pricing (RTP) and Time of Use Pricing (TOU), to encourage consumers to voluntarily participate in the DSM program, to lower peak demand, and to economically balance the power consumption in residential areas[11]. The RTP based DSM in the home energy management system (HEMS) has proved successful in minimising costs and increasing energy efficiency[12]. Here, smart appliances that can communicate with smart meters and control systems are managed remotely by HEMS to optimize the electricity cost and energy efficiency without reducing user comfort. A new 2-stage hybrid method of HEMs has been proposed by the authors that schedule the power consumption of the trading participants having DERs and the optimization is based on the user preferences, cost of electricity and the amount of energy produced or stored [13]. A coalitional game was used to mimic real-time direct trading between small-scale suppliers and end users in [14]. The trade prices are derived using the Shapley value. Moradzadeh et al. [15] have developed a two-stage pricing scheme to minimize electricity costs and maximize consumer satisfaction. According to Tsagarakis et al. [16], the load has been managed on the consumer at different seasons of the year to minimize the cost. To reduce the price of power and CO2 emissions, Lauinger et al. [17] devised an optimization of household energy systems using linear programming.

For an RTP-based HEMS, the twin delayed deep deterministic policy gradient learning technique has been proposed to reduce the electricity cost [18]. The EMS becomes more active when combined with a demand response optimization of P2P energy trading. On the other hand, a new interactive RTP has been created by including the consumer's level of discomfort while using the DR approach[19]. Zhu et al. [20] developed an energy trading platform based on real-time with a combination of grid-connected prosumers who use varieties of DERs. They proposed an energy trading system by forming an energy management system where individual prosumers will be able to manage their energy consumption and storage schedule. The total system was designed based on Lyapunov theory. Under this theory, each prosumer can place their bid for trading by determining their current power consumption and generation from the energy source. Liu et al. formulated an internal pricing and cost model for prosumers willing to shift the load. The internal price is co-decided among the prosumers by using a distributed iterative algorithm to solve this problem. This project uses realistic data to achieve cost savings as compared to trading with the grid[21]. P2P energy has made it possible to trade excess energy from prosumers to consumers[22]. The consumer will benefit from P2P energy trading as the trading cost for the prosumer is less than that of the utility electricity cost[23]. With the P2P method, consumers choose the most affordable electricity cost among prosumers based on the time slot. According to Paudel et al. [24], the prosumers have been modeled as buyer or sellers depending on the SDR. The prosumer behaves as a seller when the generation exceeds the demand, whereas the buyer does when the demand exceeds the generation. Energy trading has primarily benefited prosumers, leaving consumers out, which is the leading cause for concern [24], [25]. The bidding-based trading best suits wind power producers to maximize their profit [26]. The peers have been communicated with power requirements and their availability. Telecommunications cables have connected the prosumers and consumers within a close radius to create a virtual microgrid [27]. Umer et al. [28] have developed communication-based energy trading for secure and economical energy trading. Paudel et al. [24] have suggested a decentralized market clearing mechanism, and Esmat et al. [29] have further proposed a blockchain-based decentralized market clearing mechanism. In 2019, Alam et al. developed an energy cost optimization algorithm for energy sharing between smart homes to minimize the electricity [30].

In [31], Spiliopoulos et al. has proposed a framework for improving the economic and resilient operation of Microgrid and impact of P2P energy exchange on system resilience and battery lifetime has been examined. Effectiveness of this method has been examined on different locations and for different fault scenarios.

In the course of this study, a wide range of literature reviews have been conducted, and some of these are presented here. We learned that most research papers have focused on trading techniques and pricing strategies. Still, they did not highlight an in-depth framework when multiple participants are available for trading simultaneously. Under this circumstance, we focused on developing the appropriate algorithm to handle dynamic interaction between the Outstanding Prosumers with other consumers in the energy trading platform to reduce the unwanted traffic in the trading network, bringing out an efficient trade which can be scaled up to larger networks. The implemented pricing mechanism is based on Supply and Demand Ratio (SDR), which projects the price high when demand is high and vice versa. The main objective is to optimize electricity cost and to motivate more and more participants to get involve in the trade and extensive usage of Distributed Energy Resources making the microgrid community independent of the main utility grid. Thus, in this paper, we have designed the microgrid with two different prosumers and execute P2P trading to examine the internal pricing trend among buyers and sellers at different times of the day. The internal pricing method is derived from the mathematical modeling of the supply and demand ratio between the peers. We also focused on the significance of self-optimization, which can increase the profit of the peers while they perform the trading. The trading algorithm and pricing technique are implemented based on real-time data in Dhaka, Bangladesh. Recently, Bangladesh has been facing frequent load-shedding and energy crises due to reducing fossil fuels. The key contributions of the project are:

- The process has been categorized into three layers: Registration, matchmaking, and pricing. Each layer has a distinctive role in executing the whole P2P trading.
- The excess energy of the prosumers will be consumed by the consumers. The pricing pattern depends on the peers' total selling and buying power.
- As the excess energy will be utilized in the trading, peer self-optimization of electricity will be given prior importance. Higher self-optimization will enable the prosumers to store more energy; therefore, they will be able to trade more electricity, ensuring more profits for both parties.
- Homer Pro software has been used to simulate real-time data. To assess the potential of P2P, we have followed the consumption pattern of July as the peers consume more energy this month due to the frequent usage of air conditioners and ceiling fans. Therefore, this month is considered the ideal month to validate the effectiveness of P2P as the load consumption is relatively higher, which turns out to lesser excess energy.

The rest of the paper is organized as follows: Section 2 describes the whole project principle, including project methodology in section 2.1, followed by the system architecture in section 2.2. Section 3 explains the inconvenience factor, whereas section 4 illustrates the project's case study, which shows the benefits of P2P. Section 5 and 6 discuss and concludes the fundamental prospects of the paper and outlines future research, respectively.

2. Project Description and Methods

2.1 Proposed Project Methodology

The main objective of any P2P energy trading is to utilize the excess generation of different DERs. The proposed trading will also limit the interaction with the grid and reduce electricity bills. The trading price and mechanism will be regulated and developed by live market variables (i.e., generation, consumption, excess energy, SDR). Thus, the system creates a fair sharing of profits for all prosumers. The implementation of our proposed scheme will be done in the following stages.

- A microgrid community has been designed in Homer Pro for P2P energy trading between two prosumers and one consumer. Hourly generation, consumption, and excess energy are extracted and examined by simulating the proposed system. The available excess energy from the prosumers is used for trading and consumed by the consumers. As a result, the prosumers do not have to dump the surpass energy through a dump load.
- The prosumer's total selling power and the consumer's total buying power is used to calculate SDR. Based on the SDR, prosumer and consumer buying and selling prices are declared.
- Load flow analysis is performed to verify the effectiveness of P2P trading among buyers and sellers in the peak month of July, when the consumption is generally higher than in other months. The average electricity bills and integration with the centralized network of the consumers are compared before and after the implementation of the P2P trading.
- The peers are encouraged to self-optimize the electricity consumption to maintain the supply and demand at an equilibrium level, ensuring maximum benefit to both prosumers and consumers from the pricing model.
- Record and facilitate transactions between generators and consumers via a third-party regulator.

