Strategy for Optimizing the Bidirectional Time-of-Use Electricity Price in Multi-Microgrids Coupled with Multilevel Games

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Abstract

Demand response (DR) based on the time-of-use (TOU) electricity price is an effective method for addressing the source–load mismatch in microgrids by improving the load curve on the user side, thereby improving source–load matching. However, the degree to which users respond to DR strategies is not only influenced by economic factors but also closely related to psychological factors. Therefore, considering the TOU electricity prices on both the generation side and the load side, this paper presents an optimization strategy for the bidirectional TOU electricity price for multi-microgrids (MMGs) coupled with multilevel games. First, the DR model based on the endowment effect is constructed with close attention to the influence of psychological factors on user behavior in the context of electric energy trading in an MMG system. A bidirectional TOU electricity pricing incentive mechanism is designed that simultaneously targets both power producers and users, promoting the active participation of various stakeholders in scheduling within MMG systems. Second, a multilevel differential game model is established, which takes power producers, microgrid operators (MGOs), and microgrid users as the main actors, couples a noncooperative game and a leader–follower game, achieves game balance by optimizing the bidirectional TOU electricity price, and makes appropriate decisions. Finally, the case study results demonstrate that the proposed strategy can optimize energy management, reduce the system's operating cost and the user's power consumption cost, and improve the power producers' economic benefit and user satisfaction.

Keywords: Multi-microgrids, Time-of-use electricity price, Multilevel games, Energy management

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1. Introduction

With the continuous growth of energy demand and increasing severity of environmental problems, microgrids (MGs), which are important carriers of renewable energy technology, play an increasingly important role in energy systems [1], [2]. As a further development of MGs, multi-microgrids (MMGs) have greater complexity and flexibility [3], [4]. By appropriately arranging the energy exchange between MGs and maximizing the use of renewable energy, the dependence on traditional energy can be reduced, and the sustainable development of energy can be promoted [5], [6]. However, the economic operation efficiency of MMG systems is closely related to user engagement, which relies on an effective price incentive mechanism to increase the enthusiasm of users. For this purpose, demand response (DR) has been widely used [7].

DR guides consumers in adjusting their electricity consumption behavior by setting different prices at different times, thereby increasing grid flexibility and reducing operating costs [8], [9]. The method of reference [10] encourages users to participate in DR by providing compensatory incentives. Reference [11] established an energy management framework for MGs on the basis of a price-based DR model and optimized it using a greedy rat swarm optimization to minimize MG generation costs and environmental impact. Reference [12] proposed a novel order characteristic load shifting policy to achieve coordinated improvements in efficiency and economy for the distribution system. Reference [13] established an elastic DR model considering load demand and studied the impact of the DR model on scheduling results by comparing scenarios with and without the DR model. Reference [14] proposed a DR model considering uncertainty to analyze and model the risk cost of DR uncertainty. The above research considers the impact of DR on grid operation and scheduling, providing important reference data for operators to make scheduling decisions. However, the design and implementation of current DR strategies rely on relatively simplified and idealized models of user behavior, which generally assume that users' response to price signals or incentives is immediate and linear and ignore economic factors into users' decision-making process. Reference [15] assessed the impact of the DR model on the cost of electricity incurred by users, thereby helping energy providers develop more effective DR plans. Reference [16] considered the impact of electricity prices and economic incentives on users' willingness to participate and constructed a hybrid DR model that effectively increases user satisfaction. Given the conflict between interest subjects on the demand side and the supply side, reference [17] aimed to maximize the welfare of users and the economic benefits of microgrid operators (MGOs) and achieve peak cutting and valley filling while ensuring economic benefits to both sides. The above research mainly encourages users to increase their participation in DR from the perspective of economic incentives, ignoring the influence of psychological factors on users' degree of response participation. The introduction of the endowment effect can provide a unique perspective for DR models, enabling users' irrational evaluations of energy resources to be captured more comprehensively [18]. The endowment effect is a psychological phenomenon in behavioral economics, which refers to the fact that people assign a higher subjective value to the items or rights they possess. It manifests as "loss aversion" when faced with the relinquishment or alteration of these assets. This effect indicates that people are more inclined to avoid losses than to pursue equivalent-value gains when making decisions. In the field of energy, users not only are consumers but also perceive themselves as having an endowment of energy resources. The incorporation of the endowment factor into DR models allows for a more accurate simulation of users' subjective assessments of energy 'ownership,' addressing gaps in traditional models.

As a DR strategy, the TOU electricity price is an important means of motivating users to consume energy and has gradually become a key factor in improving the efficiency of the power market and the utilization rate of renewable energy [19], [20]. Reference [21] proposed an economic scheduling scheme for MGs on the basis of the TOU electricity price and verified the effectiveness of the TOU price in reducing MG operational costs. Reference [22] constructed multiple MG operation scenarios and, on the basis of these scenarios, compared and analyzed the power generation cost of MGs when the TOU price of the electricity market was the same or different. However, all of the aforementioned studies adopted a fixed TOU price mechanism in model construction, which has limited effectiveness in peak–valley regulation and cost optimization. Reference [23] proposed a peak-valley segmentation method and established a TOU electricity price model through an in-depth study of user response characteristics. Reference [24] established a virtual real-time TOU electricity price optimization model based on a credit mechanism, which adopted a linear-decline inertial particle swarm optimization algorithm to optimize the user electricity price and minimize the total electricity cost. Reference [25] proposed a real-time variable peak pricing scheme that is effective in terms of reducing consumer energy bills, system peak, and system complexity and incentivizing active consumer participation in demand-side management programs. However, the above research fails to consider that the utility of each subject in the process of electric energy trading not only depends on the subject's economic behavior but is also affected by other subjects. The incentive mechanism based on game theory can encourage participants to take actions considering the interests of individuals and the system as a whole [26]. Reference [27] proposed a dynamic game model of the TOU electricity price that considers the desires of multiple users to maximize user satisfaction and benefits. Reference [28] proposed an interbuilding energy optimization method based on a noncooperative game, which minimizes the cost to each participant by adjusting the electric energy trading strategies of both buyers and sellers while increasing the overall benefits of the system. However, the above studies only rely on a single-game relationship to describe the interaction between electric energy trading entities, and the incentive effect of this method is limited. Reference [29] used the traditional TOU electricity price strategy under peer-to-peer transactions based on a noncooperative game and peer-to-network transactions based on a cooperative game to carry out a comparative study of the electricity energy transactions between MMGs. Reference [30] established a mixed game model with nested bidding strategies of leader–follower games to simulate the trading processes of various stakeholders. Scholars worldwide have obtained many research results in the field of user-side TOU electricity prices, but in such research, power producers do not adopt a TOU electricity price mechanism but maintain a unified electricity selling price. This approach ignores the subjective initiative of the generation-side operator and the potential advantages of setting the generation-side TOU electricity price to improve energy efficiency.

To solve the above problems, this paper presents an optimization strategy for the bidirectional TOU electricity price in MMGs coupled with multilevel games. First, to optimize the ability of the DR model to fit user behavior, the model is constructed on the basis of the endowment effect by deeply analyzing the psychological factors of users while they are participating in DR. Then, a bidirectional TOU electricity price incentive mechanism is designed. Setting electricity prices for power producers and MGOs in different periods encourages power producers, MGOs, and users to participate in dispatching according to their interests. Finally, a noncooperative game model between the power producers and the MGOs and a leader–follower game model between the MGOs and the MG users are established to optimize the bidirectional TOU electricity price on the power generation side and the user side. By analyzing and utilizing the specific game relationships between different participants, the optimization mechanism effectively encourages each participant to participate in optimizing the MMG and brings greater flexibility and economic benefits to the MMG.

The main contributions of this paper are summarized as follows:

- To address the shortcomings of existing DR models in ignoring the psychological factors of user decision-making, a DR model based on endowment effect theory is proposed. Unlike references [15] and [16], this model comprehensively considers the psychological and behavioral factors of users, making it more aligned with their psychological needs.
- A bidirectional TOU electricity price collaborative incentive mechanism is proposed. Unlike reference [27], this mechanism focuses on the mutual influence between generation-side electricity prices and consumption-side electricity prices, optimizing power distribution and

promoting the utilization of renewable energy by promoting active interactions among power producers, MGOs, and users. This mechanism encourages power producers to generate electricity when the electricity demand is high and users to use electricity when the price is low by setting electricity prices for different periods. Thus, supply and demand are balanced, system operating costs are reduced, and energy utilization efficiency is improved.

