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Cooperative Game Cooperative Control Strategy for Electric Vehicles Based on Tariff Leverage

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Abstract: To address the negative impact of large-scale disorderly grid connection of EVs on the stable operation of the power grid, a cooperative game cooperative control strategy for EVs based on tariff leverage is proposed, taking the grid-side and user-side economy as the objective function, taking into account the EV load state constraint, distribution grid power constraint, bi-directional charging and discharging pile power constraint, dynamic tariff constraint, and cooperative game members' revenue constraint. A dynamic cooperative game model based on bi-directional charging and discharging piles is established, and the weight of users in the game is increased. Based on the cooperative game model, an optimal real-time tariff is determined for both the electric power operators and the charging and discharging pile users and based on the real-time updated dynamic tariff and the EV power connected to the charging and discharging pile at the current moment, a genetic algorithm is used to solve the simulation based on the Receding Horizon Control principle. The simulation results show that this control strategy has a smoother load curve and better peak and valley reduction than the fixed tariff and the time-of-use tariff, and it reduces the operating cost of the electric power operators. In addition, it brings the best economic benefits to the users, with the overall revenue of the charging and discharging piles increasing by up to 6.3% under the dynamic tariff.

Keywords: bi-directional charging and discharging piles; cooperative control; cooperative game; tariff leverage; dynamic tariff; peak shaving and valley filling

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1. Introduction

With the large-scale operation of EVs, the more EVs connected to the grid, the greater the impact on system load fluctuations, and the negative impact on the stable operation of the grid is exacerbated by the disorderly grid connection of large-scale EVs [1]. Therefore, it is necessary to study the participation of EVs in grid regulation as distributed energy storage units in an orderly manner [2]. The energy transition is diversified by developing energy demand-side management plans to improve the efficiency of energy use [3].

V2G technology is a technology that uses multiple EVs with their own energy storage batteries as buffers to deliver electrical energy to the grid [4]. EV users can purchase or sell electricity from the grid according to the grid tariff at each time period using the difference to gain revenue. With V2G technology, grid efficiency can be improved, the instability and volatility of renewable energy can be mitigated, and some revenue can be generated for the user [5].

Centrally managed V2G integrates the regulable EVs in a certain area, and the grid centrally dispatches the EVs in the area and controls their charging and discharging behavior according to the actual situation of the day's load [6]. However, in real life, EVs are parked in scattered locations and cannot be centrally managed and controlled, so distributed charging piles are generally used for charging, tariff information is released according to the current power demand or current voltage fluctuation of the grid, and V2G is automatically implemented in combination with the battery charge state of EVs [7]. Karfopoulos et al. proposed an adaptive pendant flow-based regulation and scheduling algorithm to achieve distributed coordination of EVs [8], which was subsequently improved by Zhang et al., who proposed an innovative and effective framework to provide vehicle-to-grid regulation services [9]. Each EV in this model is an individual, and the location is more dispersed and unable to be managed in a unified manner, so the randomness of charging and discharging each EV is high, making prediction difficult and unable to fully take into account the individual needs of the vehicle owner.

In the tariff-guided EV scheduling strategy, when a large number of EVs are connected to the grid and participate in scheduling, the tariff strategy can be used as a control signal to guide vehicle owners to charge and discharge in an orderly manner when the tariff is low, and the user performs charging behavior when the tariff is high and changes to a discharging state, so as to improve the grid load curve, achieve peak and valley reduction, and reduce charging costs and grid-side generation costs [10,11].

Cui et al. investigated the offset of the grid load curve by adjusting the tariff strategy for the electricity consumption habits of customers under different tariff strategies [12]. Zhang et al. proposed a real-time updated dynamic with a time-sharing tariff issued by the grid, and the tariff was readjusted by the owner's independent response to finalize the charging and discharging schedule [13]. Chen et al. considered the transformer capacity at each moment and developed a dynamic tariff based on the current moment electricity, upper and lower limits of power supply, and tariff range restrictions [14]. Based on fuzzy Bayesian learning theory, Zhang et al. proposed a bilateral negotiation model with the participation of electric power operators and EV agents [15]. Melendez et al. developed a cooperative rule to reduce the cost of electricity and proposed a trade-off strategy to balance the contradiction between cost and fairness [16]. Fei et al. developed a real-time tariff for microgrids based on the law between the expected charging duration and the actual parking duration of EVs considering the personalized charging demand of users, but the strategy only discusses the charging behavior and does not consider the role of discharging energy feedbacks [17]. Lai et al. proposed a dynamic pricing strategy with competitive effects to attract more charging demand to avoid possible electricity congestion in the grid. However, the strategy ignores the randomness of EVs and cannot guarantee overall optimality [18]. In addition, San et al. pointed out that users under time-sharing tariffs concentrate on charging at low tariffs, while the system cannot respond to the increase in load at this time in real time and continues to maintain low tariffs to wake up users for charging, thus triggering a clustering effect and forming a new load spike [19].

In summary, existing studies mainly focus on centralized charging stations and consider the regulation of charging behavior and less simultaneously consider the impact of charging and discharging plans on EV grid connections. The expenses generated by EV users purchasing electricity are the main revenue of charging stations, while the main revenue path for EV owners is discharging to the grid through idle periods. At the same time, EV charging and discharging behavior will affect the load curve of the grid, and even form new load spikes. Therefore, new regulation strategies need to be developed based on real-time changes in distribution network load. It is necessary to study the impact of dynamic system charging/discharging behavior on the load fluctuation of the grid and the revenue of the supply and demand sides.

In this paper, when setting the pricing strategy, we set the parameter weights between grid companies and users as equal values. Based on the cooperative game model to determine the real-time tariff with optimal revenue for both electric power operators and charging and discharging pile users, we use the tariff lever to guide the charging and discharging behavior of users in real time. The control strategy of this cooperative game does not consider the differences and special characteristics of each member's market position and raises the status of users to be equal to that of the grid, which improves the enthusiasm of users to participate in the regulation system. A distributed energy storage cooperative scheduling optimization method based on bidirectional charging and discharging piles is proposed to study the effects of different pricing strategies on users' charging and discharging behaviors. For users, purchasing or selling electricity according to a dynamic tariff can obtain the best return. For the electric power operators, the real-time change for tariffs of this control strategy avoids the clustering effect and can more effectively cut the peak and fill the valley, smooth the load curve, and reduce the operating costs.

2. Mathematical Model of Distributed Energy Storage Cooperative Game under Tariff Leverage

To construct a mathematical model of a distributed energy storage cooperative scheduling charging and discharging optimization system under tariff leverage with dynamic tariff as the incentive, the following factors need to be considered: the variability of EVs connected to the distribution network as fluctuating loads, the stability of the distribution network operation, the economy of bi-directional charging and discharging pile operation (i.e., the revenue on the user side), and the cooperative relationship between the EVs connected to the grid and the distribution network participating in regulation.

2.1. Objective Function of Optimal Scheduling Model under Cooperative Game

If the participants seek to maximize only their own interests, the best interests of the whole game may be affected, so it is necessary to establish cooperation among the participants to form a collective to maximize the needs of the collective interests and thus maximize individual interests. Under the cooperative game principle, collaboration among each other generates additional benefits, so the total collective benefit is not simply the sum of individual benefits, and individual members involved in the cooperative game can all improve their own benefits.

Combined with the influence of tariff leverage on users' participation in grid connections, the user side aims to maximize the revenue of bi-directional charging and discharging piles, and the grid side aims to optimize the cost of power generation.

