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Charge and discharge scheduling method for large-scale electric vehicles in V2G mode via MLGCSO

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This paper addresses the challenge of charging and discharging scheduling for large-scale electric vehicles (EVs) in the Vehicle-to-Grid (V2G) mode by proposing a user-oriented scheduling algorithm. First, a large-scale EV charging and discharging scheduling model grounded in the V2G mode is developed, where the objective function mainly focuses on the load variance at the user side and the charging and discharging costs for EV owners, and constraints such as the available time of EVs, charging and discharging power limits, available state of charge values, and upper and lower bounds of real-time prices are incorporated to make the model more applicable to practical engineering scenarios. Based on this model, a multi-level grouping based competitive swarm optimizer (MLGCSO) is put forward. Compared with traditional methods, the diversity and convergence of particle swarm learning are enhanced, and the optimization performance is improved. Simulation results indicate that when compared with three state-of-the-art optimizers, the optimization accuracy of the proposed algorithm is increased by at least 34% and the total cost is reduced by 3.14% and 1.62% respectively, demonstrating that the MLGCSO exhibits high optimization performance and remarkable optimization effects.

Keywords Electric vehicle, V2G, User side, Competitive group optimization algorithm

V2G technology enables bidirectional interaction between electric vehicles (EVs) and the power grid, facilitating energy scheduling and conservation through the exchange of information and electricity between the two[1–4]. In V2G mode, EVs can feed the stored energy in their batteries back to the grid, contributing to peak shaving and valley filling, thereby enhancing overall power utilization efficiency. However, in the car-grid interaction environment, the charging and discharging of EVs introduce fluctuations in grid load, potentially affecting the stability of the power system[5,6]. To mitigate these challenges, intelligent charging scheduling models are typically designed to minimize load fluctuations, reduce grid stress, and lower user costs. However, the current large-scale, uncoordinated charging behavior of EVs leads to increased peak loads, compromising the safety, stability, and economic efficiency of power grid operations. Moreover, existing scheduling algorithms suffer from limitations such as low optimization accuracy and delayed response, making them inadequate for real-world applications[7,8]. Therefore, this paper focuses on the optimization of large-scale EV charging and discharging scheduling in V2G mode to address these critical issues effectively.

At present, the research on charge and discharge scheduling is divided into two categories: user-side scheduling and power-grid side scheduling. Starting from the power grid side, a real-time scheduling strategy of electric vehicles combined with the power grid model was proposed in[9] to achieve the orderly control of large-scale electric vehicles. The existing optimization work in the V2G system was analyzed in[10], and the effectiveness of the artificial intelligence-driven algorithm in optimizing V2G operation was proven. However, the owner's electricity cost was not considered from the user-side perspective. A two-stage optimal scheduling strategy with game decision, based on the microgrid with EV participation in V2G mode, was proposed in[11], taking into account the load fluctuation of EV and the operating cost of the microgrid. Nevertheless, numerous requirements and constraints on the grid side are imposed by the above-mentioned method, and the analysis and utilization of users' charging behaviors and habits are lacked. As a result, the user benefit is made low, and the needs of the EV charging and discharging scheduling system in V2G mode cannot be met.

In response to the above problems, improvements have been made by a large number of scholars in aspects such as enhancing car-owner satisfaction, controlling voltage and current, and reducing the peak valley difference of the power grid. An optimal bidding and coordination strategy was established in[12], which takes into account the orderly charging and discharging behavior of electric vehicles and the overall satisfaction of the owners after

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electric vehicles are connected to the new energy microgrid, thus achieving a win–win situation between the owners and the microgrid. A novel bidirectional V2G scheduling application program was proposed in[13] from both the grid side and the user side. However, when the V2G control strategy on the grid side is considered, the total power constraint of the actual line is not taken into account. When the V2G control strategy on the user side is considered, the influence of the actual spatial distribution on the user distribution of electric vehicles is not considered. In[14], control strategies for electric vehicles were carried out using multiple objective functions from the perspectives of both the power grid side and the user side. This not only takes into account the cost of users but also significantly improves the peak valley difference on the power grid side. However, in the process of weighting multiple objective functions to the total objective function, the best value of the weight coefficient is difficult to obtain, resulting in the optimization on both sides being difficult to achieve the expected effect. Although the demand balance on both sides of the grid and users is considered by the above-mentioned method, there are still some problems such as the emergence of new load peaks, poor effect of peak cutting and valley filling, and low user participation.