- To analyze the interactions and decision-making processes among various entities in the electricity market in detail, a multilevel differentiated game framework coupled with noncooperative games and leader–follower games is constructed to obtain the optimal electricity trading strategy in the TOU electricity price environment, including the electricity sales strategy of power producers, the electricity purchase strategy of MGOs, the TOU electricity price on the load side, and the electricity consumption plan of users.

The rest of this article is organized as follows: Section 2 establishes an MMG structure and a bidirectional TOU electricity price incentive mechanism. Section 3 presents a multilevel game mechanism and model. Section 4 presents several case studies to evaluate the performance of the proposed strategy. Section 5 summarizes the entire text.

2. Problem formulation

2.1. MMG system architecture and model

The structure of the MMG system is shown in Fig. 1, which includes three main entities: power producers, MGOs, and MG users. Power producers include traditional energy sources such as hydroelectric power and thermal power generation; MGOs are responsible for the economic operation and maintenance of distributed generation and energy storage devices in the MG; and the user loads of the MG can be divided into translatable loads and nontranslatable loads. The power producers and MG users are connected through MGOs to form a fully coordinated MMG system. Each entity aims to maximize its own benefits through game theory and finally obtains an equilibrium solution in the game

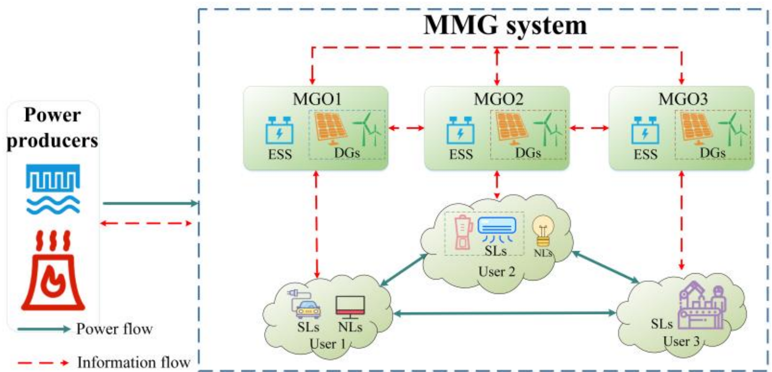

Fig. 1. Structural diagram of an MMG system.

while balancing its own and overall economic benefits.

2.2. Participants and objective functions

(1) Power producers influence MGOs to adopt more stable purchasing plans by setting TOU electricity prices for electricity sales, which not only reduces power generation costs but also improves the efficiency of power producers and reduces carbon emission costs. The power producers aim to maximize profits, and their objective function is as follows:

$$C_{\mathrm{F}} = C_{\mathrm{Mbuy}} - C_{\mathrm{Fy}} - C_{\mathrm{Fe}} \tag{1}$$

$$C_{\mathrm{Mbuy}} = \sum_{t=0}^{23} \sum_{m=1}^{M} P_{\mathrm{Mbuy},m}^{t} S_{\mathrm{F}}^{t} \tag{2}$$

$$C_{\mathrm{Fy}} = \sum_{t=0}^{23} [k_{\mathrm{f}} (P_{\mathrm{e}}^{t})^2 + (k_{\mathrm{es}} + k_{\mathrm{f}}) P_{\mathrm{e}}^{t}] \tag{3}$$

$$C_{\mathrm{Fe}} = \sum_{t=0}^{23} k_{\mathrm{CO_2}} P_{\mathrm{e}}^{t} \tag{4}$$

where C_{F} represents the revenue of the power producers; C_{Mbuy} represents the purchase cost for MGOs and the sales revenue of power producers; C_{Fy} is the operation and maintenance cost for the power producers; C_{Fe} is the environmental cost for the power producers; $P_{\mathrm{Mbuy},m}^{t}$ is the electricity purchased by MGO m from the power producers; S_{F}^{t} represents the electricity selling price set by the power producers; P_{e}^{t} represents the electricity generated by the power producers; and k_{f}, k_{es}, and $k_{\mathrm{CO_2}}$ represent the comprehensive power generation cost coefficient, operation and maintenance cost coefficient, and carbon governance cost coefficient of the power producers, respectively.

(2) The costs for MGOs mainly include the operation and maintenance costs of each piece of power generation and storage equipment (wind turbine (WT), photovoltaic (PV), gas turbine (GT) and energy storage (ES)), the fuel cost of the GT and the cost of purchasing power from power producers. The benefits come from selling electricity to MG users. MGOs seek the maximum benefit in the game, and their objective function is as follows:

$$C_{\mathrm{M},m} = C_{\mathrm{Ubuy},m} - (C_{\mathrm{PV},m} + C_{\mathrm{WT},m} + C_{\mathrm{GT},m} + C_{\mathrm{ESS},m} + C_{\mathrm{Mbuy},m} + C_{\mathrm{Ms},m} + C_{\mathrm{Me},m}) \tag{5}$$

$$C_{\mathrm{Ubuy},m} = \sum_{t=0}^{23} P_{\mathrm{Ubuy},m}^{t} S_{\mathrm{M}}^{t} \tag{6}$$

$$C_{\mathrm{GT},m}=\sum_{t=0}^{23}(\frac{\varsigma_{\mathrm{GT}}P_{\mathrm{GT},m}^{t}}{H_{\mathrm{GT}}\kappa_{\mathrm{GT}}}+k_{\mathrm{GT}}P_{\mathrm{GT},m}^{t}) \tag{7}$$

$$C_{\mathrm{Me},m}=\sum_{t=0}^{23}k_{\mathrm{CO}_2}P_{\mathrm{GT},m}^{t} \tag{8}$$

where $C_{\mathrm{M},m}$ represents the total revenue of the MGO in MG system m; $C_{\mathrm{Ubuy},m}$ is the electricity cost for MG user m, which is equivalent to the electricity sales revenue of MGO m; $C_{\mathrm{PV},m}$ is the operation and maintenance cost of PV; $C_{\mathrm{WT},m}$ is the operation and maintenance cost of the WT; $C_{\mathrm{GT},m}$ is the cost of GT power generation, operation, and maintenance; $C_{\mathrm{ESS},m}$ is the cost of charging and discharging operation and maintenance for ES; $C_{\mathrm{Mbuy},m}$ is the cost of purchasing electricity for MGOs and is equivalent to the electricity sales revenue of the power producers in formula (2); $C_{\mathrm{Ms},m}$ is the interaction cost between MGs; $C_{\mathrm{Me},m}$ is the environmental cost of MGOs; $P_{\mathrm{Ubuy},m}^{t}$ represents the amount of electricity purchased by MG users from MGOs; S_{M}^{t} is the TOU electricity price set by MGOs for electricity sales; k_{GT} is the operating and maintenance cost coefficient of the GT; $P_{\mathrm{GT},m}^{t}$ is the GT output for each period t; ς_{GT} is the price of natural gas; H_{GT} is the calorific value of natural gas; and κ_{GT} is the efficiency of GT power generation.

(3) In DR models, users perceive their electricity usage rights as an endowment, implying that users have become accustomed to the current way of using electricity and regard it as their interest. Therefore, during the DR process, users are generally resistant to changing their existing consumption habits, as such a change would make them feel a "loss," thereby affecting their willingness to participate actively in DR scheduling.

To better understand the user behavior in DR, we construct the user’s endowment effect utility function on the basis of the economic principle, which reflects the psychological cost caused by changing the user's electricity consumption habits. Specifically, the electricity load deviation is closely related to the endowment effect: when the electricity load deviation of the user is small, the endowment effect is weak, and the negative psychological feeling of the user is lighter, so the user is more inclined to participate in the DR. In contrast, when the electricity load deviation is large, the endowment effect is strong, the user's resistance psychology is intensified, and the willingness to participate is reduced. The weak endowment effect means that the psychological loss caused by the change in electricity consumption is small, which increases the user's enthusiasm to participate in the DR.

