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Energy Management Optimization of Microgrid Cluster Based on Multi-Agent-System and Hierarchical Stackelberg Game Theory

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ABSTRACT To realize the win-win benefits and resource coordination of the multilevel operating entities of a ‘‘microgrid cluster (MGC), microgrid (MG) and user’’ and improve the self-consumption of new energy in the MGC, this paper proposes an energy trading model and solution algorithm of an ‘‘MGC, MG and user’’ based on a multi-agent-system, incentive demand response, and hierarchical Stackelberg game theory. By analyzing the game objectives and strategies of these participants, the unique Stackelberg equilibrium (SE) of the hierarchical Stackelberg game is proved theoretically. The game optimization process is divided into two levels. In the upper-level game, the MGC as a leader stimulates the MG to participate in intracluster dispatching by establishing an internal price incentive mechanism. As the follower, the MG determines the number of electricity transactions based on the realized internal price to maximize its own profits. In the lower-level game, the MG leads the game by deciding electricity selling prices based on the load demands of users, and the user as follower adjust electricity consumption using strategies to balance expenditure and experience of electricity usage. Simulation results verified the effectiveness and good convergence of the proposed method and demonstrated that the proposed hierarchical game strategy can improve the economic benefits of each participant, which is conducive to the establishment of friendly grid-connected MGC.

INDEX TERMS Microgrid cluster, hierarchical Stackelberg game, multi-agent, demand-side response, Stackelberg equilibrium, distributed algorithm.

I. INTRODUCTION

With the development of smart grid and renewable energy technologies, microgrid (MG) projects have been vigorously developed. Microgrids (MGs) are combined to form a microgrid cluster (MGC) system [1], [2]. The MGC provides an intermediate coordination layer between the large grid and the MGs. Each MG undertakes power mutual aid through the MGC, which enhances the power supply reliability and operating economy of the overall MGC system [3].

The actual operation of the MGC can include three levels of interest agents: the MGC, MG, and user. Each MG and its users need to be coordinated and dispatched to achieve a win-win situation for both the MG and the users [4]–[6]. Furthermore, coordinated dispatching is needed between the MG and the MGC to realize the MG's interconnection and mutual benefit [7], [8]. The MGC, MG, and users are interrelated and mutually restricted, and they can form a hierarchical Stackelberg game model. For example, the influence of load participation in dispatching is transmitted to the dispatching of the MGC through its MGs, and the dispatch strategy at the MGC level is transmitted to the load through the MGs and affects the participation with the load. Therefore, the optimal dispatch of the MGC is an integrated and hierarchical coordination dispatching problem involving ‘‘MGC, MG and user’’ multilevel operation entities.

Using the traditional multiobjective optimization aspect in the MGC, researchers [9], [10] considered the power mutual aid between MGs when carrying out the optimal operation and MGC dispatching to realize power sharing and the optimal dispatch in the interconnected operation mode. Researchers [11] and [12] used a hybrid energy management

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system to propose a two-stage MGC energy management strategy under hour-level, day-ahead, optimal dispatch and minute-level, real-time dispatch. This model does not reflect the enthusiasm of electricity trading between microgrids. In [13], a hierarchical energy management structure of the MGC was proposed, and a two-layer optimal scheduling model of interconnected MGs was established to coordinate the operation of the MGs in the upper layer and manage the local operation of each MG in the lower layer. However, the aforementioned optimization methods did not fully consider various agents' interests, and these methods were not suitable for competitive hierarchical electricity market structures.

Currently, multi-agent system (MAS) is widely used for MGs and MGCs [14], [15], and multi-agent models, including those of a large power grid and MGs, have been established. Depending on the level of their interactions between agents and their ability to deal with complex problems quickly, agents can coordinate the optimal operation of each microgrid, but in this case, the user agent model is not taken into account. Xu *et al.* [15] proposed a hierarchical optimization dispatching mode based on the autonomous collaborative operation of the MGC. However, they did not fully consider that users can also adjust their own benefits as agents through a demand-side response. Therefore, the division and modeling of ae multi-agent main body in the MGC and the collaborative optimization of multilevel agents need further research.

Compared to traditional multiobjective optimization, the game theory optimization method can effectively deal with complex interactive decision-making behaviors among multiple stakeholders. Rui *et al.* [16] established the master-slave game model of a microgrid and multimicrogrid (MMG) system, which effectively improved the income of each MG but ignored the independent benefit of the user load side. Liu *et al.* [17] established a noncooperative game model between a single MG and users. Lee *et al.* [18] proposed a hierarchical optimization as a multileader–multifollower Stackelberg game among MGs in a competitive market. In [19], a multiple-leader–multiple-follower Stackelberg game model between a microgrid and users was proposed. In [20], a Stackelberg game between providers and users in the MG was established. To improve the economic efficiency of a micro energy grid, a Stackelberg game considering the time-of-use price of gas in the micro energy grid was proposed in [21]. Anoh *et al.* [22] established a Stackelberg game between producers and consumers with a virtual MG. Wang *et al.* [23] proposed a bilevel Stackelberg game model for a MG with commercial buildings (CBs). In this article, the MG is the leader and the CBs are the followers. Other researchers [24] proposed a Stackelberg game model between generators and MGs. In [25], each prosumer in a pelagic islanded MG tries to maximize its own profit; a competitive energy trading model was formulated based on the Stackelberg game. To provide financial and technical benefits to the community, a novel game model for peer-to-peer energy trading among the prosumers was proposed in [26]. Zhou *et al.* [27] established a three-stage Stackelberg game to maximize the individual payoff of different participants in the MG. Lin *et al.* [28] formulated an energy trading model of a micro energy grid based on a bilevel Stackelberg game. However, researchers [27] and [28] did not consider the collaborative optimization of multiple MGs in the MG cluster. Liu *et al.* [29] proposed a two-level intelligent instrument based on a Stackelberg game for multimicrogrids to stimulate MGs participating in the economic dispatch. Feng *et al.* [30] formulated a Bayesian three-level Stackelberg game in relay-assisted, anti-jamming systems. This game model can be used for the energy management of the microgrid cluster. Fu *et al.* [31] proposed a bilevel optimization model of microgrid clusters based on noncooperative game theory, but they did not fully consider that users as stakeholders can participate in market transactions. In the aforementioned literature, most of the game models in the microgrid cluster do not integrate the MGC, MG, and user together for optimization. They use only a one-level Stackelberg game model to study the communication between the two agents of an MGC. In fact, there are three types of participants in a microgrid cluster; therefore, a single-level Stackelberg game is not an accurate or effective model. In addition, previous studies failed to consider the autonomous initiative of the MGC, MG, and users in the decision-making process at the same time under current market-transaction conditions. Modeling of different participants of the MGC in the electricity market are not sufficiently integrated in these references.

The situation of multiple game participants needs in-depth discussion. The collaborative optimization between multiple agents of the MGC also needs further study, and users must also be involved in the electricity market.

In the dispatch of each MG, the game model between the MG and the user needs to be implemented. In addition, in the dispatch of the MGC, the game model between the MGC and the MG needs to be implemented. Therefore, the game optimization of "MGC, MG, and user" is a type of bilevel optimization game. In this process, the MG plays a dual role. However, it is necessary to study the cooperative optimization scheduling problem of the bilevel game between the MGC, MG, and user.

This article proposes an integrated benefit game optimization strategy between the MGC, MG, and user based on the hierarchical Stackelberg game and incentive demand response idea. Based on the difference of the "MGC, MG, and user" stakeholders in the microgrid cluster, the focus is on the division of agents in the microgrid cluster, the bilevel Stackelberg game scheduling strategy, and the optimal scheduling modeling and solution. The main contributions of this work are as follows:

- The models of the microgrid cluster agent (MGCA), microgrid agent (MGA) and user agent (UA) are established, so that each participant has individual initiative and self-decision-making ability in the process of an electricity transaction. Moreover, the MGCA and MGA

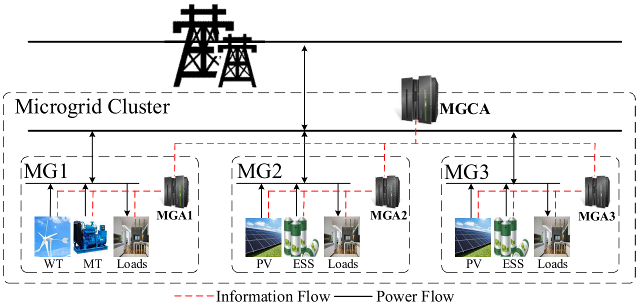

FIGURE 1. Schematic of the MGC.

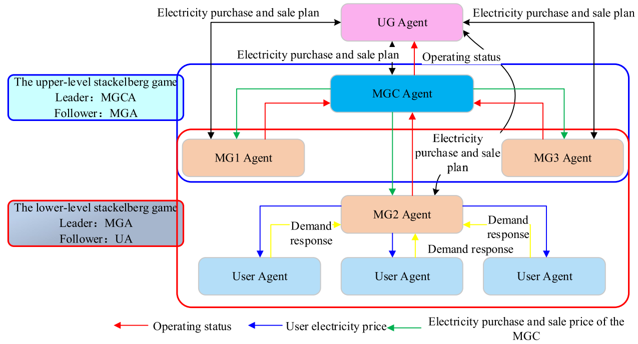

FIGURE 2. Multi-agent hierarchical game model of the MGC.

can make up for the electricity surplus or the electricity lack by trading with the utility grid agent (UGA).

