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RESEARCH ARTICLE

Security-Constrained P2P Energy Trading Strategy via Priced-Based Regularization of ADMM in a Distribution Network

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ABSTRACT The emerging peer-to-peer (P2P) energy market is gaining momentum due to its escalating market value and sustainability, granting prosumers the autonomy to trade and obtain economic benefits. As the market expands and individual energy transactions intensify, ensuring secure operation to maintain the system within safe boundaries becomes vital. This paper introduces a security-constrained P2P energy market strategy for distribution networks (DNs), incorporating price-based regularization via the alternating direction method of multipliers (ADMM). The resulting bid price reflects network constraints, imposing penalty costs or incentives on prosumers based on the energy transaction's impact on the system. This leads to a clear understanding of the price formation in energy transactions. The proposed market strategy is decentralized and easily implementable, thereby improving market-clearing scalability and computational efficiency. We verified effectiveness and scalability of the proposed strategy, considering network constraints of voltage deviation, line congestion, and power losses, through numerical case studies based on the IEEE 33-node and 119-node test systems. In a 119-node test system involving 500 prosumers, all network constraints were fulfilled with a marginal 0.6% decrease in social welfare compared to a market strategy without regularization. The market-clearing convergence time was approximately 21 seconds, demonstrating its suitability for a short-term, large-scale P2P energy market.

INDEX TERMS Alternating direction method of multipliers, distribution network, energy pricing, market-clearing strategy, peer-to-peer energy market.

NOMENCLATURE

SETS, INDICES, AND FUNCTIONS

i, j	Indices of sellers and buyers.
m, n	Indices of nodes.
l	Index of distribution lines.
k	Index of ADMM iterations.
$\mathcal{V}$	Set of nodes in the distribution network.
$\mathcal{E}$	Set of lines in the distribution network.
$\mathcal{V}_S,\ \mathcal{V}_B$	Set of sellers and buyers.
$\mathcal{E}_{SB}$	Set of trading relationships.
$\mathcal{B}(i)$	Set of trading counterparts (buyers) for seller i.
$\mathcal{S}(j)$	Set of trading counterparts (sellers) for buyer j.
Ω_S	Feasible set of the seller's problem.
Ω_B	Feasible set of the buyer's problem.
Ω_{DSO}	Feasible set of the DSO's problem.
US_i	Utility function of seller i.
UB_j	Utility function of buyer j.
UD	Utility function of DSO.
C_i	Flexibility activation cost function of seller i.
B_j	Revenue function of buyer j.
D_j	Additional trading cost function of buyer j.
$\mathcal{I}_S$	Indicator function associated with regularization of sellers' constraints.
$\mathcal{I}_B$	Indicator function associated with regularization of buyers' constraints.

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$\mathcal{I}_{DSO}$	Indicator function associated with regularization of the DSO.
$P_{\Omega_{DSO}}$	Projection function onto Ω_{DSO}.
$\mathcal{L}_{DSO}$	Equivalent augmented Lagrangian function of the DSO's problem.

PARAMETERS

N	Number of nodes in the distribution network [-].
L	Number of lines in the distribution network [-].
N_S, N_B	Numbers of sellers and buyers [-].
a_i, b_i	Coefficients of the cost function of seller i [¢/kW^2, ¢/kW].
w_j, t_j	Coefficients of the utility function of buyer j [¢/kW^2, ¢/kW].
$u_{i,j}$	Bilateral trading weight between seller i and buyer j [$¢/kW$].
$p_i^{\mathrm{s,max}}$	Maximum of total selling energy of seller i [kW].
$p_i^{\mathrm{s,min}}$	Minimum of total selling energy of seller i [kW].
$p_j^{\mathrm{b,max}}$	Maximum of total buying energy of buyer j [kW].
$p_j^{\mathrm{b,min}}$	Minimum of total buying energy of buyer j [kW].
$\upsilon_n^{\mathrm{base}}$	Base voltage magnitude at node n [p.u.].
$\upsilon_n^{\mathrm{max}}$	Maximum of voltage magnitude at node n [p.u.].
$\upsilon_n^{\mathrm{min}}$	Minimum of voltage magnitude at node n [p.u.].
f_l^{base}	Base power flow of line l [kW].
f_l^{max}	Maximum of power flow of line l [kW].
f_l^{min}	Minimum of power flow of line l [kW].
$\gamma_{i,j}^n$	Sensitivity factor for voltage deviation at node n according to the energy trade $\mathrm{z}_{i,j}$ [p.u./kW].
$\varphi_{i,j}^l$	Sensitivity factor for line congestion of line l according to the energy trade $z_{i,j}$[-].
$\tau_{i,j}$	Sensitivity factor for power losses according to the energy trade $z_{i,j}$ [-].
c_{retail}	Retail price of purchasing energy from utility to distribution network [¢/kW].
c_{FiT}	Export price of selling energy from distribution network to utility [¢/kW].
ρ	Penalty parameter [-].

VARIABLES

v_n	Voltage magnitude at node n [p.u.].
f_l	Active power flow on line l [kW].
P^{loss}	Total active power loss [kW].
p_i^{s}	Total trading energy by seller i [kW].
p_j^{b}	Total trading energy by buyer j [kW].
$z_{i,j}$	Global variable for trading energy between seller i and buyer j [kW].
$e_{i,j}^{\mathrm{s}}$	Local variable of the bidding for trading energy by seller I [kW].
$e_{i,j}^{\mathrm{b}}$	Local variable of the bidding for trading energy by buyer j [kW].
$\lambda_{i,j}^{\mathrm{s}}$	Bidding energy price by seller i for the energy transaction with buyer j [¢/kW].
$\lambda_{i,j}^{\mathrm{b}}$	Bidding energy price by buyer j for the energy transaction with seller i [¢/kW].
$\overline{\lambda}_{i,j}$	Energy price for trading energy between seller i and buyer j [¢/kW].
$\widetilde{\lambda}_{i,j}$	Extra price for trading energy between seller i and buyer j [¢/kW].
$\overline{\xi}$, $\underline{\xi}$	Dual variables for voltage magnitude constraints [¢/p.u.].
$\overline{\eta}$, $\underline{\eta}$	Dual variables for line capacity constraints [¢/kW].
$NUP_{i,j}$	Network usage price for the energy transaction between seller i and buyer j [¢/kW].

I. INTRODUCTION

A. MOTIVATION AND BACKGROUND

The surge in distributed energy resources, smart meters, energy storage systems (ESSs), electric vehicles (EVs), and home energy management systems (HEMSs) is paving the way for a peer-to-peer (P2P) energy trading market. This emerging platform allows market participants to make independent decision-making for energy trades in accordance with the business opportunity and the energy flexibility [1]. With the expansion of the P2P energy trading market, traditional passive consumers are becoming active prosumers. These prosumers can dynamically manage their energy production and consumption, trading energy with utilities and other prosumers [2]. While maximizing social welfare is a primary objective in the P2P energy market, prosumer-centric energy exchanges pose challenges to the secure operation of a distribution network (DN) due to increased power flow variations [3]. Therefore, market mechanisms and clearing strategies should appropriately reflect both prosumer benefits and system reliability.

Grid support or ancillary services (ASs) are commonly used strategies for the secure operation of DNs, providing solid management in uncertain market situations [4], [5], [6]. They implement imbalance settlement and regulation services. Usually, these strategies are radical and processed between P2P market clearing and market gate closure. Moreover, the cost of implementing additional services is usually non-negligible [7], and sensitive energy transaction information could potentially be exposed to the service provider [8]. A P2P energy market-clearing strategy can be easily integrated into the existing market. Furthermore, a decentralization-based approach is highly desirable for scalable P2P energy markets with diverse renewables [9], respecting the privacy of prosumers [10]. Along with these advantages, the efficient management for network constraints of DNs is of great interest in the research field of P2P energy markets.

To this end, this paper explores a security-constrained P2P energy trading strategy, considering an aspect of decentralization and a price-based regulation for network constraints.

B. LITERATURE REVIEW

Several emerging issues in the field of P2P energy markets, such as social welfare maximization [11], implementing coordination strategies [12], improving system reliability [13], and maintaining security against cyberattacks [14], pose major challenges. Many market mechanism approaches, including various auctions using game theory, have been explored. One study [15] suggested a sensitivity analysis-based methodology to assess the effects of P2P energy transactions on power flows, voltages, and power losses; the distribution system operator (DSO) ensures safe energy transactions by rejecting high-risk trades in a continuous double auction market. A multi-round double-auction mechanism using distribution locational marginal pricing signals to manage network constraints has also been proposed [16]. Other researchers [17] have suggested a coalition graph game paired with a local voltage management scheme to encourage prosumers to trade cooperatively.

As another application of market mechanisms, a Stackelberg game-based energy sharing framework was also proposed, considering line capacity constraints [18], in which an energy-sharing provider sets varied prices for each region, accounting for the operation of the DN. Meanwhile, a cooperative energy market mechanism was proposed for an active DN, in which the DSO manages voltages by controlling tap changers and shunt capacitors [19]. A zero-sum P2P settlement method focused on demand-side reserve comfort and allocating costs related to constraint violation using the Vickrey–Clarke–Groves mechanism [20]. Two studies [21], [22] presented P2P energy market strategies that consider uncertainties in energy prices, renewable generation, and load demand. In one [21], an uncertainty price is charged to the equipped prosumers according to their energy reserves, while the other [22] proposes a general Nash bargaining model based on a hybrid stochastic/robust optimization approach that achieves market balance by adjusting the computational burden and conservativeness.

Optimization-centric approaches have proven highly effective in addressing P2P energy market reliability issues [23]. For instance, in an electrical-distance-driven matching strategy, the DSO prioritized matching agents based on the shortest electrical distance [24]; this strategy efficiently reduced power losses and line use, although it did not consider voltage impact. For applications in building-to-building energy transactions, a multilevel bidding method for inverter-based heating, ventilation, and air conditioning (HVAC) systems was proposed, factoring in transactive capacity and historical locational marginal prices [25]; this approach helped save user energy costs and alleviate network power congestion. In a P2P energy sharing strategy for a cluster of smart energy buildings, the two-level optimization problem for each building helped establish a fully distributed strategy, resulting in load profile smoothing in the regional building cluster [26].

For the short-term market clearing, a generalized fast dual ascent method was applied to improve the convergence region [27]; this research implemented the sensitivity analysis of nodal voltage and power losses and leveraged the Lagrangian-relaxation method to enhance the computational performance in a distributed manner. A primal–dual gradient method was also proposed, considering line flow constraints and potential line use charges as congestion signals [28], in which convergence time was significantly reduced. For a framework of P2P energy market, a blockchain-based on-chain power flow calculation model was proposed in a P2P negotiation, allowing the swift smart contract between market participants [29]. This scheme applied a self-adjustment power loss allocation to the result of initial power flow calculation and updated nodal voltage within network voltage requirements.

