Balancing Benefits of Distribution System Operator in Peer-to-peer Energy Trading Among Microgrids Based on Optimal Dynamic Network Usage Fees

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***Abstract*—Peer-to-peer (P2P) energy trading provides a promising solution for integrating distributed microgrids (MGs). However, most existing research works on P2P energy trading among MGs ignore the influence of the dynamic network usage fees imposed by the distribution system operator (DSO). Therefore, a method of P2P energy trading among MGs based on the optimal dynamic network usage fees is proposed in this paper to balance the benefits of DSO. The interaction between DSO and MG is formulated as a Stackelberg game, in which the existence and uniqueness of optimal dynamic network usage fees are proven. Additionally, the optimal dynamic network usage fees are obtained by transforming the bi-level problem into single-level mixed-integer quadratic programming using Karush-Kuhn-Tucker conditions. Furthermore, the underlying relationship among optimal dynamic network usage fees, electrical distance, and power flow is revealed, and the mechanism of the optimal dynamic network usage fee can further enhance P2P energy trading among MGs. Finally, simulation results on an enhanced IEEE 33-bus system demonstrate that the proposed mechanism achieves a 17.08% reduction in operation costs for MG while increasing DSO revenue by 15.36%.**

***Index Terms*—Distribution system operator, microgrid, bi-level stochastic programming, network usage fee, peer-to-peer energy trading, Stackelberg game.**

I. Introduction

THE growing tension in energy demands and environmental concerns is driving a shift towards cleaner and lower-carbon power systems [1]-[3]. With the maturity of distributed generation technologies and the widespread adoption of renewables like wind power into the grid, new challenges have arisen in grid operation and management. Microgrids (MGs), as a vital link, effectively integrate various distributed energy sources [4]-[6]. The collaboration of multiple MGs through peer-to-peer (P2P) energy trading can enhance the integration of renewable energy sources and lower operation costs [7].

The P2P energy trading mechanism among MGs has attracted significant attention due to its potential applications [8]-[10]. A significant number of studies have addressed the bidding and matching problem among MGs in terms of supply and demand [11], [12]. For example, a fully P2P energy trading market for residential MG has been developed in [13]. The proposed market mechanism aims at reducing household costs, decreasing overall electricity purchases from the main grid, improving efficiency, and potentially alleviating stress on the grid. A P2P energy trading system within a virtual MG with heterogeneous prosumers is presented in [14] where interactions among prosumers are modeled as a non-cooperative game. For the purpose of maximizing the social utility of both buyers and sellers in producer-based community MGs, a game-theoretical P2P energy trading pricing model is put forward in [15]. The above-mentioned studies primarily focus on virtual-level energy trading business models among MGs. However, the practical implementation faces several challenges. ① The exchange of electricity among MGs is often idealized and does not consider the limitations of a physical network. In reality, the transmission of electricity through physical power lines may not fully align with these idealized conditions. ② During the transmission process of P2P energy trading among MGs, it is inevitable that the distribution system (DS) will incur electrical losses. The distribution system operator (DSO) may not approve interactions among MGs solely on ideal transaction volumes. Therefore, how to achieve P2P energy trading among MGs with the assistance and approval of DSO is a critical issue in practical implementation.

Recognizing these limitations, many research works have incorporated network constraints [16], [17] into the design of P2P energy trading mechanisms, thereby ensuring their

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feasibility [18], [19]. To ensure that energy transactions do not violate network limitations, [20] presents a P2P energy trading system under network constraints and conducts a sensitivity analysis to evaluate the impact of P2P energy transactions on the network. In [21], a two-tier network-constrained P2P energy transaction model for multiple MGs is introduced, enabling flexible energy exchanges within the DS while ensuring its security. These methods have addressed the transmission issues of P2P energy trading at the physical layer. Nonetheless, the profitability and sustainability of such systems from the perspective of DSO remain largely unexplored.

Network usage fees are widely considered by many scholars as a crucial avenue for the grid to profit from the P2P market [22], [23]. In this context, a P2P energy trading mechanism is established in [24] that considers network losses and network usage fees. In [25], a novel P2P energy-sharing framework based on an improved Nash bargaining cooperative game model and network usage fees with preset rules is introduced. In [26], the predefined network usage fees are also considered. The above studies have already verified the effectiveness of adopting network usage fees in the P2P market. However, existing research works predominantly focus on the impact of network usage fees on consumer behavior in the P2P market without considering DSO and MG as different stakeholders. Moreover, the dynamic nature of network usage fees and their impacts on both DSO and MG have not been systematically investigated.

Table I provides a comparison of this paper with current research works. Through a literature review on P2P energy trading in MGs, we have identified the following research gaps.

TABLE I
COMPARISON OF THIS PAPER WITH CURRENT RESEARCH WORKS

Ref.	Network constraint	P2P energy trading	Network usage fee	Game
[13], [14]	×	√	×	×
[15]	×	√	×	Evolutionary
[18]-[21]	√	√	×	×
[24], [25]	√	√	Fixed	×
[26]	×	√	Fixed	Cooperative
This paper	√	√	Dynamic optimal	Stackelberg

Note: √ indicates the aspect is considered; and × indicates the aspect is not considered.

1) Existing research works often focus on virtual-level trading models among MGs [13] - [15], [26], without adequately considering the physical limitations and network constraints of DS, which are critical for the practical implementation of P2P energy trading.

2) The use of fixed network usage fees [24]-[26] in existing models is primarily designed from the perspective of MGs. While these fees are intended to protect the interests of the grid, they can lead to insufficient transaction control and inequitable profit distribution among MGs. Otherwise, existing studies have not modeled optimal dynamic network usage fees as a Stackelberg game model.

This paper proposes a mechanism of optimal dynamic network usage fee to address the research gap. This mechanism considers the varying demands of DS for transmission services and the needs of MG for efficient P2P energy trading. We employ Stackelberg games to model the interactions between DSO and MG, with DSO acting as the leader in setting adaptive network usage fees, and MG as the follower optimizing the energy strategies in response. Our primary contributions are as follows.

1) We develop a model that integrates DSO-imposed physical network constraints into the P2P energy trading among MGs, ensuring practical implementation by considering the operation limitations of the DS.

2) To the best of our knowledge, the mechanism of optimal dynamic network usage fee is firstly proposed in this paper, encouraging optimized trading strategies among MGs, balancing DSO benefits, and fostering a more balanced and efficient P2P market.

3) A method is developed to transform the complex Stackelberg game between DSO and MG into a single-layer mixed-integer quadratic programming (MIQP) problem using the Karush-Kuhn-Tucker (KKT) conditions. Simulations on an enhanced IEEE 33-bus system demonstrate that the proposed method ensures the operation feasibility and economic efficiency.

The structure of the remaining part is as follows. The P2P market architecture and problem formulation are presented in Section II. Section III presents the methodology. In Section IV, a case study is presented. Finally, Section V serves as the conclusion.

II. P2P MARKET ARCHITECTURE AND PROBLEM FORMULATION

Electricity market transactions, whether in day-ahead or real-time markets, typically rely on periodic updates rather than continuous real-time processing. Therefore, we adopt a quasi-online method for the design of an energy trading framework, as illustrated in Fig. 1. In this framework, the P2P energy trading among MGs relies on DS. Therefore, the MGs are always grid-connected, and the DSO has the right to impose network usage fees on the MGs. These prices are communicated to the MGs, influencing their trading strategies. MGs then decide whether to trade electricity directly with each other through P2P energy trading or engage in transactions with the DSO. These decisions are influenced by the dynamic network usage fees and the current generation and consumption status of MGs.

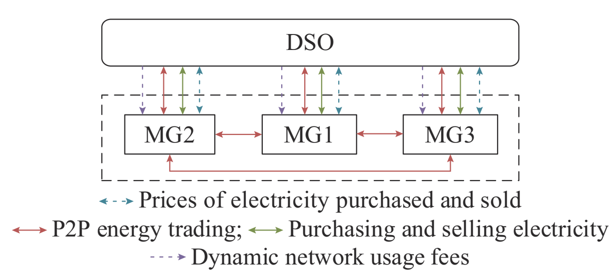

Fig. 1. Energy trading framework.

In the energy trading framework, we primarily address the issue of pricing network usage fees between DSO and MG, which can incentivize MGs to participate in P2P energy trading market, consequently improving energy distribution efficiency and revenue generation from the DSO standpoint. Conversely, from the perspective of MGs, the proposed mechanism of optimal dynamic network usage fees can guide optimal energy trading and consumption strategies, thereby maximizing cost savings. Considering the hierarchical nature of decision-making processes between DSO and MG, employing a Stackelberg game framework emerges as an appropriate and effective method, as shown in Supplementary Material A Fig. SA1.

A. Network Usage Fee Model

The network usage fee for P2P energy trading among MGs remains an unresolved issue [27]. The network usage fee is the cost paid by MGs for utilizing the network to transmit the electricity, which has a potential relationship with power flow, electrical distance, and interaction volume. If the electrical distance and interaction volume between MGs i and j at time t are denoted as d_{ij} and P_{ij}^t, respectively, the dynamic network usage fee Cg_{ij}^t can be expressed as:

$$Cg_{ij}^t = \varepsilon_{ij}^t d_{ij} P_{ij}^t \tag{1}$$

where ε_{ij}^t is the network usage fee paid by the MGs to the DSO for the energy trading between MGs i and j at time t.