- A hierarchical Stackelberg game optimization model between the MGC, MG, and user is proposed to optimize the energy transaction. The hierarchical Stackelberg equilibrium (SE) is proven to exist uniquely; therefore, the interests of each participant can reach an equilibrium value, and a nested distributed algorithm for solving the hierarchical Stackelberg game model is given.
- The MGA model in this article considers the ability of the MGA to independently select transaction objects by introducing transaction probability, which is more in line with the true electricity market. Moreover, the MGA formulates real-time electricity price incentive policies to guide users to adjust electricity consumption strategies.
- The utility function of the UA is established, which considers the user's power consumption experience and power consumption expenditure.

The paper is structured as follows: In Section II, the multi-agent structure and interaction mechanism of the MGC are introduced. Each agent model in the MGC is described in detail in Section III. The hierarchical Stackelberg game model of the MGC is described in Section IV, and the case study is presented in Section V. Finally, the conclusions are presented in Section VI.

II. MULTI-AGENT STRUCTURE AND INTERACTION MECHANISM OF THE MGC

A. BASIC STRUCTURE OF THE MGC SYSTEM

The microgrid generally includes a wind turbine (WT), photovoltaic (PV), microturbine (MT), energy storage system (ESS), and various other types of user loads.

Based on the MGC model of the European Union (EU) More Microgrids project, as shown in Fig. 1, this paper constructs a layered coordinated optimal dispatch strategy between the MGC, MG, and user in the MGC.

B. MULTI-AGENT DIVISION AND OPERATION INTERACTION MECHANISM OF THE MGC

When the MGC is in operation, the interconnection and mutual benefit between MGs can improve the local consumption capacity of new energy in the MGC to make up for the inability of some MG sources to absorb their own internal new energy due to insufficient or excessive output. Multiple MGs in the MGC belong to different business entities, each pursuing the maximization of their own interests. Therefore, it is necessary to coordinate the mutual energy benefit between each MG, consider the individual and overall interests, and improve each MG's independent interests while improving the overall benefits of the MGC.

As shown in Fig. 2, combined with the MAS mechanism, a four-layer coordinated control system architecture of the MGC has been established, including four participants: the utility grid agent (UGA), microgrid cluster agent (MGCA), microgrid agent (MGA), and user agent (UA).

The structure of the proposed three-layer Stackelberg game model is shown in Fig. 2.

In the upper-level game, the MGCA, as the leader, encourages the purchase and sale of electricity between MGs by adjusting the price of electricity purchases and sales within the MGCA and maximizes the income of the MGCA. As a follower, each MGA responds to the purchase and sale price of the electricity in the cluster to adjust its own transaction power to maximize each MG's income. At the same time, the amount of electricity traded also affects the income of the MGCA, thus affecting the adjustment of the electricity price of the MGCA.

In the lower-level game, an MG optimal dispatch strategy is proposed based on the real-time electricity price incentive. As the leader, the MGA formulates electricity price incentive policies based on the supply and demand status of the sources and loads, guides users to adjust electricity consumption strategies, and makes full use of the controllable green adjustment capabilities of the loads. As a follower, the UA adjusts the load power through the demand response based on the internal electricity price of the MG to maximize the comprehensive benefits on the user side. At the same time, the adjusted electricity consumption results of the users also affect the income of the MG agents, thereby encouraging the MGs to adjust their electricity price incentive policies.

During the operation of the MGC system, each MG may show unequal power between the source and load. Therefore, the MGC system generally has total power-purchase demand and total power-sales demand. Since MGs belong to different economic entities, noncooperative transactions may be adopted between MGs. To enable the orderly operation of the multi-agent MGC, it is important to ensure that the interests of the MGCA and each MGA are maximized and that individual and overall interests are taken into account. The MGCA needs to set up a reasonable internal purchase and sale price system based on the purchase and sale price of the large grid. In this way, the MGA is encouraged to prioritize electricity trading within the MGC, improve the power mutual aid level of each MG, and improve the level of power consumption in the MGC.

Utilizing their own subjective initiative, multi-agents coordinate to achieve the established goals and benefits of MGCA, MGAs, and UA, which is more in line with the true operating status of the MG and MGC. This initiative also establishes the foundation for the game model of the MGC, which is explained later, and realizes coordinated optimization among the various entities.

III. EACH AGENT MODEL IN OPTIMAL DISPATCH OF THE MGC

MGCA and MGAs formulate a game model with one-leader–multiple-follower. The MGA mainly purchases and sells electricity with the MGCA in the MGC. The MGs are in a noncooperative state, and the optimal dispatch of MGA can be solved in parallel. The time-of-use (TOU) price of the large grid is used as a reference for the MGC to determine the internal electricity price in the cluster. When the MGCA cannot absorb the unbalanced amount of source and load through internal mutual aid, the MGCA can make up for the surplus and lack of electricity by trading with the UGA.

A. PROFIT MODEL OF THE MGCA

The MGCA can be regarded as a virtual energy pool or power service provider with two-way energy flow, and it is the coordinator and leader of the transaction market between MGs. The MGCA is responsible for balancing the source and load power of each MG in the MGC. Each MG can exchange electricity with other MGs through the MGCA.

The MGCA, as a new type of electricity trading party, sets the intragroup transaction electricity price according to the TOU electricity price of the large power grid, which is more attractive than the electricity price of the large power grid. That is, there is a preferential power price, which guides the MGA and MGCA to conduct power transactions.

1) OBJECTIVE FUNCTION OF THE MGCA

The objective function of the MGCA is composed of the income obtained by the MGCA and each MGA-traded electricity, and the MGCA and UGA-traded electricity. The expression is as follows:

$$\max E_{MGCA} = \sum_{i=1}^{N}\sum_{t=1}^{24}[(\lambda_{sell,t}P_{sell,i,t} + \mu_{buy,t}P_{gridbuy,t}) - (\lambda_{buy,t}P_{buy,i,t} + \mu_{sell,t}P_{gridsell,t})] \quad (1)$$

where N is the number of MGs in the MGC. $\lambda_{sell,t}$ and $\lambda_{buy,t}$ are the electricity prices sold and purchased by the MGCA from each MGA in period t, respectively. $P_{sell,i,t}$ and $P_{buy,i,t}$ represent the electricity sold and purchased by the MGCA from each MGA i in period t, respectively. $\mu_{buy,t}$ and $\mu_{sell,t}$ are the prices for the electricity purchased and sold by the UGA from the MGCA in period t, respectively. $P_{gridbuy,t}$ and $P_{gridsell,t}$ represent the electricity purchased and sold by the UGA from the MGCA in period t, respectively.

2) OPERATION CONSTRAINTS

a: TRANSACTION PROBABILITY

In fact, the MGA has two choices in the power transaction mode, namely, directly trading with the UGA or trading with the MGCA, so the independent selection ability of the MGA cannot be ignored. Purchasing electricity directly from the UGA has a more stable and reliable power guarantee. Therefore, the MGCA needs to attract MGA and MGCA transactions in the MGC through electricity price incentives. The selection probability of a microgrid in two-power trading modes is used to select trading objects [34]. The transaction probability model between the MGA and UGA or the MGA and MGCA is constructed by adjusting the ratio of purchase and sale of electricity prices. The constraints are as follows:

$$\begin{cases} \varphi_{b,t} = \dfrac{\lambda_{buy,t} - \mu_{buy,t}}{\mu_{sell,t} - \mu_{buy,t}} \\ \varphi_{s,t} = \dfrac{\mu_{sell,i} - \lambda_{sell,i}}{\mu_{sell,i} - \mu_{buy,i}} \\ p_{MGCA,t} = a[(\varphi_{b,t} + \varphi_{s,t})/2] + b \\ p_{UGA,t} = 1 - p_{MGCA,t} \end{cases} \quad (2)$$

where $\varphi_{b,t}$ is the power purchase price adjustment ratio established by the MGCA. $\varphi_{s,t}$ is the power sale price adjustment ratio established by the MGCA. $p_{MGCA,t}$ is the probability of the MGA choosing to trade with the MGCA in period t. $p_{UGA,t}$ is the probability of the MGA choosing to trade with the UGA in period t. a and b are the parameters of the linear function, respectively.

b: ELECTRICAL POWER BALANCE CONSTRAINT

$$\sum_{i=1}^{N} P_{buy,i,t} + \varphi_t P_{gridbuy,t} = \sum_{i=1}^{N} P_{sell,i,t} + (1 - \varphi_t)P_{gridsell,t} \quad (3)$$

where φ_t is the MGCA and the large grid transaction state sign in period t. It is 0 or 1.

c: INTERNAL PRICE CONSTRAINT

The internal prices produced by the MGC should be between the selling price and the buying price to maximize its own profits under the constraint as follows:

$$\mu_{buy,t} \le \lambda_{buy,t} \le \lambda_{sell,t} \le \mu_{sell,t} \quad (4)$$

d: TIE-LINE POWER BALANCE CONSTRAINT

$$0 \leq (P_{gridbuy,t}, P_{gridsell,t}) \leq P_{grid,\max} \tag{5}$$

where $P_{grid,\max}$ is the upper limit of the transmission power of the tie line between the MGCA and the UGA.