Aiming at the above requirements and problems, this paper proposes a balanced charging and discharging scheduling algorithm for large-scale electric vehicles. The innovations are as follows:

(1) The constructed mathematical model is more suitable for the background of flexible load scheduling of large-scale electric vehicles. Compared with[13] and[14], the operating cost index and user evaluation index are added, and load balance constraints are considered.
(2) A multi-Level Grouping based Competitive Swarm Optimizer (MLGCSO) is proposed to ensure the diversity and convergence of particle swarm learning through dynamic grouping of particle swarm. It can effectively solve the optimization problem of charging and discharging scheduling for large-scale electric vehicles, and the optimization accuracy and stability are higher than those in the[15–18].

The chapter arrangement of this paper is as follows: the first chapter builds the optimization mathematical model of scheduling problem, the second chapter designs the optimization algorithm to solve the optimization model, the third chapter conducts simulation experiments to verify the effectiveness and efficiency of the MLGCSO, and the fourth chapter summarizes the full text.

Model of charging and discharging scheduling optimization for large-scale electric vehicles

The application of V2G technology varies significantly across different geographic regions and electricity market environments. In a fixed time-of-use pricing environment, vehicle owners can earn price difference profits by charging during off-peak periods and discharging during peak periods. In a dynamic time-of-use pricing mechanism, the V2G system must have a higher market responsiveness to adjust charging and discharging behavior in real time according to price fluctuations. In regions with a large peak-to-valley price difference, V2G technology can provide significant price difference profits for users while effectively balancing the grid load and alleviating peak demand pressure. In markets with a smaller peak-to-valley price difference, the economic appeal of V2G is weaker, and its widespread adoption relies more on policy subsidies or grid stability needs. Furthermore, in urban areas with high electricity demand and a large load peak-to-valley difference, V2G helps with peak shaving and valley filling, reducing grid peak loads. In underdeveloped areas, although infrastructure may be weaker, V2G can serve as an emergency power source, enhancing the reliability of electricity supply. In regions with a high proportion of renewable energy, V2G technology balances electricity supply and demand by charging during periods of surplus electricity and discharging during shortages. This approach effectively enhances the utilization of clean energy. Therefore, by customizing V2G application plans according to local electricity pricing mechanisms and peak to valley load fluctuations, the value of this technology can be maximized in different market environments.

Problem description

From the user perspective, optimizing the large-scale scheduling of electric vehicle charging and discharging is crucial for ensuring efficiency, cost-effectiveness, and grid stability. Given the increasing complexity of the optimization process as the number of EVs grows, the method proposed in this paper is specifically designed to enhance applicability and computational efficiency in large-scale EV scenarios. By focusing on scalability and real-world feasibility, this approach aims to provide a practical and effective solution for managing EV charging and discharging at scale. Suppose there are m centralized charging stations in the area, each equipped with k energy storage units and e charging points. Each charging point can supply up to n_{max} electric vehicles. There are approximately n electric vehicles in the area, where $n \gg e \times n_{max}$. Assume all charging points and electric vehicles are homogeneous. The rated charging time for electric vehicles is T, and the battery capacity is Q. Let the number of charging vehicles at the charging station be n_1 vehicles, where $n_1 \geq e \times n_{max}$. This paper achieves large-scale electric vehicle charging and discharging scheduling by controlling the power of charging stations, with a focus on user-side optimization.

Optimization objective function
(1) Minimizing discharge costs
To achieve economic benefits for electric vehicle users participating in V2G services, a charging and discharging control strategy for electric vehicles involved in V2G should be formulated. Electric vehicles participating in V2G perform charging and discharging operations during specific time periods each day, choosing only one mode (charging or discharging) per session, which does not significantly impact the battery life. Based on time-

of-use pricing, the objective function for minimizing the charging and discharging costs for vehicle owners is as follows:

$$f_1 = \min \sum_{t=1}^{m} \sum_{i=1}^{n} (s_t^c P_{it} p_{ct} E_c \Delta t - s_t^d P_{it} p_{dt} \Delta t / E_d + C_{it}) \tag{1}$$

where, s_t^c and s_t^d represent the charging and discharging parameters, respectively. During charging, $s_t^c = 1$ and $s_t^d = 0$; during discharging, $s_t^c = 0$ and $s_t^d = 1$; when neither charging nor discharging, $s_t^c = 0$ and $s_t^d = 0$. p_{ct} and p_{dt} are the charging and discharging electricity prices for time period t, respectively. Δt is the duration of the unit control time period. E_c and E_d represent the charging and discharging efficiencies of the on-board battery. C_{it} is the cost associated with battery degradation due to discharging behavior. P_{it} is the charging or discharging power of the vehicle.

(2) Minimum charging waiting time
In charging station operations, minimizing charging waiting time is a key goal for optimizing station utilization. Extended wait times not only affect user experience but may also lead to inefficient use of charging facilities and resource wastage. Therefore, minimizing charging waiting time is chosen as an objective function, specifically:

$$\min f_2 = \min \sum_{i=1}^{n} \max (0, t_{\text{start},i} - t_{\text{get},i}) \tag{2}$$

where, $t_{\text{start},i}$ and $t_{\text{get},i}$ represent the start time of charging and the arrival time at the charging station for vehicle *i* respectively.

