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RESEARCH ARTICLE

Optimal Peer-to-Peer Energy Trading Under Load Uncertainty Incorporating Carbon Emission and Transaction Cost for Grid-Connected Prosumers

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ABSTRACT With the increasing deployment of renewable energy sources, peer-to-peer (P2P) energy trading has recently garnered considerable attention. Many studies have investigated P2P energy trading between prosumers without considering the existing main grid. However, integrating the P2P energy trading of renewable energy in microgrids into the existing systems is a key measure to meet the requirements of energy policy and complement the existing systems. Thus, we propose a decentralized P2P energy trading model to encourage and manage energy transactions among prosumers in a grid-connected microgrid network with photovoltaic systems. Each peer, as a prosumer in the network, forms relationships in which an agent only needs to communicate and negotiate with its neighbors through communication layer to reach an optimal solution for P2P trading in a decentralized manner without requiring any central authority. In our proposed P2P energy trading model, prosumers with demand response availability optimize their objectives by maximizing social welfare and minimizing costs while considering carbon emissions and transaction costs. The proposed model is completely decentralized, privacy-preserving, and scalable by effectively applying a distributed alternating direction method of multipliers. A detailed case study considering a group of eight prosumers is presented to demonstrate the performance and superiority of the proposed P2P energy-trading system. Considering the global convergence criterion, prosumers achieved a maximum total social welfare while minimizing both the energy cost from the grid and costs related to trading with other prosumers.

INDEX TERMS ADMM, carbon emission, demand response, energy trading, peer-to-peer, peer-to-grid, transaction cost.

NOMENCLATURE

ABBREVIATIONS

ADMM	Alternating Direction Method of Multipliers.
CO_2	Carbon Dioxide.
RU	Residential Unit.
DR	Demand Response.
RESs	Renewable Energy Sources.
P2P	Peer-to-Peer.
P2G	Peer-to-Grid.
SWM	Social Welfare Maximization.
PV	Photovoltaic.

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INDICES AND SETS

$\mathcal{N}_S$	Set of producers in the energy market.
$\mathcal{N}_B$	Set of consumers in the energy market.
$\mathcal{N}$	Set of prosumers (peers) in the energy market.
ω	Set of N peers in the communication graph.
ω_i	Set of neighbors of peer i in the communication graph.

$\mathcal{V}$ Set of edges in the communication graph.
$\mathcal{G}$ Undirected connected graph.

SYMBOLS

α_i, w_i	Positive parameters for the utility function of prosumer i.
$\delta_{P2P}, \sigma_{P2P}$	Emission penalty constants for P2P.
$\delta_{Grid}, \sigma_{Grid}$	Emission penalty constants for P2G.
p_i	Energy consumption/generation of prosumer i.
p_i^{min}, p_i^{max}	Maximum and minimum energy of prosumer i.
p_i^G	Energy traded between the grid and prosumer i.
p_{ij}	Energy traded between prosumer i and partner j.
γ_{ij}	Transaction price per unit between prosumer i and partner j.
γ	Unique unit fee (¢ /kWh).
γ_d	Distance unit fee ¢ /kWh · km).
$dist\ (i, j)$	Geographical distance between prosumer i and partner j.
$\underline{\lambda}^G, \overline{\lambda}^G$	Selling and buying price to/from the grid.
λ_{ij}^k	Bilateral price of prosumer i and partner j at iteration k.
ρ	Penalty parameter.
$\epsilon^{pri}, \epsilon^{dual}$	Primal and dual feasibility tolerances.
r_i^{k+1}, s_i^{k+1}	Local primal and dual residuals of prosumer i in each iteration k.
W_i	Welfare function of prosumer i.
$U\ (p_i)$	Utility function of prosumer i.
$D_E\ (p_j)$	Carbon emission cost of prosumer i.
$D_L\ (p_{ij})$	Transaction cost of between prosumer i and partner j.

I. INTRODUCTION

The increasing penetration rate of renewable energy sources (RESs) in energy systems has triggered the development and adoption of a more decentralized paradigm for energy systems and electricity market operations. Enabling energy trading in microgrids is effective for energy resources. In such a market, each residential unit (RU) is considered a prosumer that can act as a producer or consumer. RUs are equipped with demand response (DR) programs [1] and photovoltaic (PV) systems that allow them to optimize their energy costs. Prosumers who own an amount of surplus energy expect to earn some benefit by selling it, whereas those with an energy deficit opt to purchase the required energy from another house or the main grid. Subsequently, energy matching is used to solve the problem of social welfare maximization (SWM) [2] whose objective is to maximize participants' profits or minimize their electricity cost subject to individual energy balance constraints of electricity for both the generation and demand sides.

Peer-to-peer (P2P) trading is a promising approach to implement a decentralized electricity market [3], [4], in which each agent has the capability to operate autonomously and independently and can set individual preferences based on certain interests. This form of trading allows market participants to perform direct negotiations in energy transactions with the minimum amount of any intervention; thus, agents can enhance their profits when the market is clear. However, users may not be willing to join the market by revealing their private information [5]. This leads to an imbalance between the supply and demand in the market system. Therefore, developing P2P energy trading that incentivizes the participation of agents in the market while maintaining their privacy is needed; however, it is a challenging task.

In addition, the integration of P2P with the existing grid network is a challenging task because prosumers must deal with both regulated markets, including the main grid and deregulated P2P trading markets [6]. For example, a prosumer should purchase energy from a regulated electricity market (i.e., main grid) and a deregulated market (i.e., P2P trading) only during peak hours [7]. Moreover, without grid connection, the P2P market may not converge when consumers cannot buy minimum required amount of energy from their partners to run their base loads. In this case, the decentralized market will fail because the demand–supply balance constraint cannot be satisfied for all participants. Thus, all prosumers should be able to trade with the grid, and developing a flexible P2P trading structure that permits prosumers to trade with both P2P and peer-to-grid (P2G) simultaneously is necessary.

Another challenge when integrating P2P with the existing grid is that the design of a P2P trading market needs to fit the current political, economic, and environmental policies associated with the existing grid [8], [9]. Political and economic policies are referred to as transaction costs, which must be considered in a practical environment in which the grid operator charges a fee to the participants using its services. Environmental policies, such as carbon emissions, are also considered as emission costs to minimize the damage of energy consumption to the environment. To calculate these costs, two conventional methods exist: one considers a third party of the network owner and the other assumes no third party. With a third party of the network owner, these costs can be calculated readily; however, relaying data to a centralized entity may lead to a low system reliability. Moreover, without a third party, the complexity of the agent model and associated running time can increase because each agent calculates those costs independently. Therefore, the third challenge is to develop a P2P trading market without sharing data with the network owner such that each prosumer considers carbon emissions and transaction costs with a minor effect on the computation time.

Hence, we aimed to address these challenges by designing a privacy-preserving and flexible structure between P2P and P2G systems at different times of day. In addition, carbon emissions and transaction costs were considered, while maintaining a low computation time for decentralized P2P energy trading among prosumers in a grid-connected system. In particular, we examined a P2P energy trading system among prosumers that functioned in a decentralized manner based on the alternating direction method of multipliers (ADMM) without revealing each user's private information such as energy generation, consumption, and user behavior. The main contributions of this study are summarized as follows:

1) A completely decentralized P2P energy trading optimization model for residential energy systems with DR capability is presented in which grid-connected prosumers can freely adjust their generation or demand to maximize their benefit according to the supply and demand balance constraints from other prosumers. Trading is decomposed and solved in a decentralized manner using ADMM in a microgrid network.
2) A new P2P solution is proposed to maximize social welfare for each grid-connected participant with PV systems, while minimizing the overall costs. Using bilateral negotiation, prosumers autonomously determine their optimal energy usage with their partners.
3) The SWM problem, which includes a utility function, grid cost, carbon emissions, and transaction cost, was solved using a decentralized approach without revealing any private information of agents. In our proposed method, optimal social welfare was achieved without requiring any of agents' preferences or violating their privacy.
4) We try to evaluate our proposed method by performing extensive simulations with a variety of scenarios. Simulation results show that our proposed method maximizes total social welfare and achieves convergence. We further analyze the effect of carbon emission cost and transaction cost in detail. We finally provide detailed analysis on scalability and the operation of an intraday market.