B. UTILITY MODEL OF THE MGAs

The typical model of the MG is shown in Fig. 1. Each MGA is distributed and autonomous. The MGA maximizes revenue by setting a reasonable price for electricity sales and optimizing the management of each equipment output. The MGA sets a reasonable price for power purchase by the UA and adjusts each user's load power, thereby using source-load collaborative management optimization to maximize its own benefits. By formulating a reasonable electricity price for selling electricity, each user is encouraged to adjust the load power, to use "MG and user" coordinated management optimization to maximize their own benefits. Therefore, the optimal pricing can maximize the benefits of the MGA and make the UA adjust its electricity consumption strategy to obtain the greatest benefit.

1) OBJECTIVE FUNCTION OF THE MGAs

The MGA objective function is established as follows:

$$\max E_{MGA.i} = \sum_{t=1}^{24} \{\gamma_{sell,i,t} l_{i,t} - [C_{co2,i,t} + C_{om,i,t} + C_{en,i,t} + C_{ex,i,t}]\} \tag{6}$$

$$\max E_{MGA.i} = \sum_{t=1}^{24} (\gamma_{sell,i,t} l_{i,t} - C_{m\arg inal,i,t} g_{i,t}) \tag{7}$$

where $\gamma_{sell,i,t}$ is the price for power purchased by users in the MG i in period t. $l_{i,t}$ is the actual load power of users in the MG i in period t. $C_{co2,i,t}$ is the cost of carbon transaction for the MG i. $C_{om,i,t}$ is the operation and maintenance cost of generating units in the MG i in period t. $C_{en,i,t}$ is the pollution cost of generating units in the MG i in period t. $C_{ex,i,t}$ is the transaction costs of the MG i in period t. $C_{m\arg inal,i,t}$ is the marginal cost of the MG i in period t. $g_{i,t}$ is the total output of the MG i in period t.

$C_{co2,i,t}$ is the carbon transaction cost of the MGA. Currently, most studies adopt free initial carbon emission rights based on the allocation of power generation when constructing carbon trading models. When the carbon allowance used in the MG exceeds the free quota, the excess carbon emission allowance needs to be purchased and paid. If the used carbon allowance is less than its free allocation, it can be sold to the electricity market for profit. This paper uses the baseline method based on power generation to establish a carbon allowance trading model as follows:

$$C_{co2,i,t} = \alpha_{co2}[\sum_{k=1}^{Ki} (\varphi_k - \varepsilon) P_{G,i,k,t}] \tag{8}$$

where α_{co2} is the carbon trading price, which is 0.25 Yuan/kg. φ_k is the carbon emission intensity of unit output for device k, and the carbon emission parameter of MT in this paper is taken as 810 g/kWh. ε is the distribution coefficient of carbon emissions per unit of electricity, which is 728 g/kWh. This article considers only the MT contribution to carbon emissions. Ki is the number of the devices in MG i. $P_{G,i,k,t}$ is the output of device k in period t.

$C_{om,i,t}$ is the operation and maintenance cost of the MGA, which is given by the following:

$$\begin{aligned} C_{om,i,t} = {} & (a_{op,mt} + a_{m,mt}) P_{mt,i,t} + (a_{op,wt} + a_{m,wt}) P_{wt,i,t} \\ & + (a_{op,pv} + a_{m,pv}) P_{pv,i,t} \\ & + (a_{op,ess} + a_{m,ess})(P_{c,i,t} + P_{d,i,t}) \end{aligned} \tag{9}$$

where a_{op} is the operating cost coefficient of the device. a_m is the maintenance cost coefficient of the device. $P_{mt,i,t}$, $P_{pv,i,t}$, and $P_{wt,i,t}$ are the power of the MT, PV, and WT in the MG i in period t, respectively. $P_{c,i,t}$ and $P_{d,i,t}$ are the charge power and discharge power of the ESS in the MG i in period t, respectively.

$C_{en,i,t}$ is the pollution abatement cost of the MGA, which is given by the following:

$$C_{en,i,t} = \sum_{j=1}^{J} \alpha_{e,j} \beta_{e,j} P_{mt,i,t} \tag{10}$$

where $\alpha_{e,j}$ is the emission cost of pollutant j. $\beta_{e,j}$ is the discharge amount of pollutant j. This article considers only the pollution cost of the MT.

$C_{ex,i,t}$ is the transaction cost between the MGA and MGCA and between the MGA and UGA, which is given by the following:

$$\begin{aligned} C_{ex,i,t} = {} & (\lambda_{sell,t} P_{sell,i,t} + \mu_{sell,t} P_{gsell,i,t}) \\ & - (\lambda_{buy,t} P_{buy,i,t} + \mu_{buy,t} P_{gbuy,i,t}) \end{aligned} \tag{11}$$

where $P_{gbuy,i,t}$ and $P_{gsell,i,t}$ are the electricity purchased and sold by the UGA from the MGA i in period t, respectively.

2) OPERATION CONSTRAINTS

a: ELECTRICAL POWER BALANCE CONSTRAINTS

$$\begin{cases} P_{d,i,t} + P_{mt,i,t} + P_{pv,i,t} + P_{wt,i,t} + f_{i,t}(P_{sell,i,t} + P_{gsell,i,t}) \\ \quad = P_{c,t} + P_{l,i,t} + (1 - f_{i,t})(P_{buy,i,t} + P_{gbuy,i,t}) \\ \dfrac{P_{buy,i,t}}{P_{buy,i,t} + P_{gbuy,i,t}} = p_{MGCA,t} \\ \dfrac{P_{sell,i,t}}{P_{sell,i,t} + P_{gsell,i,t}} = p_{MGCA,t} \end{cases} \tag{12}$$

where $P_{l,i,t}$ is the sum of the load power of all users in the MG i. f_t is the binary variable indicating the state of buying and selling electricity of the MG i.

b: DEVICE OUTPUT CONSTRAINT

$$P_{G,i,k,\min} \leq P_{G,i,k,t} \leq P_{G,i,k,\max} \tag{13}$$

where $P_{G,i,k,\min}$ and $P_{G,i,k,\max}$ are the upper limit output power and lower limit output power of device k, respectively.

c: CLIMB SPEED CONSTRAINT

$$-R_{down,i,k} \leq P_{G,i,k,t-1} - P_{G,i,k,t} \leq R_{up,i,k} \tag{14}$$

where $R_{down,i,k}$ and $R_{up,i,k}$ are the maximum downward and upward climb speeds of the device k, respectively.

d: ESS CONSTRAINTS

$$\begin{cases} 0 \leq P_{c,i,t} \leq P_{c,i,t,\max} \\ 0 \leq P_{d,i,t} \leq P_{d,i,t,\max} \\ S_{oc,i,t+1} = S_{oc,i,t} + \dfrac{(\eta_{c,i} S_{c,i,t} P_{c,i,t} - \frac{S_{d,i,t} P_{d,i,t}}{\eta_{d,i}})}{E_{ess,i}} \\ S_{oc,i,t,\min} \leq S_{oc,i,t} \leq S_{oc,i,t,\max} \\ S_{oc,i}(0) = S_{oc,i}(24) \\ S_{c,i,t} + S_{d,i,t} \in (0, 1) \end{cases} \tag{15}$$

where $P_{c,i,t,\max}$ and $P_{d,i,t,\max}$ are the maximum charge power and discharge power of the ESS in the MG i in period t, respectively. $S_{oc,i,t}$ is the state value of the ESS. $\eta_{c,i}$ and $\eta_{d,i}$ are the charging and discharging efficiency of the ESS, respectively. $S_{c,i,t}$ and $S_{d,i,t}$ are the charging and discharging state values of the ESS in the MG i in period t (0 means off, 1 means on), respectively. $E_{ess,i}$is the capacity of the ESS in the MG i.

e: ELECTRICITY PRICE CONSTRAINT

According to (27), the relationship between the price of electricity sold and the electricity consumption strategy of users can be obtained, as shown in (16). In addition, the constraint range of the electricity price strategy of the MGA is derived from the electricity consumption range of users, as shown in (17):

$$\gamma_{sell,i,t} = (\frac{l_{i,t}}{d_{i,t}})^{1/\alpha_{i,t}} \cdot \beta_{i,t} \tag{16}$$

$$\max(C_{m\arg inal,i,t}, (\frac{l_{i,t,\max}}{d_{i,t}})^{\frac{1}{\alpha_{i,t}}} \beta_{i,t}) \leq \gamma_{sell,i,t} \leq (\frac{l_{i,t,\min}}{d_{i,t}})^{\frac{1}{\alpha_{i,t}}} \beta_{i,t} \tag{17}$$

where $l_{i,t,\max}$ and $l_{i,t,\min}$ are the maximum and minimum power consumption of user load in MG i in period t, and this paper takes 1.2 and 0.8 times of the demand load power, respectively. $d_{i,t}$ is the demand load power of users.

C. THE MODEL OF THE UA

After the MGA sets the price of electricity sold in the MG, the UA will respond to the electricity price set by the MGA and flexibly adjust the power of various adjustable intelligent loads. The UA considers its satisfaction and expenditure based on load priority to adjust its electricity consumption behavior in response to demand side to maximize its own benefits. Each MG must ensure a continuous power supply for critical loads.