After incorporating the endowment effect utility function into the user's objective function, the optimization goals of MG users are low electricity cost, high electricity satisfaction, and a weak endowment effect. The objective function is as follows:

$$F_{\mathrm{U}}=\sum_{t=0}^{23}\lambda^{t}=\omega_{1}\alpha^{t}+\omega_{2}\beta^{t}+\omega_{3}\gamma^{t} \tag{9}$$

$$\alpha^{t}=\frac{-\frac{\rho_{1}}{2}(P_{\mathrm{Ubuy},m}^{t})^{2}+\rho_{2}P_{\mathrm{Ubuy},m}^{t}}{-\frac{\rho_{1}}{2}(P_{\mathrm{b}}^{t})^{2}+\rho_{2}P_{\mathrm{b}}^{t}} \tag{10}$$

$$\beta^{t}=1-\frac{S_{\mathrm{M}}^{t}P_{\mathrm{Ubuy},m}^{t}-S_{\mathrm{M,b}}^{t}P_{\mathrm{b}}^{t}}{S_{\mathrm{M,b}}^{t}P_{\mathrm{b}}^{t}} \tag{11}$$

$$\gamma^{t}=a(P_{\mathrm{Ubuy},m}^{t}-P_{\mathrm{b}}^{t})-b(P_{\mathrm{Ubuy},m}^{t}-P_{\mathrm{b}}^{t})^{2} \tag{12}$$

where λ^{t} represents the comprehensive satisfaction of users; ω_1, ω_2 and ω_3 represent the weight coefficients of users' satisfaction with electricity consumption behavior, users' satisfaction with electricity cost, and endowment effect satisfaction, respectively, and $\omega_1+\omega_2+\omega_3=1$; P_{b}^{t} represents the original load before DR; ρ_1 and ρ_2 represent the users' electricity efficiency coefficients; $S_{\mathrm{M,b}}^{t}$ is the original electricity price before DR; and a and b are the endowment effect parameters.

2.3. Constraint condition

To ensure that the optimization results of the MMG system are within a reasonable range, the operating constraints are as follows:

(1) Power balance constraint:

$$P_{\mathrm{PV},m}^{t}+P_{\mathrm{WT},m}^{t}+P_{\mathrm{GT},m}^{t}+\eta_{\mathrm{dischar}}P_{\mathrm{dischar},m}^{t}+P_{\mathrm{Msbuy},m}^{t}+P_{\mathrm{Mbuy},m}^{t}=P_{\mathrm{Ubuy},m}^{t}+\eta_{\mathrm{char}}P_{\mathrm{char},m}^{t}+P_{\mathrm{Mssell},m}^{t} \tag{13}$$

(2) Power constraint for GT climbing:

$$P_{\mathrm{GT,min}}^{\mathrm{up}}\le P_{\mathrm{GT}}^{t}-P_{\mathrm{GT}}^{t-1}\le P_{\mathrm{GT,max}}^{\mathrm{up}} \tag{14}$$

where $P_{\mathrm{GT,max}}^{\mathrm{up}}$ and $P_{\mathrm{GT,min}}^{\mathrm{up}}$ are the upper and lower limits of the climbing power of the GT, respectively.

(3) Power constraints for power producers to sell electricity:

$$0\le P_{\mathrm{Mbuy},m}^{t}\le P_{\mathrm{e}}^{t}\le P_{\mathrm{M,max}} \tag{15}$$

where $P_{\mathrm{M,max}}$ is the maximum power of the interconnection line between the power producers and the MGOs.

(4) Endowment effect constraint:

Consumers expect their electricity comfort needs to be satisfied and feel that they have this kind of electricity comfort. This endowment effect is reflected by adjusting the endowment factors in the model when the electricity consumption experience worsens.

$$\begin{aligned} & 0 \le \Delta P_{\mathrm{f}}^{t} \le \Delta P_{\mathrm{f,max}} * \sqrt{1-\vartheta(t)} \\ & 0 \le \Delta P_{\mathrm{p}}^{t} \le \Delta P_{\mathrm{p,max}} * \sqrt{1-\vartheta(t)} \\ & 0 \le \Delta P_{\mathrm{g}}^{t} \le \Delta P_{\mathrm{g,max}} * \sqrt{1-\vartheta(t)} \end{aligned} \tag{16}$$

where $\Delta P_{\mathrm{f}}^{t}$, $\Delta P_{\mathrm{p}}^{t}$ and $\Delta P_{\mathrm{g}}^{t}$ are the DR quantities for the load during peak, flat, and valley periods, respectively; $\vartheta(t)$ is the endowment factor; and $\Delta P_{\mathrm{f,max}}$, $\Delta P_{\mathrm{p,max}}$ and $\Delta P_{\mathrm{g,max}}$ represent the maximum values to which the load can respond.

2.4. Bidirectional TOU electricity price synergistic incentive mechanism

In the MMG system, reasonable adjustment of the electricity price is one of the key means of achieving efficient energy utilization and cost optimization. By setting up a bidirectional TOU electricity price incentive mechanism, positive interactions between power producers, MGOs, and users are promoted, power distribution is optimized, and the utilization of renewable energy is encouraged.

(1) TOU electricity price period division:

The TOU electricity prices for MGOs need to be clustered on the basis of the power purchased by MGOs to determine the periods of the generation-side peak, flat and valley TOU prices. The TOU electricity prices for MG users need to be clustered on the basis of the power purchased by users to determine the periods of the load-side peak, flat and valley TOU prices. Since the purchased power data are one-dimensional, the k-means clustering algorithm is used to determine the TOU period [31]. The objective function value of the k-means clustering algorithm is the sum of the mean square error of the data and the cluster center to which the data belong. The basic idea of k-means is that once the number of clusters j is determined, j initial cluster centers are randomly selected. On the basis of the distance between each object and the cluster centers, other objects are subsequently assigned to the nearest cluster center.

The flowchart for determining cluster labels via the k-means clustering algorithm is shown in Fig. 2, and the specific steps are as follows:

Step 1: Input the purchased electricity P of the MGO/MG user.

Step 2: Set the number of clusters j for the TOU periods.

Step 3: Initialize the electricity purchase centers (i.e., cluster centers) for each period.

Step 4: Calculate the distance between each electricity purchase data point and each electricity purchase center.

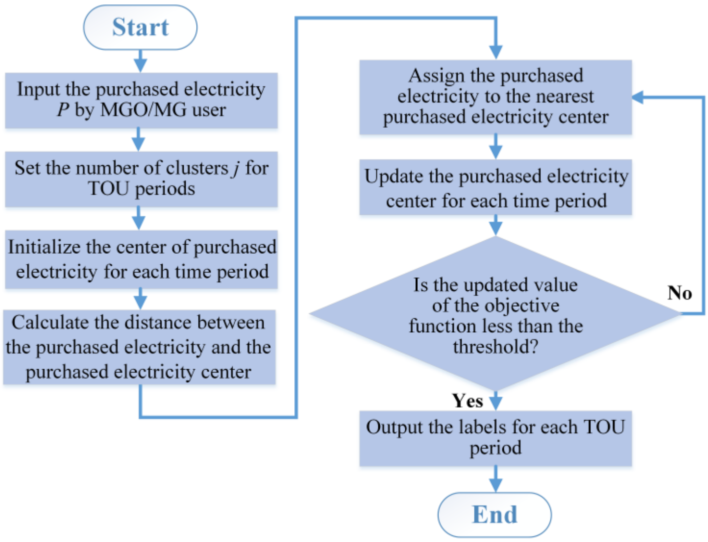

Fig. 2. Flowchart for solving the clustering labels.

Step 5: Allocate each electricity purchase data point to the nearest electricity purchase center.

Step 6: Recalculate the electricity purchase center for each period on the basis of the allocation results.

Step 7: Repeat steps 5-6 until the objective function value is less than the set threshold.

Step 8: Output the cluster labels for each period.

On the basis of the k-means clustering algorithm, the clustering label of the purchased electricity is obtained, and the peak, flat and valley TOU periods are determined according to the clustering label. This is expressed as follows:

$$S_{\mathrm{a}} = [\delta_1, \delta_2, \cdots, \delta_{24}] \tag{17}$$

$$\begin{cases} T_{\mathrm{F}} = \{t \mid \delta_t \in \delta_{\mathrm{F}}\} \\ T_{\mathrm{P}} = \{t \mid \delta_t \in \delta_{\mathrm{P}}\} \\ T_{\mathrm{G}} = \{t \mid \delta_t \in \delta_{\mathrm{G}}\} \end{cases} \tag{18}$$

$$T_{\mathrm{F}} \cup T_{\mathrm{P}} \cup T_{\mathrm{G}} = \{0, 1, 2, \cdots, 23\} \tag{19}$$

$$\begin{cases} T_{\mathrm{F}} \cap T_{\mathrm{P}} = \varnothing \\ T_{\mathrm{F}} \cap T_{\mathrm{G}} = \varnothing \\ T_{\mathrm{P}} \cap T_{\mathrm{G}} = \varnothing \end{cases} \tag{20}$$

where S_{a} is the cluster label vector of the purchased electricity; δ_t is the cluster label of the purchased power generation in period t; and δ_{F}, δ_{P} and δ_{G} are the peak, flat, and valley TOU cluster labels, respectively. T_{F}, T_{P} and T_{G} are the peak, flat and valley TOU sets of purchased electricity, respectively.