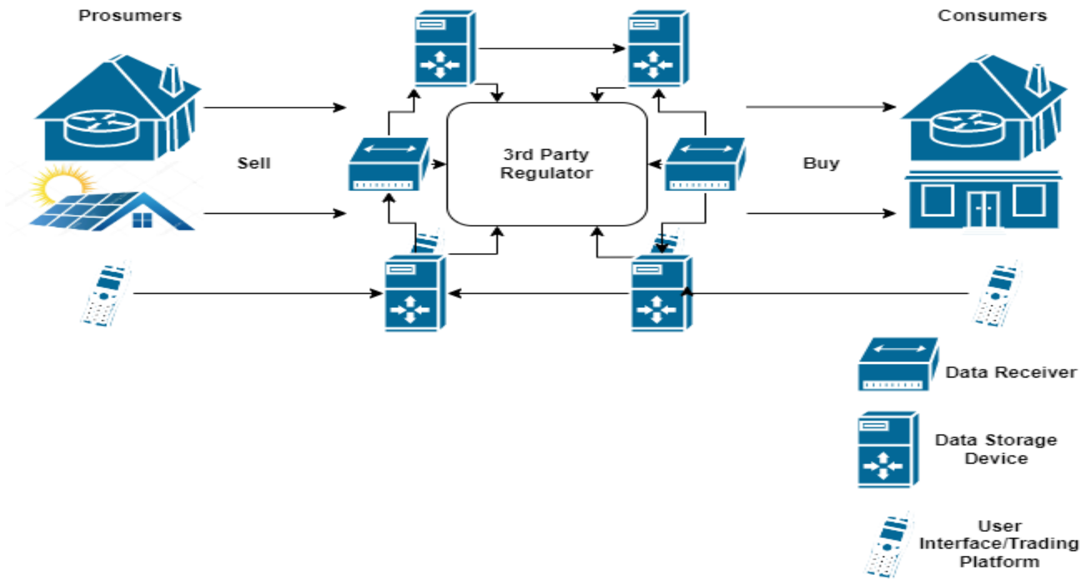

Figure 1 System architecture of the proposed system

2.2 Architectural Model of the P2P Trading

The step-down model is developed to automate the peer-to-peer trading platform. The process workflow has been divided into three layers, which execute a series of input, process, and output. Registration Layer prompts to imports all the necessary information of the market participants by establishing a secure connection with the smart meter and retrieves the real-time values of load consumption, energy generation, geographical location, and national identity number. The second layer executes the matchmaking process among the peers. The main goal of this layer is to maximize the surplus energy utilization without creating the need to store the energy, which contributes to lowering the capital cost of distributed energy resources. The other matchmaking utility feature is executing the energy trading process to the nearest in-demand peer. This will allow minimal energy loss in the transmission process and maximize efficiency. The final layer is defined as the price execution layer responsible for maintaining the unit price of energy lower than the utility grid price, encouraging the peers to accommodate their load demand by the distributed energy resources. Frequent use of electrical devices, such as dishwashers and washing machines, will increase overall consumption, resulting in less trade energy. Therefore, the peer self-optimization factor will be integrated into the system to differentiate the profit made by each prosumer.

To monitor and facilitate the exchange of electricity between prosumer and consumer, we introduce a third-party entity. This third party will be equipped with trading algorithms which, according to the requirements of the circumstances, automatically execute, control, or record all legally necessary events and acts. Therefore, the prosumers and consumers will exchange electricity of utility grid via this third party regulator. Figure-02 displays how the energy sharing between the peers will be executed in the presence of the third party regulator.

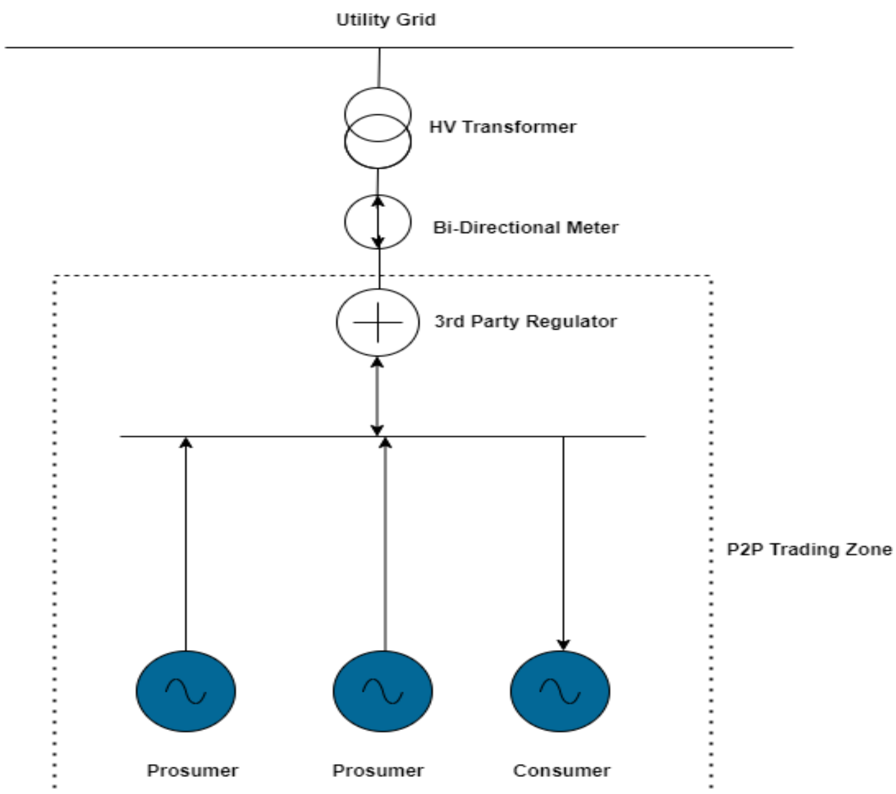

Figure 2 Single line diagram of the proposed P2P zone

The third party agent will calculate the available excess energy of prosumers that can be sold to the consumer and will proceed with payment accordingly. Hence, it will eliminate all the tedious paperwork required for the customers for energy trading as this agent are responsible for the energy sharing between the peers.

2.2.1 Registration Layer

The job of this layer is to allow market participants to register themselves as a prosumer or just a consumer in the P2P system. An agreement contract is executed between the energy trading entity and the participants generating a unique identifier to track the participants in the energy trading network. The algorithm for the registration layer is presented in figure 3.

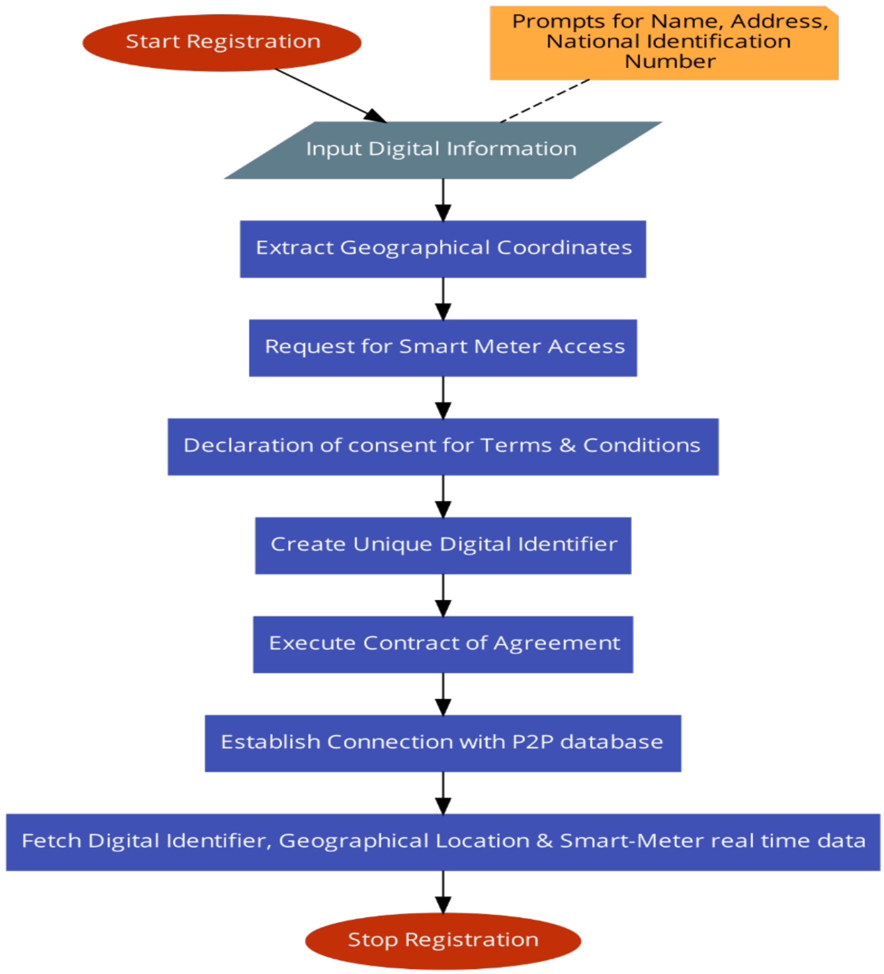

Figure 3 Working model of registration layer

A relational database system should be integrated into the registration layer of the P2P platform. It requires special attention and care from security breaches and risks to data privacy. A fast and responsive server is required to host the database for all the market participants involved in distributed energy sources. It requires greater computation power, an extensive developer team, and more capital cost. Nonetheless, with the emerging use of DER resources, there is a higher demand for P2P trading facilities in the energy market for a better, efficient, resilient, and robust trading stack.

