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Distributed Day-Ahead Peer-to-Peer Trading for Multi-Microgrid Systems in Active Distribution Networks

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ABSTRACT Developing a reasonable, efficient distributed market transaction mechanism is an important issue in distribution systems. The gaming relation between distributed transaction market entities has yet to be fully elucidated in various trading links, and the impact of distributed transactions on distribution network operations has yet to be comprehensively analyzed. This paper proposes a novel distributed Peer-to-Peer (P2P) day-ahead trading method under multi-microgrid congestion management in active distribution networks. First, a flexible load model for price-based demand response load and an autonomous microgrid economic scheduling model are constructed. Second, under normal operation of the distribution network, a non-cooperative game model and Stackelberg game model are employed to separately and comprehensively analyze gaming relationship among sellers, and between sellers and buyers. Thereafter, a congestion management method based on market capacity is established from the perspective of distribution network control centers. Finally, the impact of end energy consumption characteristics on microgrid economic scheduling and P2P trading is analyzed through a modified IEEE 33-node power distribution system. The economic and technical benefits such as congestion mitigation and network loss reduction that produced by P2P trading to the operation of microgrid systems are analysed with specific indicators.

INDEX TERMS Multi-microgrid cluster, active distribution network, peer-to-peer trading, non-cooperative game, Stackelberg game, congestion management.

NOMENCLATURE

Variables

$C_{\mathrm{MEP},i}^{\mathrm{PDR}}$	Inconvenience equivalent cost, CNY
$C_{\mathrm{MEP},i}^{\mathrm{OM}}$	Operation and maintenance cost, CNY
$C_{\mathrm{invest}}^{\mathrm{ES}}$	One-time ES purchase cost, CNY
$C_{\mathrm{MEP},i}$	Power deviation cost of the net load demand, CNY
$P_{\mathrm{B},i,\mathrm{G}}$	Quantity of electricity purchased from utility power grid, kW
$P_{\mathrm{B},i,\mathrm{G}}$	Price of electricity purchased from utility power grid, CNY/kW
$p_{\mathrm{B},i}$	Price of electricity purchased from other MEPs, CNY/kW
$P_{\mathrm{MEP},i}^{\mathrm{PDR}}(t)$	Flexible demand after demand response, kW
$P_{\mathrm{MEP},i}$	Power demand before demand response is adjusted, kW
$P_{\mathrm{MEP},i}^{\mathrm{MG}}(t)$	Total electric power demand during time period t, kW
$P_{\mathrm{MEP},i}^{\mathrm{O}}(t)$	Non-flexible power loads during time period t, kW
$P_i^{\mathrm{PV}}(t)$	PV output power during time period t, kW
$P_i^{\mathrm{WT}}(t)$	WT output power during time period t, kW
$P_{\mathrm{D},i}^{\mathrm{ES}}(t)$	ES discharge power of MEP_i during time period t, kW
$P_{\mathrm{C},i}^{\mathrm{ES}}(t)$	ES charge power of MEP_i during time period t, kW

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$P_{S,i,G}$	Quantity of electricity sold to utility power grid, kW
$p_{S,i,G}$	Price of electricity sold to utility power grid, CNY/kW
$p_{S,i}$	Price of electricity sold to other MEPs, CNY/kW
$p_{S,i,\max}(t)$, $p_{S,i,\min}(t)$	Upper and lower limits of acceptable transaction price, CNY/kW
$P^{ex}_{S,i}$	Quantity of electricity sold to other MEPs, kW
$P^{ex}_{B,i}$	Quantity of electricity purchased from other MEPs, kW
P^{k}_{MS}	Transaction power set for MEP-S in k-round iteration, kW
p^{k}_{MS}	Transaction price set for MEP-S in the k-round iteration, CNY/kW
$s_i(t)/b_i(t)$	Identifier of prosumers
$S(t)$	Gradient search direction
$SOC(t)$	Electric quantity of ES during time period t, kW· h

Parameters

E_{SOC}	Rated capacity of ES, kW· h
$M^{m}_{\max}(t)$, $M^{m}_{\min}(t)$	Maximum/minimum capacity of ES equipment of MEP$_i$, kW· h
P_{cap}	Available transmission capacity of power distribution system, kW
$P^{m}_{[C/D],\max}(t)$	Maximum charge/discharge power of ES equipment, kW
α_i	Sensitivity coefficient of the microgrid-i
β	Learning factor
μ^{ES}	Regulating coefficient of ES
$\mu_{MEP,i}(t)$	Weighting factor related to the power deviation
η^{ES}_{C}	Charging efficiency of ES, %
η^{ES}_{D}	Discharging efficiency of ES, %

Indices

i	index of the MEP
k	index of the iteration
t	index of the scheduling period
S	Quantity of MEP sellers participating in P2P transactions
T	Total number of scheduling periods

Functions

$N(\cdot)$	Discharge depth function
$z(\cdot)$	Buyer MEP' action strategy based on seller's quotation

Abbreviations

BS	The bill sharing
DER	Distributed energy resource
DR	Demand response
DTO	Distributed transaction operator
EBI	The energy balance index
ES	Energy storage
MEP	Microgrid energy service prosumer
MMR	The mid-market rate
P2P	Peer to Peer
PV	Photovoltaic components
SDR	The supply and demand ratio
TOU	Time-of-use
VTI	The value tapping index
WT	Wind turbine

I. INTRODUCTION

Ever-accelerating advancements in distributed energy resources (DERs) have introduced an abundance of DERs connecting terminal users to power systems. This interaction can facilitate energy security and minimize carbon emissions. However, the modes of power generation and supply in existing power systems are still centralized. The grid service and power market trading mechanism needed for promoting distributed energy are not yet perfect. This leads to low returns for DERs projects and drives down their marketization [1]. To this end, many countries have made power distribution transaction policies, seeking to reform their national power systems [2]. For example, China issued the *Notice on Launching a Pilot Market for Distributed Power Generation Markets* in November 2017 to further explore grid technology service management systems that adapted to DERs, power trading mechanism, and the reform of transmission and distribution prices, as well as other objectives. This *Notice* also called for distributed energy resources to percolate in the competitive market through distributed transactions.

The P2P transaction is based on computer overly network concept [3] and has been extensively investigated to realize electricity trading. Some countries, including the United Kingdom [4], Germany [5] and the United States [6], have trailed demonstration applications. The P2P transaction allows local users to conduct distributed transactions directly, which relieves the burden on the distribution network control center and streamlines the demand-side response, making the whole power distribution system more flexible. However, the distributed energy transaction market is subject to real-time price fluctuations, dynamic adjustment of power consumption plans, and frequent electricity bill settlements, and other issues. An equal, highly-efficient trading mechanism is necessary to manage the fast changes in information and energy prices during these transactions.

Two major trading mechanisms are now used in P2P transaction markets [7]. The first trading mechanism is "united" P2P market supported by a centralized pricing clearing mechanism. The supply-demand balance inside the "union" is realized by distributed transactions organized by the aggregator. The second mechanism is a P2P market wherein market participants can adjust transaction prices according to actual market environment. For the first trading mechanism, Zhou *et al.* [8] comprehensively summarized the concept, simulation framework, and evaluation methods of

P2P transaction mechanisms. Three typical transaction price settlement mechanisms were also discussed including the supply and demand ratio (SDR), the mid-market rate (MMR), and the bill sharing (BS). This work established a solid theoretical foundation for further exploring subsequent P2P trading mechanisms. Liu *et al.* [9], for example, studied P2P transactions between photovoltaic prosumers based on transaction price clearing via SDR, transaction user satisfaction, and price-based demand response (DR) factors. Kumar Nunna and Srinivasan [10] established a comprehensive energy management system (CEMS) under which optimization is achieved via scheduling aggregators deployed on microgrid clusters and transacted electricity prices. Internal trading can be managed by CEMS with multi-microgrid distribution systems and DR strategies can be formulated based on different types of loads. Yazdani-Damavandi *et al.* [11] established a multi-energy system embodying energy markets, regional energy operators, microgrid systems, and load users (i.e., a four-layer operational framework). Based on the optimized scheduling strategies within the energy microgrid system, the regional energy operator clears the transaction price of the microgrid cluster in the region, thereby balancing regional energy sources and reducing operating costs. Alexandra *et al.* [12] focused on the role of battery storage equipment in distributed transactions and proposed a Flexi User and a Pool Hub market for the community of prosumers incorporating battery storage systems respectively, the economic benefits of the community through distributed transactions were compared and analyzed by practical cases. Nguyen *et al.* [13] presented an optimization model for rooftop PV distributed generation with battery storage in P2P energy trading, aiming at the net energy cost optimality of all households. It also analyzed the impact of different PV system scales, different generation scenarios, and other factors on user costs. Long *et al.* [14] proposed a two-stage control method that includes optimizing the energy costs of the community and developing the control set-points to realize P2P energy sharing in community microgrids. This paper used the SDR method to clear P2P buying and selling prices to ensure that each prosumer and consumer is able to obtain economic benefits. The comparison of energy costs, self-consumption of PV energy, self-sufficiency ratio, electricity bills of individual consumers were analyzed through actual cases.

In above reference, transaction prices were optimized and cleared based on the operation of each microgrid system. Previous researchers have also introduced game theory into P2P transactions to enhance the autonomy of trading users [15]. Thus, the profits are guaranteed to be fairly distributed between microgrid systems participating in the transaction. Some studies have also explored the economic benefits of transaction users under the second trading mechanism described above. By using non-cooperative game theory, Liu *et al.* [16] analyzed "selfish" strategies adopted by different microgrid systems in the sole pursuit of profit, which involves adjusting the charge and discharge states of energy storage. The cooperative game theory was used to analyze the trading strategies of microgrid systems to optimize the overall economy of the microgrid cluster. A distributed algorithm was proposed for solving and proving the Nash equilibrium of the game. Paudel *et al.* [17] proposed the utility function of producers in P2P trading. The non-cooperative game and evolutionary game were used to analyze seller and buyer choice competition in P2P transaction. The economic and technical benefits of P2P trading were validated via an iterative algorithm. In a study on the internal transactions between multi-energy hubs, Songli *et al.* [18] targeted at the optimal economics of various energy hubs and realized multi-energy hub coordinated scheduling by solving the Pareto optimality as the balanced, feasible solution of the cooperative game. The economic benefits of coordinated operation of multi-energy hubs have also been comprehensively explored.

