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ORIGINAL RESEARCH

Peer-to-peer decentralized energy trading in industrial town considering central shared energy storage using alternating direction method of multipliers algorithm

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Abstract

Distributed energy resources are being progressively deployed by industry. The penetration of distributed generation in low voltage (LV) networks can position traditional consumers as market participants. With the improvements in communication networks and the introduction of new energy markets, these prosumers are incentivized to sell their excess production to other industries by participating in peer-to-peer (P2P) energy markets. This market paves the way for developing new technologies such as a shared battery energy storage system (SBESS). In this paper, a central storage unit rents its capacity for the prosumers to reduce the overall peak-load of the microgrid. Each user requests the required SBESS capacity and calculates the best charging and discharging times to reduce their cost. To this end, this paper organized a P2P energy trading paradigm with the presence of SBESS. The optimization problem was simulated and solved using the alternating direction method of multipliers (ADMM) algorithm. Results demonstrate how combining features of P2P energy trading and SBESS can save up to 29% for the industrial town.

1 | INTRODUCTION

Conventional power systems have undergone fundamental changes mainly driven by the penetration of new technologies such as distributed energy resources (DERs) and energy storage systems (ESS) [1]. In modern power systems, photovoltaics (PV) energy is one of the most low-cost energy resources among various types of DERs. It is generally perceived that PVs will become the most economical form of electric energy across the world [2, 3]. Furthermore, some government supporting programs make a suitable opportunity for the industrial and residential units to install PV systems. With the presence of this local generation, new markets are emerging. Consumers with PV generation become a prosumer that can be both a consumer and a producer. Hence, these prosumers can sell their surplus production to the upstream grid or to other units. Subsequently, the conventional market should be upgraded and organized to manage this kind of energy transaction. It is expected that the smart home market size will reach $53.45 billion by 2022 [4].

A conventional energy market is a platform that allows consumers, on the one side, and producers, on the other side, to trade electricity. In this traditional market, energy flows from large producers to micro and macro consumers [5]. However, in the new energy market with prosumers, energy flow can change frequently. Advances in the communication technologies between prosumers have enabled peer-to-peer (P2P) energy trading among interconnected peers [6]. In this paper, units that participate in a P2P market are named peers. The feasibility of employing P2P trading in a microgrid empowers the peers to increase income for DER producers and reduce the cost for consumers due to the difference between the selling and buying price of the grid and the P2P market [7]. In the P2P market, similar to other market architecture, several types of energy technologies such as rooftop PV and battery energy storage system (BESS) can be employed [8]. Furthermore, peers can participate in demand response (DR) programs which are an effective tool to limit electricity consumption at peak times [9].

One of the most effective technologies to facilitate energy trading in a local energy market is the ESS. The presence of ESS allows prosumers to take full advantage of renewable energy resources (RESs) [10]. Also, using the ESS in industrial premises helps to reduce the peak demand and participate in the DR programs. And this possibility reduces the electrical bill of the customers [11]. Batteries are one of the best storage devices in terms of cost and safety in industrial environments. But, besides their advantages, all kinds of ESS, including batteries, can generate noise and heat [12], which can limit their application in particular industry sites. As a solution, using a central shared ESS has been proposed recently. A central shared battery energy storage (SBESS) is a relatively large facility that contains a considerable number of batteries that are integrated into a specific location. This equipment is established with an initial investment of microgrid. The initial investment returns with the revenue that is received by capacity allocation. SBESS can allocate its capacity for participants in the P2P market by receiving a rental fee. This integrated facility allows the customers to remove the small-size storage from their sites. These integrated facilities can reduce the overall cost of maintenance and investment [12–15]. The authors in [16] prove that employing shared energy storage can save the participant cost up to 13.82% rather than using individual energy storage. This facility is located next to industrial towns and rents its capacity to industrial units under conditions that will be examined in this paper.

P2P energy trading schemes at the distribution level offer promising potential to reduce transmission losses, improve system reliability, decrease the backup electric infrastructure and reduce the overall cost of peers. Also, in this concept, DERs can perfectly be restrained while reducing the total peak demand. But individual peer's behaviour affected the performance of the P2P market and increased the complexity. Accordingly, many optimization frameworks and market architectures have emerged to manage energy transactions of multiple peers [17, 18]. In this paper, a decentralized architecture is proposed for P2P trading. In a decentralized architecture, peers can take control actions to manage their storage, energy production and consumption. However, in centralized architectures, some entities can take direct control of some appliances [19]. The P2P market description that is proposed in this paper is based on the cooperative behaviour of peers within a microgrid. All peers cooperate with each other without any competitive strategy for the goal of minimizing the costs of the microgrid [20]. Nowadays, new communication technologies like blockchain and distributed ledger make decentralized approaches available, transparent, and secure [21]. Due to the consensus mechanism in blockchain, the honesty of the P2P transactions data record can be ensured without a third party [22]. But this innovation brings new challenges to the power system to solve the optimization problem.

Recent studies have employed several approaches to solve a P2P problem. These algorithms should be flexible enough to solve a decentralized P2P market problem. The game theory approach is one of the methods that used in several papers for modelling the P2P market. For example, [23–25] employed the framework of a cooperative game to obtain energy transactions in a centralized optimization problem. Furthermore, the authors in [26] presented a model of cooperative game to maximize social welfare. In this study, prosumers are considered as followers, and the retailer is placed as a leader in a bi-level framework. In [27], the upstream grid controls the peak demand period price under the Stackelberg game to reduce the total demand of the participants. In [28], a stochastic day-ahead scheduling model is proposed with full clean energy generation to maximize economic benefits. In [29], an information gap decision theory (IGDT)/stochastic hybrid technique is employed to model the uncertainties. This paper proposed a model of the transactive energy market with 100% RESs. The authors of [30, 31] addressed the continuous double auction (CDA) as a market mechanism to enable interactions among the P2P energy trading. There are several ways to encourage peers to cooperate with the upstream network and participate in programs like peak-shifting. For example, [32] employed a hierarchical incentive mechanism to encourage peers to follow the smart contracts. In [33], the authors used parametric optimization in cooperative multi-microgrids to consider the willingness of other peers for trading in the P2P market. In [34], the authors presented a competitive decentralized P2P market in the presence of prosumers and retailers. This study employed a primal-dual sub-gradient method to clear the market. Furthermore, the multi-objective framework can be employed for minimizing the overall cost in the P2P market [35]. But, in the multi-objective framework, the system operator has direct control over the peers and decides how to participate in the P2P market. This paper employed the ADMM algorithm for solving P2P optimization problems in a microgrid of interconnected peers. Recently, the ADMM algorithm has been extensively used to solve distributed optimization problems [36–39]. ADMM algorithm devised as an iterative method in which, large global problem decomposed to the sub-problems and solution find with coordination of local sub-problems. It is a form of a decomposition-coordination procedure in which the coordination and iterations of sub-problem provide a global optimal solution [40]. As described above, a centralized approach requires the peer's information to solve the P2P market. However, employing the ADMM algorithm limits the information exchange between peers. Hence, the energy exchange information is enough for updating the algorithm multipliers [41, 42]. Furthermore, in a centralized market, the power system (leader) decides on a price of energy [27], but in a decentralized market, peers solve a separate optimization problem for obtaining their own energy management pattern. Therefore, in decentralized market peers decide on the energy selling price in the P2P market.