Decentralization-based methods have attracted substantial interest. For example, a fully decentralized mechanism for coordinated active/reactive power management achieved P2P energy trading with voltage regulation [30]. In addition, a fully decentralized market-clearing mechanism was developed using a Lagrangian approach [31]; it employed a projected gradient method to integrate power loss constraints into the market mechanisms, considering a network fee associated with the electrical distance. Another research group developed an alternating direction method of multipliers (ADMM)-based market clearing for P2P energy trading, albeit without considering technical constraints [32]. Subsequently, various enhancements to the ADMM-based market clearing have been introduced [13], [33], [34], [35], [36]. The works [13] and [33] leveraged the projected gradient method to integrate line flow and voltage constraints into the ADMM-based market-clearing process. In [34], the power losses and transaction fees allocation strategy was integrated into the market-clearing process. Another enhancement used an exogenous cost allocation scheme to alleviate line congestion [35]; however, this scheme did not guarantee safe network conditions with complete certainty. Meanwhile, the work [36] verifies the effectiveness of the ADMM-based market clearing algorithm through a real-time simulation using Hardware-in-the-Loop (HIL). Table 1 represents a comparison of this work to the reviewed articles in the literature review. In comparison to other studies, this work comprehensively accounts for all relevant physical factors, including voltage, line constraints, and power loss. These factors are addressed by introducing a regularization step in the global variable update of the ADMM algorithm, which also establishes pricing related to network constraints. Additionally, the decentralized and privacy-preserving properties are essential in P2P energy trading, ensuring both the autonomy of the participants and the protection of sensitive prosumer data. The proposed method is designed to maintain these properties with minimal intervention from the DSO.

C. MAIN CONTRIBUTIONS

This paper presents a novel security-constrained P2P energy market-clearing strategy, designed to optimize bidding,

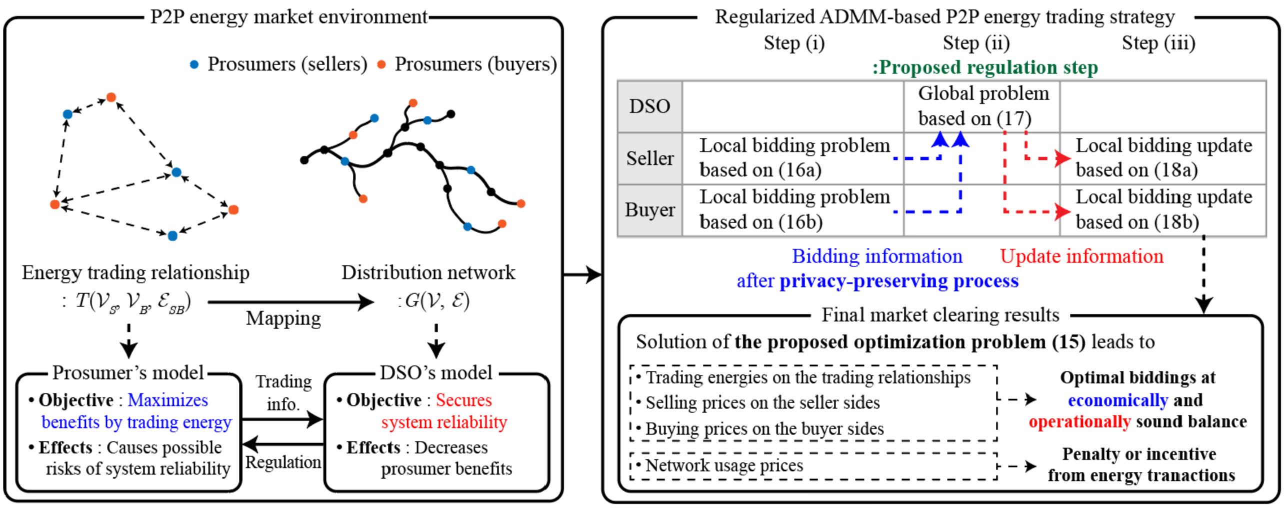


FIGURE 1. Overall schematic diagram of the proposed security-constrained P2P energy trading strategy. The main contribution of this work is the incorporation of Step (ii) in the ADMM process, resulting in a regularized ADMM for P2P energy trading.

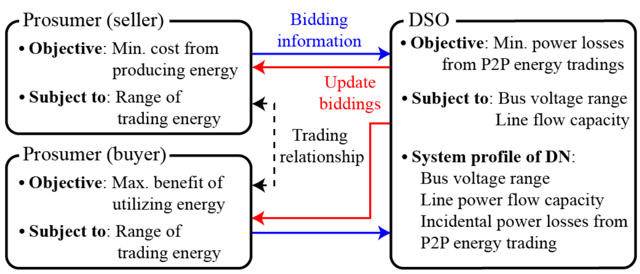


FIGURE 2. Modeling of players in the P2P energy market.

TABLE 1. Comparison of relevant literature on P2P energy markets. 'X' means that the property is not considered, 'O' means that the property is considered.

Property \ Ref.	[10]	[13]	[15]	[16]	[20]	[27]	[28]	[29]	[30]	[31]	[34]	This work
Voltage deviation	X	O	O	O	O	O	X	O	O	X	X	O
Line congestion	X	O	O	O	O	X	O	X	X	X	X	O
Power losses	X	X	O	X	X	O	X	O	X	O	O	O
Decentralized	O	O	O	X	O	O	O	O	O	O	O	O
Privacy-preserving	O	O	X	X	O	O	O	O	O	O	O	O
Pricing associ-ated with net-work constraints	X	O	X	O	X	O	O	X	O	X	X	O

ensure prosumer benefits, and efficiently manage network constraints, including bus voltage deviation, line congestion, and power losses. An overall schematic of this process is depicted in Fig. 1. The proposed strategy entails modeling the interests of each market player via energy trading. The prosumers' interest is to maximize their benefits by trading energy. Their energy trading can change the power flow of the distribution network, and the DSO's interest is to maintain system reliability during the trading. To satisfy all their interests, a price-based regularization of ADMM is utilized in this paper. Through the price-based regularization of ADMM, the DSO adjusts local prosumer bids for enhanced reliability management. Notably, a penalty cost or an incentive imposed on each energy transaction properly reflects the associated network constraints, of which extra cost can be applied to a design of transaction fee. In addition, the proposed strategy provides the privacy-preserving property of prosumers, making it practical for real-world P2P energy trading.

The primary contributions of this paper are summarized as follows. 1) The proposed P2P energy trading strategy optimizes bidding outcomes, considering both the maximization of social welfare and the secure operation of the distribution network. 2) Within the formulation of market model, the regularization of ADMM method evaluates the breach of network constraints, including voltage deviation, line congestion, and power losses. 3) The pricing mechanism is tied to network constraints. Depending on the impact of the energy transaction on the distribution network, either a penalty cost or an incentive is imposed on prosumers. This mechanism is applied to a novel design of the energy transaction fee in the P2P energy market. 4) The proposed P2P market strategy is decentralized, scalable, and computationally efficient, supporting the privacy-preserving property of prosumers.

D. PAPER ORGANIZATION

The structure of this paper is organized as follows: Section II details the models for a seller, a buyer, and the DSO within the P2P energy market. In Section III, the design of the P2P energy market is presented, along with the formulation of optimization problem based on ADMM regularization.

Section IV provides detailed steps for the implementation of the proposed strategy. The results of numerical case studies are presented in Section V. Finally, Section VI offers concluding remarks.

II. MODERING OF MARKET PLAYERS

A. PLAYERS IN THE P2P ENERGY TRADING MARKET

The P2P energy market considered in this paper adopts the decentralized approach, a major trend among recent P2P frameworks [11]. The setup involves prosumers (sellers and buyers) and the DSO on a DN (Fig. 2). The prosumers, positioned at local buses, interact with the system, prioritizing their profits through minimization of activation costs or maximization of usage benefits. The DSO ensures system operational reliability by moderating energy trading between prosumers. As depicted in Fig. 2, sellers and buyers engage in bidding, which could result in potential issues such as voltage deviation or line congestion. The DSO reviews bidding information from the sellers and buyers and adjusts the bidding quantity by updating network usage price when the potential issues arise. The model for each market player is designed with a specific objective, represented as a utility function; these are further elaborated in the following sections.

B. BENEFIT-SEEKING PROSUMERS

Let us assume the voltage and the power flow in a DN can be analyzed based on algebraic graph theory, which first generates a DN in the graphical notation $G(\mathcal{V}, \mathcal{E})$. Here, $\mathcal{V} = \{1, \dots, N\}$ is the set of nodes and $\mathcal{E} = \{1, \dots, L\}$ is the set of distribution lines. The prosumers, among the buses in G, can be either sellers or buyers depending on the energy availability. Each group of sellers and buyers can be denoted as $\mathcal{V}_S := \{1, \dots, N_S\}$ and $\mathcal{V}_B := \{1, \dots, N_B\}$, respectively. Let us further define the set of the trading relationship $\mathcal{E}_{SB} \subset \mathcal{V}_S \times \mathcal{V}_B$; then, the P2P energy market in the DN G can be written as $T(\mathcal{V}_S, \mathcal{V}_B, \mathcal{V}_{SB})$. Additionally, the counterpart set of a prosumer can be defined as $\mathcal{B}(i) \subset \mathcal{V}_B$ for the seller $i \in \mathcal{V}_S$ and $\mathcal{S}(j) \subset \mathcal{V}_S$ for the buyer $j \in \mathcal{V}_B$.

In case of the group of sellers, each seller $i \in \mathcal{V}_S$ maximizes its utility US_i by minimizing the flexibility activation cost C_i [11]. The seller's problem is stated as:

$$\max\ US_i = -C_i(p_i^{\mathrm{s}}), \tag{1a}$$
$$C_i(p_i^{\mathrm{s}}) = a_i(p_i^{\mathrm{s}})^2 + b_i p_i^{\mathrm{s}}, \tag{1b}$$
$$p_i^{\mathrm{s}} = \sum_{j \in \mathcal{B}(i)} e_{i,j}^{s}, \tag{1c}$$
$$p_i^{\mathrm{s,min}} \le p_i^{\mathrm{s}} \le p_i^{\mathrm{s,max}}, \tag{1d}$$
$$e_{i,j}^{s} \ge 0, \quad \forall j \in \mathcal{B}(i). \tag{1e}$$

Here, a_i and b_i are positive coefficients subject to each seller, ensuring the convexity of the problem. (1c), (1d), and (1e) are constraints enforced on the trading energy $e_{i,j}^s$ from seller i to buyer j and the total trading energy p_i^s from the seller i. First, (1c) indicates the total energy sold by seller i is equal to the sum of traded energy with all partners $j \in \mathcal{B}(i)$. Constraint (1d) insists that the total energy sold is bound by minimum and maximum limits. The constraint (1e) imposes a non-negativity condition on the traded energy.