Apart from transaction pricing and clearing mechanism and the autonomous optimization scheduling strategies of microgrid systems, the energy utilization behaviors of end customers also affect transaction outcomes. Some studies have shown that clean energy accommodation rate can be increased by 2-15% through demand-side management [19]. Several researchers have considered the impact of user DR in studying P2P transaction patterns [9], [10]. Jalali *et al.* [20], for example, considered the load DR factor in a study on the coordinated operation of the multi-microgrid system. Noor *et al.* [21] investigated a demand-side management method in a domestic microgrid system, containing energy storage equipment and electric vehicles. They also explored the application of blockchain technology in the energy management of the microgrid system. The effect that the demand-side management wields on "peak load shifting" and amelioration of the grid load distribution was proven by analyzing real-world cases. Alam *et al.* [22] investigated P2P transaction modes among smart home users. Transaction optimization and price clearing were achieved to enhance the economic efficiency of each household user in the region. The DR factors of energy-using load were explored in the study as well. P2P transaction modes and DR factors are also analyzed in details according to real-world cases of economic benefit among smart home users.

There is indeed a sound theoretical and model foundation for the research conducted in the present study. However, existing research has some limitations. First, some research considers the impact of DR but do not recognizes the effects of flexible load regulation strategies on the transaction of microgrid systems. Diverse load demands in the microgrid system often create a large schedulable space. The composition varies corresponding to the cost and benefit due to the distinct compositions of the internal equipment and loads of different microgrid systems. Unified pricing modes may also sabotage the interests of certain entities in exchange to maximize the union's interests. The aggregators require each microgrid system to report its own production and energy consumption information, which may interfere with the autonomy and privacy of the microgrid system.

Despite some research on applying game theory in P2P transactions, the game relationship involved in multi-microgrid distributed P2P transactions has yet to be fully understood. A simple cooperative game or non-cooperative game do not fully reflect the relationship between participants in all aspects of the transaction. Many extant studies on multi-microgrid transactions only involve the transaction mode from the economic point of view, but do not explicitly study the impact of distributed transactions between microgrid systems on the operation of distribution networks in a specific region.

To resolve these problems, a distributed day-ahead P2P trading for multi-microgrids is investigated in this study. Single microgrid autonomous scheduling, microgrid clustering distributed transactions, and distribution networks are considered to comprehensively analyze the impact of P2P transaction modes on the active distribution network with multiple microgrids. The main contributions of this paper are summarized as follows.

(1) A non-cooperative game model and Stackelberg game model are constructed to analyze the relationship among sellers and between sellers and buyers of microgrid systems. The interest of each microgrid system is guaranteed as the game model is improved from the "sell" and the "buy" link.

(2) The technical and economic benefits brought by P2P distributed transaction mode to the microgrid system and distribution network are quantitatively analyzed with specific indicators, i.e., the value tapping index and the energy balance index. While exploring the advantages of P2P trading, the factors affecting the benefits are also analyzed.

(3) Methods that based on the market capacity for controlling distribution network congestion are considered in the context of real-world distributed market operation and trading scenarios. The effect of P2P trading on distribution network operation is further explained.

The rest of this paper is organized as follows. Section II describes the overall framework of distributed P2P transactions for multi-microgrids in the active distribution network. Section III presents the terminal flexibility load DR model, which includes price DR load, and the autonomous operation scheduling optimization model of the market entity. Section IV applies a non-cooperative game model and Stackelberg game model to P2P distributed transactions in the microgrid cluster under normal operating conditions. Section V discusses the control methods adopted by the distribution network control center in the case of congestion. Section VI comprehensively analyzes the autonomous operation scheduling results, P2P transaction results, and the impact on the microgrid system and power distribution network through simulation analyses. Section VII summarizes the work.

II. OVERALL SYSTEM FRAMEWORK

The framework of the P2P transaction model proposed in this paper is shown in Figure 1. The microgrid is the primary market participant, consisting terminal users and DES, such as wind turbine (WT) and photovoltaic (PV) components. Only some microgrid systems are equipped with energy storage (ES) devices in the system framework discussed here, as per the economic cost of the device. All microgrids are connected to the utility grid via local distribution networks, and support bilateral transactions. Each microgrid system is equipped with intelligent measurement devices and a microgrid energy service prosumer (MEP). The intelligent measurement devices meter the energy production and load demand of the system, as well as the trading of other systems or the utility grid before sending the data to the MEP for processing. By rationalized P2P transactions, ES equipment and flexible load scheduling, the MEP balances the demand for distributed generation and terminal load in the microgrid system to economically optimize the operation of the microgrid.

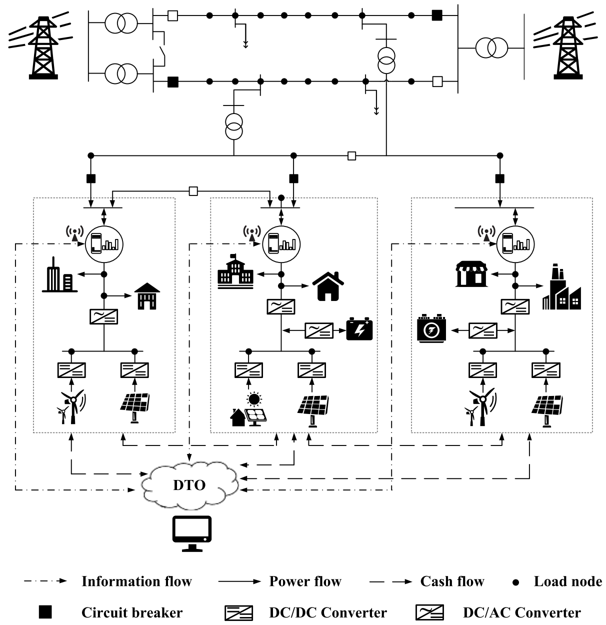

FIGURE 1. Overall framework of active distribution system with multiple microgrids.

Suppose that there is also a distributed transaction operator (DTO) in the local area which is responsible for assisting P2P transactions between microgrid systems. In the P2P transaction, each MEP first embarks on an optimal scheduling for its internal grid consumption demand, ES equipment, flexible load, P2P transacted power, and electricity to the access grid. Based on the internal optimal scheduling, the MEP then submits the quantity of tradable electricity and the quotation to the day-ahead distributed trading market and the DTO, while considering the electricity price signals of the distribution network. The DTO publicizes the information after receiving the transaction information from MEPs. Considering the gaming behaviors between MEPs, the DTO updates the transaction information continuously and assists the MEPs to achieve final P2P transactions under all relevant safety constraints for practical operation in the distribution network.

III. MICROGRID SYSTEM MARKET ENTITY MODEL

A. TERMINAL FLEXIBLE LOAD MODEL

The advancements in energy-utilizing equipment allow flexible loads to effectively realize DR responding to price signals. Given that users have distinct sensitivity to different types of load shifts, the price-based DR load can be considered a relevant example here. The incomfort of DR was measured by the changes in the power and time of flexible load [23]. The equivalent cost of DR from flexible load inconvenience is defined as:

$$C_{\mathrm{MEP},i}^{\mathrm{PDR}} = \alpha_i \sum_{t=1}^{T} \left(P_{\mathrm{MEP},i}^{\mathrm{PDR}}(t) - P_{\mathrm{MEP},i}(t)\right)^2 \tag{1}$$

In summary, the total electrical power demand of the microgrid system during period t is: $P_{\mathrm{MEP},i}^{\mathrm{MG}}(t) = P_{\mathrm{MEP},i}^{\mathrm{PDR}}(t) + P_{\mathrm{MEP},i}^{\mathrm{O}}(t)$, where $P_{\mathrm{MEP},i}^{\mathrm{O}}(t)$ is the power demand of other non-flexible loads during time period t.

B. MICROGRID SYSTEM AUTONOMOUS OPERATION SCHEDULING MODEL

The microgrid system discussed here is under uniformed scheduling and management by the MEP. Regarding the internal scheduling of the microgrid system, the MEP takes optimized costs as the operation goal. Relevant factors include the cost of purchasing energy from the utility grid, the operating costs of equipment, the DR cost of flexible load, and the benefits of selling electricity to the utility grid. In microgrid system i, the benefit function of MEP_i can be expressed as:

$$u_i = \sum_{t=1}^{T} \begin{bmatrix} \left(p_{\mathrm{B},i,\mathrm{G}}(t) P_{\mathrm{B},i,\mathrm{G}}(t)\right) + \left(C_{\mathrm{MEP},i}^{\mathrm{OM}}(t)\right) \\ + \left(C_{\mathrm{MEP},i}^{\mathrm{PDR}}(t)\right) - \left(p_{\mathrm{S},i,\mathrm{G}}(t) P_{\mathrm{S},i,\mathrm{G}}(t)\right) \end{bmatrix} \tag{2}$$

The operation maintenance cost $C_{\mathrm{MEP},i}^{\mathrm{OM}}$ of the MEP_i mainly refers to the life loss cost of ES equipment in the microgrid system [24]:

$$C_{\mathrm{MEP},i}^{\mathrm{OM}} = \frac{\mu^{\mathrm{ES}} C_{\mathrm{invest}}^{\mathrm{ES}}}{N(|ES(t-1) - ES(t)|)} \tag{3}$$

where ES(t) denotes the charge state of the energy of the current ES equipment, and is calculated as follows:

$$ES(t) = \frac{SOC(t)}{E_{SOC}} \tag{4}$$

When conducting autonomous scheduling management of the microgrid system, the MEP should consider the following constraints.