The recent studies in this matter prove the effectiveness of the ADMM algorithm in P2P markets. For example, [43] presented a cooperative P2P market framework by using the ADMM algorithm, and this paper also considered the costs of the reactive power for participants. In the following, [44] analyzed the strategic bidding of market participants in ADMM-based P2P market-clearing to maximize social welfare. Also, [45] used the ADMM algorithm for the dynamic pricing strategy in the P2P market that, in this case, no central coordinator exists. The authors in [46] employed the ADMM algorithm in day-ahead scheduling of multi-energy microgrids under a robust optimization model. This paper also used power-to-hydrogen technology to refuel fuel cell vehicles.

This paper proposes an interconnected network of peers in a large industrial town that are participating in a P2P market. Every peer can participate in this P2P market and sell surplus energy to other peers or meet the demand by buying energy from other peers. It should be noted that peers can exchange energy with the upstream grid despite participating in the P2P market. Various units with different load profiles like industrial and office buildings can participate in the P2P market. Peers can have PV systems and can shift a part of their load from peak to off-peak times to save money or sell it in the P2P market. Also, this paper focuses on peers transactions and does not consider the role of network constraints in P2P energy trading. The ADMM algorithm is compatible with the proposed model of the P2P market. In this market, participants decide and act individually. In the ADMM algorithm, decomposed sub-problems are solved individually. Also, this algorithm needs a limited amount of information about other sub-problems, which can preserve the participants' privacy. Furthermore, the dual variable in the algorithm can be interpreted as the price of energy in each iteration.

The main contributions of this paper are as follows:

- An ADMM algorithm is employed in which each peer locally solves a sub-problem and optimizes its own energy trades. Then, peers iteratively exchange a limited amount of information with each other to cooperate in cost minimization of the whole microgrid.
- SBESS facilities are considered for industrial towns to maximize the utilization of RESs.
- The capacity allocation problem has been solved with the ADMM algorithm. In this method, data exchange between peers is minimum. In each iteration, the storage allocation price is calculated by the storage manager and the results enounce to the peers that are participating in the market.
- Shiftable loads are enabled in this market to give more flexibility to the peers to participate in the market.

The organization of this paper is the following: ADMM-based optimal scheduling of P2P energy trading and SBESS model with related objective function (OF) and constraints are illustrated in Section 2. Section 3 is dedicated to demonstrating the ability of the proposed method and simulation results. Finally, this paper's conclusion is brought in Section 4.

2 | PROBLEM FORMULATION

Figure 1 illustrates the conceptual scheme of the P2P market studied in this paper. In this model, if two prosumers are interconnected with the energy and communication network infrastructure, they can make P2P energy exchange between each other. By growing the number of participants, the P2P energy trading market will emerge. Most of the time, the P2P selling price is lower than the upstream grid price. Therefore, peers can save money by joining the P2P market and buying energy from other customers. Producers can share their excess energy in the P2P market and earn extra revenue because the purchase price in this market is often higher than the upstream network price.

In this work, all customers are equipped with bidirectional meters that measure the energy exchange between a peer and the upstream grid or other peers. Some of the customers are equipped with a rooftop solar system. Moreover, in this industrial town, SBESS are installed to increase the utilization of renewable generation and to help prosumers with shifting their loads. This paper develops an optimization model for P2P energy trading by employing the ADMM algorithm. The OF of this paper is to minimize the overall cost of an industrial town by finding the optimal energy trading decision. This paper considers the selling and purchase prices of the upstream grid are predetermined and prices scheduled based on the time of use (TOU). The billing process for every individual customer can be explained as follows. Billing of each customer is calculated individually at every time interval, in such a way that the customer is responsible for the scheduling of their own account. Every peer, while trying to reduce the total cost of microgrid, also consider their own cost and decide to meet the demand from which kind of several energy sources. Every peer in every time period has complete freedom to participate in the P2P market. The ADMM algorithm and its decomposability let to solve the optimization problem individually for each peer. Therefore, each peer can decide based on the condition, which consists of price, load, and PV generation, to participate in the market or not. Also, they decide about charging and discharging the ESS that is allocated from the shared energy storage. Finally, every peer shares the energy exchange information to update the multiplier of the ADMM algorithm.

This study considers $T = \{1, 2, \dots, t_{\text{end}}\}$ the set of time intervals with each duration of $\Delta t = 1\,h$ and $N = \{1, 2, \dots, n_{\text{end}}\}$ the set of P2P market participants. As described above, the decentralized procedure employed the ADMM algorithm to solve the distributed problem. This algorithm iteratively solves the optimization problem. After the problem is solved at each iteration, the energy exchange between the peers is considered a parameter. In the following, this energy exchange report is dispensed into the P2P market. Then, the data is used for updating the multiplier of the ADMM algorithm in the next iteration.

2.1 | Objective function

$$Obj = \min \sum_{t\in T} \sum_{i\in N} \left(P_B^t E_{B\_Gridi}^t - P_S^t E_{S\_Gridi}^t \right) \tag{1}$$

The OF (1) minimizes the energy exchange cost between the microgrid and upstream grid. So, all peers participating in the P2P market are cooperating to achieve this goal.