(1) Bi-directional charging and discharging pile user revenue model

The cost of electricity for bi-directional charging and discharging pile users can be divided into three parts: the cost of purchasing electricity, the revenue of selling electricity to the grid, and the loss of power battery by frequently changing charging and discharging states. The electricity consumption cost function is defined as:

$$C_{\mathrm{u}} = \left(\alpha P_{\mathrm{dis}}(t) C_1(t) + \beta P_{\mathrm{cha}}(t) C_2(t) + C_{\mathrm{bat}}(t)\right)\Delta t \tag{1}$$

where α is the discharge coefficient, P_{dis} is the discharge power, β is the charging coefficient, P_{cha} is the charging power, and C_{bat} is the loss cost of power battery.

The EVs in this model are connected to the distribution grid through the bi-directional charging and discharging piles, and the idle state EVs are not considered, and the EVs are only divided into two vehicle fleet states: charging state and discharging state. When $C_{\mathrm{u}} > 0$, the user side pays for the purchase of electric energy from the grid, and when $C_{\mathrm{u}} < 0$, the user side sells electric energy to the grid to gain revenue.

The revenue model for users is defined as follows:

$$f_1 = -\sum_{t=1}^{T} C_{\mathrm{u}} = -\sum_{t=1}^{T} \left(\alpha P_{\mathrm{dis}}(t) C_1(t) + \beta P_{\mathrm{cha}}(t) C_2(t) + C_{\mathrm{bat}}(t)\right)\Delta t \tag{2}$$

To satisfy the maximization of user-side benefits, the bi-directional charging and discharging pile user benefit optimization problem can be described as follows:

$$\begin{cases} \max f_1 = -\sum_{t=1}^{T} (\alpha P_{\text{dis}}(t) C_1(t) + \beta P_{\text{cha}}(t) C_2(t) + C_{\text{bat}}(t) \Delta t \\ \alpha + \beta = 1 \\ -P_{\text{EV.max}} \le P_{\text{dis}}(t) < 0 \\ 0 < P_{\text{cha}}(t) \le P_{\text{EV.max}} \end{cases} \tag{3}$$

(2) Revenue model of the grid company

The revenue function of the grid company includes the revenue and spend generated from the power interaction between the grid company and the charging and discharging pile system, the revenue from the base load's power purchase from the grid, and the cost of renewable energy generation, expressed as:

$$C_{\text{g}} = (\alpha P_{\text{dis}}(t) C_1(t) + \beta P_{\text{cha}}(t) C_2(t) + P_{\text{Load}} C_3(t) - C_{\text{re}}) \Delta t \tag{4}$$

$$C_{\text{re}} = C_{\text{WT}} P_{\text{WT}}(t) + C_{\text{PV}} P_{\text{PV}}(t) \tag{5}$$

where P_{Load} is the daily base load of the grid, C_1 is the real-time dynamic tariff published by the grid, C_2 is the price of electricity sold by the EV owners to the grid, C_3 is the traditional price of electricity for the base load, C_{re} is the cost of renewable energy generation, and C_{WT} and C_{PV} are the cost of wind power and photovoltaic power, respectively. When $f_2 > 0$, the grid company sells electricity at a profit, and when $f_2 < 0$, the grid company loses money.

The grid company revenue model is defined as:

$$f_2 = \sum_{t=1}^{T} C_{\text{g}} = \sum_{t=1}^{T} (\alpha P_{\text{dis}}(t) C_1(t) + \beta P_{\text{cha}}(t) C_2(t) + P_{\text{Load}} C_3(t) - C_{\text{re}}) \Delta t \tag{6}$$

To satisfy the grid-side revenue maximization, the grid-side revenue optimization problem can be described as:

$$\begin{cases} \max f_2 = \sum_{t=1}^{T} (\alpha P_{\text{dis}}(t) C_1(t) + \beta P_{\text{cha}}(t) C_2(t) + P_{\text{Load}} C_3(t) - C_{\text{re}}) \Delta t \\ C_{1.\text{min}} \le C_1(t) \le C_{1.\text{max}} \\ C_{2.\text{min}} \le C_2(t) \le C_{2.\text{max}} \end{cases} \tag{7}$$

where $C_{1.\text{max}}, C_{1.\text{min}}, C_{2.\text{max}}, C_{2.\text{min}}$ are the upper and lower limits of the charging and discharging tariffs, respectively.

Therefore, the objective function is the collective total revenue after the cooperative game, including EV users and electricity marketers. By analyzing various factors such as the status and voice of the participating members, their pursued goals and preferences, market demand and national policies, we consider how to achieve a relatively fair distribution of benefits among the members and improve the DP parameter indicator according to the differences of different members to ensure that each participant in the collective can obtain reasonable benefits and continue to participate in the cooperation. Gately proposed an indicator parameter, DP (Disruption Propensity), used to describe the reasonable distribution of the overall gains of the cooperative game among individual participants [20]. Later, some scholars [21] proposed an improved DP indicator, MDP, which represents the ratio of the average losses of other participants when participants i do not participate in the cooperative game to the losses of participants i:

$$D(i) = \frac{1}{\text{n} - 1} \frac{\sum_{j \in \{N \setminus \text{i}\}} x(j) - v(N \setminus \text{i})}{x(i) - v(i)} \tag{8}$$

Set N contains all the participants of the cooperative game; set N/i denotes the entire set excluding the participants i; $x(i) - v(i)$ denotes the loss of participant i not participating in the cooperative game.

In the traditional pricing strategy, the grid company, as the industry giant, dominates the market and is the main leader among the participants, with a significant weight, while the users of bi-directional charging and discharging piles are subordinate and have a small weight. In order to improve the enthusiasm of users to participate in the regulation system, this paper sets the pricing strategy without considering the differences and special characteristics of each member's market position, sets the parameter weights between the grid company and users to equal values, and raises the users' status to equal with the grid. This improves the weight of users in the game and ensures the interests of users, thus increasing their willingness to connect to the grid.

The equivalence index parameter indicates the equal status of each participant in the cooperative game and the fair distribution of benefits, which ensures a stable cooperative relationship. From Equation (8), $D(i)$ intuitively reflects the benefits of the participants under the cooperative game, and the benefits of the electric power operator and bi-directional charging and discharging pile users are allocated according to the equivalence index, which leads to the allocation Equation (10), which is simplified to obtain Equation (11).

$$D(f_1) = D(f_2) \tag{9}$$

$$x(f_1) - v(f_1) = x(f_2) - v(f_2) \tag{10}$$

$$x(f_1) + x(f_2) = C \tag{11}$$

2.2. Constraint Conditions

(1) Set the charge state constraint from the user's perspective

As an important means of transportation for people to travel, private EVs have high requirements for range, so the constraints of distributed energy storage systems for the charge state of EVs need to give priority to the requirements of users.

For comprehensive power batteries' own safety and user experience of both aspects, the threshold value of the setting needs to be combined with the range of both to take the intersection. The regulation system needs to consider the convenience of the owner's travel. Before the EV is connected to the grid, the owner sets the upper and lower limits, $SOC_{i.\max}$ and $SOC_{i.\min}$, of the EV charge state SOC in the charging and discharging pile regulation system according to the travel plan, satisfying:

$$SOC_{i.\min} \leq SOC_{\mathrm{EV}}(t) \leq SOC_{i.\max} \tag{12}$$

Bi-directional charging and discharging pile control systems should fully consider the common constraints of user requirements and EV battery life and meet the personalized settings of users as much as possible under the premise of ensuring the safety and health of the power battery. Therefore, the expected charge and discharge thresholds set by users have certain limits, as shown in Figure 1. In order to ensure the good cycle life of an EV power battery, the expected threshold set by the user cannot exceed the upper and lower limits, $SOC_{i.\min}$ and $SOC_{i.\max}$, of the EV power battery for a long time.