(1) Power balance constraint: When ES is considered, the power supply and demand in the microgrid system should achieve real-time balance.

$$\begin{aligned} &P_i^{\mathrm{PV}}(t) + P_i^{\mathrm{WT}}(t) + P_{\mathrm{D},i}^{\mathrm{ES}}(t) + P_{\mathrm{B},i,\mathrm{G}}(t) \\ &\quad = P_i^{\mathrm{MG}}(t) + P_{\mathrm{C},i}^{\mathrm{ES}}(t) + P_{\mathrm{S},i,\mathrm{G}}(t) \\ &\quad \Rightarrow P_i^{\mathrm{PV}}(t) + P_i^{\mathrm{WT}}(t) + P_{\mathrm{D},i}^{\mathrm{ES}}(t) + P_{\mathrm{B},i,\mathrm{G}}(t) \\ &\quad = P_i^{\mathrm{PDR}}(t) + P_i^{\mathrm{O}}(t) + P_{\mathrm{C},i}^{\mathrm{ES}}(t) + P_{\mathrm{S},i,\mathrm{G}}(t) \end{aligned} \tag{5}$$

(2) ES constraints: ES must meet rated charging and discharging power and rated capacity constraints when in operation:

$$M_{i,\min}^{\mathrm{ES}}(t) \le M_i^{\mathrm{ES}}(t) \le M_{i,\max}^{\mathrm{ES}}(t) \tag{6}$$

$$P_{[\mathrm{C/D}],i}^{\mathrm{ES}}(t) \le P_{[\mathrm{C/D}],i,\max}^{\mathrm{ES}}(t) \tag{7}$$

In addition, in order to meet charge and discharge requirements of ES at the beginning of the next scheduling day, the charge state needs to be consistent at the beginning and end of each scheduling day [25], i.e.,:

$$\eta_C^{\mathrm{ES}} \sum_{t=1}^{T} \left(P_{\mathrm{C},i}^{\mathrm{ES}}(t)\Delta t\right) - \eta_{\mathrm{D}}^{\mathrm{ES}} \sum_{t=1}^{T} \left(P_{\mathrm{D},i}^{\mathrm{ES}}(t)\Delta t\right) = 0 \tag{8}$$

(3) Flexible load constraints

(3a) The total amount of load flexibility is constant. Based on the external price signal, flexible load can be transferred by the MEP to different time periods but the demand for load power is constant [26]. The specific expression of the constraint is as follows:

$$\sum_{t=1}^{T} P_{\mathrm{MEP},i}^{\mathrm{PDR}}(t) = \sum_{t=1}^{T} P_{\mathrm{MEP},i}(t) \tag{9}$$

(3b) Load energy consumption constraint: The load adjusted by DR should meet the actual power usage. It means, neither the basic power load of users can be shed nor can the supply capacity of the microgrid system be violated. The specific expression is as follows:

$$\min\left(P_{\mathrm{MEP},i}(t)\right) \le P_{\mathrm{MEP},i}^{\mathrm{PDR}}(t) \le \max\left(P_{\mathrm{MEP},i}(t)\right) \tag{10}$$

where the maximum supply capacity of the microgrid system is constrained by equipment configuration and the tie-line capacity with the utility grid.

To summarize, the MEP models the minimization of benefit function in Equation (2) as the objective function, but P2P transactions are not considered. With the strategies of utility power purchase strategy, ES equipment operation, and flexibility load adjustment as decision variables, the MEP performs autonomous scheduling and management of the microgrid system. The specific scheduling framework of the MEP is shown in Figure 2, where the red outline represents the schedulable part of the MEP. This model has a relatively sophisticated solution algorithm, which can be solved in CPLEX/GUROBI/LINGO. In this study, CPLEX was used to obtain solutions based on the YALMIP platform in MATLAB [27].

IV. MARKET GAME MODEL AMONG MICROGRID SYSTEMS

A. MARKET ROLE AND UTILITY FUNCTION OF MEP UNDER P2P TRADING MODE

Under normal operating conditions, MEPs may have insufficient or surplus power when participating in autonomous scheduling and management due to the fluctuation of distributed power output and terminal load demand. Under the traditional trading mode, they trade directly with the DTO.

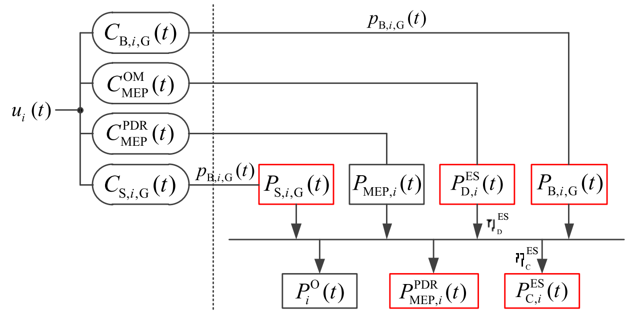

FIGURE 2. MEP autonomous scheduling framework.

Conversely, in P2P distributed transactions, MEPs can conduct nearby distributed transactions among them, thus facilitating the accommodation of local distributed energy.

When P2P distributed transactions are considered, the utility function of MEP_i is further considered the impact of transactions with other MEPs according to Equation (2). The specific expression is as follows:

$$u_i = \sum_{t=1}^{T} \left[\begin{array}{l} \left(p_{\mathrm{B},i,\mathrm{G}}(t) P_{\mathrm{B},i,\mathrm{G}}(t)\right) + \left(C_{\mathrm{MEP},i}^{\mathrm{OM}}(t)\right) + \left(C_{\mathrm{MEP},i}^{\mathrm{PDR}}(t)\right) \\ + b_i(t)\left(p_{\mathrm{B},i}(t) P_{\mathrm{B},i}^{\mathrm{ex}}(t)\right) - s_i(t)\left(p_{\mathrm{S},i}(t) P_{\mathrm{S},i}^{ex}(t)\right) \\ - \left(p_{\mathrm{S},i,G}(t) P_{\mathrm{S},i,G}(t)\right) \end{array} \right] \tag{11}$$

where $s_i(t)$ and $b_i(t)$ are respective prosumer identifiers. During time period t, there are $b_i(t) = 1$ and $s_i(t) = 0$ if the MEP_i is a buyer; or, $b_i(t) = 0$ and $s_i(t) = 1$ if the MEP_i is a seller.

The MEPs participating in the P2P transaction are also required to meet the power price constraints and power flow constraints [25] of power distribution systems, apart from autonomous operation constraints shown Equations (5)-(10).

With electricity price constraint, the response of other MEPs to the price is taken into account when setting prices at which they sell or purchase to/from other MEPs so as to maximize profits. When determining the price of electricity, MEPs are under the following constraints:

$$p_{\mathrm{S},i,\min}(t) \le p_{\mathrm{S},i}(t) \le p_{\mathrm{S},i,\max}(t) \tag{12}$$

$$\frac{1}{T}\sum_{t=1}^{T} p_{\mathrm{S},i}(t) \le \frac{1}{T}\sum_{t=1}^{T} p_{\mathrm{B},i,\mathrm{G}}(t) \tag{13}$$

The power flow constraints serve mainly to prevent network congestion problems that may occur in the actual operation of the distribution network.

B. GAME RELATIONSHIP AMONG SELLERS

In distributed P2P transactions among MEPs, it is assumed that each seller MEP tries to maximize its own profits by selling electric energy to the buyer MEPs or to the utility power grid. The seller MEPs are independent from each other and there is no cooperative relationship among them. It is also assumed that the seller MEPs act rationally during transactions. Under these assumptions, a non-cooperative game model can be developed to describe the competitive relationship among the seller MEPs. Here, the game participants are the seller MEPs participating in the P2P transaction. The game strategy is the tradable electricity price and quantity $\langle P_{\mathrm{M}}, p_{\mathrm{M}} \rangle$ for each seller MEP. Based on the cost utility function of autonomous operation, the MEP divides the final acceptable quotation interval by n together with the range interval in Equation (12) to determine the feasible quotation of the MEP. The game utility is the cost/benefit of each seller MEP.

The game process among seller MEPs is a dynamic process. The Nash equilibrium is finally achieved by the game, including electricity price and electricity quantity sold by each seller MEP. The conditions for its existence include: 1) The number of players in the game is limited and the participants are denoted as $j \in S$; 2) the quote range for each MEP is certain. After being equally divided into n subintervals, the new quote scope can guarantee that the game strategy is closed and bounded; 3) The utility function is continuous in the game strategy space. The non-cooperative game environment set between seller MEPs satisfies the existence condition of Nash equilibrium state [17]. The improved iterative search algorithm [28] is used here to solve this Nash game problem. The iterative process of the game is as follows.