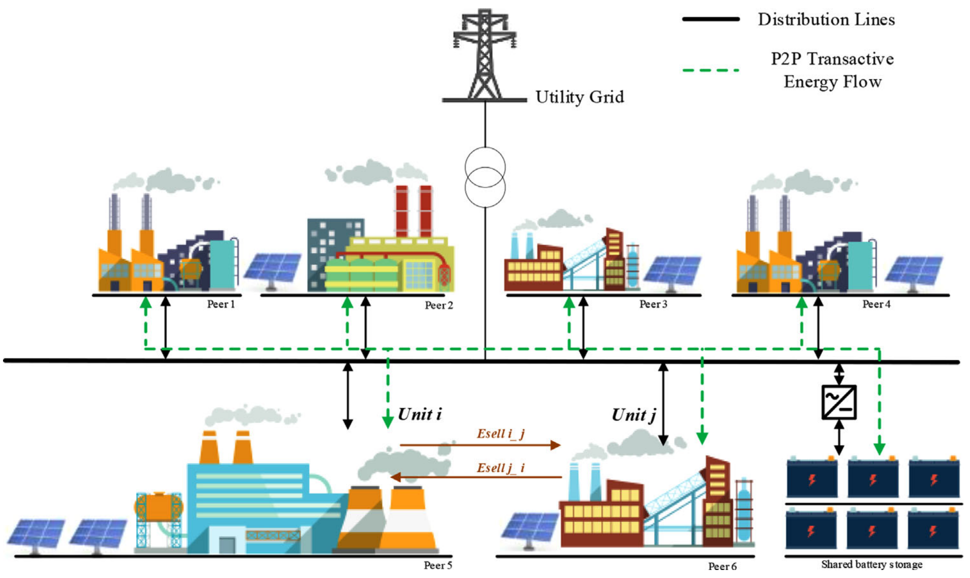

FIGURE 1 The scheme of interconnected distributed P2P energy trading network in an industrial town with the presence of PV and SBESS. P2P, peer-to-peer; PV, photovoltaics; SBESS, shared battery energy storage system

2.2 | Constraints

$$E^t_{\text{Buy\_P2P}i,j} = E^t_{\text{Sell\_P2P}j,i} \quad \forall t \in T, i \neq j, i, j \in N \tag{2}$$

$$E^t_{\text{DER}i} + E^t_{\text{B\_Grid}i} + \sum_{\substack{j\in N \\ j\neq i}} E^t_{\text{Buy\_P2P}i,j} + E^t_{\text{SBES\_Dch}i} + E^t_{\text{SL}i}$$
$$= E^t_{\text{Load}i} + E^t_{\text{S\_Grid}i} + \sum_{\substack{j\in N \\ j\neq i}} E^t_{\text{Sell\_P2P}i,j}$$
$$+ E^t_{\text{SBES\_Ch}i} \quad \forall t \in T,\ i \in N \tag{3}$$

$$E^t_{\text{B\_Grid}i} \geq 0, E^t_{\text{S\_Grid}i} \geq 0 \quad \forall t \in T, i \in N \tag{4}$$

$$E^t_{\text{Buy\_P2P}i,j} \geq 0,\ E^t_{\text{Sell\_P2P}i,j} \geq 0 \quad \forall t \in T, i \neq j, i, j \in N \tag{5}$$

$$E^t_{\text{B\_Grid}i} + \sum_{\substack{j\in N \\ j\neq i}} E^t_{\text{Buy\_P2P}i,j} \leq u^t_{\text{B}i} E^{\max}_{\text{Buy}i} \quad \forall t \in T, i \in N \tag{6}$$

$$E^t_{\text{S\_Grid}i} + \sum_{\substack{j\in N \\ j\neq i}} E^t_{\text{Sell\_P2P}i,j} \leq u^t_{\text{S}i} E^{\max}_{\text{Sell}i} \quad \forall t \in T, i \in N \tag{7}$$

$$u^t_{\text{S}i} + u^t_{\text{B}i} \leq 1 u^t_{\text{S}i}, u^t_{\text{B}i} \in \{0, 1\} \quad \forall t \in T, i \in N \tag{8}$$

$$SOC^t_i = SOC^{t-1}_i + \eta_{\text{Ch}} E^t_{\text{SBES\_Ch}i} - \left(\frac{1}{\eta_{\text{Dch}}}\right) E^t_{\text{SBES\_Dch}i} \quad \forall t \in T, i \in N \tag{9}$$

$$SOC^{\text{Min}}_i \leq SOC^t_i \leq SOC^{\text{req}}_i \quad \forall t \in T, i \in N \tag{10}$$

$$\sum_{i\in N} SOC^{\text{req}}_i \leq SOC^{\text{Max}}_{\text{SES}} \tag{11}$$

$$SOC^t_{\text{SBES}} = SOC^{ini}_{\text{SBES}} \text{if} \quad t = 0 \tag{12}$$

$$0 \leq E^t_{\text{SBES\_Ch}i} \leq I^t_{\text{Ch}i} E^{\text{Max}}_{\text{SBES\_Ch}i} \quad \forall t \in T, i \in N \tag{13}$$

$$0 \leq E^t_{\text{SBES\_Dch}i} \leq I^t_{\text{Dch}i} E^{\text{Max}}_{\text{SBES\_Dch}i} \quad \forall t \in T, i \in N \tag{14}$$

$$I^t_{\text{Dch}i} + I^t_{\text{ch}i} \leq 1 I^t_{\text{Dch}i}, I^t_{\text{ch}i} \in \{0, 1\} \quad \forall t \in T, i \in Nj \tag{15}$$

$$0 \leq E^t_{\text{SL}i} \leq E^{\text{Min}}_{\text{SL}i} \quad \forall t \in T, i \in N \tag{16}$$

$$\sum_{t\in T} E^t_{\text{SL}i} = 0 \quad \forall i \in N \tag{17}$$

Constraint (2) shows the balance between the energy that the customer j sold to i and the energy that customer i bought from. In fact, this constraint is an energy transaction bridge that enables the P2P energy trading between the peers.

