Strategic Peer-to-peer Energy Trading Framework Considering Distribution Network Constraints

Yanbo Jia, Can Wan, and Biao Li

Abstract—**With the development of smart home energy management technology, prosumers are endowed with increased initiative in peer-to-peer (P2P) transactions, bringing new potential for cost savings. In this study, a novel strategic P2P energy trading framework is proposed considering the impact of network constraints on personal transaction strategies. Prosumers can estimate the allowed power injection before engaging in the P2P energy trading, which is solved in a distributed manner based on the sharing form alternating direction method of multipliers (ADMM) algorithm. To quantify the network usage cost for each prosumer and promote local transactions among prosumers at the same bus, a modified continuous double auction (CDA) matching algorithm is proposed including a transaction fee. An adaptive aggressiveness-based bidding strategy is generated considering the risk of uncertainty in real-time energy delivery amount under the limitations of the distribution network. The proposed strategic P2P energy trading framework is tested with the IEEE 37-bus distribution network and it is effective in creating profits for prosumers and supporting distribution network operations.**

Index Terms—**Bidding strategy, continuous double auction (CDA), distribution network, distributed algorithm, peer-to-peer (P2P) transaction.**

I. Introduction

WITH the increasing concerns related to fossil-fuel energy shortage, climate change, and environmental issues, developing renewable energy and improving energy usage efficiency have become common strategies for countries to accelerate their energy transition and achieve sustainable energy development. With the advancements in the technologies related to renewable energy integration, distributed renewable energy has become critical for energy transition.

Considering the advantages of economy and flexibility, distributed energy resources (DERs) can meet the demands of local consumers, which reduces the electricity production and transmission losses. In addition, the smart home energy management systems (HEMSs) have rapidly developed in recent years and are considered as an essential technology for successful demand-side management. Smart prosumers are becoming more flexible by monitoring and arranging various home appliances using HEMS, reducing electricity bills [1], and improving their energy utilization efficiency [2]. The boosting flexibility on the demand side transforms the traditional passive consumers into active providers with the capability of offering energy services to the upstream grid [3], [4]. The emergence of numerous prosumers requires a new electricity market structure, i. e., a prosumer-centric market structure, to coordinate the distributed renewable generation management with the decision-making process of self-interested prosumers. In contrast to demand-reduction or demand-response programs, where prosumers passively react to price signals, prosumers in prosumer-centric markets can actively offer energy services or strategically bid for energy products [5].

Among various prosumer-centric market structures, the peer-to-peer (P2P) market inspired by the sharing economy concept is considered an efficient platform to operate heterogeneous DERs, where prosumers can bid and directly trade electricity and services [6]. Current studies on P2P energy trading models can be roughly divided into two categories: ① one based on economic dispatch [7]-[9]; and ② the other one based on multilateral and bilateral negotiation [10], [11]. Typically, the impact of a distribution network is considered by incentive price signals before trading [8], [11]. Because the economic dispatch based distributed energy trading is essentially an optimization problem, the distribution network constraints can be directly included in the social-welfare maximization problem [12]. In addition, the distribution network constraints could be included by a third-party validations after P2P energy trading [13]. However, to the best of our knowledge, the impact of the network constraints on the strategic bidding behavior of prosumers has not yet been discussed.

A two-stage bidding strategy for P2P energy trading is proposed in [14] to facilitate the local consumption of DERs and increase the social welfare. In the first stage, the ideal energy transaction amount is obtained using forecasting information. In the second stage, all P2P market participants can decide their trading prices individually through a simultaneous game-theoretic approach. Whereas, the two-stage bidding strategy is essentially a data-driven approach in which

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the restraints of the physical network are ignored. Prosumers are formulated as zero-intelligence plus traders using an adaptive mechanism in [13], which can imitate human traders in stock markets.

The P2P transaction results of prosumers are restrained by the power injection limitations due to the distribution network constraints during real-time power delivery. This deviation between the actual amount of energy delivered and the P2P transaction volume exposes prosumers to deviation assessment and return risk. To handle the uncertainty in the delivered energy, a price signal is given by the distribution system operator using the probabilistic distribution locational marginal price (DLMP) in [15] to reflect the network conditions and instruct the energy usage arrangements of prosumers. This type of incentive-compatible price signal helps reduce the risk of violating the network constraints by incentivizing prosumers to use local flexibility. However, the price signal indicating the network usage conditions is still a type of indirect soft constraint compared with the power injection limits.

In the traditional electricity market environment, the operation and network usage costs comprise a critical part of electricity bills [16]. Since prosumers can directly trade with each other in P2P markets, there would be no extra payments to cover the operation and loss costs of distribution networks. To quantify the usage cost of distribution networks, network utilization fees measured by power transfer distance are formulated as a social welfare maximization problem based on P2P energy trading in [17], which is solved in a decentralized manner to optimize the P2P energy transaction amount. However, no price signal is released in this P2P energy trading process, and the prosumer's independent and selfish decision-making is ignored. Network usage charges are defined in [6] on the basis of DLMP components using the second-order cone AC optimal power flow (OPF) model. A third-party utility is assumed to calculate the DLMP by collecting the power injections into the bus for trades, which may face difficulties in deriving a suboptimal or infeasible solution. Continuous double auction (CDA) is generally used to exploit the dynamics of the free market to efficiently balance the demand and supply with decentralization features [18]. It is considered a concise and efficient way to implement P2P transactions owing to the advantage of robustness and move towards Pareto efficiency.

In this study, a novel strategic P2P energy trading framework is proposed considering the impact of distribution network constraints on the individual decision-making process. Prosumers are capable of estimating the allowed power injection before the local P2P energy trading in a distributed manner to autonomously generate their bidding strategy for the transaction price and volume. A modified CDA matching algorithm is proposed to account for the network usage and encourage local transactions at the same bus. In contrast to general CDAs, with time and price priorities considered, each bidding order is signed with a location stamp to highlight the impact of the location priority. Considering the risk of the amount of real-time energy delivered under distribution network constraints, a risk-perceived bidding strategy is developed based on an aggressive adaptive (AA) strategy. The main contributions of this study are summarized as follows.

1) A novel strategic P2P energy trading framework is proposed considering the impact of the distribution network on the P2P bidding strategies of prosumers.

2) A modified CDA matching algorithm is proposed to account for the network usage and facilitate local P2P transactions at the same bus.

3) An adaptive risk-perceived bidding strategy is developed by estimating the power injected into the bus, which is limited by the distribution network constraints and the uncertainty in the actual amount of power delivered.

II. System Model

A. Prosumer Model

Prosumers denoted as $\mathbb{P}:=\{1,2,\ldots,M\}$ are classified according to: ① whether they have renewable energy generation; and ② whether they have elastic loads. Generally, an operation day is divided into several time slots, which are denoted as $\mathbb{T}:=\{1,2,\ldots,T\}$.

1) Renewable Energy Generation

The photovoltaic (PV) generation for prosumer $i\in\mathbb{P}$ during time slot $t\in\mathbb{T}$ is denoted as $p^{\mathrm{g}}_{i,t}$. Each prosumer with PV generation is assumed to be equipped with a reactive power compensation device. Thus, a prosumer with PV generation that can provide reactive power is limited by:

$$\underline{q}^{\mathrm{g}}_{i,t}\leq q^{\mathrm{g}}_{i,t}\leq\bar{q}^{\mathrm{g}}_{i,t} \tag{1}$$

where $\underline{q}^{\mathrm{g}}_{i,t}$ and $\bar{q}^{\mathrm{g}}_{i,t}$ are the lower and upper bounds of reactive power that prosumer i can provide during time slot t, respectively.