2.2.2 Matchmaking Layer

The second layer matches the trading peers who produce the highest amount of excess energy and thereby putting the peers in the pole position to initiate the trading. For optimization, the following information needs to be validated by each prosumer. The total electricity consumption (TC_i) and total production (TP_i) from DERs for every hour interval in a day are bypassed from the registration layer, which allows extracting the microgrid of each connected participant in the DER network.

$$TC_i = \left[TC_1{}^1, \ldots\ldots, TC_n{}^h\right] \tag{1}$$

$$TP_i = \left[TP_1{}^1, \ldots\ldots, TP_n{}^h\right] \tag{2}$$

Where i is the number of prosumers and h is the number of hours. With the help of the above two equations, the net power value (NP_i) of the overall system can be determined.

$$NP_i = TC_i - TP_i \quad (3)$$

As per the above equation, an algorithm is created which will select a peer who produces more excess energy (NP_i) than other peers. For simplicity, we will consider two prosumers and a consumer to demonstrate the scenario. Once a specific prosumer is selected for trading, a suitable consumer will be sorted out if multiple consumers request for trading. In that case, the ratio of current demand and total available power from the prosumer will be calculated. Based on the resulted ratio, the decision will be taken. The whole scenario can be summarized from the following equations. The total electricity consumption (TC_{ci}) from consumer and total net power (NP_i) from prosumers for every hour interval in a day is as follows.

$$TC_{ci} = \left[TC_1{}^1, \ldots\ldots, TC_n{}^h\right] \quad (4)$$

$$NP_i = \left[NP_1{}^1, \ldots\ldots, NP_n{}^h\right] \quad (5)$$

Where i is the number of prosumers and ci is the number of consumers. h ndicates the number of hours. The consumption-generation (CG) ratio of the consumer is as follows.

$$CG = \frac{TC_{ci}}{NP_i} \quad (6)$$

An algorithm is created which will select a peer based on the CG ratio. Depending upon the usage pattern, different consumers will have different demands. Higher consumption will increase the CG ratio, whereas lower consumption will reduce the CG ratio. As we prioritize the self-optimization of electricity, the consumer with the lowest CG ratio will start the trading first. Hence, by implementing this scheme, more consumers will give importance to self-optimization, and the prosumer will also have the opportunity to sell electricity to multiple consumers.

Algorithm for Matchmaking Layers

1: **Start:** Initialize Matchmaking Layer
2: **Process:** Establish Connection with Registration Layer Database
3: **Process:** Compute Net Power (Np) of each participant
4: **Process:** If (Np < 0)?
5: **True** Insert Digital Identifier in Supplier Array
6: **True** Sort Supplier Array with sort algorithm & Identify Outstanding Prosumer (OP)
7: **True** Compute Total Selling Power (TSP)
8: **False** Insert Digital Identifier in demand array
9: **False** Sort demand array with sort algorithm
10: **False** Compute Total Buying Power (TBP)
11: **Process**: Compute Supply Demand Ratio (SDR)
12: **Process:** If (SDR >= 1)?
13: **True** **Process:** if (OP > C(j))
14: **True** **True** Process: **Matchmaking Succeed** Trade energy from outstanding prosumer to C(j)

15:	**True**	**True**	Process: Increment j = j + 1	
16:	**True**	**True**	Process: Establish Connection with pricing layer	
17:	**True**	**True**	Process: Establish loop network with 13	
18:	**True**	**False**	Process: Compute energyDeficit < C(j) – P(i) >	
19:	**True**	**False**	Process: If energyDeficit < P(i+1)	
20:	**True**	**False**	**True**	Process: Trade Energy to Outstanding Prosumer
21:	**True**	**False**	**True**	Process: Establish connection with pricing layer
22:	**True**	**False**	**True**	Process Establish loop network with algorithm number 19
23:	**True**	**False**	**False**	Process: Trade energy from P(i+1) to outstanding prosumer (OP)
24:	**True**	**False**	**False**	Process: Compute energyDeficit = energyDeficit – P(i+1)
25:	**True**	**False**	**False**	Process: Increase i = i + 1
26:	**True**	**False**	**False**	Process: Establish loop network with algorithm number 19
27:	**False**	**Process:** if (0 < SDR <1)		
28:	**False**	**True**	**Process:** energyDeficit = TBP - TSP	
29:	**False**	**True**	**Process:** Trade deficit energy from utility grid to Outstanding Prosumer (OP).	
30:	**False**	**True**	**Process:** Establish Connection with pricing layer.	
31:	**False**	**True**	**Process:** Establish loop network with 13	
32:	**False**	**False**	**Process:** energyDeficiet = TBP	
33:	**False**	**False**	**Process:** Trade deficit energy from utility grid to outstanding prosumer (OP)	
34:	**False**	**False**	**Process:** Establish Connection with pricing layer	
35:	**False**	**False**	**Process:** Establish loop network with after check	

The matchmaking layer is one of the main architectures that operate beneath the P2P energy trading application. In order to automate an efficient matchmaking process, an outstanding prosumer is defined as the player that generates the highest energy in the network. The sort algorithm sorts out all the participants in a descending manner. In that way, an outstanding prosumer is always responsible for feeding the energy to the demand array. At the same time, the other prosumer contributes to energy trading only by interacting with the outstanding prosumer. This will allow fast smooth, and error-free energy trading in the complex group of participants. The battle of being an outstanding prosumer will also encourage all other prosumers to produce more energy to leverage the market by interacting with more consumers. This workflow also indicates the minimum involvement of the utility grid, improving their load stability, less chance of power outage, and more flexibility in organizing the demand side loads.

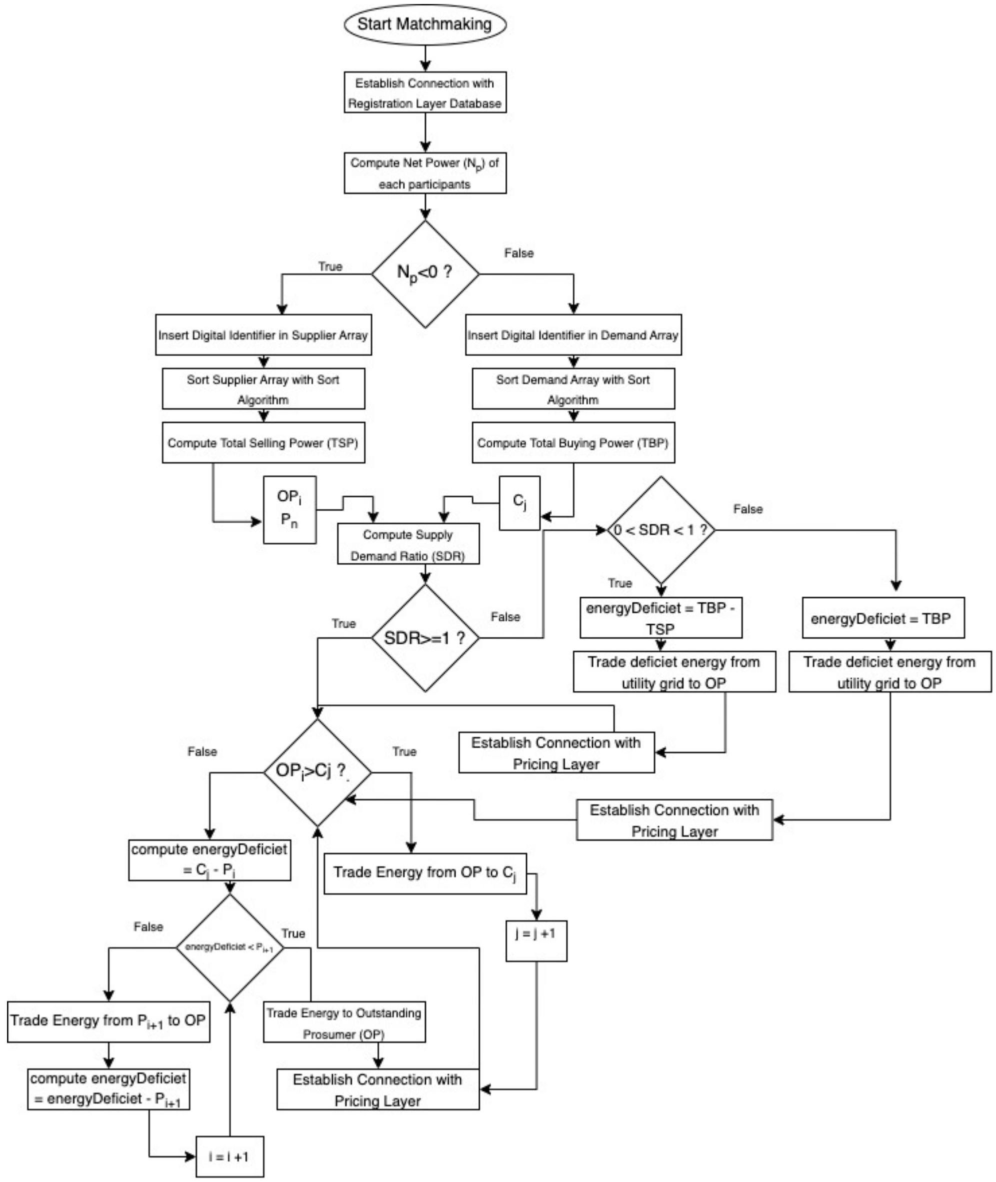

Figure 4 Match-Making peer-peer for energy trade

2.2.3 Pricing Mechanism

The internal pricing method will define the electricity price during the electricity exchange between a buyer and a seller. A positive value of NP means the consumption of the prosumers is higher than the generation. Hence, the prosumer will not be able to participate in the trade and must buy electricity from the grid. The negative value of NP indicates that there is surpassed energy available; therefore, the peers will be able to sell electricity to other peers. Therefore, the total selling power (TSP) of the prosumers and the total buying power (TBP) of the consumer are.