Constraints (3)–(5) show that energy trading variables are non-negative and ensure the energy balance for the ith prosumer at each time interval. Constraints (6)–(8) are utilized to limit energy transactions and prevent arbitrage. So, peers cannot benefit from buying and selling energy at the same time. The SBESS model is described by (9)–(15). In this model, central SBESS facilities do not participate in the market. They just sell the capacity to the prosumers. The central SBESS decides about the capacity price. The customer's sent capacity demand to the SBESS facilities depends on the price. After the customers have purchased their capacity, in other words, it can be said that the customers have installed a virtual capacity in their unit. Customers can send their charging and discharging profiles to central storage. The stored virtual energy at each time interval is shown in (9) and it is obtained by applying changes due to charging and discharging to the stored energy at the previous time interval. It should be noted that every peer's charging and discharging profile is different from others, and this kind of energy storage sharing can help to reduce the congestion in the distribution grid. In the following, the constraint (10) limits the SOC of virtual capacity between the requested capacity and the minimum limit of SOC. Constraint (11) ensures that the sum of all requested capacities does not exceed the installed central range. Also constraints (12)–(15) specify the initial SOC of central shared storage and prevent simultaneous charge and discharge by each peer. As shown in (16)–(17), peers can participate in DR programs and transfer their specific load like dishwashers in the scheduling period to reduce the energy cost. This paper assumes that customers can shift 30% of the forecasted load from the peak time to off-peak.

2.3 | ADMM implementation on P2P energy trading

The ADMM algorithm is a distributed approach to solve decentralized optimization iteratively. At any iteration, energy transaction data in the previous iteration is shared between the peers. This data includes P2P trading and upstream grid transactions. We consider the calculated energy transaction data in each iteration as a parameter that is not included in decision variables and they are signified by a hat in the formulation. The aforementioned data updates the ADMM multipliers.

By employing the ADMM algorithm on this model, the OF (1) is decomposed by the augmented Lagrangian methods for each prosumer i. The augmented Lagrangian includes the OF (1) and constraint (2) that it makes peers interdependent. As shown in (18), the augmented OF for each customer i at each iteration v is obtained by adding the squared norm of the aforementioned interconnecting constraint multiplied by the penalty parameter ρ_{P2P}.

$$\mathrm{Obj}_i^v = \min \sum\nolimits_{t\in T} \left[\begin{array}{l} P_{\mathrm{B}}^t E_{\mathrm{B\_Grid}i}^{v,t} - P_{\mathrm{S}}^t E_{\mathrm{S\_Grid}i}^{v,t} \\ + \sum\limits_{\substack{j\in N\\ j\neq i}} \lambda_{j,i}^{v,t} E_{\mathrm{Buy\_P2P}i,j}^{v,t} - \lambda_{i,j}^{v,t} \sum\limits_{\substack{j\in N\\ j\neq i}} E_{\mathrm{Sell\_P2P}i,j}^{v,t} \\ + \dfrac{\rho_{\mathrm{P2P},i}^{v,t}}{2} \left[\sum\limits_{\substack{j\in N\\ j\neq i}} \left(E_{\mathrm{Buy\_P2P}i,j}^{t} - \widehat{E}_{\mathrm{Sell\_P2P}j,i}^{t} \right)^2 \right. \\ \left. + \sum\limits_{\substack{j\in N\\ j\neq i}} \left(E_{\mathrm{Sell\_P2P}i,j}^{t} - \widehat{E}_{\mathrm{Buy\_P2P}j,i}^{t} \right)^2 \right] \end{array} \right] \quad \forall i \in N \tag{18}$$

The second part of the decomposed OF is named the penalty value. As the process converges, the penalty value decreases to zero, so the final OF for the entire system is expressed as follows:

$$\mathrm{Obj} = \sum_{i\in N} \mathrm{Obj}_i^v \tag{19}$$

$$\lambda_{i,j}^{v+1,t} = \lambda_{i,j}^{v,t} + \rho_{\mathrm{P2P},i}^{v,t} \left[\sum_{\substack{j\in N\\ j\neq i}} E_{\mathrm{Buy\_P2P}j,i}^{v,t} - \sum_{\substack{j\in N\\ j\neq i}} E_{\mathrm{Sell\_P2P}i,j}^{v,t} \right] \quad \forall t \in T, i \in N \tag{20}$$

Constraint (3)–(17) that is described above is involved in the distributed optimization problem. Consequently, all peers solve their optimization problem and they get the outcomes, then they update the ADMM multiplier via (20). So, in the incoming iteration, the optimization problem is solved with new ADMM multipliers. To show the convergence rate, a new remaining parameter ($r_{\mathrm{P2P},i}^{v,t}$) is defined for each iteration. This procedure iteratively continues until the remaining parameters $r_{\mathrm{P2P},i}^{v,t}$ become less than $\varepsilon_{\mathrm{P2P}}$.

$$r_{\mathrm{P2P},i}^{v,t} = \sum_{\substack{j\in N\\ j\neq i}} E_{\mathrm{Buy\_P2P}j,i}^{v,t} - \sum_{\substack{j\in N\\ j\neq i}} E_{\mathrm{Sell\_P2P}i,j}^{v,t} \forall t \in T, i \in N \tag{21}$$

This paper also updates the penalty multiplier for reducing the influence of the initial choice on the performance of the algorithm. So updating the penalty parameter in each iteration by (22), (23) can improve the convergence [20, 40].

$$s_{\mathrm{P2P},i}^{v,t} = \rho_{\mathrm{P2P},i}^{v,t} \left[\sum_{\substack{j\in N\\ j\neq i}} E_{\mathrm{Buy\_P2P}i,j}^{v,t} + \sum_{\substack{j\in N\\ j\neq i}} E_{\mathrm{Sell\_P2P}i,j}^{v,t} \right] - \left[\sum_{\substack{j\in N\\ j\neq i}} E_{\mathrm{Buy\_P2P}i,j}^{v-1,t} + \sum_{\substack{j\in N\\ j\neq i}} E_{\mathrm{Sell\_P2P}i,j}^{v-1,t} \right] \forall t \in T, i \in N \tag{22}$$

$$\rho_{\mathrm{P2P},i}^{v+1,t} = \begin{cases} \tau^{inc/dec} \rho_{\mathrm{P2P},i}^{v,t} \text{if} \left\| r_i^{v,t} \right\|_2 > \mu \left\| s_i^{v,t} \right\|_2 \\ \rho_{\mathrm{P2P},i}^{v,t} / \tau^{inc/dec} \text{if} \left\| s_i^{v,t} \right\|_2 > \mu \left\| r_i^{v,t} \right\|_2 \\ \rho_{\mathrm{P2P},i}^{v,t} \qquad \text{Otherwise} \end{cases} \quad \forall t \in T, i \in N \tag{23}$$

In the numerical test of this paper, we assume the $\tau^{inc/dec}$ and μ to be equal to 2 and 10, respectively. Also, this paper considers the initial value of the ADMM multiplier ($\lambda_i^{0,t}$) as follows:

$$\lambda_{i,j}^{0,t} = (P_{\mathrm{B}}^t + P_{\mathrm{S}}^t)/2 \forall i,j \in N, t \in T \tag{24}$$

2.4 | ADMM implementation on the shared battery storage model

As shown in Figure 1, shared battery storage facilities put their daily capacity at the disposal of others for a fee. Market participants decide the amount of capacity to offer based on the price of the shared storage. Participants have limited access to information from other peers. Therefore, they should make decisions only based on the capacity price and their own situation. In such a way that the storage unit collects bids before the start of the day and manages its capacity by updating the dual price variable in each iteration. In this paper, SBESS and independent peers have a separate role in the P2P market. In other words, the central SBESS employs the economic model of supply and demand to determine the market price. SBESS tries to sell whatever it can to the P2P market. Therefore, a decrease/increase in the prices of shared capacity is based on excess storage supply/demand. By applying the ADMM algorithm for the shared energy storage allocation problem, the augmented OF is updated using constraint (11).

