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Collaborative optimal dispatch of microgrid and electric vehicles based on the Stackelberg game

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The development of both microgrids and electric vehicles has become an important part of the current energy scenario. Useful complementary advantages can be formed between electric vehicles and microgrids, the consumers of which can utilize renewable energy and narrow the peak–valley differences of the net load curve while ensuring their own pecuniary interests. Based on the idea of the Stackelberg game, an optimal dispatch model of a microgrid with electric vehicles is proposed herein, where the benefits of the state of charge are taken into account. In the upper layer of the model, the charging and discharging behaviors of electric vehicles are guided by the goal of minimizing the operating cost of the microgrid. In the lower layer of the model, electric vehicle users adjust the charging and discharging strategies with the goal of maximizing their individual interests. The study results demonstrate that the proposed model not only reflects the benefits of both the master and slave but also reduces the peak–valley differences of the microgrid load. Further, the charging and discharging times of electric vehicles are reduced, and their state of charge is maintained at a high level.

KEYWORDS

microgrid, electric vehicles, Stackelberg game, optimal dispatch, state of charge

Introduction

Microgrids have rapidly gained popularity and are being increasingly applied in recent years. There is good complementarity between the energy structure characteristics of microgrids using renewable energy and the use of electric vehicles. The ability of an electric vehicle to gain access to a microgrid will become one of the important considerations in microgrid and electric vehicle applications (Cecati et al., 2011; Dagdougui et al., 2019; Ma et al., 2021a). However, because of the randomness of renewable energy availability and electric vehicle charging behaviors, there are some uncertain factors in the microgrid dispatch optimization process. Therefore, research on microgrid dispatching related to electric vehicles must consider the corresponding stochastic dispatch optimization method and establish energy dispatch models for uncertain environments to improve the economy and stability of the microgrid dispatch optimization scheme (Sortomme et al., 2011; Li Z. et al., 2019; Teng et al., 2020; Ma et al., 2021b). At the same time, in the interactions between microgrids and electric vehicle users, different interests are expressed by both sides. Electric vehicle users hope to participate in microgrid dispatch without affecting their normal use to obtain maximal benefits. Microgrid users hope to reduce their electricity costs and improve the operating environments through the charging and discharging behaviors of electric vehicles (Fu et al., 2021; Ma et al., 2021c). Although the interests and benefit objectives of the two sides are different, there are certain conflicts of interest; this can result either in a win-win situation for both sides through cooperation or in competition between both sides to maximize their own profits. Therefore, when studying the interaction behaviors between microgrids and electric vehicle users, it is very important to choose a reasonable strategy that conforms to the actual behavioral characteristics of both parties and to establish an optimal scheduling model that meets the interests of both parties (Tushar et al., 2012; Yang et al., 2019; Ma et al., 2021d).

At present, neither the grid operators nor electric vehicle users engage in organized orderly charging of electric vehicles, so disorderly charging is still the dominant behavior (Gong and Li, 2021; Zheng and Yao, 2021). However, the influence of the disorderly charging of electric vehicles on the power grid cannot be ignored (Wolsink, 2012; Kakran and Chanana, 2018; Muhtadi et al., 2021). The charging conditions of electric vehicles are analyzed from the perspectives of energy consumption and use. The charging load of an electric vehicle increases the running burden on the transmission and distribution networks, and the increase in line load rate increases equipment losses. Generally speaking, the influence of electric vehicles on the power grid can be examined from three aspects, namely power grid reliability, power quality, and operational economy (Wang et al., 2018; Ma et al., 2019; Zhu et al., 2019; Zhang et al., 2021). When considering the spatial distribution of electric vehicles as the research objective, the charging locations of the vehicles must be guided in an orderly manner. The utilization rates of the charging facilities and electricity balance rates of different regions can be improved by preventing high charging loads in certain regions (Richardson et al., 2012; Shafiee et al., 2013; Li F. et al., 2019). Temporally, the goal involves reducing the load fluctuation variance and peak–valley differences; spatially, the goal is minimizing the charging cost of the user. At the same time, the scheduling of the charging load has been considered from the perspectives of both time and space (Wan et al., 2018; Yang et al., 2020; Wang et al., 2021). The abovementioned works examine only the charging behavior control of electric vehicle users; therefore, electric vehicles are regarded as electrical equipment that can only reduce and translate loads, and the control methods and achieved effects are not flexible enough as they usually achieve only the load filling function.