In the first iteration, each seller submits tradable electricity price and electricity quantity to the DTO according to its autonomous scheduling. While satisfying the system security level constraint, the DTO publishes the first-round iteration results and feeds back the information to each seller. Each seller modifies the bidding according to the feedback information and then bids again, completing one iteration. Assume that the bidding power and price of each MEP in the k-round iteration are as follows:

$$\left\{ \left\langle P_{\mathrm{M1}}^{k}, p_{\mathrm{M1}}^{k} \right\rangle, \left\langle P_{\mathrm{M2}}^{k}, p_{\mathrm{M2}}^{k} \right\rangle, \cdots, \left\langle P_{\mathrm{M}(S-1)}^{k}, p_{\mathrm{M}(S-1)}^{k} \right\rangle, \left\langle P_{\mathrm{MS}}^{k}, p_{\mathrm{MS}}^{k} \right\rangle \right\} \tag{14}$$

Similarly, the bidding power and price of each MEP in the $k+1$th iteration are:

$$\left\{ \left\langle P_{\mathrm{M1}}^{k+1}, p_{\mathrm{M1}}^{k+1} \right\rangle, \left\langle P_{\mathrm{M2}}^{k+1}, p_{\mathrm{M2}}^{k+1} \right\rangle, \cdots, \left\langle P_{\mathrm{M}(S-1)}^{k+1}, p_{\mathrm{M}(S-1)}^{k+1} \right\rangle, \left\langle P_{\mathrm{MS}}^{k+1}, p_{\mathrm{MS}}^{k+1} \right\rangle \right\} \tag{15}$$

Set $u_{\mathrm{M}j}$ to be the utility function value of the j-th MEP, then $\arg\max u_{\mathrm{M}j}(\langle P_{\mathrm{M1}}^{k}, p_{\mathrm{M1}}^{k}\rangle, \langle P_{\mathrm{M2}}^{k}, p_{\mathrm{M2}}^{k}\rangle, \cdots, \langle P_{\mathrm{M}(S-1)}^{k}, p_{\mathrm{M}(S-1)}^{k}\rangle,$ $\langle P_{\mathrm{M}j}^{k}, p_{\mathrm{M}j}^{k}\rangle$
$\langle P_{\mathrm{MS}}^{k}, p_{\mathrm{MS}}^{k}\rangle)$ is the bidding tradable power and price corresponding to the j-th MEP in the k-th round. The k-th iteration equation is expressed as follows (16), as shown at the bottom of the next page.

When the tradable electricity and price in two rounds of iterations are equal, then:

$$\begin{aligned} &\left\{ \left\langle P_{\mathrm{M1}}^{k+1}, p_{\mathrm{M1}}^{k+1} \right\rangle, \left\langle P_{\mathrm{M2}}^{k+1}, p_{\mathrm{M2}}^{k+1} \right\rangle, \cdots, \left\langle P_{\mathrm{M}(S-1)}^{k+1}, p_{\mathrm{M}(S-1)}^{k+1} \right\rangle, \left\langle P_{\mathrm{MS}}^{k+1}, p_{\mathrm{MS}}^{k+1} \right\rangle \right\} \\ &= \left\{ \left\langle P_{\mathrm{M1}}^{k}, p_{\mathrm{M1}}^{k} \right\rangle, \left\langle P_{\mathrm{M2}}^{k}, p_{\mathrm{M2}}^{k} \right\rangle, \cdots, \left\langle P_{\mathrm{M}(S-1)}^{k}, p_{\mathrm{M}(S-1)}^{k} \right\rangle, \left\langle P_{\mathrm{MS}}^{k}, p_{\mathrm{MS}}^{k} \right\rangle \right\} \end{aligned} \tag{17}$$

In effect, no seller MEP can obtain a higher utility function value by changing the bidding power or price. The solution can be regarded as a Nash game equilibrium solution. Once the non-cooperative game reaches its Nash equilibrium point, any change in the equilibrium quoted behavior will result in a loss of benefit.

C. GAME RELATIONSHIP BETWEEN SELLERS AND BUYERS

At the time of pricing, the seller MEPs consider not only their own interests but also the price elasticity of the buyer MEPs. Namely, there is also a profit game relationship between the seller MEPs and the buyer MEPs. The seller MEPs act as the management party and have priority pricing power. The game relationship between seller and buyer MEPs is described as a Stackelberg game. At the upper level, the seller MEPs are the leader in setting the transaction price. At the lower level, the buyer MEPs play the role of a follower, responding to the transaction price signal and sending energy demand to the seller MEPs. In general, the participants in the Stackelberg game are the seller MEPs and buyer MEPs participating in the P2P transaction. The game strategy is electricity price and quantity of electricity sold for each seller MEP and the choice of each buyer MEP to the seller MEPs; the game utility is the respective income/cost of the seller/buyer MEPs.

If the sum $\Gamma_{S,j}^{\text{MEP}}$ and $\Gamma_{B,l}^{\text{MEP}}$ are the strategy set of the seller MEP$_j$ and the buyer MEP$_l$, respectively, then the strategy sets of all seller and buyer MEPs are: $\Gamma_S^{MEP} = \Gamma_{S,1}^{\text{MEP}} \times \Gamma_{S,2}^{\text{MEP}} \times \cdots \times \Gamma_{S,j}^{\text{MEP}}$; $\Gamma_B^{\text{MEP}} = \Gamma_{B,1}^{\text{MEP}} \times \Gamma_{B,2}^{\text{MEP}} \times \cdots \times \Gamma_{B,l}^{\text{MEP}}$. For the seller MEP$_j$, assuming that $\left\langle P_j^*, p_j^* \right\rangle \in \Gamma_S^{\text{MEP}}$ is a Stackelberg game equilibrium strategy, then:

$$\begin{aligned} &u_{\text{S},j}^{\text{MEP}}\left(\left\langle P^{k*}, p^{k*}\right\rangle; z(\left\langle P^{k*}, p^{k*}\right\rangle)\right) \geq \\ &u_{\text{S},j}^{\text{MEP}}\left(\left\langle P_j^k, p_j^k\right\rangle, \left\langle P_{-j}^{k*}, p_{-j}^{k*}\right\rangle; z(\left\langle P_j^k, p_j^k\right\rangle, \left\langle P_{-j}^{k*}, p_{-j}^{k*}\right\rangle)\right) \end{aligned} \tag{18}$$

The upper-level seller MEPs reach Nash equilibrium via price competition after they receive the feedback of $z(\left\langle P^{k*}, p^{k*}\right\rangle)$. The equilibrium price is once again reported to all the buyer MEPs, and the above processes $\langle P^*, p^* \rangle$ & $z(\langle P^*, p^* \rangle)$ are repeated until the sum remains stable. The vector $(\langle P^*, p^* \rangle, z(\langle P^*, p^* \rangle))$ is then the Stackelberg game equilibrium.

The game may not reach the Nash equilibrium or the Stackelberg game equilibrium if the maximum number of iterations is small or the MEP default bid range is unreasonable. The bid interval may be affected by weather or related policies. The process ends if the Nash equilibrium is not reached at a specified maximum number of iterations. The transaction in the distributed P2P market thus fails. Each MEP in this case still achieves internal power balance in a traditional manner of bilateral transaction with the DTO.

V. CONGESTION MANAGEMENT MODEL BASED ON MARKET CAPACITY

Under normal operating conditions, the DTO participates in market transactions at a predetermined time-of-use (TOU) price. The traditional distribution network is affected by the vertical regulation of the power system scheduling organization and its own structural characteristics, so the network capacity is sufficient to meet the power demand of the distribution network without congestion [29]. However, with the wide access of the user-side microgrid system, renewable energy, and various flexible loads, most users prioritize their own economy in conducting transactions or developing scheduling plans, which complicates the power market environment. There are often a large-scale "aggregation" of loads in time and the unbalanced distribution of power flows in space which can congest the system [30]. High-permeability penetration of renewable energy and demand for low-carbon replacements can create power reverse peaks and load demand peaks in the network [31].

The DTO take two typical responses to any congestion in the distribution network [32]. One is direct control based on distribution network reconfiguration, reactive power control, load shedding, and installation of soft open point (SOP) [33]. The second involves indirect control, where market mechanisms are employed to regulate the system [34]. Given that the scope of this study is distributed market transactions, the distribution capacity market approach is used to solve the congestion problem here.

The power flow is calculated by DisFlow algorithm [35]. When congestion occurs, the congestion cost function is first constructed from the perspective of the DTO. This function

$$\begin{cases} \left\langle P_{\text{M1}}^{k+1}, p_{\text{M1}}^{k+1}\right\rangle = \arg \max\limits_{\langle P_{\text{M1}}^k, p_{\text{M1}}^k \rangle} u_{\text{M1}}\left(\left\langle P_{\text{M1}}^k, p_{\text{M1}}^k\right\rangle, \left\langle P_{\text{M2}}^k, p_{\text{M2}}^k\right\rangle, \cdots, \left\langle P_{\text{M}(S-1)}^k, p_{\text{M}(S-1)}^k\right\rangle, \left\langle P_{\text{M}S}^k, p_{\text{M}S}^k\right\rangle\right) \\ \left\langle P_{\text{M2}}^{k+1}, p_{\text{M2}}^{k+1}\right\rangle = \arg \max\limits_{\langle P_{\text{M2}}^k, p_{\text{M2}}^k \rangle} u_{\text{M2}}\left(\left\langle P_{\text{M1}}^{k+1}, p_{\text{M1}}^{k+1}\right\rangle, \left\langle P_{\text{M2}}^k, p_{\text{M2}}^k\right\rangle, \cdots, \left\langle P_{\text{M}(n-1)}^k, p_{\text{M}(n-1)}^k\right\rangle, \left\langle P_{\text{M}n}^k, p_{\text{M}n}^k\right\rangle\right) \\ \cdots\cdots \\ \left\langle P_{\text{M}(S-1)}^{k+1}, p_{\text{M}(S-1)}^{k+1}\right\rangle = \arg \max\limits_{\langle P_{\text{M}(S-1)}^k, p_{\text{M}(S-1)}^k \rangle} u_{\text{M}(S-1)}\left(\left\langle P_{\text{M1}}^{k+1}, p_{\text{M1}}^{k+1}\right\rangle, \left\langle P_{\text{M2}}^{k+1}, p_{\text{M2}}^{k+1}\right\rangle, \cdots, \left\langle P_{\text{M}(S-1)}^{k+1}, p_{\text{M}(S-1)}^{k+1}\right\rangle, \left\langle P_{\text{M}S}^k, p_{\text{M}S}^k\right\rangle\right) \\ \left\langle P_{\text{M}S}^{k+1}, p_{\text{M}S}^{k+1}\right\rangle = \arg \max\limits_{\langle P_{\text{M}n}^k, p_{\text{M}n}^k \rangle} u_{\text{M}n}\left(\left\langle P_{\text{M1}}^{k+1}, p_{\text{M1}}^{k+1}\right\rangle, \left\langle P_{\text{M2}}^{k+1}, p_{\text{M2}}^{k+1}\right\rangle, \cdots, \left\langle P_{\text{M}(S-1)}^{k+1}, p_{\text{M}(S-1)}^{k+1}\right\rangle, \left\langle P_{\text{M}S}^k, p_{\text{M}S}^k\right\rangle\right) \end{cases} \tag{16}$$