As shown in (25), the new augmented OF for each customer i at each iteration v is obtained by adding the squared norm of the shared storage constraint multiplied by the new penalty parameter ρ_{SBES}^v.

$$\mathrm{Obj}_i^v = \min \sum_{t\in T} \begin{bmatrix} P_{\mathrm{B}}^t E_{\mathrm{B\_Grid}i}^{v,t} - P_{\mathrm{S}}^t E_{\mathrm{S\_Grid}i}^{v,t} + \sum_{\substack{j\in N\\ j\neq i}} \lambda_{j,i}^{v,t} E_{\mathrm{Buy\_P2P}i,j}^{v,t} \\ -\lambda_{i,j}^{v,t} \sum_{\substack{j\in N\\ j\neq i}} E_{\mathrm{Sell\_P2P}i,j}^{v,t} + \lambda_{\mathrm{SBES}}^{v,t} SOC_i^{\mathrm{req}} \\ + \frac{\rho_{\mathrm{P2P},i}^{v,t}}{2} \begin{bmatrix} \sum_{\substack{j\in N\\ j\neq i}} (E_{\mathrm{Buy\_P2P}i,j}^t - \widehat{E}_{\mathrm{Sell\_P2P}j,i}^t)^2 + \\ \sum_{\substack{j\in N\\ j\neq i}} (E_{\mathrm{Sell\_P2P}i,j}^t - \widehat{E}_{\mathrm{Buy\_P2P}j,i}^t)^2 \end{bmatrix} \\ + \frac{\rho_{\mathrm{SBES}}^v}{2} \left[(\sum_{i\in N} SOC_i^{\mathrm{req}} - SOC_{\mathrm{SBES}}^{\mathrm{Max}})^2 \right] \end{bmatrix} \quad \forall i \in N \tag{25}$$

As described above, SBESS collects the bids and updates the ADMM multiplier by (26), and also we have a similar remaining parameter (27) for SBESS to show the convergence rate. Furthermore, (28) and (29) update the penalty multiplier for reducing the influence of the initial choice on the performance of the algorithm.

$$\lambda_{\mathrm{SBES}}^{v+1} = \lambda_{\mathrm{SBES}}^v + \rho_{\mathrm{SBES}} \left[\sum_{i\in N} SOC_i^{\mathrm{req}} - SOC_{\mathrm{SBES}}^{\mathrm{Max}} \right] \tag{26}$$

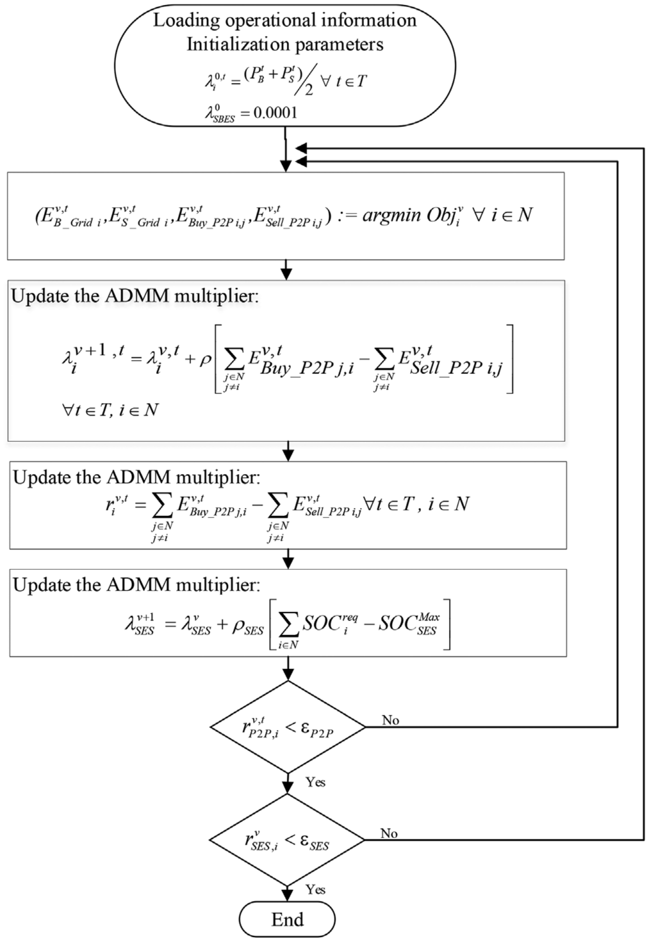

FIGURE 2 Solving process of the P2P energy trading with the presence of SBESS

$$r_{\mathrm{SBES}}^v = \sum_{i\in N} SOC_i^{\mathrm{req},v} - SOC_{\mathrm{SBES}}^{\mathrm{Max}} \tag{27}$$

$$s_{\mathrm{SBES}}^v = \rho_{\mathrm{SBES}}^v \left[\sum_{i\in N} SOC_i^{\mathrm{req},v} - \sum_{i\in N} SOC_i^{\mathrm{req},v-1} \right] \tag{28}$$

$$\rho_{\mathrm{SBES}}^{v+1} = \begin{cases} \tau^{inc/dec} \rho_{\mathrm{SBES}}^v \text{if} \left\| r_{\mathrm{SBES}}^v \right\|_2 > \mu \left\| s_{\mathrm{SBES}}^v \right\|_2 \\ \rho_{\mathrm{SBES}}^v / \tau^{inc/dec} \text{if} \left\| s_{\mathrm{SBES}}^v \right\|_2 > \mu \left\| r_{\mathrm{SBES}}^v \right\|_2 \\ \rho_{\mathrm{SBES}}^v \quad \text{otherwise} \end{cases} \tag{29}$$