The electrical distance is determined by the topology of the power grid [28]. As shown in (2) and (3), the power transfer distribution factor (PTDF) is employed to calculate the electrical distance of the DS under a given topology.

$$d_{ij} = \sum_{l \in L} \left| PTDF_{l,ij} \right| \tag{2}$$

$$\boldsymbol{PTDF} = \boldsymbol{B}_{\text{line}} \boldsymbol{B}_x^{-1} \tag{3}$$

$$B_{x,ij} = \begin{cases} \sum_{k=1}^{N} 1/X_{ik} & j = i \\ -1/X_{ik} & j \neq i \end{cases} \tag{4}$$

where $\boldsymbol{PTDF}$ represents the overall absolute change in power flow throughout the network caused by transferring one unit of power from one node to another; $PTDF_{l,ij}$ is the element of the $\boldsymbol{PTFD}$, representing the change in power flow on line l when a unit power is transferred from nodes i to j; L is the set of lines; X_{ik} $(j=1,2,...,k)$ is the reactance of the line between nodes i and k; $B_{x,ij}$ is the element of nodal admittance matrix $\boldsymbol{B}_x$, which is calculated using Kirchhoff's law, describing the relationship between nodal current and voltage; and $\boldsymbol{B}_{\text{line}}$ is the line-to-node admittance matrix, depicting the relationship between line current and voltage difference at nodes.

Assuming there are line connections between nodes 1 and 2, as well as between nodes 1 and 3, $\boldsymbol{B}_{\text{line}}$ can be represented as:

$$\boldsymbol{B}_{\text{line}} = \begin{bmatrix} 1/X_{12} & -1/X_{12} & 0 & 0 & 0 & \dots & 0 \\ 1/X_{13} & 0 & -1/X_{13} & 0 & 0 & \dots & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & 0 \\ 0 & 0 & -1/X_{ij} & \dots & \dots & \dots & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \end{bmatrix} \tag{5}$$

B. DSO Decision-making Model

The DSO, as a leader, considers the power flow constraints of the transmission network and formulates ε_{ij}^t by evaluating the factors such as the revenue from the network usage fee, prices of electricity purchased from and sold to the MG, network losses, and regulation costs. In order to facilitate the calculation of electrical distances, we refer to the power flow method in [29]. The decision-making model for DSO is constructed as:

$$\max C_{DSO} = \sum_{t=1}^{T} \left[\sum_{i=1}^{N} \left(\mu_{\text{Pb}}^t P_{i,t}^{\text{buy}} - \mu_{\text{Ps}}^t P_{i,t}^{\text{sell}} \right) - \sum_{(m,n) \in L} b_{mn} \left(\theta_{m,t} - \theta_{n,t} \right)^2 \right] + \sum_{t=1}^{T} \sum_{i=1}^{N} \sum_{j=1, j \neq i}^{N} \frac{\varepsilon_{ij}^t d_{ij} \left(P_{ij,+}^t + P_{ji,-}^t \right)}{2} - \sum_{t=1}^{T} \sum_{q=1}^{Q} \lambda_t P_{\text{gb},t}^q \tag{6a}$$

s.t.

$$\boldsymbol{P}_{\text{gb},t}^{\min} \leq \boldsymbol{P}_{\text{gb},t} \leq \boldsymbol{P}_{\text{gb},t}^{\max} \tag{6b}$$

$$\varepsilon_{\min} \leq \varepsilon_{ij}^t \leq \varepsilon_{\max} \tag{6c}$$

$$\boldsymbol{P}_{\text{gb},t} - \boldsymbol{P}_{\text{load},t} - \boldsymbol{P}_{\text{MG},t} = \boldsymbol{P}_{mn,t} \tag{6d}$$

$$P_{\text{MG},t}^i = B_{\text{MG}}(s,i) \left(P_{i,t}^{\text{buy}} - P_{i,t}^{\text{sell}} + \sum_{j \in N/i} P_{ij,+}^t - \sum_{j \in N/i} P_{ij,-}^t \right) \tag{6e}$$

$$\left| \left(\theta_{m,t} - \theta_{n,t} \right) b_{mn} \right| \leq F_{mn}^{\max} \tag{6f}$$

$$P_{mn,t} = B_{mn} \left(\theta_{m,t} - \theta_{n,t} \right) \tag{6g}$$

where C_{DSO} is the cost function for DSO; μ_{Pb}^t and μ_{Ps}^t are the prices of electricity purchased from and sold to MG at time t, respectively; $P_{i,t}^{\text{buy}}$ and $P_{i,t}^{\text{sell}}$ are the volumes of electricity purchased from and sold to MG i at time t, respectively; $\theta_{m,t}$ and $\theta_{n,t}$ are the phase angles at nodes m and n at time t, respectively; $q \in Q$ is the node where the main grid is connected to the DS; $P_{\text{gb},t}^q$ is the volume of electricity purchased for DSO from the main grid at node q at time t; $\boldsymbol{P}_{\text{gb},t} = \left[P_{\text{gb},t}^q \right]$ is the matrix of volume of electricity purchased; b_{mn} is the admittance of the line connecting nodes m and n; λ_t is the price for DS from the main grid at time t; $\boldsymbol{P}_{\text{gb},t}^{\max}$ and $\boldsymbol{P}_{\text{gb},t}^{\min}$ are the matrices of the maximum and minimum volumes of electricity purchased for DS from the main grid at time t, respectively; $\varepsilon_{\max}$ and $\varepsilon_{\min}$ are the maximum and minimum network usage fee prices, respectively; $\boldsymbol{P}_{\text{load},t}$ is the matrix of load of DS at time t; $\boldsymbol{P}_{\text{MG},t} = \left[P_{\text{MG},t}^i \right]$ is the matrix of power flow between MG and DS at time t; $\boldsymbol{P}_{mn,t}$ is the matrix of power flow of line $(m,n) \in L$ at time t; $B_{\text{MG}}(s,i)$ is the element in the s^{th} row and i^{th} column of matrix $\boldsymbol{B}_{\text{MG}}$, which is the node association matrix of MG; $P_{ij,+}^t$ and $P_{ij,-}^t$ are the traded power between MGs i and j in P2P market; $F_{mn}^{\max}$ is the network transmission capacity of nodes m and n; and B_{mn} is the admittance value of the line connecting nodes m and n.

As shown in (6a), $\sum_{t=1}^{T} \sum_{(m,n) \in L} b_{mn} \left(\theta_{m,t} - \theta_{n,t} \right)^2$ represents network losses and regulation costs. Constraints (6b) and (6c) represent that the DSO purchases power from the main grid and with higher network usage fees to the extent permitted, respectively. The power balance is denoted in (6d). The exchange of electricity between MG and DS is indicated in (6e). The modeling of the transmission line capacity limits is carried out in (6f). Constraint (6g) represents the DC power flow equation. All of these constraints collectively form the foundation of the DSO decision-making process. By adhering to these constraints, the DSO can effectively balance supply and demand, ensure network stability, and optimize the utilization of resources.

C. MG Decision-making Model

MGs, acting as followers, respond to DSO charging standards and aim to maximize the interests through the scheduling of internal devices. The inter-MG includes loads, wind turbine (WT), photovoltaic (PV), and energy storage (ES). The i^{th} decision-making model of MG i is constructed as:

$$\min C_{\text{MG}}^{i}=\sum_{t=1}^{T}\left[c_{\text{E}}^{i}\left(P_{i,t}^{\text{dis}}+P_{i,t}^{\text{ch}}\right)+\mu_{\text{Pb}}^{t}P_{i,t}^{\text{buy}}-\mu_{\text{Ps}}^{t}P_{i,t}^{\text{sell}}\right]+\sum_{t=1}^{T}\sum_{j=1,j\neq i}^{N}\frac{\varepsilon_{ij}^{t}d_{ij}\left(P_{ij,+}^{t}+P_{ji,-}^{t}\right)}{2} \tag{7a}$$

s.t.