The remainder of this paper is organized as follows. Section II presents a literature review on P2P energy trading. In Section III, the problem is defined and mathematical models representing the participants are presented. Section IV provides a P2P energy-trading algorithm for RUs that operates in a decentralized manner. Section V discusses the simulation results to verify the efficacy of the proposed approach. Section VI discusses the conclusions.

II. LITERATURE REVIEW

The existing studies have considered P2P trading using negotiation models among participants in electricity markets, such as game theory, cooperative or noncooperative games, auction-based mechanisms, and optimization-based approaches such as consensus protocols and ADMM.

The game theory can be used to model the behavior and decision making of market participants. In [7], a cooperative game representing P2P trading using the Stackelberg game was introduced in which centralized power systems acted as the leader and prosumers as followers. In the interaction, the follower made decisions corresponding to the price set by the leader to optimize their objectives. The game exhibited a unique and stable equilibrium for all participants. In [10], two noncooperative games for supply side traders that considered coordinators were introduced in which dynamic pricing was applied to suppliers. External pricing signals determined the selling price for the supplier and an internal price model determined the buying and selling prices of local prosumers. In addition, implementation of the blockchain technology using smart contracts was considered.

In auction-based methods, each participant in the P2P trading market submits a bid/ask to the auctioneer [11], [12]. In [11], an intraday P2P trading mechanism for residential houses was proposed. The platform could update and modify user schedules corresponding to DR of devices in a house. In [12] using a similar method, P2P energy trading with a combination of double auctions and the game theory was proposed. The double auction was used to determine the range of trading prices and winner lists, and the Stackelberg game was used to determine the clearance price for all participants in the market. The implementation of P2P energy trading in blockchain has also been studied.

An optimization-based approach in which P2P trading was considered as an optimization problem was presented in [13] and [14] for the consensus protocol and ADMM [15], [16]. In [13], local energy trading with voltage management in a microgrid was proposed. The pricing mechanism determined the energy price and each market participant calculated its optimal quantity. Once energy was received from the market participants, voltage management was executed to achieve an optimal power flow. In [14], a novel two-tier market that operated through coordinated negotiation among multiregional prosumers was presented. The gradient projection method and a consensus-based algorithm were used as pricing algorithms to solve the SWM problem considering network constraints. Another study presented a model using ADMM [15] and proposed bi-level energy trading for prosumers with energy storage systems in which prosumers interacted with an operator of distributed systems. To prevent cheating behavior of some users to achieve higher profits, an ADMM was used to clear the market. In [16], energy trading on a small-scale in which prosumers negotiated with the operator to optimize their benefit, was proposed, and a combined technique called the distributed Douglas–Rachford splitting method was used to find a global solution. Although all aforementioned studies considered the economic aspect of increasing welfare or decreasing the cost of agents, they assumed negotiations through an intermediary centralized authority instead of direct negotiation among agents.

TABLE 1. Comparison of Our Model With Existing Proposals.

References	Detail Description	Algorithm	Communication Structure	Load Uncertainty	Direct Negotiation	Transaction Cost	Carbon Emission	Trading Structure
[7]	Energy trading through centralized power system	Cooperative game	Centralized					P2P and P2G separately
[10]	Energy market with dynamic pricing	Non-cooperative game	Centralized					P2P and P2G simultaneously
[11]	Optimal bidding strategy for energy management in intraday residential	Auction-based	Centralized	✓				P2P
[12]	Real-time P2P trading in smart grid for PV prosumers	Auction-based	Centralized	✓				P2P and P2G separately
[13]	Local energy management system in microgrid	Consensus-based	Decentralized	✓				P2P
[14]	A two-tier market clearing for P2P energy sharing in smart grid	Consensus-based	Centralized and decentralized	✓				P2P
[15]	A bi-level energy trading for prosumers with community energy storage systems	ADMM	Centralized and decentralized					P2P
[16]	Distributed market clearing investigate a locational marginal price	ADMM	Decentralized	✓				P2P
[17]	Multiple-leader and multiple-follower Stackelberg game for energy trading in microgrid	Non-cooperative game	Decentralized		✓			P2P
[18]	Distributed energy management for a microgrid	Consensus and innovation	Decentralized	✓	✓			P2P
[19]	Bilateral negotiation a mutually agree on the energy quantity and price	Cooperative negotiation-based	Decentralized	✓	✓			P2P
[20]	Local energy market using one-to-one negotiation framework	Concession algorithm	Decentralized		✓			P2P
[21]	Multiagent-based algorithm with distributed uncertainty is considered	Averaging consensus protocol	Decentralized	✓	✓			P2P
[22]	Bilateral energy trading system for consumer-centric market	Primal-dual gradient	Decentralized	✓	✓	✓		P2P
[23]	Peer-centric and system-centric architecture for distribution grid operation	Iterative mechanisms	Centralized and decentralized	✓	✓	✓		P2P
[24]	Consumer-centric framework with different grid cost allocation strategies	Optimization-based	Decentralized	✓	✓	✓		P2P
[25]	Exogenous manner impact on P2P trade	ADMM	Decentralized	✓	✓	✓		P2P
Our Proposed Work	Optimal peer-to-Peer energy trading under load uncertainty for grid-connected prosumers	ADMM	Decentralized	✓	✓	✓	✓	P2P and P2G simultaneously

Direct negotiation is another type of P2P energy trading in which prosumers do not relay their data to a centralized entity. In [17], a noncooperative game representing pricing competition among sellers was proposed, while the selection of buyers with their partners was considered as an evolutionary game. Once sellers determined their price and quantity, each buyer could adjust their energy consumption in response to their behavior. In contrast, in [18], a distributed approach based on consensus and innovation methods was proposed to coordinate local generation, flexible load, and storage devices in microgrids to derive a distributed economic dispatch algorithm. Other examples of direct negotiations can be found in [19] and [20]. In [19], a peer-selection strategy using learning-based intelligence to increase the quality of agreements considering the fairness and success rate of negotiation was proposed. In [20], a framework for local energy markets was presented in which all prosumers automated negotiations with one another through P2P trading. Subsequently, the negotiation strategy of each prosumer was determined using a negotiation concession algorithm. In [21], a decentralized energy management system for multiagent-based smart grids is developed. In addition, the uncertainty of generation is considered using deep learning, and the averaging consensus protocol is used to clear the energy market. A limitation of these studies is that no grid-related costs, such as transmission fees, were considered.

Many studies have employed transaction fees for trade in P2P markets to recover the costs incurred owing to energy transactions [22], [23]. In [22], decentralized bilateral energy trading, in which market participants can directly negotiate with each other to match demand and supply, was proposed. The primal-dual gradient method was then used to clear the market with network constraints. In [23], a peer-centric architecture for P2P trading was proposed. A distribution locational marginal pricing coordinator was used to coordinate and design the network charge fees in a distributed system. Nevertheless, these studies calculated grid-related costs using third-party network operators. Other studies [24], [25] were conducted considering each participant to directly calculate the related costs of trading. In [24], a consumer-centric framework with different grid cost allocation strategies was developed that permitted grid operators to benefit from P2P energy transactions among users. In [25], a P2P trading was introduced in which sellers considered power losses in transferring energy and buyers considered the network fees of their use. However, in these studies [22], [23], [24], [25], the proposed energy models and market systems did not consider the grid connection, which is a key factor for decision-making in energy transactions. Hence, in this study, we assumed that the market prosumer is aware of both the buying price from the grid and selling price to the grid, and the interaction with the grid is considered to be a part of the welfare function. Moreover, as noted in Section I, the decentralized market in those papers [22], [23], [24], [25] can fail to converge due to minimum generation or load is not enough and there is zero profit for the prosumer. In contrast, the proposed model allows prosumers to trade simultaneously with P2P and the main grid. Thus, our proposed model can benefit all participants with the help of the grid even if the minimum energy is not satisfied by P2P trading, in comparison to those papers [22], [23], [24], [25]. Additionally, this study examined the interaction between the energy trading and environmental pollutant proxies of carbon dioxide (CO_2) emissions that each prosumer should consider when consuming energy to decrease greenhouse gas emissions and carbon emission costs. Table 1 provides comparison of our proposed method with existing works to emphasize our contributions.