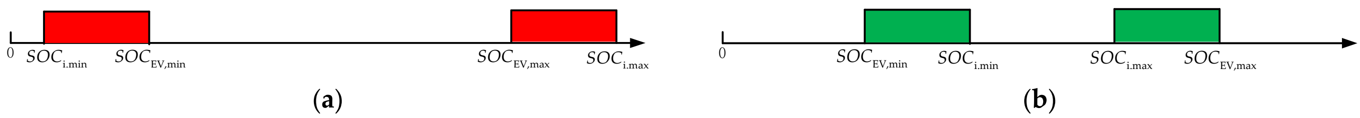

Figure 1. Daily load curve of disorderly charging. (**a**) Unreasonable threshold setting; (**b**) Reasonable threshold setting.

SOC_{down} and SOC_{up} are the final charge state constraint values after regulation by the bi-directional charging and discharging pile system (Figure 2). The upper limit takes the maximum value of the user's expected charge state and the safe operation power of the power battery, and the lower limit takes the minimum value of both, that is, Equations (13) and (14). However, the expected charge state value set by the user cannot exceed the safety limit of the power battery for a long time.

$$SOC_{\text{down}} = \min(SOC_{\text{EV,min}}, SOC_{i.\text{min}}) \tag{13}$$

$$SOC_{\text{up}} = \max(SOC_{\text{EV,max}}, SOC_{i.\text{max}}) \tag{14}$$

$$SOC_{\text{down}} \leq SOC_{\text{EV}}(t) \leq SOC_{\text{up}} \tag{15}$$

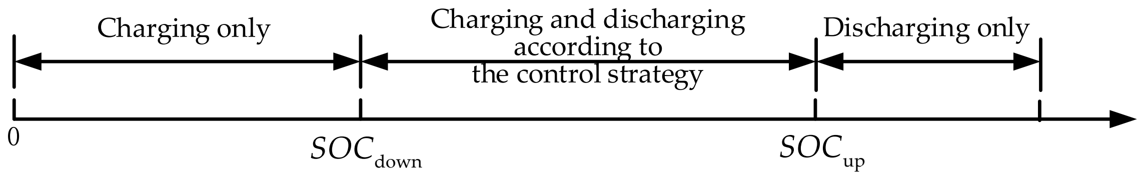

Figure 2. Relationship between SOC and charge/discharge status.

In order to meet the requirements of the user's travel plan range, the charge state of the private EV when it exits the system after charging shall meet:

$$SOC_{\text{end}} > SOC_0 + \frac{LE_{\text{d}}}{E} \tag{16}$$

where L is the number of miles traveled by the EV owner on the day of the planned trip, and E_d / E is the ratio of the electric energy consumed per kilometer to the total power battery capacity.

Taking one hour as the period of dynamic tariff update, the charge state of each EV participating in the dispatch in the next time period cycle satisfies:

$$SOC(t+1) = SOC(t) + \frac{(P_{\text{cha}} + P_{\text{dis}})\Delta t}{E} \tag{17}$$

(2) Power constraint for members of cooperative game

In order to ensure that the cooperative game model can produce correct results through simulation, it is necessary to impose capacity constraints on the members participating in the cooperative game in advance. In this way, it is possible to avoid the power of a member exceeding the limit, which will break the balance and affect the benefit distribution among other members. The maximum load P1 that the distribution network can bear should satisfy the sum of the base load P2 of the distribution network and the charging and discharging power P3 of the bidirectional charging and discharging pile, i.e.,

$$P_{\mathrm{dis}}^{t} \geq P_{\mathrm{Load}}^{t} + P_{\mathrm{EV}}^{t} \tag{18}$$

where the power interacting with the distribution network via the bi-directional charging and discharging pile should meet the safety threshold of the bi-directional charging and discharging pile, i.e.,

$$-P_{\mathrm{EV}}^{\max} \leq P_{\mathrm{EV}}^{t} \leq P_{\mathrm{EV}}^{\max} \tag{19}$$

(3) Bi-directional charging and discharging pile charging and discharging state constraints

As a distributed energy storage unit, the EV has both charging and discharging functions, which can be used as a load to obtain power from the grid for charging and as a power source to discharge to the grid during peak load periods.

$$P_{\mathrm{EV}}(t) = \alpha P_{\mathrm{dis}}(t) - \beta P_{\mathrm{cha}}(t) \tag{20}$$

where α, β are the working state parameters of EVs. $\alpha = 1$ represents the group of vehicles discharging as a distributed energy storage system at this time and providing power P_{dis} to the load; $\alpha = 0$ represents the group of vehicles connected to charging and discharging piles without connecting to the grid for discharging; $\beta = 1$ represents the group of vehicles connecting to the grid for charging as a load and absorbing power P_{cha} from the grid; $\beta = 0$ represents no charging. At any moment, the energy storage system works in only three ways: charging, discharging, and idle.

The bi-directional charging and discharging piles can only perform a single operation of charging or discharging at the same moment, i.e., the charging and discharging states are mutually exclusive in a dynamic tariff update cycle, thus satisfying the operating state constraint that:

$$P_{\mathrm{cha}} \cdot P_{\mathrm{dis}} = 0 \tag{21}$$

(4) Dynamic tariff upper and lower limit constraints

In the cooperative game model, based on the optimization of the objective function for different purposes, the members involved in the game can set different weight parameters between them. Under different parameter settings, the cooperative game model generates different real-time updated tariff laws, but all must follow the price laws of the electricity market and set constraints on the fluctuation range of tariffs. Considering the cost of the grid and the consumption capacity of the user side, the dynamic tariff adjustment needs to satisfy the set upper and lower limits of:

$$C_{\mathrm{d.min}} \leq C_{\mathrm{d}}(t) \leq C_{\mathrm{d.max}} \tag{22}$$

(5) Alliance benefit constraint

Based on the characteristics of the cooperative game model, coalition members will have additional benefits generated by cooperation with each other after cooperation, so the benefits of the coalition as a whole should be greater than the sum of their respective benefits when they are separated:

$$C_{\mathrm{N}}^{\mathrm{sum}} > \sum_{i \in N}^{n} C_i \tag{23}$$

3. Implementation of a Dynamic Cooperative Game Model Based on Bi-Directional Charging and Discharging Piles

3.1. Bi-Directional Charging and Discharging Pile Operation Model

A V2G charging pile usually consists of two parts: an AC-DC circuit and a DC-DC circuit, and the bidirectional flow of active and reactive power can be realized by controlling the amplitude and phase of the AC-side voltage in the AC-DC circuit [22]. A bi-directional charging and discharging pile is set up in each garage so that it can be used exclusively for vehicles, which is more conducive to collecting user information, making accurate load prediction, and facilitating grid regulation. EVs are connected to the new bi-directional charging and discharging piles, which are connected to the power grid through the charging and discharging piles. By combining the low usage rate of EVs at night, the current situation of power consumption at night when the load of the power grid is at the bottom of the valley, and the large spare capacity of the new energy generation system, tariff leverage and power grid regulation information are used to regulate the energy of the power grid and the consumption of the new energy. This approach can also generate significant revenue while ensuring the maximum freedom and comfort of using the vehicles for users.