(2) TOU electricity price optimization decision model:

The core objective of setting the TOU electricity price is to smooth the load curve by reducing the peak–valley difference in the load. Therefore, the construction of the TOU electricity price optimization decision model should consider the minimization of the peak load and the peak–valley difference and consider the economic income constraints of both sides to ensure that the interests of both sides are balanced.

In determining the electricity price set by the power producers, the objective functions are as follows: (1) minimize the peak value of the power producer's generation curve F_1; (2) maximize the valley value of the power producer's generation curve F_2; and (3) minimize the peak–valley difference F_3 of the power producer's generation curve. The specific model is as follows:

$$F_1 = \min(\max_{0 \le t \le 23} P_{\mathrm{e}}^t) \tag{21}$$

$$F_2 = \max(\min_{0 \le t \le 23} P_{\mathrm{e}}^t) \tag{22}$$

$$F_3 = \min[(\max_{0 \le t \le 23} P_{\mathrm{e}}^t) - (\min_{0 \le t \le 23} P_{\mathrm{e}}^t)] \tag{23}$$

When the price of electricity sold by MGOs is determined, the objective functions are as follows: (1) minimize the peak value of the MG users' load curve F_4; (2) maximize the valley value of the MG users' load curve F_5; and (3) minimize the peak–valley difference F_6 of the MG users' load. The specific model is as follows:

$$F_4 = \min(\max_{0 \le t \le 23} P_{\mathrm{Ubuy},m}^t) \tag{24}$$

$$F_5 = \max(\min_{0 \le t \le 23} P_{\mathrm{Ubuy},m}^t) \tag{25}$$

$$F_6 = \min[(\max_{0 \le t \le 23} P_{\mathrm{Ubuy},m}^t) - (\min_{0 \le t \le 23} P_{\mathrm{Ubuy},m}^t)] \tag{26}$$

The constraint conditions of game equilibrium cover the income of power producers, the benefit to MGOs, and the comprehensive satisfaction of users. After the TOU electricity price adjustment, the interest or satisfaction of all relevant parties should be maintained at least at the preadjustment level to ensure that no party loses under the new pricing mechanism. The constraints are shown below:

$$C_{\mathrm{F,after}} \geq C_{\mathrm{F,before}} \tag{27}$$

$$C_{\mathrm{Fy,after}} \leq C_{\mathrm{Fy,before}} \tag{28}$$

$$C_{\mathrm{M,after}} \geq C_{\mathrm{M,before}} \tag{29}$$

$$F_{\mathrm{U,after}} \geq F_{\mathrm{U,before}} \tag{30}$$

$$\frac{F_{\mathrm{U,after}}}{P_{\mathrm{Ubuy,after}}^{t}} \leq \frac{F_{\mathrm{U,before}}}{P_{\mathrm{Ubuy,before}}^{t}} \tag{31}$$

In formulas (27) - (31), the subscript “after” represents the value after the price adjustment, and the subscript “before” represents the value before the price adjustment. Formulas (27), (29), and (30) indicate that each subject objective function should be optimized after adjustment; formula (28) indicates that the operation and maintenance costs of the power producers should be reduced after the electricity price adjustment. Formula (31) indicates that the users’ unit power purchase cost cannot be increased after the price adjustment.

3. Multilevel game mechanism and model

3.1 Multilevel game mechanism

The multilevel game architecture of the MMG system is shown in Fig. 3. To maximize their own interests, power producers, MGOs, and MG users participate in the game by making decisions regarding the TOU price of the electricity sold by power producers, the TOU electricity price on the load side and the TOU electricity consumption behavior, respectively.

In the multilevel game mechanism, there is a noncooperative game between power producers and MGOs and a leader–follower game between MGOs and MG users. In accordance with the power demand of each MG, the power producers consider the fixed cost of power generation and the operation and maintenance costs and determine the electricity selling price of the power producers. The MGOs carry

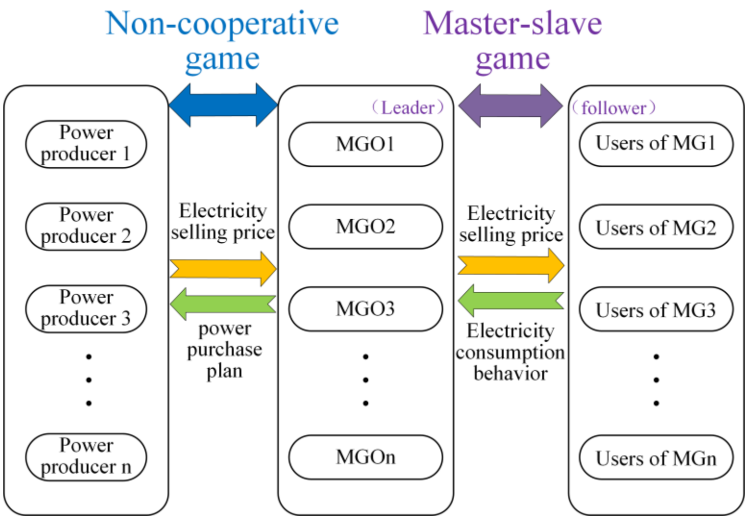

Fig. 3. Multilevel game architecture diagram.

out day-ahead planning and scheduling, giving priority to the consumption of renewable energy output and energy storage within the MG; if there is remaining demand, they purchase electricity from other MGs, and finally, they purchase electricity from power producers. MGOs consider their own benefits in setting the load-side TOU electricity price; users adjust their electricity consumption behavior according to the TOU electricity price on the load side and their psychological expectations. The three stakeholders—the power producers, the MGOs, and the users—influence each other by determining the on-grid TOU electricity price, the load-side TOU electricity price, and the TOU electricity consumption behavior, respectively, and obtain the optimal equilibrium solution through the game. The game process is shown in Fig. 4, and the specific steps are as follows:

Step 1: The power producers formulate the initial TOU on-grid electricity price on the power generation side.

Step 2: On the basis of the TOU on-grid electricity price and its own electricity demand, the MGOs formulate the power purchase strategy and the TOU electricity price on the load side.

Step 3: The MG users independently carry out load shifting or reduction according to the TOU electricity price on the load side.

Step 4: The MGOs update the dispatching strategy and power purchase plan according to the TOU electricity demand of the users.

Step 5: The power producers adjust the power generation plan and update the TOU on-grid electricity price according to the power purchase plan of the MGOs.

Step 6: Steps 2 to 5 are repeated until the TOU on-grid electricity price of the power producers, the

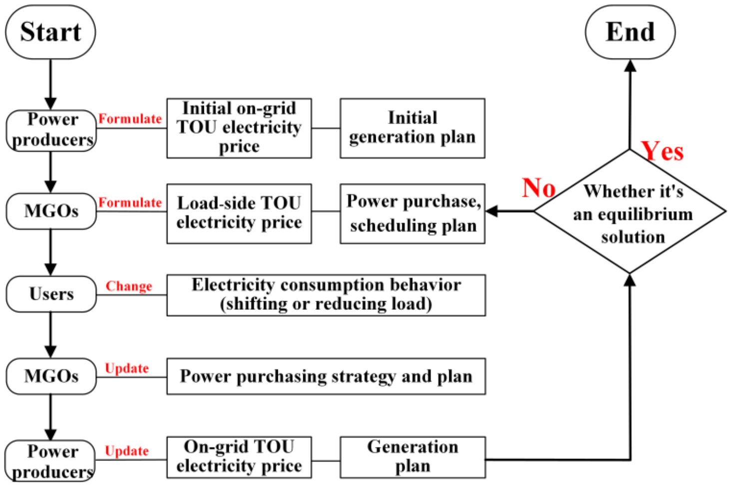

Fig. 4. Game flow chart.

power purchase strategy of the MGOs, the TOU electricity price on the load side, and the electricity consumption plan of the users remain stable, achieving game equilibrium.

Step 7: Conduct electricity transactions with the game equilibrium solution as the final result.

3.2 Noncooperative game model

Games can be categorized as cooperative or noncooperative according to whether the participants can form binding agreements for mutual cooperation [32]. In the MMG system structure studied in this paper, power producers tend to increase electricity prices to maximize profits, whereas MGOs aim to purchase electricity at the lowest possible prices to reduce costs. The conflicting interests of the two parties, along with the lack of direct cooperation, have given rise to a noncooperative game relationship. The two parties participating in the noncooperative game set up the economic optimization model for this game on the basis of the MMGs, taking the on-grid TOU electricity price and the power purchase plan as the game terms; this is expressed as follows:

(1) Participant set

$$Y = \{\mathrm{F}, \mathrm{MO}_1, \mathrm{MO}_2, \cdots, \mathrm{MO}_m, \mathrm{MO}_\mathrm{M}\} \tag{32}$$

where F represents the power producers and where MO_m indicates the m th MO.