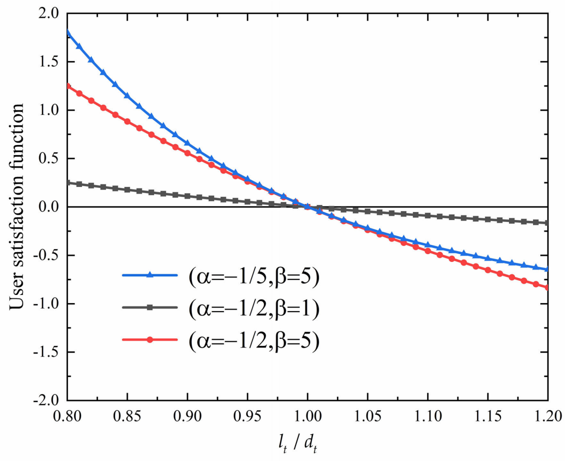

FIGURE 3. User satisfaction function with different parameters (with unit d_t).

1) OBJECTIVE FUNCTION OF THE UA

This paper considers the establishment of an optimization model based on the user's power consumption satisfaction and expenditure [15], [17], [21], [25], [26], [33]–[36].

In the research of this article, user-load satisfaction is reflected by quantifying user's actual electricity demand combined with the ratio of user-demand electricity consumption to actual electricity consumption [34]–[36]. The constructed user satisfaction target can be expressed as follows:

$$\begin{cases} S_{user,i} = \sum_{t=1}^{24} S_{user,i,t} = \sum_{t=1}^{24} \{-d_{i,t} \frac{\alpha_{i,t}\beta_i}{1+\alpha_{i,t}} [(\frac{l_{i,t}}{d_{i,t}})^{\frac{1+\alpha_{i,t}}{\alpha_{i,t}}} - 1]\} \\ -1 < \alpha_{i,t} < 0, \beta_i > 0 \end{cases} \tag{18}$$

where $\alpha_{i,t}$ and β_i are the relevant parameters of the user satisfaction function, respectively. The parameter $\alpha_{i,t}$ is related to the elasticity of electricity price; the parameter $\beta_{i,t}$ corresponds to the regular electricity price under regular load.

Fig. 3 shows the user's satisfaction function curve of the unit power consumption under different set parameters.

According to the electricity price incentive policy, users adjust their own electricity consumption. Therefore, the user's power purchase cost can be expressed as follows:

$$C_{user,i} = \sum_{t=1}^{24} C_{user,i,t} = \sum_{t=1}^{24} (\gamma_{sell,i,t} l_{i,t}) \tag{19}$$

In summary, because the user's function is to maximize its own benefits, the UA's utility function can be expressed as follows:

$$\max E_{UA,i} = -C_{user,i} - S_{user,i} \tag{20}$$

2) OPERATION CONSTRAINTS

a: CONSTRAINT OF THE USER'S LOAD STRATEGY

$$\sum_{t=1}^{24} (d_{i,t} - l_{i,t}) \leq \xi \sum_{t=1}^{24} d_{i,t} \tag{21}$$

where ξ is the maximum adjustable load ratio, which is taken as 10% in this paper.

b: LOAD ADJUSTABLE POWER RANGE CONSTRAINT

$$l_{i,t,\min} \leq l_{i,t} \leq l_{i,t,\max} \tag{22}$$

IV. HIERARCHICAL STACKELBERG GAME MODEL OF THE MGC

A. GAME FORMULATION

The salient feature of noncooperative games is the inclusion of multiple decision-making bodies, each of which attempts to maximize its own benefits. The Stackelberg game is a noncooperative game model with a hierarchical structure. The leader with proactive characteristics gives its strategy first, and then, the follower gives the optimal response according to the leader's strategy and passes the strategy to the leader. Due to the incompleteness of the strategy information obtained by each agent, multiple iterations are needed to stabilize the game and reach the optimal value of the system.

According to the definition of the SE, when the game model has the SE, the interests of each subject can reach equilibrium. The hierarchical Stackelberg game model of the MGCA, MGA, and UA is constructed as follows:

- Participants: Three agents with autonomous and controllable capabilities: MGCA, MGA, and UA.
- Strategies: During the game, the MGCA sets the purchase and sale price of electricity, the MGA uses transaction electricity and sets the sale price, and the UA uses the demand-response, adjusted-load electricity, as a set of strategies to adjust the utility benefits of various stakeholders. The game's equilibrium point is the optimal strategy of the game, and the game leader cannot obtain higher operating income by unilaterally changing the electricity price strategy. At the same time, the followers of the game cannot obtain higher profits by adjusting the scheduling power strategy.
- Utility Functions: MGCA, MGA, and UA utility functions correspond to (1), (6), and (20), respectively.

B. EQUILIBRIUM OF THE STACKELBERG GAME

According to the related definition of SE [16]–[36], assuming that the proposed model exists the only Stackelberg equilibrium strategy $(\lambda_{buy}^{*}, \lambda_{sell}^{*}, P^{*}, \gamma_{sell}^{*}, l^{*})$, the interests of each participant can reach an equilibrium value.

Therefore, when the hierarchical Stackelberg game reaches the Stackelberg equilibrium, the MGCA can no longer improve its own benefits by changing the price of electricity purchased and sold in the MGC, the MGA can no longer independently change the price of electricity sold or adjust the transaction electricity to improve its own utility benefits, and the UA can no longer improve its own utility benefits by individually changing the load power value, which can be expressed as follows:

$$\begin{cases} E_{MGCA}(\lambda_{buy}^{*}, \lambda_{sell}^{*}, P^{*}, \gamma_{sell}^{*}, l^{*}) \\ \quad \geq E_{MGCA}(\lambda_{buy}, \lambda_{sell}, P^{*}, \gamma_{sell}^{*}, l^{*}) \\ E_{MGA}(\lambda_{buy}^{*}, \lambda_{sell}^{*}, P^{*}, \gamma_{sell}^{*}, l^{*}) \\ \quad \geq E_{MGA}(\lambda_{buy}^{*}, \lambda_{sell}^{*}, P_i, P_{-i}^{*}, \gamma_{sell}, l^{*}) \\ E_{UA}(\lambda_{buy}^{*}, \lambda_{sell}^{*}, P^{*}, \gamma_{sell}^{*}, l^{*}) \\ \quad \geq E_{UA}(\lambda_{buy}^{*}, \lambda_{sell}^{*}, P^{*}, \gamma_{sell}^{*}, l_k, l_{-k}^{*}) \end{cases} \tag{23}$$

where l^* is the actual power consumption strategy of all UAs in a single microgrid after the game equilibrium is reached; P_i^* and P_{-i}^* represent the interactive power of the MGA i and MGCA and the interactive power of other MGAs, except MGA i, with the MGCA, respectively. l_k^* and l_{-k}^* represent the actual power consumption of the load of the UA k and the actual power consumption of other user agents, except UA k, respectively.

According to previous studies [16]–[36], the Stackelberg game can reach the Stackelberg equilibrium only if the following theorem is satisfied:

Theorem 1: In a multiparticipant game, if (a) the leader and the followers are continuous functions of their respective decision variables, that is, their strategy spaces are all nonempty compact convex sets; (b) for the leader's optimal strategy, the follower's objective function has the only optimal strategy solution; (c) for the follower's optimal strategy, the leader's objective function has the only optimal strategy solution.

Proof: (1) Since the strategy sets of the MGCA, MGA, and UA are all nonempty, closed, and bounded convex sets in Euclidean space, and their objective functions are continuous functions of various variables, they satisfy the condition (a) of Theorem 1.

(2) In the upper-level game, an optimization model with one leader and multiple followers is constructed. For MGA, the utility function changes linearly within the set of power purchases and sales strategies. That is, the E_{MGA} of each MGA is a continuous quasi-concave function about the power purchase and sales strategy. Therefore, for the optimal purchase and sale price strategy of the microgrid cluster agent, as the leader, the MGA, as the follower, has the optimal purchase and sales strategy. The utility function of the MGCA also changes linearly within the set of electricity-purchase and sale-price strategies. Therefore, the MGCA utility function is a continuous quasi-concave function of its strategy. This shows that for the MGA with the follower's optimal purchase and sales strategy, the MGCA as the leader has the optimal and unique purchase- and sale-price strategy. That is, there is a unique equilibrium point between the MGCA and each MGA.

(3) In the lower-level game, from the MGC's utility function (6) and the UA's utility function (20), we can see that each utility function is a continuous function with respect to each decision variable. Therefore, the following is the main proof: the optimal electricity price strategy given by the leader MGA depends on whether the follower user agent has a unique

optimal electricity consumption strategy.

$$\max E_{UA} = -C_{user} - S_{user} \tag{24}$$

According to the theorem rules, we take the derivative of the UA's function E_{UA} with respect to l_t, and we obtain:

$$\frac{\partial E_{UA}}{\partial l_t} = (\frac{l_t}{d_t})^{1/\alpha_t} \cdot \beta_t - \gamma_{sell.t} \tag{25}$$

Taking (25) as equal to 0, the theoretically optimal strategy on the user side can be obtained as:

$$l_t(\gamma_{sell}) = d_t(\frac{\gamma_{sell.t}}{\beta_t})^{\alpha_t} \tag{26}$$

MGA adjusts the electricity price to achieve the goal of optimizing its own benefits by adjusting the electricity consumption after the user side responds to the demand side according to the electricity sales price.