III. SYSTEM MODEL

A. NETWORK MODEL

Let $\mathcal{N}_S$ denote the set of producers with surplus energy and $\mathcal{N}_B$ the set of consumers with deficit energy indexed as 1, 2, $\ldots, \mathcal{N}_S$ and $\mathcal{N}_S+1,\ldots,\mathcal{N}$, respectively, where $\mathcal{N}=\mathcal{N}_S+\mathcal{N}_B$ is a set of prosumers in the energy market. An undirected connected graph $\mathcal{G} = \{\omega, \mathcal{V}\}$ is used to represent the communication topology of the network, where ω is the set of $\mathcal{N}$ peers and $\mathcal{V} \subset \omega \times \omega$ is the edge set. We assume that the prosumers are connected to a physical network layer and main grid. In the information layer, prosumers and grid operators communicate through a P2P platform. Three types of communication structures exist in the P2P trading market, including unstructured, structured, and hybrid [26] models. In this study, we considered a structured communication graph, as shown in Fig. 1, such that each prosumer could negotiate with any other prosumer. Notably, $(i, j) \in \mathcal{V}$ if and only if peer i could receive information from peer j, that is, peer j was the incoming neighbor of peer i. The neighbor set of peer i is defined as $\omega_i = \{j| (j, i) \in \mathcal{V}, j \neq i\}$. Each prosumer have the capability to negotiate with other prosumers based on their deficit or surplus energy.

B. P2P ENERGY TRADING

An energy market system consisting of RUs is considered. Each RU can be an individual house with RESs, such as installed PV systems. The entire community can be divided as follows:

1) *Prosumers*: End users are prosumers who can sell or buy energy in the P2P trading market. Each prosumer chooses its role based on the predicted PV generation and energy consumption in the next time slot.
2) *Grid operator*: This entity provides the entire energy trading service, that is, the grid price, database, and grid-related costs. Notably, the grid operator does not manage P2P energy trading.
3) *Smart controller*: This component supports the prosumer in exchanging market information. Each prosumer has a smart controller that communicates and exchanges information with others in the P2P trading market.

A simplified diagram of the bilateral P2P energy trading system is shown in Fig. 1. Prosumers participating in a P2P market scheme are divided into two subsets: producers and consumers. Prosumer i ($i \in \mathcal{N}$) is a producer, where $i \in \mathcal{N}_S$ if it has more energy generation than demand and can sell that energy to consumers or the main grid. Otherwise, prosumer i ($i \in \mathcal{N}$) is a consumer ($i \in \mathcal{N}_B$) if it has less generation than demand; consumers must opt to purchase energy from producers or the main grid to meet their demand.

In a forward market, prosumers negotiate trades for the next time interval. Let us consider the length of each slot to be constant $\Delta t = 1$ h and each day to be divided into different slots $t \in T$. Let $t = \{1, 2, \ldots, T\}$ denote the set of operating time slots, where $T \triangleq$ T indicates the total number of operating time slots.

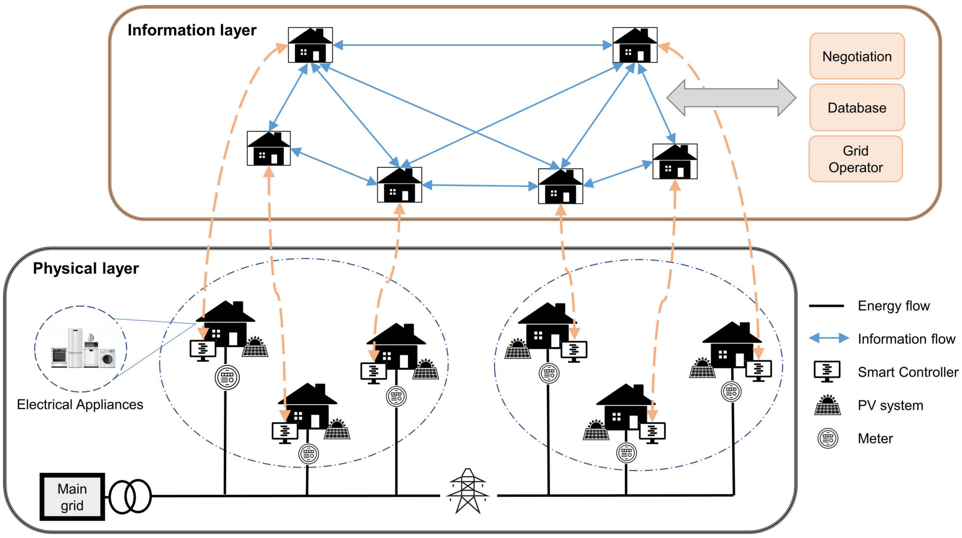

FIGURE 1. Structured communication graph of the P2P energy trading system.

C. PROSUMER MODEL

Prosumer behavior can be modeled as a utility function with the amount of energy generated or consumed to measure the satisfaction level. A utility function is a common concept used to measure preference for a set of goods and services, which represents the welfare or satisfaction of a prosumer when consuming or producing a certain amount of energy. The common form of the utility function is a non-decreasing function. The level of satisfaction is represented by a non-increasing marginal benefit. In addition, zero-energy generation or consumption does not benefit prosumers. Thus, the utility function $U(p_i)$ for prosumer i with an energy amount of p_i should satisfy the following three properties:

$$\frac{\partial U(p_i)}{\partial p_i} \geq 0; \ \frac{\partial^2 U(p_i)}{\partial p_i^2} \leq 0; \ U(0) = 0. \tag{1}$$

To satisfy these three properties, a piecewise quadratic utility function for prosumer i was considered, as proposed in [27] and [28].

$$U(p_i) = \begin{cases} w_i * p_i - \alpha_i * (p_i)^2, & if\, 0 \leq p_i \leq \dfrac{w_i}{2\alpha_i} \\ \dfrac{w_i^2}{4\alpha_i}, & p_i > \dfrac{w_i}{2\alpha_i}, \end{cases} \tag{2}$$

where p_i indicates the total energy generated by producer i or that consumed by consumer i. Moreover, α_i and w_i are predetermined positive parameters. These parameters determine how prosumer i responds to different prices from its neighbors. As each prosumer in the market behaves independently, these parameters vary among prosumers and throughout the day. Prosumers with a lower α_i and higher w_i are willing to sell or buy more energy. In contrast, prosumers with higher α_i and lower w_i would sell or buy less energy. According to (2), prosumers with higher α_i tend to achieve lower utility than those with lower α_i when w_i is fixed. In this study, we assumed that each prosumer could choose its own trading strategy in each time slot by selecting different α_i and w_i.

Any prosumer can buy or sell energy from/to different prosumers or the main grid. The total energy deficit or surplus of each prosumer i is represented as

$$p_i^{min} \leq p_i \leq p_i^{max}, \quad \forall_i \in \mathcal{N}, \tag{3}$$

where p_i^{min} and $p_{i,t}^{max}$ are the minimum and maximum required/available electricity of the prosumer i, respectively. We can set p_i^{min} and p_i^{max} by considering a realistic load demand to enable scheduling flexible loads, that is, scheduling the use of flexible devices to later time slots or rescheduling devices from later time slots to the present time slot. Moreover, p_i^{min} and p_i^{max} are determined independently at each time slot [2].

