

Research on Electric Vehicle Charging and Discharging Optimization Scheduling based on Improved Sparrow Algorithm

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Abstract: In order to solve the impact of disorderly charging of large-scale electric vehicles on the stability, security and economy of the power grid, a scheduling model was established, which considered the optimization objectives of the distribution network side as the minimum load peaking difference and minimum standard deviation, and the optimization objectives of the user side as the minimum charging cost and maximum user comfort. In order to achieve efficient and fast solution, the Sparrow Search Algorithm (SSA) is improved. In this algorithm, the compound mapping of Logistic-Tent (LT), which combines Logistic chaotic mapping and Tent chaotic mapping, is used to optimize the initial population. Enhance global search capability; The Levy flight strategy is used to improve the follower position update and increase the ability to jump out of the local optimal. In the example analysis, the improved Sparrow algorithm (ISSA), standard SSA, Dung Beetle Optimizer (DBO) and improved Dung Beetle algorithm (IDBO) are used to solve the optimization objectives of orderly charging and discharging of electric vehicles, and the results show that ISSA has higher efficiency and practicability.

Keywords: Electric Vehicle; Orderly Charge and Discharge; Improved Sparrow Algorithm (ISSA); Composite Mapping of Logistic-Tent (LT); Levy Flight Strategy.

1. Introduction

With the intensification of global energy shortage, environmental pollution and driving safety issues, the global automobile industry is shifting to the direction of electrification, intelligence, networking and sharing, and energy saving and emission reduction has become a global trend. In China, actively developing new energy vehicles represented by electric vehicles and phasing out traditional fuel vehicles has become a social consensus and development strategy. However, the charging demand of a large number of electric vehicles may put pressure on the grid and bring new challenges to the stable operation of the power system. Therefore, how to effectively optimize the scheduling of large-scale electric vehicles has become a hot issue that has been paid more and more attention.

In recent years, through the application of efficient control strategies and advanced optimization algorithms, orderly charging of electric vehicles has become an effective strategy in electric vehicle scheduling. Literature [1] established a multi-objective optimization model considering load variance, peaking valley difference and user charging cost in combination with users' travel needs, adopted improved particle swarm optimization algorithm to solve the problem and compared the optimal scheduling results under different electricity pricing systems to achieve the optimization of orderly charging and discharging scheduling for electric vehicles. In literature [2], a simulation model of orderly charge and discharge control was constructed, and on this basis, optimization research was carried out on power distribution and scheduling control strategies to achieve orderly charge and discharge control strategies for electric vehicle energy sharing and more efficient energy management. Literature [3] uses EV network access technology to optimize hierarchical control strategies for target collaborative control at different stages and finally

determine EV charging and discharging power. Literature [4] constructs an optimization model that comprehensively considers minimum distribution network load fluctuation, user cost and aggregator revenue. By using the improved grey Wolf algorithm, the load can be clipped and valley filled and the economic efficiency can be maximized.

The practical application value of heuristic algorithms is becoming more and more prominent, such as typical gray Wolf algorithm, genetic algorithm, moth extinguishing algorithm and so on. In this paper, Sparrow Search Algorithm (SSA) is an innovative swarm intelligence optimization strategy that has been widely concerned by the academic community. At the same time, many researchers have not only deeply explored the principle and application of this algorithm, but also proposed a series of innovative improvement measures to improve the performance and efficiency of the algorithm. Literature [5] uses an initialization method based on the good point set to configure the initial population of the SSA algorithm. Levy flight strategy and Cauchy reverse learning strategy are introduced to effectively enhance the ability of the algorithm to jump out of the local optimal solution. This improvement significantly improves the accuracy of the inversion process, and achieves remarkable optimization results in convergence accuracy and speed. Reference [6] uses an improved infinite folding iterative mapping (ICMIC) method to initialize the population and introduces an adaptive step factor in the position updating process. In addition, the Sine-Cosine Algorithm (SCA) was combined to enhance the ability of the algorithm to escape the local optimal solution, thus improving the overall performance of the algorithm. Literature [7] introduced an oppositional search strategy to configure the initial population of the SSA algorithm to enhance its diversity. Further, by implementing the elite reverse learning strategy, the diversity of the population is effectively improved. In addition, the variation correction of the population is combined with

differential evolution technology, which significantly enhances the performance of SSA algorithm in terms of convergence accuracy and speed.