$$P_{i,t}^{\text{PV}}+P_{i,t}^{\text{WT}}+P_{i,t}^{\text{dis}}-P_{i,t}^{\text{ch}}-P_{i,t}^{\text{sell}}+P_{i,t}^{\text{buy}}=P_{i,t}^{\text{load}}-\sum_{j\in N/i}P_{ij,+}^{t}+\sum_{j\in N/i}P_{ij,-}^{t}\quad \lambda_{i,t}^{\text{pro}} \tag{7b}$$

$$0\leq P_{i,t}^{\text{PV}}\leq P_{i,t}^{\text{PV,max}}\quad \underline{\lambda}_{i,t}^{\text{PV}},\bar{\lambda}_{i,t}^{\text{PV}} \tag{7c}$$

$$0\leq P_{i,t}^{\text{WT}}\leq P_{i,t}^{\text{WT,max}}\quad \underline{\lambda}_{i,t}^{\text{WT}},\bar{\lambda}_{i,t}^{\text{WT}} \tag{7d}$$

$$0\leq P_{i,t}^{\text{sell}}\leq Z_{i,t}^{\text{sell}}P_{i,t}^{\text{sell,max}}\quad \underline{\lambda}_{i,t}^{\text{sell}},\bar{\lambda}_{i,t}^{\text{sell}} \tag{7e}$$

$$0\leq P_{i,t}^{\text{buy}}\leq Z_{i,t}^{\text{buy}}P_{i,t}^{\text{buy,max}}\quad \underline{\lambda}_{i,t}^{\text{buy}}+\bar{\lambda}_{i,t}^{\text{buy}} \tag{7f}$$

$$0\leq P_{i,t}^{\text{ch}}\leq Z_{i,t}^{\text{ch}}P_{i,t}^{\text{ch,max}}\quad \underline{\lambda}_{i,t}^{\text{ch}},\bar{\lambda}_{i,t}^{\text{ch}} \tag{7g}$$

$$0\leq P_{i,t}^{\text{dis}}\leq Z_{i,t}^{\text{dis}}P_{i,t}^{\text{dis,max}}\quad \underline{\lambda}_{i,t}^{\text{dis}},\bar{\lambda}_{i,t}^{\text{dis}} \tag{7h}$$

$$SOC_{i,t}\cdot Cap_{i}=SOC_{i,t-1}\cdot Cap_{i}+\eta_{\text{ESS}}^{\text{ch}}P_{i,t}^{\text{ch}}-P_{i,t}^{\text{dis}}/\eta_{\text{ESS}}^{\text{dis}}\quad \lambda_{i,t}^{\text{SOC}_1} \tag{7i}$$

$$SOC_{i,1}\cdot Cap_{i}=SOC_{i,\text{ini}}\cdot Cap_{i}+\eta_{\text{ESS}}^{\text{ch}}P_{i,1}^{\text{ch}}-P_{i,1}^{\text{dis}}/\eta_{\text{ESS}}^{\text{dis}}\quad \lambda_{i,1}^{\text{SOC}_1} \tag{7j}$$

$$SOC_{i,\text{ini}}=SOC_{i,T}\quad \lambda_{i}^{\text{SOC}_2} \tag{7k}$$

$$SOC_{i}^{\min}\leq SOC_{i,t}\leq SOC_{i}^{\max}\quad \underline{\lambda}_{i,t}^{\text{SOC}},\bar{\lambda}_{i,t}^{\text{SOC}} \tag{7l}$$

$$0\leq P_{ij,+}^{t}\leq Z_{ij,+}^{t,\text{P2P}}P_{ij,+}^{t,\max}\quad \underline{\lambda}_{ij,+}^{t},\bar{\lambda}_{ij,+}^{t} \tag{7m}$$

$$Z_{ji,-}^{t,\text{P2P}}P_{ji,-}^{t,\min}\leq P_{ji,-}^{t}\leq 0\quad \underline{\lambda}_{ji,-}^{t},\bar{\lambda}_{ji,-}^{t} \tag{7n}$$

$$Z_{ij,+}^{t,\text{P2P}}+Z_{ji,-}^{t,\text{P2P}}\leq 1 \tag{7o}$$

$$Z_{i,t}^{\text{sell}}+Z_{i,t}^{\text{buy}}\leq 1 \tag{7p}$$

$$Z_{i,t}^{\text{ch}}+Z_{i,t}^{\text{dis}}\leq 1 \tag{7q}$$

where ε_{ij}^{t}, $P_{i,t}^{\text{PV}}$, $P_{i,t}^{\text{WT}}$, $P_{i,t}^{\text{dis}}$, $P_{i,t}^{\text{ch}}$, $P_{i,t}^{\text{sell}}$, $P_{i,t}^{\text{buy}}$, $P_{ij,+}^{t}$, $P_{ij,-}^{t}$, $\forall i,j,t$ are the decision variables, including P2P energy trading among MGs, scheduling volume of devices within the MG, and network usage fees; C_{MG}^{i} is the cost function for MG at time t; c_{E}^{i} is the unit operation cost of ES; $P_{i,t}^{\text{ch}}$ and $P_{i,t}^{\text{dis}}$ are the ES charging and discharging volumes at time t, respectively; $P_{i,t}^{\text{PV}}$ and $P_{i,t}^{\text{WT}}$ are the PV and WT outputs at time t, respectively; $P_{i,t}^{\text{load}}$ is the load at time t; $P_{i,t}^{\text{PV,max}}$ and $P_{i,t}^{\text{WT,max}}$ are the maximum PV and WT outputs at time t, respectively; $P_{i,t}^{\text{sell,max}}$ and $P_{i,t}^{\text{buy,max}}$ are the maximum volumes of electricity purchased and sold at time t, respectively; $Z_{i,t}^{\text{sell}}$ and $Z_{i,t}^{\text{buy}}$ are the 0-1 variables of the volumes of electricity purchased and sold at time t, respectively; $P_{i,t}^{\text{ch,max}}$ and $P_{i,t}^{\text{dis,max}}$ are the maximum ES charging and discharging volumes at time t, respectively; $SOC_{i,t}$ is the state of charge (SOC) of ES at time t; $\eta_{\text{ESS}}^{\text{ch}}$ and $\eta_{\text{ESS}}^{\text{dis}}$ are the charging and discharging efficiencies of ES in MGs, respectively; $SOC_{i,\text{ini}}$ and $SOC_{i,T}$ are the initial and final SOCs of the ES, respectively; $SOC_{i}^{\max}$ and $SOC_{i}^{\min}$ are the maximum and minimum limitations of SOCs, respectively; $P_{ij,+/-}^{t,\max}$ and $P_{ij,+/-}^{t,\min}$ are the maximum and minimum traded power between MGs i and j in the P2P market, respectively; $Z_{ji,-}^{t,\text{P2P}}$ and $Z_{ij,+}^{t,\text{P2P}}$ are the 0-1 variables of the volumes of electricity purchased and sold by MG i to MG j in the P2P market at time t, respectively; $Z_{i,t}^{\text{ch}}$ and $Z_{i,t}^{\text{dis}}$ are the 0-1 variables of the charging and discharging states of the ES at time t, respectively; and λ is the Lagrange multiplier with symbols $^-$ and _ indicating the lower and upper bounds of the variables, respectively.

As shown in (7a), the objective of the follower includes the operation and maintenance costs of ES, the cost of electricity purchased from and sold to the DSO, and network usage fees in P2P energy trading. Constraint (7b) ensures power balance within each MG, which is crucial to maintaining the stability of the MGs and preventing any overloading or underutilization of its resources. The output of each device within the MG is represented as (7c)-(7h). Constraints (7i) and (7j) calculate the SOC for each moment of ES. Constraint (7k) indicates that the initial and final SOCs of the ES must be identical. Constraint (7l) imposes the limits on the SOC of the ES, defining its upper and lower bounds, which are used to prevent the ES from being overcharged. Constraints (7m) and (7n) set the upper and lower limits of the P2P energy trading among MGs, which ensures that the energy trading among MGs is within manageable limits, preventing excessive strain on the network. Constraint (7o) ensures that MG i does not simultaneously purchase and sell electricity from/to MG j in the P2P market. Constraints (7p) and (7q) ensure that the MG cannot simultaneously purchase and sell electricity from/to the DSO and ES cannot charge and discharge at the same time.

D. Existence and Uniqueness of Stackelberg Equilibrium (SE)

The proof of the existence and uniqueness of the SE is proved according to Theorem 1 [30].

Theorem 1: a unique SE exists if the Stackelberg game model satisfies the following conditions.

1) The strategy sets for both the leader and the follower are non-empty, compact, and convex.

2) For any given strategy of the leader, each follower has a unique optimal solution.

3) For any given strategy of the follower, the leader has a unique optimal solution.

Proof: the leader-follower game model for optimal dynamic network usage fees is proven to satisfy the three conditions for the existence and uniqueness of the SE as follows.

1) Based on the leader-follower game model, the strategy

set of the leader must adhere to constraints (6b)-(6g). While the strategy set of the follower must comply with the constraints (7b)-(7m). Therefore, the strategy sets of both leaders and participants are non-empty and continuous.

2) Given the strategy of the leader, it is proven that each follower has a unique optimal solution. The first-order partial derivative for (7a) of the MGs with respect to $P_{ij,+}^t$ and $P_{ij,-}^t$ is obtained as:

$$\frac{\partial C_{MG}^{i,t}}{\partial P_{ij,+}^t}=\frac{\partial C_{MG}^{i,t}}{\partial P_{ij,-}^t}=\frac{d_{ij}\varepsilon_{ij}^t}{2} \tag{8}$$

It is evident that the first derivative of (7a) with respect to the variable remains constant, thus the objective function of the MGs is linear. A linear function is characterized as both convex and concave. Therefore, regardless of the values, once ε_{ij}^t of DSO is given, MGs have a unique optimal solution.

3) Given the strategies of followers, it is proven that the DSO has a unique optimal solution. The first-order partial derivative for (6a) of ε_{ij}^t is obtained as:

$$\frac{\partial C_{DSO}^t}{\partial \varepsilon_{ij}^t}=\frac{d_{ij}\left(P_{ij,+}^t+P_{ij,-}^t\right)}{2} \tag{9}$$

Similarly, the objective function in (6a) is linear. Therefore, regardless of the values, once the P2P energy trading volume for the MGs is given, the DSO has a unique optimal solution. In conclusion, the Stackelberg game model outlined in this paper has a unique SE, thereby finalizing the proof.