Users set their personalized travel plans and charging and discharging thresholds through the setting interface of the charging and discharging piles. The charging and discharging pile control system initially formulates the charging and discharging strategy of the current vehicle according to the charging and discharging thresholds set by users and their personal vehicle plans. It then adjusts and reformulates a reasonable charging and discharging control strategy through the current system load situation and real-time tariff transmitted by the power grid control center, converts the current working state of the EV, and performs charging or discharging operations as needed. The charging or discharging operation is carried out as needed. The real-time process of regulation will be transmitted to the user side through the charging and discharging pile, and the current charging and discharging status, real-time charge state, dynamic tariff, expected revenue, and other related information will be fed back in real time. The workflow diagram of the interaction between the bidirectional charging and discharging piles, and the distribution network is shown in Figure 3:

(1) The grid dispatch command center sets the corresponding tariff based on the current grid power consumption and renewable energy output, which is transmitted down to the bi-directional charging and discharging piles.
(2) The bi-directional charging and discharging pile announces the tariff released by the grid to the users through the user-setting interface.
(3) The user sets the charging and discharging threshold tariff, personal usage plan, and other information in the control panel according to the previous day's tariff and the current day's usage plan.
(4) According to the information set by the user, the bi-directional charging and discharging pile makes the corresponding charging and discharging strategy and uploads it to the grid control center.
(5) The grid control center adjusts the control strategy of the bi-directional charging and discharging pile according to the change in the day-ahead load, and a cooperative game model is formed between the user and the grid to maximize the interests of both parties.
(6) The details of charging and discharging are displayed on the control panel in real time. After charging and discharging are completed, the bi-directional charging and discharging pile uploads the completion signal and waits for the next instruction from the grid control center.

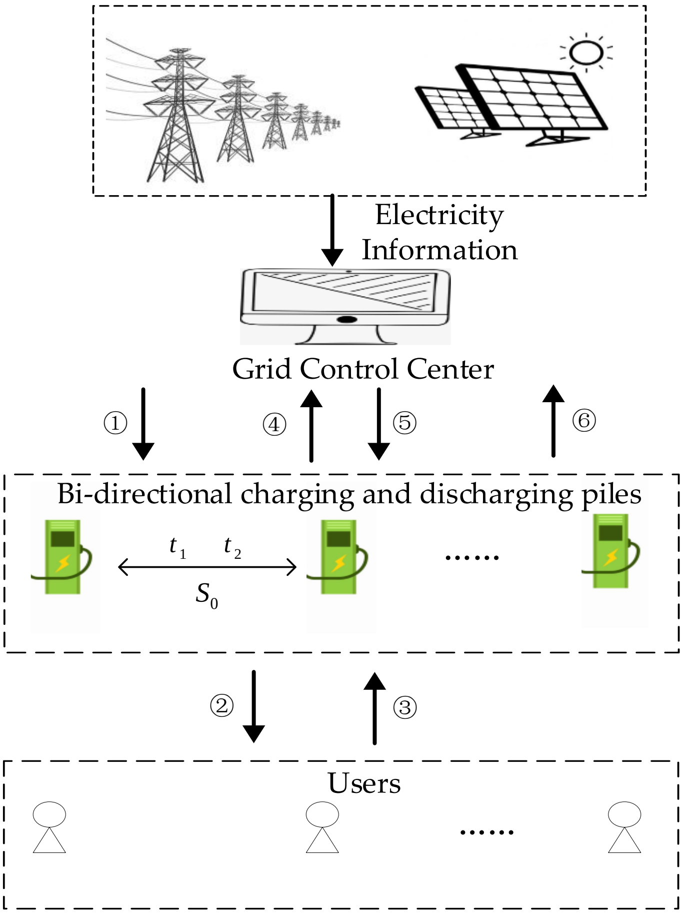

Figure 3. Workflow diagram of a bi-directional charging and discharging pile.

3.2. Implementation of the Dynamic Cooperative Game Model

According to the relationship between charging duration T_m and docking duration T_s of EVs, the private EVs integrated into the grid are divided into an elastic load vehicle group and an inelastic load vehicle group. The charging time of the elastic load group $T_m < T_s$ and the inelastic load group $T_m \geq T_s$.

According to the *i* time period gaming process, the grid regulation center timely adjusts the charging and discharging tariffs for each time period through the real-time grid entry of bi-directional charging and discharging pile users and sends the real-time tariffs for that time period to the users. After receiving the dynamic tariff information released by the grid, users are divided into flexible and inelastic vehicle groups according to their travel plans, and make different charging plans according to their own conditions: inelastic vehicle groups are equivalent to fixed loads, respond to the dynamic tariff strategy of the grid, and participate in charging during that time; flexible vehicle groups participate in charging during low load hours when the charging tariff is lower than the user's expected value, and during peak load hours of the grid, the charging tariff is not involved in charging when the charging tariff is higher than the upper limit of the user's expected value. Bi-directional charging and discharging pile users update their respective charging information, send the adjusted entry strategy for each time period to the grid regulation center, and roll over to the next round of the game.

A genetic algorithm is used to solve the game problem between electric power operators and bidirectional charging and discharging pile users (Figure 4). The discrete population of the genetic algorithm is the game tariff strategy, the appropriate coding method is selected, the evaluation indexes are evaluated individually with the revenue of both sides of the game, and the optimized game strategy is obtained by crossover mutation and elite strategy.

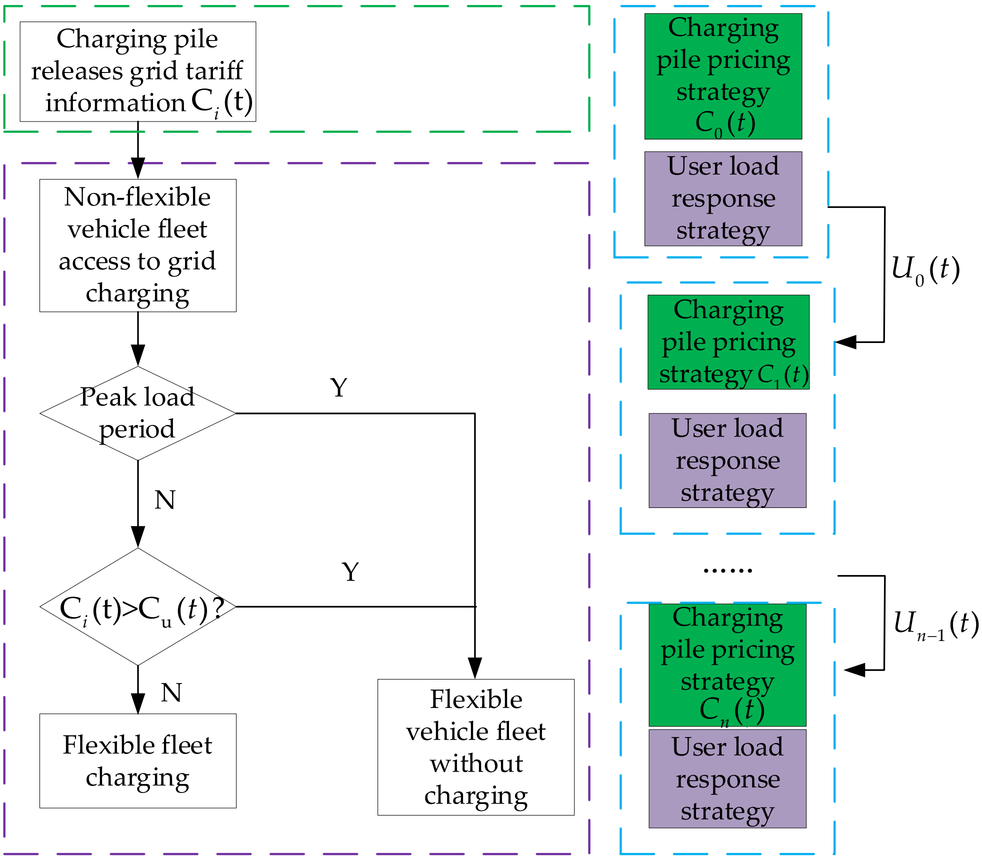

Figure 4. Dynamic cooperative game flow chart.