(3) Maximizing state of charge (SOC)
During the period when an electric vehicle is connected to and then disconnected from the grid, the vehicle is utilized as a mobile energy storage device for microgrid scheduling. When participating in V2G discharging, battery degradation is considered. After the vehicle's participation in scheduling ends, it is required to achieve the desired State of Charge (SOC) value before disconnection to ensure sufficient energy for daily travel tasks. Therefore, the objective function for maximizing the SOC after charging and discharging is expressed as follows:

$$\max f_2 = \sum_{i=1}^{n} \left[S_{0i} + 1/4 \sum_{t=1}^{m} (P_{it}/Q_i) \right] \tag{3}$$

where S_{0i} denotes the initial SOC of vehicle *i*, Q_i represents the battery capacity of vehicle *i*.

(4) Maximizing user electricity cost savings
Based on real-time fluctuations in electricity prices, the charging and discharging behaviors of electric vehicles connected to the grid yield economic gains for users through price differentials. The objective function for maximizing the economic benefits of electric vehicles participating in grid peak and off-peak period charging and discharging is formulated as follows:

$$f_3 = \max \sum_{i=1}^{n} (D_{it} - l_{it} - C_{it}) \tag{4}$$

where $D_{it} = p_t \times p_{it}/P_t$, represents the revenue from discharging for vehicle *i* at time *t*, with p_t being the market standard price at time *t* and p_{it} the exchange power between vehicle *i* and the grid. $l_{it} = p_t \times p_{it} \times P_t$, represents the charging cost for vehicle *i* at time *t*. C_{it} is the cost associated with battery degradation. E_v denotes the exchanged energy of the vehicle participating in V2G.

Constraints
(1) Electric vehicle availability constraint
As transportation tools, electric vehicles meet travel needs, but they are not always connected to the grid and do not participate in V2G charging and discharging when disconnected. Therefore, the acceptable scheduling time range for electric vehicles is given by:

$$t_{in}^i \leq t^i \leq t_{out}^i \tag{5}$$

where t^i represents the time available for scheduling for vehicle *i* during orderly charging and discharging.

(2) Charging and discharging power
To ensure that the charging and discharging power remains within a normal range and to maximize user discharge revenue, while considering that exchange power is not continuously adjustable, the range of charging and discharging power is specified as:

$$-P_d^{\max} \leq P_{it} \leq P_c^{\max} \tag{6}$$

where $P_c^{\max}$ is the maximum charging power of the vehicle, $P_d^{\max}$ is the maximum discharging power of the vehicle.

(3) Available SOC constraint
To extend the lifespan of the electric vehicle battery, it is necessary to ensure that the SOC remains within a safe range. This imposes constraints on the maximum and minimum charge levels of the battery, as follows:

$$S_{\min} \leq S_{it} \leq S_{\max} \tag{7}$$

where S_{it} represents the SOC of vehicle i at time t, $S_{\max}$ and $S_{\min}$ are the maximum and minimum safe operational limits of the battery, respectively.

(4) Real-time electricity price bound
Time-of-use pricing better leverages the economic incentives of electricity pricing, effectively reducing peak-to-valley ratios, lowering grid generation costs, and improving the overall economic efficiency of the power system. Considering the operational costs of agents and the financial capacity of users, the dynamic range of charging and discharging electricity prices is set as:

$$V_t' \leq V_t \leq V_t'' \tag{8}$$

where V_t' represents the minimum electricity price at time t, which should be lower than the average residential electricity price, V_t'' represents the maximum electricity price at time t.

(5) Depth of discharge safety constraint
The depth of discharge (DOD) is an important factor affecting battery lifespan and is usually adjusted dynamically according to the battery's health condition to avoid irreversible damage from excessive discharge, thus protecting the interests of electric vehicle owners participating in the scheduling.

$$0 \leq D_{DOD} \leq D_{DOD,\max} \tag{9}$$

where: D_{DOD} is the depth of discharge, $D_{DOD,\max}$ is the maximum allowable depth of discharge.

(6) Charging and discharging electric vehicle quantity constraint
Electric vehicles can only charge or discharge at the same time, so during the scheduling process, the sum of the number of electric vehicles charging and discharging at any given moment cannot exceed the total number of electric vehicles.

$$n_{charge}(t) + n_{discharge}(t) \leq n \tag{10}$$

where: $n_{charge}(t)$ and $n_{discharge}(t)$ represent the number of electric vehicles charging and discharging at time t respectively.