In this paper, the Sparrow search algorithm is deeply analyzed and improved to enhance its global search ability and convergence rate when dealing with large-scale problems. Taking private electric vehicles as the research focus, Monte Carlo method is used to simulate the large-scale travel mode of electric vehicles. On this basis, a multi-objective optimization model is constructed, which minimizes the peak-valley difference at the grid level and the charging cost at the user level. Finally, the Improved Sparrow Search Algorithm (ISSA) is applied to effectively solve the proposed optimization objective function.

2. Orderly Charging and Discharging of Electric Vehicles

2.1. Rules of Electric Vehicle Travel

Based on the survey and statistical analysis of US traffic travel data (NHTS2009) [8], it is concluded that the daily mileage driven by electric vehicle users approximately meets the lognormal distribution, and its probability density function is as follows:

$$f_D(x) = \frac{1}{x\sigma_D\sqrt{2\pi}} \exp\left[-\frac{(\ln x - \mu_D)^2}{2\sigma_D^2}\right] \quad (1)$$

Where, μ_D is the expected value 3.20, σ_D is the standard deviation 0.88.

Considering the charge-discharge time characteristics of electric vehicles, the basic data of electric vehicles are normalized and fitted using maximum likelihood estimation method. The probability density function is as follows:

$$f_i(x) = \begin{cases} \frac{1}{\sigma_i\sqrt{2\pi}} \exp\left(-\frac{x-\mu_i}{2\sigma_i^2}\right), \mu_i - 12 < x < 24 \\ \frac{1}{\sigma_i\sqrt{2\pi}} \exp\left(-\frac{x+24-\mu_i}{2\sigma_i^2}\right), 0 < x < \mu_i - 12 \end{cases} \quad (2)$$

Where, μ_i is the expected value 17.6, σ_i is the standard deviation 3.4.

2.2. Orderly Charging and Discharging Model of Electric Vehicles

objective function

The formulation of a reasonable charge and discharge strategy can greatly alleviate the problem of centralized load charging and reduce the stability and security caused by large load fluctuations. In this paper, two objective functions considering the collaborative optimization of the grid side and the user side are established. For the power grid side, in order to alleviate the problem of "peak plus peak", the minimum function f_1 of the peak-valley difference of the power grid load is established, as shown in equation (3):

$$\min f_1 = \bar{P}_{load} - \underline{P}_{load} \quad (3)$$

$$\bar{P}_{load} = \max_{1 \leq t \leq 24} (P_{e,t}^{load} + \sum_{n=1}^N P_{n,t}^{EV}) \quad (4)$$

$$\underline{P}_{load} = \min_{1 \leq t \leq 24} (P_{e,t}^{load} + \sum_{n=1}^N P_{n,t}^{EV}) \quad (5)$$

Where, and respectively represent the load peak and valley value when electric vehicles are connected to the power grid; Represents the charge and discharge power of the NTH electric vehicle t .

Whether EV users respond to the orderly charging and discharging policy is particularly important. In order to improve the enthusiasm of users in participating in the policy, this paper establishes the objective function f_2 , which considers the lowest total charging cost on the user side, as shown in equation (6):

$$\min f_2 = \sum_{t=1}^T \left[(P_{CH,t}^{EV} - P_{DC,t}^{EV}) C_{price,t}^{grid} + C_{loss,t} \right] \quad (6)$$

Where, and respectively represent the charging power and discharging power of the electric vehicle at time t ; Represents the time-of-use price of distribution network at time t ; Represents the battery loss cost of electric vehicle at time t .