$$TSP= -\sum_{i}^{n} NP_i, \text{ when } NP_i < 0 \quad (7)$$

$$TBP= \sum_{i}^{n} TSP, \text{ when } NP_i < 0 \quad (8)$$

The pricing method will be determined by the SDR [18]. The SDR is a term used in economics to illustrate the relation between supply-demand and price. By using this principle, the internal price of P2P will be fixated. As per this principle, the relation between internal price and SDR is inverse-proportional. The ratio of the SDR can be derived from the following function.

$$SDR=\frac{TSP}{TBP} \tag{9}$$

TBP is the total amount of buying power the consumer purchases from the prosumer. When *SDR>0,* the excess electricity will be used for trading. For this paper, we consider that the maximum selling price will be less than the average utility price; thus, the consumer will buy electricity at a lower price than the grid. When 0≤ *SDR≤1,* the amount of available energy is lower than the demand; hence, the internal price of the system will be set as per inverse proportion function 1*/(ax+b).* This function will demonstrate the variation of internal selling price (Pr_{sell}) according to SDR.

$$Pr_{sell}=f\,(SDR)=\begin{cases}\frac{1}{aSDR+b}, & 0\leq\ SDR\leq 1\\ \lambda_{sell}, & SDR>1\end{cases} \tag{10}$$

To simplify the above formulation, first, we will consider *SDR*=0, which means there is no surpass energy from the prosumer; hence, they need to purchase electricity (λ_{buy}) from the utility grid. After that, we will consider *SDR*=1; the prosumer will be able to sell electricity to other peers, which can be denoted as λ_{sell}. Thus, we can obtain the following equation by putting (0,1) in the equation (10).

$$\begin{cases}\frac{1}{a\times 0+b}=\ \lambda_{buy}\\ \frac{1}{a\times 1+b}=\lambda_{sell}\end{cases} \tag{11}$$

By solving the above equation, we can get

$$\begin{cases}\frac{\lambda_{buy}-\lambda_{sell}}{\lambda_{buy}\lambda_{sell}}=\ a\\ \frac{1}{\lambda_{buy}}=b\end{cases} \tag{12}$$

By putting equation (12) into equation (10), we can obtain the following equation.

$$Pr_{sell}=f\,(SDR)=\begin{cases}\frac{\lambda_{buy}\lambda_{sell}}{(\lambda_{buy}-\lambda_{sell}).SDR+\lambda_{sell}}, & 0\leq\ SDR\leq 1\\ \lambda_{sell}, & SDR>1\end{cases} \tag{13}$$

Similarly, based on the internal selling price Pr_{sell}, we can derive the internal buying price Pr_{buy} which will facilitate generation and consumption balance in the system. When, $0\leq\ SDR\leq 1$, the internal buying price (Pr_{buy}) of the system can be described as follows.

$$Pr_{buy}.TBP=TBP.SDR.Pr_{sell}+(TBP-TBP.SDR)\lambda_{buy} \tag{14}$$

If $SDR>1$, then the internal buying price λ_{buy} will be equal to the internal selling price λ_{sell}. Therefore, finally the internal buying price of the system can be formulated as.

$$Pr_{buy} = \begin{cases} SDR.Pr_{sell} + (1 - SDR)\,\lambda_{buy}\,, & 0 \leq \; SDR \leq 1 \\ \lambda_{sell}, & SDR > 1 \end{cases} \quad (15)$$

Based on the mentioned internal pricing scheme, the per kWh buying and selling price for the peers are formulated as follows.

$$Pr_{sell} = \begin{cases} \frac{\lambda_{buy}\lambda_{sell}}{(\lambda_{buy}-\lambda_{sell}).SDR + \lambda_{sell}}\,.TSP, & 0 \leq \; SDR \leq 1 \\ \lambda_{sell}.(TSP - TBP), & SDR > 1 \end{cases} \quad (16)$$

$$Pr_{buy} = \begin{cases} SDR.Pr_{sell} + (1 - SDR)\lambda_{buy}.TSP + (TBP - TSP).\lambda_{buy}\,, & 0 \leq \; SDR \leq 1 \\ \lambda_{sell}.TBP, & SDR > 1 \end{cases} \quad (17)$$

The SDR will be calculated every hour interval. If there is surpassed amount of electricity the consumer does not consume in a specific hour interval, that excess amount cannot be used later. Therefore, a constraint needs to be set while calculating the SDR.

$$SDR_h = \frac{TSP_h}{TBP_h} \text{ when } TSP = -\sum_i^n NP_i \quad (18)$$

Where h indicates every hour interval for the consumers, which is $0 \leq h \leq 24$.

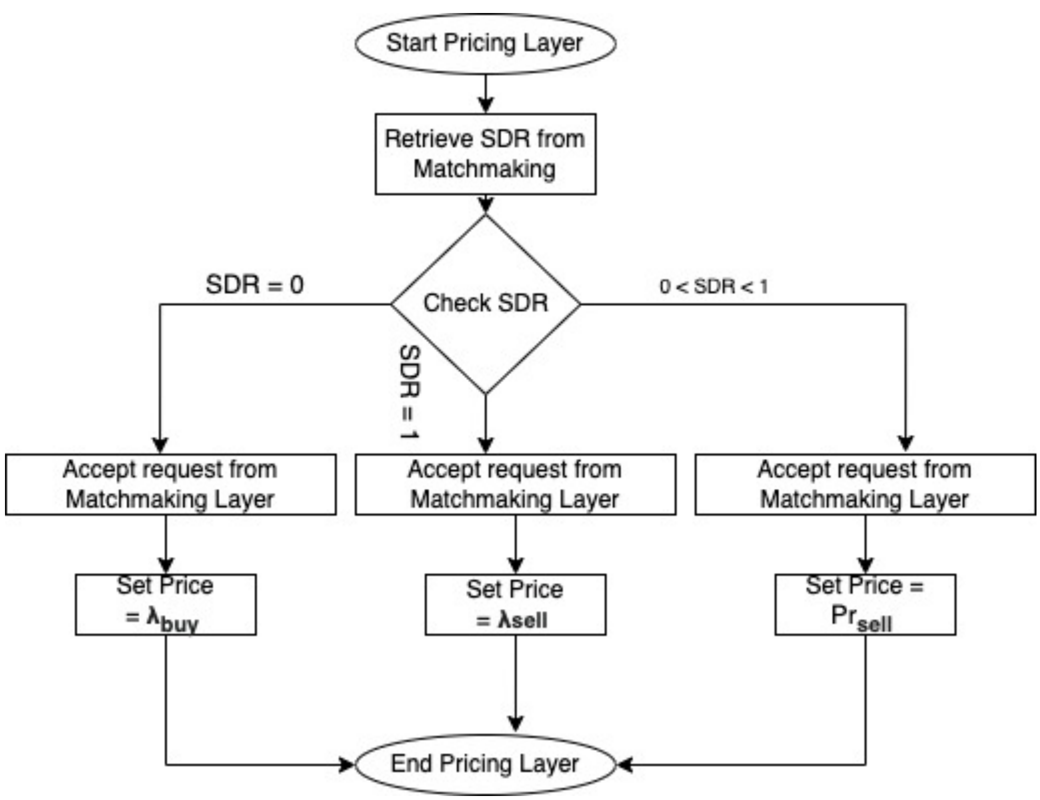

Figure 5 Pricing Layer for Different SDR Ratio

3. Inconvenience Factor

When the value of *SDR* is 0, there is no excess energy available; hence, prosumers and consumers must rely on the central entity to cover up the load demand. To increase the ratio of SDR greater than zero, the peers need to minimize the self-consumption that will make the value of *TSP* higher than the *TBP*. Due to this price incentive, the peers may adjust the load profile by changing the usage pattern of some shiftable devices, such as dishwashers and washing machines [18]. Therefore, if the total adjustable load is x_i for peer *i* at a time interval of *h*, the equation (3) can be rewritten as.

$$NP_i = x_i^h - TP_i \tag{19}$$

$$x_i^h = [\, x_i^1, x_i^2, \ldots.\ x_i^H] \tag{20}$$

We will consider the inconvenience factor α to illustrate the difference in internal cost function when P2P trading occurs. As different peers will have different preferences, the inconvenience factor will vary depending upon their usage pattern of electrical appliances. Lower α means the peers are unwilling to adjust their load, and the higher α indicates the peers are more concerned about reducing their self-consumption. Hence, the incentive cost of the prosumer is.

$$inc^i = \alpha_i\,(\, x_i^h - {TC_i}^h)^2 \tag{21}$$

By integrating the inconvenience factor α, the optimized cost function c_i^h of a prosumer becomes as follows.

$$c_i^h\left(x_i^h\right) = Pr_i^h\left(x_i^h - TP_i\right) + \alpha_i\,(\, x_i^h - {TC_i}^h)^2 \tag{22}$$

Here Pr_i^h is the price of power, which can be either selling price or buying price depending on the value of *NPi*. If the value of *NPi* is negative, then the Pr_i^h will be equivalent to Pr_{sell} which will minimize the $c_i^h\left(x_i^h\right)$ hence maximizing the profit of the peer. If the *NPi* is positive, then the Pr_i^h will be equal to Pr_{buy} which indicates the peer needs adjust the inconvenience factor α to reduce the cost of $c_i^h\left(x_i^h\right)$.

$$Pr_i^h = \begin{cases} Pr_{sell}, & NP_i < 0 \\ Pr_{buy}, & NP_i > 0 \end{cases} \tag{23}$$

The following constraint needs to be considered while adjusting the load x_i.

$$Min\,(TC_i) \le x_i^h \le Max\,(\,TC_i) \tag{24}$$

It is important to remember for peers ,while adjusting the inconvenience factor α so that total adjustable does not go below the base load or does not go above the rated load capacity of the residence.

