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Multi-Objective Comprehensive Charging/Discharging Scheduling Strategy for Electric Vehicles Based on the Improved Particle Swarm Optimization Algorithm

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To solve the problems that a large number of random and uncontrolled electric vehicles (EVs) connecting to the distribution network, resulting in a decrease in the performance and stability of the grid and high user costs, in this study, a multi-objective comprehensive charging/discharging scheduling strategy for EVs based on improved particle swarm optimization (IPSO) is proposed. In the distribution network, the minimum root-mean-square error and the minimum peak valley difference of system load are first designed as objective functions; on the user side, the lowest charge and discharge cost of electric vehicle users and the lowest battery loss cost are used as objective functions, then a multi-objective optimization scheduling model for EVs is established, and finally, the optimization through IPSO is performed. The simulation results show that the proposed method is effective, which enhances the peak regulating capacity of the power grid, and it optimizes the system load and reduces the user cost compared with the conventional methods.

Keywords: electric vehicle, multi-objective optimization, improved particle swarm algorithm, grid peak shaving, charging/discharging scheduling

INTRODUCTION

The new energy source has made a great contribution to solving the increasingly serious energy shortage and environmental degradation. It will gradually replace non-renewable energy sources that cannot be recycled or reused (Teng et al., 2021). Electric vehicles (EVs) have gradually gained popularity in recent years due to their energy-saving (Xiong et al., 2020; Huang et al., 2021; Zhang et al., 2021) and environmentally friendly features. However, a large number of EVs connected to the distribution network increase the load of the power grid, which may lead to problems such as the increase of the peak-valley difference of the load, the local overload of the grid load, the increase of the line loss, and the over-limit of the transformer capacity of the distribution network (Wang et al., 2020). In addition, the electricity consumption of residents is increasing, and unreasonable charging costs will limit the popularization of EVs. EVs with vehicle to grid (V2G) capability can feed electricity back to the grid when their state of charge (SOC) is high. The maturity of the V2G technology and autonomous vehicle communication technology enables EVs to participate in optimal dispatch and reduce the load pressure on the distribution network. In addition, the charging/discharging of EVs are similar and clustered. EVs in the same street or community have similar charging behaviors, which increases the dispatch ability of EVs (Badawy and Sozer, 2017). The dispatching strategy of EVs is mainly to study the load balancing factors and distribution capacity on the distribution network side, while the user side aims to improve user satisfaction, battery loss costs, and the charging/discharging costs of EVs. The optimal charging/discharging scheduling of EVs was used to eliminate the influence of a large number of EVs connected to the grid, reduce the fluctuation of the grid load, and reduce user costs.

At present, intelligent scheduling has become one of the research hotspots. The economic cost is minimized, but the power grid load fluctuation is not considered (Habib et al., 2020). When a large number of EV users charge during the valley period, an “avalanche effect” will occur (Gottwalt et al., 2011). In the study by Jin et al. (2020), a probability mass function (PMF)-based model is proposed to provide more accurate forecasts of future EV behaviors. In addition, it developed an EV aggregator (EVA) optimization schedule model that combines a day-ahead optimization schedule and a real-time optimization schedule to reduce EVA operation costs and maximize the travel utility for users participating in this service of EVs. So as to resolve the conflict of interest between customers and system operators during the implementation of the vehicle to the grid, it proposed to use an augmented epsilon constrain-based technique to implement two-way and three-way multi-objective optimization (Maigha and Crow 2018). Amamra and Marco (2019) established an optimization strategy for V2G scheduling, which solved the problems of EV’s plug in time, adjustment price, EV’s expected leaving time, battery degradation cost, and vehicle charging demand, but the article does not optimize the load on the distribution grid. Hadian et al. (2020) similarly used a multi-objective particle swarm optimization (PSO) algorithm to control the charging/discharging rate and time of EVs to achieve the peak shaving, valley filling, and flattening goals of the grid load curve. The power routing strategy for EVs was proposed in the study by Esfahani and Mohammed (2019); the objective function involves minimization of power loss and the power imbalance factor along with improved system load ability as well as voltage profile. PSO reoptimized the received sub-optimal solution (site and the size of the station), which leads to an improvement in the algorithm functionality and enhances quality of the solution; the author shows the superior performance of the proposed method on the genetic algorithm and PSO in terms of improvement in the voltage profile and quality through simulation (Awasthi et al., 2017). Ma et al, (2019) studied the load fluctuation of the distribution network and the charge/discharge cost of EVs on the basis of the peak-valley time-of-use (TOU) price, and finally, a coordinated dispatch strategy and an optimized dispatch model were proposed to reduce the peak-valley difference of the power grid and improve the economic benefits of users.

