Electrical Power and Energy Systems 137 (2022) 107865

Contents lists available at ScienceDirect

International Journal of Electrical Power and Energy Systems

journal homepage: www.elsevier.com/locate/ijepes

A priority-based approach for peer-to-peer energy trading using cooperative game theory in local energy community

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ARTICLE INFO

Keywords:
Peer-to-Peer
Cooperative game theory
Coalitions
Energy trading
Renewable energy
Prosumer

ABSTRACT

The energy sector is undergoing a paradigm shift to integrate the increasing volume of embedded renewable energy generation and create Local Energy Communities (LEC). Peer-to-Peer (P2P) energy trading is an encouraging paradigm used to increase usage of renewable energy, decrease consumers' electricity bills, and provide revenue to prosumers. It also improves the usage of Distributed Energy Resources (DERs) in the smart grid and reduces transmission and distribution losses. However, challenges such as unpredictability and intermittency of DER's may result in instability of P2P energy trading. In our work, we propose a cooperative game theory framework to expedite stable trading algorithms and incentivize individual users. This trading algorithm offers various priorities at each time interval depending on parameters such as geographic location, maximum energy demand, maximum energy generated, and pricing mechanism. We have considered a grand coalition whose objective is to maximize the coalition's social welfare and ensure a win-win approach for both consumers and prosumers. Hence the grand coalition made by the cooperative game is in Nash equilibrium as no peer wants to perform the merge and split from its current location. In the proposed algorithm, LEC includes 100 players (50 prosumers and 50 consumers), a community energy storage system (CES), and 15 Electric Vehicle charging points. The best operational output priority was also evaluated in this work for each time interval with associated distributed solar PV and CES. Results strongly support that using the best suitable priority for each time interval is beneficial rather than having one priority for an entire day. An economic analysis to distribute the revenue generated from the grand coalition in a fair manner is analyzed in this work. From the economic evaluation, it is apparent that prosumers have high revenue, and consumers save electricity bills when using the proposed algorithm.

1. Background

Recently the Covid-19 pandemic has triggered energy sector disruption than any other occurrence, leaving impacts that will be felt for years to come. According to World Energy Outlook 2020 [1], global energy demand has dropped by 5%, CO_2 emissions related to energy by 7%, and energy expenditure by 18% due to the pandemic. The energy sector is undergoing a paradigm shift to integrate the increasing volume of embedded renewable generation with distributed solar PV at the center of this modern power grid. According to [2], the EU have set ambitious energy and climate targets of integrating up to 32% renewable sources cutting greenhouse gas emissions by 40%, and increasing energy efficiency by 32.5%.

With the significant growth of various renewable types in the energy sector, such as solar rooftop panels, energy storage (ES), electric vehicles (EV), and small wind turbines, our traditional unidirectional grid is changing into a bidirectional smart grid [3]. In a conventional grid, electricity is generated in large power plants, transmitted using long-distance transmission networks, and provided to end-users at a fixed price. However, a smart grid allows the multidirectional flow of electricity where generation can also be performed at the distribution side, avoiding long transmission lines and fixed price distribution networks. Enhanced information and communication technology (ICT) devices [4] in the smart grid play a significant role in distributing electricity.

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https://doi.org/10.1016/j.ijepes.2021.107865
Received 30 April 2021; Received in revised form 5 September 2021; Accepted 7 December 2021
Available online 21 December 2021

Moreover, end-users on the distribution side can now actively control their energy behavior. However, it is challenging to forecast the end user's behavior due to the unpredictable nature of renewable resources and the intermittent nature of DERs, leading to dependability issues on the distribution side. This shift transforms customers into prosumers when a user manages several renewables and simultaneously produces and consumes electricity [5].

A **prosumer** [6] is a consumer capable of generating energy using a DER in their premises and trading excess energy to consumers in a distribution network. They may sell the energy to other consumers at a period of excess energy or pump it back into the main grid. A prosumer is financially incentivized by other consumers in the network when selling energy to consumers. The combination of prosumers and consumers in a network forms a local energy community (LEC). However, many distribution networks are not designed to handle the reverse power flows occurring with a rise in distributed energy resources. This reverse power flow can potentially endanger a power system's stability by increasing the bus voltage. Potential solutions to avoid such situations are therefore given in the present work. ES sharing [7] is one such tool used in our work to address this issue. Community energy storage (CES) provides economic benefits to the user by allowing them to trade energy within the LEC, as the trading price at which peers discharge CES is lower than that of the grid tariff and the price at which peers charge the CES is higher than the tariff offered by the grid.

One of the options for curbing the flow of surplus energy, which will help maintain a dynamic equilibrium in the power grid between supply and demand, is **Peer-to-Peer (P2P) energy trading** [8,9,10]. A peer can be referred to as a single user or a group of users that can trade electricity directly with other peers in the community. The energy demand of the consumers, called deficit energy, is fulfilled by the surplus energy generated by prosumers in a community. However, in a case where there is no surplus energy in the community, a peer asks for the deficit energy from the grid. With the greater adoption of solar rooftop energy, the P2P concept for energy trading was first introduced in 2007. Some of the benefits of P2P energy trading, when compared to supplying energy to the main grid, are as follows:

- Reducing the load and dependency on the power grid provides a win-win strategy [11] by choosing a trade price to be cheaper than the time of usage (TOU) tariff for consumers and higher than the grid tariff for prosumers [12].
- This trading model also referred to as the transactive grid, will allow prosumers to make more revenue than buying/selling to the main grid. Therefore, prosumers financial advantage can be improved with the aid of P2P energy trading due to a negotiated price. With the help of P2P trading, consumers can save their electricity bill [13] when switching from buying electricity from peers rather than from the grid at a lower price, and prosumers can generate higher revenue when selling energy to the peers rather than to the grid.
- Since trading takes place over shorter distances, one of the most significant benefits of P2P is greater use of power network capacity and reduction of distribution and transmission losses.

Game theory [14] is a mathematical tool to study strategic situations where players are free to choose the most acceptable economic result for themselves. Because of its function of solving complicated interactions between provider and receiver, it is a commonly used method for local energy markets(LEM) [15]. Cooperative game theory and non-cooperative game theory are the two primary forms of game theory. **Cooperative game theory**-based schemes rely on the fair distribution of the revenue first suggested in [16]. All the players in cooperative game theory are in Nash Equilibrium, i.e., no player or coalition can be economically better off by leave of the grand coalition. A **non-cooperative game** examines the decision-making strategy of a group of autonomous players in the game that have partially or entirely opposing interests resulting from a decision-making process impacted by their actions. Here, non-cooperative does not imply that players do not cooperate; it means that any cooperation in this type of game is not the result of the coordination of players [17]. We have considered a cooperative game theory mechanism in the present work, whose objective is to increase the coalition's total benefit. The trading algorithm aims to scale up players in a grand coalition while maintaining a high precision of revenue distribution to each player. Therefore, a secure technology like blockchain [9,18] can be introduced in the network to offer all peers the same access and anonymity.

2. Related literature and contribution

Several R&D projects with relation to P2P trading have been carried out in recent years [19]. The authors of [20] identify and analyze the core areas of P2P energy trading, including an analysis of current research and industrial activities based on the most recent global growth of P2P energy trading. An overview of the large and growing body of literature on various P2P markets (full, community and hybrid), future market potential development in this field, recommendations on business models and grid operation is discussed in [21]. However, this study does not consider methods for integrating the P2P market with existing wholesale and retail markets that will allow peers to switch from one market to another as per its convenience. A detailed background of various aspects of P2P is also discussed in [22], including identification of the challenges that need to be addressed to scale up the P2P mechanism in the electricity market.

Different optimization methods for P2P system operation have been considered. According to consumers preferences, the authors in [23,17] demonstrated a P2P market structure using a multi-bilateral economic dispatch (MBED) model for multi-bilateral trade. In [24], a two-stage model for energy sharing in a community microgrid was demonstrated where first, an optimization problem was used to decrease the energy cost. Then rule-based control was applied by revising the control setpoints. Using this two-stage analysis, the model reduced electricity bills by 12.4% for consumers, and the revenue of prosumers increased by 57% annually. The authors of [25] investigated a peer-to-peer energy trading scheme that takes advantage of social collaboration among network prosumers. In [26] a two-stage optimization strategy to increase interaction and cooperation between prosumers and consumers within a community is demonstrated. Based on prosumers preference, authors in [27] proposed a model to trade energy between prosumers and wholesale market to decrease the cost associated with losses and storage using price direct optimization. For peer-to-peer energy exchange, a motivational psychology system has been developed to increase prosumer engagement for those who have battery storage [28]. The authors suggested a coalition forming game that will assist each participating prosumer to decide whether to place their battery in the peer-to-peer energy trading market or not on an opportunistic basis.

More recently, attention has focused on a game-theoretic approach to transforming the distribution network using P2P energy trading. The literature on game-theoretic approaches is reviewed in [29], i.e. cooperative games and non-cooperative games for P2P energy trading, energy management of EV, DERs, storage domains and service domains. A framework considering both cooperative game theory and non-cooperative game theory is proposed in [30], where a pivotal player acts as a controller to distribute revenue among the peers fairly. The proposed approach uses a cooperative game so that small-scale prosumers can also survive in the market, and it automatically converges from a non-cooperative game to a cooperative game approach.