Figure 2 presents the whole solving process. Firstly, the initial value of the updating parameters like $\lambda_i^{0,t}$ and λ_{SES}^0 are fixed. Secondly, optimization problem solves for each customer. Then transaction data, which include the P2P energy trading information, grid energy exchanges, and storage capacity requests, reveal. In the following, the multiplier of the ADMM algorithm is updated for both P2P and shared storage allocation problems. Finally, the procedure is iteratively repeated until the conditions $r_{\mathrm{P2P},i}^{v,t} \leq \varepsilon_{\mathrm{P2P}}$ and $r_{\mathrm{SES},i}^v \leq \varepsilon_{\mathrm{SES}}$ are met. This paper

TABLE 1 Prosumers PV panel and load detail

Parameters	Peer 1	Peer 2	Peer 3	Peer 4	Peer 5	Peer 6
Number of panels	N/A	38	100	52	93	24
Panel max power	N/A	325 W	167 W	275 W	275 W	275 W
System size	N/A	12,350 W	16,700 W	14,300 W	25,575 W	6600 W
Inverter size	N/A	8200 W	10 × 2000 W	2 × 6000 W	25,000 W	5000 W
Maximum demand	5.4 kW	6 kW	44 kW	42 kW	390 kW	20 kW
Maximum flexible demand	1.62 kW	1.8 kW	13.2 kW	12.6 kW	117 kW	6 kW

assumed $r^{v,t}_{\mathrm{P2P},i}$ and $r^{v}_{\mathrm{SES},i}$ to be equal to 20 W in all the test results.

3 | RESULTS AND ANALYSIS

The numerical analysis evaluates the P2P energy trading in industrial town. The results demonstrate how decentralized energy management can decrease the overall cost by developing energy sharing between peers. Next, the analysis examines the effectiveness of SBESS. Finally, the results of the centralized and decentralized study are compared.

3.1 | Model implementation and data

As shown in Figure 1, this paper assumed a microgrid with six prosumers for the case study. The test system is composed of one LV feeder that consists of six peers and shared battery storage, which is connected with seven lines to the main feeder. Every customer that is interconnected to the other peers is equipped with a smart meter to measure the energy transactions. As shown in Figure 4, all peers have a photovoltaic power generation unit with various sizes and generation profiles, except Peer 1. This paper uses real numerical detail of the installed PV and load profile from [47]. Details of the installed PV system capacity and shiftable load are given in Table 1. As shown in Figure 3, the industries located in the industrial town do not have a similar load profile. For example, customer 5 has a larger and relatively constant load throughout the day and therefore has a greater impact on the market.

Customers also have two types of flexible and non-flexible industrial demands on their premises. So they can participate in a DR program with 30% of their load.

This paper assumes that the shared storage capacity is equal to 80 kWh and the inverter connected to it can charge or discharge the entire capacity of the unit within 4 h.

The ADMM model was implemented on GAMS software (V24.9.1) and solved with MIQCP (Mixed Integer Quadratically Constrained Program) solver. Simulation runs for 24 h that is divided into one-hour time slots. In this test, the effect of P2P energy trading on several characteristics of the microgrid evaluates. First, the centralized calculation is carried out by a central coordinator with no P2P trading.

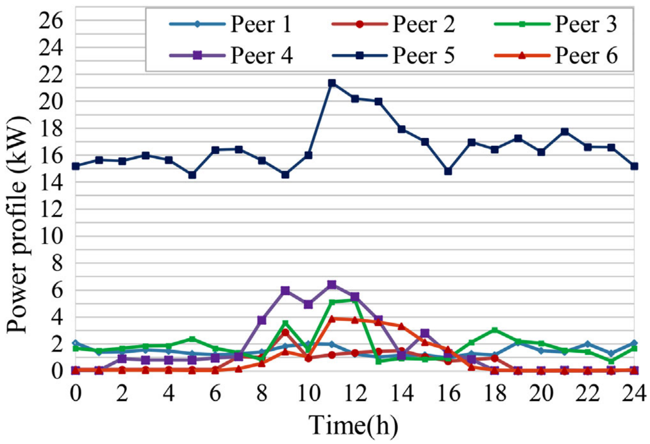

FIGURE 3 Load profile for each peer

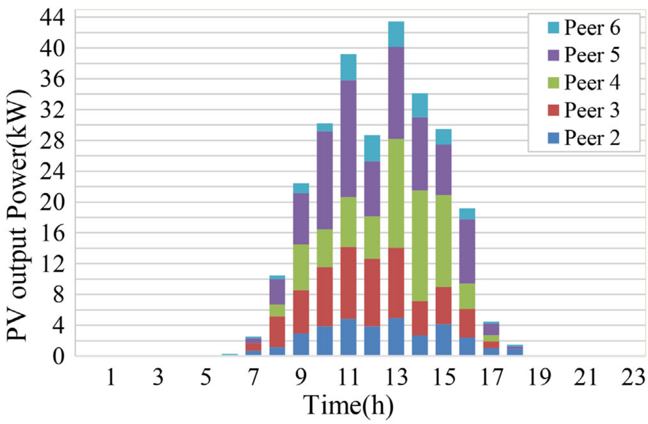

FIGURE 4 Profile of photovoltaic production

Secondly, units cooperate with each other and the decentralized calculation is carried out by P2P energy trading activation. Also, the shared storage effect was investigated similarly.

In the initial iteration, the dual value P2P energy exchange price is set to the average of grid selling and the grid buying price. At the next iteration with employing the ADMM algorithm, each peer selling price updates in order to reduce the energy unbalance.