represents the power deviation cost of the net load demand of the microgrid system during each scheduling period, which is:

$$C_{\text{MEP},i}(t) = \mu_{\text{MEP},i}(t)\Big[\tilde{P}_i(t) - \big(\left|P_{\text{B},i,\text{G}}(t)\right| + \left|P_{\text{S},i,\text{G}}(t)\right| + \left|P^{\text{ex}}_{\text{B},i}(t)\right| + \left|P^{\text{ex}}_{\text{S},i}(t)\right|\big)\Big]^2 \quad (19)$$

where $\tilde{P}_i$ represents the decision variables of each microgrid related to the exchange of power with the utility power grid or other microgrid systems, which is related to $P_{\text{B},i,\text{G}}$, $P_{\text{S},i,\text{G}}$, $P^{\text{ex}}_{\text{S},i}$, and $P^{\text{ex}}_{\text{B},i}$.

In a network congestion situation, the main goal of each microgrid is to minimize the congestion cost while meeting the DTO operating requirements. That is:

$$\begin{aligned}
&\min \sum_{t=1}^{T} \mu_{\text{MEP},i}(t) \\
&\Big[\tilde{P}_i(t) - \big(\left|P_{\text{B},i,\text{G}}(t)\right| + \left|P_{\text{S},i,\text{G}}(t)\right| + \left|P^{\text{ex}}_{\text{B},i}(t)\right| + \left|P^{\text{ex}}_{\text{S},i}(t)\right|\big)\Big]^2 \\
&s.t. \\
&\tilde{P}_i(t) \le P_{\text{cap}}(t)
\end{aligned} \quad (20)$$

The above optimization model is a convex optimization problem. The shadow price $\Lambda(t)$ is then introduced as a Lagrangian multiplier [36]. The above optimization model can be converted into the following Lagrangian problem:

$$\begin{aligned}
L = &\sum_{t=1}^{T} \mu_{\text{MEP},i}(t) \\
&\Big[\tilde{P}_i(t) - \big(\left|P_{\text{B},i,\text{G}}(t)\right| + \left|P_{\text{S},i,\text{G}}(t)\right| + \left|P^{\text{ex}}_{\text{B},i}(t)\right| + \left|P^{\text{ex}}_{\text{S},i}(t)\right|\big)\Big]^2 \\
&+ \sum_{t=1}^{T} \Lambda(t)\Big(\tilde{P}_i(t) - P_{\text{cap}}(t)\Big)
\end{aligned} \quad (21)$$

Each microgrid thus re-optimizes the external exchange power $P_i^*(\Lambda)$ based on the shadow price set by the DTO.

The optimization shown in Equation (20) can be dualized as (22), as shown at the bottom of the next page.

The above dual problem is solved by the projection gradient method [37], and the direction of search of the optimization variable Λ(t) is:

$$\Lambda(t)^{k+1} = \Lambda(t)^k + \beta_k \cdot S(t) \quad (23)$$

where β is the learning factor, and $S(t)$ is the sub-gradient search direction.

The specific calculation method is:

$$S(t) = P_i^*(\Lambda) - P_{\text{cap}}(t) \quad (24)$$

In summary, the flow of distributed algorithms involved in DTO and MEP in the P2P trading market and distribution network is as follows. The relation between DTO and MEP is in Figure 3.

Algorithm 1 MEP autonomous operation scheduling plan

Input: Predicting curve of load demand and distributed power output, configuration, capacity and constraints of ES equipment.
Output: Tradable power and demand power during the scheduling period.
for all $t \in T$ **do**
Based on the objective function (Equation (2)), optimize the operating economy of the microgrid system by adjusting the operating state of the ES device and the flexible load supply.
On the basis of autonomous operation optimization in a microgrid system, calculate the tradable and demand power during different time periods.
end for

Algorithm 2 Stackelberg game equilibrium between seller MEPs and buyer MEPs

Input: Seller MEPs provide the tradable power and trading price. Buyer MEPs provide the demand of power.
Output: Seller MEPs and buyer MEPs eventually reach the equilibrium state of Stackelberg game: $(\langle P^*, p^*\rangle, z(\langle P^*, p^*\rangle))$.
$k = 0$
do
$k = k+1$
for all $j \in S$; $i \in B$ **do**
Execute Algorithm 3 and based on Equation (18), calculate:
$u^{MEP}_{\text{S},j}\left(\left\langle P^{k*}, p^{k*}\right\rangle; z(\left\langle P^{k*}, p^{k*}\right\rangle)\right)$
end for
Algorithm iteration is conducted based on Equation (16). The electricity price for trade and the tradable power offered by the seller MEPs are updated.
While

$$u^{\text{MEP}}_{\text{S},j}\left(\left\langle P^{k*}, p^{k*}\right\rangle; z(\left\langle P^{k*}, p^{k*}\right\rangle)\right) \ge u^{\text{MEP}}_{\text{S},j}\left(\left\langle P^{k}_{j}, p^{k}_{j}\right\rangle, \left\langle P^{k*}_{-j}, p^{k*}_{-j}\right\rangle; z(\left\langle P^{k}_{j}, p^{k}_{j}\right\rangle, \left\langle P^{k*}_{-j}, p^{k*}_{-j}\right\rangle)\right)$$

VI. CASE ANALYSIS AND COMPARISON

A. CASE OVERVIEW

In this study, a modified IEEE 33-node power distribution system [38] in Fig. 4 is adopted for demonstrating the proposed scheme. Several nodes are connected with microgrid systems [39] including smart buildings, DES, and ES equipment. The load types in microgrid systems and the configuration of devices are shown in Table 1.

The specifications of the ES equipment in the microgrid system are shown in Table 2. Its initial capacity is set as 50% of the total capacity, and the maximum charge and discharge power as 20% of the capacity [24], [40]. The typical daily load curves and distributed power output curves for

Algorithm 3 Non-cooperative game equilibrium among seller MEPs

Input: Seller MEPs offer the tradable power and the price for trade.

Output: Seller MEPs eventually reache the Nash equilibrium state:

$$\left\{\left\langle P^*_{\mathrm{M1}}, p^*_{\mathrm{M1}}\right\rangle, \left\langle P^*_{\mathrm{M2}}, p^*_{\mathrm{M2}}\right\rangle, \cdots, \left\langle P^*_{\mathrm{M}(S-1)}, p^*_{\mathrm{M}(S-1)}\right\rangle, \left\langle P^*_{\mathrm{M}S}, p^*_{\mathrm{M}S}\right\rangle\right\}$$

Each seller MEP submits the initialization trade price and the tradable power to the bidding system

$k = 0$

for all $t \in T$

do

$k = k+1$

for all $j \in S$ **do**

Execute Algorithm 2 and based on Equation (17), calculate:

$$\left\langle P^k_{\mathrm{M1}}, p^k_{\mathrm{M1}}\right\rangle, \left\langle P^k_{\mathrm{M2}}, p^k_{\mathrm{M2}}\right\rangle, \cdots, \left\langle P^k_{\mathrm{M}(S-1)}, p^k_{\mathrm{M}(S-1)}\right\rangle, \left\langle P^k_{\mathrm{M}S}, p^k_{\mathrm{M}S}\right\rangle$$

end for

Algorithm iteration was conducted based on Equation (16). The trade price and the tradable power offered by the seller MEPs are updated.

While

$$\left\{\left\langle P^{k+1}_{\mathrm{M1}}, p^{k+1}_{\mathrm{M1}}\right\rangle, \left\langle P^{k+1}_{\mathrm{M2}}, p^{k+1}_{\mathrm{M2}}\right\rangle, \cdots, \left\langle P^{k+1}_{\mathrm{M}(S-1)}, p^{k+1}_{\mathrm{M}(S-1)}\right\rangle, \left\langle P^{k+1}_{\mathrm{M}S}, p^{k+1}_{\mathrm{M}S}\right\rangle\right\}$$
$$= \left\{\left\langle P^k_{\mathrm{M1}}, p^k_{\mathrm{M1}}\right\rangle, \left\langle P^k_{\mathrm{M2}}, p^k_{\mathrm{M2}}\right\rangle, \cdots, \left\langle P^k_{\mathrm{M}(S-1)}, p^k_{\mathrm{M}(S-1)}\right\rangle, \left\langle P^k_{\mathrm{M}S}, p^k_{\mathrm{M}S}\right\rangle\right\}$$

Algorithm 4 Market-based active distribution network congestion management

Initialization: For the dual variable $\Lambda(t)^k := \Lambda_0(t) \geq 0$, for example, let $\Lambda_0(t) = 0$ or $\Lambda_0(t) = \Lambda(t-1)$.

Output: The shadow price $\Lambda(t)$ and the optimal exchange power $P^*_i(\Lambda)$ of each microgrid system following the end of congestion management.

for all $t \in T$, $i \in$MG **do**

loop

Based on the result $P^*_i(\Lambda)$ of Equation (22), DTO adopts Equation (24) to calculate the search gradient direction and Equation (23) to update until the shadow price $\Lambda(t)$ is converged.