In a study to investigate the feasibility of social cooperation between prosumers [31], a canonical coalition game (type of cooperative game) is used, where a group of prosumers makes a coalition to trade with each other according to the mid-market price. However, the proposed trading scheme does not consider multiple P2P trading platforms with each proposing different pricing mechanisms for trading. The findings in [32] show that cooperative mechanisms outperform the nucleolus in terms of

computational efficiency and also in terms of incentivizing prosumers to stay in the grand coalition. Another study proposed a framework for small-scale energy trading using a flexible hybrid P2P model based on transactions between communities and peers [33]. Each peer can change its function at any moment, and both prosumer and producer peers can provide their generated energy based on the price. On the other hand, the authors of [34] proposed a dynamic model to trade depending on the surplus and deficit energy in a day ahead energy trading process.

Authors in [35], used transaction zoning in distribution network to trade energy according to bids and offers to avoid network constraints. In a study to explore the feasibility of social cooperation between prosumers [31], authors used mid-market price for trading to form a stable grand coalition. They found that the revenue of prosumers coming from mid-market pricing provided more stable coalitions than any other pricing mechanism. The assumption in most present systems is that a buyer pays the same price per unit of energy to all providers at any given moment. However, a discriminating pricing approach based on game theory is investigated in [36]. The focus is on determining fairness standards to maximize total benefits to end users and guarantee an energy trading system free of envy. In [37], an optimum pricing scheme is proposed with various priorities depending only on energy demand, i.e. buyers with energy demand less than 25% of their peak demand, from 25% to 75% and more than 75% of their peak demand. A P2P energy trading framework based on a coalition graph game is created in [38], where prosumers create a coalition to negotiate based on energy requirement and bidding price. However, no financial analysis to ensure fair P2P power curtailment is considered. To minimize the total cost daily, storage, shiftable loads, and local generation are used in [39]. Moreover, two methods (Nash Equilibrium and Shapely Value) are compared to distribute the revenue generated. Another study [40] creates their priority list based on incentive contracts to trade energy analyzing different loads, such as residential, industrial, and commercial. The authors of [41] present a novel price calculating technique that formalizes the challenge of setting retail rates as a multi-criteria optimization problem using a simulation-based optimization approach that accounts for prosumer reactions.

Based on the recent literature and to the best of the author's knowledge, most of the significant research in P2P energy trading is focused on optimization of a single parameter, such as energy demand, transaction zoning, energy bill savings, while considering different pricing schemes. In addition, most of the studies are either consumer-centric or prosumer-centric, while coordination between the economic benefits of both consumers and prosumers is not investigated. This paper addresses this gap and advances the state-of-the-art by proposing a novel framework for a local energy community (LEC) that effectively considers various priorities for each time interval and selects the optimal scenario. The framework determines the optimal priority for a grand coalition at each time interval according to factors such as maximum revenue generated, savings in electricity bills, and number of transactions. The trading priorities considered allow peers to trade energy based on energy demand, energy generation, geographical distance, and optimal pricing scheme. Thus, the contributions of the paper can be summarized as follows:

- This paper proposes a cooperative game theory-based framework for peers to interact and trade energy in a LEC. The proposed framework aims to encourage all peers to form a grand coalition by maximizing economic benefits for both prosumers and consumers.
- The study develops an algorithm that helps the aggregator to select the best priority according to energy demand (Priority A), geographical distance (Priority B), or trading price (Priority C). Within the selected priority, the algorithm also facilitates the peers to decide whether to charge or discharge the community energy storage (CES) to contribute to the proposed P2P energy trading.
- We also evaluate revenues for prosumers earned from trading energy to other peers in the distribution network, along with the savings in consumers' electricity bills when buying energy from prosumers in the distribution network.
- We demonstrate and evaluate our mechanism on an IEEE European low voltage test feeder dataset based on the electricity consumption and solar generation of 100 households and 15 EV charging points, all connected to a community energy storage (CES). The results are analyzed for the best priority of the formed grand coalition over 24 h. Results show that peers can get the best economic benefits if the trading is done according to geographical distance and price during daytime, and maximum energy demand and generation at night.

2.1. Paper organization

The remaining part of the paper is arranged as follows: Section 3 describes the system model. Section 4 introduces the algorithm for coalition creation in P2P trading and illustrates the algorithm's flow with various priorities. Results are analyzed in Section 5, accompanied by discussions. Lastly, Section 6 concludes the paper with recommendations for future work.

3. System model

To consider a system model for a low voltage distribution network, we consider the proposed LEC considering peers, smart meters, distributed solar PV, CES, EV charging points and aggregator that is presented in this section:

3.1. Peer

A **peer** can be referred to as a single user or a group of users that can trade electricity directly with other peers in the community. A peer can be a consumer or prosumer in a distribution network. Depending on the energy gap between distributed solar PV generation and household energy usage, a prosumer would first satisfy their own demand and then share the surplus energy with other network users. In the system model presented and shown in Fig. 1, we are considering 100 peers, out of which 50 peers have installed distributed solar rooftops of 5 kW each and 50 peers are consumers. Each peer has a smart meter mounted to provide the aggregator generation and consumption patterns built in a 24 h load profile format. Smart meters simultaneously track documents and transmits data to the aggregator. The smart meter also records the location and tells the time of use tariff by serving as a two-way contact between peers and aggregator. More smart meters are mounted in the CES system and EVs to access the batteries state of charge. The average power consumption and peak power consumption of the 100 peers in the LEC is 38 kW and 86 kW, respectively, using 5 min time intervals.

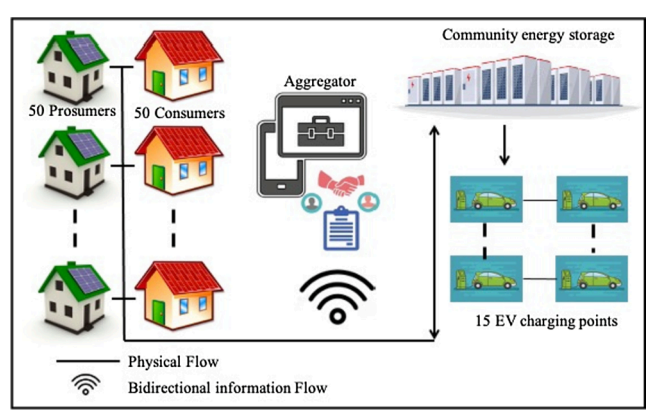

Fig. 1. Proposed Local Energy Community (LEC) having 100 users divided equally into prosumers and consumers, CES to fulfil energy demand during nighttime and 15 EVs charging points.

3.2. Community storage

As discussed above, one frequent option to curb surplus energy is to export excess distributed solar PV power to the grid. However, if distributed solar PV becomes more widely used, the export of energy from numerous households to the main grid at peak generation periods may produce grid imbalances and peak contingencies, resulting in extra system expenses. Furthermore, because export tariffs are generally lower than purchase energy costs in trading, the value of self-consumption or P2P trading of solar electricity for a peer is typically considerably more significant than the benefits from exporting electricity to the grid. Therefore, in the proposed system model, prosumers choose to discover new ways to enhance their P2P trading, such as charging CES after fulfilling the energy demand of LEC. When there is no surplus energy to charge the CES by distributed solar PV, the main grid will charge the CES. It should be noted that the grid will charge the CES only if the available capacity goes down to 30%.

If prosumers excess energy does not match the consumers' energy demand, the energy can be exported to or imported from the CES in charging and discharging, respectively. Hence, a prosumer either trades energy to other peers or charge the CES at a time interval T. As the PV generation is higher during daytime than at night, thus allowing all prosumers to join together in the supplier mode, which implies that the maximum number of prosumers is self-sufficient and will have surplus energy, which can charge the CES. However, as the surplus energy declines during nighttime, the energy demand rises, and the reliability of energy trading within the LEC using distributed solar PV also decreases. Hence, consumers need to take electricity from the CES or main grid to satisfy their energy demand. The community battery's capacity, state of charge, the overall capacity to charge and discharge it, and the network limit for transmitting energy are all taken into account when charging and discharging the battery. The power balance between generated energy and P2P energy traded can be expressed as:

$$\underset{V}{Min}\sum_{N\in\varnothing} P_N\left(E_d, E_S, W_c, W_p\right) + B(Chg, Dhg) \tag{1}$$

$$s.t.\ \ E_d + E_S + W_c - W_p = 0; \quad \sum_{N\in\varnothing_b} E_d = 0$$

$$\sum_{N\in\varnothing_b} W_c\ \ x\ \ Deficit\ \ energy = Dhg; \quad \sum_{N\in\varnothing_s} W_p\ \ x\ \ Surplus\ \ energy = Chg$$

Here $P_N\left(E_d, E_S, W_c, W_p\right)$ are decision variables for energy trading, W_c and W_p denote the willingness factors of consumer and prosumer, respectively, and is calculated at each time interval. Let us assume the energy demand of the consumer at time interval t is E_d and surplus energy of the prosumer is E_s. Willingness factors help identify users willing to trade in the P2P market ($W_c, W_p = 1$) or not ($W_c, W_p = 0$). P_N in the above equation expresses the cost dependent on decision variables. $B(Chg, Dhg)$ is the parameter for charging and discharging the CES.