The PSO algorithm requires fewer parameters and has low requirements on the objective function, which is widely used. Many literature studies use PSO to solve the scheduling problem (Yousif et al., 2019), but when the problem dimension is high, the algorithm is prone to precocity. Contrastively, in the study by Kang et al. (2017), it established a multi-objective optimization model and used the improved particle swarm optimization (IPSO) algorithm to find out the solution with the minimum electricity cost; the results verify that this method can better meet the economic benefits and environmental protection requirements of microgrid power generation than PSO, but it does not consider the optimization of the grid side.

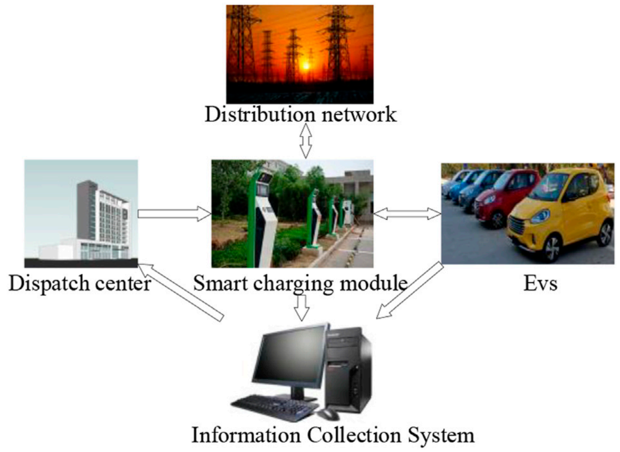

FIGURE 1 | Structure of V2G.

To summarize, this study mainly conducts the following research on the basis of the above research work and combined with the background of an odd–even license plate restriction policy:

1) The charging/discharging cost and battery loss cost of EVs are constructed as objective functions on the user side of EVs, and the two objective functions of load mean square deviation and load peak-valley difference are established in terms of power grid load.
2) The influence of the current odd–even license plate restriction policy on EV scheduling is considered, and the charging power and state of charge/charging quantity of EVs are constrained.
3) An IPSO algorithm is proposed, which can effectively avoid the premature phenomenon of particles.
4) Finally, experiments have verified that the algorithm has better EV scheduling performance, and it reduces the user cost of EVs and plays the role of peak shaving and valley filling for the system load.

The rest of this article is organized as follows: the first section introduces the scheduling system, objective function, and model constraints of V2G; the second section describes the dispatching strategy scheme of EVs; the third section gives simulation results to prove that the proposed IPSO algorithm has a better power grid peak regulating ability and is beneficial to reducing user costs; finally, the fourth part gives the conclusion.

VEHICLE TO GRID AND THE SCHEDULING MODEL

Vehicle to Grid Dispatching System

The V2G dispatching system is divided into five parts: the distribution network, information collection system, V2G

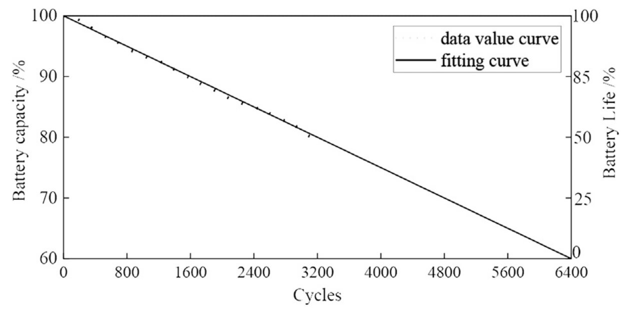

FIGURE 2 | Relationship between cycle number and life.

dispatching center, intelligent charging module, and EVs. The structure of the V2G scheduling system is shown in **Figure 1**.

Lithium Ion Battery Model

Battery aging is mainly caused by EV's cyclic charge and discharge, which is also related to the type of battery. In this study, a linear model proportional only to the total number of battery cycles is used to study lithium ion batteries. The curve diagram of cycle times and life as shown in **Figure 2** is presented in the study by Neubauer and Wood (2014), and the value is given by the battery manufacturer. The model is related to the battery replacement cost, and the battery aging cost is obtained.