To address the spatiotemporal uncertainties of electric vehicle operation, a robust optimal dispatch model has been constructed by combining a data-driven algorithm with the risk coefficient method (Wei et al., 2017). The intraday real-time scheduling of electric vehicle charging and discharging has been realized using deep learning without generation selection calculation (Huang et al., 2017). The imbalance rate of the microgrid is calculated from the real-time data of renewable energy output and load. Then, the reasonable electricity price information based on the imbalance rate is released to guide the charging and discharging behaviors of electric vehicles and to realize coordinated operations of electric vehicles and renewable energy in the microgrid (Wu et al., 2017). However, the aforementioned studies are concerned with centralized management of electric vehicles in the microgrid without considering user independence; users cannot respond to the demand side depending on their situation, and the dispatch center must perform extensive data processing and calculations.

The dispatching problem of connecting electric vehicles to the microgrid is compared with the traditional scheduling problem, and the randomness of both renewable energy and load in the microgrid is considered in this study. By analyzing the benefits of the microgrid and electric vehicle user participation in dispatching based on the master–slave game theory, an optimal dispatch strategy is proposed for the microgrid with electric vehicles considering the state of charge (SOC). Further, a microgrid scheduling model with electric vehicles is established based on the master–slave theory, and the existence of the equilibrium solution of the benefit function is proven. Finally, the model is solved to obtain the real-time electricity pricing scheme for optimal scheduling.

Distributed output modeling of the microgrid considering prediction error

Photovoltaic and wind powers are two of the commonly used distributed power sources in a microgrid. However, as the outputs of both photovoltaic and wind power generation are greatly affected by environmental conditions, there may be errors in their power forecast. The influences of these errors increase with the increasing penetration of the two renewable energy sources. Therefore, the optimal dispatch of the microgrid must be modeled to improve the reliability of the dispatch results.

Photovoltaic output model considering prediction error

The output from photovoltaic power generation is not only affected by environmental factors but also related to the characteristics of the system components, such as the photoelectric conversion efficiencies of materials and series–parallel modes of the components. However, these factors do not obviously influence the output forecast of the photovoltaic system. The main factors affecting the photovoltaic output prediction results are random and uncontrollable natural environmental conditions, such as solar light intensity, cloud layer position and thickness, and weather conditions. The output power of the photovoltaic power generation equipment can be represented by (1)

$$P_{\mathrm{pv}} = e\sum_{p=1}^{P}\eta_p S_p \tag{1}$$

where e is the incident light intensity, η_p is the photoelectric conversion efficiency of the pth photovoltaic module, and S_p is the area of the pth photovoltaic module. Owing to the influence of the natural environment and other factors, the prediction error of the photovoltaic equipment output is random. However, the prediction and error data from historical records are sampled and analyzed using probability and statistical theories. Combined with actual data from the natural environment, it can be considered that the short-term prediction error of the photovoltaic output is normally distributed. For the expression $\varepsilon_{\mathrm{PV}} \sim N(0, \sigma_{\mathrm{PV}})$, the probability density function is as shown in (2):

$$f(\varepsilon_{\mathrm{PV}}) = \frac{1}{\sqrt{2\pi}\sigma_{\mathrm{PV}}} e^{-\frac{\varepsilon_{\mathrm{PV}}^2}{2\sigma_{\mathrm{PV}}^2}} \tag{2}$$

where ε_{PV} is the photovoltaic output prediction error, and σ_{PV} is the variance of the normally distributed photovoltaic output prediction error.

Once the probability distribution of the prediction error is obtained, the predicted value of the photovoltaic equipment output can be expressed as a superposition of the predicted value and prediction error:

$$P_{\mathrm{PV}}' = P_{\mathrm{PV}} + \varepsilon_{\mathrm{PV}} \tag{3}$$

where P_{PV} is the predicted photovoltaic output value, and P_{PV}' is the actual photovoltaic output value.

Wind power output model considering prediction error

Similar to the factors affecting the output predictions of photovoltaic equipment, the outputs of wind power equipment are affected mainly by the wind speed. The relationship between the unit output and wind speed can be expressed by (4)

$$P_{\mathrm{PW}}(v) = \begin{cases} 0 & v < v_{\mathrm{in}},\ v > v_{\mathrm{out}} \\ \dfrac{v - v_{\mathrm{in}}}{v_* - v_{\mathrm{in}}} & v_{\mathrm{in}} \le v < v_* \\ P_{\mathrm{PW}*} & v_* \le v < v_{\mathrm{out}} \end{cases} \tag{4}$$

where v_{in} is the cut-in wind speed, v_{out} is the cut-out wind speed, v_* is the rated wind speed, v is the actual wind speed, and $P_{\mathrm{PW}}(v)$ is the functional relationship between the wind power generation equipment output and actual wind speed.

From (4), it is observed that when the actual wind speed is less than the cut-in or greater than the cut-out wind speeds, the output of the equipment is 0. When the actual wind speed is between the cut-in and cut-out wind speeds, the output of the wind power equipment is directly proportional to the wind speed as shown in Figure 1.