Overview of the optimization model

As the number of electric vehicles increases, the optimization problem's dimension grows exponentially, significantly complicating the process. The vast solution space intensifies the global search burden on the algorithm, while blurred gradient information in high-dimensional spaces slows convergence and complicates the search for the global optimum. To address these challenges in ensuring network stability and minimizing charging or discharging costs for large-scale electric vehicles, this paper proposes a multi-level grouping and dynamic grading mechanism in the algorithm design. The overall objective function J is expressed as:

$$J = \min(\lambda_1 f_1 + \lambda_2 f_2 + \lambda_3 f_3 + \lambda_4 f_4)$$

$$\text{S.T.} \begin{cases} t_{in}^i \leq t^i \leq t_{out}^i \\ -P_d^{\max} \leq P_{it} \leq P_c^{\max} \\ S_{\min} \leq S_{it} \leq S_{\max} \\ V_t' \leq V_t \leq V_t'' \\ 0 \leq D_{DOD} \leq D_{DOD,\max} \\ n_{charge}(t) + n_{discharge}(t) \leq n \end{cases} \tag{11}$$

where λ_1, λ_2, λ_3 and λ_4 are the weight coefficients for each objective function. To better evaluate the effectiveness of different schemes and make more informed decisions, the importance of each objective model is considered by assigning weights to each objective. In this study, the weights are set as $\lambda_1 = 0.6$, $\lambda_2 = 0.005$, $\lambda_3 = 0.0008$ $\lambda_3 = 0.07$, to optimize both the demand side and the supply side simultaneously.

Scheduling method based on MLGCSO
Standard CSO algorithm

The Competitive Swarm Optimizer (CSO)[15] is an evolutionary computation method derived from the Particle Swarm Optimization (PSO) algorithm[15]. It enhances PSO's performance by introducing a competitive mechanism that eliminates weaker particles, guiding the population toward the optimal solution, accelerating convergence,

and improving global search capability. As a result, CSO has become a widely used algorithm framework for large-scale optimization problems. Several notable CSO variants exist, including two-particle grouping (LLSO)[18], three-particle grouping (MCSO)[16], and multi-level structures with two or three layers (TPLSO)[17]. However, due to the fixed size of the fundamental evolutionary unit, particle swarm diversity tends to decline in the later stages of optimization. This reduction in diversity leads to instability in solution performance when dealing with complex optimization problems. Consequently, CSO and its variants struggle to effectively address the large-scale charging and discharging scheduling optimization problem studied in this paper.

Proposed MLGCSO

In the framework of CSO algorithm, a MLGCSO algorithm is designed according to the existing problems of the above algorithms. The following is the algorithm flow.

In the first stage, through particle coding, a complete scheduling scheme is transformed into particle coding, and particle swarm containing particles is randomly generated (that is, several random scheduling schemes are generated), and then sorted according to the particle fitness value, which is divided into three groups according to the Level of Level-1, Level-2 and Level-3.

In the second stage, the Level-1 group random is divided into several four-particle units, the Level-2 group random is divided into several three-particle units, and the Level-3 group random is divided into several two-particle units.

In the third stage, the competition and learning are carried out in each basic unit of each group. The particle with the least fitness is denoted as particle1, and then sorted in order. The particle marked as 1 retains its own information and directly enters the next iteration. The evolution formula of updating its own position and speed is

$$V_l^{k+1} = R_1 V_l^k + R_2(X_{w1}^k - X_l^k) + \cdots + \phi(\overline{X}^k - X_l^k) \tag{12}$$

$$X_l^{k+1} = X_l^k + V_l^{k+1} \tag{13}$$

where V represents the velocity of a particle, X represents the position of a particle, l denotes the losing particle when comparing fitness values pairwise, w denotes the winning particle, k represents the iteration count, $\overline{X}$ denotes the average position of the swarm particles, and ϕ represents the learning rate.