4. Simulation of Cooperative Game Control Strategy

4.1. Optimal Genetic Algorithm under Receding Horizon Control

In this paper, based on the principle of Receding Horizon Control, an improved optimal genetic algorithm is used to solve the orderly grid-connected regulation problem of EVs, which is used to solve the optimal control problem with a finite time duration.

The traditional fixed time-domain optimization produces a control sequence $\{u(i), u(i+1), \ldots, u(i+N-1)\}$ starting from the moment i to the end of the moment $i+N-1$, but the prediction results under this strategy have disadvantages. If the system is perturbed outside the prediction in the interval $[i, i+N-1]$, the original control sequence is no longer applicable at this time, and it is no longer possible to obtain information from the objective function at the short interval near the moment $i+N-1$ because of the short interval. In order to avoid Receding Horizon Control and the problem of inaccurate prediction results caused by these drawbacks, Receding Horizon Control is introduced.

Receding Horizon Control (RHC) is a special time-invariant state feedback control law, which is a model-based finite-time domain closed-loop optimal control algorithm, where the same input can be obtained by taking the same state quantities with a constant model and objective function [23]. The RHC algorithm can exclude the influence of disturbances on prediction by rolling prediction, so it can also play a good role in solving the mathematical model with less accurate accuracy, and it is widely used in industrial production.

The control process can be expressed by the mathematical equation as:

$$x(i+1) = f(x(i), u(i))(i = 0, 1, \cdots, N-1) \tag{24}$$

$$x(0) = x_0 \tag{25}$$

$$y(i) = h(x(i), u(i)) \tag{26}$$

where $x(i) \in R^n$ is the system state quantity constraint, $u(i) \in R^m$ is the input quantity constraint, and $y(i) \in R^n$ is the output quantity constraint.

The Receding Horizon Control model predictive optimal control process is shown in Figure 5.

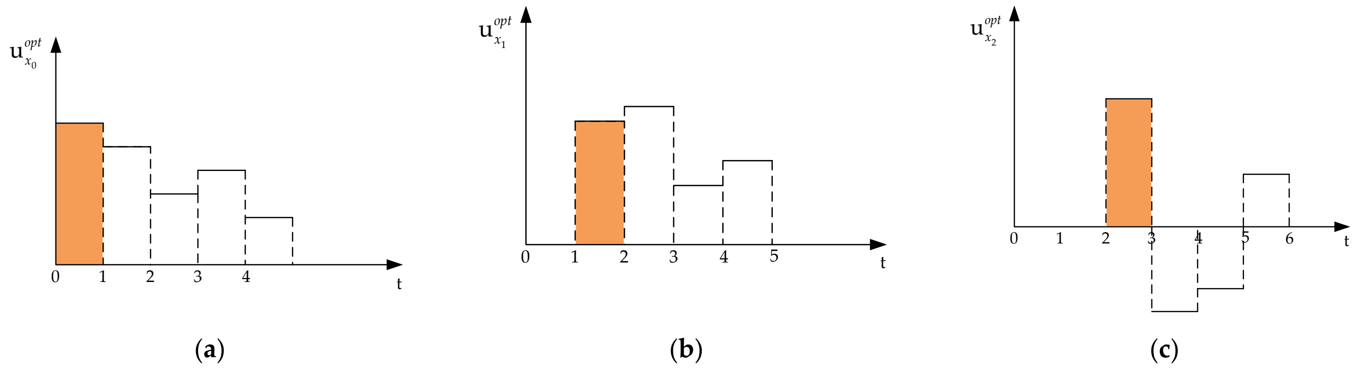

Figure 5. Principle of the RHC model predictive optimal control process. (**a**) x_0 Moment; (**b**) x_1 Moment; (**c**) x_2 Moment.

(1) Solve the optimal control problem for the interval $[i, i + N - 1]$ based on the current state x_i, taking into account the constraints of both the current moment and the next moment.
(2) Perform the first step of the prediction to obtain the predicted state quantity x_{i+1} for moment $i + 1$.
(3) Measure the actual control quantity u_{i+1} at moment $i + 1$. The predicted state quantity should be the same as the actual control quantity if the system is not disturbed by anything other than prediction, i.e., $u_{i+1} = x_{i+1}$.
(4) Repeat the above process prediction on the basis of x_{i+1} to obtain the control quantity of the interval $[i, i + N - 1]$.

The optimization performance index can be a quadratic optimization function:

$$\min J(k) = \sum_{i=1}^{N} \left\| y(k+i|k) - \widetilde{y}(k+i) \right\|_Q^2 \tag{27}$$

where the k moment is the current moment of the actual control quantity input; $y(k + i|k)$ denotes the output variable at $k + i$ moments predicted based on the current moment; $\widetilde{y}(k + i)$ denotes the output reference value at $k + i$ moments.

Solve the quadratic optimization performance index to find the optimal control sequence:

$$\Delta u_M(k) = [\Delta u^T(k+1|k), \Delta u^T(k+2|k), \cdots, \Delta u^T(k+M|k)] \tag{28}$$

where $\Delta u^T(k + M|k)$ denotes the column vector of control variables at M moment predicting the future $K + M - 1$ to $K + M$ moments.

The improved genetic algorithm control model under the RHC principle is shown in Figure 6.

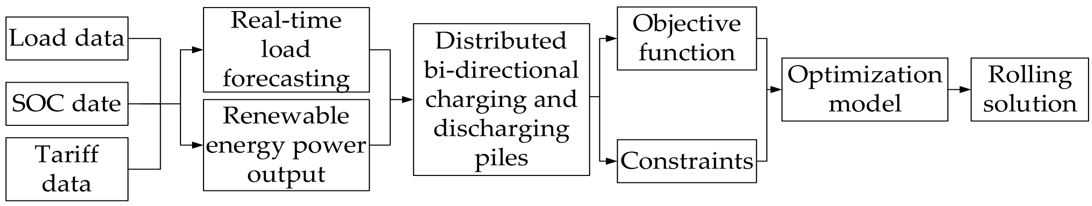

Figure 6. Control model of the genetic algorithm under RHC.

Under the constraints of the current moment and the next moment of the collaborative scheduling optimization strategy are satisfied, the optimal solution $P_{\mathrm{EV}}(k)$ at moment k is found using the RHC genetic algorithm based on the load power P_{Load}^{k} of the system at the current moment, the dynamic tariff data of the cooperative game, and the power SOC_{star}^{k} of the EVs connected to the charging and discharging piles at the moment, so that the system achieves the minimum user-side and grid-side objective function f under the currently found optimal interaction power of the system. Then let $t = k + 1$, repeat the above process, and keep rolling forward the solution in an hourly cycle to realize the real-time control of the charging and discharging pile interaction power. This method can fully take into account the impact of real-time changes in the power system on the prediction in the future period and can achieve a better control effect without establishing an extremely detailed prediction model by eliminating disturbances through rolling prediction.

The flow of the RHC-GA is shown in Figure 7.