Each buyer $j \in \mathcal{V}_B$ maximizes the utility composed of the revenue B_j from utilizing the purchased energy and the bilateral trading cost. Likewise, the buyers' problem is stated as:

$$\max\ UB_j = B_j(p_j^{\mathrm{b}}) - D_j(e_j^{\mathrm{b}}), \tag{2a}$$
$$B_j(p_j^{\mathrm{b}}) = t_j p_j^{\mathrm{b}} - w_j (p_j^{\mathrm{b}})^2, \tag{2b}$$
$$D_j(e_j^{\mathrm{b}}) = \sum_{i \in \mathcal{S}(j)} u_{i,j} e_{i,j}^{b}, \tag{2c}$$
$$p_j^{\mathrm{b}} = \sum_{i \in \mathcal{S}(j)} e_{i,j}^{b}, \tag{2d}$$
$$p_j^{\mathrm{b,min}} \le p_j^{\mathrm{b}} \le p_j^{\mathrm{b,max}}, \tag{2e}$$
$$e_{i,j}^{b} \ge 0,\ \forall i \in \mathcal{S}(j). \tag{2f}$$

The benefit for the buyer is defined as the convex quadratic form shown in Equation (2b), where t_j and w_j are positive coefficients. The buyer's problem is also considered an additional cost given in Equation (2c), which is associated with the preference for the energy type and is represented by the bilateral trading weight $u_{i,j}$ [10], [32]. For instance, the trading coefficient $u_{i,j}$ is small when buyer j prefers the low-carbon energy resource from seller i, and vice versa. Alongside the utility function, trading energy constraints are provided in Equations (2d), (2e), and (2f). These respectively refer to the condition of the total trading energy p_j^b for buyer j, the bounds of the total trading energy, and the non-negativity condition on the trading energy $e_{i,j}^b$ from seller i to buyer j.

C. RELIABILITY-SEEKING DSO

Network issues often discussed include voltage deviation, line congestion, and incidental power losses [13], [15]. From the perspective of system reliability, the DSO addresses these issues to ensure stable operation of the DN. Initially, network constraints for voltage deviation and line congestion are formulated based on the presented sensitivity factor. Given these constraints, indicator functions are modeled to validate whether the network status lies within the feasible operation set, which is explained in the following section.

Let υ_n represent the voltage magnitude at node $n \in \mathcal{V}$ and f_l represent the active power flow in line $l \in \mathcal{E}$, which lead to the corresponding vectors $\upsilon := [\upsilon_1, \dots, \upsilon_N]^{\mathrm{T}}$ and $\boldsymbol{f} := [f_1, \dots f_L]^{\mathrm{T}}$, respectively. For υ and $\boldsymbol{f}$, let $\upsilon^{\min}$, $\upsilon^{\max}$, $\boldsymbol{f}^{\min}$, and $\boldsymbol{f}^{\max}$ denote the minimum and maximum limits of nodal voltages and line power flows, respectively. We also consider the base conditions under the normal operating state are given as $\upsilon^{\mathrm{base}} = [\upsilon_1^{\mathrm{base}}, \dots, \upsilon_N^{\mathrm{base}}]^{\mathrm{T}}$ and $\boldsymbol{f}^{\mathrm{base}} = [f_1^{\mathrm{base}}, \dots, f_L^{\mathrm{base}}]^{\mathrm{T}}$. The sensitivity factors for the voltage deviation and line congestion are then provided in terms of the trading energy $z_{i,j}$ between seller i and buyer j:

$$\gamma_{i,j}^{n} = \frac{\partial \upsilon_n}{\partial z_{i,j}}, \tag{3}$$

$$\varphi_{i,j}^{l} = \frac{\partial f_l}{\partial z_{i,j}}, \tag{4}$$

which is motivated from the mutual voltage sensitivity coefficient and the power transfer distribution factor [8]. The detailed derivation of Equations (3) and (4) are described in Appendix A. With the above sensitivity factors, the node voltage and the line power flow have the following deviations in consequence of the energy trading:

$$\Delta\upsilon_n = \sum_{(i,j)\in\,\mathcal{E}_{SB}} \gamma_{i,j}^{n} z_{i,j}, \tag{5a}$$

$$\Delta f_l = \sum_{(i,j)\,\in\,\mathcal{E}_{SB}} \varphi_{i,j}^{l} z_{i,j}. \tag{5b}$$

Each lower and upper margin of the voltage magnitude at node n and the power flow at line l is obtained from the bound constraints and the base conditions, leading to:

$$\delta\upsilon_n^{\text{lower}} = \upsilon_n^{\min} - \upsilon_n^{\text{base}}, \tag{6a}$$
$$\delta\upsilon_n^{\text{upper}} = \upsilon_n^{\max} - \upsilon_n^{\text{base}}, \tag{6b}$$
$$\delta f_l^{\text{lower}} = f_l^{\min} - f_l^{\text{base}}, \tag{6c}$$
$$\delta f_l^{\text{upper}} = f_l^{\max} - f_l^{\text{base}}. \tag{6d}$$

Here, the relationship between (5) and (6) clearly provides the information of the feasible region to maintain system reliability.

Regarding power losses, the DSO adjusts bids between prosumers with the aim of minimizing total power loss. While line power loss results from energy transactions, the associated economic impact is often excluded from prosumer benefit calculations. To accurately account for the cost arising from incidental power losses, we introduce a sensitivity factor to evaluate power loss due to energy trading, and subsequently propose an opportunity cost for recovery.

First, the sensitivity factor to assess the incidental power loss due to the energy trading between seller i and buyer j can be given as below:

$$\tau_{i,j} = \frac{\partial P^{\text{loss}}}{\partial z_{i,j}}, \tag{7}$$

which is motivated from the bilateral exchange coefficient [15]; its detailed derivation is provided in Appendix. Using this sensitivity factor, the total power loss can be estimated by $\sum_{i,j} \tau_{i,j} z_{i,j}$. Assuming there are the non-negative incidental power losses resulting from the energy trading, it is possible to estimate the opportunity cost of the recompense by the DSO. Specifically, the recovery cost is calculated based on the retail price c_{retail} in the case of purchasing and the export price c_{FiT} in the case of selling [37], of which understanding leads to:

$$c_{i,j}^{\text{loss}} = \begin{cases} c_{\text{retail}} \cdot \tau_{i,j}, & \text{if } \tau_{i,j} \geq 0 \\ c_{\text{FiT}} \cdot \tau_{i,j}, & \text{otherwise} \end{cases} \quad \text{for } \forall (i,j) \in \mathcal{E}_{SB}. \tag{8}$$

Thus, the total recovery cost in the DN can be obtained from the collective vector of the recovery cost $\boldsymbol{c}^{\text{loss}}$ as below:

$$\pi^{\text{loss}} := \sum_{(i,j)\in\,\mathcal{E}_{SB}} c_{i,j}^{\text{loss}} z_{i,j} = (c^{\text{loss}})^{\text{T}} z. \tag{9}$$

Using (5), (6), and (9), the DSO problem maximizes the system reliability in terms of voltage deviation, line congestion, and incidental power losses.

$$\max\ UD = -(c^{\text{loss}})^{\text{T}} z, \tag{10a}$$
$$\delta\upsilon_n^{\text{lower}} \leq \sum_{(i,j)\in\mathcal{E}_{SB}} \gamma_{i,j}^{n} z_{i,j} \leq \delta\upsilon_n^{\text{upper}} \text{ for } \forall n \in \mathcal{V}, \tag{10b}$$
$$\delta \boldsymbol{f}_l^{\text{lower}} \leq \sum_{(i,j)\in\mathcal{E}_{SB}} \varphi_{i,j}^{l} z_{i,j} \leq \delta \boldsymbol{f}_l^{\text{upper}} \text{ for } \forall l \in \mathcal{E}. \tag{10c}$$

The adjustment based on (10) naturally sacrifices a portion of prosumer benefits, of which the relationship implies the trade-off between the system reliability and the market economy. The proposed market strategy captures the gap between the interests of the DSO and prosumers and secures the best bid as an operationally and economically sound balance. The gap of interests is evaluated as a network usage price (NUP) and is used to calculate a penalty cost or an incentive of the P2P market clearing problem, of which supplementary ideas are presented in the overall market design.

III. MARKET DESIGN

A. OPTIMIZATION PROBLEM OF THE P2P ENERGY TRADING MARKET

The P2P energy market is generally concerned with maximizing overall utility. Typically, the most considered objective function is social welfare, which combines generation costs and benefits accrued from energy purchased by prosumers [11]. The proposed optimal problem considers both financial interests and system reliability. The overall utility of the P2P energy market can be derived from the sum of individual utilities of prosumers and the DSO. Considering the overall utility and all the network constraints, the P2P energy trading problem can be formulated as:

$$\max U = \left\{ -\sum_{i\in\mathcal{V}_S} C_i(p_i^{\text{s}}) + \sum_{j\in\mathcal{V}_B} \left(B_j(p_j^{\text{b}}) - D_j(e_j^{\text{b}}) \right) - (c^{\text{loss}})^T z \right\},$$

subject to: (1c), (1d), (1e), (2d), (2e), (2f), (10b)), (10c), and (11a)

$$e_{i,j}^{\text{s}} = z_{i,j}, : \lambda_{i,j}^{\text{s}}, \ \forall (i,j) \in \mathcal{E}_{SB}, \tag{11b}$$
$$e_{i,j}^{\text{b}} = z_{i,j}, : \lambda_{i,j}^{\text{b}}, \ \forall (i,j) \in \mathcal{E}_{SB}. \tag{11c}$$

Here, dual variables are denoted at the right side of the corresponding constraints. $\lambda_{\text{i,j}}^{\text{s}}$ and $\lambda_{\text{i,j}}^{\text{b}}$ refer to the bidding by sellers and the buyers, also called the energy price. Normally in this formulation, the price biddings from seller and buyer differs, i.e., $\lambda_{i,j}^{\text{s}} \neq \lambda_{i,j}^{\text{b}}$, and the final bid of energy price is derived from the average of $\lambda^{s}_{i,j}$ and $\lambda^{b}_{i,j}$. The price gap between the biddings from seller and buyer is called a NUP, and the split price is imposed on prosumers.