TABLE 2 Comparison between the overall cost of centralized and decentralized approach with and without the presence of P2P exchange and SBESS

	With P2P exchange and shared storage	With P2P exchange without shared storage	With Shared storage without P2P exchange	Without shared storage without P2P exchange
Centralized	46.79 $	53.45 $	51.34 $	58.81 $
Decentralized	51.52 $	58.74 $	72.28 $	N/A

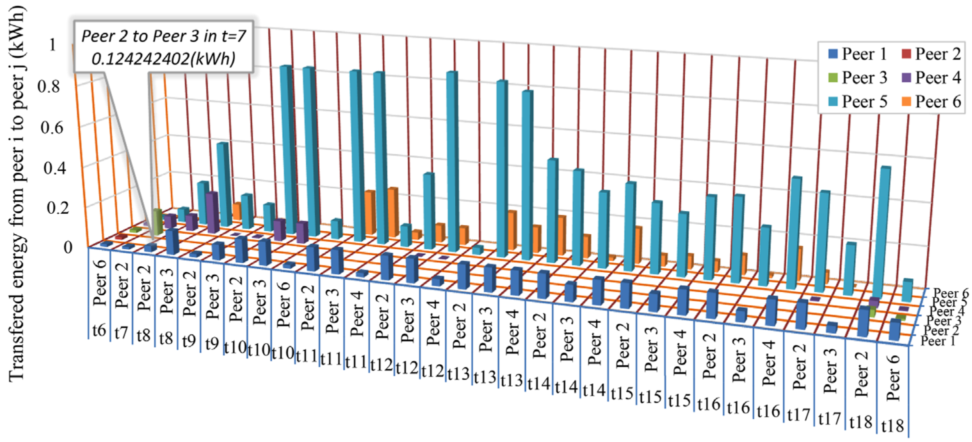

FIGURE 5 Profile of energy transactions between the peers participating in the P2P market (e.g. P2 sells 124 W in T = 7 to P3)

3.2 | Simulation results

Without considering the limitation in the communication network and any delays in solving the optimization problem, finding an optimal solution for each iteration requires about 5 s. This paper solves the overall problem in 14 iterations. And reaching the final answer requires about 76 s.

As shown in Table 2, the problem is solved centrally and the impact of P2P is examined separately. Then the same problem is solved with a decentralized approach. Due to the operator's complete access to all subscriber data, the problem is solved more accurately and quickly in a centralized way. However, as mentioned in the introduction, the purpose of this paper is to make energy exchange more realistic, reduce information exchange, and solve the problem in a decentralized manner.

Therefore, the volume of information exchanged is limited compared to the centralized state. Due to the limited information of many customers, we see a slight difference between the cost function in the centralized and decentralized approaches. As table 2 shows, facilitating the industrial town with SBESS and P2P market decrease the overall cost and P2P activation has a greater impact on the decentralized model. The comparison of the results shows that equipping the industrial town with SBESS and P2P reduces the overall cost by 20.4% in centralized and 28.7% in decentralized approach.

Figure 5 shows the energy exchange between customers at different hours. For example, peer 2 sells 127 W to peer 3 at 7 o'clock. Load profile, PV generation, and other factors influence customer behaviour in the P2P market. So, we expect peer 5 to become a buyer most of the time and customer 2 to sell the overproduction to other peers. Also, Figure 5 emphasizes that most P2P energy trading happens between 6 and 18 o'clock. Indeed, it is the PV surplus energy that is sold in the P2P market.

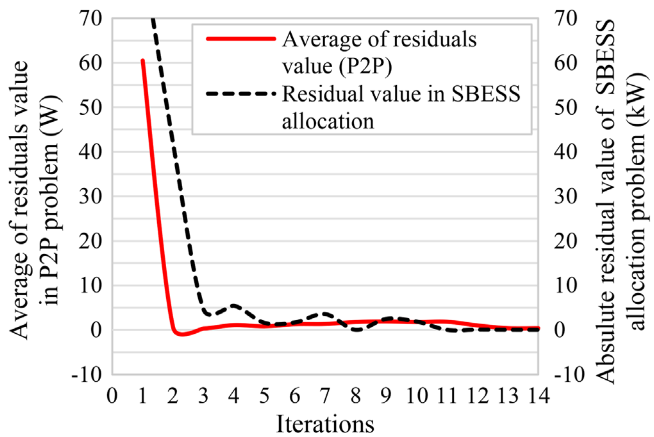

FIGURE 6 Convergence profile of ADMM algorithm for the average value of residuals of P2P energy trading and the residual value of shared storage capacity allocation. ADMM, alternating direction method of multipliers

This paper shows the convergence rate of the ADMM algorithm in Figure 6. As mentioned in (21) residual value ($r^{v,t}_{\mathrm{P2P},i}$) for peer i is the difference between the total energy purchased and energy sold. The ideal value for this parameter, which is obtained in the centralized state, is zero. However, in the decentralized method, values less than $\varepsilon_{\mathrm{P2P}}$ are also

TABLE 3 SBESS capacity allocation results

	Peer 1	Peer 2	Peer 3	Peer 4	Peer 5	Peer 6
Capacity (kWh)	2.32	0.22	13.52	0.29	63.31	0.27

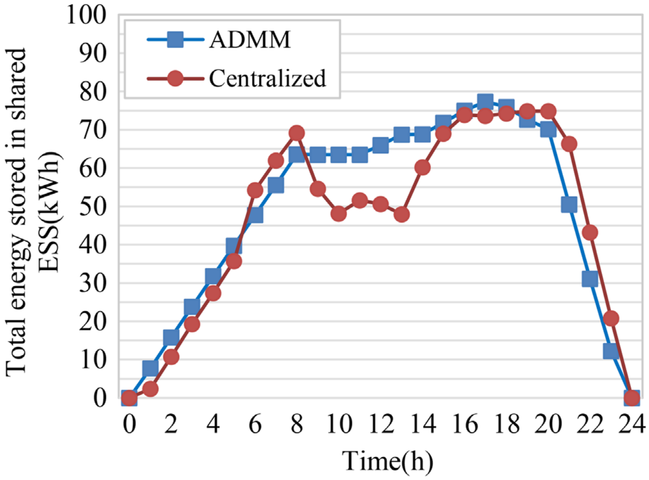

FIGURE 7 The total energy stored in SBESS

acceptable. A similar method has already been considered for shared stored energy. In this method, the difference between the total purchased capacity and the total capacity is considered the residual value of SBESS ($r^{v}_{\mathrm{SES},i}$).

As described in Figure 2, this paper suggests a termination criterion for residual values that must be smaller than $\varepsilon_{\mathrm{P2P}}$ and $\varepsilon_{\mathrm{SES}}$. Figure 6 shows how the decentralized optimization converges with decreasing the residuals values. Iteration number 3 confirms the convergence condition for SBESS allocation, but the P2P market does not achieve the convergence condition. This procedure iteratively continues until both residual parameters confirm the convergence condition. Figure 6 declares that this termination condition is established in the 14th iteration.