III. Methodology

The optimal dynamic network usage fees among MGs represent the equilibrium point in the Stackelberg game, which is a bi-level problem characterized by its NP-hard complexity and the inherent difficulty in obtaining solutions [31]. In this section, the bi-level problem is converted into a single-level problem by considering the underlying structures of the problem. The KKT conditions of lower-level problems are utilized to reformulate the bi-level model into a single-level model with equilibrium constraints [32]. The partial derivatives of the Lagrange function $\mathcal{L}$ to the decision variables are given in (10a)-(10j).

$$\frac{\partial \mathcal{L}}{\partial P_{i,t}^{\text{buy}}}=\mu_{\text{Pb}}^t+\lambda_{i,t}^{\text{pro}}-\underline{\lambda}_{i,t}^{\text{buy}}+\overline{\lambda}_{i,t}^{\text{buy}}=0 \tag{10a}$$

$$\frac{\partial \mathcal{L}}{\partial P_{i,t}^{\text{sell}}}=-\mu_{\text{Ps}}^t-\lambda_{i,t}^{\text{pro}}-\underline{\lambda}_{i,t}^{\text{sell}}+\overline{\lambda}_{i,t}^{\text{sell}}=0 \tag{10b}$$

$$\frac{\partial \mathcal{L}}{\partial P_{ij,+}^t}=\frac{\varepsilon_{ij}^t d_{ij}}{2}-\lambda_{i,t}^{\text{pro}}-\underline{\lambda}_{ij,+}^t+\overline{\lambda}_{ij,+}^t=0 \tag{10c}$$

$$\frac{\partial \mathcal{L}}{\partial P_{ji,-}^t}=\frac{\varepsilon_{ij}^t d_{ij}}{2}-\lambda_{i,t}^{\text{pro}}-\underline{\lambda}_{ji,-}^t+\overline{\lambda}_{ji,-}^t=0 \tag{10d}$$

$$\frac{\partial \mathcal{L}}{\partial P_{i,t}^{\text{ch}}}=c_{\text{E}}^i-\lambda_{i,t}^{\text{pro}}-\underline{\lambda}_{i,t}^{\text{ch}}+\overline{\lambda}_{i,t}^{\text{ch}}-\lambda_{i,t}^{\text{SOC}_1}\eta_{\text{ESS}}^{\text{ch}}=0 \tag{10e}$$

$$\frac{\partial \mathcal{L}}{\partial P_{i,t}^{\text{dis}}}=c_{\text{E}}^i+\lambda_{i,t}^{\text{pro}}-\underline{\lambda}_{i,t}^{\text{dis}}+\overline{\lambda}_{i,t}^{\text{dis}}+\frac{\lambda_{i,t}^{\text{SOC}_1}}{\eta_{\text{ESS}}^{\text{dis}}}=0 \tag{10f}$$

$$\frac{\partial \mathcal{L}}{\partial P_{i,t}^{\text{PV}}}=\lambda_{i,t}^{\text{pro}}-\underline{\lambda}_{i,t}^{\text{PV}}+\overline{\lambda}_{i,t}^{\text{PV}}=0 \tag{10g}$$

$$\frac{\partial \mathcal{L}}{\partial P_{i,t}^{\text{WT}}}=\lambda_{i,t}^{\text{pro}}-\underline{\lambda}_{i,t}^{\text{WT}}+\overline{\lambda}_{i,t}^{\text{WT}}=0 \tag{10h}$$

$$\frac{\partial \mathcal{L}}{\partial SOC_{i,t}}=\overline{\lambda}_{i,t}^{\text{SOC}}-\underline{\lambda}_{i,t}^{\text{SOC}}+\lambda_{i,t}^{\text{SOC}_1}\cdot Cap_i-\lambda_{i,t+1}^{\text{SOC}_1}\cdot Cap_i=0 \tag{10i}$$

$$\frac{\partial \mathcal{L}}{\partial SOC_{i,T}}=\overline{\lambda}_{i,T}^{\text{SOC}}-\underline{\lambda}_{i,T}^{\text{SOC}}+\lambda_{i,\text{T}}^{\text{SOC}_1}\cdot Cap_i+\lambda_i^{\text{SOC}_2}\cdot Cap_i=0 \tag{10j}$$

For inequality constraints, introducing Lagrange multipliers leads to transforming them into equality conditions. In practice, constraints often hold true only for a subset of variables while being inactive for others. Therefore, complementary relaxation conditions are utilized to transform the constraints into a form of “original constraint plus relaxation variable equals 0”. The introduction of relaxation variables allows the constraints to be “relaxed” under certain circumstances. The complementarity slackness conditions are given in (11a)-(11j).

$$\begin{cases}0\le P_{i,t}^{\text{buy}}\perp\underline{\lambda}_{i,t}^{\text{buy}}\ge 0\\ 0\le\overline{\lambda}_{i,t}^{\text{buy}}\perp\left(P_{i,t}^{\text{buy,max}}-P_{i,t}^{\text{buy}}\right)\ge 0\end{cases} \tag{11a}$$

$$\begin{cases}0\le P_{i,t}^{\text{sell}}\perp\underline{\lambda}_{i,t}^{\text{sell}}\ge 0\\ 0\le\overline{\lambda}_{i,t}^{\text{sell}}\perp\left(P_{i,t}^{\text{sell,max}}-P_{i,t}^{\text{sell}}\right)\ge 0\end{cases} \tag{11b}$$

$$\begin{cases}0\le P_{ij,+}^t\perp\underline{\lambda}_{ij,+}^t\ge 0\\ 0\le\overline{\lambda}_{ij,+}^t\perp\left(P_{ij,+}^{t,\max}-P_{ij,+}^t\right)\ge 0\end{cases} \tag{11c}$$

$$\begin{cases}0\le\left(P_{ji,-}^{t,\min}+P_{ji,-}^t\right)\perp\underline{\lambda}_{ji,-}^t\ge 0\\ 0\le\overline{\lambda}_{ji,-}^t\perp\left(-P_{ji,-}^t\right)\ge 0\end{cases} \tag{11d}$$

$$\begin{cases}0\le P_{i,t}^{\text{PV}}\perp\underline{\lambda}_{i,t}^{\text{PV}}\ge 0\\ 0\le\overline{\lambda}_{i,t}^{\text{PV}}\perp\left(P_{i,t}^{\text{PV,max}}-P_{i,t}^{\text{PV}}\right)\ge 0\end{cases} \tag{11e}$$

$$\begin{cases}0\le P_{i,t}^{\text{WT}}\perp\underline{\lambda}_{i,t}^{\text{PV}}\ge 0\\ 0\le\overline{\lambda}_{i,t}^{\text{PV}}\perp\left(P_{i,t}^{\text{WT,max}}-P_{i,t}^{\text{PV}}\right)\ge 0\end{cases} \tag{11f}$$

$$\begin{cases}0\le P_{i,t}^{\text{ch}}\perp\underline{\lambda}_{i,t}^{\text{ch}}\ge 0\\ 0\le\overline{\lambda}_{i,t}^{\text{ch}}\perp\left(P_{i,t}^{\text{ch,max}}-P_{i,t}^{\text{ch}}\right)\ge 0\end{cases} \tag{11g}$$

$$\begin{cases}0\le P_{i,t}^{\text{dis}}\perp\underline{\lambda}_{i,t}^{\text{dis}}\ge 0\\ 0\le\overline{\lambda}_{i,t}^{\text{dis}}\perp\left(P_{i,t}^{\text{dis,max}}-P_{i,t}^{\text{dis}}\right)\ge 0\end{cases} \tag{11h}$$

$$0\le\underline{\lambda}_{i,t}^{\text{SOC}}\perp\left(SOC_{i,t}-SOC_i^{\min}\right)\ge 0 \tag{11i}$$

$$0\le\overline{\lambda}_{i,t}^{\text{SOC}}\perp\left(SOC_i^{\max}-SOC_{i,t}\right)\ge 0 \tag{11j}$$

where $x\perp y$ denotes the orthogonality between x and y, $x\perp y\rightarrow xy=0$. Note that the complementary relaxation conditions mentioned above are non-convex constraints, and the big-M method is employed to linearize the model [33].