Utility 1 (U_{01}) refers to the state when batteries are discharged to complete the community's energy demand, and Utility 2 (U_{02}) refers to the condition in which batteries are charged when surplus energy is greater than the energy demand.

$$U_{01,s}(t) = k\left[E_c(\mathrm{t})xC - 0.5xSx(E_c(t))^2\right] - (d + P_c)E_c(\mathrm{t}) \tag{2}$$

$$U_{02,d}(t) = k\left[E_d(\mathrm{t})xSoC - 0.5xSx(E_d(t))^2\right] + (P_d - d)E_d(\mathrm{t}) \tag{3}$$

The goal of calculating P_c (charging price for unit energy at time interval T) and P_d (discharging price for unit energy at time interval T) is always to measure the maximum and minimum cost to use CES, where k is a scaling factor ($0 \le k \le 1$), E_c (t) is total energy charged by all peers at time t, E_d (t) is total energy discharged by all peers at time t, and C is the accessible capacity of the CES, S is satisfaction factor (which is always greater than 0), d is degradation cost per kWh and state of charge is denoted by SoC. The size of CES in the system model presented is 15 MW, which is enough to fulfil the LEC demand at night as well as when no generation is possible.

3.3. Electric vehicles

There are 15 EV charging points assumed in the system model for LEC. EVs are charged directly from CES. At each time interval, a fixed price by the aggregator for EV to take energy from CES is calculated. According to the data used for the system model, most EVs get charged at night.

3.4. Aggregator

As the framework works as a centralized market, an aggregator communicates with each peer or entity involved in peer-to-peer energy trading. It decides the energy import/export of the peers or the operating state of the devices among the peers based on the information gathered from the peers. An aggregator oversees the trading network and management, operation, exchange, and transfer of revenue generated by P2P energy trading. Advantages of a centralized market are: (a) an aggregator will help optimise the system model's social welfare and choose social welfare as the optimization function; (b) with the centralized market, the aggregator can manage energy generation and demand patterns resulting in less uncertainty. This is because, unlike distributed or decentralized markets, the aggregator (coordinator) has direct control over the operational state of peers.

A time interval is set by the network aggregator that can be 5, 15 or 30 min. At a time interval T, if the user has no excess energy, it acts as a consumer and informs the aggregator about its electricity demand, E_d. Similarly, if a user can generate excess energy after completing its own demand, it works as prosumer and informs the aggregator about the extra energy, E_s.

A prosumer will first meet their demand and then share the surplus energy with other network users, depending on the energy difference between distributed solar PV generation and household energy consumption. Each peer with a solar panel acts as a prosumer, and their excess energy is distributed to other peers in the network or to the CES. A prosumer can also act as a consumer at a specific time interval T if the energy generated is less than the energy demand. Hence, the aggregator calculates an energy balance for all peers and assigns all peers as a prosumer or a consumer accordingly. When a peer with an energy deficit (consumer) receives a transaction request from a peer with an energy surplus (prosumer), it first decides if the energy shown for the transaction is sufficient to satisfy the energy demand. If this is the case, the peer acting as a supplier will send a confirmation message to the receiver peer, confirming the transaction. Otherwise, it sends a termination letter, and the recipient will send a transaction request to another peer before all the conditions are met. All the network consumers try to complete their energy demand by purchasing from prosumers at a calculated trading price rather than getting from the main grid or CES. When prosumers do not generate any energy from distributed solar PV during night, all peers will act as consumers and trade energy from the CES. Properties of forming a grand coalition using cooperative game theory to properly execute peer-to-peer energy trading are as follows [15]:

- Superadditivity: The establishment of a grand coalition must benefit all coalition consumers and prosumers, i.e., trading P2P should be better than trading with the main grid. As a result, both types of peers want to maximize the coalition's total social welfare. To do so, however, the value function υ must be superadditive, which implies that the overall revenue gained by a group of peers by forming the grand coalition must be at least equivalent to the total benefit gained by trading independently.
- The core: All revenue should be distributed fairly among all peers in the coalition. This revenue may be distributed in P2P energy trading

by appropriately changing the trading price (*TP*) such that no subgroup of peers can earn more significant income by the merge and split method. The core of a coalition is the possible distribution of this revenue among members, and if the core of a coalition is nonempty, no group of peers has any reason to leave that coalition.

- Stability: When all peers receive their essential revenue, no one wants to leave the coalition, keeping it stable. As a result, all network consumers continue to engage in P2P energy trading.

4. Proposed algorithm for stable coalition formation using various priorities

In this section, an algorithm is proposed to help the peers in the network to select one of the priorities from the available options at each time interval T. Priorities presented in this work are based on maximum energy demand, maximum energy generation, geographical distance between 2 peers and lowest price. The aggregator is responsible for setting up the priorities, managing the transaction between peers, scheduling energy at each time interval, and balancing the LEC's energy demand and generation. The aggregator assigned will ensure that energy transactions are conducted in a timely and orderly manner. The number of transactions depends on the selected priority and the energy required to balance supply and demand. Each transaction can consist of 2 or more peers. When forming pairs, a group of prosumers will deliver a single consumer's energy requirement when the generation from one prosumer is not capable of completing the demand of one consumer. Similarly, when demand is less than generation between peers, a single prosumer will deliver to multiple consumers. Fig. 2 illustrates the flowchart of a priority-based Peer-to-Peer energy trading algorithm to form a grand coalition. We tackle the stability of the grand coalition by using the concept of Nash Equilibrium. A coalition is said to be Nash stable if no peer has incentive to move from its current state Sπ to join a different state S'π or to trade alone. Overall, the trading algorithm follows three critical steps in each time interval: Step 1 is to establish players as consumers and prosumers with reference to the surplus and deficit energy; Step 2 is to decide the role of CES in charging, discharging or standby; Step 3 is for the selection of priorities (energy demand, geographical distance, or lowest price).

Step1: Let us assume that N peers are ready to trade with each other at a time interval T. Among N peers, there are prosumers denoted by N_S, and consumers represented by N_B such that $N_S, N_B \in N$. All prosumers first meet their own energy demand (E_d) using the surplus energy generated by distributed solar PV (E_s). Each peer in the network broadcasts its address, surplus energy, energy necessity, timestamp, state (provider or receiver), and price for exchanging energy with other peers. Then, the algorithm calculates the difference between energy demand and produced energy, i.e., surplus energy and the sum of all peer's surplus energy, denoted by α.

Step2: If distributed solar PV is inadequate to satisfy the LEC energy needs, the aggregator will check whether energy can be bought from the CES. When α is positive, the LEC will meet its own demand without relying on energy from CES. However, when α is negative, the CES may serve as a provider and helps the network fulfil its demand. This condition is most likely to arise during the night Hrs. when a DER would fail to satisfy the entire community electricity demand. According to the CES's charging or discharging mode, the aggregator chooses whether to use Utility 1($U_{01,s}$) or Utility 2($U_{02,d}$) as explained in section 3.2.

A detailed description of priorities applied in Step 3 is provided in the following sections:

4.1. Priority A (Energy demand)

Based on the information delivered to the aggregator by all parties, the aggregator initiates a ranking system in priority A according to the energy demand of consumers N_B and excess energy available of prosumers N_S. Here, prosumers prioritize high demand consumers to initiate an agreement for P2P trading. Priority A initiates by positioning distributors and receivers in descending and ascending order, respectively. Once the system's priority list is ready, the list is sent back to the users to start trading. Let us assume that J_i is the first consumer in the J_n list and I_i is the first prosumer in the I_n list. We can say that J_nI_n becomes engaged in trading and make a pair. As a result, the J_nI_n pair can trade 'δ' energy in the P2P market. Once the trade of δ energy is completed, the algorithm checks the consumer's energy demand and available excess energy. If I_n still has surplus energy, i.e.$E_S \neq 0$ after completing Jn demand, the algorithm allows In to establish a smart contract again with the next highest demand consumer. Similarly, if consumer J_n demand is not fulfilled by prosumer I_n, the algorithm allows Jn to establish a smart contract with the next highest excess energy prosumer. The advantage of this priority over others is that it benefits prosumers or selling electricity with the highest demand, limiting the number of smart contracts fulfilled by a single supplier at the same time. This situation minimizes the number of transactions between consumers and prosumers in each time interval *T*. The financial savings of the recipient are more significant