4. Results

This section represents a real-time data analysis of P2P trading in Homer Pro based on the above mathematical equations. To illustrate this scenario, we have designed a microgrid with two prosumers in Homer Pro software. The average monthly load consumption of the peers have been calculated from the monthly electricity bills from different residential households in Dhaka, Bangladesh and integrated into the software.

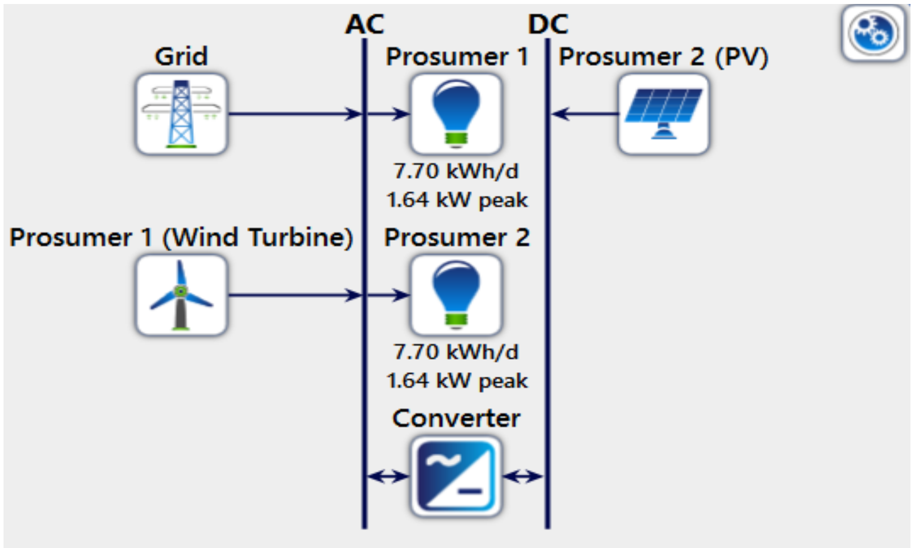

Figure 6 The Microgrid schematic diagram designed in Homer Pro

Three different scenarios have been tested in this model. In the first scenario, the prosumer is connected to a wind turbine. In scenario 02, the prosumer gets power from the PV source. Lastly, in scenario 03, the amount of excess energy is compared between two prosumers to decide who will participate in the trading with the consumer. The inconvenience factor α is changed among prosumers to differentiate the income variation. A lower value of α indicates the peers are concerned about self-consumption, whereas a higher α means the peers consume high electricity. As the Bangladesh government does not have a feed-in-tariff, we have considered the λ_{sell} is equivalent to 4 Taka/kWh. λ_{buy} is calculated as per the current per unit price set by the power generation authority of Bangladesh. The inconvenience factor α is set as 0.01. Table 1 shows the Bangladesh government's electricity rate at different kWh in residential households [29].

Table 1 Electric bills in residential households in Bangladesh

Range of kWh	Rate (Taka)/kWh
0-50	3.75
0-75	4.19
76-200	5.72
201-300	6.00
301-400	6.34
401-600	9.94
600+	11.56

As per our collected utility bills, most of the residential households in Dhaka, Bangladesh, consumed 250-350 units of electricity in July. Based on this consumption, the rate of λ_{buy} is considered 6.34 Taka/kWh for this paper. A significant consumption difference will create a major difference between selling and buying power; therefore, we have chosen three peers who consume almost the same amount of electricity to keep the SDR optimal. Table 2 displays the hourly generation and consumption of the prosumers and consumers on a typical day of July extracted from Homer. SDR is written as N/A when P2P trading does not occur between prosumers and consumers.

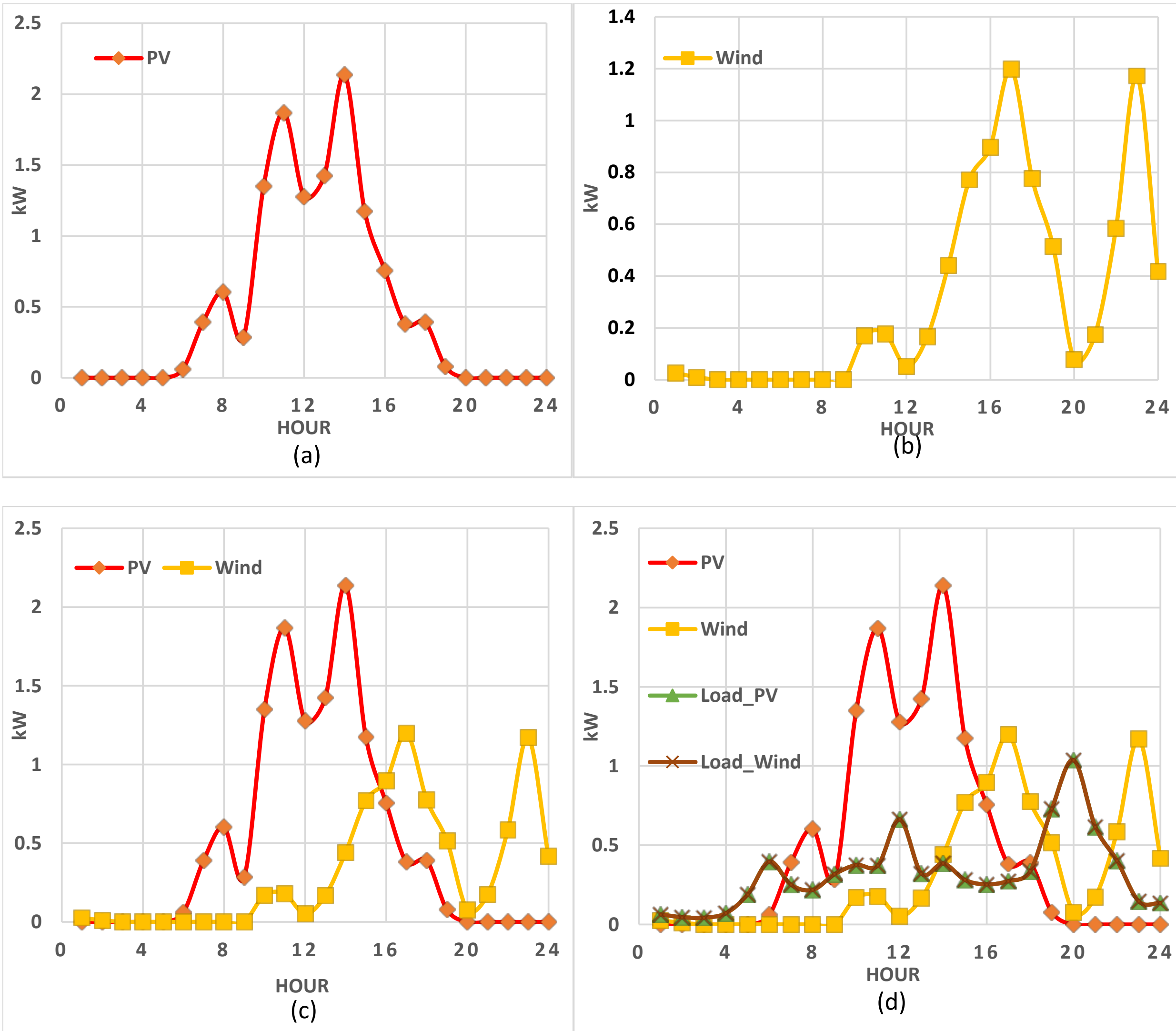

Figure 7 Daily load profile of prosumers in a typical day in July: a) PV generation; b) Wind turbine generation; c) Combined generation: d) Combined generation with consumption