According to the strong duality theory, the optimal solutions of the primal problem and dual problem are the same. Therefore, the dual theory is employed to eliminate the bilinear product terms in the original problem, thereby linearizing the objective function of the mathematical programming with equilibrium constraints.

$$\begin{aligned}&\sum_{i=1}^{N}\sum_{t=1}^{T}\left[\mu_t^{\mathrm{sell}}P_{i,t}^{\mathrm{sell}}-\mu_t^{\mathrm{buy}}P_{i,t}^{\mathrm{buy}}-\sum_{j=1,j\neq i}^{N}\frac{\varepsilon_{ij}^{t}d_{ij}\left(P_{ij,+}^{t}+P_{ji,-}^{t}\right)}{2}\right]-\\&\quad c_{\mathrm{E}}^{i}\sum_{t=1}^{T}\left(P_{i,t}^{\mathrm{ch}}+P_{i,t}^{\mathrm{dis}}\right)=-\sum_{i=1}^{N}\sum_{t=1}^{T}\left(\bar{\lambda}_{i,t}^{\mathrm{buy}}P_{i,t}^{\mathrm{buy,max}}+\bar{\lambda}_{i,t}^{\mathrm{sell}}P_{i,t}^{\mathrm{sell,max}}\right)-\\&\quad\sum_{i=1}^{N}\sum_{t=1}^{T}\left(\bar{\lambda}_{ij,+}^{t}P_{ij,+}^{t,\max}+\bar{\lambda}_{ji,-}^{t}P_{ji,-}^{t,\min}+\bar{\lambda}_{i,t}^{\mathrm{PV}}P_{i,t}^{\mathrm{PV}}+\bar{\lambda}_{i,t}^{\mathrm{WT}}P_{i,t}^{\mathrm{WT}}\right)-\\&\quad\sum_{i=1}^{N}\sum_{t=1}^{T}\left(\underline{\lambda}_{i,t}^{\mathrm{SOC}}\cdot SOC_i^{\min}+\bar{\lambda}_{i,t}^{\mathrm{SOC}}\cdot SOC_i^{\max}+\lambda_{i,1}^{\mathrm{SOC_1}}\cdot SOC_{i,\mathrm{ini}}\cdot Cap_i\right)-\\&\quad\sum_{i=1}^{N}\sum_{t=1}^{T}\left(\bar{\lambda}_{i,t}^{\mathrm{dis}}P_{i,t}^{\mathrm{dis,max}}+\lambda_{i,t}^{\mathrm{pro}}P_{i,t}^{\mathrm{load}}+\bar{\lambda}_{i,t}^{\mathrm{ch}}P_{i,t}^{\mathrm{ch,max}}+\lambda_i^{\mathrm{SOC_2}}\cdot SOC_{i,1}\right)\end{aligned}\tag{12}$$

After the linearization process, the model is reformulated into a single-level MIQP, which is computationally more tractable compared with the original bi-level problem. This transformation enables a more efficient and practical method to optimize dynamic network usage fees C among MGs. The specific formulation is given as:

$$\left\{\begin{aligned}&\max C=\\&\sum_{t=1}^{T}\left[2\sum_{i=1}^{N}\left(\mu_t^{\mathrm{buy}}P_{i,t}^{\mathrm{buy}}-\mu_t^{\mathrm{sell}}P_{i,t}^{\mathrm{sell}}\right)-\sum_{(m,n)\in L}b_{mn}\left(\theta_{m,t}-\theta_{n,t}\right)^2\right]-\\&\sum_{t=1}^{T}\lambda_tP_{\mathrm{buy}}^{t}+\sum_{i=1}^{N}\sum_{t=1}^{T}\left[c_{\mathrm{E}}^{i}\left(P_{i,t}^{\mathrm{ch}}+P_{i,t}^{\mathrm{dis}}\right)+\bar{\lambda}_{i,t}^{\mathrm{buy}}P_{i,t}^{\mathrm{buy,max}}+\bar{\lambda}_{i,t}^{\mathrm{sell}}P_{i,t}^{\mathrm{sell,max}}\right]+\\&\sum_{i=1}^{N}\sum_{t=1}^{T}\left(\bar{\lambda}_{ij,+}^{t}P_{ij,+}^{t,\max}+\bar{\lambda}_{ji,-}^{t}P_{ji,-}^{t,\min}+\bar{\lambda}_{i,t}^{\mathrm{PV}}P_{i,t}^{\mathrm{PV}}+\bar{\lambda}_{i,t}^{\mathrm{WT}}P_{i,t}^{\mathrm{WT}}\right)+\\&\sum_{i=1}^{N}\sum_{t=1}^{T}\left(\underline{\lambda}_{i,t}^{\mathrm{SOC}}\cdot SOC_i^{\min}+\bar{\lambda}_{i,t}^{SOC}\cdot SOC_i^{\max}+\lambda_{i,1}^{\mathrm{SOC_1}}\cdot SOC_{i,\mathrm{ini}}\cdot Cap_i\right)+\\&\sum_{i=1}^{N}\sum_{t=1}^{T}\left(\bar{\lambda}_{i,t}^{\mathrm{dis}}P_{i,t}^{\mathrm{dis,max}}+\lambda_{i,t}^{\mathrm{pro}}P_{i,t}^{\mathrm{load}}+\bar{\lambda}_{i,t}^{\mathrm{ch}}P_{i,t}^{\mathrm{ch,max}}+\lambda_i^{\mathrm{SOC_2}}\cdot SOC_{i,1}\right)\\&\text{s.t. (6b)-(6g), (7b)-(7q)}\quad\text{primal constraints}\\&\qquad\text{(10a)-(10j), (11a)-(11j)}\quad\text{KKT constraints}\end{aligned}\right.\tag{13}$$

In summary, the complex bi-level problem has been converted into a single-level MIQP by applying the KKT constraints, complementary relaxation conditions, and dual theory. This reformulation simplifies the computational complexity while retaining the accuracy of the model.

IV. Case Study

In this section, the P2P energy trading mechanism based on the optimal dynamic network usage fee is verified via an enhanced IEEE 33-bus system with three MGs. The above optimization is solved using the CPLEX solver on a computer equipped with an Intel Core i5 2.50 GHz CPU and 8 GB of RAM. The models proposed in this paper are defined as scenario IV, and four additional scenarios are introduced for comparative analysis. Different scenario configurations are outlined in Table II. Each scenario progressively considers different aspects such as fixed or dynamic network usage fees, P2P energy trading and network constraints, which allow us to assess the effectiveness of dynamic network usage fees in optimizing economic outcomes, balancing DSO benefits, and facilitating P2P energy trading.

TABLE II
DIFFERENT SCENARIO CONFIGURATIONS

Scenario	Network usage fee	P2P energy trading	Network constraint
I	×	×	×
II	×	√	×
III	Fixed	√	√
IV	Dynamic	√	√
V	Dynamic	√	×

Note: √ indicates that the aspect is considered; and × indicates that the aspect is not considered.

A. Basic Data

The enhanced IEEE 33-bus system is illustrated in Fig. 2, with the three MGs connected to nodes 6, 16, and 30, respectively. Specifically, MG3 incorporates WTs, ES units, electrical loads, and P2P energy trading with other MGs. MG1 and MG2 possess a similar configuration to MG3, with the distinction that the WTs in MG3 are replaced by PV systems in MG1 and MG2.

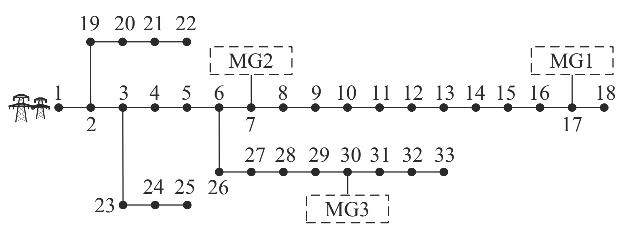

Fig. 2. Enhanced IEEE 33-bus system.

The load demand and renewable energy generation of the three MGs are shown in Fig. 3. To optimize energy utilization efficiency, the time-of-use electricity pricing mechanism is employed and shown in Table III. The basic parameters are consistent for the proposed models, as shown in Table IV.

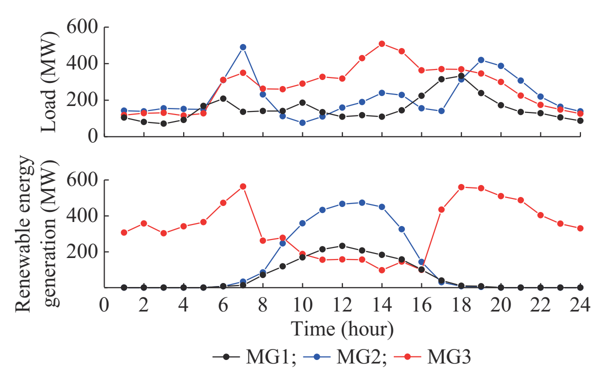

Fig. 3. Load demand and renewable energy generation of three MGs.