Objective Function

Battery Aging Cost

The battery aging cost includes the charge and discharge power and the cost caused by the fluctuation of charge and discharge power. The battery aging cost caused by charging/discharging power is expressed as

$$C_{1,i} = \sum_{t=1}^{T} \alpha\left(\Delta t p_{i,t}\right)^2, \tag{1}$$

where $c_{1,i}$ is the battery aging cost caused by charging/discharging power of EV i in 24 h; α is the model coefficient, set to a small positive number, because the battery aging caused by charging power is small; and $p_{i,t}$ is the charging power of the EV i in t periods ($p_{i,t} > 0$, EV charging; $p_{i,t} < 0$, EV discharge).

The battery aging cost caused by charge and discharge power fluctuation in adjacent periods is expressed as

$$C_{2,i} = \sum_{t=1}^{T-1} \beta\left(\Delta t p_{i,t} - \Delta t p_{i,t+1}\right)^2, \tag{2}$$

where $c_{2,i}$ is the battery aging cost of EV i in 24 h due to the charge and discharge power fluctuation; β is the model coefficient; and $x_{i,t+1}$ is the charging power of EV i in the period t+1. The greater the fluctuation of charge and discharge power in adjacent periods, the greater the battery aging. The change of charging/discharging state (charging to discharge or discharge to charge) of EVs will cause greater battery aging. Therefore, in the 24 h scheduling process, the more frequently the charge and discharge status changes, the greater the battery aging cost is.

The aging cost of the battery is expressed as

$$C_{ij} = \sum_{i=1}^{N} \left(C_{1,i} + C_{2,i}\right), \tag{3}$$

where N is the total number of EVs.

Charging Cost

The charging cost of EVs participating in the V2G program depends on the charging consumption and discharge income. When the discharge revenue of EVs is higher than the charging consumption, the charging cost may be negative. The reducing charging cost is the most important incentive factor for EV owners to participate in the V2G program, but a high-frequency discharge will cause irreversible loss of the battery, which limits the enthusiasm of EV owners to feed the power grid.

The electricity price is designed as a linear function of the instantaneous load of the grid:

$$S_t = k_0 + k_1 z_t, \tag{4}$$

where s_t is the electricity price of period t, k_0 and k_1 are normal numbers, and z_t is the load of period t.

Under the real-time electricity price, EV charging cost is expressed as

$$C_{ev} = \sum_{t}^{24} \sum_{i=1}^{N} P_{it} S_t. \tag{5}$$

Mean Square Error of Power Grid Load

The smaller the load mean square error, the more stable the load fluctuation. The charge and discharge power of each EV in 24 periods of a day is regarded as the control variable:

$$\begin{cases} P_{avr} = \sum_{t=1}^{24} \left(P_{0t} + \sum_{i=1}^{N} P_{it} \right) / 24 \\ Z_{mse} = \sum_{t=1}^{24} \left(P_{0t} + \sum_{i=1}^{N} P_{it} - P_{avr} \right)^2, \end{cases} \tag{6}$$

where P_{ot} is the power of the original power grid at time t without the load of EVs and P_{avr} is the average daily load after the scheduling.

Peak and Valley Difference of Power Grid Load

Peak load is expressed as

$$P_{0t}^{\Delta} = P_{0t} + \sum_{i=1}^{N} P_{it}. \tag{7}$$

The peak and valley difference of the load curve is expressed as

$$\Delta P = \max\left(P_{0t}^{\Delta}\right) - \min\left(P_{0k}^{\Delta}\right), \tag{8}$$

where $\max\left(P_{0t}^{\Delta}\right)$ represents the peak load before adjustment and $\min\left(P_{0k}^{\Delta}\right)$ indicates the peak value of the adjusted load.

Objective Function

The optimized objective function is expressed as

$$\min f = \min\left(C_{ij} + C_{ev} + Z_{\mathrm{mse}} + \Delta P\right). \tag{9}$$

From the perspective of comprehensive indicators, only considering a single target does not truly reflect the actual cost of users. The four costs represent the interests of the power grid and vehicle owners. When setting the weight coefficient, the importance of the four costs is the same, which is closer to the actual use cost of users. If only the charging cost is considered, the charging cost is the smallest near the load valley, but a too long charging time increases the battery aging cost, and the charge and discharge power under the constraint of charging cost will produce a short-term peak, so the cost in this period is not necessarily the smallest. Considering comprehensively, set the same weight for the four objectives.