We consider the case in which a prosumer is a producer $i \in \mathcal{N}_S$, and p_i^G and p_{ij} indicate the amount of energy sold to the grid and consumer j from producer i, respectively. Similarly, when a prosumer is a consumer $i \in \mathcal{N}_B$, p_i^G and p_{ij} indicate the amount of energy purchased from the grid and producer j by consumer i, respectively. Thus, the sum of bilaterally traded quantities by each prosumer i is expressed as

$$p_i = p_i^G + \sum_{j \epsilon \omega_i} p_{ij}. \tag{4}$$

D. CARBON EMISSION COST

Environmental protection has recently emerged as a major goal owing to increasing carbon emissions resulting from extensive energy consumption. Carbon emissions are typically generated from fossil fuels. To reduce carbon emissions, using the energy generated by RESs such as PV systems, and avoiding the use of energy generated by non-RESs such as fossil fuels, is highly encouraged. In addition, according to [29], the use of energy from both RESs and non-RESs generates significant carbon emissions. Thus, the environmental costs associated with environmental damage are presented in the proposed model. We considered a factor that reduces carbon emissions by defining a cost function in the energy exchange. Moreover, the cost function varies for different types of participants and differs between the P2P and P2G trading mechanisms.

For a prosumer to buy energy and satisfy demand, the cost of carbon emission for the consumed electricity can be represented as a linear function [30]. Therefore, we assumed that the carbon emission cost model when consumer j purchases electricity p_{ji} from producer i and electricity p_j^G from the main grid can be expressed as

$$D_E\left(p_j\right) = \left(\delta_{P2P}\right)^2 p_{ji} + \sigma_{P2P} p_{ji} + \left(\delta_{Grid}\right)^2 p_j^G + \sigma_{Grid} p_j^G, \tag{5}$$

where $\delta > 0$, $\sigma > 0$, and δ and σ are the emission penalty constants for the consumer [30]. In addition, δ_{P2P} and σ_{P2P} are the carbon emission parameters for P2P trading. Similarly, δ_{Grid} and σ_{Grid} are carbon emission parameters for P2G trading. In a realistic environment, the energy generated by RESs has a lower pollutant level than that of non-RESs such as the main grid [29]. Thus, the values of δ_{P2P} and σ_{P2P} were considerably lower than those of δ_{Grid} and σ_{Grid}.

Nonetheless, a prosumer as a producer with DR can sell its surplus energy generated by RES to other prosumers after satisfying its local minimum load, which helps other prosumers reduce trading with the main grid as a non-RES, thereby, reducing carbon emissions. Hence, it is reasonable to assume that producers do not need to pay for emission costs and thus, $\delta = 0, \sigma = 0$; therefore, $D_E\left(p_i\right) = 0$ [30].

E. TRANSACTION COST

Network operators who provide energy-trading services consider their benefits when building an energy-trading system. A transaction fee is one approach to allow the network operator to collect money from participants when they use its services. The transaction cost can be used for any purpose, including the recovery of the maintenance cost, modernization of power lines, taxes, and policies. The bilateral transaction fee is calculated as a linear function of the quantity traded with each neighboring prosumer [25]. Thus, the transaction fee between prosumers i and j is written as follows:

$$D_L\left(p_{ij}\right) = \gamma_{ij} p_{ij}, \tag{6}$$

where p_{ij} represents the quantities bilaterally traded with a neighboring prosumer $j \in \omega_i$. The transaction price γ_{ij} is the price coefficient indicated by the grid operator to set the price for recovering the aforementioned costs.

Moreover, we consider an equal allocation cost for all participants involved in the network and thus, the cost is shared between a producer and consumer as follows:

$$\gamma_{ij} = \frac{\gamma}{2}. \tag{7}$$

where γ is a unique unit fee expressed in ¢ /kWh for an hourly time unit.

Moreover, transaction costs can be allocated according to the transmission distance of participants. This cost-allocation policy encourages prosumers to trade with their partners. Therefore, the transaction fee can be expressed as

$$\gamma_{ij} = \frac{\gamma_d dist\left(i, j\right)}{2}, \tag{8}$$

where γ_d is the distance unit fee expressed in ¢ /kWh · km for an hourly time unit; and, $dist\left(i, j\right)$ is the geographical distance between prosumer i and its neighbor $j \in \omega_i$, which is often measured by the proximity level according to a predefined distance measurement, such as the Euclidean distance [31].

At each time slot, each prosumer attempts to trade with partners with whom exchanging energy yields a lower transaction cost, that is, each prosumer avoids trading energy with partners far from their house because of increase in transaction costs.

IV. PROPOSED DECENTRALIZED ENERGY TRADING APPROACH BASED ON DISTRIBUTED ADMM

In this study, we aimed to solve the local problem of each prosumer using only P2P communications to guarantee the data privacy of prosumers. Therefore, a completely decentralized and efficient P2P energy-trading algorithm based on ADMM [32] was proposed. The benefit of this approach was that a central authority was completely avoided and data were shared only with neighbors.

A. MARKET OBJECTIVE

The welfare function of a prosumer as producer i in the market can be defined as

$$W_i = U\left(p_i\right) + \underline{\lambda}^G p_i^G, \quad \forall_i \in \mathcal{N}_S, \tag{9}$$

where $U\left(p_i\right)$ is the utility function of producer i in (2); $\underline{\lambda}_t^G$ denotes the price of selling energy to the grid, which is fixed for each time slot; and p_i^G is the amount of energy sold by producer i to the main grid.

Similarly, the welfare function of a prosumer as consumer i in the market is expressed as

$$W_i = U\left(p_i\right) - D_E\left(p_i\right) - \overline{\lambda}^G p_i^G, \quad \forall_i \in \mathcal{N}_B, \tag{10}$$

where $U\left(p_i\right)$ is the utility function of consumer i; $D_E\left(p_i\right)$ is the carbon emission cost that consumer i must pay when buying energy of p_i; $\overline{\lambda}^G$ denotes the price of buying energy from the grid, which is fixed for each time slot; and, p_i^G is the amount of energy that consumer i buys from the main grid.

The market aims to find the optimal solution in energy dispatch among prosumers such that their total cost is minimized or total economic surplus is maximized, in which each prosumer considers a transaction fee, as indicated by γ_{ij} in (6), required by the grid operator. Hence, the SWM problem can be described as

$$\max_{p_{ij},p_i^G} \sum_{i\epsilon\Omega} \left[W_i - \sum_{j\epsilon\omega_i} \gamma_{ij} * p_{ij} \right]. \tag{11}$$

By taking negative sign, the optimization problem can be reformulated as

$$\max_{p_{ij},p_i^G} \sum_{i\epsilon\Omega} \left[f\left(p_{ij}, p_i^G\right) + \sum_{j\epsilon\omega_i} \gamma_{ij} * p_{ij} \right], \tag{12a}$$

subject to

$$P = -P^T, \quad [\Lambda], \ \forall_i \in \mathcal{N}, \tag{12b}$$

$$p_i = p_i^G + \sum_{j\epsilon\omega_i} p_{ij}, \quad [\mu_i], \ \forall_i \in \mathcal{N}, \tag{12c}$$

$$p_i^{min} \leq p_i \leq p_i^{max}, \quad \forall_i \in \mathcal{N}, \tag{12d}$$

where $f\left(p_{ij}, p_i^G\right) = -W_i, \forall_i \in \mathcal{N}$. Matrix P contains the quantities of all bilateral trades in the network. In addition, it is associated with the dual-variable matrix $[\Lambda]$, which contains the prices of all trades. The reciprocity of trading quantities P and trading prices $[\Lambda]$ is enforced by Constraint (12b) in the optimal solution of the SWM problem. Constraint (12c) originates from the local demand or supply in which the net energy of prosumer i represents the relationship between the total amount of traded energy of prosumer i and its partner prosumer j, and the amount of energy traded with the grid to satisfy their demand or generation. The dual variable μ_i in (12c) associated with Constraint (12c) represents the energy price perceived by prosumer i. The objective is to maximize the overall benefit of the network for both producers and consumers. These benefits stem from electricity trade through the bilateral energy mechanism with other households and the main grid.