(2) Policy set

The strategy set of the power producers is expressed as:

$$P_{\mathrm{e}}^{t} \in \Omega_{\mathrm{F}} = \left[P_{\mathrm{e}}^{\min}, P_{\mathrm{e}}^{\max} \right] \tag{33}$$

$$S_{\mathrm{F}}^{t} \in \Omega_{\mathrm{F}} = \left[S_{\mathrm{F}}^{\min}, S_{\mathrm{F}}^{\max} \right] \tag{34}$$

where P_{e}^{t} represents the power generated by the power producers during period t; Ω_{F} represents the strategy set of the power producers; $P_{\mathrm{e}}^{\max}$ and $P_{\mathrm{e}}^{\min}$ represent the upper and lower limits of power generation, respectively; S_{F}^{t} represents the TOU price of the electricity sold by the power producers during period t; and $S_{\mathrm{F}}^{\max}$ and $S_{\mathrm{F}}^{\min}$ represent the upper and lower limits of the price of the electricity sold by the power producers, respectively.

The policy set of the m th MGO is expressed as:

$$P_{\mathrm{Mbuy},m}^{t} \in \Omega_{\mathrm{M},m} = \left[P_{\mathrm{Mbuy},m}^{\min}, P_{\mathrm{Mbuy},m}^{\max} \right] \tag{35}$$

where $P_{\mathrm{Mbuy},m}^{t}$ represents the electricity purchased by the m th MGO from the power producers during period t; $\Omega_{\mathrm{M},m}$ represents the policy set of the m th MGO; and $P_{\mathrm{Mbuy},m}^{\max}$ and $P_{\mathrm{Mbuy},m}^{\min}$ represent the upper and lower limits of purchased electricity, respectively.

(3) Utility function

In the game process, the power producers seek to maximize their own profits C_{F}, which is expressed as formula (1); the MGOs pursue the maximum benefits C_{M} in the game process, as shown in formula (5).

(4) Nash equilibrium

When the game reaches equilibrium, the power producers and MGOs meet the following conditions:

$$\begin{aligned} & C_{\mathrm{F}}(P_{\mathrm{e}}^{t*}, S_{\mathrm{F}}^{t*}, P_{\mathrm{Mbuy},m}^{t*}) \geq C_{F}(P_{\mathrm{e}}^{t}, S_{\mathrm{F}}^{t*}, P_{\mathrm{Mbuy},m}^{t*}) \\ & \forall P_{\mathrm{e}}^{t} \in \Omega_{\mathrm{F}} \end{aligned} \tag{36}$$

$$\begin{aligned} & C_{\mathrm{F}}(P_{\mathrm{e}}^{t*}, S_{\mathrm{F}}^{t*}, P_{\mathrm{Mbuy},m}^{t*}) \geq C_{F}(P_{\mathrm{e}}^{t*}, S_{\mathrm{F}}^{t}, P_{\mathrm{Mbuy},m}^{t*}) \\ & \forall S_{\mathrm{F}}^{t} \in \Omega_{F} \end{aligned} \tag{37}$$

$$\begin{aligned} & C_{\mathrm{F}}(P_{\mathrm{e}}^{t*}, S_{\mathrm{F}}^{t*}, P_{\mathrm{Mbuy},m}^{t*}) \geq C_{F}(P_{\mathrm{e}}^{t*}, S_{\mathrm{F}}^{t*}, P_{\mathrm{Mbuy},m}^{t}) \\ & \forall P_{\mathrm{Mbuy},m}^{t} \in \Omega_{\mathrm{M}} \end{aligned} \tag{38}$$

According to formulas (36) to (38), when the noncooperative game between the power producers and the MGOs reaches the Nash equilibrium, none of the participants can unilaterally change their strategies to obtain a better benefit function while leaving other participants unaffected.

3.3 Leader–follower game model

In the process of MMG scheduling, the MGOs guide the users' power purchases through price signals to maximize the benefit of the users' power consumption. Moreover, the benefits of the MGOs depend on the users' power purchase status. The decision-making behavior of the participants in the power market can be described as a leader–follower game model [33].

The leader–follower game model proposed in this paper is a decision-making process in which MGOs and MG users participate in the game as leaders and followers and pursue their respective goals. The leader–follower game model can be expressed as follows:

(1) Participant set:

$$Y = \left\{ \mathrm{MO}_m, \mathrm{U}_m \right\} \tag{39}$$

where U_m indicates the set of users of the m th MG.

(2) Policy set:

The strategy of the leading MGOs is $S_{\mathrm{M},m}^{t} \in \Omega_{\mathrm{M},m} = \left[S_{\mathrm{M}}^{\min}, S_{\mathrm{M}}^{\max} \right]$, and the strategy of the following MG users is $P_{\mathrm{Ubuy},m}^{t} \in \Omega_{\mathrm{U},m} = \left\{ P_{\mathrm{Ubuy},m}^{\min}, P_{\mathrm{Ubuy},m}^{\max} \right\}$. $S_{\mathrm{M}}^{\max}$ and $S_{\mathrm{M}}^{\min}$ represent the upper and lower limits of the electricity price determined by the MGOs, respectively, and $P_{\mathrm{Ubuy},m}^{\max}$ and $P_{\mathrm{Ubuy},m}^{\min}$ are the upper and lower limits of the power purchased by MG users, respectively.

(3) Utility function

As the leaders, MGOs seek to maximize their own benefits in the game process, as shown in formula (5). MG users pursue the highest comprehensive satisfaction with electricity consumption during the game, which is expressed in formula (9).

(4) Stackelberg equilibrium

When the following MG users determine an optimal response according to the strategy of the leading MGOs and the MGOs accept this response, the game reaches the Stackelberg equilibrium. If $(S_{\mathrm{M},m}^{t*}, P_{\mathrm{Ubuy},m}^{t*})$ is the equilibrium solution of the leader–follower game, it must satisfy:

$$\begin{aligned} & C_{\mathrm{M}}(S_{\mathrm{M},m}^{t*}, P_{\mathrm{Ubuy},m}^{t*}) \ge C_{\mathrm{M}}(S_{\mathrm{M},m}^{t}, P_{\mathrm{Ubuy},m}^{t*}) \\ & \forall S_{\mathrm{M},m}^{t} \in \Omega_{\mathrm{M},m} \end{aligned} \tag{40}$$

$$C_{\mathrm{U}}(S_{\mathrm{M},m}^{t*},P_{\mathrm{Ubuy},m}^{t*})\geq C_{\mathrm{U}}(S_{\mathrm{M},m}^{t*},P_{\mathrm{Ubuy},m}^{t})$$
$$\forall P_{\mathrm{Ubuy},m}^{t}\in\Omega_{\mathrm{U},m} \tag{41}$$

After the leader–follower game between the MGOs and MG users reaches an equilibrium solution, neither side can achieve greater benefits by unilaterally changing strategies.

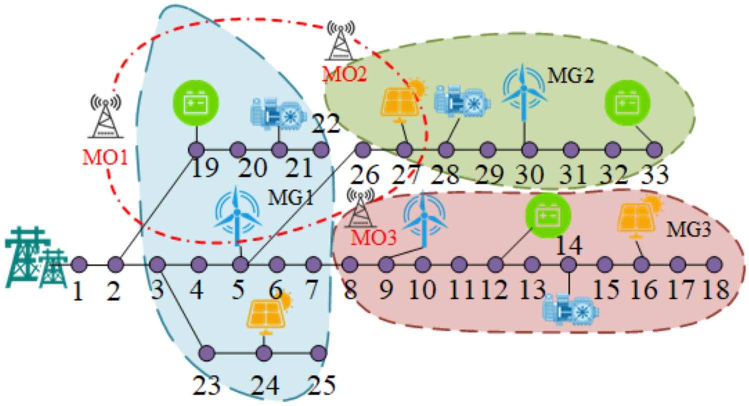

Fig. 5. IEEE 33-node system diagram.