Constraints of the Model

SOC Constraints

Reasonable upper and lower limits of state of charge can delay battery aging as

$$SOC_{it\,\min} \le SOC_{it} \le SOC_{it\,\max}, \tag{10}$$

where SOC_{it} is the state of charge of EV i at time t, $SOC_{it\,\min}$ is the lower limit of the state of charge of EV i at time t, and $SOC_{it\,\max}$ is the upper limit of the state of charge of EV i at time t. Considering the safety of the vehicle battery, $SOC_{it\,\min}$ is 0.2 and $SOC_{it\,\max}$ is 0.9.

Charging/Discharging Power Constraints

When the EVs support V2G,

$$-P_{it\,\max} \le x_{it} \le P_{it\,\max} \quad \forall i \in N_{v2g}. \tag{11}$$

When the EVs do not support V2G,

$$0 \le x_{it} \le P_{it\,\max} \quad \forall i \in N_{chg}, \tag{12}$$

where $P_{it\,\max}$ represents the constraint of the maximum charging power of EV i at time t, N_{v2g} is the number of EVs supporting V2G, and N_{chg} is the number of rechargeable EVs.

Battery Power Constraints

$$E_i^{ini} + \sum_{t=t^{sta}}^{t=t^{end}} \Delta t x_{it} \ge E_i^{\exp}, \tag{13}$$

$$E_i^{batt} SOC_{it\,\min} \le E_i^{ini} + \sum_{t=t^{sta}}^{t=t^{end}} \Delta t x_{it} \le E_i^{batt} SOC_{it\,\max}, \tag{14}$$

where t^{sta} is the charging start time of EV, t^{end} is the departure time of EV, $E_i^{in\,i}$ is the initial battery level, $E_i^{\exp}$ is the expected battery capacity, and E_i^{batt} is the battery capacity of EV i.

Equation 13 ensures that the battery power can meet the requirements when the EVs leave, and **Eq. 14** ensures that the power in the dispatching section is always within the allowable range, neither excessive discharge nor overcharge.

Even–Odd License Plate Method

In order to alleviate urban traffic pressure and environmental pollution, it is imperative to implement a restriction policy on odd and even numbers. On the other hand, the traffic restriction policy can improve the enthusiasm of EV owners to participate in power grid dispatching and alleviate the burden of the distribution network. However, not all EV owners are willing to participate in the scheduling during the travel restriction period, so the probability of participating in the scheduling is selected as 0.95 in this study. In addition, most unrestricted EVs are actually idle almost 95% of the time in a day (Shen et al., 2021). This part of EVs can participate in the scheduling under the condition of meeting the model constraints. In this study, the probability of unrestricted driving participating in the scheduling is 0.8.

SOLUTION OF THE SCHEDULING POLICY

It is difficult to solve the multi-variable, non-linear, multi-constrained, and high-dimensional EV charging/discharging scheduling optimization problem by using classical optimization algorithms such as linear programming (Liu et al., 2020). Considering that the standard PSO algorithm is prone to fall into local optimum, this study adopts the IPSO algorithm for optimization.

Particle Swarm Optimization

PSO needs a certain amount of initial solution and then through iteration to find the optimal solution. In the process of each iteration and update, the particle needs to update two quantities, which are the individual optimal position and the population optimal position.

Supposing that in a D-dimensional solution space, the population is composed of N particles, where the position of particle i can be expressed as follows

$$X_i = (x_{i1}, x_{i2}, \ldots, x_{iD}). \tag{15}$$

The velocity of particle i can also be represented as follows:

$$V_i = (v_{i1}, v_{i2}, \ldots, v_{iD}). \tag{16}$$

The optimal position searched by particle i is called the individual optimal position, denoted as

$$P_{best} = (p_{i1}, p_{i2}, \ldots, p_{iD}). \tag{17}$$

The optimal position found by the whole particle swarm is called the optimal position of the population, denoted as

$$G_{best} = (g_{i1}, g_{i2}, \ldots, g_{iD}). \tag{18}$$

The whole particle swarm is described as $\{X_1^k, X_2^k, \ldots, X_N^k\}$, where k is the number of iterations. After finding the two quantities of individual optimal position P_{best} and population optimal position G_{best}, the particle updates its speed and position according to the following equation:

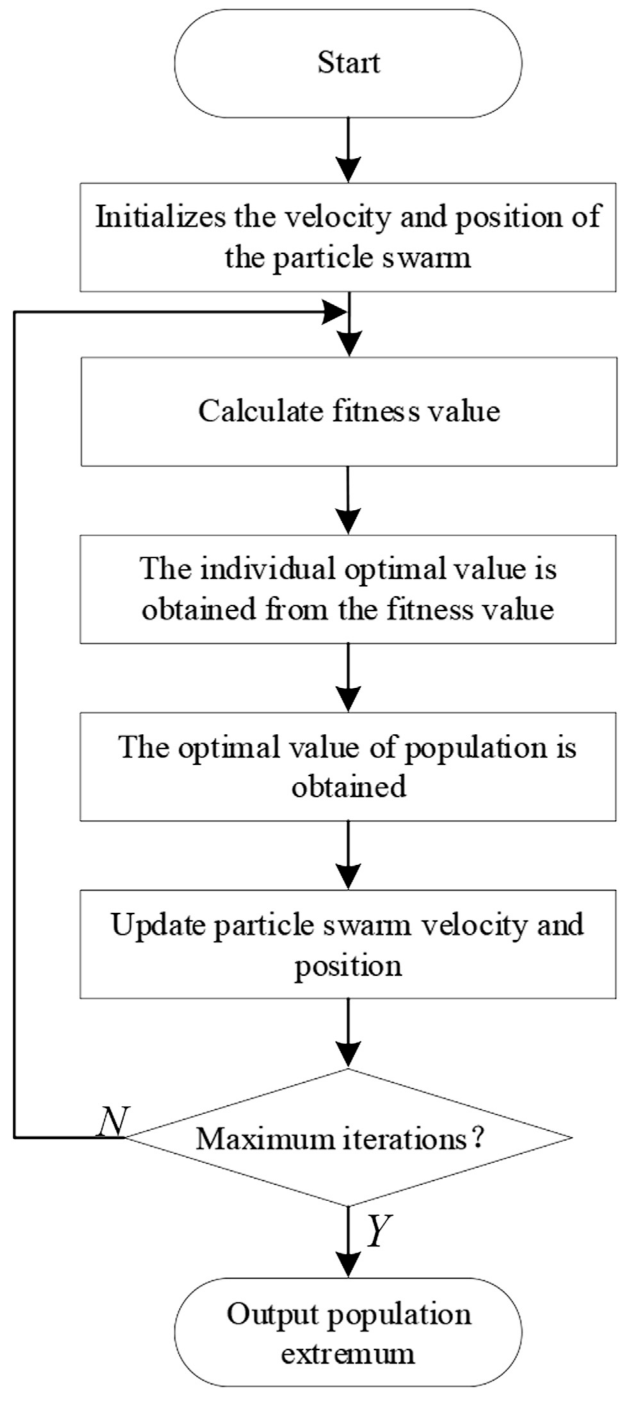

FIGURE 3 | Block diagram of the PSO process.

$$\begin{cases} V_i^{k+1} = wV_i^k + c_1 r_1 \left(P_{best}^k - X_i^k\right) \\ \qquad\qquad + c_2 r_2 \left(G_{best}^k - X_i^k\right) \\ X_i^{k+1} = X_i^k + V_i^{k+1}, \end{cases} \tag{19}$$

where ω is the weight of inertia, which is generally 0.9; c_1 and c_2 are called learning factors or acceleration factors; and r_1 and r_2 are random numbers from 0 to 1 that follow a uniform distribution.

The flow chart of the PSO algorithm is shown in **Figure 3**.