The new shadow price, together with the conventional electricity price determined by the DTO, make up the electricity price at the congestion period. The DTO announces the price to each MEP. In accordance with the price, the MEP then amends its autonomous scheduling strategy. The iteration ends when $\Lambda(t) < 0$.

end

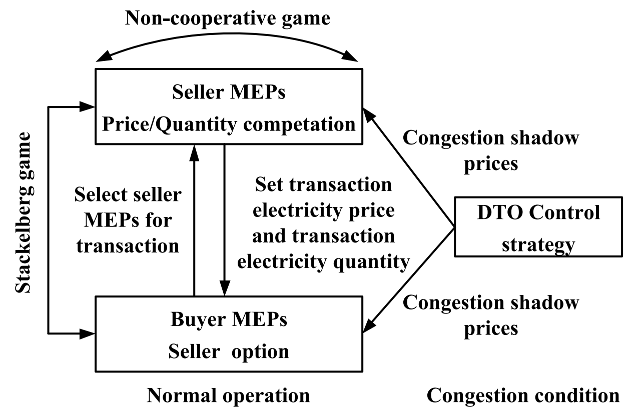

FIGURE 3. Game relationship in P2P trading market.

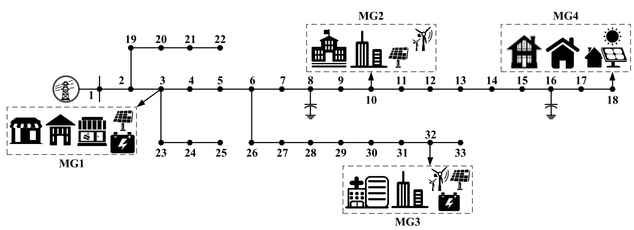

FIGURE 4. Architecture of the test system.

different microgrid systems are in Figures 5 and 6, respectively, where 20% of the load demand of MG1, MG2, and MG4 is flexible; 30% of the load demand of MG3 is flexible. The sensitivity coefficients of load are $\alpha_{\mathrm{MG1}} = 0.01$, $\alpha_{\mathrm{MG2}} = 0.01$, $\alpha_{\mathrm{MG3}} = 0.03$, and $\alpha_{\mathrm{MG4}} = 0.01$. The TOU price set by the DTO is shown in Figure 7. The power system includes three types of lines with the current upper limits of 400A, 300A, and 200A [41]. The voltage level is 12.66 kV and the power factor is 0.8. The upper limit of the active power of line is 7017 kW, 5263 kW, and 3508 kW, respectively.

$$\max\ f(\Lambda) = \inf \left(\begin{array}{l} \sum\limits_{t=1}^{T} \mu_{\mathrm{MEP},i}(t) \left[P^*_i(\Lambda) - \left(\left|P_{\mathrm{B},i,\mathrm{G}}(t)\right| + \left|P_{\mathrm{S},i,\mathrm{G}}(t)\right| + \left|P^{\mathrm{ex}}_{\mathrm{B},i}(t)\right| + \left|P^{\mathrm{ex}}_{\mathrm{S},i}(t)\right| \right) \right]^2 \\ + \sum\limits_{t=1}^{T} \Lambda(t) \left(P^*_i(\Lambda) - P_{\mathrm{cap}}(t) \right) \end{array} \right) \tag{22}$$

TABLE 1. Microgrid system information.

No.	Equipment configuration	Building types
MG 1	PV: 980 kW; ES: 300 kWh	Supermarket 1; Supermarket 2; Restaurant
MG 2	PV: 350 kW; WT: 450 kW	School; Office building
MG 3	PV: 200 kW; WT: 300 kW; ES: 180 kWh	Hospital; Office building
MG 4	PV: 700 kW	Resident buildings

TABLE 2. Device parameters.

Parameters	Values
μ^{ES}	1
C^{ES}_{invest} (CNY/kW·h)	600
$\eta^{ES}_{C}/\eta^{ES}_{D}$ (%)	90%
γ	0.1

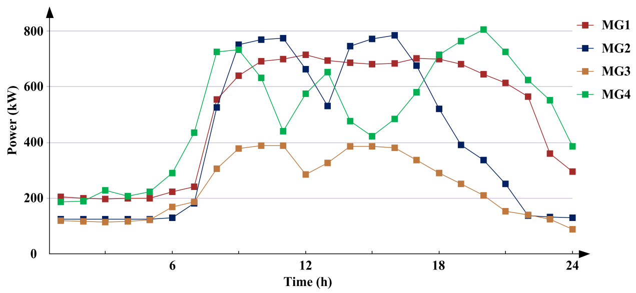

FIGURE 5. Typical load curves of different microgrid systems.

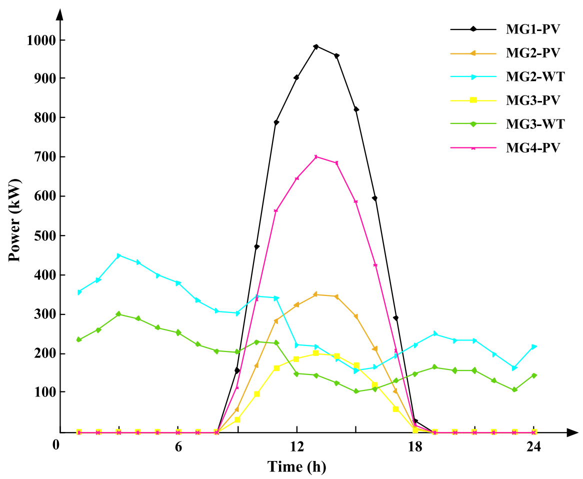

FIGURE 6. Distributed power output of different microgrid systems.

B. ANALYSIS OF AUTONOMOUS SCHEDULING AND TRANSACTION RESULTS

The daily autonomous scheduling operation and P2P transaction outcomes of the multi-microgrid system are analyzed based on the case setting with a scheduling time step of $\Delta t = 1$h. The autonomous scheduling results of different microgrid systems are shown in Figure 8. As seen, MEPs use as much clean energy as possible to meet user demands for electricity and reduce the cost of purchased electricity, as WT and PV are cost-effective clean energy sources [42].

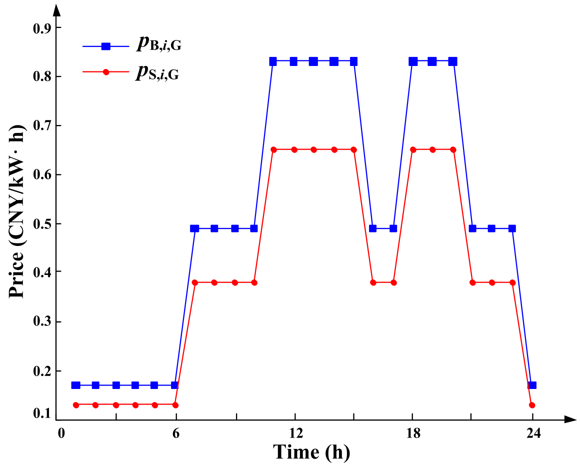

FIGURE 7. Regional TOU power price.

Two microgrid systems with ES devices, MG1 and MG3, are analyzed in details here. In the energy schedule of MG1, PV output is abundant from 11:00 to 14:00. During this period, MG1 is self-sufficient and has excess power available for trading. At other time, insufficient PV output forces MG1 to purchase power from outside sources to meet its own demand. The ES equipment is discharged when electricity price is higher (from 16:00 to 20:00) to satisfy part of electricity load demand and reduce the cost of purchased electricity. ES charging is initiated at the moment when the output of the distributed power source is higher or the electricity price is lower than a threshold. The MEP then keeps load requirements flexible to the greatest extent when TOU price is low or the distributed power output is sufficient to keep costs low. All MEPs take operating economy as the scheduling objective; the scheduling strategies of MG3 and MG1 are similar. Because the flexible load in MG3 is relatively large, the energy consumption characteristic of the flexible load is not as obvious as that in MG1 because of the high sensitivity of the load.

Based on the analysis of the autonomous scheduling results of each microgrid system, the transaction results at a typical time point in regards to P2P transactions are shown in Figure 9.

At 1:00, MG1 and MG4 have 127.7 kW and 128.7 kW demand for electricity, respectively. However, MG2 and MG3 have 231.4 kW and 170.6 kW of tradable electricity. Considering the circuit network transmission loss, the tradable power MG2 and MG3 possess separately at this time does not satisfy the entire transaction demand of the buyer MEPs. Compared with MG3, MG2 has more tradable electric energy and is more active in the transaction. Therefore, MG2 continuously reduces prices to sell as much electricity as possible at the beginning of the sellers' game to optimize profit. MG3 has less tradable electric energy

