Research on Charging Strategy Optimization of Electric Vehicle based on AGA

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Abstract: Because the charging load of electric vehicles is random in time and space, a large number of disorderly charging of electric vehicles will lead to the peak load of distribution network exceeding the limit of equipment, which will bring adverse effects on the operation of power grid. In order to smooth the daily load curve of distribution network, this paper establishes a solution model of intelligent charging control strategy for large-scale electric vehicle considering the charging demand constraints of electric vehicle users, and uses adaptive genetic algorithm (AGA) to solve the model. Taking IEEE33 bus distribution network as an example, based on Monte Carlo stochastic simulation of large-scale electric vehicle grid-connected scene, the impact of electric vehicle load on distribution network under two control modes of disorderly charging and intelligent charging is studied comparatively, and the effectiveness of this method is verified.

1 INTRODUCTION

Global climate and environmental issues have prompted countries around the world to develop and utilize renewable energy on a large scale as a strategy for energy security. The development of electric vehicles (EVs) is of dual importance in promoting the efficient use of renewable energy and reducing fossil fuel consumption, which has attracted wide attention (ZHANG Wen-liang, WU Bin, LI Wu-feng, et al., 2009).

If large-scale electric vehicles are randomly and disorderly connected to the grid to charge, it will have a significant impact on the scheduling, planning, control and protection of the entire power system. On the time scale, random charging may lead to peak load "bee-on-bee" phenomenon, which exceeds the power supply capacity and affordability of the existing distribution network, thus causing a series of problems such as voltage overshoot, branch overload and so on. On the spatial scale, disorderly decentralized access may lead to three-phase unbalance of distribution network, damage the power quality of the network and increase the power loss and other adverse effects (MA Ling-ling, YANG Jun, FU Cong, et al, 2013; GAO Ci-wei, ZHANG Liang, 2011; KRISTIEN CN, EDWIN H, JOHAN D, 2010). Therefore, the research on charging control strategy aiming at reducing the impact of large-scale electric vehicle access on distribution network has become a hot issue.

Documents (SUN Xiao-ming, WANG Wei, SU Su, et al, 2013; GE Shao-yun, HUANG Liu, LIU Hong, 2012) put forward the method of transferring charging power of EV to daily load trough through the guidance of time-sharing tariff policy. But when large-scale EV is centralized connected to grid or unreasonable design of valley tariff period may lead to new load peaks and new problems. Literature (LUO Zhuo-wei, HU Ze-chun, SONG Yong-hua, et al, 2012) studied the charging control strategy of EV under the mode of switching power, aiming at minimizing the total charging cost and minimizing the fluctuation of the total load curve. However, based on a large number of assumptions, this paper lacks certain practicability. Literature (ERIC S, MOHAMMAD M H, JAMES MAC PHERSON S D, et al, 2011) proposes three different objective functions: minimum load variance, maximum load factor and minimum network loss, and compares the optimization results and calculation time of the three models. However, it investigates the total load power of load nodes and does not involve making appropriate charging plans for each electric vehicle. Literature (WANG Xiu-yum, REN Zhi-qiang, CHU

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Dong-qing, 2008) establishes a charging optimization model for EV with the objective of minimizing the loss of distribution network, and considers the user's charging demand and voltage amplitude constraints. Literature (TIAN Wen-qi, HE Jing-han, JIANG Jiu-chun, et al, 2013) studies the multi-objective optimization problem aiming at the uniform distribution of charging load, the minimum charging time and the minimum distance of electric vehicles, and compares the computational characteristics of particle swarm optimization (PSO) and genetic algorithm (GA).

This paper takes the conventional charging mode of electric private car as the research object, combines the space-time characteristics and charging characteristics of large-scale electric vehicle, considers the user's charging demand and the constraints of safe and stable operation of the power grid, and takes the minimum standard deviation of the total load curve of the power grid as the control objective, establishes the intelligent charging strategy of large-scale electric vehicle. The mathematical model is solved slightly, and an adaptive genetic algorithm is proposed to optimize the charging plan. Based on the proposed model and method, taking IEEE33 bus distribution system as an example, the effects of intelligent charging and disordered charging on distribution network are studied.

2 INFLUENCING FACTORS OF CHARGING LOAD OF LARGE-SCALE ELECTRIC VEHICLE

There are many factors affecting the charging load of large-scale electric vehicles, which can be summarized as the scale of electric vehicles, battery characteristics, charging mode, user behavior, charging strategy, etc. (YANG Bing, WANG Li-fang, LIAO Cheng-lin, 2013). The battery capacity of electric vehicle determines the maximum mileage and charging frequency of the vehicle. The larger the battery capacity, the farther the vehicle travels, the lower the charging frequency correspondingly. However, the battery capacity of different models is different. Generally speaking, the battery capacity requirement of electric bus is much larger than that of electric private car.