The above steps are repeated until the maximum number of iterations is reached, and then the particle with the lowest fitness value is output and decoded into the EV charge–discharge scheduling scheme. The principle of the algorithm is shown in Fig. 1, and the pseudo-code is shown in algorithm 1, in which the three colors in Phase I represent different levels respectively. In Phase III, Level-1 records particles as particles 1, 2, 3 and 4 according to their fitness ability, among which the lowest fitness value is recorded as particle 1. The particle with the highest fitness value is denoted as particle 4; the particles are denoted by Level-2 as L, R and W according to their fitness value, where L represents the winner particle, W represents the loser particle, and R represents the runner-up; the particles with the smaller fitness value are denoted by Level-3 as the winner L, and the particles with the larger fitness value are denoted as the loser W.
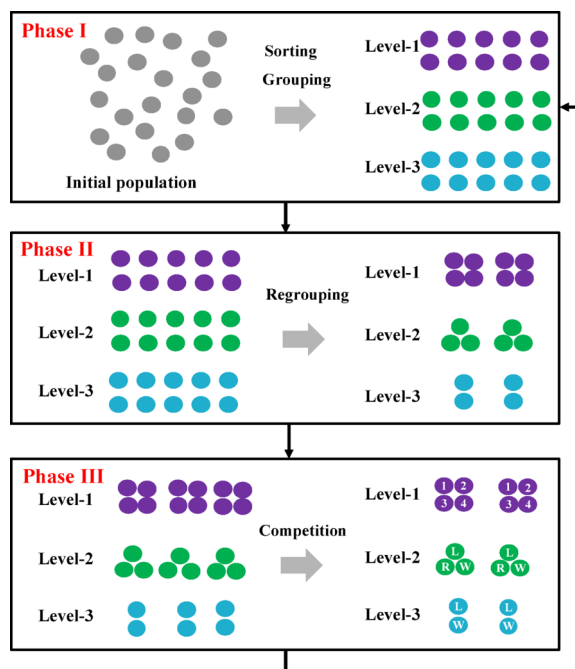

Fig. 1. Schematic diagram of MLGCSO algorithm.

Compared with the basic CSO algorithm, the algorithm has the following three improvements:

(1) To accommodate the scheduling requirements of large-scale electric vehicle fleets, this paper divides a day into 12 time slots and uses the charging and discharging power of each electric vehicle in each time slot as decision variables for particle encoding. This encoding method allows for a more precise reflection of the charging and discharging behavior of large-scale electric vehicle fleets.

(2) The MLGCSO algorithm employs multi-level dynamic grouping to divide the particle swarm into different levels and subgroups. Particles are ranked and grouped based on their fitness values, which helps maintain both the diversity and convergence of the swarm's learning process. This approach is especially suitable for solving the complex optimization problem of charging and discharging scheduling for large-scale electric vehicle fleets.

(3) At the highest level, for high-quality particles, a four-particle grouping is used, with greater competition, ensuring the highest learning effectiveness and maximizing the potential of high-level particles. At lower levels, where particle quality is lower, the scale of the basic units is reduced to avoid waste of computational resources.

In the MLGCSO algorithm, when there are no redundant particles, for every 9 particles, there are 6 instances of competitive learning and one cluster fitness calculation. Let the problem dimension be D. The algorithm's time complexity is given by:

$$O(NP) + O((2*NP/3)*D) \tag{14}$$

By analyzing the CSO, LLSO, and TPLSO, we observe the following:

$$\begin{cases} O_{CSO} = O(NP) + O(D*NP/2) \\ O_{LLSO} = O(NP + NP\log(NP)) + O(NP*D) \\ O_{TPLSO} = O(NP + NP\log(NP)) + O((7*NP/6)*D) \end{cases} \tag{15}$$

Therefore, the time complexity relationship is:

$$O_{\text{CSO}} < O_{\text{MLGCSO}} < O_{\text{LLSO}} < O_{\text{TPLSO}} \tag{16}$$

This indicates that the time complexity of the MLGCSO algorithm is more efficient than that of the LLSO and TPLSO algorithms, and only slightly higher than the basic CSO algorithm.

Furthermore, the MLGCSO algorithm does not require storing the best positions of the clusters and individuals, so it does not need $O(NP*D)$ space. It only needs to store its own information and that of its competitors. At most, during the third stage in Level-1, it stores the information of three winning particles. Therefore, compared to swarm optimization algorithms that rely on individual best positions, the space complexity of MLGCSO is significantly lower.

Coding mode

The day is divided into 12 segments according to the hour, and the charging and discharging power of every thousand electric vehicles in each period is taken as the decision variable, and the 12 charging and discharging power is taken as the scheduling scheme for particle coding. The particle dimension is set to, the particle size is between 0 and 1, and each code is multiplied by four decimal places when decoding, which is the size of the power exchange between 1000 electric vehicles and the grid during the period.

```
1:      While  fes ≤ FEs  do
2:          Sorting initial population
3:          Grouping initial population
4:          Divide level-1 into 4-particle units
5:          Divide level-2 into 3-particle units
6:          Divide level-3 into 2-particle units
7:          For  i = 1 : (NP/12)  do
8:              Particle-4 learns from particle-3\2\1
9:              based on formula (12)&(13)
10:             Particle-3 learns from particle-2\1
11:             based on formula (12)&(13)
12:             Particle-2 learns from particle-1
13:             based on formula (12)&(13)
14:         End for
15:         For  i = 1 : (NP/9)  do
16:             Particle-3 learns from particle-2
17:             based on formula (12)&(13)
18:             Particle-2 learns from particle-1
19:             based on formula (12)&(13)
20:         End for
21:         For  i = 1 : (NP/3)  do
22:             Particle-2 learns from particle-1
23:             based on formula (12)&(13)
24:             fes+ = 1
25:     End While
```

Algorithm 1. Pseudocode of MLGCSO.