2) Power Demand

Each prosumer has both elastic demand and inelastic demand. Using $p^{\mathrm{d}}_{i,t}$ to represent the power demand of prosumer i during time slot t, the elastic demand is considered to be time-shiftable [19], which is subjected to:

$$\underline{p}^{\mathrm{d}}_{i,t}\leq p^{\mathrm{d}}_{i,t}\leq\bar{p}^{\mathrm{d}}_{i,t}\quad t\in\mathbb{T},i\in\mathbb{P} \tag{2}$$

$$\sum_{t\in\mathbb{T}}p^{\mathrm{d}}_{i,t}\geq E^{\mathrm{d}}_{i}\quad i\in\mathbb{P} \tag{3}$$

where $\underline{p}^{\mathrm{d}}_{i,t}$ is the lower bound of the power demand including the inelastic demand and a basic requirement of the elastic demand; $\bar{p}^{\mathrm{d}}_{i,t}$ is the upper bound of the power demand indicating the maximum power limit; and E^{d}_{i} is the total basic energy demand of prosumer i over all operation periods $t\in\mathbb{T}$. Because the demand schedule determined by the original energy consumption habits of prosumers is their most preferred power consumption, any deviation from this original demand schedule, denoted as $p^{\mathrm{p}}_{i}:=\{p^{\mathrm{p}}_{i,1},\, p^{\mathrm{p}}_{i,2},\,\ldots,\, p^{\mathrm{p}}_{i,T}\}$, will incur an extra discomfort cost. A quadratic penalty $C^{\mathrm{d}}_{i,t}$ is utilized to quantify the discomfort cost of the demand deviation:

$$C^{\mathrm{d}}_{i,t}=\alpha_i\,(p^{\mathrm{d}}_{i,t}-p^{\mathrm{p}}_{i,t})^2 \tag{4}$$

where the coefficient α_i denotes the willingness of prosumer i to adjust its power consumption.

B. Distribution Network Model

P2P energy trading is organized in a radial distribution network, which is described using a branch flow model in this paper. The distribution network is denoted as $\mathbb{D}:=(\mathbb{N}, \mathbb{E})$, where $\mathbb{N}$ is the set of buses; and $\mathbb{E}$ is the set of lines. In the radial distribution network, each bus $n \in \mathbb{N}$, except the root bus labeled by 0, has a unique ancestor bus denoted as A_n and a set of children buses denoted as $\mathbb{C}_n$. Hence, each line pointing from bus n to its ancestor bus A_n can be uniquely labeled by the index n, indicating the set of lines $\mathbb{E}:=\{1, 2, \ldots, N\}$. The branch flow model of the distribution network $\mathbb{D}$ is given by [20]:

$$p_{n,t}=P_{n,t}-\sum_{m\in\mathbb{C}_n}(P_{m,t}-r_m l_{m,t}) \quad n\in\mathbb{N},\ t\in\mathbb{T} \tag{5}$$

$$q_{n,t}=Q_{n,t}-\sum_{m\in\mathbb{C}_n}(Q_{m,t}-x_m l_{m,t}) \quad n\in\mathbb{N},\ t\in\mathbb{T} \tag{6}$$

$$v_{n,t}=v_{A_n,t}+2(r_nP_{n,t}+x_nQ_{n,t})-(r_n^2+x_n^2)l_{n,t} \quad n\in\mathbb{E},\ t\in\mathbb{T} \tag{7}$$

$$l_{n,t}=(P_{n,t}^2+Q_{n,t}^2)/v_{n,t} \quad n\in\mathbb{N},\ t\in\mathbb{T} \tag{8}$$

where $z_n=r_n+\mathrm{j}x_n$ is the complex impedance of line $n\in\mathbb{E}$; $p_{n,t}$ and $q_{n,t}$ are the active and reactive power injected into bus n during time slot t, respectively; $P_{n,t}$ and $Q_{n,t}$ are the active and reactive power flow through line n during time slot t, respectively; and $l_{n,t}$ and $v_{n,t}$ are the squares of the magnitudes of the current flow through line n and the voltage at bus n during time slot t, respectively.

The constraint in (8) is convexified using the second-order cone relaxation [21] as:

$$\|(2P_{n,t}, 2Q_{n,t}, v_{n,t}-l_{n,t})\|_2 \le l_{n,t}+v_{n,t} \quad n\in\mathbb{N}, t\in\mathbb{T} \tag{9}$$

C. P2P Energy Trading Framework

Generally, P2P energy trading mechanisms consider the network constraints by inspection and correction after P2P trading, which validates the P2P transactions in the distribution network by a local distribution system operator (LDSO). To the best of our knowledge, no existing studies have considered the impact of the network constraints on the strategic bidding process of prosumers in a P2P market. In this study, a strategic P2P energy trading framework for distribution networks is proposed considering distribution network constraints in the bidding process before P2P transactions.

The proposed P2P energy trading framework can be divided into three stages. In the bidding stage, prosumers generate bids locally in a distributed manner before engaging in the P2P market. In this stage, prosumers first estimate their competitive equilibrium price $\hat{\rho}$ using the historical price information disclosed by the P2P market. Then, the competitive equilibrium price and network state information from the buses are used to estimate the instructive bidding amount $\hat{e}$ of the prosumers in a distributed manner by communication with the buses, as detailed in Section III. Simultaneously, the target bidding prices ρ^{tg} are generated using $\hat{\rho}$. Prosumers generate their bids according to adaptive bidding rules. Specifically, the strategic bidding process is presented in Section IV. In the transaction stage, prosumers interact with each other in the P2P market using a modified CDA algorithm with a unit transaction fee to reach deals and obtain new price information. Finally, in the settlement stage, the LDSO verifies and settles the contracts in the P2P market. In this framework, there are numerous interactions and communications among players including prosumers, buses, and the LDSO in the three stages. Let $\psi_{n,t}^{\mathrm{b}}$ and $\psi_{n,t}^{\mathrm{s}}$ be the retail price for buying energy from the LDSO at bus n and the feed-in tariff for selling energy to the LDSO at bus n, respectively. The entire P2P energy trading framework is shown in Fig. 1.

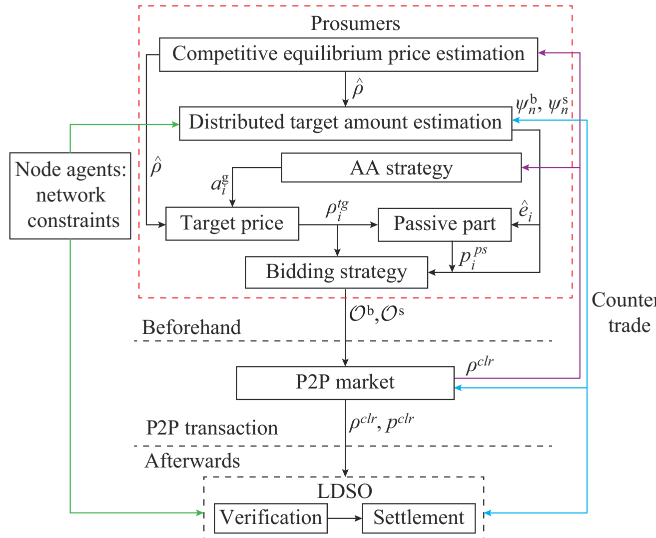

Fig. 1. Entire P2P energy trading framework.

III. Estimation of Distributed Target Transaction Amount Under Network Constraints

A. Estimation of Target Transaction Amount

In previous studies, the P2P energy trading amount of prosumers is either treated as a surplus after direct self-consumption or passively scheduled by a local system operator. Because distribution network constraints are included, there may be potential deviations between the preferred load schedule of the prosumers and the allowed power injection of a distribution network. Considering the potential cost of the demand deviations, the prosumer wants to know the amount of the highest cost-saving transaction bounded by the power injection limits of the distribution network before P2P energy trading, which is defined as the target transaction amount $\hat{e}_{i,t}$ for prosumer i during time slot t. For the LDSO, it is expected that the P2P transaction results will not pose a security risk to the operation of the distribution network. Hence, the estimation of the target transaction amount is formulated as a social welfare maximization problem, which is solved in a distributed manner based on the sharing form of the alternating direction method of multipliers (ADMM) method [22].