Similarly, from theoretical analysis of the probability and statistics combined with historical data, the prediction error of the wind power output can be described by a normal distribution with a mean value of 0. Given that $\varepsilon_{\mathrm{PW}} \sim N(0, \sigma_{\mathrm{PW}})$, the probability density expression is

$$f(\varepsilon_{\mathrm{PW}}) = \frac{1}{\sqrt{2\pi}\sigma_{\mathrm{PW}}} e^{-\frac{\varepsilon_{\mathrm{PW}}^2}{2\sigma_{\mathrm{PW}}^2}} \tag{5}$$

where ε_{PW} is the forecast error of the wind power output, and σ_{PW} is the variance of the normally distributed wind power output prediction error.

The wind power output forecast before today can also be expressed as a superposition of the forecast value and forecast error:

$$P_{\mathrm{PW}}' = P_{\mathrm{PW}} + \varepsilon_{\mathrm{PW}} \tag{6}$$

where P_{PW} is the predicted wind power output value, and P_{PW}' is the actual wind power output value.

Load model considering forecasting error

Past research shows that the load power fluctuation can be represented as a normal distribution with the predicted value as the average. Thus, the actual load value can be decomposed into the predicted load and predicted error values that are normally distributed. The actual output expression of the load and probability density expression of the prediction error are shown in (7, 8):

$$P_{\mathrm{L}}' = P_{\mathrm{L}} + \varepsilon_{\mathrm{L}} \tag{7}$$

$$f(\varepsilon_{\mathrm{L}}) = \frac{1}{\sqrt{2\pi}\sigma_{\mathrm{L}}} e^{-\frac{\varepsilon_{\mathrm{L}}^2}{2\sigma_{\mathrm{L}}^2}} \tag{8}$$

where P_L is the predicted load power value, P_{L}' is the actual load power value, ε_L is the load power prediction error, and σ_L is the variance of the normally distributed load power prediction error.

Net load of the microgrid

In the established model, the microgrid itself is affected by three variables: wind power, photovoltaic output, and load. In

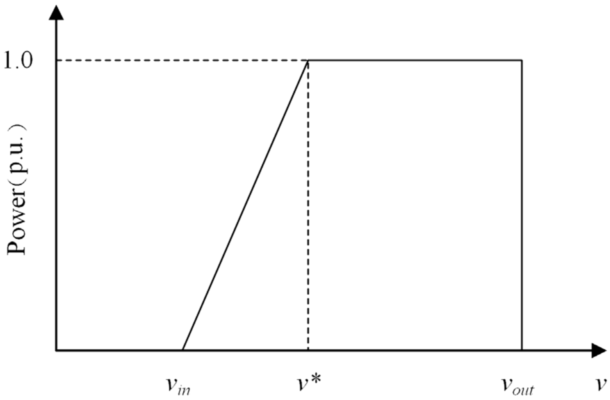

FIGURE 1
Relationship between wind power and wind speed.

this study, the net load is used to represent the algebraic sum of these three variables:

$$P_{NL} = P_L' - P_{PV}' - P_{PW}' \tag{9}$$

where P_{NL} is the net load of the microgrid.

Optimal dispatch of the microgrid with electric vehicles considering the state of charge

Dispatch structure of the microgrid when electric vehicles are connected

In the optimal dispatch of a microgrid with electric vehicles under the Stackelberg game structure, the electric vehicles and microgrid not only maintain electrical energy interactions during the dispatch period but also sustain information exchange during the scheduling plan. The electric vehicles considered in this study are the working vehicles and private cars of the microgrid users. The electric vehicle users in the microgrid reported parameters such as the access times and battery information of the electric vehicles to the microgrid dispatch center a few days prior. Based on the information reported by the users, forecast results are generated for the new energy outputs and electricity loads in the microgrid as well as the purchase and sale prices of its superior power grid. Then, the charging and discharging prices are released to the electric vehicle users to obtain responses. Next, based on the user responses, the electricity price and amounts of electricity purchased and sold by the superior power grid are adjusted. To improve the consumption rate of new energy generation and the economy of electricity consumption, unified dispatch of the electrical energy in the microgrid is completed. Figure 2 shows a schematic of the microgrid dispatch structure when electric vehicles are connected.

Optimal dispatch model of the microgrid based on the Stackelberg game

Under the framework of the master–slave game theory, the microgrid as the leader has the initiative in the game, with priority being assigned to the electric vehicle users to release the electricity pricing scheme. As the followers, the electric vehicle users respond to the microgrid dispatch by comprehensively considering their own SOC and the economic benefits derived from electrical energy exchange with the microgrid; these responses are returned to the charging and discharging power scheme. The electricity pricing scheme of the microgrid is then adjusted according to the user return strategy. Finally, the Nash equilibrium scheme of the Stackelberg game is obtained.