B. DECENTRALIZED FORMULATION

To solve the SWM problem, we adopted the approach presented in [33], where the ADMM algorithm decomposes the problem into subproblems and solves locally for each consumer and producer. Each prosumer solves the subproblems by updating the local decision variables. The set of decision variables for the prosumer was $\{p_{ij}, p_i^G\}$. Moreover, a negotiation process exists in the market in which prosumers iteratively determine their variables and exchange their information p_{ij} without revealing their private information such as user satisfaction, energy generation, and energy consumption.

According to [33], a new global variable $C = (P - P^T)/2$ is defined as the average trading quantity sent from prosumer i to prosumer j and the average trading quantity sent back from prosumer j to prosumer i. C contributes to reaching consensus and aims to represent all possible amounts of trade, P. Convergence between all prosumers is achieved when their trading values are equal, which is confirmed by an optimal ADMM because the optimization problem formulated in (12) is convex. Therefore, for each iteration k, the completely decentralized augmented Lagrangian for the bilateral trading model for each prosumer i can be formulated as

$$\left(p_{ij}, p_i^G\right)^{k+1} = \arg\min_{p_{ij},p_i^G} f_i\left(p_i, p_i^G\right) + \sum\nolimits_{j\epsilon\omega_i} \left[\gamma_{ij} * |p_{ij}| + \frac{\rho}{2}\left(\frac{p_{ij}^k - p_{ji}^k}{2} - p_{ij} + \frac{\lambda_{ij}^k}{\rho}\right)^2 \right], \tag{13a}$$

subject to

$$p_i = p_i^G + \sum\nolimits_{j\epsilon\omega_i} p_{ij}, \quad [\mu_i], \forall_i \in \mathcal{N}, \tag{13b}$$

$$p_i^{min} \leq p_i \leq p_i^{max}, \quad \forall_i \in \mathcal{N}, \tag{13c}$$

where ρ is the penalty parameter; p_i^{min} and p_i^{max} in Constraint (13c) of each prosumer is positive if prosumer i is a producer, or negative if prosumer i is a consumer; λ_{ij}^k is a dual variable that represents the price of each bilateral trade updated in each iteration k of ADMM, which is formulated as

$$\lambda_{ij}^{k+1} = \lambda_{ij}^k - \rho\left(p_{ij}^{k+1} + p_{ji}^{k+1}\right)/2. \tag{14}$$

The algorithm was repeated iteratively until the convergence conditions were reached. Conditions (15) and (16) were evaluated based on the primal and dual residual values, which can be defined as follows:

$$\left\| r^{k+1} \right\|_2 = \sum_{i=1} r_i^{k+1} \leq \epsilon^{pri}, \tag{15}$$

$$\left\| s^{k+1} \right\|_2 = \sum_{i=1} s_i^{k+1} \leq \epsilon^{dual}, \tag{16}$$

where ϵ^{pri} and ϵ^{dual} are primal and dual feasibility tolerances. The local primal r_i^{k+1} and dual s_i^{k+1} residuals are expressed as

$$r_i^{k+1} = \sum_{j=1} (p_{ij}^{k+1} + p_{ji}^{k+1})^2, \tag{17}$$

$$s_i^{k+1} = \sum_{j=1} (p_{ij}^{k+1} - p_{ij}^k)^2. \tag{18}$$

Both thresholds are typically assigned an extremely low value [32]. The local subproblem (13a) can be solved using an optimization tool such as Gurobi [34].

C. PROCEDURE OF PROPOSED P2P ENERGY TRADING

In this subsection, we describe the detailed procedure of our proposed P2P energy trading method based on the presented market objective and formulas.

First, each prosumer submits their role to the database according to their generation and demand, and then calculates the distance between their house and the trading partner's house, as shown in Fig(s). 2 and 3. After all the participants have finished this process, the matching algorithm begins, and each prosumer i determines their trade proposal p_{ij} locally by solving the optimization problem, as presented in (13a).

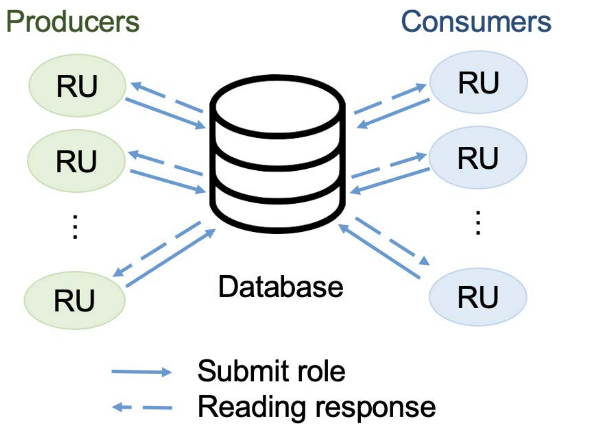

FIGURE 2. Interactions between prosumers and a database where producers and consumers access the database to obtain the information of partners and prices of the main grid.

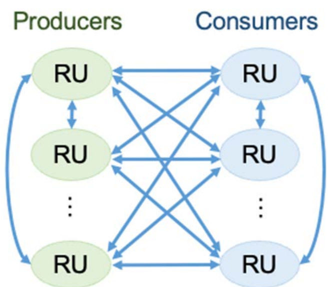

FIGURE 3. Communication graph representing data transmission in negotiation processes between producers and consumers.

Subsequently, each individual prosumer sends trade proposals to each of their partners $j \epsilon \omega_i$. After receiving all proposals p_{ij}, the prosumer can update the trading prices λ_{ij} in (14) and local residuals (r_i, s_i) using (17) and (18), respectively. Each prosumer broadcasts its local residuals when they receive all other local residuals from their neighbors, and then prosumer i checks the global stopping criteria (15) and (16). This process is repeated when the global convergence criteria are not met or the maximum iteration is reached, as illustrated in Algorithm 1.

In our decentralized energy-trading model, each prosumer is supposed to be a rational and non-strategic prosumer [35]. Thus, through the decentralized solution and by decomposing the objective function, all prosumers focus on solving their local welfare maximization problem and contribute to the total welfare of market players in the electricity market.

V. PERFORMANCE EVALUATION

In this section, we analyze our proposed P2P energy trading model under a variety of scenarios in full detail. We first show that our proposed model maximizes the total social welfare and converges to the optimal value very fast. We then investigate the effect of carbon emission cost and transaction cost. After discussing the scalability, we further demonstrate the efficacy of the proposed model for intraday operations.

Algorithm 1 Completely Decentralized for Energy Trading

Initialization:
for prosumer $i \epsilon \mathcal{N}$ **do**
  Access the database to get a list of participants, γ_{ij}, $\underline{\lambda}^G$, $\overline{\lambda}^G$, and partners location
  Set $\lambda_{ij}^0 = p_{ij}^0 = 0$
end for
//run the energy matching
while $1 \leq k \leq$ max_*iteration* or convergence condition does not meet:
  for prosumer $i \epsilon \mathcal{N}$ **do**
    //update quantity step
    Calculate $(p_{ij}, p_i^G)^{k+1}$ according to (13a)
    //update price step
    Calculate λ_{ij}^{k+1} according to (14)
    Send p_{ij} to partners of i and receives p_{ji} neighbors' information
    Compute r_i^{k+1} and s_i^{k+1}, then broadcast to all participants
  end for
  $k = k + 1$
end while
if $k >$ max_*iteration*
  All participants trade directly with main grid
end if
Close market

To evaluate the performance of the proposed model, we conducted a simulation using eight prosumers generated based on the parameters $(\alpha_i, w_i, p_i^{min}, p_i^{max})$ employed from [27]. The pollutant parameters were inspired and modified from [29] and [30]. We assumed that all consumers had an extremely small and identical δ_{P2P} of 0.01 and σ_{P2P} of 0.1. Because the carbon emission for trading with the grid is described as a linear function, we can merge the pollutant parameter $(\delta_{Grid})^2 + \sigma_{Grid}$ in (5) into the selling price of the main grid $\overline{\lambda}^G$ in (10). In addition, the buying price $\underline{\lambda}^G$ and selling price $\overline{\lambda}^G$ of the main grid during the entire day were fixed at 20 and 2 ¢/kWh employed from Singapore dataset [36], respectively. The penalty parameter ρ was set to 0.01 and the maximum number of iterations k was 5,000. The primal ϵ^{pri} and dual ϵ^{dual} values were selected as 10^{-4}, which was acceptable termination criteria of the ADMM-based optimization algorithm [32]. Table 2 summarizes all parameters used in the simulation. It is important to note that the chosen parameters were specific to this study and can be changed depending on the energy demand, PV generation, countries, number of RUs, and trading policy.