By setting (25) equal to zero, we obtain the optimal MGA price strategy for electricity sales:

$$\gamma_{sell.t} = (\frac{l_t}{d_t})^{1/\alpha_t} \cdot \beta_t \tag{27}$$

Then, we take the second-order derivation of the UA's utility function with respect to l_t and l_i, and we obtain:

$$\frac{\partial^2 E_{UA}}{\partial l_t \partial l_i} = \begin{cases} \frac{\beta_t}{\alpha_t} \cdot \frac{l_t^{1/\alpha_t - 1}}{d_t^{1/\alpha_t}} \cdot \beta_t & t = i \\ 0 & t \neq i \end{cases} \tag{28}$$

It can be seen from (28) that the Hessian matrix of the UA's utility function E_{UA} is a negative definite matrix. This indicates that the utility function of the UA is concave, and the user has the only optimal power-purchase strategy ($\{l_t^*\}_{t=1}^{24}$). Therefore, the condition (b) of Theorem 1 is satisfied.

Substituting the optimal load power based on the user demand response into the benefit function of the MGA, the following equations can be obtained:

$$\max E_{MGA}(\gamma_{sell.t}) = \sum_{t=1}^{24} \{\gamma_{sell,t} l_t^* - [C_{co2,t} + C_{om,t} + C_{en,t} + C_{ex,t}]\} \tag{29}$$

$$\frac{\partial^2 E_{MGA}}{\partial \gamma_{sell.t} \partial \gamma_{sell.i}} = \begin{cases} (d_t \cdot \alpha_t + d_t \cdot \alpha_t^2) \frac{(\gamma_{sell.t})^{\alpha - 1}}{(\beta_t)^{\alpha_t}} & t = i \\ 0 & t \neq i \end{cases} \tag{30}$$

In (29), none of the variables, except $\gamma_{sell.t} l_t$, are functions of $\{\gamma_{sell.t}\}_{t=1}^{24}$ and do not change with the change of price strategy; therefore, they can be regarded as constants. After substituting the optimal strategy formula ($\{l_t^*\}_{t=1}^{24}$), it can be seen from (30) that the Hessian matrix of the objective function is a negative definite matrix. That is, the objective function is a concave function. Therefore, for the optimal electricity consumption strategy given by the user side load, the MGA has the only optimal electricity price strategy. Therefore, the condition (c) of Theorem 1 is satisfied.

In summary, the hierarchical Stackelberg game optimization model of the MGC proposed in this paper has Stackelberg equilibrium.

C. SOLUTION ALGORITHM

Fig. 4 shows the specific solution steps of the hierarchical Stackelberg game. The entire model solution is divided into two stages as follows:

- Stage 1: In the first stage of the upper-level game: The MGCA, as the leader, releases the purchase and sale price to the MGA first. When the MGA obtains the purchase and sale price issued by the MGCA, it adjusts the source and load power in response to the price and changes its own trading-power strategy.
- Stage 2: In the second stage of the lower-level game: The MGA, as the leader, sets the initial electricity price based on the user's historical data and electricity demand, and the user as the follower adjusts the electricity strategy according to the MGA incentive electricity price and feeds it back to the MGA.

Algorithm 1 Distributed algorithm for Obtaining SE

Input: Parameters of the MGCA, the MGA and the UA;
Output: (λ_{buy}^*, λ_{sell}^*, P^*, l^*) when the SE is reached.
1: **for** MGCA sets purchase price (λ_{buy}) and sale price (λ_{sell}) **do**
2: **for** Each MGA sets electricity sales price γ_{sell}^{ast} **do**
3: UA solves the l* for the given γ_{sell} by MGA, calculates E_{UA} and send back *(l*)* to MGA.
4: According to t he feedback demand loads of the UA, MGA optimizes the output of each device and selects the electricity transaction with the MGCA (P_{buy}^* or P_{sell}^*) and sends back P_{buy}^* or p_{sell}^* to the MGCA.
5: **if** the UA's demand load power reach the game suspension conditions **then**
6: break
7: **end if**
8: **end for**
9: Calculate E_{MGA} and E_{MGCA} according to the feedback information.
10: **if** Each MGA's transaction power with the MGCA reach the game suspension conditions **then**
11: break
12: **end if**
13: **end for**
14: The SE (λ_{buy}^*, λ_{sell}^{ast}, P*, l*) has been reached.

Algorithm 1 is the solution process for obtaining the SE. To judge whether the game has reached equilibrium, the optimization operation adjustment values of the adjacent two iteration participants are compared and should be maintained within a certain error range, less than 1% [16]–[36]. The three main objective solutions influence each other, and their optimization objectives are not consistent. When the master and the slave optimize each other, they use each other's optimal strategy from the previous round as input and optimize their own optimal strategy for the current round. The model decoupling feature is used to solve the optimization model from the inside to the outside until the Stackelberg

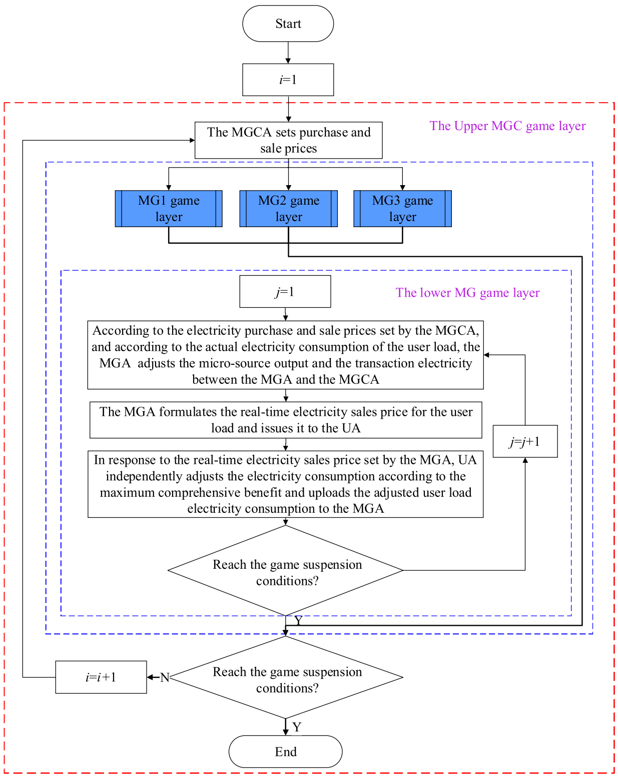

FIGURE 4. Flow chart of solving the hierarchical Stackelberg game.

equilibrium is solved. Therefore, the distributed optimization method is used to solve the hierarchical Stackelberg game model.

V. CASE STUDIES AND DISCUSSION

A. SIMULATION SETTINGS

The relevant configuration of each MG is shown in Fig. 1. According to [16], the renewable energy outputs of the MGs and load demands of the users are shown in Fig. 5 and Fig 6, respectively. The values of α_t are shown in Fig. 7 [35]. The parameters of the devices in each MG are shown in Table B1. The pollution cost coefficient of the MT is shown in Table B2. In the simulation, the coefficients a and b are 4 and -0.1, respectively. The upper limit of the interactive power on each tie-line is 200kW. The value of β_t is 1.

B. NUMERICAL RESULTS ANALYSIS

The hierarchical Stackelberg game between the MGCA, MGA, and UA is simulated in two cases.

Case 1: The MGCA adopts the large grid price.

Case 2: The MGCA adopts the internal game price.

According to the proposed optimal scheduling model and strategy, the optimization problem is solved by particle swarm optimization (PSO) and CPLEX in the MATLAB platform. In view of the proposed hierarchical Stackelberg model results, the following mainly analyzes the behavior and benefits of three different stakeholders: MGCA, MGA, and UA.

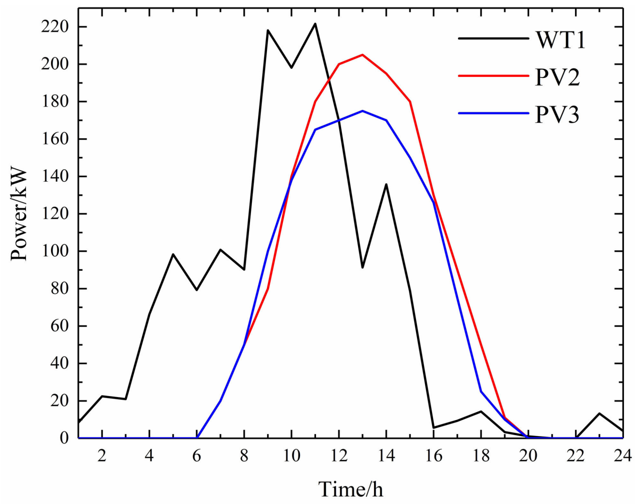

FIGURE 5. Renewable energy output for the MGs.

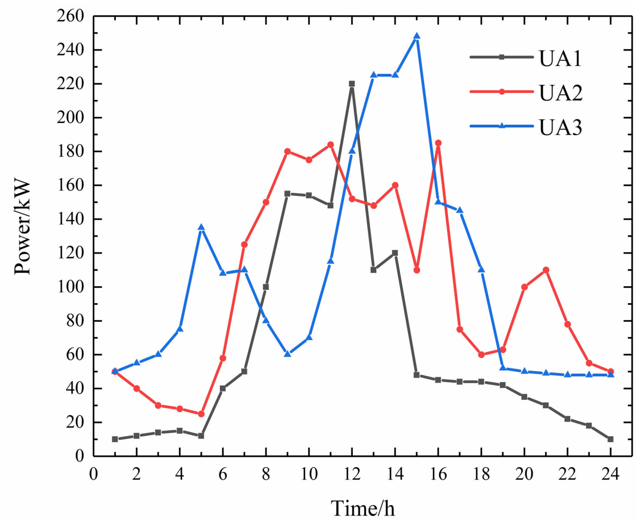

FIGURE 6. Load demands of UA1, UA2 and UA3.