In this paper, function f_1 and function f_2 are normalized and solved as a single objective function, and the weight coefficients are ω_1 and ω_2 . Different weight coefficients are set to control the proportion of the two optimization objectives, so as to meet the needs of practical engineering applications.

$$\min f = \omega_1 \frac{f_1}{f_{\max,1}} + \omega_2 \frac{f_2}{f_{\max,2}} \quad (7)$$

Constraints

(1) Limit of battery charging state

$$SOC_{\min} \leq SOC_{n,t} \leq SOC_{\max} \quad (8)$$

Where $SOC_{n,t}$ represents the state of charge of the NTH electric vehicle at time t ; $SOC_{\min}$ is the minimum value of the charged state. $SOC_{\max}$ indicates the maximum value of the charged state.

(2) Battery charge state continuity constraints

$$\begin{cases} SOC_{n,t} = SOC_{n,t-1} + \frac{P_{n,t} \eta_{CH} \Delta t}{C^{EV}}, P_{n,t} > 0 \\ SOC_{n,t} = SOC_{n,t-1} + \frac{P_{n,t} \Delta t}{\eta_{DC} C^{EV}}, P_{n,t} < 0 \end{cases} \quad (9)$$

Where, $SOC_{n,t-1}$ is the charge state of the NTH electric vehicle in the $t-1$ period; C^{EV} is the battery capacity of electric vehicles; η_{CH} and η_{DC} are the charging efficiency and discharge efficiency of electric vehicles respectively, and their values in this section are 0.9.

(3) Power constraints of battery charging and discharging

$$\begin{cases} 0 \leq P_{CH,t}^{EV} \leq P_{CH,\max}^{EV} \\ 0 \leq P_{DC,t}^{EV} \leq P_{DC,\max}^{EV} \end{cases} \quad (10)$$

Where, is the upper limit of charging power of electric vehicle; Is the upper limit of discharge power;

(4) Discharge loss constraint

$$\sum_{t=1}^{24} C_{loss,t}^{EV,n} \leq \sum_{t=1}^{24} C_{sell,t}^{EV,n} \quad (11)$$

Where, is the battery loss cost of the NTH electric vehicle

in time period t ; I_n is the income of the n electric vehicle feedback back to the distribution network during t period.

3. Improve Sparrow Algorithm

In the SSA algorithm, the three groups of sparrow, finder, follower and watcher cooperate with each other to complete the whole foraging process. The discoverer has the optimal resources of the population and provides the foraging direction of the population. During each iteration, the discoverer's position update formula is:

$$X_{i,j}^{t+1} = \begin{cases} X_{i,j} \times \exp\left(\frac{-i}{\omega_1 \times N_{\max}}\right), R_2 < ST \\ X_{i,j} + \omega_2 \times L, R_2 \geq ST \end{cases} \quad (12)$$

Where, $X_{i,j}$ represents the information of sparrow i at time $t+1$ in dimension j , $X_{i,j}^t$ represents the information of sparrow i at time t in dimension j , $N_{\max}$ is the maximum number of iterations, ω_1 is the random value between 0 and 1, ω_2 is the random number satisfying the normal distribution, L is the $1 \times d$ vector with all elements being 1, R_2 is the random number between 0 and 1, represents the early warning value at this time. ST is a random number between 0.5 and 1, indicating the safe value at this time.

In foraging, the follower will compete for the food found by the finder. If the follower wins, the ownership of the food belongs to the stalker; if the follower fails, the position is updated according to formula (13).

$$X_{i,j}^t = \begin{cases} \omega_2 \times \exp\left(\frac{X_{\text{worst}} - X_{i,j}^t}{i^2}\right), i > \frac{n}{2} \\ X_p^{t+1} + |X_{i,j} - X_p^{t+1}| \times A^+ \times L, \text{otherwise} \end{cases} \quad (13)$$

Where, X_p is the optimal position explored by the discoverer, X_{worst} is the worst position of the current global, A is a $1 \times d$ matrix, whose elements are all 1, and.