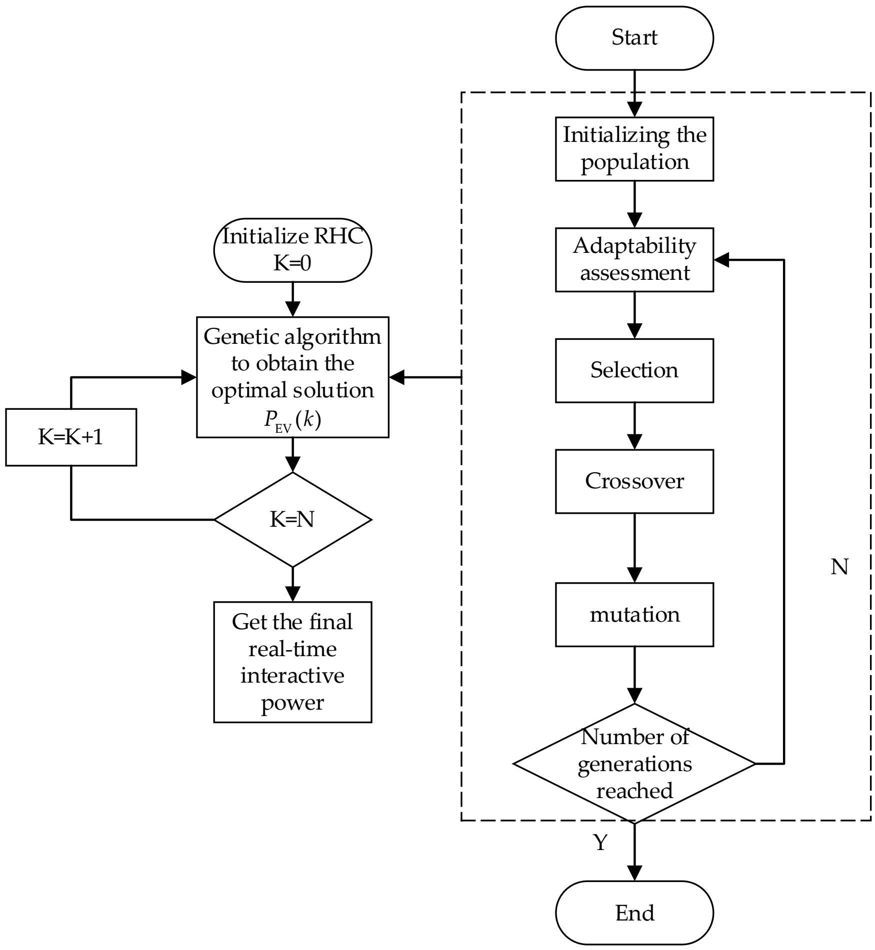

Figure 7. RHC-GA flow chart.

4.2. Setting of Load Parameters under Tariff Leverage

Through the research and analysis of the EV market situation in 2021, the market retention rates of several common different models of EVs in China and their various parameters for charging and discharging in daily use are summarized, as shown in Table 1.

Table 1. Common EV model market share and charging data.

EV Types	Battery Capacity/ kW·h	Charging Power (Fast Charging)/ kW	Charging Power (Slow Charging) /kW	Annual Sales Volume/Unit
Wuling Hongguang MINI	9.3	—	1.5	380,278
Tesla Model 3	55	120	5.5	144,592
Tesla Model Y	77	120	5.5	129,353
BYD QinPLUS	53	84	6	93,582
BYD Han	80	140	6.2	85,787

This experiment is based on the daily load curve of a region in Shandong Province in 2021 during the non-heating period, and considering the randomness of the EV owner's travel, the initial charging time t_1, the ending charging time t_2 and the driving path D_1 of each EV are generated by MCMC prediction. It is set that each EV has the same battery type, and the user's initial charge S_0 is randomly distributed between 0.2–0.5. From the perspective of battery protection, the battery itself is set with a safe charging and discharging threshold. Combined with the bi-directional charging and discharging pile user personalized perspective, assuming that the user unified expected charge and discharge charge is set to $SOC_{i.\max} = 0.9$, $SOC_{i.\min} = 0.2$, the specific EV parameters are set as shown in Table 2.

Table 2. EV parameters.

Parameters	Numerical Value	Parameters	Numerical Value
Power Battery Capacity E/kW·h	53	Discharge Threshold SOC_{down}	0.2
Maximum charging power of charging pile $P_{EV.\max}$/kW	6	Charging Threshold SOC_{up}	0.9
Maximum discharge power of charging pile $P_{EV.\min}$/kW	−6	Power consumption per kilometer E_d/kW·h	0.2
Time interval Δt/h	1		

Table 3 shows the base load of electricity consumption in a residential district in one day, and its peak value is 970.3 kW. Based on the method described in this section, the orderly charging and discharging of EVs in the district is optimally regulated, and the maximum capacity of the distribution network in the residential district is set to 1000 kW. Each household has at least one charging post, and there is no queuing for charging. There are a total of 200 charging piles, and EVs are charged in slow-charging mode.

Table 3. Daily base load of a residential community.

Time	Load/kW	Time	Load/kW
1:00	270.696	13:00	670.162
2:00	251.722	14:00	574.804

Table 3. *Cont.*

Time	Load/kW	Time	Load/kW
3:00	232.764	15:00	552.65
4:00	216.974	16:00	648.272
5:00	239.392	17:00	893.498
6:00	350.924	18:00	938.198
7:00	481.572	19:00	951.054
8:00	497.614	20:00	970.294
9:00	497.742	21:00	894.026
10:00	536.068	22:00	731.82
11:00	612.606	23:00	642.838
12:00	755.974	0:00	461.534

4.3. Simulation Results Analysis under Different Optimal Scheduling Control Strategies

Considering the cooperative game, the real-time tariff is obtained based on the update of the cooperative game model with equal weight index assignment with the objective of maximizing the interests of the user side and the grid side, as shown in Figures 8 and 9. Scenario 1 shows the game tariff after 50 private EVs participate in the regulation system using equal weight index assignment, and Scenario 2 shows the tariff after 100 private EVs participate in the regulation under equal weight index assignment.

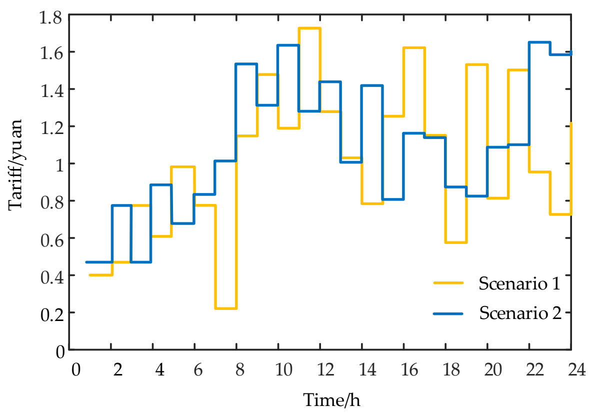

Figure 8. 24-h charging tariff.

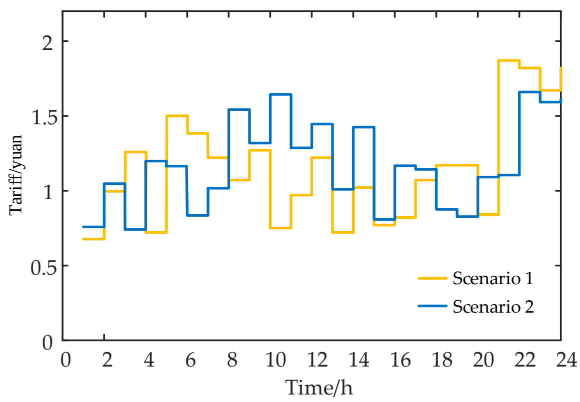

Figure 9. 24-h discharge tariff.

As can be seen from Figures 8 and 9, with the increase in the number of EV users, it can be seen that the dynamic tariff response speed is more sensitive and the tariff fluctuations are more stable, which can avoid the damage to battery life caused by frequent changes in charging and discharging status due to tariff changes for private EVs. The dynamic tariff change speed of 50 samples has a certain lag compared to 100 EV samples. During the load valley period of 0:00–7:00, the tariff shows a low trend, guiding EV users to participate in the regulation system for charging. When the load gradually rises to the first peak of a typical day, at 8:00–11:00, the dynamic tariff as a whole shows a rising trend in order to avoid users' connection to the grid to increase the burden of the power system and cause further growth of the load curve, reducing users' charging behavior through the tariff lever and making users increase their EV discharging behavior to gain revenue. During the peak load hours of 15:00–22:00, with the increase in the number of EV users, the change in the real-time dynamic tariff gradually becomes smaller, and the tariff is lower and tends to be stable, which can guide vehicle owners to concentrate on discharging and achieve the peak-shaving effect.