Also, the regularizations from the constraints of (1c), (1d), (1e), (2d), (2e), (2f), (10b), and (10c) are formulated apart from the constraints pertaining to the consensus terms (11b) and (11c). The regularization terms are formulated as the indicator functions enforced on each market player:

$$\mathcal{I}_{\mathcal{S}}(e^s) = \begin{cases} 0, & \text{if } e^s \in \Omega_S \\ \infty, & \text{otherwise} \end{cases}, \tag{12a}$$

$$\Omega_S = \left\{ e^s \in \mathbb{R}^{|\mathcal{E}_{SB}|} : \text{(1c), (1d), and (1e) for } \forall i \in \mathcal{V}_S \right\}. \tag{12b}$$

$$\mathcal{I}_{\mathcal{B}}(e^b) = \begin{cases} 0, & \text{if } e^b \in \Omega_B \\ \infty, & \text{otherwise} \end{cases}, \tag{13a}$$

$$\Omega_B = \left\{ e \in \mathbb{R}^{|\mathcal{E}_{SB}|} : \text{(2d), (2e), and (2f) for } \forall j \in \mathcal{V}_B \right\}. \tag{13b}$$

$$\mathcal{I}_{DSO}(z) = \begin{cases} 0, & \text{if } z \in \Omega_{DSO} \\ \infty, & \text{otherwise,} \end{cases} \tag{14a}$$

$$\Omega_{DSO} = \left\{ z \in \mathbb{R}^{|\mathcal{E}_{SB}|} : \text{(10b) and (10c)} \right\}. \tag{14b}$$

Based on the indicator functions, the optimization problem of (11) is reformulated as:

$$\min \left\{ \begin{array}{l} \sum_{i\in\mathcal{V}_S} C_i(p^s_i) - \sum_{j\in\mathcal{V}_B} \left(B_j(p^b_j) - D_j(e^b_j) \right) + \\ (c^{\text{loss}})^T z + \mathcal{I}_{\mathcal{S}}(e^s) + \mathcal{I}_{\mathcal{B}}(e^b) + \mathcal{I}_{DSO}(z) \end{array} \right\}, \tag{15a}$$

$$e^{s}_{i,j} = z_{i,j}, \quad : \lambda^{s}_{i,j}, \ \forall (i,j) \in \mathcal{E}_{SB}, \tag{15b}$$

$$e^{b}_{i,j} = z_{i,j}, \quad : \lambda^{b}_{i,j}, \ \forall (i,j) \in \mathcal{E}_{SB}. \tag{15c}$$

The global consensus problem of (15) can be computed in parallel for each player based on the ADMM approach. Considering that the calculation step k is transitioned to $k+1$, each variable is updated as follows.

- e-update by prosumers: (16), as shown at the bottom of the next page.
- z-update by the DSO:

$$\begin{aligned} z^{k+1} &= \underset{z\in\,\Omega_{DSO}}{\arg\min} \left\{ -UD + \rho \left\| z^k - \bar{e}^{k+1} - \tilde{\lambda}^k \middle/ \rho \right\|_2^2 \right\}, \\ &= \underset{z\in\,\Omega_{DSO}}{\arg\min} \left\{ (c^{\text{loss}})^T z^k + \rho \left\| z^k - \bar{e}^{k+1} - \tilde{\lambda}^k \middle/ \rho \right\|_2^2 \right\}, \end{aligned} \tag{17a}$$

$$\begin{aligned} &= \underset{z\in\,\Omega_{DSO}}{\arg\min} \left\{ \rho \left\| z^k - \bar{e}^{k+1} - \frac{\tilde{\lambda}^k}{\rho} + \frac{c^{\text{loss}}}{2\rho} \right\|_2^2 \right\}, \\ &= P_{\Omega_{DSO}}(\bar{e}^{k+1} + (2\tilde{\lambda}^k - c^{\text{loss}}) \big/ 2\rho), \end{aligned}$$

$$\bar{e}^{k+1}_{i,j} = \frac{1}{2}(e^{s,k+1}_{i,j} + e^{b,k+1}_{i,j}), \tag{17b}$$

$$\tilde{\lambda}^{k}_{i,j} = \frac{1}{2}(\lambda^{b,k}_{i,j} - \lambda^{s,k}_{i,j}). \tag{17c}$$

- λ-update by prosumers:

$$\lambda^{s,k+1}_i = \lambda^{s,k}_i - \rho(e^{s,k+1}_i - z^{k+1}), \tag{18a}$$

$$\lambda^{b,k+1}_j = \lambda^{b,k}_j + \rho(e^{b,k+1}_j - z^{k+1}). \tag{18b}$$

Here, the z-update problem includes a modification in the definition of the dual variable (17c) instead of an averaging step in the original consensus-ADMM formulation in [38]. The above sub-problems are iteratively solved by the corresponding market players, which leads to the optimal solution of the original problem (11).

Stopping criteria for the iterative process are given based on the primal and dual residuals [38]:

$$\sum_{i\in\mathcal{V}_S} \left\| r^{s,k}_i \right\|_2^2 + \sum_{j\in\mathcal{V}_B} \left\| r^{b,k}_j \right\|_2^2 \le \varepsilon^2_{\text{pri}}, \tag{19a}$$

$$\left\| s^k \right\|_2^2 = \rho^2 \left\| z^k - z^{k-1} \right\|_2^2 \le \varepsilon^2_{\text{dual}}, \tag{19b}$$

where $\boldsymbol{r}^{s,k}_i := \boldsymbol{e}^{s,k}_i - z^k_{i,j}$ and $\boldsymbol{r}^{b,k}_j := \boldsymbol{e}^{b,k}_j - z^k_{i,j}$ are the local primal residuals of seller i and buyer j at iteration k, respectively; $\boldsymbol{s}^k := \rho(z^k - z^{k-1})$ is the dual residual at iteration k.

B. ADJUSTMENT OF BIDDINGS VIA NUP

DSO problem governs the network problems pertaining to voltage deviation, line congestion, and incidental power loss, of which regularization is reflected in the z-update (17). If there is a feasible solution for (17a), the objective function is convex and the strong duality holds. Providing the feasibility of the problem, the equivalent augmented Lagrangian can be written as:

$$\begin{aligned} \mathcal{L}_{DSO} = &\sum_{(i,j)\in\mathcal{E}_{SB}} \left[c^{\text{loss}}_{i,j} z^{k+1}_{i,j} + \rho(z^{k+1}_{i,j} - \bar{e}^{k+1}_{i,j} - \tilde{\lambda}^k_{i,j} \big/ \rho)^2 \right] \\ &+ \underline{\xi}^T (\delta \upsilon^{lower} - \sum_{(i,j)\in\mathcal{E}_{SB}} \gamma_{i,j} z^{k+1}_{i,j}) \\ &+ \bar{\xi}^T (\sum_{(i,j)\in\mathcal{E}_{SB}} \gamma_{i,j} z^{k+1}_{i,j} - \delta \upsilon^{upper}) \\ &+ \underline{\eta}^T (\delta f^{lower} - \sum_{(i,j)} \varphi_{i,j} z^{k+1}_{i,j}) \\ &+ \bar{\eta}^T (\sum_{(i,j)\in\mathcal{E}_{SB}} \varphi_{i,j} z^{k+1}_{i,j} - \delta f^{upper}), \end{aligned} \tag{20}$$

where $\underline{\boldsymbol{\xi}}, \bar{\boldsymbol{\xi}} \in \mathbb{R}^M$ are dual variables for the voltage magnitude constraint (10b) and $\underline{\boldsymbol{\eta}}, \bar{\boldsymbol{\eta}} \in \mathbb{R}^L$ for the line capacity constraint (10c). Regarding the KKT conditions associated with (20), the stationarity condition with respect to $z_{i,j}$ leads to:

$$\begin{aligned} \frac{\partial \mathcal{L}_{DSO}}{\partial z^{k+1}_{i,j}} = 0 \Leftrightarrow\ & 2\rho(z^{k+1}_{i,j} - \bar{e}^{k+1}_{i,j}) - 2\tilde{\lambda}^k_{i,j} + c^{\text{loss}}_{i,j} \\ &+ (-\underline{\eta}^T + \bar{\eta}^T)\varphi_{i,j} + (-\underline{\xi}^T + \bar{\xi}^T)\gamma_{i,j} = 0 \end{aligned} \tag{21}$$

Hence:

$$\tilde{\lambda}_{i,j}^{k} = \rho(z_{i,j}^{k+1} - \bar{e}_{i,j}^{\ k+1}) + \frac{1}{2}(c_{i,j}^{\text{loss}} + c_{i,j}^{\text{const}}) \tag{22}$$

$$c_{i,j}^{\text{const}} = (-\underline{\eta}^T + \bar{\eta}^T)\varphi_{ij} + (-\underline{\xi}^T + \bar{\xi}^T)\gamma_{i,j}, \tag{23}$$

where $c_{i,j}^{\text{loss}}$ corresponds to the opportunity cost of alleviating the incidental power loss according to (8) and $c_{i,j}^{\text{const}}$ is the cost incurred by voltage deviation and line congestion. Providing that the global problem (15) is solved so $z_{i,j}^{*} = e_{i,j}^{s}$ and $z_{i,j}^{*} = e_{i,j}^{b}$ hold, (15) can be rewritten as:

$$\lambda_{i,j}^{b,*} - \lambda_{i,j}^{s,*} = c_{i,j}^{\text{loss}} + c_{i,j}^{\text{const}}. \tag{24}$$

Note that $\lambda_{i,j}^{s,*}$ and $\lambda_{i,j}^{b,*}$ are the final biddings for energy price from the seller i and the buyer j, respectively. The relationship expressed in Equation (24) implies that there is an additional cost or an incentive for the implementation of the P2P energy trading. Specifically, the collective cost for the DN is obtained as:

$$\sum_{(i,j)\in\mathcal{E}_{SB}} (\lambda_{i,j}^{b,*} - \lambda_{i,j}^{s,*}) z_{i,j}^{*} = \sum_{(i,j)\in\mathcal{E}_{SB}} c_{i,j}^{\text{loss}} z_{i,j}^{*} + \sum_{(i,j)\in\mathcal{E}_{SB}} c_{i,j}^{\text{const}} z_{i,j}^{*}. \tag{25}$$

This can be interpreted as an overhead for the P2P energy trading. Thus, from the perspective of the market design, we hereby define (24) and (25) as a network usage price (NUP) and a network usage cost (NUC), respectively. Especially, Equation (24) implies that the NUP is associated with the network constraints, reflecting the impact of energy transactions on the system reliability.