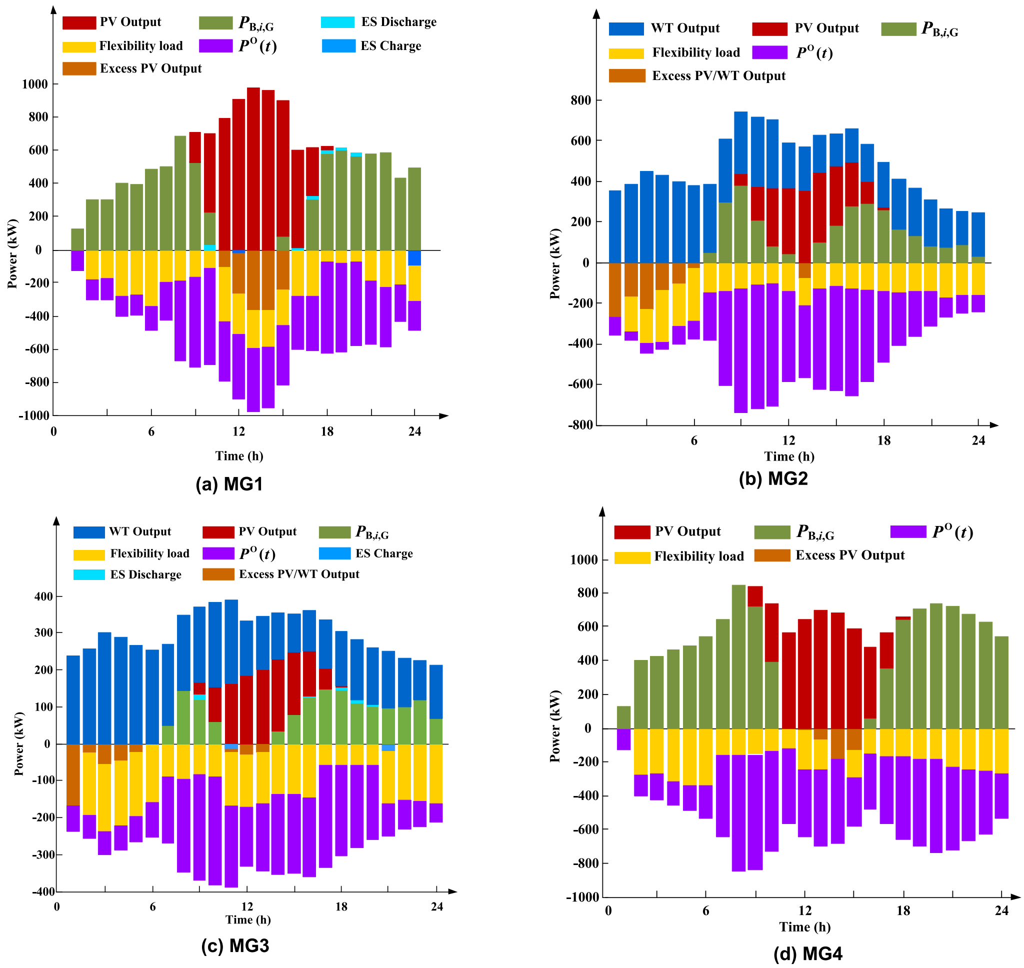

FIGURE 8. **Autonomous scheduling results of different microgrid systems.**

and continuously reduces the electricity selling price in the early stage of the game to attract other microgrid systems to conduct P2P transactions. However, the buyer MEP prefers to trade with MG2 due to its relative abundance of tradable electric energy; considering that the tradable electric energy owned by MG2 can only meet the trading requirements of one microgrid system, MG3 can gradually increase its electricity selling price in the later stage. Both MG1 and MG4 are more inclined to trade with MG2, as it announced a lower electricity sales price which was cleared through the non-cooperative game among seller MEPs. But with limited tradable power, MG2 decides to preferentially trade with MG4 as it demands a larger amount of power. In addition, MG1 will trade with MG2 and MG3 concurrently while trading its remaining power demand with the DTO.

At 3:00, MG1 and MG4 have demand for 300.9 kW and 427.8 kW, respectively. However, MG2 and MG3 have 230.1 kW and 57.6 kW of tradable electricity, respectively. At this time, there are multiple sellers and multiple buyers are in short supply. Compared to the transaction demand of MG1 and MG4, MG2 and MG3 have less tradable electricity. To secure profits, MG2 and MG3 raise their electricity sales prices as much as possible within the feasible quotation range. Compared to the TOU electricity price of the distribution network, MG2 and MG3 have relatively low electricity selling prices; MG1 and MG4 give priority to trading with MG2 and MG3 to meet some of their own electricity demand while the remaining demand is satisfied by the DTO.

At 6:00, MG1 and MG4 have power purchase requirements of 483.86 kW and 538 kW, respectively; MG2 has 27.5 kW of tradable power. This is a single-seller and multi-buyer "short supply" scenario, where MG2 preferentially chooses to trade with MG4 with greater demand for electricity. The relatively small PV output during this period and gradual increase in power load demand create a higher-load demand that congests the distribution network. The shadow price set by the DTO to ease congestion results in a higher transaction price for P2P during this time. MG4 is located at the end node of the feeder line, so it is greatly affected by this and presents a power shortage.

At 12:00, MG2 has a power demand of 44.2 kW. MG1, MG3, and MG4 have 267.1 kW, 21.1 kW, and

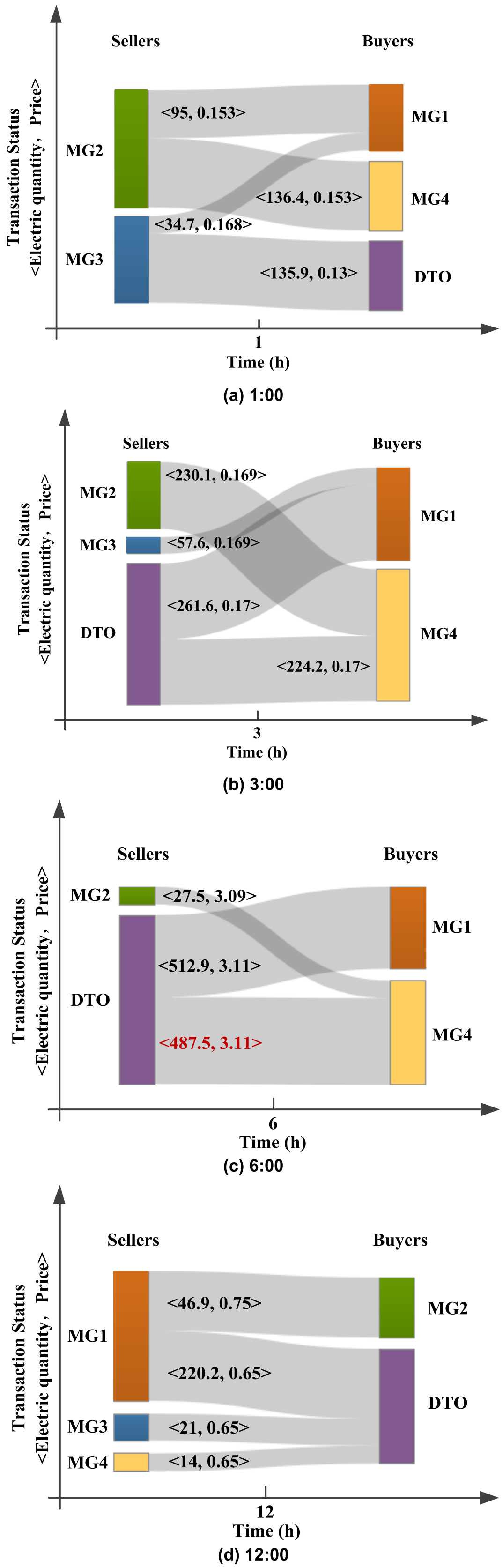

FIGURE 9. P2P distributed transaction results.

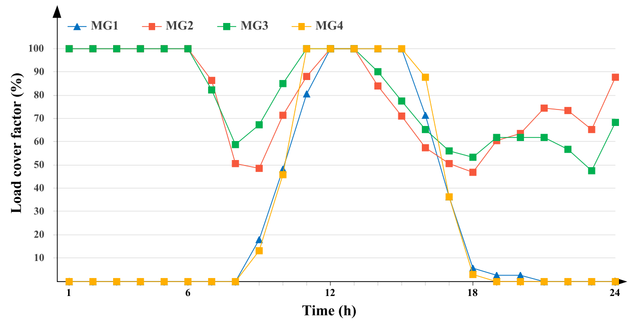

FIGURE 10. The load cover factor of different microgrid systems.

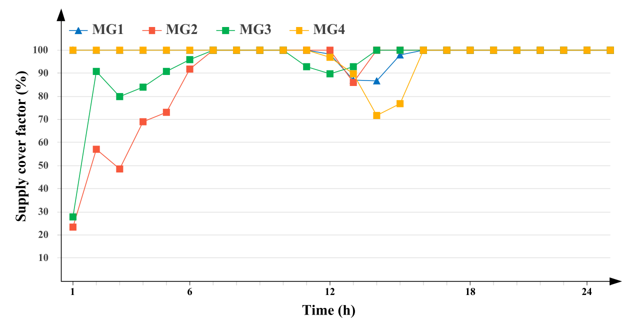

FIGURE 11. The supply cover factor of different microgrid systems.

14.1 kW of tradable power, respectively. This is a multi-seller, single-buyer "supply exceeds demand" scenario. MG1 has more tradable electricity than MG3 or MG4 at this time. To ensure priority in participating in the transaction, MG1 continuously reduces the transaction price during the game phase; the tradable energy owned by MG1 satisfies the power demand of MG2, therefore, MG3 and MG4 trade only with the DTO.

C. TRANSACTION MODE EVALUATION

The overall transaction of each microgrid system is discussed in this section. Given that the inherent device configuration of the microgrid system may impact the P2P transaction results, the "source-load" matching of different microgrid systems is first analyzed. The load cover factor γ_{load} and supply cover factor γ_{supply} are selected as evaluation indicators [43] shown in Figures 10 and 11, respectively. Per analysis of γ_{load} and γ_{supply}, the configuration capacity of energy supply equipment in all microgrid systems is generally low. This also creates the possibility of P2P transactions between microgrid systems. The "source-load" matching indicators of MG2 and MG3 are relatively good according to device configuration.