Simulation experiment and analysis
Experimental parameter setting

In this paper, an example of a microgrid in Qingdao is selected for simulation analysis. In the simulation environment, the IEEE33-node distribution network test system is taken as an example. The number of electric vehicles connected to the microgrid system is 500, the maximum charging and discharging power of electric vehicles is 5 kW, the charging and discharging efficiency is 0.9, and the upper and lower limits of the electric vehicle battery charge state are 0.2 and 0.9, respectively. Based on the IEEE33 node distribution network, 740 vehicles are the most appropriate. However, a certain load margin may still be needed to be reserved for the network to cope with other possible load changes or unexpected situations. Therefore, it is reasonable to maintain the total power of electric vehicles at 70% of the network base load, so the number of electric vehicles is finally designed to be 500. The parameters of electric vehicles are shown in Table 1. Tou price is divided into peak, valley and normal period, as shown in Table 2. In the MLGCSO algorithm, the particle swarm size, the maximum number of iterations is 5000, and the learning rate is 0.05. Compared with the CSO, LLSO and MCSO algorithms, the particle swarm size and learning rate are the same. The hardware conditions are Intel(R)Core (TM)i5-13500H and Windows10 operating system. The simulation software is MATLAB R2019b.

Parameter	Size
Total number of electric vehicles (units)	500
Battery capacity (kW·h)	80
Charging power (kW)	8
Power consumption per 100 km (kW·h)	18
Discharge power (kW)	5
Charging efficiency	90%
Average travel speed (km·h^{-1})	80

Table 1. Parameters of electric vehicles.

Period	characteristics	Purchasing price/RMB	Selling price/RMB
08:00–12:00 14:00–16:00	Peak hour	1.18	1
04:00–08:00 12:00–14:00 16:00–21:00	Mean time	0.68	0.55
00:00–04:00 21:00–23:00	Valley interval	0.35	0.28

Table 2. TOU electricity price.

Period (h)	Power (MW)	Period (h)	Power (MW)
2	1340	14	4358
4	1063	16	4609
6	1311	18	5792
8	3179	20	6698
10	5513	22	5367
12	4980	24	2649

Table 3. Time segment load value.
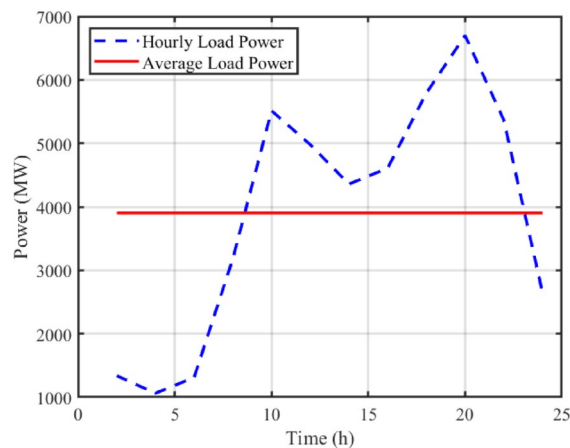
Fig. 2. Daily load characteristic curve.

Taking the typical daily load curve in summer in this region as the base load, the daily load power value is given in Table 3, and the daily load value is recorded every 2 h.

The characteristic curve is derived from the region's annual typical summer daily load, as depicted in Fig. 2. The horizontal line indicates the region's average daily load power, approximately 3900 MW, while the blue dashed line represents the variation in load power across different periods. By examining the load curve, it is evident that the daily load valley occurs between 02:00 and 06:00, and the daily peak loads are from 08:00 to 12:00 and 18:00 to 22:00. If the orderly charging and discharging of electric vehicle owners can be scientifically and effectively regulated, the effect of reducing peak loads and filling valley loads can be achieved. This will reduce the load peak-to-valley difference and save users' charging and discharging costs.