For further market design, the problem of which market player pays the NUC can be considered. There are conventional approaches to impose a transaction fee on prosumers [31], [35]. Alternatively, there can be an inducement that the DSO exclusively covers the NUC to promote the participation of newly emerging prosumers. In the following discussions in this paper, the trading energy price is defined as the average of the final energy price biddings from the seller and the buyer, leading to (26). In addition, an extra price is derived by splitting the NUP and expressed in Equation (27), which can be the penalty or incentive for the corresponding energy transaction between the seller i and the buyer j. Considering the final trading energy $z_{i,j}^{*}$, the extra cost for the energy transaction can be calculated as $\tilde{\lambda}_{i,j}^{*} z_{i,j}^{*}$, which can be considered a transaction fee of the corresponding energy trading.

$$\bar{\lambda}_{i,j}^{*} = \frac{1}{2}(\lambda_{i,j}^{b,*} + \lambda_{i,j}^{s,*}), \tag{26}$$

$$\tilde{\lambda}_{i,j}^{*} = \frac{1}{2}(\lambda_{i,j}^{b,*} - \lambda_{i,j}^{s,*}). \tag{27}$$

IV. IMPLEMENTATION OF THE PROPOSED P2P ENERGY TRADING ALGORITHM

A. OVERALL MARKET CLEARING PROCESS

To address the optimization problem described in (15), this paper introduces a market-clearing process based on ADMM regularization with global variable consensus. The complete process is depicted in Fig. 3. The optimization problem (15) can be broken down into three subproblems: (i) a local problem for updating trading energy, (ii) a global problem for adjustment, and (iii) a local problem for updating trading price. In step (i), prosumers submit their optimal bidding, accounting for both their neighbors and local constraints. In step (ii), the DSO, after undergoing privacy-preserving processes, aggregates the bidding information and adjusts the trading energy for the sake of system reliability. Finally, in step (iii), the prosumers update their trading prices based on the information broadcasted from the DSO. These three steps are iteratively performed until the market participants find the optimal bidding result according to (15).

The market clearing process is conducted in parallel for each market player (Fig. 3). Note that there are underlying communication lines among market players. Assuming a bidding on a single time slot, the DSO first casts an initiation signal to prosumers, so they can make the first bids: $(\lambda_{i,j}^{s,k}, e_{i,j}^{s,k})$ for the seller i and $(\lambda_{i,j}^{b,k}, e_{i,j}^{b,k})$ for the buyer j. Then, the seller i and the buyer j locally compute the trading energy by solving the optimization problem (16): $e_{i,j}^{s,k+1}$ and $e_{i,j}^{b,k+1}$. Next, the seller i collects the local bidding information $(\lambda_{i,j}^{b,k}, e_{i,j}^{b,k+1})$ from the buyer j, and evaluates $\tilde{\lambda}_{i,j}^{k}$ using (17c). Seller i sends an information set $(\tilde{\lambda}_{i,j}^{k}, e_{i,j}^{s,k+1}, e_{i,j}^{b,k+1})$ to the DSO. Here, note that the evaluation of (17c) is conducted locally, so the DSO cannot access the direct information of energy prices, which supports the privacy-preserving property of prosumers. For the DSO, the global variable $z_{i,j}^{k+1}$ is updated by solving the optimization problem (17a), and then broadcast to both the seller i and the buyer j. Subsequently, each prosumer updates the energy trading prices using (17b) and (18): $\lambda_{i,j}^{s,k+1}$ and $\lambda_{i,j}^{b,k+1}$. These processes are iteratively conducted until the

$$e_i^{s,k+1} = \underset{e_i^S \in\, \Omega_S}{\arg\min} \left\{ \begin{array}{l} C_i(p_i^{s}) + \\ \sum\limits_{j\in\mathcal{B}(i)} \left(-\lambda_{i,j}^{s,k}(e_{i,j}^{s,k} - z_{i,j}^{k}) + \frac{1}{2}\rho(e_{i,j}^{s,k} - z_{i,j}^{k})^2 \right) \end{array} \right\}, \tag{16a}$$

$$e_i^{b,k+1} = \underset{e_j^B \in\, \Omega_B}{\arg\min} \left\{ \begin{array}{l} -B_j(p_j^{0b}) + D_j(e_j^{b,k}) + \\ \sum\limits_{i\in\mathcal{B}(j)} \left(\lambda_{i,j}^{b,k}(e_{i,j}^{b,k} - z_{i,j}^{k}) + \frac{1}{2}\rho(e_{i,j}^{b,k} - z_{i,j}^{k})^2 \right) \end{array} \right\}. \tag{16b}$$

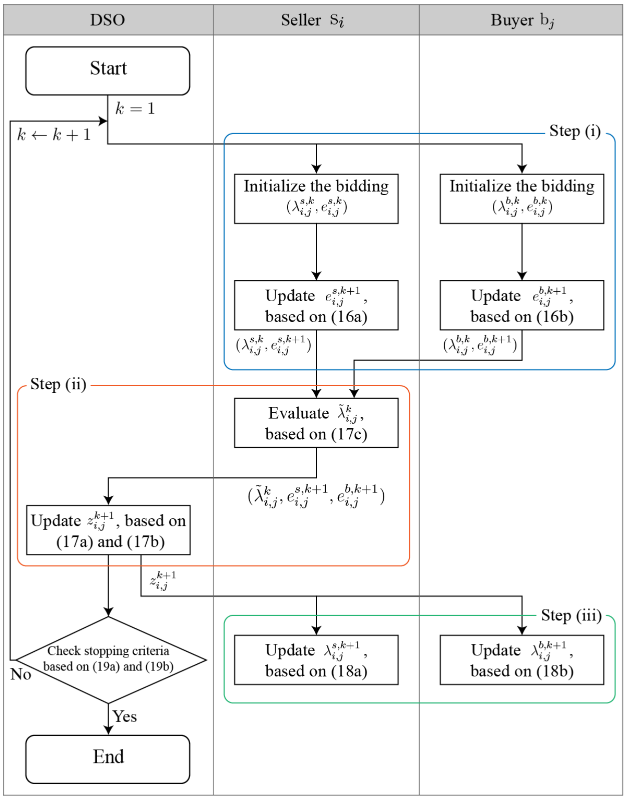


FIGURE 3. Flowchart of the proposed market clearing process. The local optimal biddings are implemented in Step (i), the global variable are ad-justed based on the obtained biddings considering network constraints in Step (ii), and then local biddings are updated by the renewed global variable in Step (iii). These processes are iteratively conducted until the stopping criteria is met.

stopping criteria (19) are met. In the market clearing process, the prosumer's optimization problem (16) and the DSO's optimization problem (17a) can be solved using a commercial optimization solver.

V. CASE STUDIES AND RESULTS

This section presents the analysis of the proposed P2P energy trading strategy, which specifically demonstrates the effectiveness and the scalability based on the case studies on the IEEE 33-node test system and 119-node test system. All simulations were performed using MATLAB, MATPOWER toolbox [39], and Gurobi Optimizer [40] on an Intel Comet Lake 3.8 GHz processor with 8 cores and 32 GB of memory.

A. SIMULATION SETUP

In the common setup for the simulations, we only consider the active power and load for the power flow calculation. In the implementation of ADMM, the penalty parameter is set to $\rho = 0.02$ and the tolerances for the stopping criteria are set to $\varepsilon^2_{\text{pri}} = 10^{-8}$ and $\varepsilon^2_{\text{dual}} = 10^{-8}$. In the market clearing process, the total communication delay per iteration is set to 60 ms as in [41]. Regarding of the extra cost due to purchasing or exporting energy by the DSO, c_{retail} and c_{FiT} are set to 7 ¢/kW and 3 ¢/kW, respectively.

First, an IEEE 33-node test system consisting of 10 prosumers (5 sellers and 5 buyers) is considered in the simulation of a single time slot (Fig. 4). Note that the DSO, virtually installed in the backbone of DN, is marked at node 0 for simplicity. The energy sellers are located in bus 13, 19, 22, 26, and 30 and the energy buyers in bus 17, 21, 24, 28, and 32, while the remaining buses are assumed to be passive consumers. The base system load is 3,715 kW, as in [42], which is used to calculate the base condition of the system: $\upsilon^{\text{ base}}$, $f^{\text{ base}}$, and P^{loss}. Before considering the network constraints, we put the DN in Fig. 4 as a graph notation $G(\mathcal{V},\ \mathcal{E})$ with the node set $\mathcal{V}$ $\{0,\ 1,\ \ldots,32\}$ and the line set $\mathcal{E} = \{1,\ldots,32\}$. Here, we also consider labels for the distribution lines as $l_1,\ \ldots, l_{32}$ for the simplicity. Then, for the nodal voltages $\upsilon_n \in [0.95,\ 1.05]$ for $n \in \mathcal{V}$, and for the line power flow $f_l \in [-4\text{MW}, 4\text{MW}]$ for $l \in \{1,\ldots,\ 11\}$ and $f_l \in [-1\text{ MW}, 1\text{MW}]$ for $l \in \{12,\ldots,\ 32\}$ are given as the network constraints.

In addition to the physical configurations, the trading relationship of prosumers can be expressed as a graph notation $T(\mathcal{V}_S,\ \mathcal{V}_B,\ \mathcal{E}_{SB})$, where $\mathcal{V}_S = \{1,\ldots,5\}$ is the set of sellers, $\mathcal{V}_B = \{1,\ldots,5\}$ is the set of buyers group, and $\mathcal{E}_{SB}$ is the set of connections between the sellers and buyers. The sellers and the buyers are labelled as $s_1, s_2, \ldots, s_5$ and $b_1, b_2, \ldots, b_5$ for the discrimination. Additionally, we use an alternative notation $s_i b_j$ for the trading relationship $(i,\ j) \in \mathcal{E}_{SB}$. Each prosumer relies on the predefined utility to make the best bid; the details, including the trading relationship, are described as shown in Fig. 5. The communication structure is also presented to help clarify how the consensus-ADMM for the proposed strategy is implemented on the system.

In another simulation set, a 119-node test system that includes various number of prosumers is considered. Specifically, the number of prosumers is set to 100, 200, 300, 400, and 500, wherein the ratio between the numbers of sellers and buyers remains consistent. It is worth noting that a single bus can host multiple prosumers, and moreover, both sellers and buyers can reside in the same bus. Additionally, each buyer has 5 randomly selected trading counterparts from the set of sellers. In this context, we employ the Monte-Carlo method to develop the set of prosumer information, including location, utility function, and trading constraints.

Leveraging the test systems described above, the effectiveness and the scalability of the proposed P2P energy trading strategy are demonstrated. Case I–III investigate the former aspect using the IEEE 33-node test system, while Case IV evaluates the latter aspect using the 119-node test system, along with a comparative analysis of the proposed strategy and other methods.