Improved Particle Swarm Optimization Algorithm

If the particle velocity is too divergent, it will lead to slow convergence in the later stage. In order to solve this problem, a simplified PSO algorithm is proposed in the literature (Lin et al., 2020). In this algorithm, the velocity term is omitted, and the evolutionary direction of particles is controlled only by the position term; **Eq. 19** in the standard PSO algorithm can be simplified as

$$X_i^{k+1} = \omega X_i^k + +c_1 r_1 \left(P_{best}^k - X_i^k\right) + c_2 r_2 \left(G_{best}^k - X_i^k\right). \tag{20}$$

Levy Flight

Levy flight is a random search path between short-distance walking and occasionally long-distance walking obeying Levy distribution. After a lot of research, it is in line with the foraging trajectory of many insects in nature, such as bees and fruit flies (Yao et al., 2020). If the algorithm falls into the local optimum, the particle position can be readjusted by Levy's flight formula to make it jump out of the local optimum. Levy's flight position update equation is expressed as

$$X_i^{k+1} = X_i^k + \alpha \oplus k^{-\lambda}, \tag{21}$$

where $\oplus$ is point-to-point multiplication and λ stands for step control.

The step length of Levy flight conforms to Levy distribution which is often simulated by the Mantegna algorithm, and the calculation formula of step s is expressed as

$$s = \frac{\mu}{|v|^{\frac{1}{\beta}}}, \tag{22}$$

where$\mu \sim N(0, \sigma_\mu^2)$, $v \sim N(0, \sigma_v^2)$, and

$$\sigma_\mu = \left\{ \frac{\Gamma(1+\beta) * \sin\left(\frac{\pi\beta}{2}\right)}{\Gamma\left(\frac{1+\beta}{2}\right) * \beta * 2^{\frac{\beta-1}{2}}} \right\}^{\frac{1}{\beta}}, \tag{23}$$

$$\sigma_v = 1, \tag{24}$$

where β is usually 1.5.

If all particles gather near the optimal particle, the algorithm will stagnate with the iteration. If it is the local optimum, the obtained solution is not the global optimum. In order to make the particles escape the local optimum and improve the population diversity, Levy flight is carried out to update the position of the particles. The adaptive adjustment strategy is written as

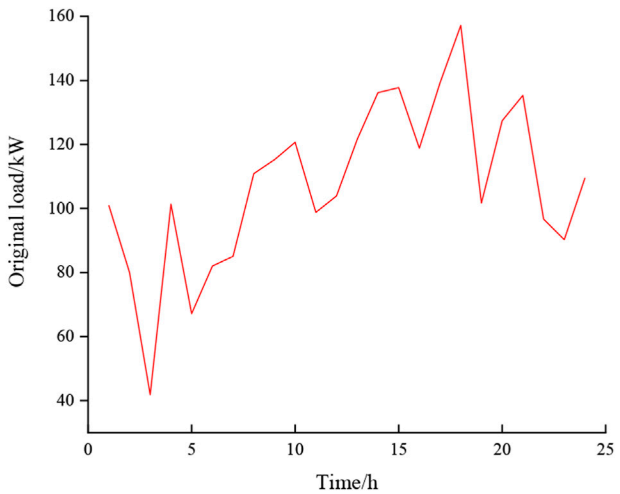

FIGURE 4 | Curve of the original daily load.

f_i^k is the fitness value of particle i in the kth iteration, and $f_{avg}^k = \frac{1}{k}\sum_{i=1}^k f_i^k$ is the average fitness value of PSO. If $f_i^k < f_{avg}^k$, the average fitness is updated; If $f_i^k > f_{avg}^k$, Levy flight is carried out according to **Eq. 21**.

Random Inertia Weight

In the PSO algorithm, a large value of inertia weight can be conducive to more extensive search, and a small inertia weight can improve the accurate local search ability of the algorithm. Therefore, the value of the inertia weight is very important. Based on this, a non-linear decreasing inertia weight with randomness is proposed. The inertia weight is as follows:

$$w = \frac{1}{k+1} * rand\,() * (w_{\max} - w_{\min}), \tag{25}$$

where k represents the current number of iterations; $rand\,()$ is a random number in the interval 0–1; and $w_{\max}$ and $w_{\min}$ represent the maximum and minimum inertia weights, respectively.

Simulated Annealing Algorithm

Aiming at the problem that PSO is easy to fall into local optimum, the idea of simulated annealing (SA) is introduced in PSO to improve PSO by using the characteristic that SA can accept inferior solutions under a certain probability.