Algorithm validity verification

MLGCSO was used for solving and conducting 100 repeated experiments, a large-scale electric vehicle charging and discharging scheduling plan was obtained. The load distribution curves under the original, CSO, LLSO, TPLSO, and MLGCSO scheduling plans are shown in Fig. 3. The original load curve shows a low load period between 02:00 and 06:00, with two load peaks occurring between 08:00–12:00 and 18:00–22:00. The scheduling strategy optimized by the CSO algorithm, while weakening the original load pattern, results in a new peak load between 12:00 and 16:00. The scheduling strategy optimized by the LLSO algorithm is smoother compared to the CSO algorithm, but still exhibits load peaks between 12:00–16:00 and 16:00–20:00. The TPLSO algorithm reduces the load peak-to-valley difference compared to CSO and LLSO, but there is still a load peak between 18:00–22:00. The MLGCSO algorithm designed in this paper significantly reduces the new load peak and load
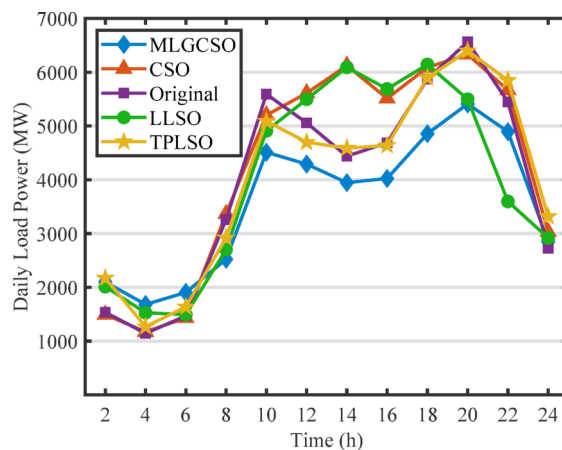
8

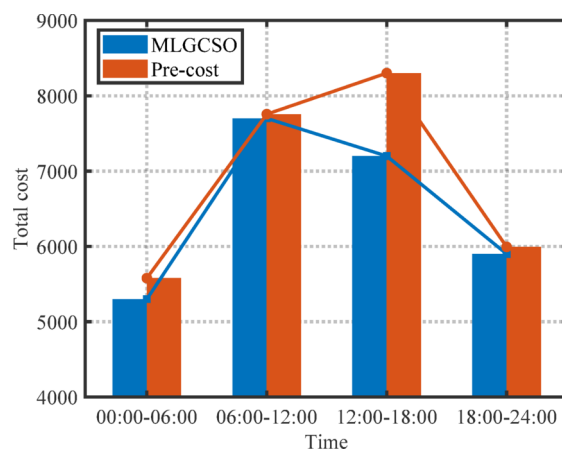**Fig. 3**. Daily load curves under different optimizations.

Fig. 4. Comparison of total operating costs.

peak-to-valley difference. The daily load curve is smoother, offering certain peak-shaving and valley-filling effects while maintaining power grid stability.

The above analysis shows that the charging cost is closely related to the total load curve. The cost analysis was conducted on the scheduling cases before and after the MLGCSO algorithm optimization, with the results shown in Fig. 4. In the original state, the charging cost was 27,630 RMB, and the average daily total cost per vehicle was 27.6 RMB. After optimization, the charging cost decreased to 25,900 RMB, and the average daily total cost per vehicle reduced to 25.9 RMB. The charging cost was reduced by 6.3%, and the average daily total cost per vehicle decreased by 6.2%. These results demonstrate that the proposed MLGCSO algorithm can effectively reduce operational costs and improve user benefits through balanced scheduling.

To further validate the effectiveness of the large-scale electric vehicle charging and discharging scheduling model based on the V2G mode, a residential area in Qingdao was selected as the research subject. The area is divided into three residential districts: District 1 contains 250 electric vehicles and 6 charging piles; District 2 contains 150 electric vehicles and 4 charging piles; District 3 contains 100 electric vehicles and 6 charging piles. The MLGCSO algorithm was applied to solve the objective function, and the resulting optimal charging and discharging load distribution curves for each residential district are shown in Fig. 5. When the charging and discharging load is high, it signifies that more electric vehicles require charging, determining the optimal charging and discharging periods for each area. This approach enables more efficient use of charging facilities, avoiding idle charging piles or queues, while also meeting the grid's high-power demand. Increased electricity generation helps balance the higher charging demand from electric vehicles. In contrast, when the charging and discharging load is low, discharging occurs, releasing stored energy into the grid. This additional power supply aids the grid in regulating and maintaining stable operation.