Each prosumer i has a preferred power consumption $p_{i,t}^{\mathrm{p}}$ during time slot t. Because any deviation from this amount will incur a discomfort cost, prosumers will trade as they prefer in the P2P market if there is no extra incentive or restriction. Once the distribution network constraints are violated, prosumers have to adjust their power demand and counter-trade with the LDSO to hedge against demand adjustments and ensure the execution of P2P contracts at a price less than the P2P transaction price. Before bidding in the P2P energy transaction market, the prosumer has to estimate the allowed P2P transaction amount in the distribution network and the potential revised trading cost. Let $\Delta p_i = \{\Delta p_{i,1}, \Delta p_{i,2}, \ldots, \Delta p_{i,T}\}$ be the estimated power demand deviation, where $\Delta p_{i,t} = p_{i,t}^{\mathrm{d}} - p_{i,t}^{\mathrm{p}}$. Then, the target bidding amount in the P2P market can be derived using $\hat{e}_{i,t} = |p_{i,t}^{\mathrm{g}} - p_{i,t}^{\mathrm{d}}|$. The potential cost associated with the revised trading process of prosumer i consists of a discomfort cost $C_{i,t}^{\mathrm{d}}$ and a counter-trade cost $C_{i,t}^{\mathrm{R}}$:

$$C_{i,t}^{\mathrm{R}}(\Delta p_{i,t}) = (\psi_{n,t}^{\mathrm{b}} - \hat{\rho}) \cdot \max(\Delta p_{i,t}, 0) + (\hat{\rho} - \psi_{n,t}^{\mathrm{s}}) \cdot \max(-\Delta p_{i,t}, 0) \tag{10}$$

where $\hat{\rho}$ can be estimated by prosumers according to the historical transaction price information before strategic bidding:

$$\hat{\rho} = \sum_{k=\tau-K-1}^{\tau} \sigma_k \rho_k^{\mathrm{his}} \tag{11}$$

where the weight coefficient σ_k satisfies $\sum_{k=\tau-K-1}^{\tau} \sigma_k = 1$ and $\sigma_{k-1} = \eta\sigma_k$; and $\rho_k^{\mathrm{his}} := \{\rho_{\tau-K+1}^{\mathrm{his}}, \rho_{\tau-K+2}^{\mathrm{his}}, \ldots, \rho_{\tau}^{\mathrm{his}}\}$ denotes the historical prices of the most recent K transactions, K is treated as a window of historical transactions, and τ is the index of the latest transaction.

The objective of LDSO is to minimize the entire operational cost for the security operation of the distribution network $\mathbb{D}$. The optimal solution is the recommended consumption for flexible prosumers, from which an estimate of the target bidding amount in the P2P market can be derived. Therefore, the problem of estimating the target transaction for prosumers is formulated as a typical OPF problem with the variables of the prosumers for each distribution network bus:

$$\min_{p_{i,t}^{\mathrm{d}}} \sum_{t\in\mathbb{T}} \sum_{i\in\mathbb{P}} \left(C_{i,t}^{\mathrm{d}}(\alpha_i, p_{i,t}^{\mathrm{d}}) + C_{i,t}^{\mathrm{R}}(p_{i,t}^{\mathrm{d}})\right) \tag{12}$$

s.t.

$$\text{(2) and (3)} \quad i \in \mathbb{P}, t \in \mathbb{T} \tag{13}$$

$$\text{(5)-(7) and (9)} \quad n \in \mathbb{N}, t \in \mathbb{T} \tag{14}$$

$$\underline{v}_{n,t} \le v_{n,t} \le \bar{v}_{n,t} \quad n \in \mathbb{N}, t \in \mathbb{T} \tag{15}$$

$$\underline{q}_{n,t} \le q_{n,t} \le \bar{q}_{n,t} \quad n \in \mathbb{N}, t \in \mathbb{T} \tag{16}$$

$$\underline{l}_{n,t} \le l_{n,t} \le \bar{l}_{n,t} \quad n \in \mathbb{N}, t \in \mathbb{T} \tag{17}$$

$$p_{n,t} = \sum_{i\in\delta_n} (p_{i,t}^{\mathrm{g}} - p_{i,t}^{\mathrm{d}}) \quad n \in \mathbb{N}, t \in \mathbb{T} \tag{18}$$

where the constraints in (15)-(17) are the security operation bounds of the distribution network; $\overline{(\cdot)}$ and $\underline{(\cdot)}$ denote the upper and lower bounds of variables, respectively; and δ_n denotes the set of prosumers connected to bus n.

B. Distributed Implementation

The solution to the problem of estimating the target bidding amount in a centralized network requires the LDSO to collect all of the bus data and a massive amount of private information such as the discomfort coefficients and preferred demands of the prosumers, causing difficulties in information processing and data security. Moreover, the estimate of the target bidding amount is considered as a portion of the strategic behavior of the prosumer in the P2P market, which is an individual decision. This practical significance also requires the estimation problem for $\hat{e}_{i,t}$ to be solved in a distributed manner, which means that prosumers can locally estimate the target bidding amount and only communicate with neighboring buses.

To handle the multiperiod constraints in (3) and solve the problem independently in parallel during each time slot, a Lagrange relaxation [23] is utilized to incorporate the multiperiod constraints in (3) into the objective function in (12):

$$\min_{p_{i,t}^{\mathrm{d}}} \left[\sum_{t\in\mathbb{T}} \sum_{i\in\mathbb{P}} \left(C_{i,t}^{\mathrm{d}}(\alpha_i, p_{i,t}^{\mathrm{d}}) + C_{i,t}^{\mathrm{R}}(p_{i,t}^{\mathrm{d}})\right) + \sum_{i\in\mathbb{P}} \pi_i \left(E_i^{\mathrm{d}} - \sum_{t\in\mathbb{T}} p_{i,t}^{\mathrm{d}}\right) \right] \tag{19}$$

where $\pi = \{\pi_i \ge 0 | i \in \mathbb{P}\}$ denotes the Lagrange multipliers of the constraints in (3). The problem satisfies the strong duality because the objective is convex and Slater's condition holds. The Lagrange duality problem of the multiperiod OPF problem is defined as:

$$\max_{\boldsymbol{\pi}} \left[\min_{p_{i,t}^{\mathrm{d}}} \sum_{i\in\mathbb{P}} \sum_{t\in\mathbb{T}} \left(C_{i,t}^{\mathrm{d}}(\alpha_i, p_{i,t}^{\mathrm{d}}) + C_{i,t}^{\mathrm{R}}(p_{i,t}^{\mathrm{d}}) - \pi_i p_{i,t}^{\mathrm{d}}\right) + \sum_{i\in\mathbb{P}} \pi_i E_i^{\mathrm{d}} \right] \tag{20}$$

The inner problem of the Lagrange duality problem is temporally decoupled and can be solved during each single period in parallel. Let $\hat{p}_t^{\mathrm{d}}[h] = \{\hat{p}_{1,t}^{\mathrm{d}}, \hat{p}_{2,t}^{\mathrm{d}}, \ldots, \hat{p}_{M,t}^{\mathrm{d}}\}$ be the optimal solution of the OPF problem during time slot t in the h^{th} iteration given the Lagrange multipliers $\pi[h]$. The iteration process of π is given by:

$$\pi[h+1] = \max\left(\pi[h] + \theta\left(E_i^{\mathrm{d}} - \sum_{t\in\mathbb{T}} p_{i,t}^{\mathrm{d}}\right), 0\right) \tag{21}$$

where $\theta(\cdot) > 0$ is the step size of an iteration.

The sharing form of the ADMM proposed in our previous work [24] is utilized to solve the problem of estimating the target amount in a distributed manner. Because the inner problem can be solved during each single period in parallel, the subscript t denoting the time index is dropped for simplicity in the following. Let $f(p_i^{\mathrm{d}}) = C_i^{\mathrm{d}}(\alpha_i, p_i^{\mathrm{d}}) + C_i^{\mathrm{R}}(p_i^{\mathrm{d}}) - \pi_i p_i^{\mathrm{d}}$ be the objective of single-period problem, which can be reformulated in standard matrix form as:

$$\min_{p_i^{\mathrm{d}}} \sum_{i\in\mathbb{P}} f(p_i^{\mathrm{d}}) \tag{22}$$

s.t.

$$\sum_{m\in\mathbb{G}_n} \mathcal{G}_{nm} y_n^{\mathrm{m}} = 0 \quad n \in \mathbb{N} \tag{23}$$

$$p_i^{\mathrm{d}} \in \Omega_i \quad i \in \mathbb{P} \tag{24}$$

$$x_n \in \mathcal{X}_n \quad n \in \mathbb{N} \tag{25}$$

$$-p_i^{\mathrm{d}} - x_i + p_i^{\mathrm{g}} = 0 \quad i \in \delta_n, n \in \mathbb{N} \tag{26}$$

$$x_n = y_n^{\mathrm{m}} \quad n \in \mathbb{G}_m, n \in \mathbb{N} \tag{27}$$

where $x_n = \{p_n, q_n, P_n, Q_n, l_n, v_n\}$ is the set of bus variables of bus n; y_n^{m} is the duplicate of the bus variables x_n at bus m; $\mathbb{G}_n = A_n \cup \mathbb{C}_n \cup \{n\}$ is the set of neighboring buses of bus n; constraint (23) is the standard matrix form of the equality constraints (5)-(7); $\Omega_i = \{\underline{p}_{i,t}^{\mathrm{d}} \le p_{i,t}^{\mathrm{d}} \le \bar{p}_{i,t}^{\mathrm{d}}\}$ denotes the lower and upper bounds of the flexible demand $p_{i,t}^{\mathrm{d}}$; $\mathcal{X}_n$ is the feasible region of the bus variables limited by the inequality constraints in (9) and (15)-(17); and x_i is the duplicate of the prosumer variable $p_{i,t}^{\mathrm{d}}$ at the connected bus $n(i)$.