TABLE III
TIME-OF-USE ELECTRICITY PRICE MECHANISM

Time	μ^t_{Pb} (CNY/kWh)	μ^t_{Ps} (CNY/kWh)
00:00-08:00	0.488	0.357
09:00, 13:00-17:00, 23:00	0.779	0.357
10:00-12:00, 18:00-22:00	1.241	0.357

TABLE IV
BASIC PARAMETERS

Parameter	Value	Parameter	Value
$\varepsilon_{\min}$	0 CNY/(kWh·km)	$SOC_i^{\max}$	85%
$\varepsilon_{\max}$	0.02 CNY/(kWh·km)	$SOC_i^{\min}$	20%
$P_{ij,+}^{t,\min}$	300 kW	Cap_i	2000 kWh
$P_{ij,-}^{t,\max}$	–300 kW	$P_{i,t}^{\mathrm{ch,max}}$, $P_{i,t}^{\mathrm{dis,max}}$	500 kW, 500 kW
$P_{\mathrm{gb},t}^{\min}$	0 kW	c_{E}^i	0.02 CNY
$P_{\mathrm{gb},t}^{\max}$	10000 kW	$\eta_{\mathrm{ESS}}^{\mathrm{ch}}$, $\eta_{\mathrm{ESS}}^{\mathrm{dis}}$	0.95, 0.95

B. Optimal Results and Analysis

In Figs. 4-6, a visual representation of the optimal operation results of MGs is presented under four different scenarios, where $P^t_{12,+}$, $P^t_{12,-}$, $P^t_{13,+}$, $P^t_{13,-}$, $P^t_{21,+}$, $P^t_{21,-}$, $P^t_{23,+}$, $P^t_{23,-}$, $P^t_{31,+}$, $P^t_{31,-}$, $P^t_{32,+}$, $P^t_{32,-}$ are the trading volumes between MG1 and MG2, MG1 and MG3, MG2 and MG1, MG2 and MG3, MG3 and MG1, MG3 and MG2, respectively. MGs play an indispensable role in safeguarding the economic sustainability of their systems. According to Fig. 4(a), MG1 has surplus PV output exceeding load demand from 11: 00 to 15: 00, which is stored in the ES. This surplus power is then discharged from 19:00 to 20:00 when electricity prices are higher, thereby minimizing the cost of electricity purchased from the DSO. Similarly, MG2 has surplus PV output between 09: 00 and 15:00, utilizing ES systems for charging and selling excess power to the DSO. In scenario I, MGs rely heavily on the internal resources, which minimizes the cost of electricity purchased from the DSO. In scenario II, P2P energy trading is introduced, allowing MGs to trade energy directly with one another. Figures 4(b), 5(b), and 6(b) illustrate that MGs begin to leverage surplus power not just for internal use but also for trading with other MGs. The absence of network constraints allows for relatively free trading, but the lack of network usage fees means that the DSO may struggle to secure its benefits in the P2P market. In scenario III, with the introduction of fixed network usage fees and P2P energy trading, as shown in Figs. 4(c), 5(c), and 6(c), MGs benefit from the ability to trade energy directly with other MGs, which are less adaptable to sudden changes in load or generation compared with scenario IV.

Furthermore, Figs. 4(d), 5(d), and 6(d) show that MG1-MG3 can adjust the energy trading and storage strategies in real time, minimizing reliance on the DSO, which improves the operation efficiency of MGs. Scenario IV demonstrates the highest level of operation efficiency, with MGs minimizing the DSO reliance through P2P energy trading and management of electricity resources.

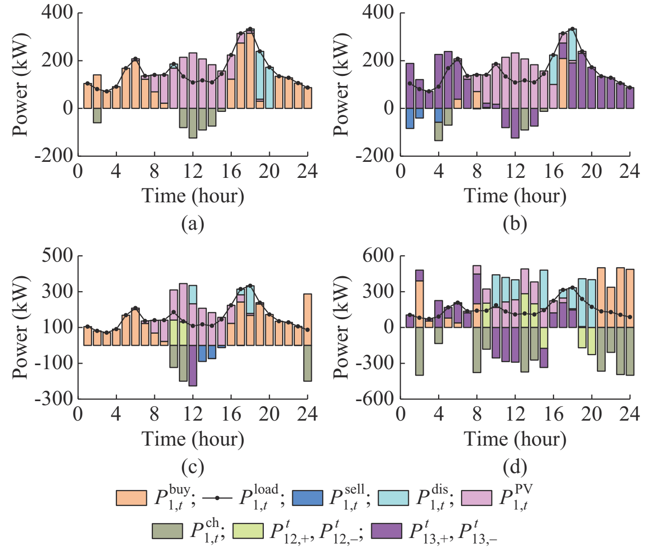

Fig. 4. Dispatching result of power flow balance on a typical day for MG1 in scenarios I-IV. (a) Scenario I. (b) Scenario II. (c) Scenario III. (d) Scenario IV.

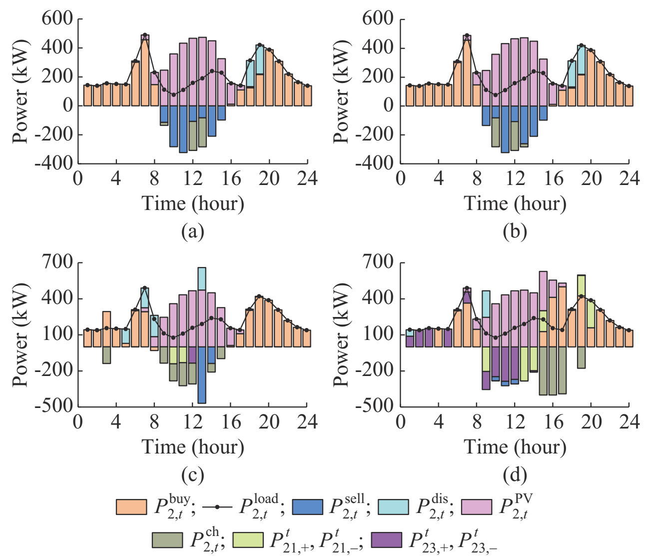

Fig. 5. Dispatching result of power flow balance on a typical day for MG2 in scenarios I-IV. (a) Scenario I. (b) Scenario II. (c) Scenario III. (d) Scenario IV.

This is contrasted with the less flexible and more static strategies observed in scenarios II and III. The results clearly indicate that while network constraints limit operation flexibility, dynamic pricing and P2P energy trading significantly enhance the ability of the system for energy distribution efficiency.

C. Analysis of P2P Energy Trading

Dynamic network usage fees can increase trading activity among MGs under network constraints. According to Fig. 4(b), interactions between MG1 and MG3 are more frequent. This is because MGs do not need to pay network usage fees to the DSO, and there are no network constraints in scenario II, making frequent interactions more beneficial for MGs.

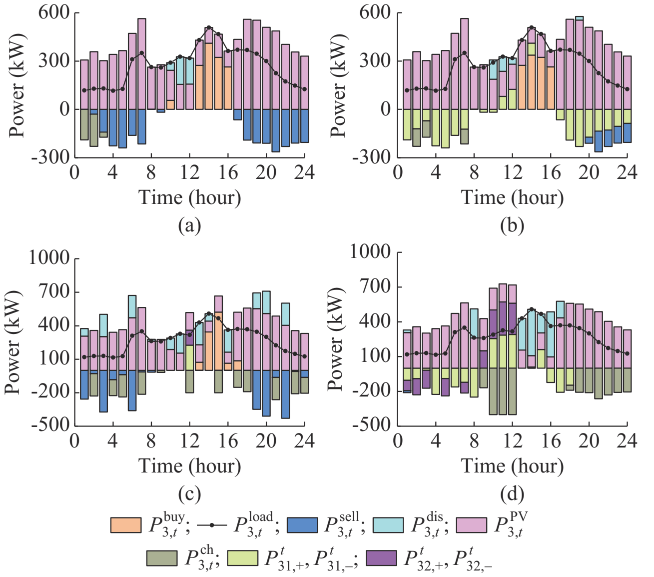

Fig. 6. Dispatching result of power flow balance on a typical day for MG3 in scenarios I-IV. (a) Scenario I. (b) Scenario II. (c) Scenario III. (d) Scenario IV.

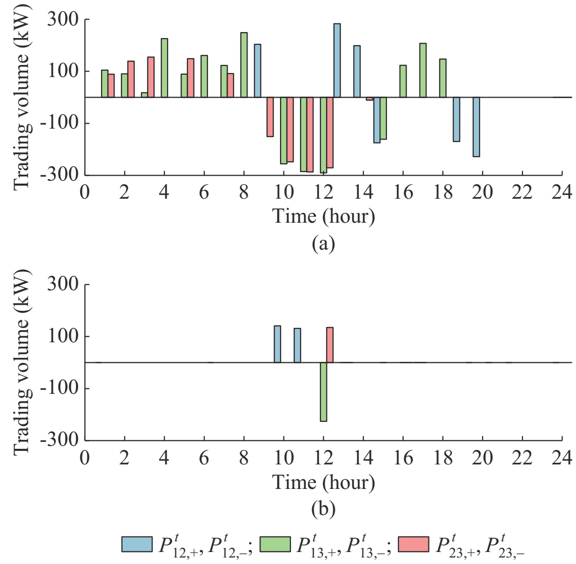

Fig. 7. Trading volumes among MGs during different time periods in scenarios IV and III. (a) Scenario IV. (b) Scenario III.

However, the lack of network constraints and the elimination of network usage fees introduce challenges related to the benefits of DSOs and the stability and security of power flow management. By contrast, Fig. 7 shows the trading volumes among MGs during different time periods in scenarios III and IV, where network constraints are considered, offering a more realistic evaluation of trading activity under constrained conditions.

The trading volume among MGs in scenario IV is more distributed across the day compared with that in scenario III, particularly between MG1 and MG2 as well as MG1 and MG3. In scenario IV, MG1 and MG2 engage in trading at six different time intervals, whereas in scenario III, its trading occurs only at 10:00 and 11:00, which indicates that the flexible adjustment of network usage fees in scenario IV promotes more frequent P2P energy trading. Similarly, MGs show increased trading activities in scenario IV compared with that in scenario III, indicating that dynamic network usage fees, which adjust in response to real-time network conditions, provide a more conducive environment for P2P energy trading. By lowering fees during off-peak periods or when network congestion is low, MGs are encouraged to trade more frequently, optimizing their energy exchanges and potentially increasing their economic benefits.