Table 2 Net generation of two prosumers, consumer consumption and SDR

Hour	Net output from PV (kWh)	• Net output from wind (kWh)	• Consumer consumption (kWh)	SDR
0	0.107	0.027	0.030	N/A
1	0.114	0.047	0.042	N/A
2	0.114	0.057	0.039	N/A
3	0.114	0.057	0.066	N/A
4	0.392	0.196	0.098	N/A
5	0.539	0.300	0.246	N/A
6	0.268	0.330	0.080	N/A

7	**-0.002**	0.300	0.168	0.013
8	0.219	0.252	0.186	N/A
9	**-0.834**	0.088	0.245	<1
10	**-1.275**	0.119	0.222	<1
11	**-0.637**	0.268	0.624	<1
12	**-0.594**	0.247	0.301	<1
13	**-1.514**	-0.129	0.224	<1
14	**-0.673**	0.000	0.260	<1
15	-0.280	**-0.659**	0.232	<1
16	0.110	**-0.952**	0.252	<1
17	0.399	**-0.380**	0.314	<1
18	1.398	0.223	0.690	N/A
19	1.204	0.524	1.006	N/A
20	0.811	0.232	0.596	N/A
21	0.576	**-0.297**	0.392	0.750
22	0.360	**-0.990**	0.135	<1
23	0.245	**-0.294**	0.124	<1

Based on the above load profile, it is evident that at certain hours of the day, the peers will be able to participate in the P2P trading. The bold mark figures indicate the trading participation by the peers in those hours. Pr_{buy} and Pr_{sell} are calculated as per the ratio of SDR. Figure 8 and Figure 9 are showing the hourly variation of internal pricing during P2P trading.

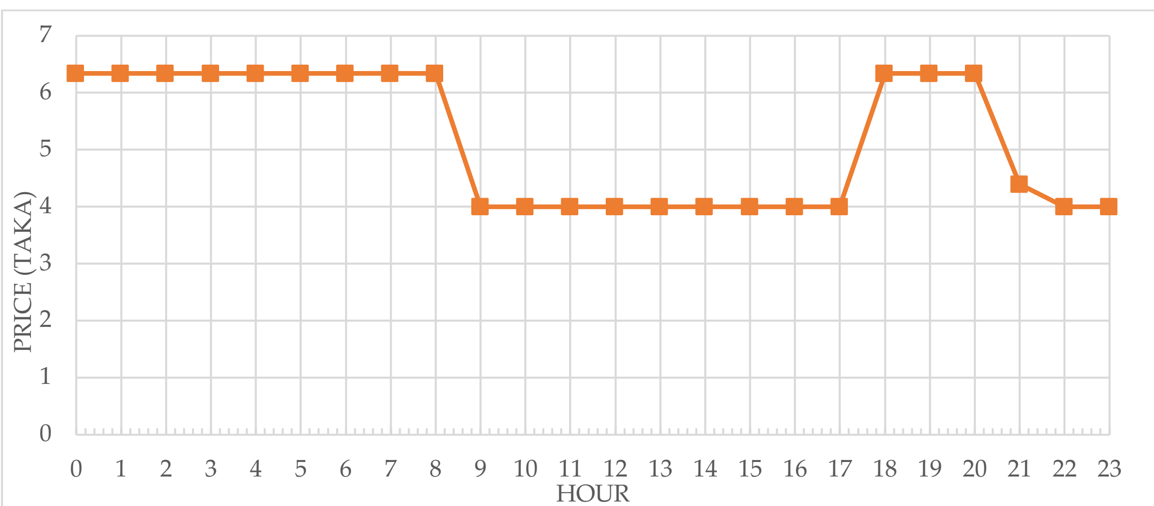

Figure 8 Hourly internal buying price of the consumer

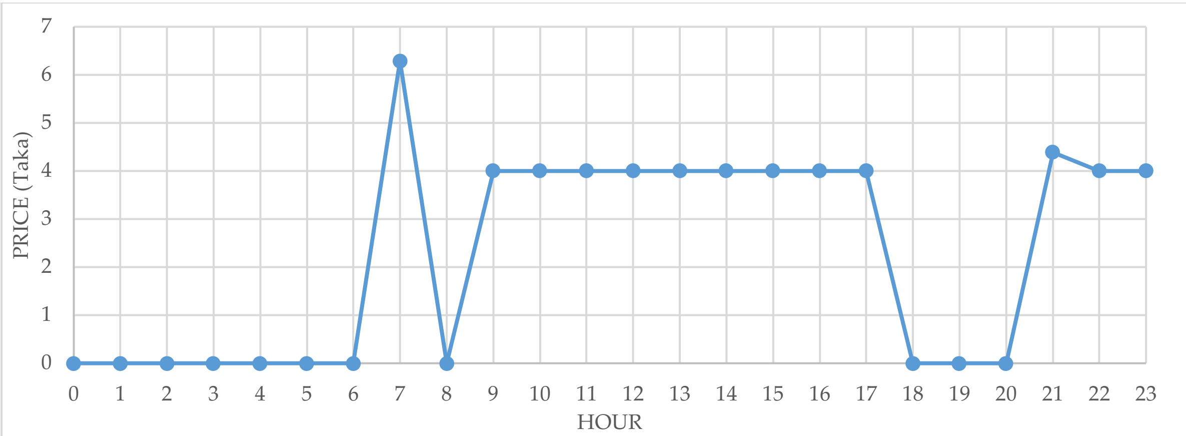

Figure 9 Hourly internal selling price of the prosumer

The first figure displays the reduction of the internal buying price of the consumer between 10:00 to 18:00 hrs. and 22:00 to 24:00 hrs. The second figure displays the internal selling price of the prosumers, which reveals that they will be able to earn money by selling their excess energy to the consumers when P2P trading takes place. Therefore, in these periods, both parties will get benefitted.

Figure 10 and Figure 11 display the difference in utility bills of the consumer and subsequent reduction with the utility grid before and after the implementation of P2P. Based on the load consumption, internal buying price, and equation (17), the optimized energy bill of the consumer is calculated.

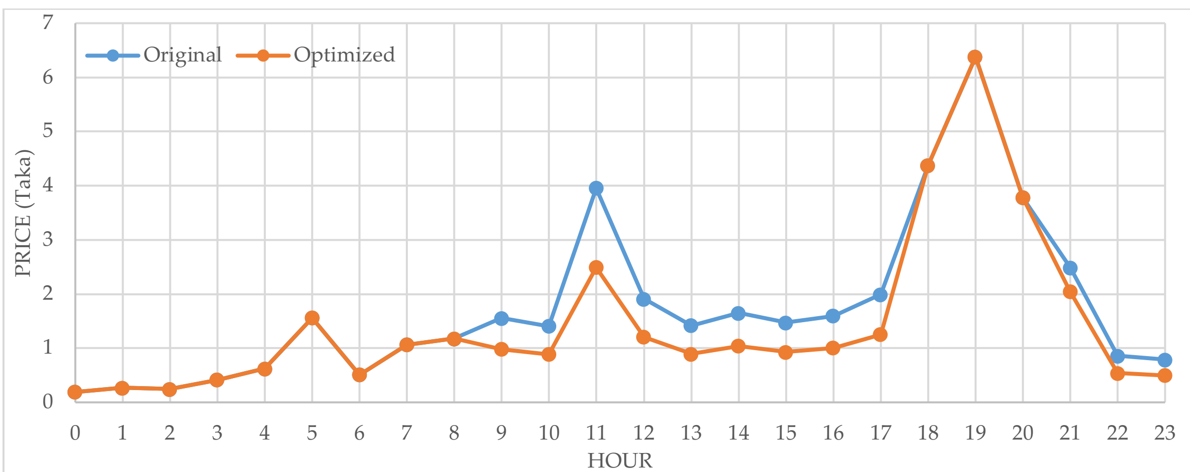

Figure 10 Reduction of utility bills

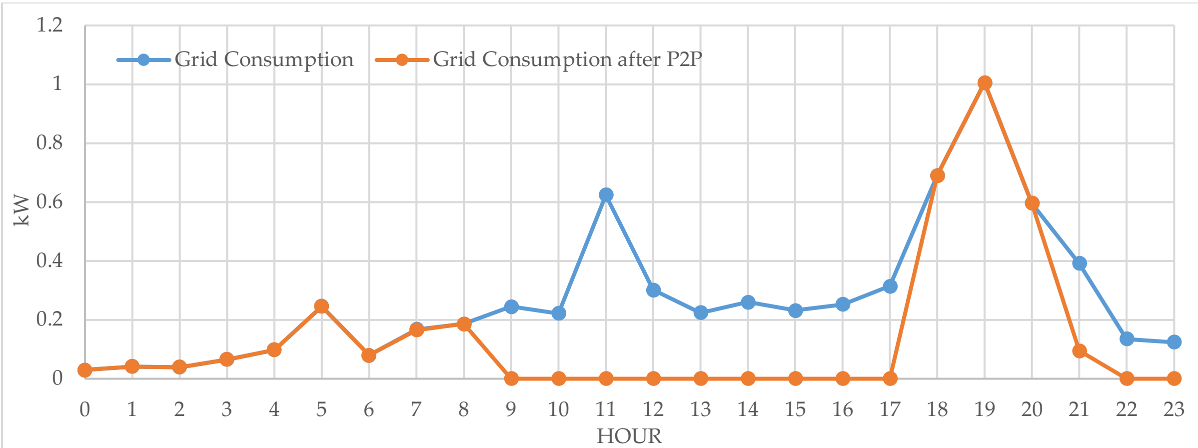

Figure 11 Reduction of exchange of electricity with the utility grid

Table 3 indicates that the consumer deducts 17.54% of the electric bill on a typical day in July. The interaction with the grid has been reduced by 49.53% as well.