Algorithm efficiency verification
In order to verify the feasibility of the improved algorithm in this paper, CSO, LLSO, TPLSO and MLGCSO were respectively used to solve the scheduling optimization model, and the results are shown in Fig. 6. The CSO has been iterated 4375 times to reach the optimal, and the convergence speed is slow. The convergence speed
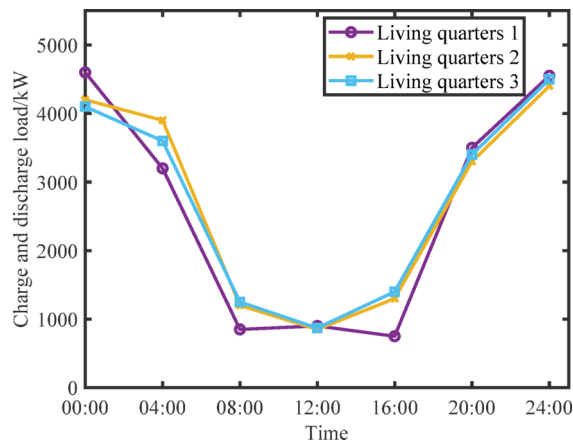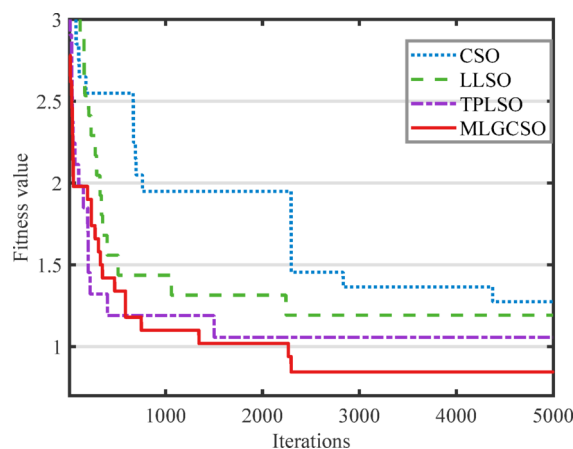
Fig. 5. Optimal charging and discharging load curve.

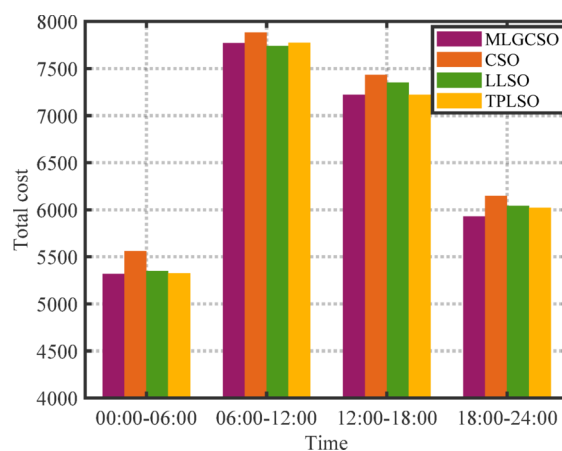**Fig. 6**. Convergence result curve of each algorithm.

Fig. 7. Cost comparison between different algorithms.

of LLSO is obviously faster than that of CSO, and it reaches the optimal after about 2255 iterations. The TPLSO algorithm has fewer iterations, faster convergence speed, and lower particle fitness than the CSO and LLSO algorithms. Compared with the above algorithms, the fitness of the MLGCSO designed in this paper is lower, and the fitness of the CSO, LLSO and TPLSO algorithms is reduced by 0.294, 0.416 and 0.417 respectively, and the optimization accuracy is improved by more than 34%, and the decline is faster in the early optimization stage,

and there is a large gradient transition in the late optimization stage. It shows that the diversity and convergence of the population are always in equilibrium, and the local search ability and global search ability are strong. To sum up, the MLGCSO algorithm used in this paper has high efficiency and better optimization accuracy, and the optimization effect is better in the charging and discharging scheduling problem in this paper.

An analysis of the grid costs for the above-mentioned algorithms is shown in Fig. 7. In all time periods, the optimization cost of the MLGCSO algorithm is lower than that of the CSO, LLSO, and TPLSO algorithms. The total cost is reduced by 2.90%, 0.91%, and 0.39%, respectively. This indicates that the MLGCSO algorithm proposed in this paper offers higher economic efficiency on the user side.

Conclusion

The balanced charging and discharging scheduling strategy for electric vehicles based on V2G technology is proposed and solved using a competitive swarm optimization algorithm with a multi-level grouping mechanism. The charging and discharging strategy is solved in real time under a time-of-use pricing system by the MLGCSO algorithm, ensuring that charging tasks are completed on time while costs for EV owners are effectively reduced. It is indicated by simulations that this method reduces charging and discharging costs for EV owners and mitigates battery degradation. In the next step, more practical constraints will be considered to enhance the practicability of the optimization model.

Data availability

Since the data is provided by China Southern Power Grid Technology Project, there is a confidentiality agreement. If you want to obtain the data, please contact the corresponding author of this article at g1821066087@163.com.

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Author contributions

Songling Pang constructed the model and completed the algorithm research; Kaidi Fan completed the main manuscript text and some basic theoretical research, Meiyi Huocompleted the data analysis and the drawing of tables and graphs, and all authors reviewed the manuscript.

Declarations

Competing interests
The authors declare no competing interests.

Additional information
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