In SSA, the finder performs the task of monitoring the lost area throughout the population, and whenever there is danger, it immediately sends out the danger signal and quickly moves to the safe area, and its position is updated as shown in equation (14):

$$X_{i,j}^{t+1} = \begin{cases} X_{\text{best}}^t + \omega_3 \times |X_{i,j}^t - X_{\text{best}}^t|, f_i > f_g \\ X_{i,j}^t + \omega_4 \times \left(\frac{X_{i,j}^t - X_{\text{worst}}^t}{(f_i - f_w) + \xi}\right), f_i = f_g \end{cases} \quad (14)$$

Where, X_{best} is the global optimal position under the current fitness; ω_3 is a random value obeying the standard normal distribution; $\omega_4 \in [-1, 1]$, f_i represents the current individual fitness value of the sparrow, f_g represents the current globally optimal individual fitness value of the sparrow, and f_w represents the current globally worst individual fitness value of the sparrow.

3.1. Improvement Methods

3.1.1. Logistic Tent Composite Mapping

The traditional algorithm randomly generates the initial

location information of sparrow population at the beginning, which will lead to poor sparrow population diversity, so the target scheme is not good, which affects the iterative performance and accuracy of the algorithm. Logistic chaotic mapping sequence has strong global ergodicity, but poor late depth searching ability. Tent chaotic mapping sequence has strong chaotic disturbance ability. Therefore, this paper proposes a scheme based on Logistic-Tent (LT) composite mapping to improve the sparrow search algorithm to generate the optimal initial population and enhance the global search ability.

$$x_{n+1} = \begin{cases} \left[rx_n(1-x_n) + \frac{(4-r)}{2}x_n \right] \bmod 1, x_n < 0.5 \\ \left[rx_n(1-x_n) + \frac{(4-r)(1-x_n)}{2} \right] \bmod 1, x_n \geq 0.5 \end{cases} \quad (15)$$

Where, x is the system variable and r are the control parameter. When $x \in [0, 1]$, $r \in (0, 3)$.

3.1.2. Levy Flight

Levy flight strategy is a particularly random wandering strategy, and the flight step size follows the heavy tail probability distribution. When short step size is present, local search can be carried out effectively. When there is a long step, it can effectively cross the local area to achieve further global search. In Mantegna algorithm, Levy flight model formula is expressed as:

$$\begin{cases} s = \frac{u}{|v|^{1/\beta}} \\ u \sim N(0, \sigma_u^2), v \sim N(0, \sigma_v^2) \\ \sigma_u = \left\{ \frac{\Gamma(1+\beta) \cdot \sin(\frac{1}{2}\pi\beta)}{\Gamma\left[\frac{1}{2}(1+\beta) \cdot \beta \cdot 2^{\frac{1}{2}(\beta-1)}\right]} \right\}^{\frac{1}{\beta}} \\ \sigma_v = 1 \end{cases} \quad (16)$$

Where, s is the flight path, and u and v are random numbers satisfying the positive distribution; β is the constant between 0 and 2, usually 1.5. In order to further improve the global search iteration capability of SSA, Levy flight strategy is applied to the follower position update formula, and the improved follower update formula is shown as follows:

$$X_{i,j}^{t+1} = \begin{cases} Q \cdot \exp\left(\frac{X_{\text{worst}}^t - X_{i,j}^t}{i^2}\right), i > \frac{n}{2} \\ s \cdot X_p^{t+1} + |X_{i,j}^t - X_p^{t+1}| \cdot s, \text{otherwise} \end{cases} \quad (17)$$

3.1.3. ISSA Algorithm Solution Flow Chart

The SSA algorithm was improved based on the Logistic-Tent composite mapping and Levy flight, and the solution flow chart of the improved Sparrow algorithm (ISSA) was obtained as follows:

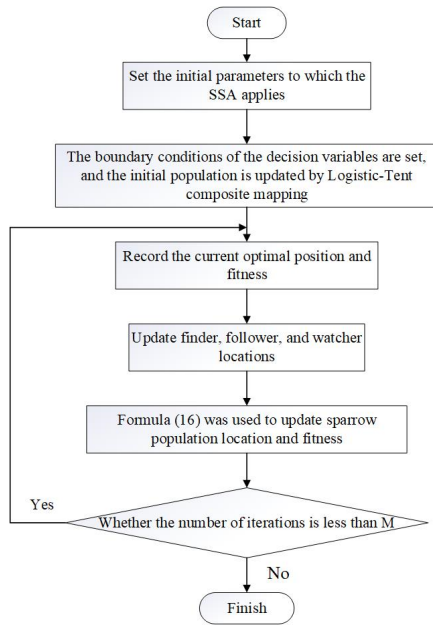


Figure 1. ISSA algorithm solution flow chart

4. Analysis of Examples

Taking a regional distribution network as an example, DBO algorithm, IDBO algorithm, SSA algorithm and ISSA