The scaled augmented Lagrangian of the estimate problem of the target bidding amount (22)-(27) is given by:

$$L(\lambda_1,\lambda_2) = \sum_{i\in\mathbb{P}} f(p_i^{\mathrm{d}}) + \sum_{i\in\mathbb{P}} \frac{\lambda_1}{2}\|-p_i^{\mathrm{d}} - x_i + p_i^{\mathrm{g}} + \mu_i\|_2^2 + \sum_{m\in\mathbb{N}}\sum_{n\in\mathbb{G}_m} \frac{\lambda_2}{2}\|x_n - y_n^{\mathrm{m}} + \omega_n^{\mathrm{m}}\|_2^2 \tag{28}$$

where μ_i and ω_n^{m} are the scaled Lagrangian multipliers of constraints (26) and (27), respectively; and $\lambda_1 > 0$ and $\lambda_2 > 0$ denote the step sizes.

The equations for iteration in the sharing form ADMM algorithm are:

$$p_i^{\mathrm{d}}[k+1] = \arg\min_{p_i^{\mathrm{d}}\in\Omega_i}\left[f(p_i^{\mathrm{d}}) + \frac{\lambda_1}{2}\left\| -p_i^{\mathrm{d}} - \frac{x_n[k]+b_n[k]-c_n[k]}{\kappa_n} + p_i^{\mathrm{d}}[k] + \mu_n[k]\right\|_2^2\right] \tag{29}$$

$$y_n[k+1] = \arg\min_{y_n\in\mathcal{Y}_n}\left[\sum_{m\in\mathbb{G}_n}\frac{\lambda_2}{2}\|x_n[k] - y_n^{\mathrm{m}} + \omega_n^{\mathrm{m}}[k]\|_2^2\right] \tag{30}$$

$$x_n[k+1] = \arg\min_{x_n\in\mathcal{X}_n}\left[\frac{\lambda_1\kappa_n}{2}\left\|\frac{x_n + b_n[k+1] - c_n}{\kappa_n} - \mu_n[k]\right\|_2^2 + \sum_{m\in\mathbb{G}_n}\frac{\lambda_2}{2}\|x_n - y_n^{\mathrm{m}}[k+1] + \omega_n^{\mathrm{m}}[k]\|_2^2\right] \tag{31}$$

$$\mu_n[k+1] = \frac{\mu_n[k] + (-b_n[k+1] - x_n[k+1] + c_n)}{\kappa_n} \tag{32}$$

$$\omega_m^{\mathrm{n}}[k+1] = \omega_m^{\mathrm{n}}[k] + x_m[k+1] - y_m^{\mathrm{n}}[k+1] \tag{33}$$

where $b_n = \sum_{i\in\delta_n} p_i^{\mathrm{d}}$; $c_n = \sum_{i\in\delta_n} p_i^{\mathrm{g}}$ is the sum of the prosumer variables calculated at bus n receiving information from the connected prosumer $i\in\delta_n$; and κ_n is the size of the prosumer set δ_n.

IV. Modified CDA-based Strategic P2P Energy Trading

In contrast to general merchandise, power transmission is transient and balanced in real time. That is, the P2P energy exchange network differs from the power delivery path in a distribution network. The locations of prosumers can indicate the usage of the distribution network in P2P energy trading. In P2P energy trading, prosumers interact and trade directly with each other, leaving the responsibility for retaining operational security to the LDSO. Considering this, location stamps and transaction fees are included in the CDA process to trace responsibility and quantify the expense of maintaining security operations during the P2P energy trading.

A. Modified CDAs

In this model, the P2P market is opened at τ^{st} ahead of each energy delivery time slot and closed at τ^{cl} ahead of each energy delivery time slot. Then, the P2P market opening period before energy delivery at t is represented as $(t-\tau^{st}, t-\tau^{cl})$, which can be divided into numerous transaction rounds. In each transaction round, prosumers can continuously bid until all bidding amounts reach a deal. During each bidding round ι, a prosumer can submit an order with the bidding side (buyer or seller), price, amount, time stamp (entry round ι^{en}), and location stamp (connected bus), which can be denoted as $\mathcal{O}^{\mathrm{b}}(b,\rho^{\mathrm{b}},p^{\mathrm{b}},\iota^{\mathrm{en}},n^{\mathrm{b}})$ for buyers and $\mathcal{O}^{\mathrm{s}}(s,\rho^{\mathrm{s}},p^{\mathrm{s}},\iota^{\mathrm{en}},n^{\mathrm{s}})$ for sellers. Each prosumer is allowed to bid only once in each bidding round. The arrived bids in each round ι are cleared by the following rules.

1) In each bidding round, all arrived bids or offers are queued in an order book $\mathcal{O}^{\mathrm{b}}$ or $\mathcal{O}^{\mathrm{s}}$ according to price in descending or ascending order. The buying and selling orders with the highest and lowest bidding prices are defined as an outstanding bid and offer, denoted as $\mathcal{O}^{\mathrm{b},ots}$ and $\mathcal{O}^{\mathrm{s},ots}$, respectively.

2) A unit transaction fee $\boldsymbol{\phi} = [\phi_1, \phi_2, \ldots, \phi_N]$ for transactions among prosumers at different buses is introduced to quantify the usage of distribution network and the contribution to security operations. For tthe transactions at the same bus, $\boldsymbol{\phi} = \mathbf{0}$. The details of matching algorithm for modified MDA, including the transaction fee, are presented in Algorithm 1 and a schematic of matching process is shown in Fig. 2.

3) For each outstanding prosumer, if all of its bids are cleared, the order will be removed from the order book. If there remains unmatched amount, the order will remain in the order book as outstanding.

4) The clearing process is finished when there is no order in the order book or the outstanding bidding price is lower than the outstanding offering price, i.e., $\rho^{\mathrm{b},ots} < \rho^{\mathrm{s},ots}$. If the bidding amount is not cleared in the current matching round, prosumers can update the bidding price in the next bidding round.

5) The unit transaction fee ϕ_i for each bus is determined by the LDSO according to the distance over which electricity is transmitted or using historical data as the feed-in tariff to cover operation and maintenance costs.

The matching process prioritizes the prices and transactions at the same bus. For each outstanding buyer (seller) with a bidding (offering) price $\rho^{\mathrm{b},ots}$ ($\rho^{\mathrm{s},ots}$), the potential transaction price matrix can be expressed as:

$$\boldsymbol{\rho}^{clr} = \frac{1}{2}\left((\boldsymbol{\rho}^{ots})^{\mathrm{T}} + [\boldsymbol{\rho}^{ots} \quad \hat{\rho}]^{\mathrm{T}} \pm \boldsymbol{F}\boldsymbol{\phi}\right) \tag{34}$$

where $\boldsymbol{\rho}^{clr} = [\rho^{clr}, \rho^{clr}]$; $\boldsymbol{\rho}^{ots} = [\rho^{\mathrm{s},ots}, \rho^{\mathrm{b},ots}]$, $\rho^{\mathrm{s},ots}(\rho^{\mathrm{b},ots})$ is the highest offering (lowest bidding) price of a seller (buyer) for the same bus with the outstanding buyer (seller) in the order book; and $\boldsymbol{F}\in\mathbb{R}^{1\times N}$ is defined as the transaction fee incidence matrix of the outstanding prosumer, in which each column corresponds to a bus. If the outstanding buyer b is not at the same bus as the outstanding seller s, $\boldsymbol{F}(n(b)) = \boldsymbol{F}(n(s)) = 1$.