By issuing an appropriate electricity pricing scheme, the electric vehicle users can be guided to provide certain charge and discharge powers within an appropriate time period. This can improve the consumption rate of new energy output in the microgrid while reducing the cost of electricity. The electricity cost objective function of the microgrid is as follows:

$$C_{mg} = \sum_{t=1}^{T} \left[\left(P_{L,t} - P_{P,t} - P_{W,t} + P_{EV,t} \right) \cdot c_{g,t} - P_{EV,t} \cdot c_{m,t} \right] \tag{10}$$

where C_{mg} is the electricity cost of the microgrid in an optimal dispatch cycle; $P_{L,t}$, $P_{P,t}$, $P_{W,t}$, and $P_{EV,t}$ are the microgrid load power, photovoltaic power, wind power, and electric vehicle charging and discharging powers in period t, respectively; $c_{g,t}$ is the time-of-use electricity price of the superior power grid in period t; and $c_{m,t}$ is the transaction price between the microgrid and electric vehicle users in period t.

a) Power balance constraint

This constraint ensures that the electric vehicles absorb the wind and light outputs from the microgrid maximally and allow full utilization of the energy storage characteristics of batteries. The microgrid structure proposed in this study does not contain any energy storage equipment, and any electricity shortage or excess electricity in the microgrid is traded directly with the superior grid.

$$\Pr\left\{ \left| P_{G,t} - P_{L,t} - P_{EV,t} + P_{P,t} + P_{W,t} \right| \le \sigma \right\} \ge \alpha \tag{11}$$

where α is the confidence level of the power balance constraint, and σ is a relaxation variable that is a small positive number. Considering that the conventional power balance is an equality constraint, this variable is introduced for facilitating a solution to the model and representing probability.

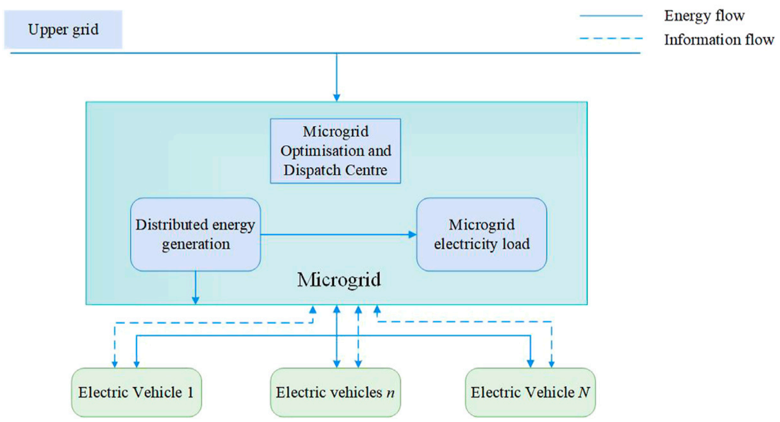

FIGURE 2
Optimal dispatch structure of the microgrid.

b) Electric vehicle trading price constraint

$$C_{\mathrm{m,\,min}} \le C_{\mathrm{m},t} \le C_{\mathrm{m,\,max}} \tag{12}$$

where $c_{\mathrm{m,\,max}}$ and $c_{\mathrm{m,\,min}}$ are the upper and lower limits of the microgrid price scheme, respectively.

c) Interactive power constraint of the microgrid

$$P_{\mathrm{G,\,min}} \le P_{\mathrm{G},t} \le P_{\mathrm{G,\,max}} \tag{13}$$

where $P_{\mathrm{G,\,max}}$ and $P_{\mathrm{G,\,min}}$ are the upper and lower limits of the interactive power between the microgrid and its superior grid.

d) Constraints of electric vehicle users

$$SOC_{\min} \le SOC_n(t) \le SOC_{\max} \quad t = 1, 2, 3 \cdots T \tag{14}$$

where $SOC_{\min}$ and $SOC_{\max}$ are the lower and upper limits of the battery SOC, respectively.

$$\mathrm{SOC}_n(T) \ge SOC_{n,\mathrm{E}} \tag{15}$$

where $SOC_{n,\mathrm{E}}$ is the expected SOC level of the nth user after scheduling.

$$P_{\mathrm{ev,dc,max}} \le SOC_n(t) - SOC_n(t-1) \le P_{\mathrm{ev,c,\,max}} \tag{16}$$

where $P_{\mathrm{ev,dc,max}}$ and $P_{\mathrm{ev,c,max}}$ are the charging and discharging power ranges of electric vehicles.