The distribution of power purchased/sold by different microgrid systems is shown in Figure 12. The electricity purchased by each microgrid system through P2P distributed transactions accounts for 7%, 16%, 10%, and 22% of the total purchased electricity, respectively. The power sold by micro-grid systems through P2P distributed transactions accounts

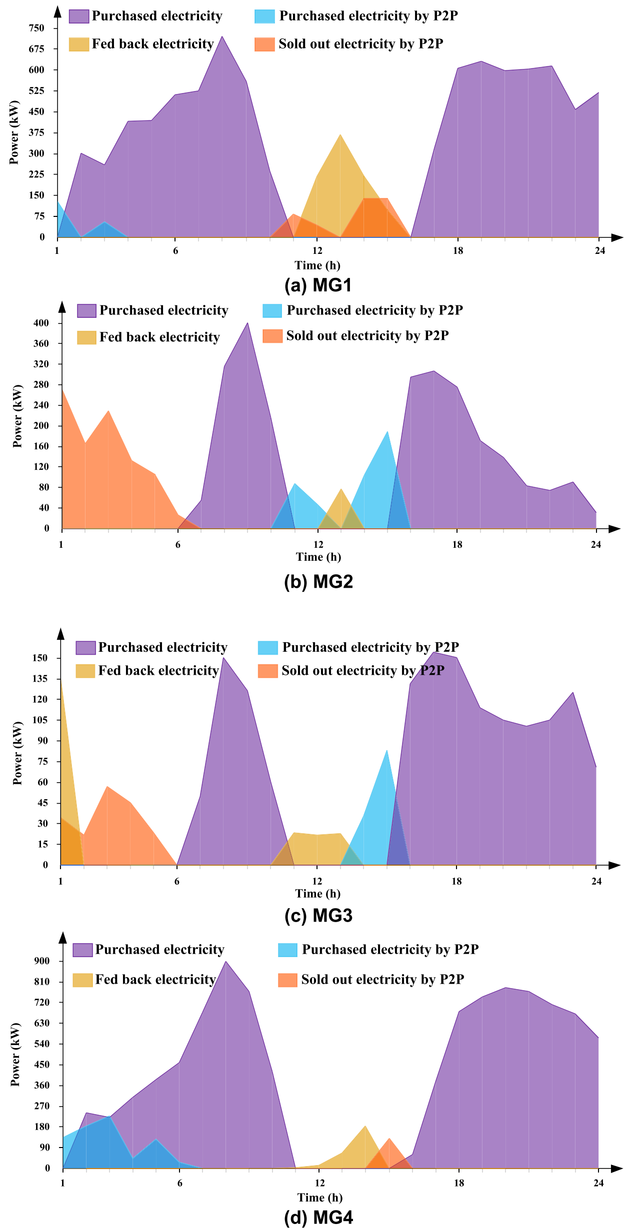

FIGURE 12. Trading power distribution in different microgrid systems.

for 31%, 92%, 60%, and 38% of the total sold electricity, respectively. Each microgrid system is in the same distribution network area, so the output of distributed power generators is intermittently similar. Moreover, the configuration of the distributed power supply in the microgrid system is more concerned with the problem of self-sufficiency. Therefore, the proportion of the power purchased by the microgrid systems through the P2P distributed transaction is not high. However, the electricity sold by the microgrid systems through P2P distributed transactions accounts for a large proportion of the total sold electricity. Excess power in the microgrid system can be effectively consumed in the area. The P2P distributed transaction maximizes the local accommodation of distributed clean energy and alleviates the congestion problems in the distribution network caused by a large amount of reverse power.

TABLE 3. Evaluation indicators of P2P trading mode.

Indicators	MG1	MG2	MG3	MG4
VTI	0.63	0.84	0.87	0.77
EBI	0.88	0.69	0.66	0.78

Further quantitative analysis was conducted on the effects of P2P distributed transaction through economic and technical indicators [8]. The value tapping index (VTI) is the economic evaluation indicator and the energy balance index (EBI) is the technical indicator [8]. The indicators are shown in Table 3.

Both VTI and EBI are in the range [0, 1], suggesting a certain economic and technical benefit to the P2P transaction remitted to each microgrid system. A larger VIT indicates greater economic benefit from P2P transactions; a smaller EBI means that the microgrid system effectively meets the internal power demand through P2P transactions. These indicators are favorable when the interaction with the utility grid is low, promoting the utilization of renewable energy.

The effective cooperation of WT, PV, and ES equipment in MG3 provides the system very high operational flexibility. Although MG2 is not equipped with ES, the economic and technological benefits through P2P transactions are relatively large as the diversified distributed power supply of WT and PV complements the electric energy production within a given one-day period. Although MG1 is equipped with ES equipment, the inherent intermittence of PV output constrains its role and the ‘‘source-load’’ matching degree is poor. The inherently high cost of ES also makes the economic and technological benefits of MG1 less obvious compared to those of other microgrid systems. In conclusion, the P2P distributed transaction comprehensively improves the economic and technical benefits of the microgrid systems tested here.

D. DISTRIBUTION NETWORK IMPACT ANALYSIS

The impact of the P2P transaction on typical operational problems, such as network congestion and network loss, are also discussed in this section.

For the distribution network in Figure 4, in the traditional transaction without considering P2P transactions, the distribution network is prone to congestion at 3:00, 6:00, 8:00, 13:00, and 18:00. There is a vigorous WT output at 3:00 and the system has less power demand, thus a large amount of reverse power causing congestion. At 6:00, 8:00, and 18:00, insufficient PV output creates a large demand for electricity, leading to congestion. At 13:00, vigorous PV output creates a large amount of reverse power leading to congestion. The network congestion problem at 3:00 can be alleviated by a distributed P2P transaction between the microgrid systems (Section VI. *B*). However, network congestion occurring at other time is not readily alleviated by P2P transactions but can be mitigated by the congestion scheduling method described in Section V.

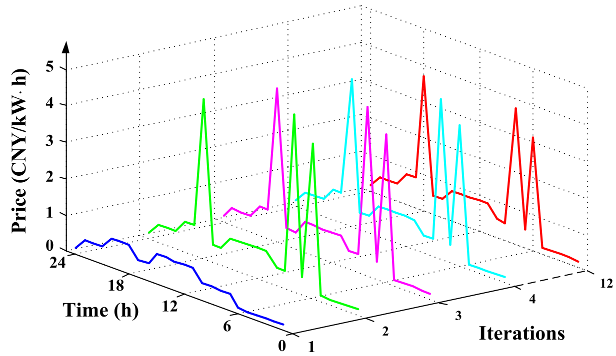

FIGURE 13. Changes of TOU power price and shadow price.

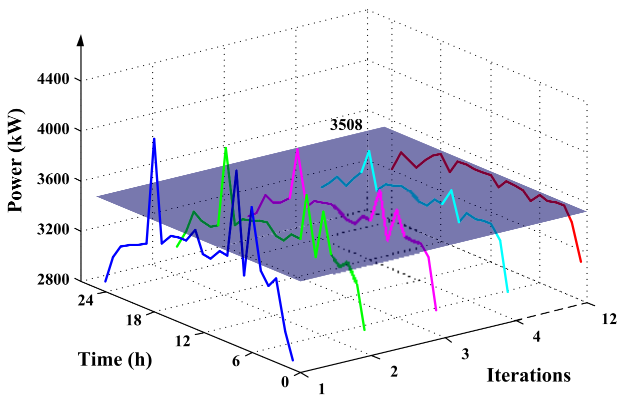

FIGURE 14. The comparisons of line power change.

The shadow price and changes in line powers in this scenario are shown in Figures 13 and 14. The initial price at the first iteration in Figure 13 is the TOU price set by the DTO under normal operating conditions. The initial value of the first iteration in Figure 13 is the line power after the congestion occurs. Figure 13 shows that the DTO sets the shadow price to increase electricity price during the congestion period. Each MEP, after receiving the shadow price signal, adjusts its power usage plan through load flexibility. Congestion in the power system is thus relieved while operation costs are consistently low. After 12 iterations, the proposed scheduling method effectively alleviates congestion in the distribution power system.

The network loss of one-day operation in the microgrid system under different transaction modes is shown in Table 4. Compared with the traditional direct trading with DTO, taking the P2P distributed transaction mode into consideration reduces the network loss of all microgrid systems by 19.1%, 30.6%, 33.7%, 8.6%, respectively. Though MG1 is close to the main transformer, the intermittent nature of internal PV output and the inherent defects in the "source-load" matching still produce high power purchase dependence on the utility power grid, resulting in relatively large network loss. MG2 and MG3 are less dependent on utility power purchases due to the complementarily of WT and PV, and the flexibility of ES. Thus, their network loss is relatively small. MG4 is located at the end of the distribution feeder,

TABLE 4. Network loss of different transaction modes.

Transaction mode	MG1	MG2	MG3	MG4
Traditional transaction mode	590.5kW	234.3kW	117.9kW	656.5kW
P2P transaction mode	477.9kW	162.7kW	78.2kW	600.1kW

i.e., its power transmission distance is long, thus resulting in substantial network loss as well. After considering the P2P transaction mode, the network loss of each microgrid system is reduced to varying degrees. P2P transactions shorten the trading distance of electric energy, promote the circulation of local electric energy and cash flow, and reduce the distribution network loss, thereby improving the operational efficiency of MEPs and the DTO.

VII. CONCLUSION

A distributed P2P day-ahead transaction in active distribution network with multi-microgrid was investigated in this paper. The P2P transactions of various market entities was coordinated to promote the accommodation of clean energy and the internal circulation of local cash flow. In a comprehensive simulation, network congestion was relieved and network loss was mitigated while ensuring economic and technological benefits across various market entities. The main conclusions can be summarized as follows.

(1) The proposed terminal flexible load model can provide scheduling space for the autonomous operation of the microgrid system. This saves operation costs while providing schedulable space for P2P transactions;

(2) Compared with the traditional transaction mode of direct bilateral transaction with the DTO, P2P transactions effectively improve the economic and technical benefits of market participants;

(3) The benefit of P2P transactions can be further enhanced when the degree of "source-load" matching is considered in the microgrid system planning and scheduling;

(4) P2P transactions can effectively relieve network congestion and mitigate network loss in the distribution network.

In the future, a daytime P2P transaction market will be added to the proposed transaction model to account for the uncertainty of distributed power output and terminal load demand. A deeper analysis will also be performed on the influence of trading habits and preferences on the results of games among market entities. "Credit" labeling will also be introduced in game models between market entities to resolve the irrational quotation behaviors that may be generated by each entity due to information asymmetry.

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