Algorithm 1: matching algorithm for modified CDA

Intended transaction price

if $\rho^{\mathrm{b},ots} \geq \rho^{\mathrm{s},ots}$
  if $n^{\mathrm{b},ots} = n^{\mathrm{s},ots}$
    Clearing price $\rho^{clr} = \dfrac{\rho^{\mathrm{b},ots} + \rho^{\mathrm{s},ots}}{2}$
    Clearing amount $p^{clr} = \min(p^{\mathrm{b},ots}, p^{\mathrm{s},ots})$
  else
    For buyer $\rho^{clr}_{1,\mathrm{b}} = \dfrac{\rho^{\mathrm{b},ots} + \rho^{\mathrm{s},ots}}{2} + \dfrac{\phi_{n^{\mathrm{b},ots}} + \phi_{n^{\mathrm{s},ots}}}{2}$
    For seller $\rho^{clr}_{1,\mathrm{s}} = \dfrac{\rho^{\mathrm{b},ots} + \rho^{\mathrm{s},ots}}{2} - \dfrac{\phi_{n^{\mathrm{b},ots}} + \phi_{n^{\mathrm{s},ots}}}{2}$
  end if
  Find $\hat{n}^{\mathrm{s}} = n^{\mathrm{b},ots}$ with the lowest offering price in $\mathcal{O}^{\mathrm{s}}$
    Potential clearing price $\rho^{clr}_{2,\mathrm{b}} = \rho^{clr}_{2,\mathrm{s}} = \dfrac{\hat{\rho}^{\mathrm{s}} + \rho^{\mathrm{b},ots}}{2}$
  Find $\hat{n}^{\mathrm{b}} = n^{\mathrm{s},ots}$ with the highest bidding price in $\mathcal{O}^{\mathrm{b}}$
    Potential clearing price $\rho^{clr}_{3,\mathrm{b}} = \rho^{clr}_{3,\mathrm{s}} = \dfrac{\hat{\rho}^{\mathrm{b}} + \rho^{\mathrm{s},ots}}{2}$
end if

Matching process

if $\rho^{clr}_{1,\mathrm{b}} \leq \rho^{clr}_{2,\mathrm{b}}$ **and** $\rho^{clr}_{1,\mathrm{s}} \geq \rho^{clr}_{3,\mathrm{s}}$
  $\mathcal{O}^{\mathrm{b},ots}$ is matched with $\mathcal{O}^{\mathrm{s},ots}$
else if $\rho^{clr}_{1,\mathrm{b}} > \rho^{clr}_{2,\mathrm{b}}$ **and** $\rho^{clr}_{1,\mathrm{s}} \geq \rho^{clr}_{3,\mathrm{s}}$
  $\mathcal{O}^{\mathrm{b},ots}$ is first matched with $\hat{\mathcal{O}}^{\mathrm{s}}$, and the remaining are matched with $\mathcal{O}^{\mathrm{s},ost}$
else if $\rho^{clr}_{1,\mathrm{b}} \leq \rho^{clr}_{2,\mathrm{b}}$ **and** $\rho^{clr}_{1,\mathrm{s}} < \rho^{clr}_{3,\mathrm{s}}$
  $\mathcal{O}^{\mathrm{s},ots}$ is first matched with $\hat{\mathcal{O}}^{\mathrm{b}}$, and the remaining are matched with $\mathcal{O}^{\mathrm{b},ots}$
else
  $\mathcal{O}^{\mathrm{b},ots}$ and $\mathcal{O}^{\mathrm{s},ots}$ are matched with $\hat{\mathcal{O}}^{\mathrm{b}}$ and $\hat{\mathcal{O}}^{\mathrm{s}}$
end if

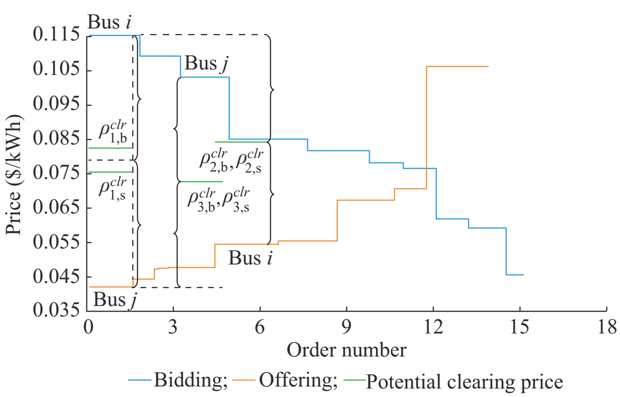

Fig. 2. Schematic of matching process in each transaction round of modified CDA.

B. Risk-perceived Bidding Strategy

In the P2P energy trading market, prosumers are assumed to be rational and selfish, trying to maximize their own utility. Each prosumer engages in the P2P market to reduce their costs rather than directly obtain energy from the upstream grid. Generally, the limit price of prosumer i at bus n during time slot t is the retail price of the upstream grid $\psi^{\mathrm{b}}_{n,t}$ for buyers and the feed-in-tariff $\psi^{\mathrm{s}}_{n,t}$ for sellers, which prevent unreasonably low offers and high bids. The proposed strategic bidding process is based on an AA strategy [18], which is designed for general merchandise. In contrast to general commodities, electricity needs to be balanced in real time, which means that prosumers have to purchase or sell a certain amount of energy to meet their deficiency or surplus in a certain period. Combining the real-time balancing characteristic, the proposed strategic bidding process is concerned with both the bidding price and amount.

1) Definition

For each P2P market participant, a trade-off always exists between the profit margins and the transaction opportunities. In other words, if a prosumer wants to earn more revenue from the P2P market, it has to bid at a price less than the evaluated competitive equilibrium price, which will conversely decrease the chance of transaction. If a prosumer wants a greater chance of trading, it has to bid a price better than the competitive equilibrium price estimate, which compresses the profit margins. This degree of trade-off is utilized in the bidding strategy of the prosumer, indicating a forecast of the market situation. In [18], the degree of trade-off between profit margins and transaction opportunities is quantified by an aggressiveness coefficient; thus, prosumers risking their profits for a greater chance to reach a deal are defined as aggressive traders. By contrast, prosumers who risk their transaction chance for more profits are passive traders.

The target bidding price ρ^{tg}_i for prosumer i is defined as its belived most competitive price, which is influenced by the limit price, the current degree of aggressiveness a^{g}, and an intrinsic parameter represented by ε. It is assumed that the transaction prices converge to the competitive equilibrium price $\hat{\rho}$. In this model, all prosumers are intramarginal traders. Therefore, the target bidding price ρ^{tg}_i is related to the aggressiveness a^{g}_i of prosumer i, which is expressed as:

$$\rho^{tg}_i = \begin{cases} \hat{\rho}\left(1 - \dfrac{\mathrm{e}^{-a^{\mathrm{g}}_i \theta} - 1}{\mathrm{e}^{\underline{\theta}} - 1}\right) & a^{\mathrm{g}}_i \in [-1, 0), i \in \mathbb{B} \\ \hat{\rho} + (\rho^{lim}_i - \hat{\rho})\left(\dfrac{\mathrm{e}^{a^{\mathrm{g}}_i \theta} - 1}{\mathrm{e}^{\theta} - 1}\right) & a^{\mathrm{g}}_i \in (0, 1], i \in \mathbb{B} \end{cases} \tag{35}$$

$$\rho^{tg}_i = \begin{cases} \hat{\rho} + (\psi^{\mathrm{b}}_{n,t} - \hat{\rho})\left(\dfrac{\mathrm{e}^{-a^{\mathrm{g}}_i \theta} - 1}{\mathrm{e}^{\underline{\theta}} - 1}\right) & a^{\mathrm{g}}_i \in [-1, 0), i \in \mathbb{S} \\ \rho^{lim}_i + (\hat{\rho} - \rho^{lim}_i)\left(1 - \dfrac{\mathrm{e}^{a^{\mathrm{g}}_i \theta} - 1}{\mathrm{e}^{\theta} - 1}\right) & a^{\mathrm{g}}_i \in (0, 1], i \in \mathbb{S} \end{cases} \tag{36}$$

where $\mathbb{B}$ and $\mathbb{S}$ are the sets of buyers and sellers, respectively; the limit prices are $\rho^{lim}_i = \psi^{\mathrm{b}}_{n,t}$ for buyer $i \in \mathbb{B}$ and $\rho^{lim}_i = \psi^{\mathrm{s}}_{n,t}$ for seller $i \in \mathbb{S}$; θ is the magnitude of the gradient of ρ^{tg}_i with a rate of change of a^{g}_i; and $\underline{\theta}$ is calculated to ensure a smooth curve.