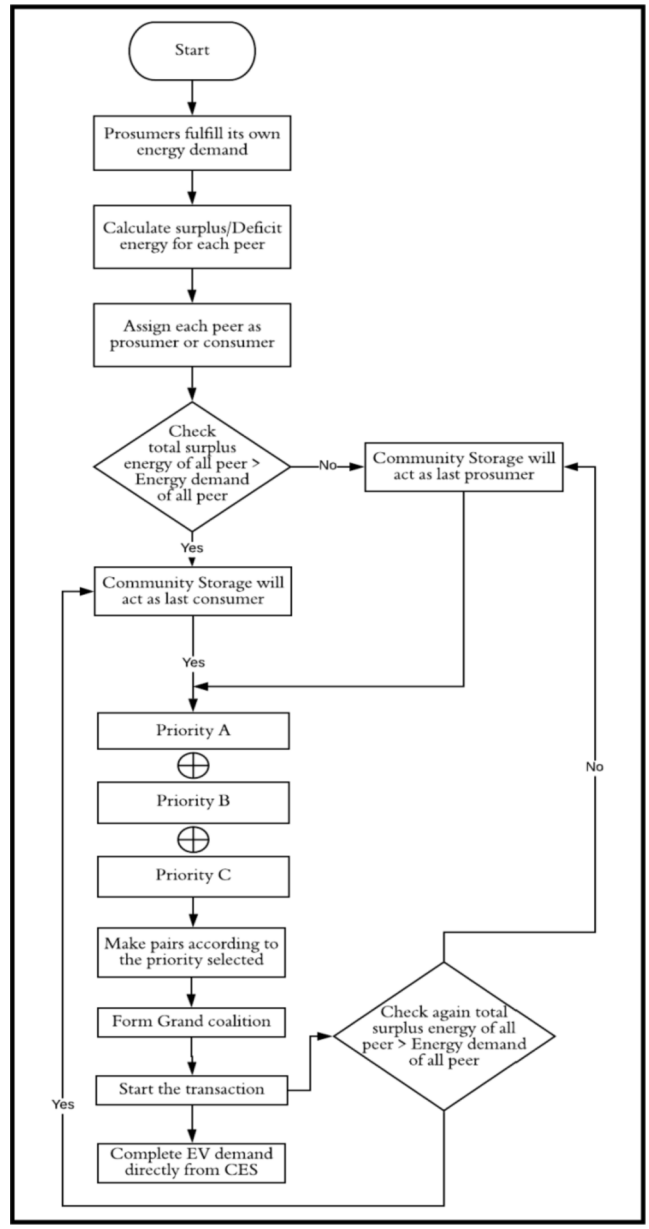

Fig. 2. Flowchart of the proposed algorithm for P2P energy trading using cooperative game theory.

than the grid tariff of the primary grid. Increasing benefits will serve as a motivation for high-energy-demand receivers to invest in the LEC-run electricity market.

4.2. Priority B (Geographical distance)

In this priority, a prosumer will always prefer to trade with the consumer nearest to its location for the energy δ at time interval T. Priority B distributors will export their excess electricity to consumers using a rating scheme based on the geographical distance between the sources of production and the demand. We assume that all the peers are connected in a ring network. Therefore, surplus energy would be delivered first to the consumption point (consumer) with the shortest distance from the generation point (prosumer), followed by the other closest consumers. After assembling the information, it is delivered to the aggregator by both parties, and the aggregator initiates a ranking system in priority B according to the distance between peers. A consumer will always tend to trade with the prosumer nearest to its geographical distance for the energy δ at time interval T. Once the priority list of both consumer and prosumer is ready, the list is sent back to the users to start trading. Subsequently, the aggregator establishes a smart contract between two parties (J_n and I_n) based on the geographical distance. As a result, the J_nI_n pair can trade δ energy in the P2P market. Once all users trade is completed, the algorithm checks the consumers energy demand and runs again until the demand or generation is equal to zero. Priority A limits a prosumer to trade electricity with the consumers only having high demand. However, priority B proposed here gives an equal opportunity to trade with several consumers rather than a consumer having high electricity demand. Hence, priority B motivates small players to participate regularly in P2P trading compared to other priorities. Priority B considers mid-market price (mid value of buying price and selling price) for trading for all time intervals.

4.3. Priority C (Pricing mechanism)

The algorithm will initiate a pricing mechanism to calculate the trading price for each pair in the network. In response, both prosumer and consumer submit the input data required, such as the consumer's electricity demand E_d, buying price BP, surplus energy offered by the prosumer E_S, and selling price SP. After assembling the data from all users, the information is announced to the aggregator. The willingness factor of buyer and seller at each time interval must remain 1. In any case, W_c, W_p is equal to zero, then trading of electricity will not take place between two users. Trading price is depended on the energy requirement, i.e., it is dependent on the load level. The trade price (TP) in cooperative game theory will be set according to the grid selling and buying energy prices (SP and BP), and it must fulfil the following condition: $BP \gg TP > SP$. Instead of assuming a mid-market methodology to calculate the trading price, which is used in literature, we introduced a factor μ to make the framework more realistic. Due to this factor, trading price is highly dependent on energy demand and surplus energy. Moreover, it will help consumers save their electricity bill and prosumers generate revenue, creating a win-win approach for both. This will push people to reduce their demand when surplus energy is low, thus, acting as an incentive. Therefore, to find the trading price, μ is defined as the ratio of prosumer surplus energy and consumer energy demand:

- If the surplus energy is greater than the demand for a time interval T, μ is greater than 1(μ >1), and the trading price is calculated as $TP = \mu*0.5*(BP + SP)$.
- If the surplus energy is less than the demand for a time interval T, μ is less than 1(μ < 1) and trading price is calculated as $TP = \mu*0.5*(BP + SP)$.
- If consumers demand is equal to the generation of prosumers, μ is equal to 1 and $TP = 0.5*(BP + SP)$

Considering the price mechanism described, the user earns a payback value after providing excess energy to the consumers at each time interval T. The aggregator calculates different trading price for each transaction. It should be noted that no two pair have same trading price. A prosumer always tries to use its surplus amount of energy in trading because a prosumer is well aware of the fact that the P2P energy market can benefit more when compared to exporting to the grid.

5. Results and discussion

Simulation Setup: In this section, we perform the simulation of 100 households in the proposed cooperative game theory for P2P energy trading on the IEEE European Low Voltage Test Feeder [42]. The simulations are based on 100 households, including 50 consumers and 50 prosumers, CES and 15 EV charging points. The dataset used is of 24 h, where generation data is only available during the daytime due to the nature of solar rooftop, and the energy demand of all the peers and EV charging points is over 24 h. A prosumer will first meet their demand and then share the surplus energy with other network users, depending on the energy difference between distributed solar PV generation and household energy consumption. A prosumer can also act as a consumer at a specific time interval T if the energy generated is less than the energy demand. When prosumers do not generate any energy from distributed solar PV during the night, all peers will act as consumers and trade energy from the CES. The grid tariff at which consumers can buy power from the grid and the export price at which prosumers can sell energy to the grid follows the California price structure: $ 0.20/kWh and $ 0.09/kWh.

Fig. 3 displays the graph of energy generated from the solar rooftop by 50 prosumers in LEC versus the energy demand of 100 peers in the network. The common area of energy demand in red and energy generated from blue shows the energy traded from time interval 50 to 240 using solar rooftop, representing CES is in charging mode. From time intervals 0 to 50 and 240 to 288, CES will fulfil the demand of 100 users and will be in discharging mode. Fig. 4 shows the demand for 15 EV charging points that are charged using CES. We can see that EV gets charged mainly during the night, and there is no demand from timeslot 90 to 160. Fig. 5 shows the experimental data of surplus and deficit energy of all peers. The positive value indicates surplus energy, while the negative value indicates deficit energy. From the graph, it can be seen that there is significant surplus energy from time intervals 60 to 200, excluding a few time intervals where consumers tend to take energy from the CES. Fig. 6 presents the results of the charging and discharging pattern of CES in P2P energy trading. CES gets charged only from the

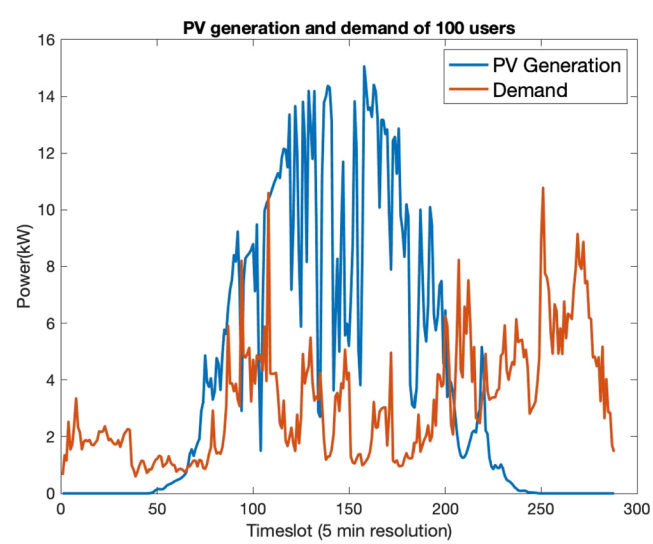

Fig. 3. Demand and generation of 100 users.

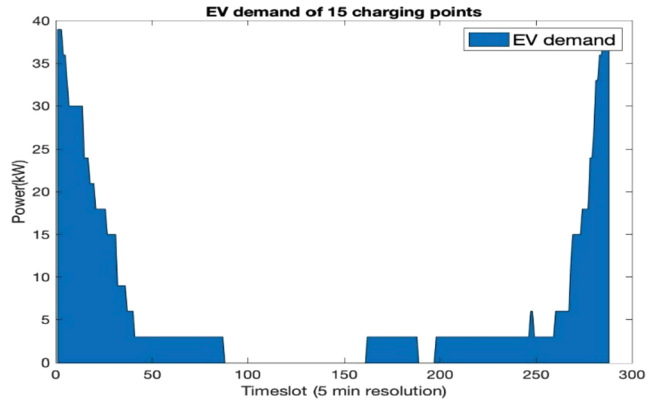

Fig. 4. Electric Vehicle demand of 15 charging points.