In the following, Table 3 illustrates the allocated capacity for each unit. Also, simulation results show that the SBESS renting fee is 0.05 $ for 1 kWh in the final iteration. In practice, peers with higher demands receive higher capacity. The energy storage management system located in each peer controlled the virtual capacity depending on the conditions and sent a non-peak charge order and a peak discharge order. Figure 7 presents the SOC profile of central SBESS in a day. This paper separates the centralized and decentralized results and shows a slight difference between them. As shown in Figure 7, by implementing the technologies described above, the load profile is formed into two curves that show the grid exchange in a centralized and decentralized approach. Indeed, the demand shifts from peak hours to off-peak and partial peak hours. In Figure 7, blue lines and red lines correspond to the decentralized and centralized approach. The slight difference between them is due to the inability of each customer to predict the load of others. Furthermore, the overall load data of microgrid and energy exchange

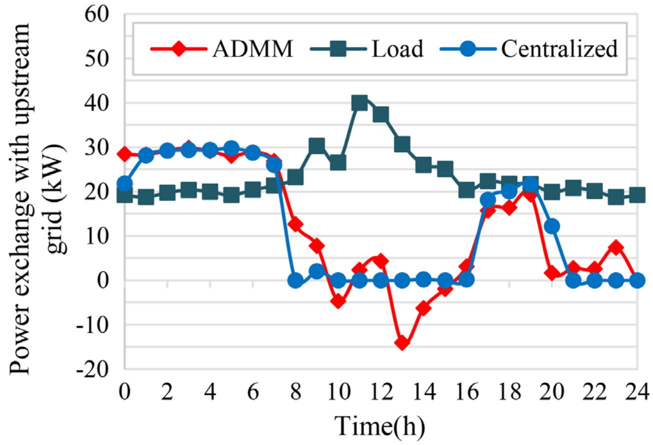

FIGURE 8 Total power exchange with upstream grid

profile with the upstream grid in the centralized and decentralized approach is shown in Figure 8.

4 | CONCLUSION

This paper proposes a distributed optimization problem in an industrial town consisting of RES, SBESS, and a local energy community. This paper analyzes the impact of P2P and SBESS energy exchange in a centralized and decentralized approach. The centralized design requires all the information of market participants. Therefore, participants must transfer all data, including load forecast data and equipment details. But in the decentralized approach, peers just need the energy exchange data in the P2P market and upstream grid to calculate their own energy transaction pattern. In this paper, the day-ahead scheduling of the P2P energy market and SBESS allocation is solved by the ADMM algorithm. The results of the SBESS capacity allocation process indicate that units with larger loads or more distributed generation have more capacity. The values of the OF for both different approaches and conditions were compared. The P2P activation has a greater impact on the decentralized model compared to the centralized model. Finally, it can be concluded that the cooperation of the participants in the form of P2P market reduces the power received from the grid, creates new sources of energy supply, and reduces the total cost of the industrial town. The utilization of a central storage unit also improves the shortcomings of small-scale type storage and helps peers to optimize their load profile. This work can be extended by considering the role of distribution network constraints in peer's transactions. Also, the electric vehicles charging system and multi-class energy systems can be considered in the community of the industrial towns.

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NOMENCLATURE

T	set of time slot in 1 day
t	index of time slot
v	index of iterations
u^t_{Bi}	binary variable that points to customer i participating in the market as a buyer
u^t_{Si}	binary variable that points customer i participating in the market as a seller
I^t_{Chi}	binary variable that indicates peer i is charging energy in the time slot t
I^t_{Dchi}	binary variable that indicates peer i is discharging in the time slot t
P^t_B	prices of the energy that the customers buy from the utility grid ($/kWh)
P^t_S	prices of the energy that the customers sell to the utility grid ($/kWh)
$E^t_{B\_Grid i}$	energy that customer i bought from the utility grid in the time slot t (kWh)
$E^t_{S\_Grid i}$	energy that customer i sold to the utility grid in the time slot t (kWh)
$E^t_{Buy\_P2P i,j}$	energy that customer i bought from the customer j in the time slot t (kWh)
$E^t_{Sell\_P2P j,i}$	energy that customer i sold to the customer j in P2P market in the time slot t (kWh)
$E^t_{DER i}$	generated energy by the customer i from DER (kWh)
$E^t_{SBES\_Dch i}$	discharging rate of allocated virtual SBESS (kWh)
$E^t_{SBES\_Ch i}$	charging rate of allocated virtual SBESS (kWh)
$E^t_{SL i}$	shifted load demand of unit i in the time slot t (kWh)
$E^t_{Load i}$	forecasted load demand of unit i in the time slot t (kWh)
SOC^t_i	state-of-charge of SBESS that allocated to the unit i in the time slot t (kWh)
SOC^{Max}_{SBES}	overall installed capacity of central SBESS (kWh)
SOC^{Min}_i	the minimum amount of state of charge (SOC) that the unit i allowed to have (kWh)
SOC^{req}_i	the requested capacity of each customer i from central SBESS (kWh)
SOC^{ini}_{SBES}	the initial charge of central SBESS (kWh)
$E^{Max}_{SL i}$	the maximum amount of shiftable load of customer i
Obj^v_i	the objective function (OF) of the customer i in the iteration v
$\rho^{v,t}_{P2P,i}$	positive penalty parameter of P2P energy trading
ρ^v_{SBES}	positive penalty parameter of SBESS allocation
$r^{v,t}_{P2P,i}$	residual value of P2P energy trading problem in ADMM algorithm
r^v_{SBES}	residual value of storage allocation problem in ADMM algorithm
i, j	index of P2P energy trading participants
$E^{max}_{Buy i}, E^{max}_{Sell i}$	the maximum energy that customer i can buy from/sell to the other peers or grid (kWh)
$\lambda^{v,t}_{i,j}, \lambda^v_{SBES}$	Lagrange multiplier of P2P energy trading/storage allocation problem
η_{Ch}, η_{Dch}	charge/discharge efficiency of SBESS
$E^{Max}_{SBES\_Dchi}, E^{Max}_{SBES\_Chi}$	maximum discharging/charging rate that allowed for the unit i (kWh)
$s^{v,t}_{P2P,i}, s^v_{SBES}$	dual residual parameter of ADMM algorithm
N	set of P2P energy trading market participants

CONFLICT OF INTEREST

The author declares that there is no conflict of interest that could be perceived as prejudicing the impartiality of the research reported.

DATA AVAILABILITY STATEMENT

Data available on request from the authors.

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