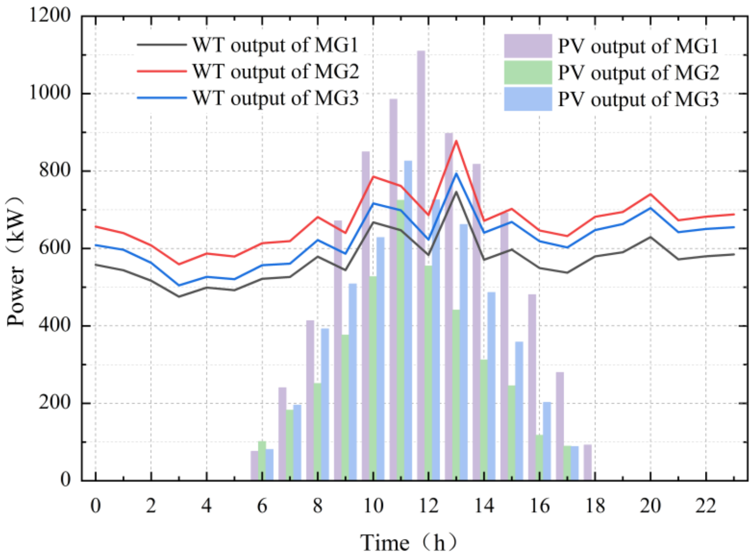

Fig. 6. Renewable energy output of each MG.

Table 1
Device parameters

	The lower limit of GT output (kW)	The upper limit of GT output (kW)	GT cost coefficient (kW)	The initial capacity of the ES device (kW)	The upper limit of ES device power (kW)	The upper limit of interconnection power between MGs (kW)	The upper limit of power exchange with the power producer (kW)
MG1	80	800	0.7939	800	200		
MG2	100	1000	0.8087	1200	300	500	1500
MG3	90	900	0.7995	900	225		

4.2. Game equilibrium results

After multilevel game equilibrium is reached, the electricity prices of power producers and MGOs and the interactive electricity prices between the MGOs considered in this paper can be obtained, as shown in Fig. 7.

As shown in Fig. 7, the TOU period is determined by the power producers according to the power generation demand, and the TOU period is determined by the MGOs according to the users' load. Therefore, the TOU period of the power producers is different from the TOU period of the MGOs' selling price and the MGOs' interactive price.

In the early morning hours (0:00-4:00), the electricity demand after DR increases compared with that before optimization. The PV output is 0, and there is no available electricity in the ES equipment. At this time, the amount of power planned to be generated by the power producers is high, and the selling price of the power producers is the peak price. From 4:00 to 9:00, the PV equipment begins to operate, the scheduling function for low charge and high discharge is used for the ES equipment, and the power planned to be generated by the power producers is lower than that at the peak period, so the TOU electricity selling price of the power producers is the typical price. From 10:00 to 16:00, the PV output reaches its peak, and the users' load after DR tends to be flat. At this time, the power demand of the MGOs for the power producers is low, and the TOU electricity price is the valley price. From 18:00 to 21:00, the PV equipment stops output, and the distributed power supply and GT output of the MGOs are not sufficient to cover the needs of users, so the amount of power planned to be generated by the power producers is large, and the TOU electricity price is the peak price.

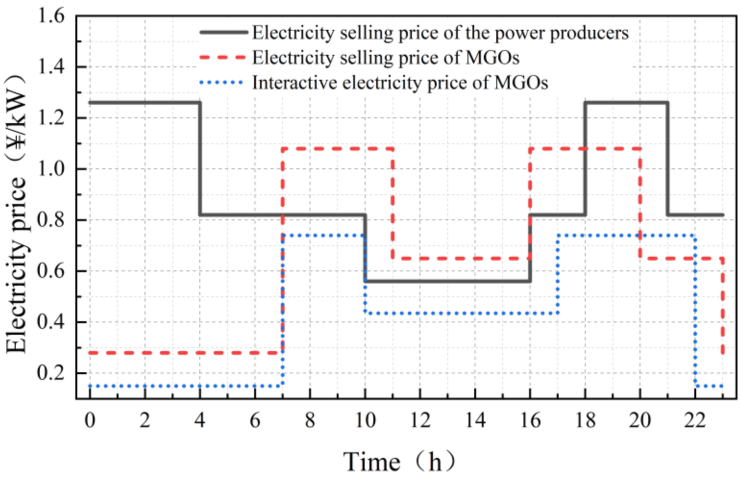

Fig. 7. Optimized TOU electricity price chart.

From 0:00 to 7:00 and from 20:00 to 23:00, the users' load is low, so the electricity selling price of MGOs and the interactive electricity price of MGOs are the valley prices. From 7:00 to 11:00 and from 16:00 to 20:00, the PV output, WT output, and GT output are not sufficient to cover the needs of users, and the MGOs need to buy electricity from power producers. At this time, the electricity selling price of the power producers is high, and the electricity purchase cost for the MGOs increases, so the electricity selling price of the MGOs also increases. From 11:00 to 16:00, the PV output increases, and the cost of buying electricity from power producers is reduced by the MGOs, so the electricity selling price of the MGOs is the valley price.

4.3. Analysis of basic operation results

To further verify the feasibility of the proposed strategy, the basic operation results are analyzed. The load optimization results for the users of MG1, MG2, and MG3 are shown in Fig. 8. The electric power balances of the MGs are shown in Figs. 9, 10, and 11, respectively. The ES state for each MG is shown in Fig. 12.

As seen from the analysis in Fig. 8, the user loads of the three MGs are all reduced during optimization. DR is carried out during periods of high electricity prices (10:00–22:00), and some of the electricity loads are transferred to periods of low electricity prices, reducing the electricity demand during peak hours. Moreover, the peak load is reduced, and the peak–valley difference is reduced, yielding energy cost savings. This optimization strategy not only reduces the pressure on the power grid but also increases the economic benefits of MGOs and MG users.

As shown in Fig. 9, there is no PV power generation in the period from 0:00 to 5:00 for MG1; in contrast, WT power generation is continuous, but its output is not stable due to the effect of the wind speed. The GT maintains stable output at a medium level according to demand to fulfill the load power

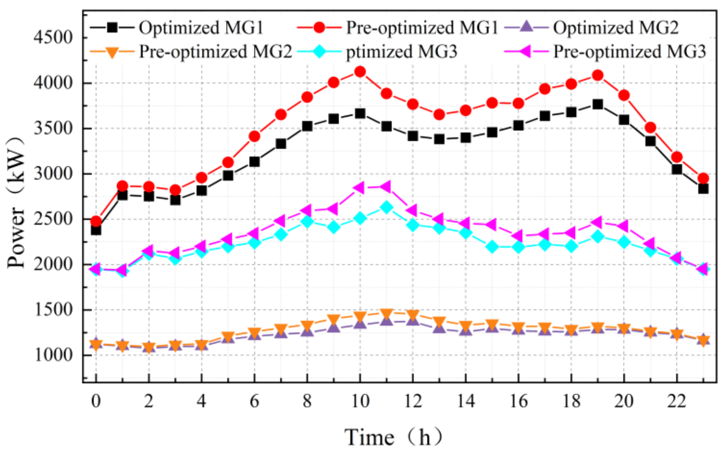

Fig. 8. User load diagram of the MGs before and after optimization.

demand. The surplus power in this period is preferentially transmitted to MG2 and MG3 or is sent to ES

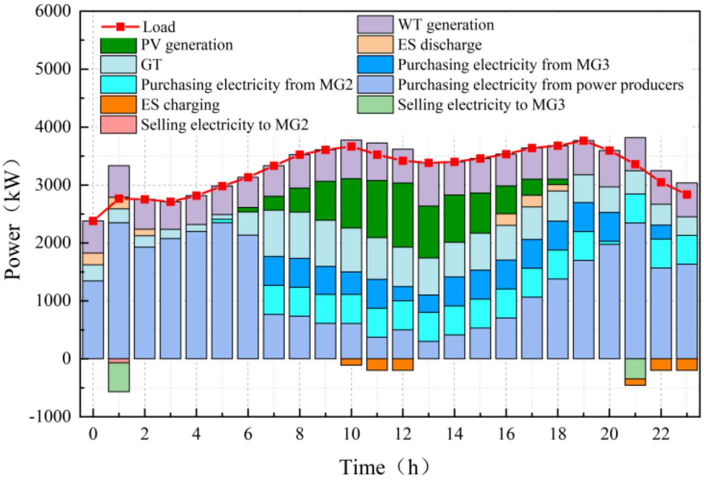

Fig. 9. Electrical power balance diagram for MG1.

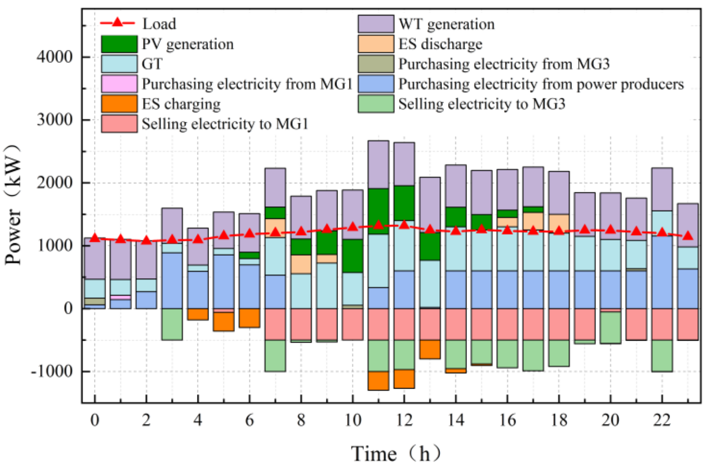

Fig. 10. Electrical power balance diagram for MG2.