2) Risk-perceived Bidding Amount

In the AA strategy, a prosumer is passive or active in a single bidding round according to their aggressiveness. As the transaction amount of P2P energy market is not a unit of energy, prosumers can have different levels of aggressiveness towards different units of energy. In the proposed bidding process, each prosumer has both an aggressive part ($a^{\mathrm{g}} > 0$), in which the prosumer wants to trade as much as possible and a passive part ($a^{\mathrm{g}} < 0$) to pursue higher profits. The target trading amount $\hat{e}_{i,t}$ derived from (12)-(18) represents the amount at which the prosumers can minimize their estimated deviation cost. If the bidding amount of the prosumer is less than the target amount, i.e., $p^{\mathrm{b}} < \hat{e}_{i,t}$, an energy deficiency $\hat{e}_{i,t} - p^{\mathrm{b}}$ will be bought from the upstream grid at the limit price with no extra profits. If $p^{\mathrm{b}} > \hat{e}_{i,\iota}$, there may be potential deviation costs. Prosumers want the P2P transaction amount to be as much as the target amount, which indicates that the aggressive bidding part $a^{\mathrm{g}} \in (0,1)$ for prosumers is exactly the target transaction amount $\hat{e}_{i,\iota}$. The passive bidding part $a^{\mathrm{g}} \in (-1,0)$ is defined as the bidding surplus that is more than the target transaction amount $p^{ps} = p^{\mathrm{b}} - \hat{e}_{i,\iota}$.

Obviously, there is a high probability that the transaction of the passive bidding part causes constraint violations during the operation of actual distribution network. Once a violation occurs, the actual amount of power delivered will be reduced from the P2P transaction amount by the LDSO solving an OPF problem. Therefore, each prosumer faces the risk arising from the uncertainty in the actual amount of power delivered p_i^{D} due to the security operation constraints of the distribution network. Prosumers will bid more than the target transaction amount only when the profits for the passive bidding part $p_i^{ps} = p_i^{\mathrm{b}} - \hat{e}_i$ can cover the risk of the uncertainty in the cost arising from the actual curtailment in the power delivered. The condition on any actual power delivered is given by p_i^{D}, and the loss function considering the uncertainty in the demand adjustment of the LDSO after P2P energy trading is given by:

$$C_i^{loss}(p_i^{ps}, p_i^{\mathrm{D}}, \rho_i^{tg}) = \begin{cases} (\rho_i^{tg} - \psi_n^{\mathrm{s}})\Delta p_i^{\mathrm{D}} + \alpha_i (\Delta p_i^{\mathrm{D}})^2 - (\psi_n^{\mathrm{b}} - \rho_i^{tg}) p_i^{\mathrm{D}} & i \in \mathbb{B} \\ (\psi_n^{\mathrm{b}} - \rho_i^{tg})\Delta p_i^{\mathrm{D}} + \alpha_i (\Delta p_i^{\mathrm{D}})^2 - (\rho_i^{tg} - \psi_n^{\mathrm{s}}) p_i^{\mathrm{D}} & i \in \mathbb{S} \end{cases} \tag{37}$$

where $\Delta p_i^{\mathrm{D}} = p_i^{ps} - p_i^{\mathrm{D}}$ denotes the actual curtailment in the delivery power from the bidding amount of passive part. Once the probability distributions of p_i^{D} are known, the prosumers can derive the parameterized mean of $C_i^{loss}(p_i^{ps}, p_i^{\mathrm{D}}, \rho_i^{tg})$, denoted as $E_i^{loss}(p_i^{ps}, \rho_i^{tg})$.

To simplify the expression, let $a^{loss} = \alpha_i$, $b^{loss} = \psi_n^{\mathrm{s}} - 2\alpha_i p_i^{ps} - \psi_n^{\mathrm{b}}$, $c^{loss} = \alpha_i (p_i^{ps})^2 + \Delta\rho_i^{tg} p_i^{ps}$, and $\Delta\rho_i^{tg} = \rho_i^{tg} - \psi_n^{\mathrm{s}}$ for buyers, and $\Delta\rho_i^{tg} = \psi_n^{\mathrm{b}} - \rho_i^{tg}$ for sellers. Then, the potential deviation cost C_i^{loss} can be transformed into a quadratic function of the uncertainty variable p_i^{D}:

$$C_i^{loss} = a^{loss}(p_i^{\mathrm{D}})^2 + b^{loss} p_i^{\mathrm{D}} + c^{loss} \tag{38}$$

For the passive bidding part, prosumers risk their allowed delivery power to pursue higher profits. Let R_i be the risk preference of the prosumer, and it could be more risky to pursue high revenue or be risk-aversion. Then, the return-risk utility function of prosumer i is expressed in a linear form as:

$$U_i = E(C_i^{loss}) - R_i \cdot CVaR_\beta(C_i^{loss}) \tag{39}$$

where $\beta \in (0,1)$ is the confidence level of the conditional value at risk (CVaR).

According to the definition and translation-equivariant, positively homogeneous, and convex properties of the CVaR, given any passive bidding part p_i^{ps} and target price ρ_i^{tg}, the CVaR of the loss function satisifies:

$$CVaR_\beta(C_i^{loss}) \le CVaR_\beta(a^{loss}(p_i^{\mathrm{D}})^2) + b^{loss} \cdot CVaR_\beta(p_i^{\mathrm{D}}) + c^{loss} \tag{40}$$

Using R_i to denote the risk preference coefficient of prosumer i, the right-hand side of inequality in (40) can be utilized as a conservative estimation to calculate the return-risk utility:

$$U_i = E(C_i^{loss}) - R_i (CVaR_\beta(a^{loss}(p_i^{\mathrm{D}})^2) + b^{loss} \cdot CVaR_\beta(p_i^{\mathrm{D}}) + c^{loss}) \tag{41}$$

Given the probability distribution of p_i^{D}, the return-risk utility is a function of the passive bidding amount p_i^{ps} and target bidding price ρ_i^{tg}.

3) Adaptive Bidding Strategy of Aggressiveness

An important feature of human traders is that they can learn from historical data. For a better description of the performance of individual traders, the aggressiveness a_i^{g} is used to reflect the learning and adaptive processes of prosumer i from the market situation. Each time the market environment changes, prosumers will update their own aggressiveness a_i^{g} using the released market information. Changes in the market environment, including new submitted bids/offers and new transactions, will influence the aggressiveness a_i^{g}. Using δ^{rel} and δ^{abs} to represent the relative increase and the absolute increase, respectively, the increase is expressed as $\delta^{\pm} = \xi[(1 \pm \delta^{rel})\hat{a}_i^{\mathrm{g}} \pm \delta^{abs}]$, where $\hat{a}_i^{\mathrm{g}}$ is the aggressiveness that could derive a price equal to the newly generated price, i.e., a newly arrived bid/offer or new transaction price. For the aggressive part, the upper bound of the aggressiveness is $\bar{a}_i^{\mathrm{g}} = 1$, and the upper bound of the passive part is calculated from the return-risk utility. The lower bounds are $\underline{a}_i^{\mathrm{g}} = 0$ and $\underline{a}_i^{\mathrm{g}} = -1$ for the aggressive and passive parts, respectively. The bidding strategy provides a bidding rule for prosumers to determine whether to bid and the bidding price in the multicriteria decision analysis (MCDA). Prosumers have no historical data to estimate the competitive equilibrium price in the first bidding round, and the target bidding prices of the prosumers in the first bidding round are unknown. Therefore, the bidding price [18] is generated by:

$$\rho^{\mathrm{b}} = \begin{cases} \rho^{\mathrm{b},ots} + \eta(\min(\psi_{n(i),\iota}^{\mathrm{b}}, \rho^{\mathrm{s},ots+}) - \rho^{\mathrm{b},ots}) & \iota = 1 \\ \rho^{\mathrm{b},ots} + \eta(\rho_i^{tg} - \rho^{\mathrm{b},ots}) & \iota > 1 \end{cases} \tag{42}$$

$$\rho^{\mathrm{s}} = \begin{cases} \rho^{\mathrm{s},ots} + \eta(\max(\psi_{n(i),\iota}^{\mathrm{s}}, \rho^{\mathrm{b},ots-}) - \rho^{\mathrm{s},ots}) & \iota = 1 \\ \rho^{\mathrm{s},ots} + \eta(\rho_i^{tg} - \rho^{\mathrm{s},ots}) & \iota > 1 \end{cases} \tag{43}$$

where $0 < \eta < 1$ denotes the approaching rate of the bidding price towards the target price; and $\rho^{\mathrm{s},ots+}$ and $\rho^{\mathrm{b},ots-}$ are given by:

$$\rho^{\mathrm{s},ots+} = (1 + \delta^{rel})\rho^{\mathrm{s},ots} + \delta^{abs} \tag{44}$$

$$\rho^{\mathrm{b},ots-} = (1 - \delta^{rel})\rho^{\mathrm{b},ots} - \delta^{abs} \tag{45}$$

The details of the adaptive process of the aggressiveness and bidding rules are presented in Algorithm 2.