The proposed mechanism allows MGs to adopt more strategic trading behaviors. MGs may choose to engage in P2P energy trading when network usage fees are low, thus minimizing costs. Conversely, when network usage fees are high, MGs might opt to store surplus power rather than sell it, preserving for future use or waiting for favorable prices.

D. Analysis of Economic Performance

Social welfare should be considered as one of the most crucial factors to for the proposed mechanism. The proposed mechanism serves as a critical link between the MG and DSO, enhancing overall social welfare. This is evidenced by the comprehensive cost and revenue analysis in different scenarios detailed in Tables V and VI.

TABLE V
COST IN DIFFERENT SCENARIOS

Scenario	C_{MG}^{1} (CNY)	C_{MG}^{2} (CNY)	C_{MG}^{3} (CNY)	Multi-MG cost (CNY)	C_{DSO} (CNY)	Total cost (CNY)
I	1841.90	2368.67	290.46	4501.03	3170.86	7671.89
II	1261.71	2192.13	208.07	3661.91	3450.18	7112.09
III	1531.50	2342.48	256.63	4130.61	2886.79	7017.40
IV	1148.06	2318.62	266.64	3733.32	2683.87	6417.19

TABLE VI
REVENUE IN DIFFERENT SCENARIOS

Scenario	Network loss (CNY)	Network usage fee (CNY)				ES operation cost (CNY)			Electricity purchasing cost (CNY)			Electricity selling revenue (CNY)		
		DSO	MG1	MG2	MG3	MG1	MG2	MG3	MG1	MG2	MG3	MG1	MG2	MG3
III	205.89	359.34	148.17	92.45	118.72	16.25	31.92	46.21	1430.06	2435.14	682.27	62.98	217.03	590.57
IV	232.79	591.04	257.12	120.43	213.49	22.36	32.83	59.34	868.58	2203.82	0	0	38.46	6.19

As shown in Table V, the proposed mechanism can enhance overall social welfare. For MGs, scenario II exhibits the best economic performance, which is attributed to the fact that MGs can utilize distribution lines for P2P energy trading without network usage fees, increased interactions among MGs, and reduced MG costs. However, for DSO, P2P energy trading among MGs leads to higher costs, resulting in an 8.09% increase in costs compared with independent operations. Both scenarios III and IV consider network usage fees, and their overall social welfare surpasses that of scenarios I and II. The operations of MGs and the DSO are linked through the proposed mechanism, and network usage fees are paid by MGs to the DSO for P2P energy trading. In scenario IV, the multi-MG cost is 3733.32 CNY, representing a 17.04% reduction compared with that in scenario I, and a 9.61% reduction compared with that in scenario III. MG1 achieves the lowest cost of 1148.06 CNY, which is a 37.67% reduction compared with that in scenario I. Meanwhile, C_{DSO} decreases to 2683.87 CNY, representing 15.35% and 7.02% reductions compared with those in scenarios I and III, respectively. Scenario IV yields the lowest total cost of 6417.19 CNY and demonstrates the highest level of overall social welfare. Both the MG and DSO are financially benefited by the proposed mechanism. In this context, MG profits from P2P energy trading, while the DSO benefits from the collection of network usage fees.

As shown in Table VI, in scenarios III and IV, network usage fees provide financial benefits to the DSO through their collection and motivate MGs to engage more in P2P energy trading, as evidenced by the detailed breakdown in Table VI. In scenario III, the network losses are 205.89 CNY, which is lower than those in scenario IV. This is because, in scenario III, a fixed fee is applied throughout the entire day, while in scenario IV, fee rates vary during different periods. Although dynamic network usage fees can facilitate P2P energy trading among MGs, they also lead to an increase in network losses. The DSO obtains greater benefits from the P2P market at the cost of increased network losses. In scenario IV, the network usage fees collected by the DSO from the P2P market are 591.04 CNY, which are higher than those in scenario III. During periods of high load for the DSO, such P2P energy trading among MGs become a burden, contributing to increased network losses and exposing the DSO to additional vulnerabilities. The DSO will charge MG higher network usage fees to compensate for this risk.

For MGs, the network usage fees in scenario III are lower than those in scenario IV, but the costs of electricity purchased are higher in scenario III than those in scenario IV. This is because dynamic network usage fees can enhance the flexibility of MGs in the P2P market, increasing their interactions and reducing their reliance on electricity purchased from the DSO. At the same time, by actively scheduling internal devices, MGs aim to minimize their costs of electricity purchased from the DSO during a scheduling period, which leads to increased operation and maintenance costs for ES. Overall, the ES operation costs for MGs are lower in scenario III than those in scenario IV.

Through this refined analysis, this paper articulates how dynamic network usage fees not only compensate for increased network losses but also incentivize sustainable and economically efficient grid operations. Therefore, the flexibility and profitability of MGs are enhanced.

E. Impact of Power Flow for Dynamic Network Usage Fees

The dynamic network usage fees are influenced by the power flow constraints. As long as the flow constraints of DS are met, P2P energy trading among MGs can reach a state of equilibrium by figuring out the right network usage fees and getting approval from the DSO. For any specified dynamic network usage fee, each MG can formulate an optimal energy management strategy. Figure 8 illustrates the dynamic network usage fees among MGs in scenarios IV-V, which confirms the equilibrium and existence of the Stackelberg game.

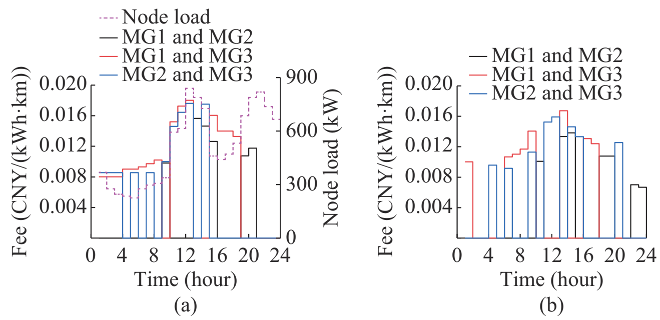

Fig. 8. Dynamic network usage fees among MGs in scenarios IV and V. (a) Scenario IV. (b) Scenario V.

According to Fig. 8, the dynamic network usage fee fluctuates within the allowed range over time. It can be observed that when the MG interacts during the load peak from 10:00 to 15:00, the corresponding network usage fee is also higher. This is reasonable, as during periods with high electricity demand, there is a reduction in the remaining transmission capacity of the DS, leading to escalated transmission costs. DSOs strive to employ higher network usage fees to curtail the interaction among MGs, aiming to increase the remaining transmission capacity of the transmission lines. Similarly, during periods with low electricity demand, there is excess transmission capacity in DS, resulting in lower transmission costs. Consequently, DSOs levy lower network usage fees on MGs.

Furthermore, Fig. 9 shows the P2P energy trading among MGs in scenarios IV and V, without accounting for power flow constraints of DS. Evidently, without considering the power flows in scenario V, the total energy trading volume among MGs is 6054.08 kWh, which is higher than 5377.02 kW when considering the power flows. This is due to the absence of line flow constraints, allowing the DSO to encourage MGs to interact with higher network usage fees during all periods in order to increase the revenue. In this context, the network usage fees are more influenced by the time-of-use electricity price. When the electricity price is higher, MGs are relatively more willing to accept higher network usage fees. In summary, we analyze the relationship between network usage fees by the DSO and DS power flow, examining both scenarios with and without considering power flow. When power flow constraints are considered, the network usage fees collected by the DSO are influenced by the DS power flows.

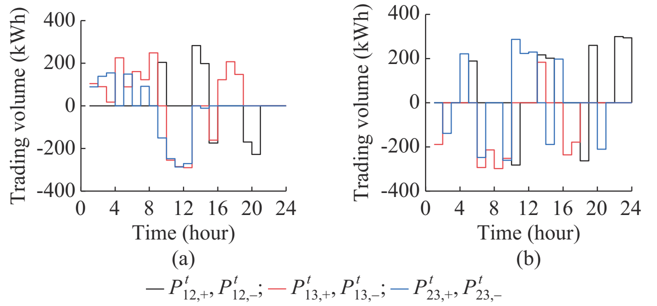

Fig. 9. P2P energy trading among MGs in scenarios IV and V. (a) Scenario IV. (b) Scenario V.

F. Impact of Electrical Distance for Dynamic Network Usage Fees

The unit network usage fee is positively correlated with the electrical distance. In other words, the farther the electrical distance, the higher the network usage fees among MGs. As the electrical distance extends, the complexities faced by the DSO amplify significantly, which includes heightened challenges related to network losses and potential risks associated with P2P exchanges among MGs. To verify the relationship between electrical distance and network usage fee, three cases of MG connection locations as shown in Fig. 10 are simulated. Besides, Fig. 11 presents the relationship between electrical distance and the unit network usage fee.