Through 10 hierarchical Stackelberg games using PSO simulation to solve the analysis, when the hierarchical Stackelberg game equilibrium is reached, the average number of iterations of the lower-level MGA and UA Stackelberg game is 4; the upper-level MGCA and MGA Stackelberg game solves the average simulation time; that is, the average total simulation time of the hierarchical Stackelberg game is 137 s and the average number of game iterations is 8. It can demonstrate that the proposed hierarchical game method in this paper can obtain equilibrium strategies effectively for each participant and has good convergence.

1) UPPER-LEVEL GAME SIMULATION DIAGRAM

In this paper, the hierarchical optimal strategy is proposed based on the hierarchical Stackelberg game theory, and it was solved by PSO. For example, Fig. 8 shows the convergence to Stackelberg Equilibrium in the upper-level game.

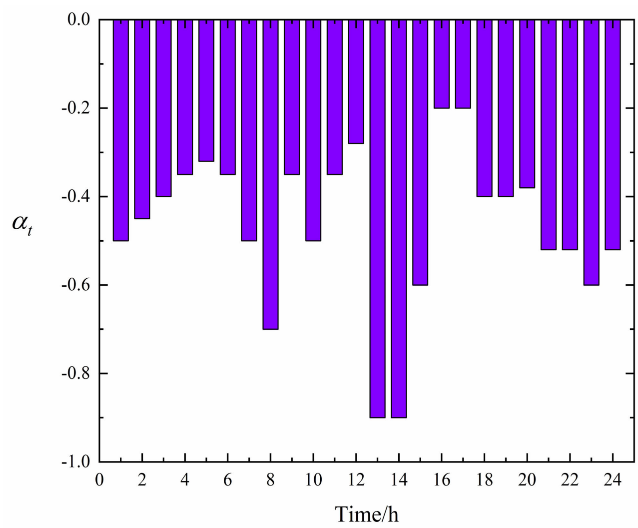

FIGURE 7. Parameter α_t values.

TABLE 1. The parameters of the devices in each MG.

Type of Devices	Parameters	MG1	MG2	MG3
MT	$P_{G,\max}$ (kW)	80	—	—
	$P_{G,\min}$ (kW)	0	—	—
	$R_{up,i}$ (kW/h)	25	—	—
	R_{down} (kW/h)	25	—	—
	a_{op} (Yuan/kWh)	0.280	—	—
	a_m (Yuan /kWh)	0.0812	—	—
ESS	P_c (kW)	—	80	60
	P_d (kW)	—	80	60
	E_{ess} (kW h)	—	225	200
	$S_{oc,\max}$	—	0.9	0.9
	$S_{oc,\min}$	—	0.1	0.1
	η_c	—	0.95	0.95
	η_d	—	0.95	0.95
	a_{op} (Yuan/kWh)	—	—	—
	a_m (Yuan /kWh)	—	0.02	0.02
PV	a_{op} (Yuan/kWh)	—	—	—
	a_m (Yuan /kWh)	0.0096	0.0096	—
WT	a_{op} (Yuan/kWh)	—	—	—
	a_m (Yuan /kWh)	—	0.0296	0.0296

In the upper-level game, the MGCA continuously adjusts the price strategy of selling electricity, and its income gradually reaches the equilibrium point from the initial unbalanced point. Since the 5th iteration, MGA's sensitivity to electricity prices has decreased, and the competitive relationship

TABLE 2. Pollution Cost Coefficient of the MT.

Types of pollutants	$\alpha_{e,j}$ (g/kWh)	$\beta_{e,j}$ (Yuan/g)
SO_2	0.206	0.021
NO_x	0.004	0.062
CO_2	649	0.000243

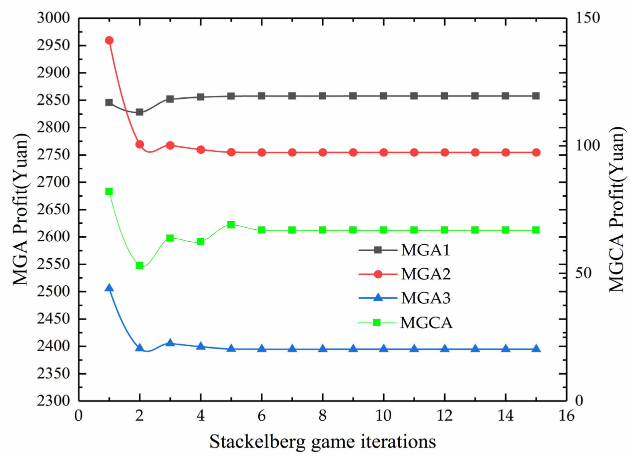

FIGURE 8. Upper-level game simulation diagram in case 2.

TABLE 3. Time-of-use price of the large grid.

Periods	Duration	Selling (Yuan/kWh)	Buying (Yuan/kWh)
Peak	8:00–11:00;13:00–16:00 18:00–22:00	1.189	0.352
Valley	0:00–7:00;22:00–24:00	0.423	0.352
Flat	7:00–8:00;11:00–13:00; 16:00–18:00	0.738	0.352

between the MGCA and MGAs in the game has eased. Convergence is achieved after 10 iterations of the optimization process, the MGCA and MGA have reached Stackelberg equilibrium, and they no longer adjust their own strategies; the revenue functions of both parties obtained local optimal solutions.

2) INTERNAL PRICES OF THE MGC

According to the established leader-follower game model, the upper-level game optimization results obtained through the simulation for different cases are shown in Fig. 9.

The optimal prices in the MGCA when the Stackelberg equilibrium is reached are shown in Fig. 9.

As shown in Fig. 9(a), the MGCA adopts the large grid price.

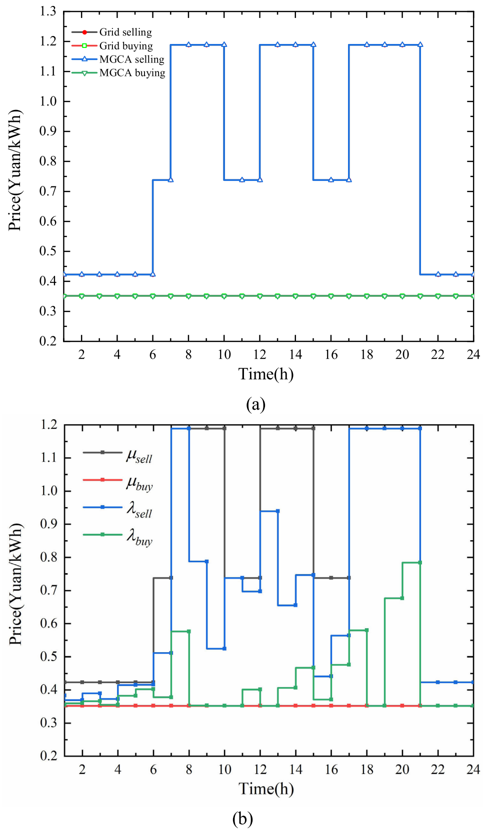

FIGURE 9. **The price of MGCA. (a) Case1, (b) Case2.**

As shown in Fig. 5, during the periods of 0:00–6:00 and 20:00–24:00, the PV generation of MG2 and MG3 was very small. During the periods of 20:00–22:00, the WT generation of MG1 was also very small. As shown in Fig. 9(b), to give priority to the consumption of new energy in the cluster and thus increasing the MGCA's own revenue, the purchase and sale price set by the MGCA is always within the time-of-use purchase and sale price of the large grid.

As shown in Fig. 5, during the periods of 0:00–6:00 and 20:00–24:00, the PV generation of MG2 and MG3 was very small. During the periods of 20:00–22:00, the WT generation of MG1 was also very small. As shown in Fig. 9(b), to give priority to the consumption of new energy in the cluster and thus increasing the MGCA's own revenue, the purchase and sale price set by the MGCA is always within the time-of-use purchase and sale price of the large grid.

During the periods of 10:00–11:00, 18:00–19:00, and 21:00–24:00, while all MGs are in the purchasing state or selling state, the MGCA could not increase its own benefits by adjusting the selling or buying prices. When there are both electricity-selling MGs and electricity-purchasing MGs in the MGC, that is, when there are electricity transactions between the MGs, the MGCA will adjust the electricity price to promote MGA and MGCA transactions. When the total power supply of the MGC is less than the total power-purchase demand, the MGCA sets a higher power-purchase price than that of the large grid, encouraging MGAs in the state of sale to sell more energy to the MGCA. When the total supply of the electricity sold in the MGC is greater than the total purchase demand, the electricity price of the MGCA is lower than that of the large grid; in this situation, MGAs in the buying state are encouraged to buy more power from the MGCA.