A. TOTAL SOCIAL WELFARE MAXIMIZATION AND CONVERGENCE

The convergence of the bilateral process in Algorithm 1 in time slot 11 is illustrated in Fig. 4. It was assumed that the market had four producers and four consumers. The chosen

TABLE 2. Parameter setup.

Parameters	Producer	Consumer
α_i	[0.5–1] ¢/kWh^2	[0.5–1] ¢/kWh^2
w_i	[10–20] ¢/kWh	[10–20] ¢/kWh
p_i^{min}	0 kW	[1–4] kW
p_i^{max}	[5–10] kW	[6–10] kW
Number of participants	4	4
γ	0.5 ¢/kWh	0.5 ¢/kWh
δ_{P2P}	0	0.01
σ_{P2P}	0	0.1
$\underline{\lambda}^G$	2 ¢/kWh	-
$\overline{\lambda}^G$	-	20 ¢/kWh
ρ	0.01	0.01
Maximum number of iterations	5,000	5,000
ϵ^{pri}	10^{-4}	10^{-4}
ϵ^{dual}	10^{-4}	10^{-4}

TABLE 3. Parameter setup of prosumer $i_j \in N$ at time slot 11.

Name	p_i^{min} (kW)	p_i^{max} (kW)	α_i (¢/kWh^2)	w_i (¢/kWh^2)
Consumer 1	-7.54	-0.83	0.65	16.59
Consumer 2	-9.22	-0.56	0.87	14
Consumer 3	-9.84	-1.34	0.85	10.4
Consumer 4	-8.44	-2.14	0.68	13.69
Producer 1	0	9.5	0.57	12.37
Producer 2	0	6.42	0.7	11.37
Producer 3	0	7.32	0.93	13.31
Producer 4	0	5.39	0.75	11.4

parameters are presented in Table 3 . According to Fig. 4, the proposed model reached global convergence at a low number of 23 iterations, in which both the primal and dual values were lower than 10^{-4}. The ADMM algorithm found the convergence for the proposed model in only 0.23 s.

In negotiations, prosumers adjust their sales or purchases using the objective function with constraints from their partners, as expressed in (13a). As shown in Figs. 5–8, P2P energy trading was successfully performed between the four selling houses and four buying houses, namely, from 1 to 4 per side. The algorithm achieved an optimal price of 2.25 ¢/kWh per prosumer, which indicates that the transaction cost is equal for all participants, clearing the market at a uniform price. The total energy generation sold to their partners by producers 1, 2, 3, and 4 was 8.96, 6.00, 6.85, and 5.02 kW, whereas the total energy purchases of consumers 1, 2, 3, and 4 from the producers was 7.54, 6.55, 4.59, and 8.16 kW, respectively. Thus, through the P2P energy market, residential energy consumers could buy sufficient energy to meet their demand from residential producers 1, 2, 3, and 4.

Moreover, there was a small amount of energy sold to the grid (1.78 kW), in which 0.53, 0.41, 0.47, and 0.37 kW was sold by producers 1, 2, 3, and 4, respectively. As mentioned in Section III.C, producers can trade their energy with both consumers and the main grid during each time slot. More specifically, producers sell their surplus energy to other prosumers

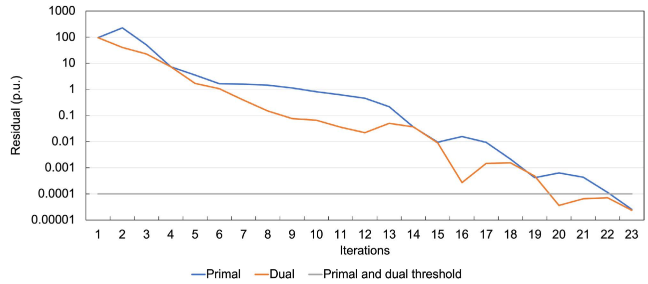

FIGURE 4. Convergence of the proposed ADMM approach.

or the grid in order to maximize their utility function and reduce transaction costs. As the buying price of the main grid is lower than that of another prosumer, a substantial amount of energy is sold to the consumer and relatively small quantities of energy are sold to the grid.

We note that the market participants are aware of other prices, such as the buying and selling prices of the main grid. Thus, a buyer cannot offer a price lower than the main grid selling price and a seller cannot provide energy at a price higher than the main grid buying price. All P2P transactions must be lower than the buying price of the main grid and higher than the selling price of the main grid. Therefore, the prosumer can make profit from more beneficial prices by participating in the P2P market.

To demonstrate the efficacy of DR in the proposed model, we compared the results of the proposed market with those of the case in which prosumers traded with the grid only (no-DR) considering the total social welfare and number of energy trades. The energy traded in case of no-DR is the maximum amount of energy bought and sold on the main grid. Comparative results are presented in Table 4 . As the results show, P2P trading reduced the imported energy from the grid and further reduced the energy consumption based on their preferences compared with no-DR, thereby reducing the energy cost. Similarly, the energy exported to the grid was reduced compared with that of the case of no-DR and increased the amount of energy sold to partners to obtain benefits. The results confirmed that prosumers can increase their social welfare by participating in P2P services, although participants must pay an extra fee, that is, the carbon emission and transaction fee to the grid operator. Meanwhile, the total social welfare of trade with the grid only had a negative value because producers sold their excess energy at low prices and consumers compensated for deficit energy at high prices.

B. EFFECTS OF CARBON EMISSION COST

To investigate the effects of the pollutant parameter σ_{P2P} on the carbon emissions in the market, δ_{P2P} was fixed for all consumers, as shown in Fig. 9. We discovered that carbon emission costs were reduced at the convergence of the ADMM algorithm. In addition, even if pollutant levels increased for each consumer, reductions in carbon emissions were linearly increased. It is because when the pollutant levels increased,

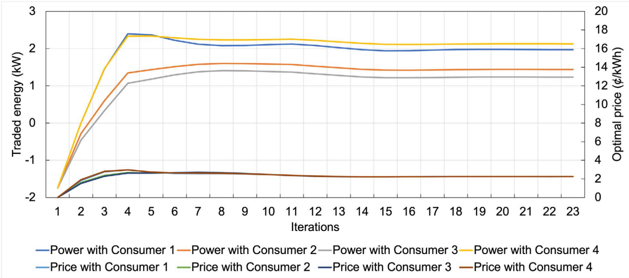

FIGURE 5. Convergence of energy and price for Producer 1.

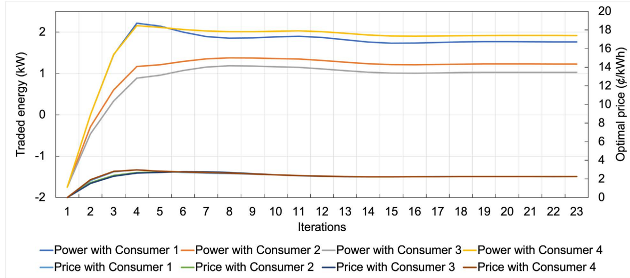

FIGURE 7. Convergence of energy and price for Producer 3.

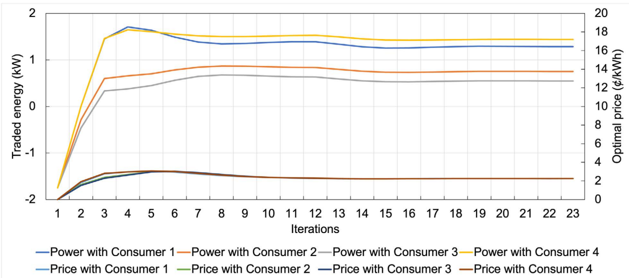

FIGURE 6. Convergence of energy and price for Producer 2.