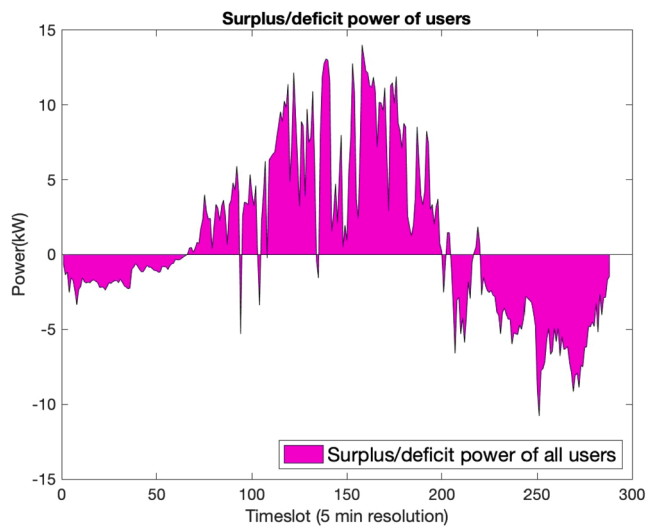

Fig. 5. Positive y-axis showing surplus power and negative.

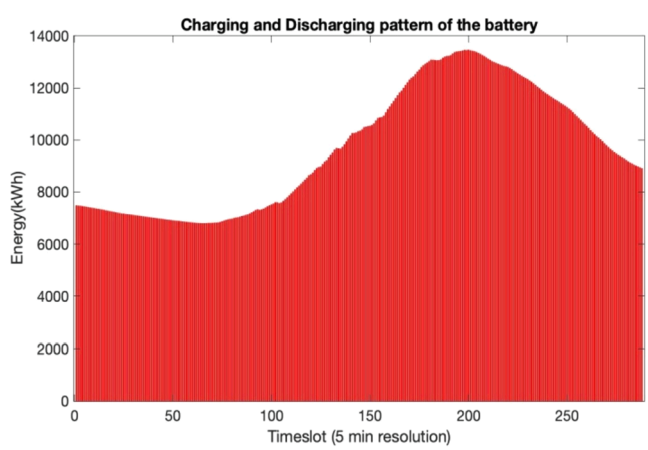

Fig. 6. Charging and discharging pattern of CES y-axis showing deficit power.

solar rooftop, and consumers and EV charging points discharge it.

Three priority studies are considered as described previously for a grand coalition in Nash equilibrium. The first priority considered pairing the highest energy demand with the highest energy generated for energy trading. The second priority allows a consumer to trade with the nearest prosumer in the ring network. The third priority focuses on the lowest price offered by the prosumer to exchange energy with the consumer.

Table 1
P2P energy trading of Priority A, B and C at four different time intervals.

Time (Hrs.)	Energy demand (kW)	PV Generation (kW)	Surplus energy after P2P trade	Deficit energy after P2P trade	Charging/ discharging of community battery
0000	6.86	0.00	0.00	6.86	−6.86
0600	18.09	29.78	11.69	0.00	11.69
1200	35.60	50.90	15.30	0.00	15.30
1800	54.86	27.77	0.00	27.09	−27.09

Table 1 shows the energy demand, energy generated, surplus energy in LEC, deficit energy in LEC and charging/discharging of CES for four different time intervals from the 24 h analysis. The analysis was done for 288 timeslots, but we will show three representative time intervals to compare trading under different conditions: 0600 Hrs. when solar PV energy is available but the demand is low; 1200 Hrs. when both solar PV and demand are relatively high and finally 1800 Hrs., when solar PV is decreasing while load demand is increasing.

5.1. Priority A (Energy demand)

To evaluate the performance of priority A as explained in section 4, we demonstrate our algorithm in Matlab and use the previously described simulation data of 100 peers and CES. The recipient with the highest energy demand will trade with the supplier with the highest surplus energy at each time interval in this priority. The algorithm's output are the sorted consumers and prosumers according to their energy demand and generation. Moreover, the algorithm provides information of pairs that can be formed with the peer number when using this priority to help the aggregator distribute the revenue. Our simulation window is 24 h.

Fig. 7(a, b) displays transactions of two different time intervals, i.e., 0600 Hrs. in Fig. 7(a) and 1200 Hrs. in Fig. 7(b) that are selected to compare with other priorities in this section. The green bar shows the number of prosumers having specified excess energy, and the yellow bar indicates the number of consumers deficit energy. According to Table 1, at 0600 Hrs., total energy demand is 18.09 kW, energy generation is 29.78 kW, energy traded is 18.09 kW, and CES is charged as generation is higher than demand. The surplus of distributed solar PV generation of individual prosumers and CES is thus accessible to the rest of the LEC. At 0600 Hrs., 47 prosumers and 53 consumers were arranged according to the energy demand and generation in descending order. The highest energy generated by prosumer 1 at 0600 Hrs. is 0.7 kW, and the highest energy demand of consumer ay 0600 Hrs. is −3.8 kW. Hence, we can say that prosumer 1 (Highest energy generated peer) alone cannot fulfil the demand, and multiple prosumers are required to complete energy demand. Once the consumer's energy demand having −3.8 kW is completed, prosumers will deliver energy to other consumers according to their ranking system. Similarly, at 1200 Hrs., energy demand is 35.60 kW, PV generation is 50.90 kW, energy traded is 35.60 kW, and CES is again charged as generation is higher than demand. From the graph, it can be seen that there are 45 prosumers ready to trade energy with 55 consumers. The highest excess energy available to trade is 1.28 kW, and the highest energy demand is −2.8 kW. In contrast to earlier transactions, there will be fewer transactions to complete the highest consumers energy demand as the energy generation is also high at 1200 Hrs. It should be noted that, as the energy level of prosumer and consumer varies, the order of the maximum energy demand and maximum surplus energy varies. Therefore, the circular graph keeps changing after each 5-minute time interval. However, the prosumer number representing household number within a ring network remains same for all time interval in circular graphs. We observe that the proposed algorithm reduces the peer dependence on the CES and the main grid.

The circular graphs in Fig. 7(c, d) presents a directed graph of the

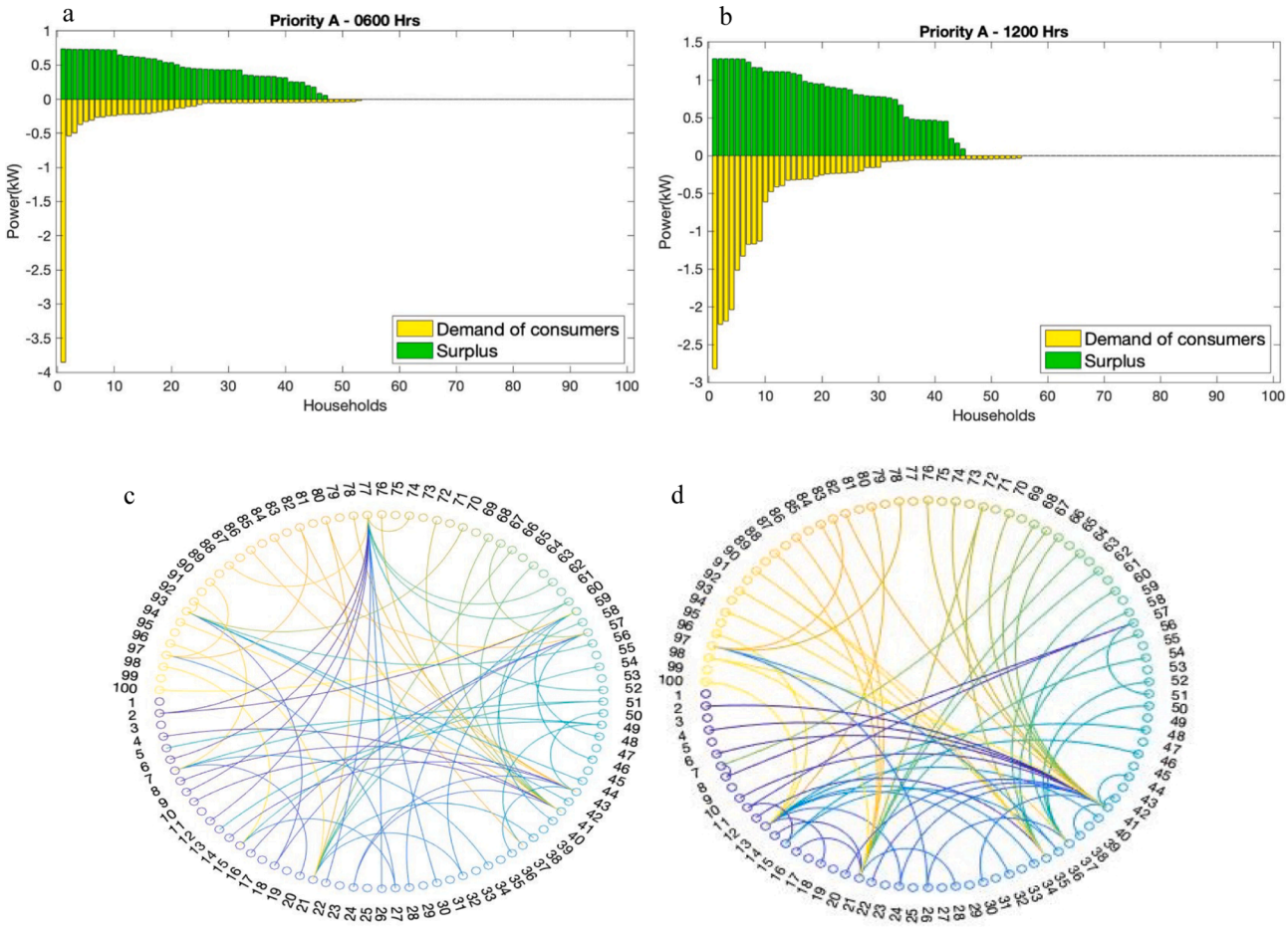

Fig. 7. Priority A (according to energy demand) based Energy trading at (a) 0600 Hrs. and (b) 1200 Hrs. with the circular graph (c, d) showing the energy transfer from prosumers to consumers.