Table 1. Time-of-use electricity price table

Period type	Period division	Electricity price (Yuan /kw.h)
Valley interval	23:00-7:00	0.369
Mean time segment	7:00-10:00	0.832
Peak hour	10:00-15:00	1.322
Mean time segment	15:00-18:00	0.832
Peak hour	18:00-21:00	1.322
Mean time segment	21:00-23:00	0.832

In this paper, the basic parameters of the three algorithms are set, in which the maximum number of iterations is 500 times, the population size is 50, and the decision is mainly made in the power grid layer, and the user layer is secondary, so the setting value is 0.6 and the value is 0.4. Due to randomness in the solution of large-scale electric vehicle disorderly charging and optimization algorithm, the optimal cost and peak clipping and valley filling value of each solution are greatly different. Therefore, this paper conducts 100 simulations, taking orderly charging load and cost of electric vehicles with practical significance as evaluation indexes, and selects a typical simulation diagram, as shown in Figure 2.

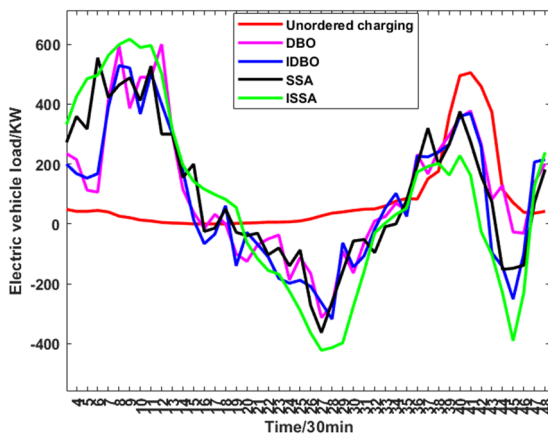


Figure 2. Ordered charging load curve

algorithm are respectively used to realize the orderly charging and discharging strategy of large-scale electric vehicles. In order to show its value in practical engineering application, a number of performance indexes, including peak-valley value, peak-valley difference rate, user charging cost and solving efficiency of the three algorithms are compared and analyzed. The total number of conventional access vehicles in this area is 1000, and the charging mode of electric vehicles follows the conventional constant power charging mode. The charging power and discharge power are both 6kW, the battery capacity of each vehicle is set at 60kW. h, and the fixed energy consumption per 100 kilometers is 15 kW. h. Make sure the battery is fully charged on each charge. The starting time of charging, the daily mileage of the vehicle, and the charging and discharging power are independent random variables. The maximum mileage of the vehicle is set to be 400km, and the mileage of the vehicle is distributed in a lognormal manner. For the driving distance of more than 400km, it will be processed according to 400km. Taking into account the calculation of charging costs for electric vehicle users, refer to the time-of-use price of domestic industrial electricity used by electric vehicle operators to purchase electricity from the electricity wholesale market, and the specific parameters are shown in Table (1).

It can be seen from the load curve in Figure 2 that the peak period of unordered charging load is concentrated from 18:00 to 22:00, and the trough period is mainly concentrated at night. Under the constraint conditions, ISSA algorithm has obviously better effect in the ability to transfer the load of electric vehicles from the peak period to the trough period. The total load curve of large-scale electric vehicles connected to the regional distribution network before and after optimization is shown in Figure 3.