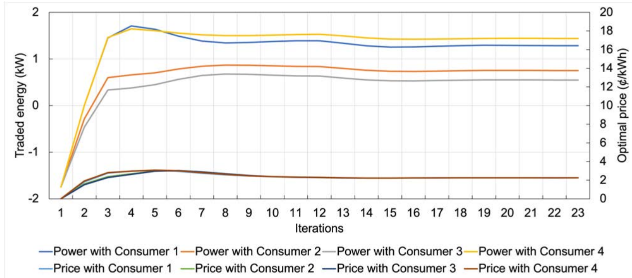

FIGURE 8. Convergence of energy and price for Producer 4.

the carbon emission cost increased in (5); thus, consumers preferred to consume less energy, which resulted in lower cost of emissions. Therefore, energy cost was reduced in the global solution when the pollutant parameter of consumers was considered in the proposed model. Clearly, a higher level of pollutants reduces the total energy consumption by consumers, thereby reducing the total social welfare in P2P energy trading; however, it is highly environmentally friendly. Conversely, a lower level of pollutants increases social welfare; however, it is less environmentally friendly. Therefore, the tradeoff between the financial development and environmental protection should be considered when choosing pollutant parameters [37].

C. EFFECTS OF TRANSACTION COST

At each trading period, an individual prosumer i involved in the P2P market attempts to maximize its profit by minimizing trading costs with their partners j, particularly the trading cost for selling or buying p_{ij} per unit distance at a transaction price γ_{ij}. Therefore, we used the proposed model to investigate the effects of the distance between producers and consumers on the decision-making of each prosumer in a microgrid.

As shown in Fig. 10, in Case 1, we first studied a market setup with zero transaction cost of preference criteria, that is, all values $dist\,(i, j)$ were equal to zero in (13a); thus, $D_T\left(p_{ij}\right) = 0$. Prosumers in green are producers, and prosumers in blue are consumers. In this situation, the communication graph is expected not to affect the global social welfare, where producer 1 decides to trade 4.53 kW with the household outside its local community, 4.78 kW is traded with the household inside its local community, and only 0.19 kW is sold to the main grid for incentive.

TABLE 4. Comparative results of p2p trading and trading with grid in time slot 11.

	Trading with P2P + grid	**Trading with grid only**
Total imported energy from grid (kW)	0.00	35.04
Total exported energy to grid (kW)	1.78	28.63
Total exchanged in energy trading (kW)	53.67	-
Total social welfare of producers (¢)	194.32	57.26
Total social welfare of consumers (¢)	229.4	−700.8
Total welfare all prosumers (¢)	423.72	−643.54

However, if transaction costs are not zero, different market outcomes occur depending on the distance $dist\,(i, j)$ between the involved prosumers, as shown in Fig. 10 in Cases 2 and 3. In Case 2, we consider trade-based transaction costs that are effective within communities. As expected, the social welfare of P2P trading was negatively affected using γ_d of 0.5 ¢/kWh · km, where $dist\,(i, j)$ between users in the community was 0.5 km, and the distance between two communities was 1 km. Compared with a zero transaction cost, the results proved that the distance forced producer 1 to raise the amount of energy sold to consumers 1 and 2 from 4.78 to 7.94 kW and to decrease the amount of energy sold to consumers 3 and 4 from 4.53 to 0.12 kW. The remaining energy of 1.44 kW was sold to the main grid.

Similarly, in Case 3, we continued to increase the distance between the two communities to 1.5 km and maintain

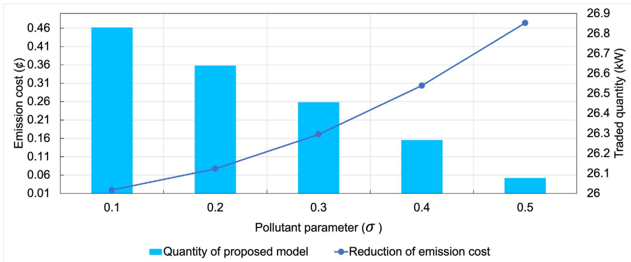

FIGURE 9. Consumer's carbon emission as the pollutant parameter $\sigma_{\mathbf{P2P}}$ varies with $\delta_{\mathbf{P2P}}= 0.01$.

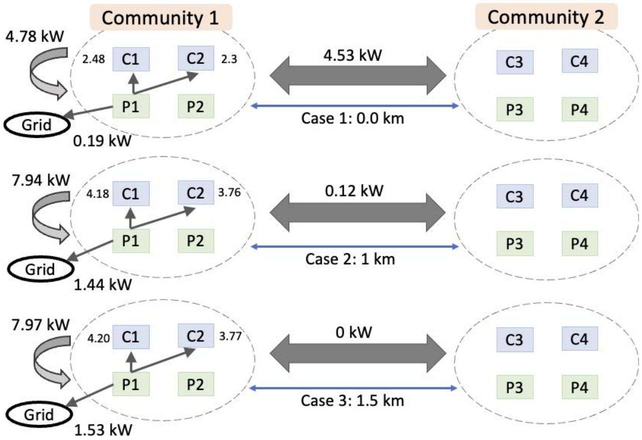

FIGURE 10. Effect of distance on the decision making of producer 1.

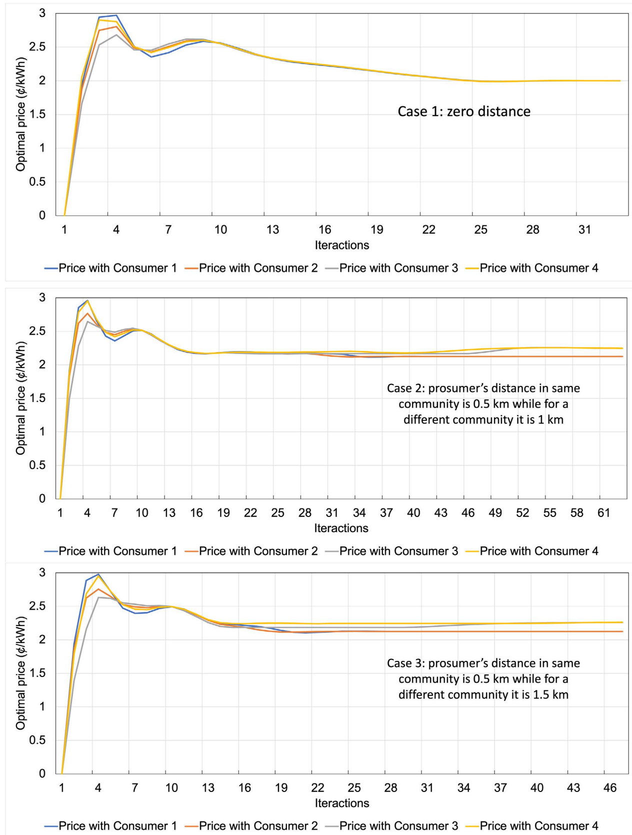

FIGURE 11. Producer 1 updates prices during P2P negotiations in different cases.

$\gamma_d = 0.5$ ¢/kWh · km. Owing to the effect of distance, producer 1 increased the results of the local community instead of trading with consumers outside its local community. Therefore, the local selling of electricity increased from 7.94 to 7.97 kW and selling to other communities was reduced from 0.12 to 0 kW, and 1.53 kW was traded with the main grid. In addition, in P2P trading scenarios, approximately all surplus PV energy was exchanged in the local community instead of being traded with other prosumers in other communities owing to the effect of the transaction costs, as discussed in Subsection III.E. Hence, considering transaction costs as a single value or energy per unit distance is an approach to improve the local P2P trade and mitigate problems in long-distance energy transactions, such as congestion and losses on the existing grid.