100 peers in the community (location marked on the graph represents location relative to neighbours) for 0600 Hrs. in Fig. 7(c) and 1200 Hrs. in Fig. 7(d). This graph illustrates how individual sets of peers interact with each other through the most efficient path in terms of energy demand and generation. These circular graph illustrates the transfer of energy from one peer to another. By circular graph, the aggregator and peers can identify the details of energy sold and thus, revenue generated. If two peers have the same amount of energy simultaneously, the one with the shorter distance would be chosen for trading. It may be noted that a transaction can be one to one (O2O), or one to many (O2M), or many to one(M2O).

5.2. Priority B (Geographical distance)

Priority B results strongly depend on the geographical distance between two peers and the network infrastructure, which is in a ring format in this case. Let us take an example; when peer 50(n) is used as the index, peers 49 and 51 will receive the highest trading preference. Until the trade is completed, this loop will continue to do transfers from $n + k$ and n-k houses before the trade is completed, where $k = 1,2 \ldots 49$. Two time intervals, i.e., 1200 Hrs. and 1800 Hrs., were used to illustrate this priority. The prosumer can send surplus energy to the consumer in priority B based on the shortest distance between a generation point and a consumption point. If two peers are at the same distance from the receiver simultaneously by chance, the one with the most surplus energy would be favoured.

Fig. 8(a, b) displays transactions of two different time intervals, i.e., 1200 Hrs. in Fig. 8(a) and 1800 Hrs. in Fig. 8(b) that are selected to compare with priority A and C in this section. The green bar shows the number of prosumers having specified excess energy, and the yellow bar indicates the number of consumers' deficit energy. It should be noted that for this priority, no sorting was prepared. According to Table 1, at 1200 Hrs., energy demand is 35.60 kW, energy generation is 50.90 kW, energy traded is 35.60 kW, and CES is charged as generation is higher than demand. The surplus of distributed solar PV generation of individual prosumers and CES is thus accessible to the rest of the LEC. According to Fig. 8(a), the energy generated by prosumer 1 (peer 1) at 1200 Hrs. is 0.2 kW, the energy demand of consumer 1 (peer 2) at 1200 Hrs. is −0.2 kW, and the energy generated by prosumer 2 (peer 3) at 1200 Hrs. is 1.1 kW. After submitting the energy data to the aggregator, the algorithm checks the n + k and n-k prosumers. As prosumer 1 can complete the demand of consumer 1, a pair will be formed between peer 1 and 2, as illustrated in Fig. 8(c). Similarly, this methodology will continue until the energy demand is completed for k = 1,2…49. Interestingly, a single prosumer can complete the demand of a single consumer in most of the transactions, which is not the case in priority A.

However, the condition is opposite at 1800 Hrs. as energy demand is 54.86 kW, energy generated is 27.77 kW, energy traded is 54.86 kW, and CES is discharged because demand is higher than generation. As shown in Fig. 8(b), peers 1&2 both act as consumers with the energy demand of −0.1 kW and −0.2 kW, respectively. Referring to the energy data in the figure, peer 3 acts as a prosumer having surplus energy of 0.4 kW, which is enough to fulfil the demand of consumers 1 and 2. Additionally, the left 0.1 kW surplus energy is traded with consumer 3 (peer 4) in the circular graph Fig. 8(d). At 1800 Hrs., the energy situation shifted drastically when the need for energy surpassed the supply. However, as

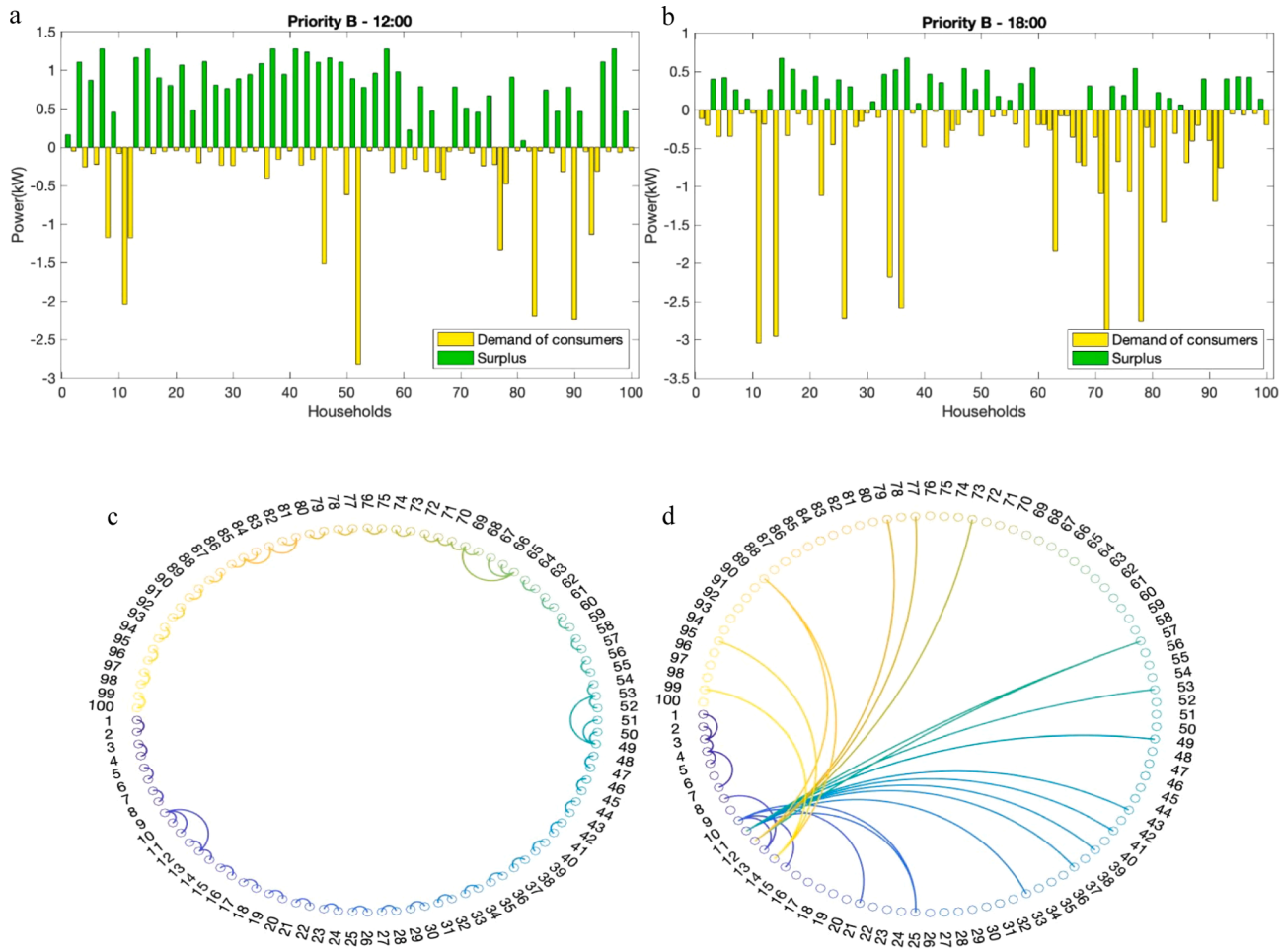

Fig. 8. Priority B (according to geographical distance) based energy trading at (a) 1200 Hrs. and (b) 1800 Hrs. with the circular graph (c, d) showing the energy transfer from prosumers to consumers.

demand is higher than generation, multiple prosumers tend to complete the demand of single consumers, as shown in Fig. 8(d). As a result, peers with the shortest network distance from the prosumers can trade first, followed by CES discharge. It should be noted that, as the energy level of prosumer and consumer varies, the order of the maximum energy demand and maximum surplus energy varies. Therefore, the circular graph keeps changing with transaction O2O, O2M, and M2O at each 5 min interval. However, the prosumer number representing household number within a ring network remains same for all time interval in circular graphs.

5.3. Priority C (Pricing mechanism)

Priority C mechanism provides consumers with the best trading price and enables prosumers to generate more overall revenue. The cooperative game complies with the issue of individual interest and fully leverages the grand coalition, thereby improving the total revenue of all the users in a coalition. Energy trading according to the buying price and selling price are analysed using priority C in Fig. 9. There are two different time intervals considered, i.e., 1800 Hrs. and 0600 Hrs. It is found that the energy demand is higher than solar generation at both the time intervals selected when compared to other times in the day. The green bar on the positive y-axis denotes the excess energy of specified household numbers after completing their own demand, and the yellow bar represents the energy demand of consumers. Prosumers indicated by the green bar are placed according to their selling price, and consumers indicated by the yellow bar are placed according to their buying price. If two peers bid the same price simultaneously by chance, the one with the most surplus energy would be favoured.