With the real-time update of the dynamic tariff, the users connected to the bi-directional charging and discharging piles are awakened and connected to the grid for charging and discharging behavior. Figure 10 shows the wake-up problem of tariff leverage on the users connected to the grid in the case of real-time updated dynamic tariff.

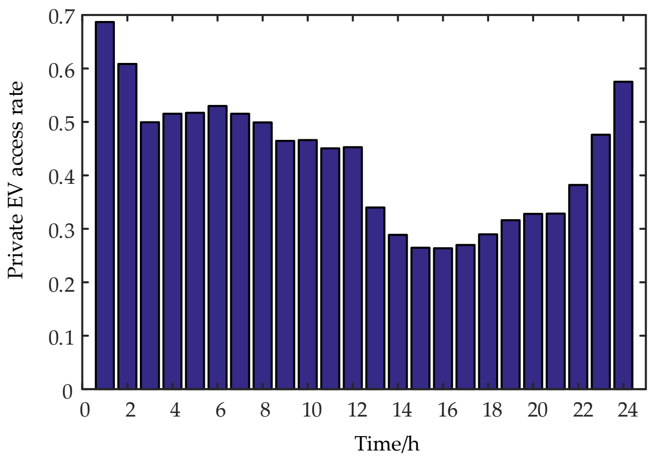

Figure 10. The wake-up rate of private EVs under dynamic tariffs.

As can be seen from Figure 10, during the peak daily base load hours of 15:00–21:00, the number of users waking up is low, with only about 20% of users connected to charging and discharging piles performing charging and discharging behaviors to participate in system regulation. during the hours of 18:00–20:00, most users end their trips for the day and connect their private EVs to bi-directional charging and discharging piles, but subject to the regulation principle of tariff leverage. Most private EVs (flexible groups of vehicles) whose power is in the safe range will enter the dormant state after connection and wait for the price change to the expected price set by the users before changing the charging and discharging state according to the regulation strategy. Some vehicles with insufficient power or in need of emergency use (non-flexible vehicles) are connected to the grid for charging immediately after connecting to the bi-directional charging and discharging piles to ensure the user's experience and comfort. The highest wake-up rate in this period is up to 68.9%.

In order to simplify the sample model, three optimal scheduling control strategies under the traditional fixed tariff, peak-valley leveling time tariff, and the cooperative game dynamic tariff proposed in this paper are simulated to study the load profile of bidirectional charging and discharging pile users participating in orderly charging and discharging, taking 50 EVs as an example, as described below:

Control strategy 1: Study the orderly charging and discharging of EVs under a traditional fixed tariff. The control strategy does not consider the impact of tariff changes on users' participation in grid connections, and the access and charging behavior are carried out spontaneously by users, without the guidance of pricing regulation on the grid side.

Control strategy 2: To study the orderly charging and discharging of EVs under the current peak-to-valley tariff in China. This control strategy considers the incentive effect of tariff changes on users' participation in grid connections and takes advantage of the consumer mentality of users. During idle hours, when users are not in a hurry to use their cars, private EVs are not immediately connected to the grid for charging behavior after accessing the charging piles, use peak and valley tariffs to sell electricity during periods of high tariff rates, and then change the access state for charging during periods of low rates.

Control strategy 3: Study the charging and discharging of EVs under the dynamic tariff generated by the cooperative game model. This control strategy considers the impact of real-time updated dynamic tariff on users' participation in grid connection and uses the flexible changing tariff as a tariff lever to wake up users who are connected to the system at that moment but do not perform charging and discharging behavior to participate in system regulation.

The analysis shows that tariff leverage can wake up users, and the sample size of users also affects the simulated load curve. Figures 11–13 show the effect of the different numbers of private EVs connected to the distribution network via bi-directional charging and discharging piles for power interaction on the optimization effect of the distributed energy storage cooperative scheduling control strategy under the three control strategies. Setting the number of users as 50 and 100, the results are as follows:

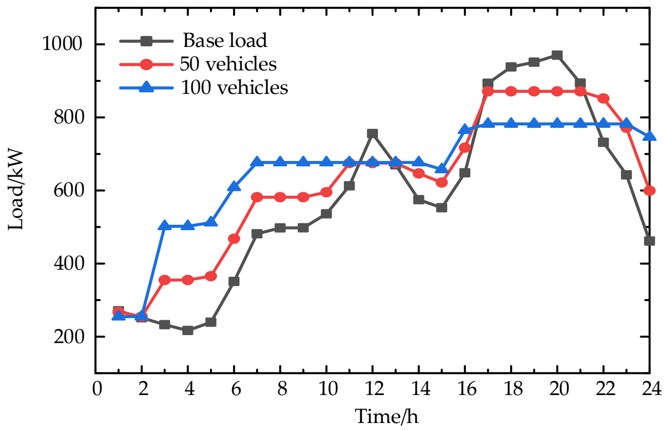

Figure 11. Load curve under conventional tariff.

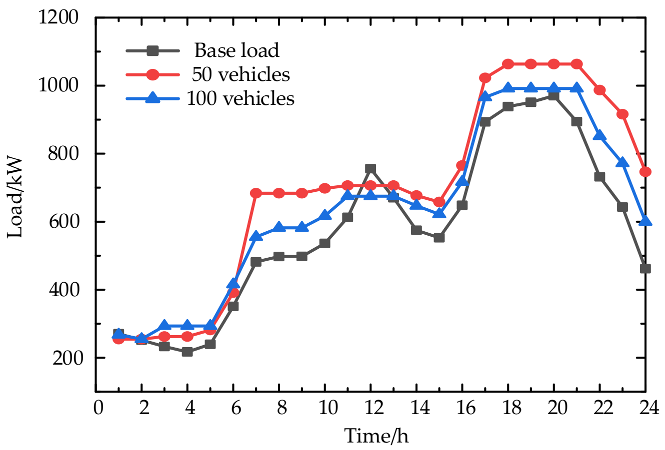

Figure 12. Load curve under time-of-use tariff.

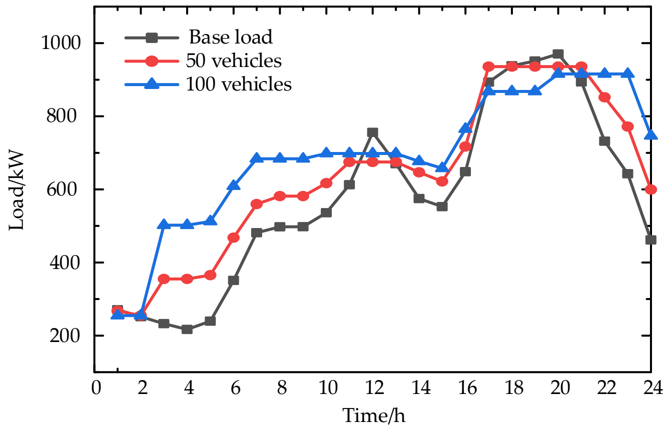

Figure 13. Load curve under dynamic tariff.

The simulation results show that the number of users participating in the regulation system has an important impact on the results of the control strategy, regardless of whether it is a traditional fixed tariff, a time-of-use tariff, or the dynamic tariff set in this paper. Therefore, the more obvious the effects of peak and valley reduction on the grid.