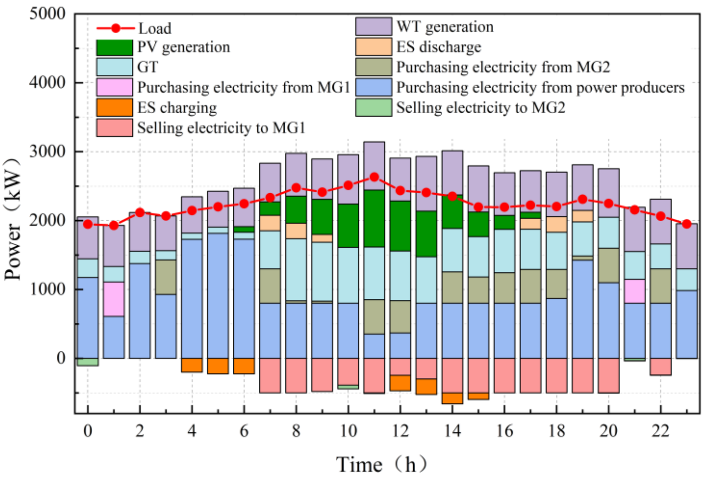

Fig. 11. Electrical power balance diagram for MG3

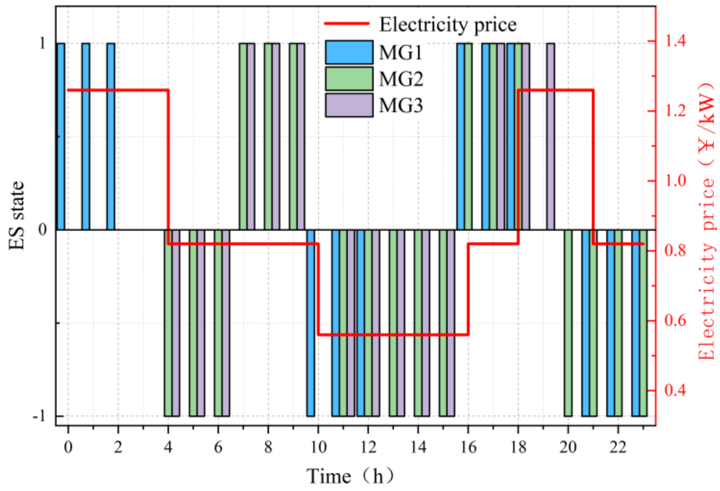

Fig. 12. State diagram of ESs.

to reduce the electricity purchased by other MGs from power producers and reduce the total cost. From 6:00 to 18:00, as the sun moves, the output of PV equipment increases with increasing sunlight intensity until it reaches a peak and then begins to decrease, and the GT maintains a stable and high level of output to cope with the increasing demand for electric energy. At this stage, MG2 and MG3 produce enough electricity to sell electricity to MG1, reducing the pressure of power transmission and the power purchase cost for MG1. From 19:00 to 23:00, with the change in load demand, the electricity purchased by MG1 from power producers also changes accordingly.

As shown in Fig. 10, MG2 maintains power balance by generating PV power, WT power, and GT power and by purchasing power from MG1 and MG2 from 0:00 to 3:00. From 4:00 to 23:00, a small amount of electricity is purchased from power producers to meet the energy needs of users of MG2, and at the same time, electricity is sold to MG1 and MG3 to reduce the electricity purchased from power producers, reduce the total cost of the system, and improve economic benefits.

As shown in Fig. 11, the user load of MG3 is higher than that of the users of MG2, so they need to purchase more electric energy from power producers, which leads to an increase in the power purchase cost. However, compared with MG1, the user load of MG3 is smaller. In the optimization process, MG3 provides stable electric energy to MG1 from 7:00 to 20:00 to reduce the energy gap of MG1. MG3 buys power from MG2 and sells power to MG1 at the same time during the periods from 11:00 to 12:00 and 14:00 to 20:00 to reduce the power in the connecting lines between MGs and improve the safety of electricity consumption.

As shown in Figure 12, the ES devices under the control of MG1, MG2, and MG3 discharge when the electricity price from the power producer is high and charge when the electricity price is flat or low, implementing a "high discharge, low charge" strategy. This strategy allows MGOs to participate more flexibly in electricity market transactions, reducing the system's operating costs through price differences and enhancing the economic performance of the MMG system. The implementation of the "high discharge, low charge" strategy for ES devices in MGs not only improves economic benefits but also optimizes energy allocation, strengthening the stability and reliability of the grid. Furthermore, this strategy promotes the integration of renewable energy, enhancing the autonomy and resilience of the MG.

The above analysis reveals that the optimization strategy for the bidirectional TOU electricity price for MMGs coupled with the multilevel games proposed in this paper can encourage the three stakeholders of power producers, MGOs, and MG users to participate in electricity price optimization. This interaction not only improves the economic efficiency of the system but also significantly reduces the operating costs of the MG, demonstrating the effectiveness of the strategy in promoting the economic interests of all parties.

4.4. Comparative analysis of multiple schemes

To verify the economic and environmental protection advantages of the strategies proposed in this study, four schemes are established for comparative analysis.

Scheme 1 is a multiobjective optimization strategy for the TOU electricity price of MMGs. Scheme 2 is a TOU electricity price optimization strategy for MMGs that is based on noncooperative game theory.

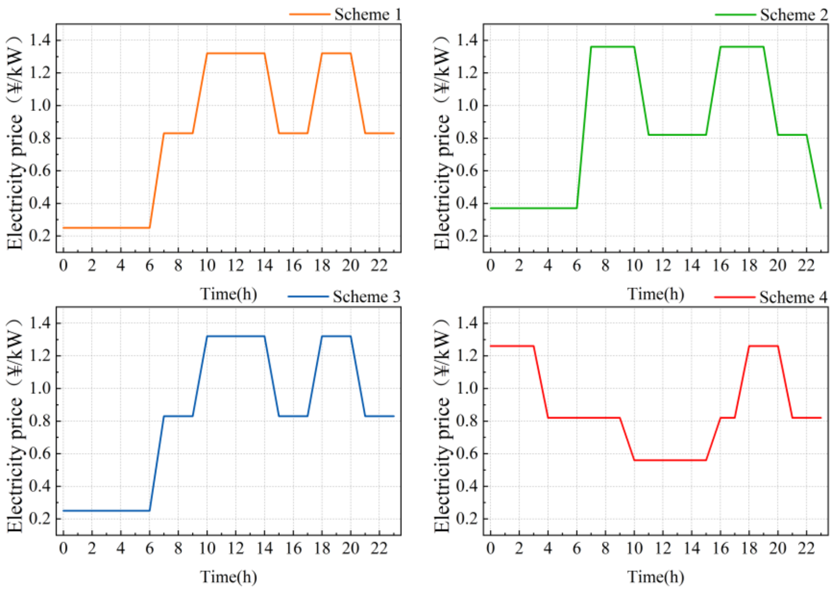

Fig. 13. Comparison of the prices of electricity sold by power producers

Scheme 3 is the optimization strategy for the TOU electricity price of MMGs considering the willingness

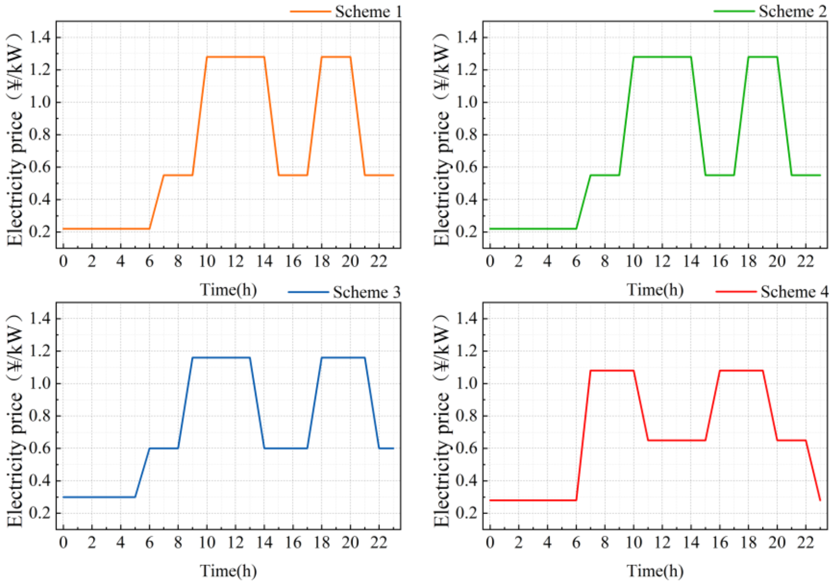

Fig. 14. Comparison of the prices of electricity sold by MGOs.