At 1800 h, energy demand is 54.86 kW, energy generated is 27.77 kW, energy traded is 54.86 kW, and CES is discharged because demand is higher than generation. Fig. 9(a) shows the bar graph for priority C at 1800 h, where consumers and prosumers are arranged according to their trading price. However, we can see peer 78 acting as prosumer and providing surplus energy to the number of consumers as illustrated in the circular graph. Peers 26, 37 and 71 show the same result acting as a prosumer since they provide best trading price. Whereas at 0600 Hrs, energy demand is 18.09 kW, energy generation is 29.78 kW, energy traded is 18.09 kW, and CES is charged. However, the number of transactions was much higher at 0600 h than 1800 Hrs., shown in the circular graph. It should be noted that, as the energy level of prosumer and consumer varies, the order of buying price and selling price varies. Therefore, the circular graph keeps changing with change in price due to the factor μ for each 5 min interval. However, the prosumer number representing household number within a ring network remains same for all time interval in circular graphs.

5.4. Economic analysis

Fig. 10 displays the comparison between the revenue prosumers get from P2P energy trading and supplying excess energy to the main grid. It is evident from the graph that prosumers earn more in grand coalition using cooperative game theory. The total revenue generated for a day is $174 when supplying to other peers in the network in a grand coalition.

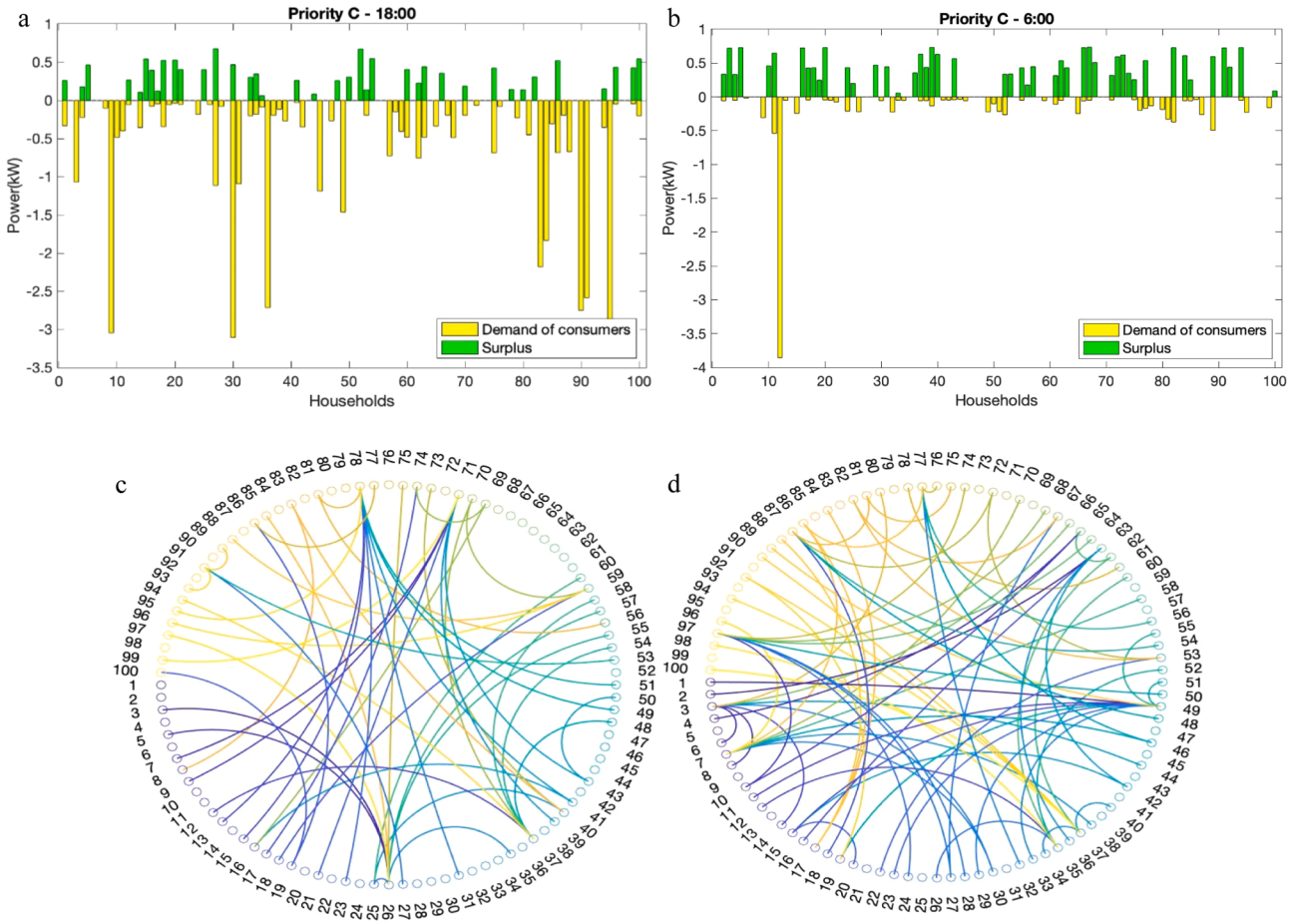

Fig. 9. Priority C (according to pricing mechanism) based Energy trading at (a) 1800 Hrs. and (b) 0600 Hrs. with the circular graph (c, d) showing the energy transfer from prosumers to consumers.

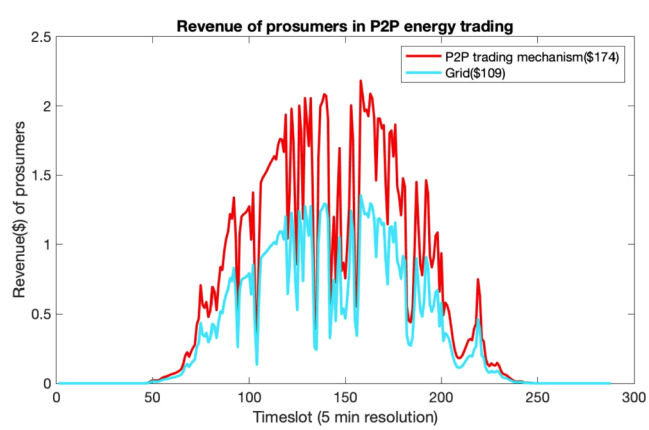

Fig. 10. Revenue of prosumers from P2P trading.

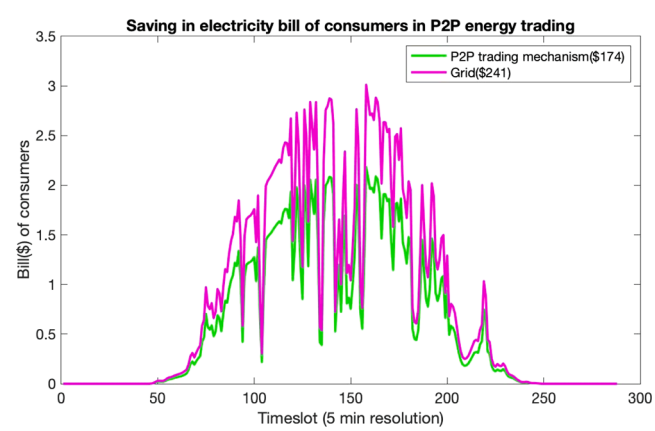

Fig. 11. Saving in the bill of consumers from P2P trading.

Whereas, if all the excess energy is transferred to the main grid at the constant grid tariff, the total revenue generated is $108. Fig. 11 shows that consumers in LEC achieve high-cost savings compared with directly taking from the main grid using consumption tariff. The total electricity bill of consumers when trading with peers is $174 compared to the electricity bill of $241 from the main grid. Therefore, the results in Figs. 10 and 11 emphasize the significant revenue savings of forming a grand coalition with respect to the individual peer optimization of payoff. Thus, the proposed algorithm can achieve high savings for peers with distributed solar PV installed in their households, decrease energy costs, and create a win-win approach for providers and receivers.

5.5. Simulation evaluations

Selection of priority: Fig. 12 summarizes the selection of best priority at each time interval according to P2P energy traded and the number of transactions used to complete the demand of LEC. The comparison of the priorities obtained for three different trading strategies demonstrates the selection of priority done by the aggregator with reference to the priority selected by the peers in the community. It shows that the aggregator selects priority A (energy demand) mainly at the beginning of the day and towards the end of the day due to less generation from solar PV. In contrast, priority B (geographical distance) is

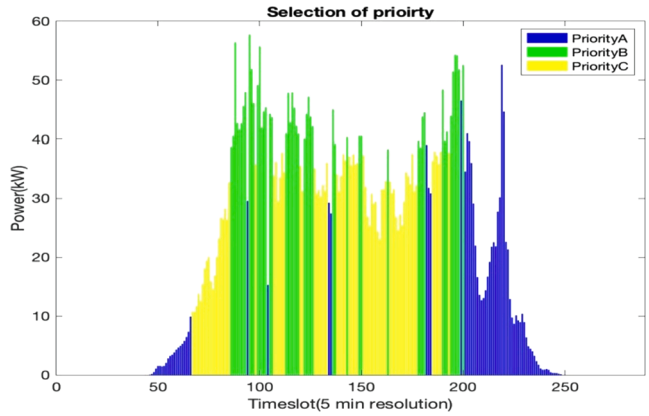

Fig. 12. Selection of priority for each time interval according to.

selected in the peak Hrs., mostly when energy traded is high. This is because priority B allows fulfilling the demand of consumers from the nearest prosumers available. However, the main priority used is C during the daytime by the aggregator to increase the grand coalition's revenue.