B. CASE I: ENERGY TRADING WITHOUT THE REGULATION BY THE DSO

Figs. 6(a)–(d) show the results of the market clearing process without any regulation by the DSO, i.e., network constraints of voltage deviation, line congestion, and power losses when

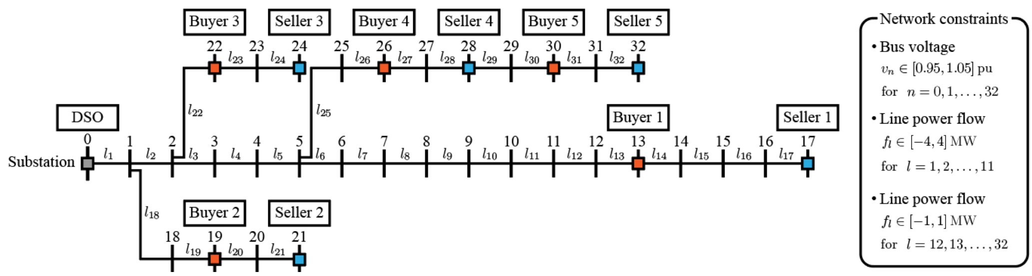
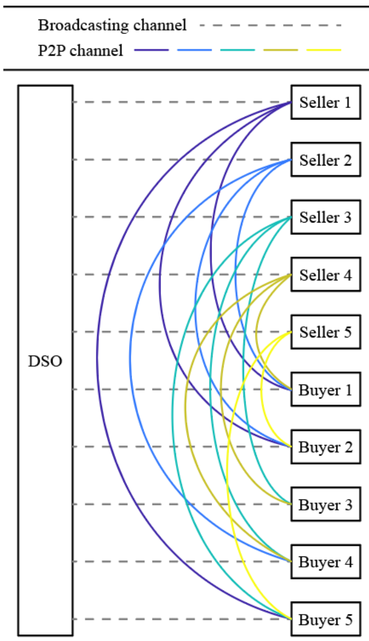


FIGURE 4. An IEEE 33-node test system with five sellers and five buyers, and network constraints for the voltage deviation and the line congestion.



Node index	Label	Energy trading counterparts	Utility function [¢]	Energy trading constraint [kWh]
17	S1	B1, B2, B5	$-0.0046(p_1^s)^2 - 4.84p_1^s$	$p_1^s \in [0, 220]$
21	S2	B1, B2, B4	$-0.0035(p_2^s)^2 - 3.52p_2^s$	$p_2^s \in [0, 260]$
24	S3	B3, B4, B5	$-0.0029(p_3^s)^2 - 3.49p_3^s$	$p_3^s \in [0, 180]$
28	S4	B1, B3, B4	$-0.0069(p_4^s)^2 - 5.03p_4^s$	$p_4^s \in [0, 240]$
32	S5	B2, B5	$-0.0080(p_5^s)^2 - 4.75p_5^s$	$p_5^s \in [0, 160]$
13	B1	S1, S2, S4	$-0.0024(p_1^b)^2 + 5.89p_1^b - \sum_{i\in S(1)} u_{i1}e_{1j}^b$	$p_1^b \in [0, 100]$
19	B2	S1, S2, S5	$-0.0042(p_2^b)^2 + 5.07p_2^b - \sum_{i\in S(2)} u_{i2}e_{2j}^b$	$p_2^b \in [0, 180]$
22	B3	S3, S4	$-0.0031(p_3^b)^2 + 4.99p_3^b - \sum_{i\in S(3)} u_{i3}e_{3j}^b$	$p_3^b \in [0, 180]$
26	B4	S2, S3, S4	$-0.0021(p_4^b)^2 + 6.54p_4^b - \sum_{i\in S(4)} u_{i4}e_{4j}^b$	$p_4^b \in [0, 200]$
30	B5	S1, S3, S5	$-0.0018(p_5^b)^2 + 6.38p_5^b - \sum_{i\in S(5)} u_{i5}e_{5j}^b$	$p_5^b \in [0, 240]$

FIGURE 5. Communication structure and prosumer information in the simulation of the IEEE 33-node test system.

only benefits of the sellers and buyers are of interest. For the specific settings, the terms of $(c^{\text{loss}})^T z$ and $\mathcal{I}_{DSO}(z)$ are assumed to be null in (15) and the bilateral trade weights are ignored; thus, $u_{i,j} = 0$ for $\forall(i,j) \in \mathcal{E}_{SB}$. Figs. 6(e) and 6(f) show the profile of bus voltage and line power flow as the result of P2P energy trading.

Fig. 6(a) shows the trading energy resulting from the ADMM-based consensus process. The total traded energy of each prosumer satisfies the given energy trading constraint. Also, some bidding points of the trading energy hit zero, where the corresponding buyers are b_2 and b_3. This is because the utilities of b_2 and b_3 as in Fig. 5, are less competitive compared to others from the perspective of the system. Fig. 6(d) illustrates each of the selling prices and the buying prices are illustrated on a two-dimensional Euclidean plane with the symmetrical price formation drawn on the solid red line. Here, the NUP can be derived directly by calculating the y-coordinate gap between the bidding point $(\lambda_{i,j}^s, \lambda_{i,j}^b)$ and the red line. In the viewpoint of market clearing, the symmetrical equilibrium price is ideal since it requires the assumption of either of the following: the system resources are limitless, or the impacts from the P2P energy trading are negligible. Such evenness is also observed in the energy prices across the trading relationships, implying that the physical characteristics of system are ignored and the energy price biddings throughout the given P2P energy trading market are conducted under the equivalent game conditions. The slightly lower points located at around 5.07 ¢/kWh are subject to the dead transactions, where the corresponding buyers are b_2 and b_3.

Thus, under unmanaged energy trading, both the bus voltage constraint and the line flow constraint are violated. In case of the node profile, the voltage magnitude at nodes 8–17 and nodes 27–32 falls short of the lower limit 0.95 *pu*, as shown in Fig. 6(e). In case of the branch profile, the power flow at lines 25–27 exceeds the 1 MW capacity,

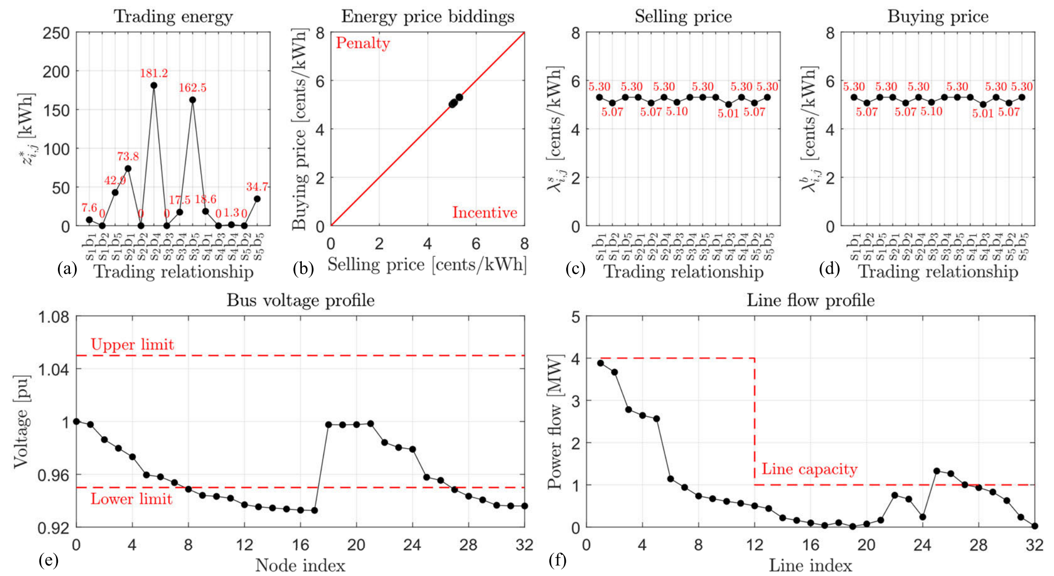


FIGURE 6. Optimal bidding results and network profiles with no regularization: (a) trading energy, (b) price biddings be-tween sellers and buyers, (c) selling prices, (d) buying prices, (e) bus voltages, and (f) power flows.

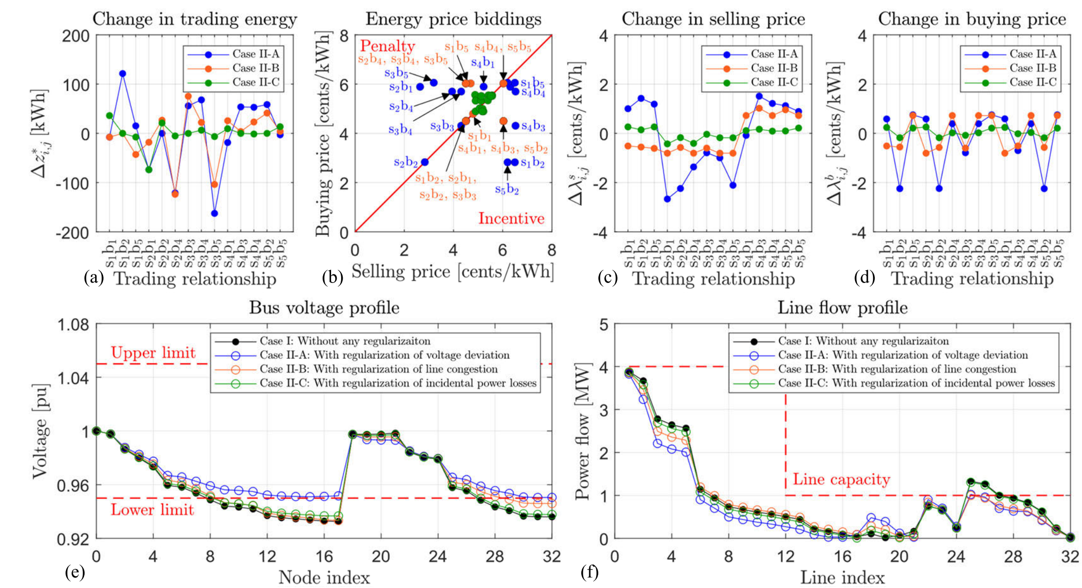


FIGURE 7. Comparison of optimal bidding results: (a) trading energy, (b) price biddings between sellers and buyers, (c) selling prices, (d) buying prices, (e) bus voltages, and (f) power flows.

as shown in Fig. 6(f). The total power loss in the system is 16.72 kW.

C. CASE II: EFFECT OF EACH REGULARIZATION BY DSO

In this case study, the regularizations of the proposed P2P market clearing strategy are explored in terms of the system reliability. The effects of regularization by the DSO are presented from three perspectives: voltage deviation, line congestion, and power losses. For each regularization, the general utility involves the indicator functions regarding of the voltage constraints (10b), line flow constraint (10c), and the cost function $(c^{\text{loss}})^{\mathrm{T}} z$, respectively. The pricing mechanism of the NUP due to the regularization is explained as well. Fig. 7 provides details followed by a comparison with the result of Case I.