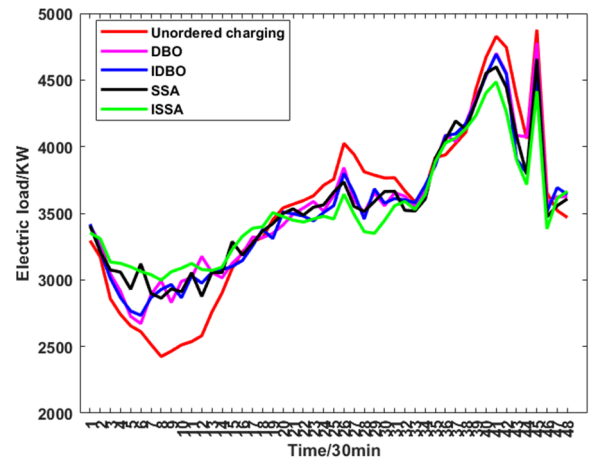


Figure 3. Total load curve of orderly charging

It can be intuitively seen from Figure 3 that DBO algorithm, IDBO algorithm, SSA algorithm and ISSA algorithm all

realize the peak cutting and valley filling of the power grid. However, for the "peak cutting" and "valley filling" segments, ISSA algorithm is superior to the two algorithms compared.

In addition, it is also necessary to compare the peak-valley difference rate and charging cost, and the specific parameters are compared in Table 2.

Table 2. Comparison of system load levels

charge mode	peak load /KW	valley load /KW	difference between peak and valley /KW	Charging fee/Yuan
No sequential charge load	4877	2425	2452	3549
DBO orderly charge and discharge	4779	2672	2107	1026
IDBO orderly charge and discharge	4555	2734	1821	923
SSA orderly charge and discharge	4658	2863	1795	974
ISSA orderly charge and discharge	4486	2998	1488	732

According to the analysis of Table 2, in the case of unordered charging, the peak load of the grid increases by 359 kW compared with the conventional load without EV. If the scale of electric vehicles continues to increase, the grid will cause serious "peak-on-peak" impact. The difference between the peak-valley value of orderly charging and unordered charging is defined as the peak cutting and valley filling value respectively, and the difference between the total charge cost of orderly charging and unordered charging is defined as the cost saving. According to the analysis, in the context of TOU price, the ordered charging using ISSA algorithm can realize peak cutting and valley filling more efficiently and save charging costs.

The speed and accuracy of the optimization algorithm are important bases to measure whether the optimization algorithm is practical. This experiment has been verified by 100 runs, and the most representative iteration diagram is selected. The iterative process of solving the optimization objective function by the three algorithms is shown in Figure 4. As can be seen from Figure 4, ISSA algorithm completed the optimization in the 34th iteration, which has higher optimization accuracy and convergence speed than the comparison algorithm, and has good robustness in the iterative process, which proves the practicability and high efficiency of ISSA algorithm in the application of ordered charging.

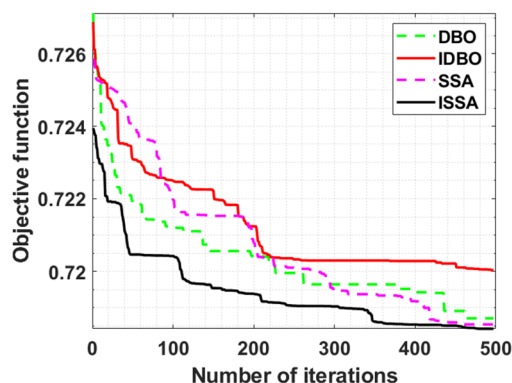


Figure 4. Iteration diagram of comparison algorithm

5. Conclusion

In this paper, an optimization model of EV orderly charging based on the grid layer and secondary to the user layer is established. ISSA algorithm shows its superiority in solving the test function, and is finally applied to the EV orderly charging solution. The simulation results show that large-

scale electric vehicles can achieve the "peaking and valley filling" of the power grid and reduce the charging cost for users after reasonably arranging the charging time. Through comparative experiments, the improved ISSA algorithm has higher optimization accuracy and convergence speed in solving large-scale problems. In the next stage, we will deeply study the application and improvement of ISSA algorithm in solving multi-objective optimization functions, and further enhance the application value of this algorithm in engineering problems.

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