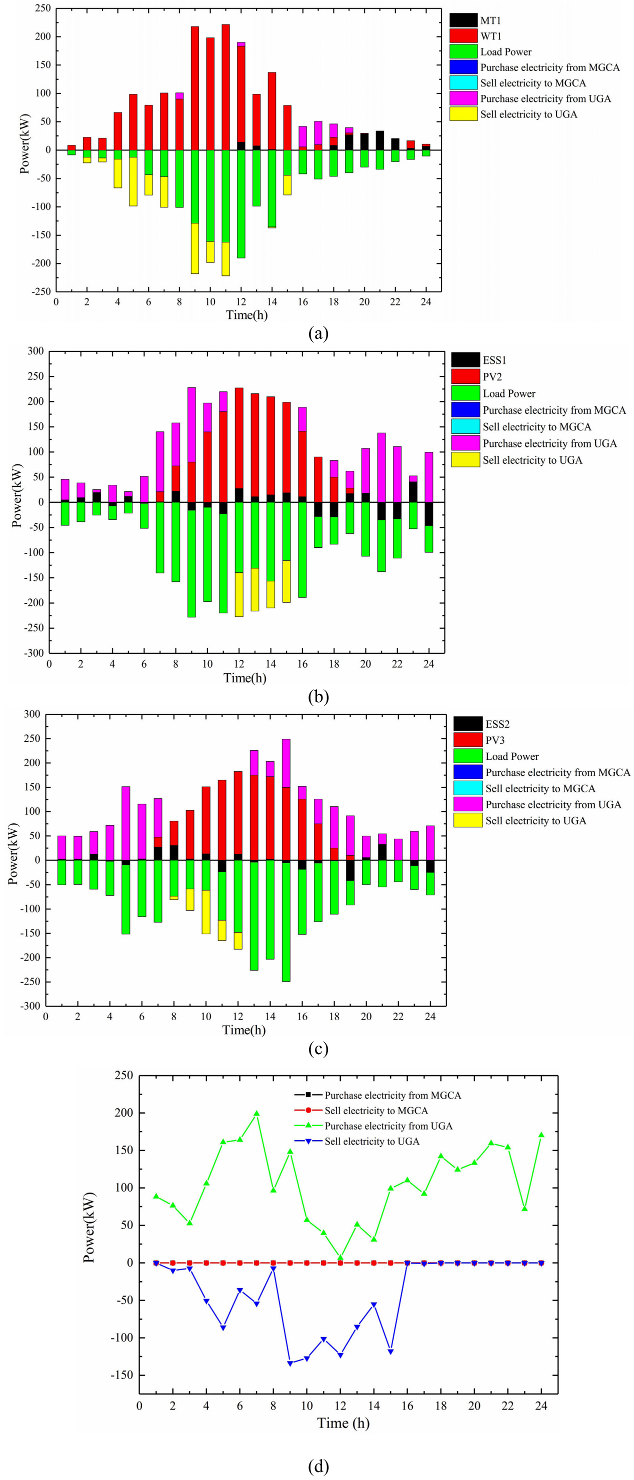

FIGURE 10. **Optimal scheduling of each MGA in Case 1: (a) The optimal scheduling in MG1, (b) the optimal scheduling in MG2, (c) the optimal scheduling in MG3, and (d) total transaction power between MGA and MGCA or UGA.**

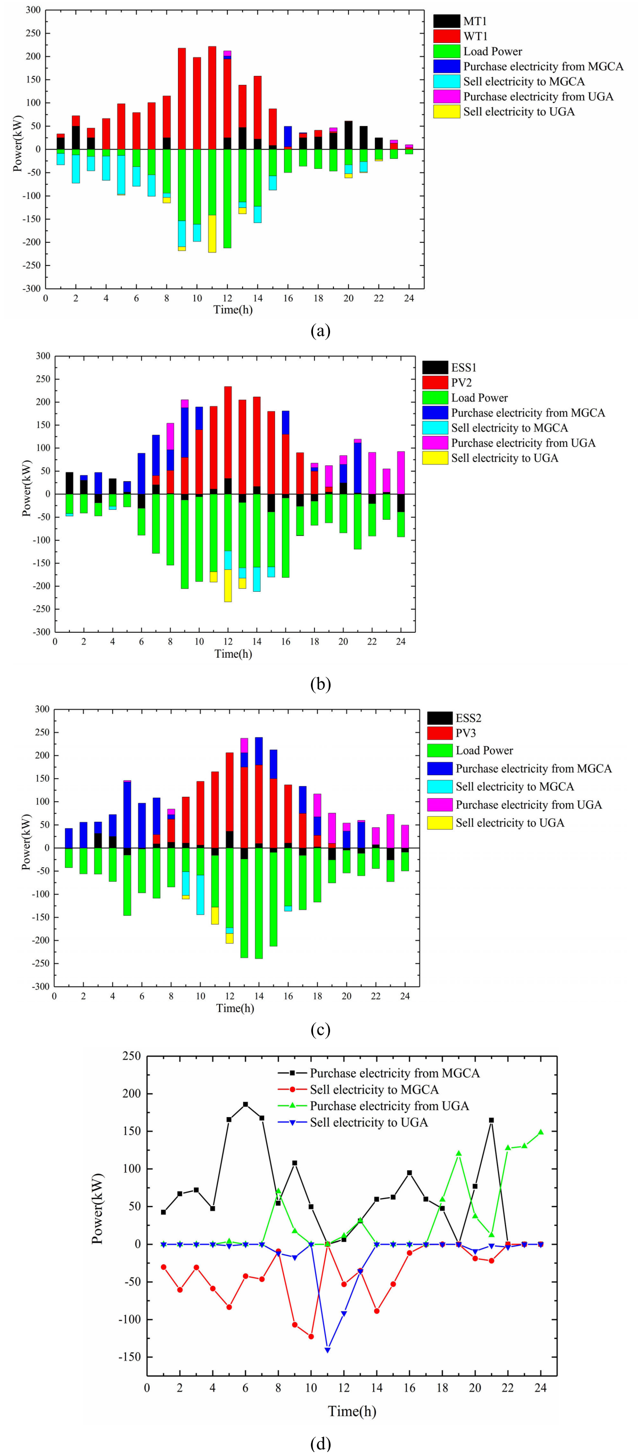

FIGURE 11. Optimal scheduling of each MGA in Case 2: (a) The optimal scheduling in MG1, (b) the optimal scheduling in MG2, (c) the optimal scheduling in MG3, (d) total transaction power between MGA and MGCA or UGA.

According to the bilevel Stackelberg model, the optimal simulation results for different cases are shown in Fig. 10 and Fig. 11. Fig. 12 shows the comparison of the profits in different cases. From Fig. 10 to Fig. 12, the following conclusions can be obtained:

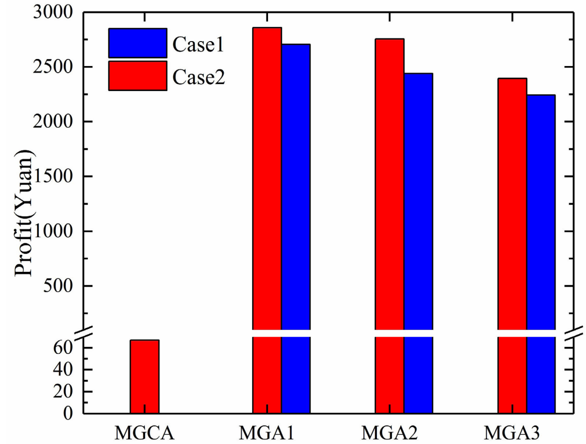

FIGURE 12. Comparison of profits between Case 1 and Case 2.

(1) As shown in Fig. 10 and Fig. 11, when the total electricity demand of the user is higher than the new energy output of the MGC, first, by comparing the peak-valley time-of-use electricity price in the MGCA with the output cost of each MGA's internal backup microsources, it is determined whether to purchase and sell electricity with other MGs or to invest in backup microsources in order of cost; when the total electricity demand of the users is lower than the new energy output of the MGC, first, by comparing the MGC's time-of-use electricity price and the charging cost of each MG's internal energy storage device, it is determined whether to purchase and sell electricity with other MGs or to charge its own internal energy storage. After the Stackelberg game optimization, the power-mutual-benefit level between MGs is improved. During most periods when the MGCA adopts the internal pricing, some MGs are in the state of selling, and some MGs are in the state of buying. In most of the periods, the MGAs in the MGC can coordinate with each other through the MGCA. The MGCA can obtain certain benefits by optimizing the price of electricity purchase and purchase based on the price difference during the purchase and sale of electricity.

(2) As shown in Fig. 10(d), when the MGCA adopts large grid pricing, because of the probability of an MGA and MGCA transaction ($p_{MGCA} = 0$), the MGA will directly trade with the UGA, and the MGCA cannot make a difference in the purchase and sale of electricity. At this time, the MGCA's revenue will be zero. Nevertheless, when the MGCA adopts the internal pricing, as shown in Fig. 11(d) and Fig. 12, the increased benefits of the MGCA and three MGAs are 66.94 Yuan, 151.64 Yuan, 315.52 Yuan, and 151.28 Yuan, respectively. Therefore, this paper's model has a significant effect on improving the income of the MGCA and MGAs.