V. Case Study

A. System Configuration

The proposed strategic P2P energy-trading framework is tested using an IEEE 37-bus distribution network with 500 prosumers in total, where each bus is connected with numerous prosumers. Hourly residential load data and rooftop PV generation data are obtained from real data from East China.

Algorithm 2: bidding process of consumer c

Adaptive process of aggressiveness
for buyers $i \in \mathbb{B}$:
if bidding price ρ^{b} is newly submitted **and** $\rho_i^{tg} < \rho^{b}$
  $a_i^{g} = a_i^{g} + \delta^{+}$
else if the transaction occurs at price ρ^{clr}
  if $\rho_i^{tg} > \rho^{clr}$
    $a_i^{g} = a_i^{g} + \delta^{-}$
  else
    $a_i^{g} = a_i^{g} + \delta^{+}$
  end if
end if
for sellers $i \in \mathbb{S}$:
if offering price ρ^{s} is newly submitted and $\rho_i^{tg} > \rho^{s}$
  $a_i^{g} = a_i^{g} + \delta^{+}$
else if the transaction occurs at price ρ^{clr}
  if $\rho_i^{tg} > \rho_{clr}$
    $a_i^{g} = a_i^{g} + \delta^{+}$
  else
    $a_i^{g} = a_i^{g} + \delta^{-}$
  end if
end if
if $a_i^{g} > \bar{a}_i^{g}$
  Set a^{g} to the upper bound $a_i^{g} = \bar{a}_i^{g}$
else
  Set a^{g} to the lower bound $a_i^{g} = \underline{a}_i^{g}$
end if
Bidding rules
for buyers $i \in \mathbb{B}$:
if $\psi_{n(i),t}^{b} < \rho^{b,ots}$
  Buyer submits no bid
else if $\rho^{s,ots} \le \rho_i^{tg}$
  Submit $\rho^{b} = \rho^{s,ots}$
else
  Submit a bid according to the function in (42)
  end if
for sellers $i \in \mathbb{S}$:
if $\psi_{n(i),t}^{s} > \rho^{s,ots}$
  Seller submits no offer
else if $\rho^{b,ots} \ge \rho_i^{tg}$
  Submit $\rho^{s} = \rho^{b,ots}$
else
  Submit a bid according to the function in (43)
end if

The retail price from the upstream grid is set to be $\psi_{n,t}^{b} = 0.12$ \$/kWh, the feed-in tariff is given as $\psi_{n,t}^{s} = 0.04$ \$/kWh from the data released by the U.S. Energy Information Administration (EIA) [25], and the competitive equilibrium price is initialized to $\hat{\rho} = 0.08$ \$/kWh. It is assumed that the amount of real-time power delivery p_i^{D} follows a normal distribution. The convege tolerances of the sharing form ADMM algorithm is set to be $\epsilon^{abs} = 10^{-7}$ and $\epsilon^{rel} = 10^{-4}$. Other configuration simulation parameters are set as listed in Table I.

TABLE I
CONFIGURATION OF SIMULATION PARAMETERS

Item	Value	Item	Value	Item	Value
α_i	500	β	0.95	R_i	0.5
θ	2	$\underline{v}$	0.95^2	$\bar{v}$	1.05^2
η	$\frac{1}{3}$	λ_1	1	λ_2	1

B. Market Efficiency of Strategic P2P Energy Trading

The zero-intelligence (ZI) strategy considers that traders generate their bids or offers following an independent, identical, and uniform distribution over the entire feasible range of trading prices [26], which does not use variable market information. Therefore, this section compares the proposed AA-based strategic P2P energy trading strategy with the ZI strategy to illustrate the validity of the bidding strategy. For a specific analysis, partial P2P energy trading results at $t = 14$ without a voltage violation and $t = 13$ with a voltage regulation are shown in Figs. 3 and 4, respectively, where the orange vertical bars denote the price gaps between the bidding prices of the buyers and the offering prices of the sellers; and the given numbers denote the prosumer No.. The P2P trading finishes in 3-14 rounds with 512 transactions at $t = 14$ and in 2-9 rounds with 587 transactions at $t = 13$. It can be observed that at $t = 14$, consumer 494 has transactions with three different producers, among which the transaction with producer 67 consists of passive and aggressive parts of 2.09 kW and 1.58 kW, respectively. Prosumers cannot reach a deal in the P2P market, and they will trade with the upstream grid at retail prices or feed-in tariffs. At $t = 14$, 438 out of 500 prosumers have completed transactions in the proposed strategic P2P energy trading market, indicating that the transaction rate is approximately 87.6%. However, the transaction rate is only about 43.8% using a ZI strategy, as indicated by the results in Table II.

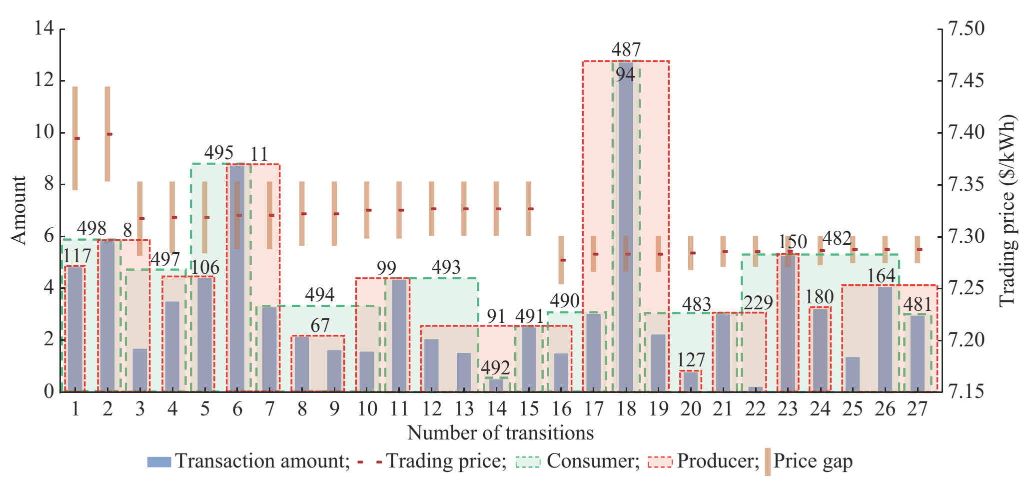

Fig. 3. Strategic P2P energy trading results at $t = 14$.

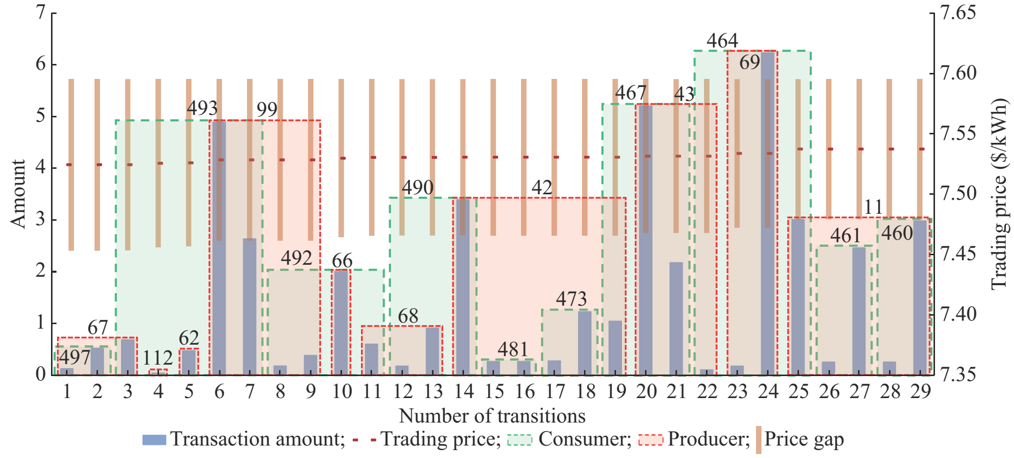

Fig. 4. Strategic P2P energy trading results at $t=13$.