As the followers in the Stackelberg game, electric vehicle users need to respond to the microgrid scheduling with the goal of maximizing their own benefits once the electricity pricing plan is issued. Under the principles of game theory, electric vehicle users should be rational and self-interested. When considering only the economic benefits, electric vehicle users will choose to discharge during high price periods and charge during low price periods as much as possible. This strategy may produce a new peak in the load curve of the microgrid or further improve the peak–valley difference. This phenomenon is particularly obvious when fast charging is adopted. Considering that changes in the SOC are of great significance to the convenience of electric vehicles and battery losses, the SOC may be regarded as an important benefit that the electric vehicle users must consider when formulating charging and discharging strategies. The benefit function of the electric vehicle users, that is, the objective function, is as shown in (17):

$$\begin{aligned} U_n &= \sum_{t=1}^{T} k_{n,t} \cdot \mathrm{SOC}_n(t)^{0.5} + \quad c_{\mathrm{m},t} \cdot (\mathrm{SOC}_n(t-1) - SOC_n(t)) \\ k_n &> 0 \end{aligned} \tag{17}$$

where k_n is the SOC preference coefficient for the nth electric vehicle user, and $SOC_n(t)$ is the SOC level of the nth electric vehicle user in time period t. The utility value is given by $k_n SOC_n(t)^{0.5}$ to the SOCs of the electric vehicles, and the economic benefits are given by $c_{\mathrm{m},t}(SOC_n(t-1) - SOC_n(t))$ for electric vehicle users trading with a microgrid.

In the optimal scheduling model, a nondecreasing convex function is generally chosen as the benefit function of the users' experiences. In addition to considering the economic benefits afforded by the users' electrical energy exchange, (17) increases the benefits derived from the SOC. This can mitigate the benefits obtained by frequent as well as deep charging and discharging of the batteries due to fluctuations in the electricity pricing.

Proof of existence of master–slave equilibrium solution in game

To optimize the dispatch of the microgrid with electric vehicles, a Stackelberg game model is established in this work, with the microgrid as the leader and electric vehicle users as the followers. The strategy set of the Stackelberg game model can be expressed by (18); when the leader and followers of the Stackelberg game choose strategies as given in (19, 20), the game can attain the Nash equilibrium solution.

$$\Gamma = \{(N \cup \{MG\}), \{S_n\}_n \in N, \{U_n\}_{n\in N}, p_m, C\} \tag{18}$$

$$C_{mg}(S^*, c_m^*) \le C_{mg}(S^*, c_m) \tag{19}$$

$$\begin{gathered} U_n(S^*, c_m^*) \ge U_n(S_n, S_{-n}^*, c_m^*) \\ \forall n \in N, \forall S_n \in S \end{gathered} \tag{20}$$

where N is the number of electric vehicles that the microgrid can dispatch, S_n is the charging and discharging strategy selected by the nth electric vehicle user, and S_{-n} is the Nash equilibrium strategy set except for the strategy of the nth user. The electricity price is c_m^* at the Nash equilibrium solution.

In the noncooperative Stackelberg game, a unique Nash equilibrium solution is obtained only when the utility functions of the leader and follower are convex and concave functions, respectively. The following proves that the utility function of the electric vehicle users is a concave function. The utility function of the electric vehicle users is differentiated with respect to SOC as the variable. When the transaction price is c_m, the surplus electricity that allows the electric vehicle users to obtain the highest benefit is as follows:

$$SOC = \left(\frac{k_n}{2 \cdot c_m}\right)^2 \tag{21}$$

When $k_n \leqslant 2c_m$, the optimal solution of the SOC is in the range of [0,1]. The second derivative of U_n then gives

$$\frac{d^2U_n}{d^2SOC} = -0.25 \cdot k_n \cdot SOC^{-0.15} \quad k_n \ge 0 \tag{22}$$

The utility function of the electric vehicle users in (22), i.e., the second derivative of U_n, is always less than 0 under the condition that k_n is not less than 0. Thus, it can be proved that (10) is always a concave function in the range of [0,1] when conditions $k_n \leqslant 2c_m$ and $k_n \ge 0$ are satisfied.

The process of proving that the utility function of the microgrid is convex is as follows. Combining (13) and (21) and taking the second derivative of (10) with respect to the variable c_m, we have

$$\frac{d^2C_{mg}}{d^2C_m} = -\frac{k^2}{C_m^{-3}} + \frac{3}{2} \cdot \frac{c_g \cdot k^2}{C_m^{-4}} \tag{23}$$

When c_m and c_g are both greater than 0, the second derivative of C_{mg} in (23) is always greater than 0, which proves that (13) is always a concave function. These prove that there is a unique Nash equilibrium solution between the utility function of the microgrid and electric vehicle users given the condition that parameters $k_n \leqslant 2c_m$, $k_n \ge 0$ in the utility function and $c_g > 0$ are established simultaneously.

TABLE 1 Piecewise linear fitting results.