(3) As shown in Fig. 11(d), during the periods of 5:00-6:00, 8:00-14:00, and 18:00-24:00, due to the probability of transaction selection, the MGA will purchase and sell electricity from the UGA. During the periods of 1:00-4:00, 5:00-10:00, and 15:00-24:00, the MGCA is unable to make

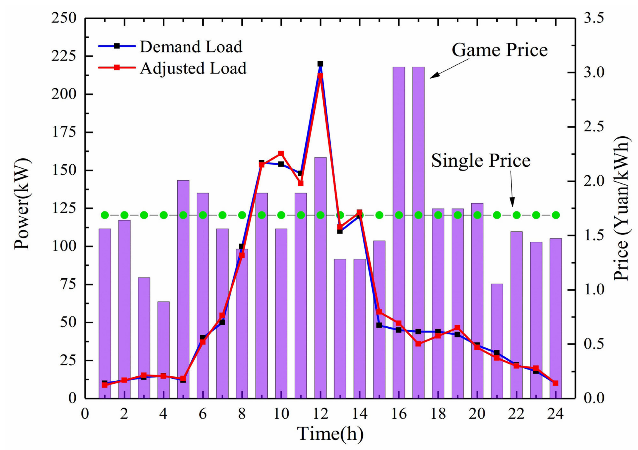

FIGURE 13. Load and price distributed curve of UA1.

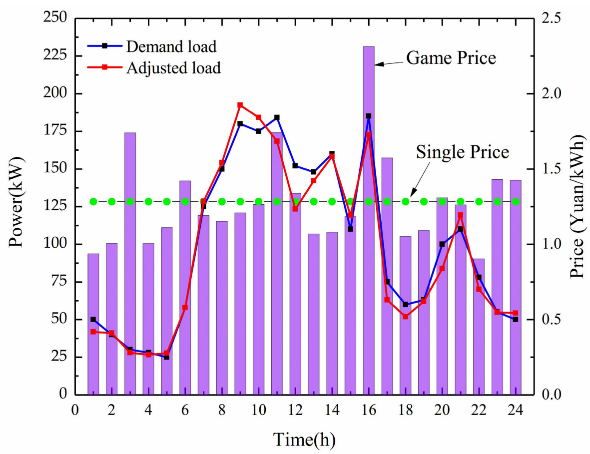

FIGURE 14. Load and price distributed curve of UA2.

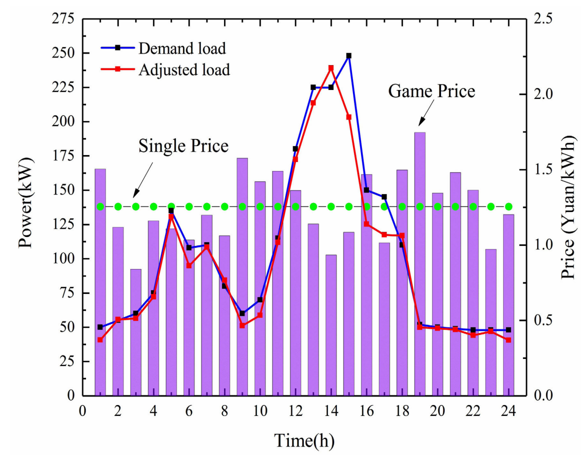

FIGURE 15. Load and price distributed curve of UA3.

up for it by purchasing electricity from the internal MGA due to the large power load, and there is a large difference between the power of the source and the load. As a result, the MGCA cannot make up for the shortage of the MGA by purchasing power from the internal MGA. At this time, the MGCA still needs to purchase power from the UGA. During the periods of 4:00-5:00 and 10:00-15:00, the load power in each MGA is small, and there is a massive difference between the power of the source and the load, resulting in a large amount of excess power in the MGC that cannot be internally absorbed through the MGCA; therefore, the MGCA still needs to sell excess power purchased from the MGA to the large grid.

(4) On the one hand, when the MGs in the state of selling or buying cannot absorb the surplus or shortage of electricity in the MGC, they can only interact with the large grid for power, which also causes each MGA and MGCA to lose a certain amount of income at the same time. On the other hand, if there are enough heterogeneous MGs in the MGC, the transaction volume between multiple MGAs and the MGCA will also increase, and the total transaction power of the MGCA to the large grid will be greatly reduced. Both the MGA and MGCA's revenue will increase.

In summary, the hierarchical Stackelberg game strategy is an effective measure for competitive hierarchical electricity market structures of the MGC. Though market of the MGC is still under construction, it is important to introduce the value and application for the hierarchical electricity market structures of the MGC.

3) THE LOWER-LEVEL GAME: MGA-UA TRANSACTION RESULTS ANALYSIS

During the peak or valley period of each user's load power, the output of each MG may all be too little or all surplus, resulting in a source-load power mismatch. At this time, the mutual power benefit derived from the interconnection between the MGs is lost. Therefore, it is necessary for the MGA to formulate dynamic electricity prices or provide adjustment compensation for the MGs.

TABLE 4. UAs' result values at SE point in Case 2.

Parameters	UA1	UA2	UA3
Satisfaction	-16.5259	-102.0621	-220.5175
Expenditure	-2616.0	-3088.8	-2828.6
Overall utility	-2632.5	-3190.8	-3049.2

Fig. 13 to Fig. 15 shows the electricity sales prices and adjusted loads for each UA after optimizing the game optimization in this paper. Table 4 shows the final objective function value of the UA's overall utility, electricity purchase expenses, and the UA's electricity satisfaction after the game reaches the SE.

As shown in Fig. 13 to Fig. 15, compared with the initial demand load, the optimized load distribution curve fits the maximum allowable power generation curve of renewable energy and meets the requirements of economy and environmental protection in each MG. The load interruption ratio of UA1, UA2, and UA3 are 2.88%, 5.05%, and 7.59%, respectively. Therefore, the users' minimum load requirement is satisfied.

TABLE 5. Comparison of Comprehensive Benefits of the UA.

Operating model	UA1	UA2	UA3
Case 1	-3293.2	-3227.3	-3267.8
Case 2, but MGA uses Single price	-2705.8	-3281.4	-3344.9
Case 2	-2632.5	-3190.8	-3049.2

After the price of the MGA is determined, the UA will determine its own electricity consumption strategy based on the optimal response to electricity consumption satisfaction. In the lower-level game, the MG leads the game by deciding electricity selling prices based on the load demand of users, and the user as follower adjusts electricity using strategies to balance the expenditure and experience of electricity usage. As shown in Fig. 13 to Fig. 15 and in Table 4, the UA has a high sensitivity to electricity sales prices. By responding to the dynamic electricity price set by the MGA, the UA can flexibly adjust its electricity consumption strategy according to the electricity price set by the MGA. While considering user load satisfaction, it reduces its own electricity expenditures and maximizes comprehensive benefits. The analysis of calculation examples shows that the model used in this paper integrates economy and power satisfaction when considering user benefits.

Table 5 shows the comparison of the comprehensive benefits of the UA in different operating models. In this paper, the average electricity price or single electricity price is obtained by averaging the game electricity price. When a single electricity price system is adopted on the MG side, the user load situation is not affected by the electricity price system, and the load distribution should be equal to the demand load. It can be seen from Table 5 that, under the hierarchical Stackelberg game interactive transactions mentioned in this article, the comprehensive benefits of each user are significantly improved, which verifies the effectiveness of the hierarchical Stackelberg game model proposed in this article to improve the overall benefits of each participant.

When the MGA increases electricity price, it causes the UA to adjust the true load power. Considering the goal of load-power satisfaction and power-purchase expenditures, the power of the UA is reduced; therefore, the power purchase expenditure is reduced to maximize users' comprehensive benefits. Therefore, the UA's true load power consumption is an adjustment made to the electricity price set by the MGA. While the MGA encourages users to adjust the power consumption of loads through electricity prices, it can also adjust its own microsource output and external purchases and electricity sales.

VI. CONCLUSION

This paper established a hierarchical Stackelberg game model based on a multi-agent system, including the balanced decision-making of the three stakeholders of the MGC, MG, and user. The action strategies of multiple agents were analyzed, and a nested distributed algorithm for solving the bilevel game model was given. The proposed method improves the initiative of multiple stakeholders in the MGC and has guiding significance for the future construction of an energy internet with multi-agent participation. In addition, the proposed hierarchical game model is also suitable for intraday rolling optimization adjustment scheduling. Through the foregoing theoretical analysis and simulation examples, the following conclusions were obtained :

(1) The proposed hierarchical Stackelberg game strategy took into account the benefits of the MGCA, the comprehensive benefits of each MGA optimal scheduling, and the comprehensive benefitted the UA in the process of the multilevel, leader-follower game optimization. While improving the operating income of the MGCA, the comprehensive benefits of the MGA and users' electricity consumption also changed to varying degrees through their respective adjustments.

(2) The comprehensive benefit function of the UA was established, which improved the comprehensive benefits of the UA and the MGA.

(3) When optimizing the solution, each MGA optimized itself according to the price given by the MGCA and then interacted with the MGCA for power; each UA also optimized the adjustment of the electricity consumption strategy according to the electricity sales price given by the MGA and sent the electricity consumption back to the MGA. Compared with centralized algorithms, this distributed algorithm can protect the private information of the MGCA, MGA, and UA.

(4) After the hierarchical Stackelberg game, the electricity purchase price and the electricity sale price set by the MGCA were more general than most cited in current literature when only the single fixed-transaction price between MGs was considered. This model increases the enthusiasm for participating in transactions between MGs.

APPENDIX

ABBREVIATIONS

MG	microgrid
MGC	microgrid cluster
SE	Stackelberg equilibrium
EU	European Union
MAS	multi-agent system
MGA	microgrid agent
MGCA	microgrid cluster agent
UA	user agent
TOU	time-of-use

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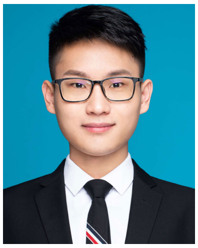

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