TABLE II
MARKET EFFICIENCY COMPARISON AT $t=14$

Strategy	Seller engaged P2P	Buyer engaged P2P	Transaction rate (%)	Overall cost ($)	Cost for buyer 460 (¢)	Profit for seller 80 (¢)
Upstream grid	0	0	0	212.60	64.13	14.13
AA-based strategy	245	193	87.6	56.89	46.61	25.84
ZI strategy	118	101	43.8	72.50	52.06	23.95

An overall cost reduction of approximately 27.4% can be achieved using the proposed AA-based strategic P2P energy trading strategy compared with the ZI strategy. In addition, for individual participants, a cost reduction for the buyer and a profit increase for the seller can be observed, indicating the market efficiency of the proposed strategic P2P energy trading strategy.

C. Support for Distribution Network Operation

As shown in Fig. 5(a), there exists a potential voltage violation in the distribution network if prosumers arrange their demand as preferred according to $\boldsymbol{p}^{\mathrm{p}}$. Using the proposed distributed estimation of target amount, the voltage can be limited within the allowable range by incentivizing prosumers to shift their flexible demand, as demonstrated in Fig. 5(b). Figure 6 shows the flexible demand regulation at $t=13$ (with voltage regulation) and $t=14$ (without voltage regulation). It can be observed that during periods with a potential voltage violation, i.e., $t=13$, prosumers reduce their demand to support the secure operation of the distribution network. The amount of demand regulation differs according to the locations of prosumers. That is, for prosumers at buses with voltage violations, i.e., prosumers 427-485 at buses 33, 34, and 35, the amounts of demand regulation are larger than others.

D. Convergence Analysis of Distributed Estimation of Target Transaction Amount

The algorithm is implemented in MATLAB 2018 on a desktop computer equipped with an Intel Core i7-7700 running at 3.60 GHz and 8 GB of random-access memory (RAM).

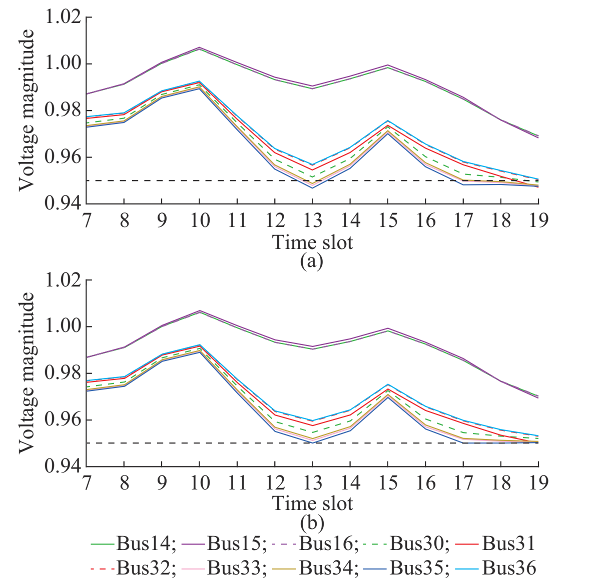

Fig. 5. Bus voltage without and with estimation of target amount. (a) Without target amount estimation. (b) With target amount estimation.

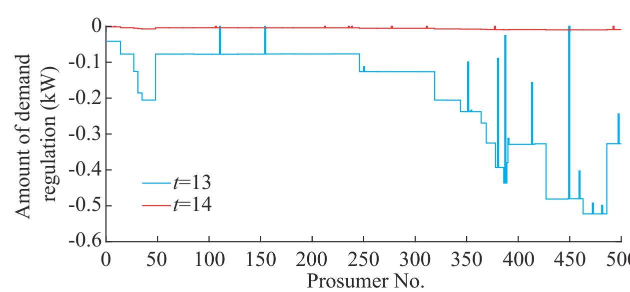

Fig. 6. Flexible demand regulation at $t=13$ and $t=14$.

As shown in Fig. 7, the problem of estimating the target transaction amount can converge to the optimal value within 2523 and 5285 iterations at $t=13$ and $t=14$, respectively, indicating good convergence of the distributed algorithm. It is noted that it takes longer calculation time at $t=13$ than $t=14$ because the demand is regulated to avoid voltage violations at $t=13$, although the number of iterations to convergence is less than that at $t=14$.

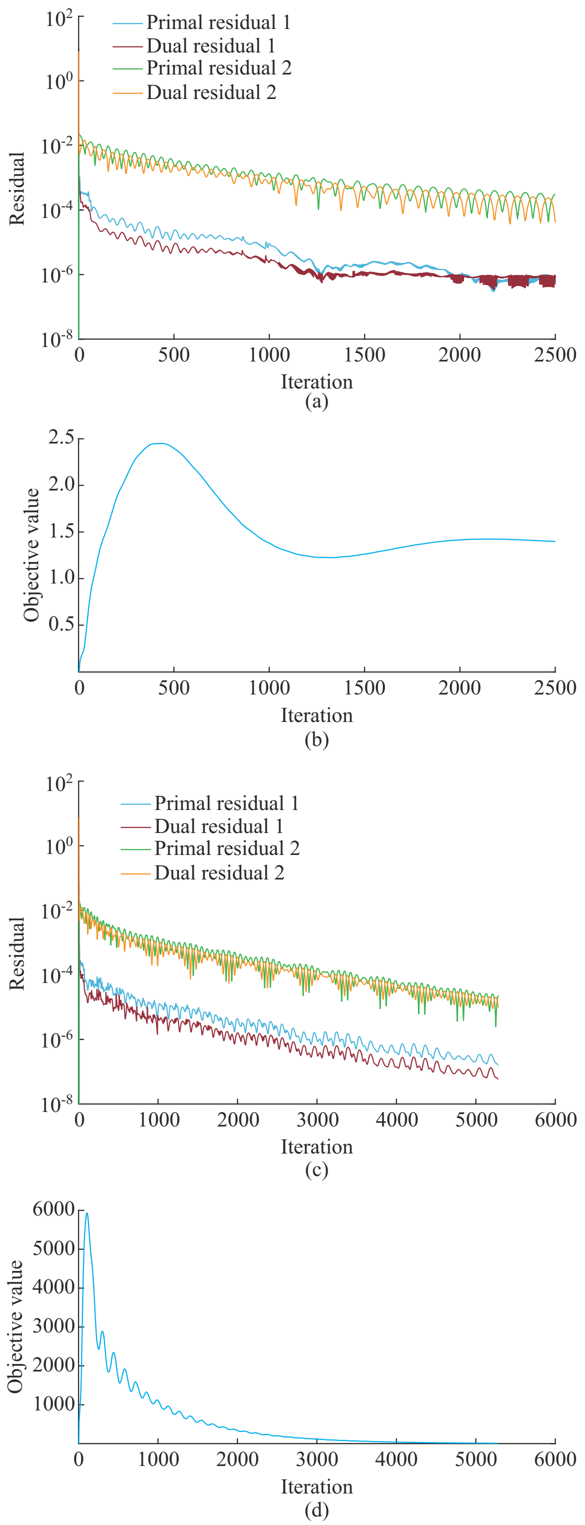

Fig. 7. Convergence analysis of target transaction amount estimation. (a) Primal and dual residuals at $t=13$. (b) Objective value at $t=13$. (c) Primal and dual residuals at $t=14$. (d) Objective value at $t=14$.

VI. Conclusion

The operational constraints of a distribution network may influence the individual decision-making process of prosumers in a P2P energy market owing to the potential deviations and penalty costs. Therefore, a strategic P2P energy trading framework for distribution networks is proposed to include the constraints of a distribution network in the bidding decision-making of prosumers. The P2P energy trading process consists of three stages: the estimation of the target energy trading amount in the distribution network before a transaction, the risk-averse adaptive P2P energy transaction, and the verification and settlement by the LDSO after the transaction. Case studies show that the proposed strategic P2P energy trading framework can dramatically decrease the overall power usage cost and proactively support the optimization of the distribution network.

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