1) CASE II-A: REGULARIZATION OF VOLTAGE DEVIATION

The results of the regularization are presented in Figs. 7(a) and 7(b), which show the changes in trading

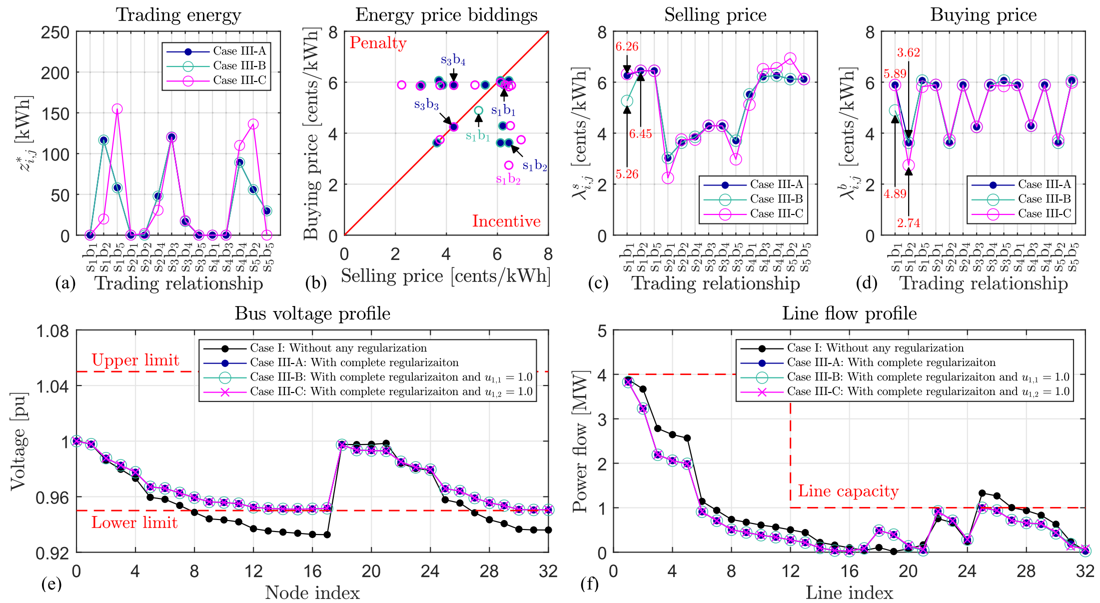


FIGURE 8. **Optimal bidding results with complete regularization by the DSO and consideration of bilateral trading weights: (a) trading energy, (b) price biddings between sellers and buyers, (c) selling prices, (d) buying prices, (e) bus voltages, and (f) power flows.**

energy and energy price bids compared to Case I, denoted by blue points. Figs. 7(c) and 7(d) illustrate the changes in selling and buying prices, respectively. As a result of regularization, the voltage deviation of the system is well-managed, satisfying the given constraint (Fig. 7(e)). However, the system still experiences a violation of the power flow constraint at line 25 (Fig. 7(f)). Furthermore, the total power loss in the system is obtained as 11.12 kW.

To rectify the low voltage condition, the proposed strategy identifies optimal biddings, resulting in increased total supply at s_1, s_4, and s_5 and decreased or vanished total consumption at b_1 and b_5 compared to Case I. Notably, in Case I, prosumers s_1, s_4, s_5, b_1, and b_5 are located at a risky area (nodes 8–17 and nodes 27–32) under a lower voltage condition. In particular, all selling prices at s_1 appear to increase, while the buying price for the trading relationship s_1b_2 decreases significantly, causing a sharp increase in trading energy $z^*_{1,2}$ (Fig. 7(a)). The price bidding of s_1b_2 is positioned in the incentive area, at the bottom right of the red line (Fig. 7(b)), hence both selling and buying energies are incentivized due to the price advantage. Note that the price bidding points for s_4b_3, s_4b_4, and s_5b_4 in Fig. 7(b) are located in the incentive area, leading to observed increased in their corresponding trading energies as in Fig. 7(a). In contrast, for buyers b_1 and b_5, the price bidding points for s_2b_1, s_4b_1, and s_3b_5 are located in the penalty area, at the top left of the red line in Fig. 7(b), thereby hindering corresponding transactions in Fig. 7(a).

2) CASE II-B: REGULARIZATION OF LINE CONGESTION

The bidding results of regularization according to line congestion are presented as orange plots as shown in Figs. 7(a)–(d). Each energy trading in the system is adjusted in accordance with the proposed strategy, followed by the network profiles of Figs. 7(e), and 7(f). Regarding power flow, it is observed from Fig. 7(f) that the flow at line 25 is kept within the acceptable capacity. However, the violations of voltage at nodes 9–17 and nodes 29–32 remain (Fig. 7(e)). The total power loss in the system is obtained as 14.11 kW.

Depending on the impacts upon the power flow at line 25, the trading relationships can be divided into three groups: moderating, exacerbating group, and neutral. These groups are based on the sensitivity factor defined by Equation (4). Thus, the group to which the trading relationship belongs, determines the area in the energy price bidding, i.e., the incentive area, penalty area, and neutral red line. Moreover, in the test system of Fig. 4, prosumers s_4, s_5, b_4, and b_5 are located in the branched distribution line starting from line 25. The trading relationships where the energy trading headed toward the reverse direction of line 25 (from the node 25 to the node 5) would moderate the power flow at line 25, i.e., s_4b_j and s_5b_j for $j \in \{1, 2, 3\}$. Conversely, the energy trading headed toward the forward direction of line 25 (from the node 5 to the node 25) would exacerbate the power flow, and the corresponding trading relationships are s_ib_4 and s_ib_5 for $i \in \{1, 2, 3\}$. The remaining relationships have no impact on the power flow at line 25. This topology-based intuition agrees with the bidding results presented in Fig. 7(b), in which the moderating group is in the incentive area, the exacerbating group in the penalty area, and the remaining points along the red line. Following the price biddings, each trading energy is adjusted as well, as shown in Fig. 7(a).

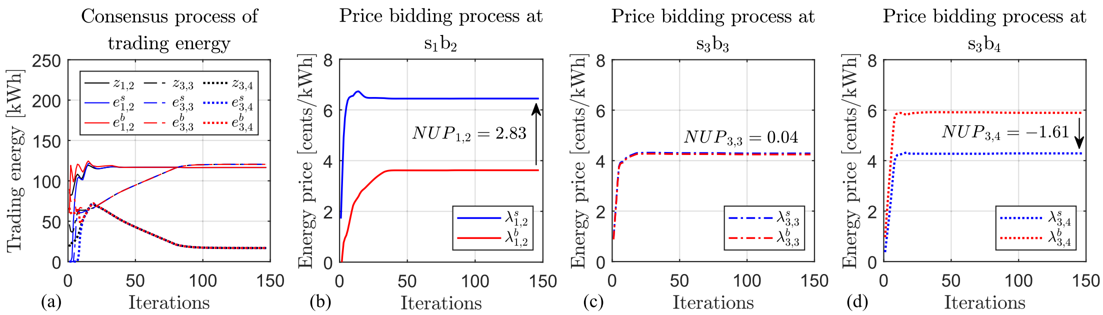


FIGURE 9. Bidding process for s_1b_2, s_2b_3, and s_3b_4: (a) trading variables evolution, (b) price bidding process between s_1 and b_2, (c) price bidding process between s_3 and b_3, and (d) price bidding process between s_3 and b_4.

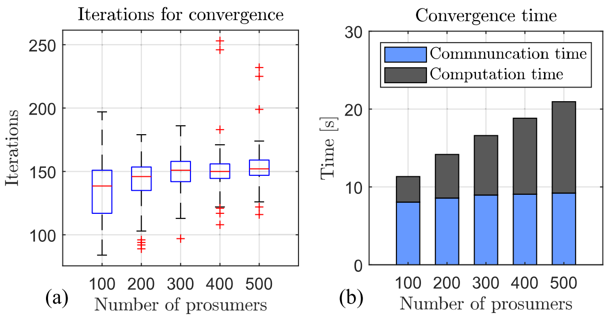


FIGURE 10. Scalability analysis of the proposed scheme according to the number of prosumers: (a) required number of iterations and (b) average communication and computation times.

TABLE 2. Comparison of the market clearing methods in the modified 119-node distribution network.

Criteria	Proposed method	Unregularized ADMM [32]	Primal-dual method [28]	Centralized method
Total traded energy (kWh)	6,187.4	6,249.2	6,187.9	6,187.4
Social welfare (¢)	8,689.9	8,742.9	8,685.4	8,689.9
Total network cost (¢)	81.97	-	81.70	-
Number of iterations	136	104	704	-
Computation time (s)	2.63	0.62	0.73	0.49
Communication time (s)	8.16	6.24	42.24	-
Convergence time (s)	10.79	6.86	42.97	0.49

3) CASE II-C: REGULARIZATION OF INCIDENTAL POWER LOSSES

The bidding results of regularization according to incidental power losses are presented as the green plots as shown in Figs. 7(a)–(d). Compared with the other regularization approaches, this regularization contributes less to the adjustment of energy trading due to the setting of the cost function $(c^{\text{loss}})^{\mathrm{T}}z$. It should be noted that an incentive can be imposed when the transaction between a seller and a buyer reduces power loss. As an example, Fig. 7(b) shows that some biddings are located in the incentive area. In the case of the network profile, there are trivial improvements compared to the results of Case I (Figs. 7(e), and 7(f)), ending up with the failure of both the managements of voltage deviation and line congestion. The total power loss is obtained as 15.65 kW, which represents a reduction of 1.07 kW compared to the result of 16.72 kW in Case I. This result shows that the total power loss can be reduced by imposing the cost associated with the power loss.

D. CASE III: ENERGY TRADING WITH THE COMPLETE REGULARIZATION

This case study describes the result of the proposed P2P energy market clearing strategy with the complete regularization by the DSO and analyzes the effect from the implementation of the bilateral trading weights (Fig. 8). In addition, to intuitively understand the proposed strategy, the evolution of trading energy and its prices is presented as in Fig. 9.

1) CASE III-A: COMPLETE REGULARIZATION

The navy blue plots in Figs 8(a)–(d) represent the bidding results of trading energy, selling price, and buying price after implementing the proposed P2P market clearing strategy with the complete regularization by DSO. Following the optimal bidding results, the system reliability against the voltage deviation and the line flow congestion is successfully achieved (Figs. 8(e) and 8(f). Additionally, the total power loss in the system is obtained as 11.09 kW, better than that obtained in via partial regularization in Case II. Fig. 9 demonstrates the evolution of selling and buying prices, showcasing three trading relationships: s_1b_2 with a positive NUP, s_3b_3 with a neutral NUP, and s_3b_4 with a negative NUP. The total computation time is found to be less than 1 second.

2) CASE III-B: COMPLETE REGULARIZATION WITH BILATERAL TRATE WEIGHT $u_{1,1} = 1.0$ ¢/kW

The results of this case are shown as cyan plots in Fig. 8. Price modification via the bilateral trade weight $u_{1,1} = 1.0\,¢/kW$ affects the buying price at s_1b_1 (Fig. 8(d)). The energy prices from buyer 1 to sellers 1, 2, and 4 are identical in Case III-A, whereas the buying price decreases to $\lambda^b_{1,1} = 4.89\,¢/kW$

in Case III-B. This represents the perceived price and is considered as the price after tax [28]. The actual cost for buyer 1 to purchase energy from seller 1 consists of the buying price and the bilateral trade weight, which gives $\lambda^b_{1,1} + u_{1,1} = 5.89$ ¢/kW.