The operation steps of simulated annealing are as follows:

1) The solution optimized by PSO is used as the initial solution to determine the initial annealing temperature;
2) Calculate the fitness function difference between the new solution and the old solution: $\Delta f = f(Y') - f(Y)$, and judge whether to accept the new solution according to the Metropolis criterion: $\min\{1, \exp(-(\Delta f/T)\}) > rand\,()$;
3) Calculate the annealing temperature according to **Eq. (26)**:

$$T = CT. \tag{26}$$

4) If the convergence criterion is reached, the final accepted state is output, otherwise turn to step 2.

Through the research of a PSO improvement strategy, when the next position of the particle is better than the current position, the particle moves to the next position. Instead, particles move with the probability controlled by temperature instead of directly moving to the next position. When the temperature drops slowly enough, the algorithm will not easily jump out of the "promising" search area. This way can enhance the local search ability of the PSO.

CALCULATION EXAMPLE ANALYSIS

Simulation Parameter Setting

Taking a microgrid as an example for simulation analysis, the scale of EVs in the planning area is 600, and 50 EVs do not support V2G; the scheduling period ranges from 0 to 24 points. The simulation stepΔt= 1 h.

The typical daily electricity load of the grid is shown in **Figure 4**.

In this study, load scheduling is dispatched under the condition of the TOU price. TOU price data obtained through **Eq. 4** are shown in **Table 1**.

In order to illustrate the effectiveness of IPSO in solving the economic dispatching of the microgrid, the solution results will be compared with those of standard PSO and adaptive particle swarm optimization (APSO). The specific parameter settings are as follows:

The maximum iteration times of each algorithm were set to 1,000 times. The population number was 100; $w_{\max}$ and $w_{\min}$ are set to 0.9 and 0.4, respectively; and the learning factor $c_1 = c_2 =$ 1.6 for PSO, APSO, and IPSO.

Analysis of Simulation Results.

The 1-day charging load demand of a single EV is obtained by Monte Carlo simulation, and the total charging load demand of 600 EV clusters is superimposed with the basic load to form the 1-day total load demand. We took the objective

TABLE 1 | Time-of-use electricity price.

Time	Price (¥)	Time	Price (¥)
1	0.65	13	0.75
2	0.54	14	0.83
3	0.35	15	0.83
4	0.65	16	0.74
5	0.48	17	0.84
6	0.56	18	0.93
7	0.57	19	0.65
8	0.70	20	0.78
9	0.72	21	0.82
10	0.75	22	0.63
11	0.64	23	0.60
12	0.66	24	0.69

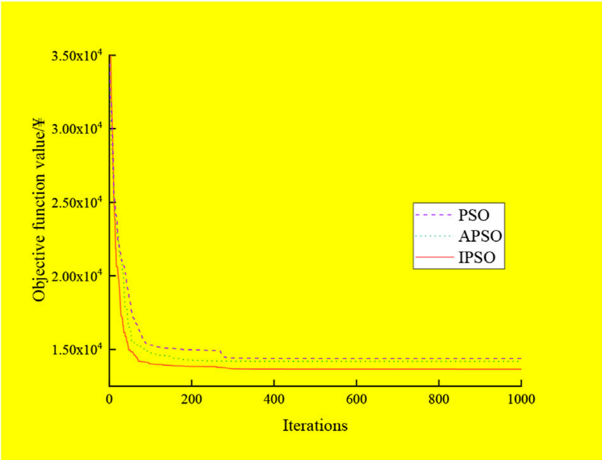

FIGURE 5 | Convergence curve of the objective function value.

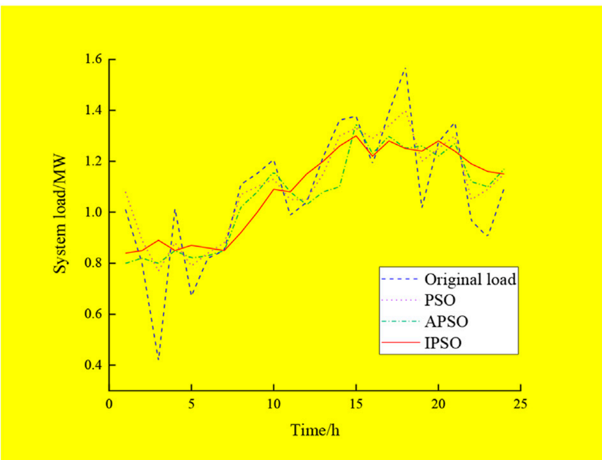

FIGURE 6 | Curve of the original and optimized daily load.