Table 3 Comparison between original exchange and modified exchange with the grid in a typical day

Original bill (Taka/Day)	**Optimized bill (Taka/Day)**	**Reduction (%)**
41.66	34.35	17.54
Original exchange (kW/Day)	**Exchange after P2P (kW/Day)**	**Reduction (%)**
6.56	3.33	49.23

The optimization leads to a change in net power for both prosumers as they can sell excess energy to the consumers. Figure 12 shows the difference in net power curves for PV and wind turbine prosumers.

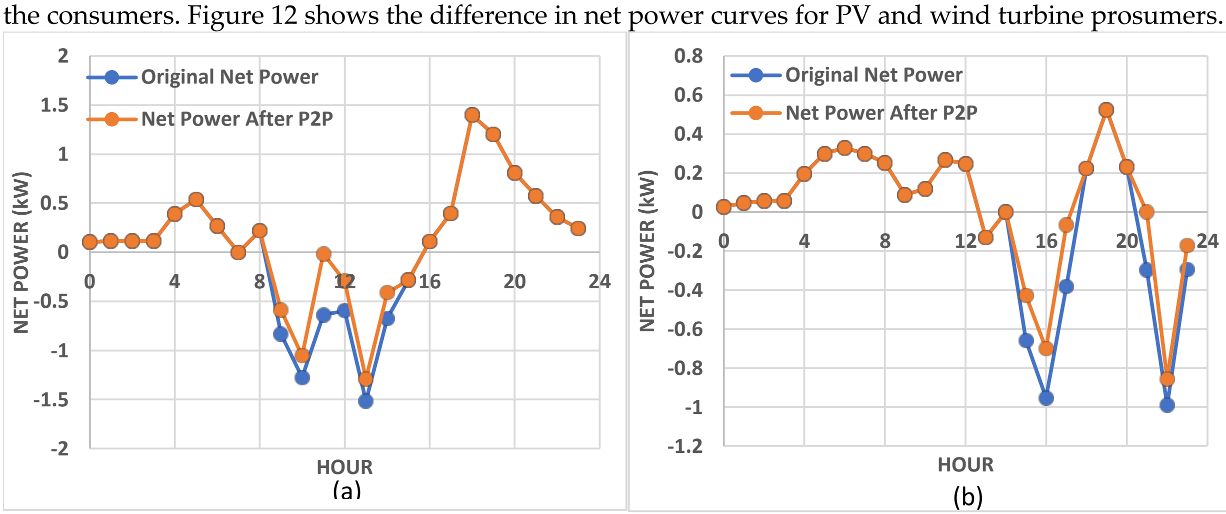

Figure 12 Difference of net power curves a) PV prosumer b) Wind turbine prosumer

4.1 Variation of the inconvenience factor α

The inconvenience factor α is used to indicate the self-optimization of the peers. A lower level of α means the peers are more willing to self-optimize their consumption; hence, they will profit more from the system. By increasing the value of α, the change in income of the prosumer can be seen in Table 4. Therefore, the prosumers need to pay more attention to keep the value of α at the minimum level. This inconvenience factor will encourage the peers to focus more on the energy management of different appliances.

Table 4 Income of the prosumers at between different value of α in a typical day

Prosumers	Income (Taka/Day) (α=0.01)	Income (Taka/Day) (α=0.02)	Income (Taka/Day) (α=0.03)
PV	14.54	14.14	13.03
Wind	10.17	9.8	8.4

5. Discussions

The case study reveals the potential of P2P trading in residential households in Dhaka, Bangladesh. Generally, the consumers have to pay high electricity bills in the peak months due to the higher consumption. But, as per the real-time data analysis in Homer Pro software based on the consumption pattern on a typical day in July, table 3 shows that the consumer still has 50% less interaction with the grid after the implementation of P2P trading. Therefore, the success of P2P during a peak month will bring economic benefits, especially among middle-class people. On the other hand, the prosumer can also earn money when they participate in the process by selling surplus energy to the consumer. As a result, the proposed trading mechanism could significantly alleviate this country's recent energy crisis. The architectural model of the P2P model has been divided into three categories: i) Registration layer; ii) Matchmaking layer; iii) Pricing layer.

The registration layer will allow the peers to register themselves as prosumer or consumers before initiating P2P trading.

The matchmaking algorithm matches the P2P participants as per their generation and consumption. The algorithm is set up in such a way so that the trading model equally benefits every prosumer. As the excess energy of the prosumer will be used for trading, the prosumers generating more excess energy will start the trading first according to the matchmaking algorithm. On the other hand, the consumer consuming the least energy will participate in the trading first with that prosumer. Hence, the SDR ratio can be maintained to one or greater than one, providing the most optimum pricing for prosumers and consumers. As a result, the peers will be more concerned to self-optimize their usage pattern, which will further increase the model's effectiveness and generate more profit.

The pricing layer will calculate the internal buying and selling price according to the matchmaking algorithm. Different SDR will provide different internal prices as the pricing will be based on the SDR ratio. Figure 06 reveals the internal buying and selling trends at different SDR.

Lastly, we have varied the inconvenience factor α to see the prosumers' income difference. Table 4 shows that by increasing the value of α, the income has been reduced for both PV and wind prosumers. When the value of α is 0.03, both prosumers' income has decreased by about 1.5 taka from the original. This will encourage the prosumers to consume less electricity and keep the SDR ideal. The overall process will be monitored and controlled by a third-party regulator. This agent will validate the energy transactions and billing process. Hence, the peers will not have to engage directly with the utility grid while they sell or buy electricity from them.

6. Conclusion

This paper represents an energy trading model between prosumers and consumers. As most prosumers produce surplus energy from renewable sources, the P2P trading model proposes a path to utilize this excess energy. By selling the extra power to other peers, the prosumer does not have to dispatch it through a dump load. The whole process will be regulated in three sets of layers. Each layer is designed by a distinctive set of algorithms that will select the most appropriate buyers and sellers according to the generation and consumption pattern of the peers. Thus, the peers generate maximum amount of profit from the platform. In contrast to the recent development going on in this sector, this paper introduces Outstanding Prosumers and proposes a simplified matchmaking algorithm to interact with other existing consumers to significantly reduce unnecessary loss of time in trading network, which enhances the efficiency of trading for larger-scale network trades.

The internal pricing model is developed based on the SDR. According to this principle, the relationship between price and SDR is inversely proportional, which means a higher SDR will lower the price, whereas a lower SDR will increase the price. Figures 8 and 9 depict that when SDR becomes less than one, the consumer starts buying the electricity at a higher rate than the original price. Therefore, peer self-optimization is prioritized among the peers to keep the SDR at the optimum level (i.e., 1). To prove the effectiveness of this scheme, a microgrid has been designed in Homer Pro with two prosumers and one consumer. The simulation results show that P2P trading opens an income source to the prosumer and reduces electricity bills and interaction with the utility grid to the consumers. During peak time, when the demand for electricity is high, the P2P scheme reduces the electricity cost. This cost has been seen to be reduced by 17.54% on a typical day of July, which is a month of peak demand. There is a reduction in interaction with the grid by 49.53%. Here, the SDR plays an important role so it should be kept at a low value to maximize the profit from the system. The success of P2P in a peak month like July when consumption is comparatively higher proves this sharing platform can make a massive difference in the renewable energy industry. Thus, site location and weather pattern are vital to examine to set up any renewable sources so that the peers can participate in this process even in peak times.

This is just the beginning of the P2P Energy trading system design; further, we should execute this algorithm using block-chain technology. A full-stack application shall be developed where all these algorithms shall be deployed using Smart-Contract Technology.

References

[1] S. Velliangiri, R. Manoharan, S. Ramachandran, and V. Rajasekar, "Blockchain Based Privacy Preserving Framework for Emerging 6G Wireless Communications," IEEE Trans. Ind. Informatics, vol. 18, no. 7, pp. 4868–4874, 2022, doi: 10.1109/TII.2021.3107556.