Segmented interval	Results of linear fitting
0.1–0.2	$y = 1.295x + 0.1952$
0.2–0.4	$y = 0.8976x + 0.3024$
0.4–0.6	$y = 0.6928x + 0.2749$
0.6–1	$y = 0.6042x + 0.3987$

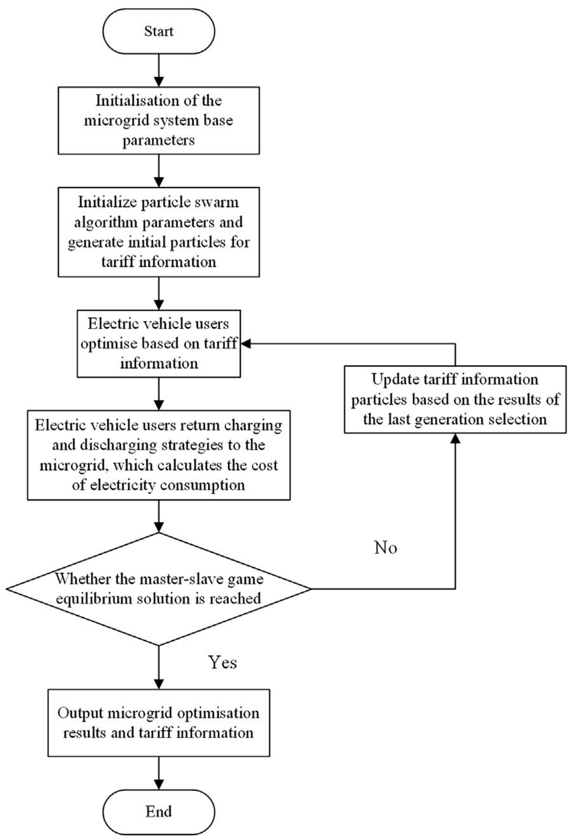

FIGURE 3
Model solving process.

Considering the characteristics of the Stackelberg game model, the bilevel optimization method is chosen in this study to solve the model. The upper model considers the transaction price of the microgrid and electric vehicle users as the variables. The charging and discharging power scheme of the electric vehicle returned by the lower model is a known quantity to optimize the electricity cost of the microgrid. The utility model of the lower electric vehicle users considers the transaction price as a known quantity and its own SOC as a variable for maximizing benefits. To solve the bilevel optimization model, the upper model uses particle swarm optimization. Because the utility

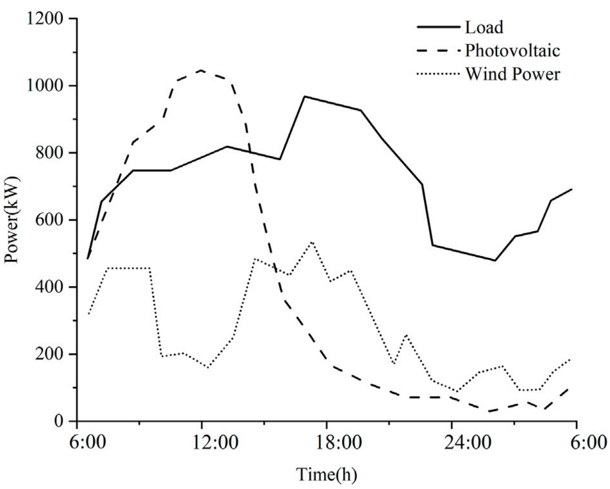

FIGURE 4
Load, wind power output, and light output curves of the microgrid.

TABLE 2 Time-of-use electricity price of superior power grid.

Period of time	Peak/valley type	Electricity rate
1: 00 to 8: 00	Valley	0.5 yuan/kW·h
18: 00 to 23: 00	Peak	1 yuan/kW·h
8: 00 to 18: 00 and 23: 00 to 24: 00	Plane	0.69 yuan/kW·h

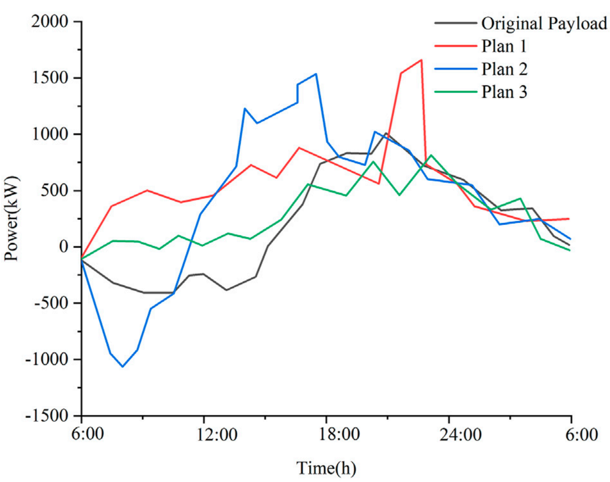

FIGURE 5
Comparison of the load curves of the three optimal dispatch plans.

function in the lower model has a nonlinear term $SOC(t)^{0.5}$, it cannot be solved directly. To linearize the model, in this work, the nonlinear parts are fitted by the piecewise linear method, which results in a mixed integer model that can be solved directly using the solver. The nonlinear part of the lower model is fitted in its domain [0.1,1], and the processing results are shown in Table 1. The specific process of the model solution is shown in Figure 3.