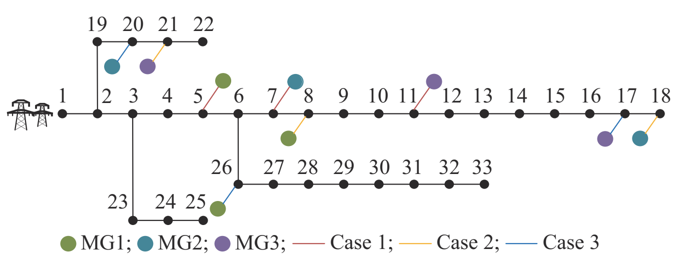

Fig. 10. Three cases of MG connection locations.

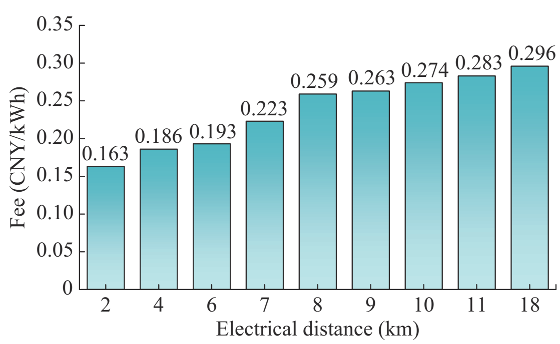

Fig. 11. Relationship between electrical distance and unit network usage fee.

It is noteworthy that the MG interconnection points vary among different cases, leading to changes in power flow and network losses. Therefore, the primary comparison focuses on the relationship between electrical distance and network usage fee among different MGs within the same case.

According to Figs. 10 and 11, in case 1, the shortest electrical distance between MG1 and MG2 is 2 km, with a corresponding unit network usage fee of 0.163 CNY/kWh. On the other hand, the longest electrical distance between MG1 and MG3 is 6 km, with the highest unit network usage fee reaching 0.193 CNY/kWh. Similarly, in cases 2 and 3, the longest electrical distance corresponds to the highest unit network usage fee, while the shortest electrical distance corresponds to the lowest unit network usage fee. Therefore, as the electrical distance increases, the unit network usage fees will also increase. Besides, longer electrical distance is associated with higher network losses, which implies a reduction in energy transmission efficiency, necessitating additional energy compensation, thereby increasing operation costs. These costs are passed on to the usage fees. Longer electrical distances require additional voltage regulators or compensation devices to maintain voltage levels, further increasing costs.

G. Validation on Robustness of Proposed Models

To validate the robustness of the proposed models, a series of test scenarios is introduced where the DSO imposes various constraints on MG operations. These test scenarios are designed to simulate the interruption of P2P energy trading and unexpected supply shortages.

1) Test scenario 1: interruption of P2P energy trading. DSO restricts MGs from engaging in P2P energy trading during peak load periods 08:00-09:00 and 19:00-20:00. These time intervals are typically associated with high load demand, increasing the pressure on power transmission and the risk of network losses. By prohibiting P2P energy trading during these critical periods, the ability is tested to optimize resource allocation under the constrained conditions of the proposed models. Figure 12 presents the P2P energy trading volume and dynamic network usage fees in test scenario 1.

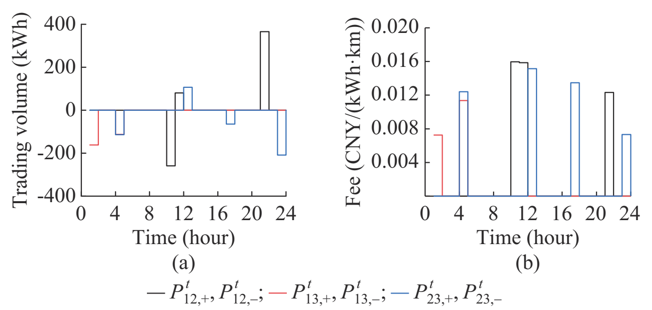

Fig. 12. P2P energy trading volume and network usage fees in test scenario 1. (a) P2P energy trading volume. (b) Dynamic network usage fee.

According to Fig. 12, during the restricted periods, P2P energy trading volume drops to zero, indicating that the MGs adhere to the restrictions of DSO. Outside of the restricted periods, P2P energy trading resumes, with varying trading volumes among the MGs. The ability of MGs to resume P2P energy trading immediately after the restricted periods showcases the robustness of the proposed models and the adaptability of MGs.

2) Test scenario 2: sudden supply shortfall. A sudden and unexpected reduction is simulated in renewable energy generation within the MG to represent a supply shortfall. This test scenario is particularly relevant given the inherent variability and unpredictability associated with renewable energy sourc-

es like PV and WT. Specifically, at three critical time of the day (04:00, 12:00, and 20:00), the actual output of PV and WT is reduced to only 50% of the predicted value. The MG scheduling results and optimal dynamic network usage fees are obtained, as shown in Fig. 13.

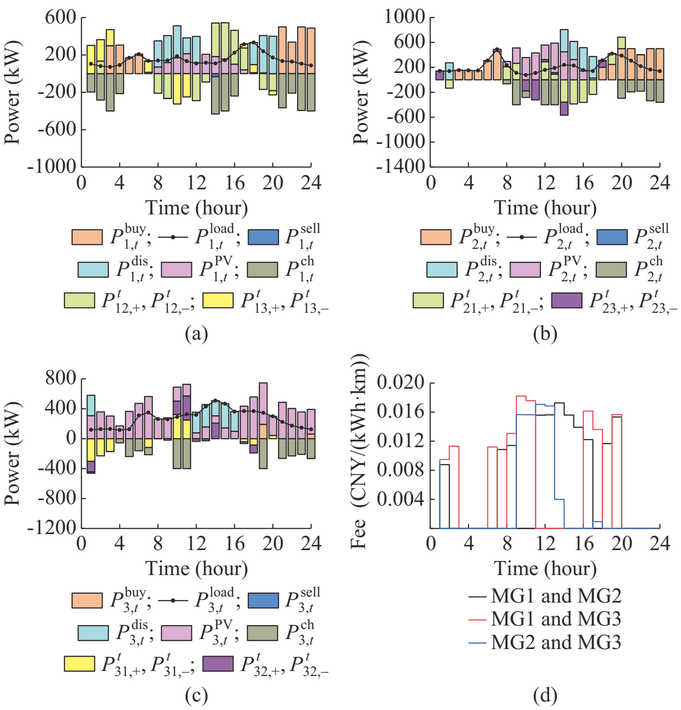

Fig. 13. MG scheduling results and optimal dynamic network usage fees in test scenario 2. (a) MG1. (b) MG2. (c) MG3. (d) Optimal dynamic network usage fees.

According to Fig. 13(a)-(c), the total P2P energy trading volume at 12:00 and 20:00 in test scenario 2 is significantly lower compared with that in scenario IV. Specifically, the total P2P energy trading volume is 325.374 kWh at 12:00, whereas in scenario IV, the volume is 560.974 kWh. This is due to the fact that after fulfilling the internal energy demands, there will be limited excess power to trade with other MGs.

Meanwhile, MG compensates by increasing the discharging rate of its ES, which allows MG to maintain a balance between the internal load and generation while minimizing the reliance on purchasing electricity from the DSO.

According to Fig. 13(d), during the supply shortfall, the average network usage fees at 12:00 and 20:00 are 0.0186 CNY/(kWh·km) and 0.0155 CNY/(kWh·km), respectively. These fees are lower compared with those in scenario IV, which are 0.0178 CNY/(kWh·km) at 12:00 and 0.0117 CNY/(kWh·km) at 20:00, respectively. As MGs rely more heavily on external sources and less involved in P2P energy trading, the cost per unit of exchanged energy increases, reflecting the increased demand on the network during these critical hours.

Overall, these test scenarios confirm that the proposed models are capable of handling various operation challenges, maintaining both operation stability and economic efficiency. The proposed models can dynamically adjust network usage fees and resource allocation, ensuring the robustness of the proposed models under different market and operation conditions.

V. CONCLUSION

This paper presents a comprehensive investigation into the proposed mechanism in P2P energy trading among MGs, focusing on balancing the benefits of DSO in P2P energy trading among MGs. The proposed mechanism effectively addresses the challenges of optimizing network usage fees to achieve mutual benefits for both parties.

1) The interaction between DSO and MG is modeled as a Stackelberg game, where the DSO determines the optimal dynamic network usage fee. This model successfully balances revenue generation for the DSO with the transmission loss costs incurred by MGs.

2) The equilibrium and uniqueness of network usage fees are established within the proposed models. The Stackelberg game is transformed into a single-level optimization problem using KKT conditions, ensuring a stable and unique solution to network usage fees.

3) Simulations on an enhanced IEEE 33-bus system validate the economic viability of the proposed mechanism. The key numerical results demonstrate that the proposed models result in a 17.08% reduction in operation costs for MGs and a 15.36% increase in revenue for DSO.

The proposed models provide valuable insights into optimizing network usage fees in a P2P energy trading framework, but has several limitations. One limitation is that the current method relies on traditional convergence algorithms under relatively stable communication networks. Second, the scalability of the proposed models has not been fully tested in larger and more complex networks. To address these limitations, future work will integrate predefined-time convergence algorithms, event-triggered mechanisms [34], and distributed optimization methods on time-varying directed communication networks [35] to enhance system adaptability and efficiency in dynamic environments.

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