By comparing the optimization results under the three control strategies through the genetic algorithm under RHC, the load curve is obtained as shown in Figure 14.

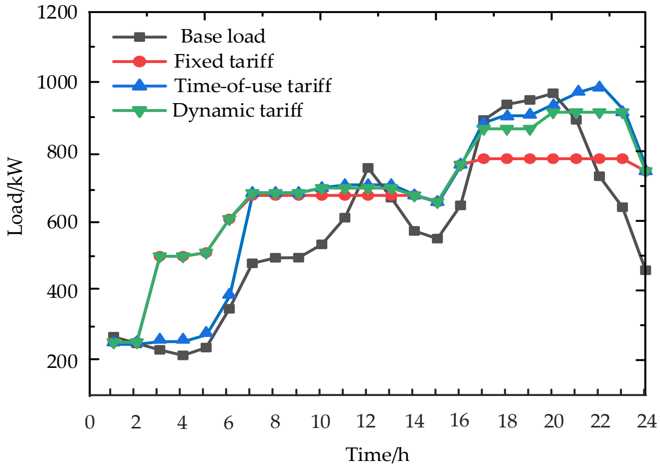

Figure 14. Load curves under different optimal scheduling strategies.

Compared with the traditional fixed tariff in Strategy 1, Strategy 2 adopts a time-of-use tariff, which can increase the motivation of vehicle owners to participate in the distribution network through bi-directional charging and discharging piles by lowering the tariff in the valley and increasing the tariff in the peak period, and this strategy has a certain effect of valley filling. However, strategy 2 will lead to a "new peak" phenomenon in the second peak period after 18:00–22:00 on a typical day. This is because the time-of-use tariff is a static tariff based on the historical load situation, which cannot be updated in time according to the change of the previous day's load and the fluctuation of private EVs connecting to the grid; therefore, there will be the phenomenon of users connecting to the grid in the valley tariff period after the peak period, which leads to a higher load in the valley period and a "new peak".

Considering the impact of tariffs on users' demand-side responses, further analysis is performed on the basis of time-of-use tariffs. Control strategy 3 adopts the real-time dynamic tariff proposed in this paper, using the principle of tariff leverage to further enhance the enthusiasm of charging and discharging pile users to participate in distribution network interaction, and the effect of valley filling is better than control strategy 2 during the low electricity consumption period of 23:00–7:00. Within 18:00–21:00, a large number of EV owners participate in the interactive system to discharge because the difference between the purchase price and the sale price is the largest during this period, so the peak-shaving effect is more obvious. Compared with the existing time-of-use tariff strategies, such as the control strategy of time-of-use tariff proposed by Guo et al., [10], the real-time update of dynamic tariff is more flexible and can better reflect the changes of grid load in the current period. It can more reasonably guide the charging and discharging behavior of users, so that they can discharge moderately during peak period and charge and store energy during valley period, thus reducing the peak load, increasing the load during valley period, and smoothing the load curve.

The sources of power acquired by the load are mainly grid and renewable energy sources. The load acquires power from the main grid with the billing method of the tariff corresponding to the three control strategies, and the cost of power exchange by the load on the renewable energy side depends on the generation cost of wind power PV. The user-side economics objective function f_1 reflects the overall user-side spending, and f_1 is expressed as:

$$f_1 = \min C_{\text{sum}} = \sum_{t=1}^{96} \left(P_{\text{WT}}^t C_{\text{WT}} + P_{\text{PV}}^t C_{\text{PV}} + C_{\text{EV}}^t \right) \tag{29}$$

$$C_{\text{EV}}^t = \alpha P_{\text{dis}}^t C_1^t - \beta P_{\text{cha}}^t C_2^t \tag{30}$$

where C_1 is the tariff issued by the grid, and C_2 is the price of electricity sold by the vehicle owner to the grid.

To model the economics of EV orderly grid-connected systems based on user-side benefits:

Without the renewable energy consumption case:

$$\begin{cases} P_{Load}^t = P_{WT}^t + P_{PV}^t + P_{EV}^t \\ P_{EV}^t = \alpha P_{\text{dis}}^t - \beta P_{\text{cha}}^t \\ P_{WT}^t = 0 \\ P_{PV}^t = 0 \end{cases} \tag{31}$$

Full utilization of renewable energy:

$$\begin{cases} P_{Load}^t = P_{WT}^t + P_{PV}^t + P_{EV}^t \\ P_{EV}^t = \alpha P_{\text{dis}}^t - \beta P_{\text{cha}}^t \\ P_{WT}^{\min} \le P_{WT}^t \le P_{WT}^{\max} \\ P_{PV}^{\min} \le P_{PV}^t \le P_{pv}^{\max} \end{cases} \tag{32}$$

The economics of the control strategy are calculated according to Equations (29)–(32). The calculated benefits of bi-directional charging and discharging piles under different control strategies are shown in Table 4.

Table 4. Total revenue of charging and discharging under different strategies.

Control Strategy	50 Vehicles	100 Vehicles
Gain under strategy 1/yuan	—	—
Gain under strategy 2/yuan	1003.7	2108.5
Gain under strategy 3/yuan	1060.7	2163.7

The total revenue of bi-directional charging and discharging piles under dynamic update tariff is 1060.7 yuan. This is mainly due to the leverage of the tariff, where the load is low between 23:00 and 5:00 a.m. When the tariff is lower and users choose to charge during this time, the cost of electricity purchase is lower, while users choose to discharge during peak load hours to earn revenue. For example, Lai et al. proposed a dynamic pricing strategy with competitive effects, and existing studies mainly consider charging behavior regulation and less simultaneously consider the impact of discharge schedules on user benefits [18]. The third control strategy considers that EV users can earn revenue by discharging to the grid during idle periods, which ensures user benefits. Compared with the first two control strategies, this control strategy takes special consideration to ensure the interests of users and bring the best economic benefits. The overall revenue of charging and discharging piles can be increased by up to 6.3% under dynamic tariffs.

5. Conclusions

For the negative impact of the large-scale disorderly grid connection of EVs on the stable operation of the power grid, a cooperative game cooperative control strategy for EVs based on tariff leverage is proposed. A cooperative game model with electric power operators and users as participants is established, a dynamic tariff strategy with real-time updates is obtained, the optimal interaction power under different control strategies is obtained using an RHC genetic algorithm, and the corresponding economic benefits are calculated. The main conclusions are as follows:

(1) A dynamic cooperative game cooperative control strategy for private EVs based on in-home bi-directional charging and discharging piles is proposed, which improves the weight of users in the game, determines the real-time tariff with optimal returns for electric power operators and charging and discharging pile users, and guides the charging and discharging behavior of users according to the dynamic tariff.

(2) Compared with the two control strategies of fixed tariff and time-of-use tariff, the control strategy of cooperative game has a smoother load curve, better achieves peak shaving and valley filling, and the total revenue of bi-directional charging and discharging pile users is the best, which can be improved by up to 6.3%.

(3) Compared with the time-of-use tariff, the wake-up rate of users is about 20% during the load peak period under dynamic tariff; the highest wake-up rate is as high as 68.9% during load valley period, which shows that dynamic tariff enhances the enthusiasm of charging and discharging pile users to participate in distribution network interaction.

The cooperative game control strategy of EVs based on tariff leverage proposed in this paper not only solves the adverse impact of large-scale grid connection of EVs on the distribution network, avoids the load "new peak" problem caused by time-of-use tariff, reduces the operation cost of electric power operators, but also increases the revenue of bi-directional charging and discharging pile users, ensures the users' satisfaction, realizing a win–win situation between power marketers and users.

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