Results and discussion

The power variation curves of the load, photovoltaic output, and wind power output of the microgrid in this study are shown in Figure 4. Table 2 shows the electricity price information for each time period of the superior power grid. To encourage the microgrid to absorb its own renewable energy output as much as possible, the transaction price of the electricity purchased from the microgrid by the superior grid is set to 0.6 times the price value. To prevent electric vehicle users from consuming too much electricity, the upper limit of the transaction prices of the electric vehicles and microgrid in each period is set to the price of the superior grid corresponding to that period, and the lower limit is 0.5 times that of the superior grid for the corresponding period. The dispatch period of the microgrid is from 8:00 to 23:00. The number of electric vehicles that can be dispatched is 200, the SOC preference coefficient k is set to 0.9, and the SOC is set to 0.6, with the average battery capacity of the electric vehicles being 40 kW h. The initial SOC obeys a uniform distribution in the range of 0.2–0.4, and the maximum, minimum, and expected SOCs are set to 1, 0.1, and 0.6, respectively. The limit of the charging and discharging power is 20 kW. The confidence level of the power balance constraint is set to 0.95, and the prediction errors of the photovoltaic and wind power outputs are normally distributed with a mean of 0 and a variance of 0.05. The load forecasting error is also normally distributed with a mean of 0 and a variance of 0.1.

To verify the feasibility and effectiveness of the proposed model, the simulation results of three models are compared in this work. Plan 1: Aiming at the lowest electricity cost of the microgrid, electric vehicle users accept the centralized and unified optimal dispatch scheme. Plan 2: Based on the Stackelberg game model, with electricity consumption and minimal cost as the objective functions for the microgrid and electric vehicle users, bilevel optimal scheduling is performed. Plan 3: The Stackelberg game optimal scheduling model that considers the SOC approach proposed here is adopted. Figure 5 shows the optimization simulation results of these three models.

By analyzing the load curves of the three optimal scheduling plans in Figure 5, we observe the following. In plan 1, the wind and light outputs of the microgrid are obviously absorbed; however, new peak and valley periods appear in the load curve owing to the influence of the time-of-use electricity pricing of the superior power grid and the expected SOC

TABLE 3 Comparison of scheduling results optimized by different methods.

	Electricity cost of the microgrid (yuan)	Charging and discharging costs of electric vehicle users (yuan)	Peak–valley difference of microgrid load curve (kW·h)
Plan 1	1780.4	1429.7	1542
Plan 2	2986.1	896.5	2569
Plan 3	1394.5	1136.2	765

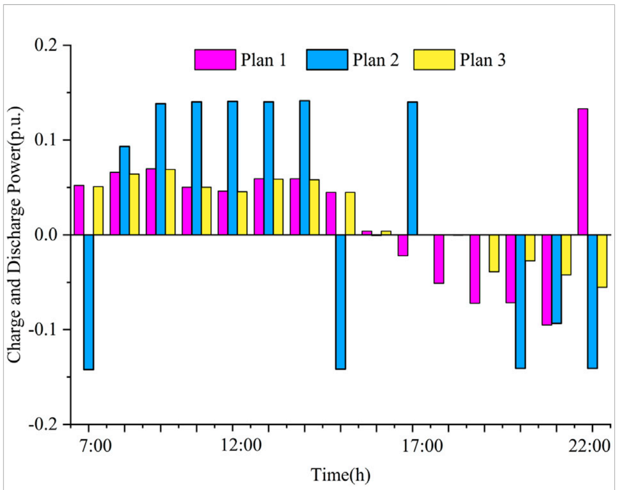

FIGURE 6
Changes in the charging and discharging curves of the three plans.

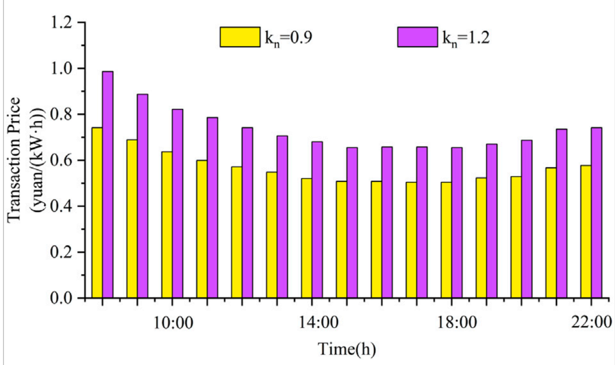

FIGURE 7
Influence of k_n change on transaction price.

constraint on the electric vehicles; further, the load curve characteristics are not improved. In plan 2, a new peak–valley period of the load is generated, in addition to an increase in the peak–valley difference of the load curve; this is because both the master and slave of the game only pursue their own economic interests, and the game does not allow win-win results for either party. In plan 3, the charging and discharging power of the electric vehicles can be changed smoothly because the charging states of the electric vehicles benefit the users; there is no new peak–valley period or peak–valley difference in the load curve, and the load curve of the microgrid is improved obviously.