TABLE 2 | Load optimized value.

Method	Peak (kW)	Valley (kW)	Load factor (%)
Original load	157.16	41.86	68.39
PSO	1,492.36	771.28	73.65
APSO	1,352.22	800.95	78.85
IHPSO	1,301.78	841.16	83.28

function f as the optimization objective for scheduling. The convergence curve of the average results of the three algorithms after running independently for 10 times is shown in **Figure 5**.

The load curve optimized by the three methods and the original load curve are shown in **Figure 6**.

The load curve optimization values of the three methods and the objective function optimization values are shown in **Table 2** and **Table 3**.

It can be seen from **Figure 5** that the objective function value of PSO in 280 generations is stable at 14,385.39 ¥, and the algebra of APSO converging to this value is generation 163. When it is stable, the objective function value is 14,186.32, and the cost is reduced by 199.07 ¥/day. In addition, according to the data in **Table 2** and **Table 3**, the load rate of APSO is 5.2% higher than that of PSO and the load mean square deviation is 4.87% lower than that of PSO and 23.55% lower than the peak valley difference of PSO, indicating that APSO is conducive to the safe and stable operation of the power grid and reducing cost. It can be seen from **Figure 5** and **Figure 6** that IPSO performs better, and it can converge to the optimal value of APSO in generation 80. Its final objective function value is 13,654.27 ¥, the cost is 532.05 ¥/day lower than that of APSO, and the effect of peak cutting and valley filling is more obvious. Meanwhile, according to the data in **Table 2** and **Table 3**, the load rate is 4.43% higher than that of APSO, the load mean square deviation is 8.08% lower than that of APSO, and the peak valley difference is 16.44% better than that of APSO. It shows that the IPSO algorithm has strong optimization ability for multi-constraint, strong coupling, and high-dimensional scheduling problems of the microgrid, and its convergence is better than that of other algorithms, so it is more suitable for the scheduling problems of the microgrid.

The numerical example shows that EVs can participate in the peak shaving and valley filling of the power grid as a flexible energy storage device on the premise of ensuring the regular vehicle demand of vehicle owners. The scheduling model based on IPSO can well enable family EVs to participate in the interaction of the power grid, actively respond to the price incentive on the power grid side, and achieve the purpose of optimizing user costs and power energy. At the same time, the example results also verify that the IPSO algorithm scheduling not only saves the economic costs of users but also can indirectly reduce the peak valley difference of the load curve, plays a better role in peak shifting and valley filling, and can effectively maintain the stability of the power grid.

TABLE 3 | Optimized value of each objective function.

Method	Objective function value (¥)	Load mean square error (kW)	Peak-valley difference (kW)
PSO	14,385.39	7,773.83	721.08
APSO	14,186.32	7,395.63	551.27
IHPSO	13,654.27	6,797.83	460.62

CONCLUSION

Aiming at the problems of large load fluctuations and high user costs caused by a large number of EVs connected to the grid, a multi-objective comprehensive charging/discharging scheduling strategy for EVs based on IPSO is proposed in this study. The strategy uses a multi-objective control scheme to simulate a typical power grid and carries on the optimization with the IPSO algorithm. The following conclusion is obtained by analyzing the results of the simulation:

1) The IPSO algorithm proposed in this study has a better search ability than the standard PSO algorithm and the APSO algorithm. This method avoids premature convergence, and the optimization iteration task is completed better.
2) This method has a good response on the price incentives on the grid side and reduces the cost of EVs for users. Meanwhile, the example also shows that the model has a good effect on the load curve.
3) Taking the comprehensive optimization of load mean square deviation, peak-valley difference, and user economic cost as the overall objective function of the scheduling model, the objective function of the scheduling model is no longer single, which is beneficial to take into account the needs of various aspects. In addition, the even–odd license plate method is considered to improve the comprehensive performance of the scheduling policy.

DATA AVAILABILITY STATEMENT

The original contributions presented in the study are included in the article/Supplementary Material; further inquiries can be directed to the corresponding author.

AUTHOR CONTRIBUTIONS

BF: conceptualization, software, and methodology. BL: data curation and writing–original draft preparation. XL: visualization and investigation. YJ: writing—review and editing. WX: supervision. YL: software and validation.

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Conflict of Interest: YJ was employed by the company Hunan Creator Information Technologies Co., Ltd.

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