Subsequently, we varied the distance to investigate its effects on the optimal price, as shown in Fig. 11. The results show that transaction costs change the optimal prices between producer 1 and its partners at different distances. Prices tend to increase when distance increases. In particular, a trading price of 2 ¢/kWh in Case 1 is unique to all consumers. In Case 2, the market is cleared at higher optimal prices that those of Case 1, and prices are different in different communities. Consumers in the same community buy their goods at a lower price than those in other communities. The selling price of producer 1 to consumers 1 and 2 is 2.125 ¢/kWh and that of consumers 3 and 4 is 2.24 ¢/kWh. In Case 3, an optimal price of 2.26 ¢/kWh is increased for consumers 3 and 4, while it remains the same for consumers 1 and 2, compared those in Case 2.

Instead of showing the decisions-making made by producer 1, Table 5 highlights the results in different cases for all prosumers using the proposed model. Because of network constraints, the amount of energy traded and total social welfare between trading prosumers was less in Cases 2 and 3 and thus, the trade with the grid was increased compared to the same situation in Case 1. Consequently, the average optimal price was higher in Cases 2 and 3 than that of Case 1. Because the complexity of each agent model was increased according to the transaction cost is considered in Cases 2 and 3 compared to that of Case 1, as presented in Subsection III.E. It is obvious that the proposed model without transaction cost achieves a lower number of iterations to find the optimal solution than with transaction cost.

D. SCALABILITY AND SIMULATION IN INTRADAY MARKET

In this subsection, we first investigate whether the number of prosumers has a significant impact on the performance of ADMM, and then analyze the social welfare, total amount of energy, and optimal price of the P2P trading market at different times of the day.

TABLE 5. Results at different distances for all prosumers with a transaction price of $\gamma_d = 0.5$ ¢/kWh in time slot 11.

	Case 1	Case 2	Case 3
Total energy traded with the grid (kW)	0.92	1.64	1.84
Total sold energy in the P2P market (kW)	28.63	28.63	28.63
Total bought energy in the P2P market (kW)	27.71	26.98	26.79
Total social welfare of all prosumers (¢)	437.36	430.39	430.37
Average price (¢/kWh)	2	2.23	2.29
Iterations	33	63	47

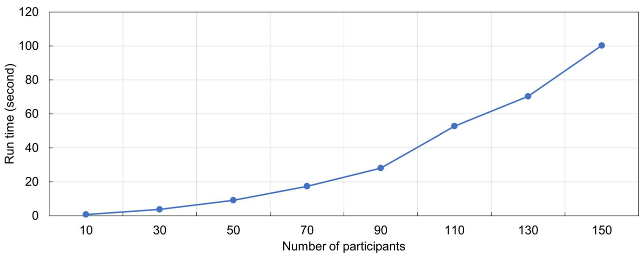

FIGURE 12. Scalability of the proposed approach.

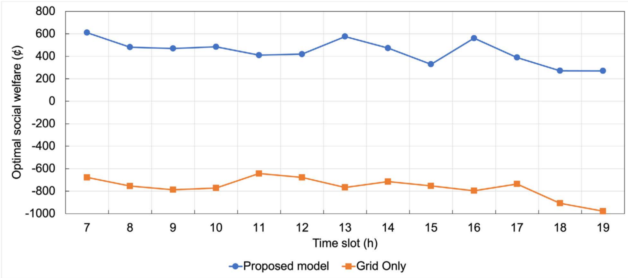

FIGURE 13. Total social welfare in the intraday market.

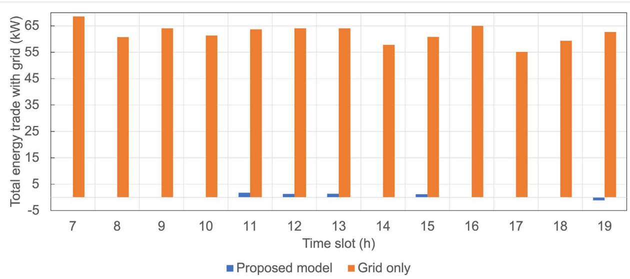

FIGURE 14. Total electricity energy exchange with the grid in the intraday market.

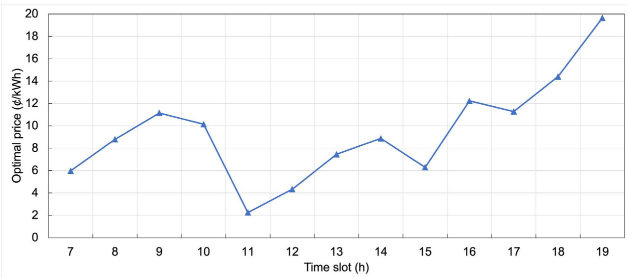

FIGURE 15. Optimal electric price in the intraday market.

The computational time for each prosumer versus the system size is shown in Fig. 12, which confirms that the computation time of the proposed model is not sufficiently high to obtain the convergence solution when the number of RUs increases. Hence, the proposed model is expected to be satisfactorily scaled in a realistic environment with many prosumers. Moreover, the computation time slightly increases in a real environment where communication and synchronization between prosumers is considered.

Finally, the simulation results of the proposed model illustrate the intraday market. Because energy generation using PV systems for each producer was zero in time slots 0–7 and 19–24, no energy could be traded inside the market. That is, producers make no profit in these time slots; hence, the social welfare of consumers in these time slots remains zero. Conversely, in time slots 7–19, as shown in Fig(s). 13–15, the surplus energy is traded; hence, the social welfare, total traded energy, and price are optimized by the proposed model.

Figure 13 shows that each prosumer in the proposed model always attempts to maximize their benefit by solving the problem expressed in (13a) at each time slot t. Therefore, our proposed method always achieves a higher benefit compared with the grid only. Figure 14 shows that the energy traded with the grid in time slots 7–10, 14, and 16–19 is zero, and only a small amount of energy is traded with the grid, which is selling 1.79, 1.32, 1.41, and 1.19 kW at high sun hours of 11, 12, 13, and 15, respectively, and buying 1.11 kW at a low sun hour of 19. Figure 15 shows that P2P trading prices are lower in time slots 11–13 owing to the increase of PV generation while the energy consumption decreases. Otherwise, during time slots 16–19, trading prices are high. In addition, all P2P trading prices in a day of the proposed model are always lower than the selling price (20 ¢/kWh) of the grid and higher than its buying price (2 ¢/kWh). In the proposed method, the lowest price is 2.25 ¢/kWh at $t = 11$ and highest one is 19.65 ¢/kWh at $t = 19$. Thus, the proposed model can handle P2P trading in a grid-connected condition in the intraday market.

VI. CONCLUSION

In this study, we introduced a P2P energy trading model for grid-connected prosumers in microgrids. We formulated a social welfare model for prosumers considering their willingness to shift loads, carbon emissions, transaction costs, and grid trading. Additionally, the proposed model permits prosumers to trade with regulated electricity markets and deregulated P2P markets simultaneously in different time slots. The negotiation process automates execution without revealing sensitive user data or relaying data to a centralized entity. The SWM problem was designed and investigated in a decentralized manner, in which all involved prosumers attempted to optimize their utility and costs, thus contributing to the total SWM of market prosumers in the electricity market. The proposed model was tested for convergence considering a wide range of scenarios. Convergence was achieved with a small number of interactions at a short calculation time. As proof of the convergence between supply and demand, primal and dual values were displayed for all network participants. The simulation results proved that PV prosumers could achieve a higher social welfare than those who directly traded with the main grid, even if they must pay carbon emissions and transaction costs, and increase PV consumption locally. Furthermore, we conducted a simulation to determine the effect of carbon emissions and transaction costs on the user's decision making. The implementation was tested for scalability in multiple interactions with hundreds of users. Finally, P2P energy trading was extended multiple times to illustrate variations in the total social welfare, prices, and quantities within an intraday market.

In a future study, we will investigate the effects of batteries on the grid-connection prosumers. In addition, we will attempt to reduce the energy mismatch between producers and consumers considering uncertainties in solar PV systems. Applying the averaging consensus protocol to our proposed method and considering the physical constraints in P2P trading will also be our future works.

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