By analyzing the information in Table 3, it is observed that the electric vehicle users in plan 2 have the lowest electricity cost. However, the electricity cost of the microgrid increases, indicating the self-interests of the users in the game. In plan 3, although the user's electricity cost is higher than that in plan 2, the interests of both the master and slave of the game are taken into account better; simultaneously, there is no deep charge and discharge, which enables a good balance of the optimal scheduling scheme. The charging and discharging power curves of the electric vehicles for the three plans are analyzed in Figure 6. Plan 3 not only improves the load curve characteristics of the microgrid but also effectively avoids frequent and deep charging and discharging of the electric vehicle batteries compared to the other two plans; this can prolong the service life of the battery and slow its losses. At the same time, it can be better applied to the users' daily-use scenarios, can better meet users' convenience needs, and can cope with uncertainties in the users' travel situations.

The user's *SOC* preference coefficient is set to k_n in this work. By analyzing the simulation results in Figures 7, 8, when the users

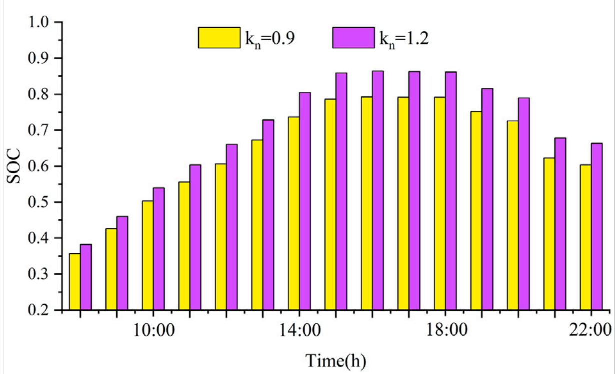

FIGURE 8
Influence of k_n change on SOC.

choose higher preference coefficients, the electric vehicles provide less charging and discharging powers for participation in the scheduling. At the same time, the microgrid needs to set a higher transaction price to mobilize the users to participate in dispatching. As the expected SOC also increases with an increase in the coefficient value, the overall schedulable capacity of users participating in scheduling also increases. Therefore, when $k_n = 1.2$, the electricity cost of the microgrid decreases. Considering the usage characteristics of different users and the development of related communication and control technologies, the microgrid dispatching center can work out point-to-point dispatch transaction agreements with each of its users to meet the needs of disconnected users.

Conclusion

In the present research, microgrid and electric vehicle users are considered as two different stakeholders. To cope with the fact that electric vehicle users only respond to microgrid control through the electricity prices, there will be new peak–valley differences in the load curves. Based on the idea of the Stackelberg game, an optimal dispatch model of the microgrid with electric vehicles is proposed by considering the SOC. From comparisons of the different optimal scheduling schemes, the following conclusions are obtained.

a) The established model guides electric vehicle users to charge and discharge based on electricity prices instead of the objective function, where the users only consider charge and discharge costs. After optimization, the proposed objective function considering the SOC not only reduces the peak–valley difference of the microgrid load curve as well as the electricity costs of the master and slave effectively but also prevents new peak values or increase in the peak–valley difference owing to the influence of the electricity price.
b) By analyzing the electrical energy interaction mode between the microgrid and electric vehicle users, it is shown that both parties interact in the form of a noncooperative Stackelberg game. The existence of the Nash equilibrium solution of the proposed master–slave game strategy is proved mathematically. When solving the model, bilevel programming is adopted, and the nonlinear terms of the model are linearized by piecewise fitting.
c) For electric vehicle users, frequent and deep discharging of the vehicle batteries can be avoided, which can reduce battery losses from dispatching. At the same time, because the battery SOC is maintained at a high level, the uncertain travel needs of users can be met. The proposed method thus ensures the greatest extent of autonomy of electric vehicle users for participation in microgrid dispatching.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material, and further inquiries can be directed to the corresponding author.

Author contributions

WB: Conceptualization, methodology, and writing—original draft preparation. WZ: Validation. RD: Investigation. DW: Writing—review ang editing. YZ: Supervision. QL: Software, formal analysis, and data curation. ZZ: Visualization.

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Conflict of interest

Author RD was employed by the State Grid Chaoyang Power Supply Company.

The remaining authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Publisher’s note

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