[2] M. J. A. Baig, M. T. Iqbal, M. Jamil, and J. Khan, "Design and implementation of an open-Source IoT and blockchain-based peer-to-peer energy trading platform using ESP32-S2, Node-Red and, MQTT protocol," Energy Reports, vol. 7, pp. 5733–5746, 2021, doi: 10.1016/j.egyr.2021.08.190.

[3] B. N. Alhasnawi, B. H. Jasim, Z. A. S. A. Rahman, J. M. Guerrero, and M. D. Esteban, "A novel internet of energy based optimal multi-agent control scheme for microgrid including renewable energy resources," Int. J. Environ. Res. Public Health, vol. 18, no. 15, 2021, doi: 10.3390/ijerph18158146.

[4] T. Alskaif, J. L. Crespo-Vazquez, M. Sekuloski, G. Van Leeuwen, and J. P. S. Catalao, "Blockchain-Based Fully Peer-to-Peer Energy Trading Strategies for Residential Energy Systems," IEEE Trans. Ind. Informatics, vol. 18, no. 1, pp. 231–241, 2022, doi: 10.1109/TII.2021.3077008.

[5] H. F. Camilo, M. E. M. Udaeta, A. L. Veiga Gimenes, and J. A. B. Grimoni, "Assessment of photovoltaic distributed generation – Issues of grid connected systems through the consumer side applied to a case study of Brazil," Renew. Sustain. Energy Rev., vol. 71, no. December 2016, pp. 712–719, 2017, doi: 10.1016/j.rser.2016.12.099.

[6] Y. Luo, S. Itaya, S. Nakamura, and P. Davis, "Autonomous cooperative energy trading between prosumers for microgrid systems," Proc. - Conf. Local Comput. Networks, LCN, vol. 2014-Novem, no. November, pp. 693–696, 2014, doi: 10.1109/LCNW.2014.6927722.

[7] M. Carrión, J. M. Arroyo, and A. J. Conejo, "A bilevel stochastic programming approach for retailer futures market trading," IEEE Trans. Power Syst., vol. 24, no. 3, pp. 1446–1456, 2009, doi: 10.1109/TPWRS.2009.2019777.

[8] L. Jia and L. Tong, "Dynamic Pricing and Distributed Energy Management for Demand Response," IEEE Trans. Smart Grid, vol. 7, no. 2, pp. 1128–1136, 2016, doi: 10.1109/TSG.2016.2515641.

[9] E. Guelpa and V. Verda, "Demand response and other demand side management techniques for district heating: A review," Energy, vol. 219, p. 119440, 2021, doi: 10.1016/j.energy.2020.119440.

[10] J. Abdella and K. Shuaib, "Peer to peer distributed energy trading in smart grids: A survey," Energies, vol. 11, no. 6, 2018, doi: 10.3390/en11061560.

[11] P. Du and N. Lu, "Appliance commitment for household load scheduling," IEEE Trans. Smart Grid, vol. 2, no. 2, pp. 411–419, 2011, doi: 10.1109/TSG.2011.2140344.

[12] H. A. Özkan, "Appliance based control for Home Power Management Systems," Energy, vol. 114, pp. 693–707, 2016, doi: 10.1016/j.energy.2016.08.016.

[13] B. N. Alhasnawi et al., "A new Internet of Things based optimization scheme of residential demand side management system," IET Renew. Power Gener., vol. 16, no. 10, pp. 1992–2006, 2022, doi:

10.1049/rpg2.12466.

[14] W. Lee, L. Xiang, R. Schober, and V. W. S. Wong, “Direct electricity trading in smart grid: A coalitional game analysis,” IEEE J. Sel. Areas Commun., vol. 32, no. 7, pp. 1398–1411, 2014, doi: 10.1109/JSAC.2014.2332112.

[15] B. Moradzadeh and K. Tomsovic, “Two-stage residential energy management considering network operational constraints,” IEEE Trans. Smart Grid, vol. 4, no. 4, pp. 2339–2346, 2013, doi: 10.1109/TSG.2013.2265313.

[16] G. Tsagarakis, R. Camilla Thomson, A. J. Collin, G. P. Harrison, A. E. Kiprakis, and S. McLaughlin, “Assessment of the Cost and Environmental Impact of Residential Demand-Side Management,” IEEE Trans. Ind. Appl., vol. 52, no. 3, pp. 2486–2495, 2016, doi: 10.1109/TIA.2016.2516478.

[17] D. Lauinger, P. Caliandro, J. Van herle, and D. Kuhn, “A linear programming approach to the optimization of residential energy systems,” J. Energy Storage, vol. 7, pp. 24–37, 2016, doi: 10.1016/j.est.2016.04.009.

[18] Y. Ye, D. Qiu, H. Wang, Y. Tang, and G. Strbac, “Real-time autonomous residential demand response management based on twin delayed deep deterministic policy gradient learning,” Energies, vol. 14, no. 3, 2021, doi: 10.3390/en14030531.

[19] Z. Wang, M. Sun, C. Gao, X. Wang, and B. C. Ampimah, “A new interactive real-time pricing mechanism of demand response based on an evaluation model,” Appl. Energy, vol. 295, no. January, p. 117052, 2021, doi: 10.1016/j.apenergy.2021.117052.

[20] H. Zhu, K. Ouahada, and A. M. Abu-Mahfouz, “Peer-to-Peer Energy Trading in Smart Energy Communities: A Lyapunov-Based Energy Control and Trading System,” IEEE Access, vol. 10, pp. 42916–42932, 2022, doi: 10.1109/ACCESS.2022.3167828.

[21] N. Liu, X. Yu, C. Wang, C. Li, L. Ma, and J. Lei, “Energy-Sharing Model with Price-Based Demand Response for Microgrids of Peer-to-Peer Prosumers,” IEEE Trans. Power Syst., vol. 32, no. 5, pp. 3569–3583, 2017, doi: 10.1109/TPWRS.2017.2649558.

[22] Y. Zhou, J. Wu, C. Long, and W. Ming, “State-of-the-Art Analysis and Perspectives for Peer-to-Peer Energy Trading,” Engineering, vol. 6, no. 7, pp. 739–753, 2020, doi: 10.1016/j.eng.2020.06.002.

[23] “Prices and factors affecting prices - U.S. Energy Information Administration (EIA).” https://www.eia.gov/energyexplained/electricity/prices-and-factors-affecting-prices.php (accessed Jul. 27, 2022).

[24] A. Paudel, K. Chaudhari, C. Long, and H. B. Gooi, “Peer-to-peer energy trading in a prosumer-based community microgrid: A game-theoretic model,” IEEE Trans. Ind. Electron., vol. 66, no. 8, pp. 6087–6097, 2019, doi: 10.1109/TIE.2018.2874578.

[25] W. Tushar et al., “A coalition formation game framework for peer-to-peer energy trading,” Appl. Energy, vol. 261, no. December 2019, p. 114436, 2020, doi: 10.1016/j.apenergy.2019.114436.

[26] M. Vahedipour-Dahraie, H. Rashidizadeh-Kermani, M. Shafie-Khah, and P. Siano, “Peer-to-Peer

Energy Trading between Wind Power Producer and Demand Response Aggregators for Scheduling Joint Energy and Reserve," IEEE Syst. J., vol. 15, no. 1, pp. 705–714, 2021, doi: 10.1109/JSYST.2020.2983101.

[27] K. Anoh, S. Maharjan, A. Ikpehai, Y. Zhang, and B. Adebisi, "Energy Peer-to-Peer Trading in Virtual Microgrids in Smart Grids: A Game-Theoretic Approach," IEEE Trans. Smart Grid, vol. 11, no. 2, pp. 1264–1275, 2020, doi: 10.1109/TSG.2019.2934830.

[28] K. Umer, Q. Huang, M. Khorasany, M. Afzal, and W. Amin, "A novel communication efficient peer-to-peer energy trading scheme for enhanced privacy in microgrids," Appl. Energy, vol. 296, no. 2018, p. 117075, 2021, doi: 10.1016/j.apenergy.2021.117075.

[29] A. Esmat, M. de Vos, Y. Ghiassi-Farrokhfal, P. Palensky, and D. Epema, "A novel decentralized platform for peer-to-peer energy trading market with blockchain technology," Appl. Energy, vol. 282, no. PA, p. 116123, 2021, doi: 10.1016/j.apenergy.2020.116123.

[30] M. R. Alam, M. St-Hilaire, and T. Kunz, "Peer-to-peer energy trading among smart homes," Appl. Energy, vol. 238, no. October 2018, pp. 1434–1443, 2019, doi: 10.1016/j.apenergy.2019.01.091.

[31] N. Spiliopoulos et al., "Peer-to-peer energy trading for improving economic and resilient operation of microgrids," Renew. Energy, vol. 199, no. May, pp. 517–535, 2022, doi: 10.1016/j.renene.2022.08.061.