For further analysis, it can be seen in Fig. 8(a) that there is no difference in the results of trading energy between Case III-A and Case III-B. Considering the buyer's problem in Section II-B, a positive bilateral trade weight debases the utility of energy transactions; thus, energy trading at s_1b_1 becomes less competitive due to $u_{1,1}$, resulting in a dead transaction without making any change. Such intactness in the P2P energy market enables a straightforward understanding of the price formation; the new price of $\lambda^b_{1,1}$ can be calculated by subtracting $u_{1,1} = 1.0$ ¢/kW from the previous price of $\lambda^b_{1,1} = 5.89$ ¢/kW. Following this, the selling price $\lambda^s_{1,1}$ is affected by the same amount while preserving the value of NUP (i.e., $\lambda^b_{1,1} - \lambda^s_{1,1}$).

As shown in Figs. 8(e) and 8(f), the system reliability against the voltage deviation and the line flow congestion is successfully achieved as intended.

3) CASE III-C: COMPLETE REGULARIZATION WITH BILATERAL TRATE WEIGHT $u_{1,2} = 1.0$ ¢/kW

The results of this case are shown as magenta plots in Fig. 8. Compared to Case III-B, the energy transaction is directly influenced by the price adjustment of $\lambda^b_{1,2}$, which affects all biddings in the P2P energy market are affected. The buying price $\lambda^b_{1,2}$ decreases to 2.74 ¢/kW due to $u_{1,2}$ and the corresponding trading energy decreases compared (Figs. 8(a) and 8(d)). The energy prices from buyer 2 to sellers 1, 2, and 5 are identical in Case III-A; however, each of the buying prices related to the buyer 2 changes, impacting the corresponding trading energies $z^*_{1,2}$, $z^*_{2,2}$, and $z^*_{5,2}$, in Case III-B. Thus, the transactions related to $z^*_{1,2}$, $z^*_{2,2}$, and $z^*_{5,2}$ are affected, of which the relationships correspond to s_1b_1, s_1b_5, s_2b_1, s_2b_4, and s_5b_5. The same process works likewise in all the related transactions. Therefore, in this case study, we find that a single manipulation of price can have widespread influences on the P2P energy market.

Although there is the price modification and the readjustment in the bidding processes, system reliability in terms of voltage deviation and line congestion is successfully achieved (Figs. 8(e) and 8(f)).

E. CASE IV: SCALABILITY ANALYSIS

For the scalability analysis, the algorithm is tested using a modified 119-node test system [43] with various numbers of prosumers. For simplicity, we assume that prosumers consist of equal numbers of sellers and buyers. The number of partners of each buyer is set to five. Additionally, we assume that the subproblems of all prosumers are solved in parallel; the maximal solver time is used to evaluate the computation time. We also assume that the communication delay is 60 ms per iteration as in [41].

First, the performance of the proposed method is compared to the performances of an ADMM without regularization [32], a primal-dual gradient method [28], and a centralized method. The number of prosumers is set to 300, and the proposed algorithms only consider the regularization pertaining to the line flow. Table 2 presents a comparison between the proposed method and other methods. In terms of the total traded energy and social welfare, both the proposed method and the primal-dual gradient method attain the optimal solution provided using the centralized method. Although the proposed algorithm requires more computation time than the primal-dual gradient approach, it requires less communication time due to fewer iterations. Since communication time is more significant, the proposed method converges faster than does the primal-dual gradient approach.

Next, the algorithm is tested by varying the number of prosumers varies; 100 Monte-Carlo simulations are performed for each case, considering the complete regularization. Fig. 10(a) displays the number of iterations required based on the number of prosumers. As the number of prosumers increases, the number of iterations does not increase significantly. Thus, the communication time remains almost constant (Fig. 10(b)). However, as the number of prosumers increases, the computational time also increases due to the increasing dimension of the projection space in the regularization step. For instance, with 500 prosumers, the number of matchings (i.e., the dimension of the projection space) is 1,250. Nonetheless, the total convergence time remains practical for real-time large-scale market operation (5 or 15 minutes). This result verifies the validity, scalability, and effectiveness of the proposed P2P market clearing strategy.

VI. CONCLUSION

This paper presents a novel P2P energy trading strategy based on ADMM regularization. The proposed strategy allows the P2P energy market to find the optimal bids to maximize prosumers benefits while satisfying network constraints. The proposed market design reflects the interests of each market player, including the economic benefits of selling and buying energy, as well as reliability considerations such as voltage deviation, line congestion, and power losses. Due to price-based regularization, an energy transaction involves a NUP that reflects the given network constraints, resulting in penalty costs or incentives imposed on prosumers. Furthermore, the proposed ADMM-based strategy is decentralized and scalable. Case studies demonstrate the computational effectiveness and scalability of this strategy for a reliable P2P energy market. Compared to the primal-dual method, the proposed method clears market with less communication and convergence time. In the case study with 300 prosumers, convergence time was reduced by 74.9%.

Future research should explore the challenges and opportunities associated with the P2P energy market clearing strategy under uncertainty conditions. As observed in the case studies, a single price modification can lead to extensive changes in bidding results. While uncertainty can introduce significant complexity in the market clearing problem, it is a common occurrence in practical operations. In addition, the proposed method requires a solution to simplify the regularization step (z-update) because the computation time of the DSO increases as the number of prosumers and the system size increase. The use of ESSs and EVs has also garnered interest due to their potential to provide flexibility to microgrids. Specifically, the sharing economy of ESSs can be beneficially applied to the P2P energy market, providing advantages for both the secure operation of the network and the social welfare of market players. For broader applicability of the P2P energy market, an AC/DC hybrid distribution system as a testbed application will be explored in future research.

APPENDIX

REFERENCES

The purpose of this Appendix is to provide detailed derivations of the proposed sensitivity factors (3), (4), and (7). The introduced factors evaluate the impacts on a DN due to energy transactions between prosumers, of which derivation hence employs branch-based matrices while the previous work in [15] presents node-based sensitivity factors. Note that the subjects of the sensitivity factors(3), (4), and (7) correspond to the bus voltage deviation, the line flow deviation, and the incidental power losses, respectively.

First, let us consider indices $i \in \mathcal{V}_S$ and $j \in \mathcal{V}_B$ for a seller and a buyer in the P2P energy market $T(\mathcal{V}_S, \mathcal{V}_B, \mathcal{E}_{SB})$, indices $n, m \in$ for nodes in the DN $G(\mathcal{V}, \mathcal{E})$, and matrices of $\mathbf{A}^S \in \mathbb{R}^{N\times N_S}$ and $\mathbf{A}^B \in \mathbb{R}^{N\times N_B}$ which map the group of sellers and buyers to nodes in the DN. A voltage sensitivity factor in [44] is presented as $\mathbf{R} \in \mathbb{R}^{N\times N}$ with the (n, m) element indicating the incremental voltage variation at node n due to the power injection at node m. By multiplying the mapping matrices, the voltage sensitivity factor can be rewritten as below:

$$\mathbf{R}^S = \mathbf{R}\mathbf{A}^S \in \mathbb{R}^{N\times N_s}, \tag{A1}$$
$$\mathbf{R}^B = \mathbf{R}\mathbf{A}^B \in \mathbb{R}^{N\times N_B} \tag{A2}$$

From (A1) and (A2), the sensitivity factor (3) can be obtained as below:

$$\gamma^n_{i,j} = \mathbf{R}^S_{ni} - \mathbf{R}^B_{nj}, \tag{A3}$$

where $\mathbf{R}^S_{ni}$ denotes the (n, i) element of $\mathbf{R}^S$ and $\mathbf{R}^B_{nj}$ denotes the (n, j) element $\mathbf{R}^B$.

Next, the sensitivity factor (4) related to the line flow congestion can be obtained from the injection shift factor, which in given by [45]:

$$\boldsymbol{\psi} := \widetilde{\mathbf{B}}_{\mathrm{d}}\mathbf{C}\mathbf{B}^{-1} \in \mathbb{R}^{L\times N}. \tag{A4}$$

For $G(\mathcal{V}, \mathcal{E})$, $\mathbf{C}$ denotes the reduced incidence matrix, and $\widetilde{\mathbf{B}}_{\mathrm{d}}$ and $\mathbf{B}$ denote the branch and nodal susceptance matrices of the DN, respectively. Here, the (l, n) element of (A4) indicates the incremental change in the line power flow at line l due to the power injection at node n. In the same manner as in (A1) and (A2), the factor (A4) can be rewritten as follows:

$$\boldsymbol{\Psi}^S = \boldsymbol{\Psi}\mathbf{A}^S \in \mathbb{R}^{L\times N_S}, \tag{A5}$$
$$\boldsymbol{\Psi}^B = \boldsymbol{\Psi}\mathbf{A}^B\mathbb{R}^{L\times N_B}. \tag{A6}$$

Then, it is straightforward to obtain the sensitivity factor (4) from (A5) and (A6), which is:

$$\varphi^l_{i,j} = \boldsymbol{\Psi}^S_{li} - \boldsymbol{\Psi}^B_{lj}, \tag{A7}$$

where $\boldsymbol{\Psi}^S_{li}$ and $\boldsymbol{\Psi}^B_{lj}$ denote the (l, i) element and the (l, j) element of each corresponding matrix, respectively.

Lastly, the sensitivity factor (7) related to the incremental power losses is to be derived. In [46], the loss sensitivity factor ν_n in terms of node n can be written as below:

$$\nu_n = \frac{\partial P^{\text{loss}}}{\partial P_n} = \sum_{l=1}^{L} 2 \cdot f_l \cdot r_l \sum_{n=1}^{N} \boldsymbol{\Psi}_{ln}, \tag{A8}$$

where P^{loss}, P_n, f_l, and r_l denote the total active power loss, the power injection at node n, the line power flow on line l, and the resistance of the line l, respectively. And $\boldsymbol{\Psi}_{ln}$ is the (l, n) element of $\boldsymbol{\Psi}$. Considering the row vector $\boldsymbol{\nu} := [\nu_1 \;\; \nu_N]$, the followings can be defined:

$$\boldsymbol{\nu}^S := \nu\mathbf{A}^S \in \mathbb{R}^{N_S} \tag{A9}$$
$$\boldsymbol{\nu}^B := \nu\mathbf{A}^B \in \mathbb{R}^{N_B}. \tag{A10}$$

Therefore, the i-th element $\boldsymbol{\nu}^S_i$ of (A9) and the j-th element $\boldsymbol{\nu}^B_j$ of (A10) lead to:

$$\tau_{i,j} = \boldsymbol{\nu}^S_i - \boldsymbol{\nu}^B_j. \tag{A11}$$

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