Available capacity: The battery's charging and discharging pattern reveal that the battery has ample time throughout the day to charge up to 80% and that the battery's lowest energy is maintained above 35%, as shown in Fig. 13. As we assumed in the system model, the grid will charge the CES if the available capacity falls below 30%. However, according to the 24-hour data, CES did not go below 35%, and no charging was needed from the main grid. Distributed solar PV ceases producing between time intervals 200 and 60, and peers can satisfy demand by discharging CES or importing it from the grid, which is the last option. During the day, PV begins to generate electricity, and the surplus power will meet LEC's total demand, allowing the community battery to be charged for revenue by P2P trading.

Fig. 14 depicts the total demand profiles of consumers and EV charging stations. It can be observed that EV charging points are during non-generation Hrs.; hence the total demand increases simultaneously. The total demand of the LEC is 13 MW, where consumer demand is 11 MW for 24 Hrs. and EV demand is 2 MW. In order to illustrate the consumption pattern of LEC, a comparative analysis with cooperative game theory is presented in Fig. 15. The blue bar shows CES's consumption, and the red bar indicates the consumption from the solar rooftop with the total load displayed from the black line plot. Load flow inside the network increases by adequately coordinating CES and distributed solar PV Peer-to-Peer trade, hence decreasing the cost.

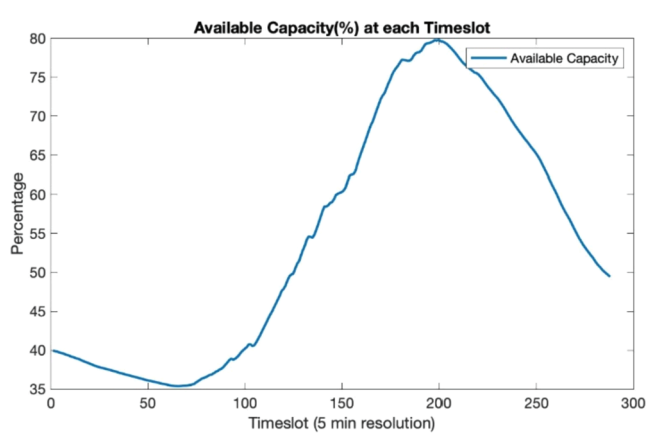

Fig. 13. Available capacity of CES at each time interval energy demand and number of transactions.

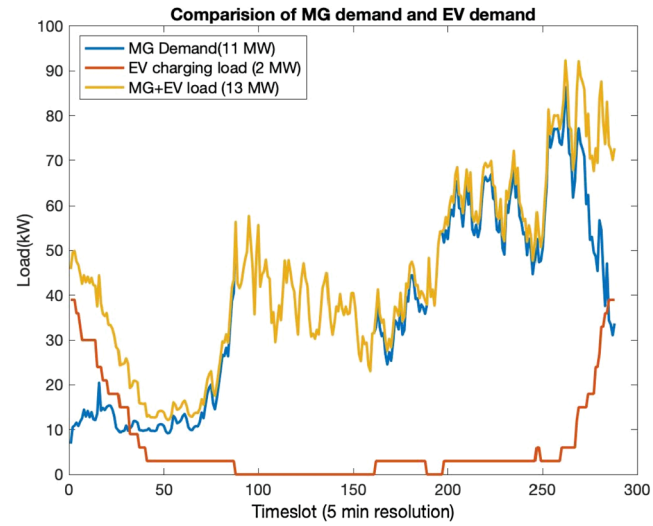

Fig. 14. Total user demand and EV demand of LEC.

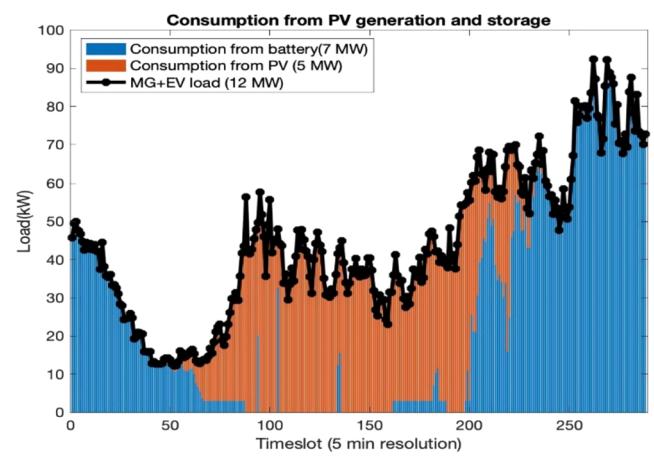

Fig. 15. Consumption from solar rooftop and CES.

6. Conclusion and future work

In this work, a cooperative game theory model for P2P energy trading is proposed, aiming to provide choices to users to select priority for each time interval T, enhancing the utilities of prosumers and consumers. This method encourages users to participate more in trading to establish smart contract according to their preference. This work considers the cooperative game theory framework to form a grand coalition to maximize the total revenue. At every time interval, all the peers who want to engage in energy trading form a grand coalition in an integrated set-in order to maximize their revenue. The proposed work shows a detailed analysis of the user preference at each time interval using the simulation result, making this algorithm appropriate to a typical distribution network. The total revenue generated at each time interval by grand coalitions is distributed fairly among peers in the network. A grand coalition's main objective is that no peer cannot be better off deviating and developing a new coalition and therefore provide stability. As a result, coalitions should have a Sustaining utility and a Satisfaction level, allowing each LEC member to actively engage in coalitions and achieve their desired level of satisfaction, ensuring that no peer wants to leave the market. Three priority-based simulations are applied in the LEC, and priority B is shown to have adequate valuation performance. The approach of this work is to create a win-win strategy for consumers and prosumers that is shown in the economic analysis. Results highlight the best priority for forming a grand coalition concerning

energy demand and the number of transactions. We then observe the charging and discharging pattern of CES when user demand and EV demand are fulfilled. CES is capable of fulfilling the entire demand of peers and EV at night time and therefore, LEC works in island mode. A stabilizing revenue distribution mechanism is proposed to improve the scalability of the cooperative game theory-based trading algorithm. The distribution of the revenue is done so that no user or a group of users is better off departing from the grand coalition. The proposed trading algorithm focuses on various priorities for the users and does not consider actual distribution network constraints in this work. A potential extension of the proposed framework is to investigate network challenges like power losses, voltage profile, line flow and reactive power requirements, all of which still need to be tackled for the application of the cooperative energy management system. Thus, it would be an essential area for future work on a larger scale.

To implement practical applications, the following interventions could be made to the proposed framework:

- Aggregator: The proposed framework explains how aggregators may include P2P energy trading into investment and operational choices to generate value across many policy dimensions. However, aggregators must create an appropriate incentive regime to guarantee that this is in the aggregator's best interests when creating a competitive market between consumers and prosumers. Overall cost savings of consumers and revenue generation of prosumers should be rewarded equally, and performance objectives should stimulate innovation.
- Technologies: To support fully decentralised P2P exchanges, a distributed ledger technology like blockchain can be used. A secure technology like blockchain can be introduced in the network to offer access and anonymity to all peers. Moreover, there has been substantial interest from the distribution network companies in the possibility for machine learning-based advances to offer lower computational burden and the capacity to learn within complicated environments. Combining various upcoming technologies with the proposed framework to harness their respective benefits might be a viable avenue for building robust and scalable inter-platforms.
- DERs forecasting: Accurately forecasting the prosumer generation with a P2P energy trading framework is critical for successfully integrating the distribution system. The level of integrated renewable sources needs to be found out to forecast the generation from DERs accurately. P2P energy trading systems will offer more dependable and localized coordination, opening new value streams if they can use more precise models and forecast the behaviours of smaller groups of prosumers.
- Policies: It is essential to put P2P energy trading models into current energy policy to understand market rules that are allowed, which will further make revenue distribution clearer. Furthermore, the relationship between P2P markets and conventional energy markets should also be considered. Energy policy lags behind technical advancements. New technologies mentioned above are developing fast and have not settled yet, so it is still unclear how regulatory schemes must follow the need for technological changes. Changes in DSO regulations should also be considered to link it with new P2P projects coming in future.

CRediT authorship contribution statement

Sweta Malik: Conceptualization, Methodology, Software, Writing – original draft. **Maeve Duffy:** Methodology, Validation, Investigation, Visualization. **Subhasis Thakur:** Methodology, Formal analysis, Project administration. **Barry Hayes:** Resources, Data curation. **John Breslin:** Writing – review & editing, Supervision, Funding acquisition.

Declaration of Competing Interest

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

Acknowledgements

This publication has emanated from research supported in part by a grant from Department of Business, Enterprise and Innovation, under the Government of Ireland's Project 2040, co-funded by the European Regional Development Fund, and also by a grant from Science Foundation Ireland under Grant Number SFI/12/RC/2289_P2. For the purpose of Open Access, the author has applied a CC BY public copyright licence to any Author Accepted Manuscript version arising from this submission.

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