Table 2
Results of multischeme system cost optimization

	Scheme 1	Scheme 2	Scheme 3	Scheme 4
GT cost (¥)	31687.7	26429.3	28482.6	23576.1
Environmental protection cost (¥)	1164.8	975.2	1071.7	942.0
Endowment benefit cost (¥)	2649.7	2866.0	2839.4	2539.2
Microgrid user cost (¥)	136354.1	129326.4	122793.6	93325.5

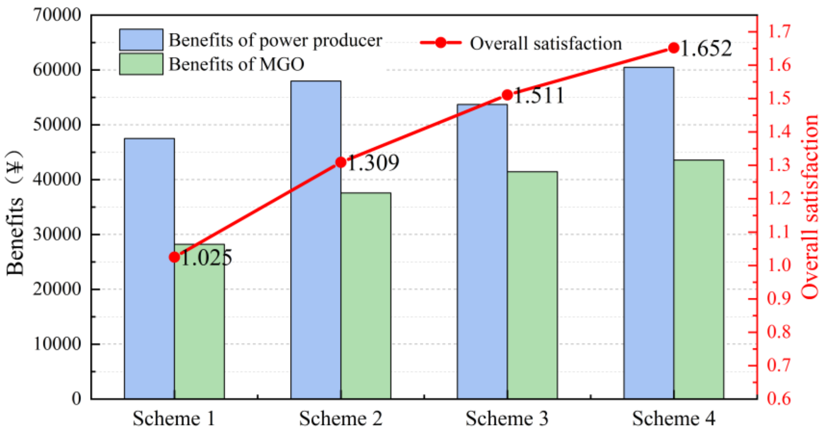

Fig. 15. Comparison of the optimization results for each subject.

for green electricity consumption. Scheme 4 shows the strategy proposed in this study. For each of the above four schemes, a comparison of the prices of electricity sold by power producers is shown in Fig. 13. A comparison of the prices of electricity sold by MGOs is shown in Fig. 14. The results of system optimization are shown in Table 2. The optimization results for each main objective function are shown in Fig. 15.

A comprehensive comparison of Scheme 1 and Scheme 4 reveals that there is no game process in Scheme 1; thus, the TOU periods for electricity prices set by the power producers are almost identical to those set by the MGOs. Scheme 4 involves a multilevel game process, where at the game equilibrium, the electricity selling price for power producers shows a pattern of being high when the selling volume is high and low when the selling volume is low. Additionally, the peak-to-valley price difference is reduced. Compared with that in Scheme 1, the GT cost in Scheme 4 is 8,111.6 ¥ lower, which is a 25.6% decrease. The environmental protection costs decreased by 222.8 ¥, a decrease of 19.1%. The total benefit of the MGOs increased by 15,343.7 ¥, an increase of 54.3%. The revenue of the power producers increased by 12,951.3 ¥, which is an improvement of 27.3%. The cost to MG users was reduced by 43,028.6 ¥, a decrease of 31.6%. The overall satisfaction of users increased by 0.627. According to the above data analysis, in Scheme 4, the power producers, MGOs, and users all participate in the game process, and the energy consumption behavior of the users is guided by the price of electricity to respond to the demand, reducing the electricity cost; additionally, the power generation plan of the power producers obtains higher returns after adjustment. Compared with those of Scheme 1, each cost of Scheme 4 is reduced by approximately 20%. The income of power producers and the total benefit of MGOs are greatly improved, which indicates the absolute advantages of Scheme 4 in terms of the economy and environmental protection.

Comparing Scheme 1 and Scheme 2, there is no game process between the MGOs and the users in Scheme 2, and a fixed TOU electricity price is used. Therefore, the TOU periods for electricity prices set by the power producers in Scheme 2 are different from those in Scheme 1. From 11:00 to 15:00, as the output of the PV power generation equipment reaches its peak, the power purchased by MGOs from power producers decreases, and the power producers better manage the power supply by reducing the price from the peak to the flat value; this balances supply and demand to reduce the impact of fluctuations caused by PV power generation on the grid. This price adjustment strategy helps entice MGOs to buy more electricity when the supply is sufficient, thereby reducing reliance on the GT and reducing the frequency and cost of starting and stopping the GT. An analysis of the data in Table 2 shows that compared with that of Scheme 2, Scheme 4's GT cost is reduced by 2,853.2 ¥, a decrease of 10.8%; the environmental costs are reduced by 33.2 ¥, a decrease of 3.4%; the total benefits for MGOs are increased by 5,978.5 ¥, an improvement of 15.9%; the power producer revenues are increased by 2,497.8 ¥, an improvement of 4.3%; the MG users' costs are decreased by 36,000.9 ¥, a decrease of 27.8%; and overall user satisfaction is increased by 0.316. This shows that in Scheme 4, the MGOs adjust the electricity price through the game with the users and guide the users to respond to the demand. This strategy increases the total benefit to the MGOs, significantly reduces the electricity cost for the MG users, and increases the economic benefit for the users.

Comparing Scheme 1 and Scheme 3, in Scheme 3, there is no game process between power producers and MGOs, and a fixed TOU electricity price is adopted. Therefore, the electricity selling price of the MGOs in Scheme 3 differs from that in Scheme 1. As shown in Fig. 14, the peak value of the electricity price of Scheme 3 is lower, and the valley value is higher. The relatively flat price of electricity helps influence MGOs to develop more sustainable and stable power purchase plans, which in turn optimizes the power generation plans of power producers and reduces their cost and environmental impact. An analysis of Table 2 shows that compared with that of Scheme 3, Scheme 4's GT cost is reduced by 4,906.5 ¥, a decrease of 18.6%; the environmental costs are reduced by 129.7 ¥, a decrease of 12.1%; the total benefits for MGOs are increased by 2,121.4 ¥, an improvement of 5.1%; the power producers' revenues are increased by 6,767.5 ¥, an improvement of 23.6%; the MG users' costs are decreased by 29,468.1 ¥, a decrease of 24.0%; and overall user satisfaction is increased by 0.141. This indicates that the game process between MGOs and power producers results in improved outcomes under Scheme 4 compared with those under Scheme 3 because the electricity selling price of power producers changes to significantly improve the income of power producers; this demonstrates the comprehensive advantages of Scheme 4 in optimizing energy management, reducing electricity costs, increasing economic benefits and reducing environmental impact.

A comparison of the economic operation results of Scheme 1, Scheme 2, Scheme 3, and Scheme 4 reveals that Scheme 4, the bidirectional TOU electricity price optimization strategy proposed in this paper, has significant comprehensive advantages. The multilevel and differentiated game process of Scheme 4 makes the interaction among subjects more dynamic and efficient. Through the multilevel game among various entities, the electricity selling price of power producers is optimized and adjusted in different periods according to the power demand, which makes the electricity price rise in periods of high load demand and fall in periods of low demand. This flexibility reduces the peak–valley difference in electricity prices and is conducive to the smooth operation of the power generation equipment of power producers.

5. Conclusion

In this paper, the optimization strategy for the bidirectional TOU electricity price for MMGs coupled with multilevel games is discussed in detail. First, a DR model based on the endowment effect is established to describe users' DR behavior more appropriately to help the MGOs plan the corresponding power supply scheme. Second, through the coordination between the TOU price of electricity sold by power producers and the price of electricity sold by MGOs, power producers are encouraged to actively participate in the scheduling plan of MGOs, and users are encouraged to participate in DR to achieve a win–win situation regarding the three parties of energy supply, distribution, and demand. Next, a multilevel differentiated game mechanism combining noncooperative games and leader– follower games is established, effectively increasing the system's economic efficiency. Finally, the economic operation results indicate that in achieving game equilibrium, the adaptability and responsiveness of the strategies of all participants are increased, confirming the superiority of this optimization strategy in practical applications. A comprehensive comparative analysis of different schemes indicates that the proposed optimization strategy effectively reduces MG users' electricity costs, increases overall user satisfaction, and ensures the economic benefits of power producers and MGOs.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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