At present, there are three charging modes: conventional charging, fast charging and battery replacement. Conventional charging is to charge batteries slowly in a relatively low charging current for a longer period of time. Generally, the charging time is 8-l0h. This mode is mainly aimed at a large number of low-voltage (220V) distributed charging points (mainly concentrated in residential buildings and office parking lots). Its advantages are low cost, small size and practicability of charging facilities. On-board now. Fast charging mode is a charging method that makes the battery reach or close to full state in a short time. Its typical charging time is 10-30 minutes. This mode can quickly solve the problem of power supply when the endurance mileage is insufficient, but it requires a higher power grid and is only suitable for large charging stations. Battery replacement is achieved by directly replacing the battery pack of electric vehicles to achieve the purpose of charging. The whole battery replacement process can be completed in 10 minutes. For the batteries replaced, the conventional charging method is generally used for centralized charging. This mode does not need on-site charging, so it can be arranged in the low load period, which is conducive to reducing the peak-valley difference of the power grid. It also effectively solves the problems of short endurance mileage of general batteries, and is conducive to the maintenance and recovery of batteries. But this mode needs to build large-scale centralized charging station, special power grid, and uniform shape and parameters of batteries.

The user behavior that affects the electric power demand of EV mainly includes the starting charging time, starting power and expected power of EV. The more concentrated the initial charging time of users, the more prominent the power demand of large-scale electric vehicles, and the greater the impact on the power grid. The initial charge reflects the user's power consumption, while the expected charge determines the charging duration at a certain charging power. Referring to reference (SOARES F J, 2016), this paper studies the travel law of EV based on Markov chain, so as to determine the charging time and the end time of EV.

Similarly, the demand for electric power varies with different charging strategies. At present, charging strategies are mainly divided into three categories: disordered charging, time-sharing pricing policy and intelligent charging. Unordered charging usually starts after the last trip or when the battery power is below a certain threshold. It can be imagined that large-scale disordered charging will bring many adverse effects to the power grid. Time-of-use tariff policy is a common market regulation mechanism, which means that in the low load period, users can be guided to charge in the low load period by lowering the tariff, thus playing a certain role in filling the valley. Intelligent charging refers to the optimal operation of the power grid by reasonably arranging the charging plan of electric vehicles.

3 MATHEMATICAL MODEL FOR OPTIMIZING INTELLIGENT CHARGING OF ELECTRIC VEHICLES

3.1 Objective Function

This paper studies the charging schedule of electric vehicles in one day, and divides the day into T periods. Taking the charging of No. i electric vehicle at time t as the independent variable and the minimum standard deviation of the total load as the control objective, i.e.

$$\min \sqrt{\frac{1}{T}\cdot\sum_{t=1}^{T}\left[\sum_{i=1}^{N}(x_t^i \times P_{EVi}) \times \eta + P_{loadt} - P_{avg}\right]^2} \quad (1)$$

Formula: N is the total number of electric vehicles; T is the total calculation time; x_t^i is the "1/0" independent variable to represent the electric vehicle i charging or not at t times; P_{EVi} is the electric vehicle i the rated charging power, unit kW; η is the charging efficiency; P_{loadt} is the total amount of conventional load in the network at t times, unit kW; P_{avg} represents the average value of the daily load curve. The specific calculation formula of P_{avg} is as follows:

$$P_{avg} = \frac{1}{T}\cdot\sum_{t=1}^{T}\left[\sum_{i=1}^{N}(x_t^i \times P_{EVi}) \times \eta + P_{loadt}\right] \quad (2)$$

3.2 Constraints

(1) Customer Charging Demand Constraints

In order to meet the user's needs when leaving, constraints need to be met:

$$SOC_t^i \leq 100 \quad (3)$$

$$0 \leq SOC_{td}^i \leq 100 - SOC_{t0}^i \leq \frac{\sum_{t=t0}^{td-1}(x_t^i \times \Delta T \times P_{EVi}) \times \eta}{C^i} \times 100 \quad (4)$$

Formula: SOC_{t0}^i represents i the starting power of an electric vehicle; ΔTrepresents the calculation time step; C^i represents the rated battery capacity of an electric vehicle of i. The formula constrains the charging time, which means that the electric vehicle's power consumption reaches the user's expectation at least when the user leaves.

The recursive formulas of electric quantity at each time are given:

$$SOC_{t+1}^i = SOC_t^i + \frac{(x_t^i \times \Delta T \times P_{EVi}) \times \eta}{C^i} \times 100 \quad (5)$$

In the formula, SOC_{t+1}^i represents the power consumption of an electric vehicle at time t+1. Obviously, if x_t^i= 0, $SOC_{t+1}^i = SOC_t^i$, which means that if the electric vehicle is not charged at the current moment, the vehicle power will not change at the next moment.

(2) Uncontrollable time constraints

$$x_t^i = 0; \quad t_d^i \leq t < x_0^i \quad (6)$$

Where, 6 is the time when the electric vehicle is connected to the grid. This paper assumes that the user will be merged into the grid at the end of the last trip; Ukraine is the time when the electric vehicle leaves. This formula indicates that only when the electric vehicle is connected to the grid can it be charged.

(3) Node Voltage Constraints

$$U_j^{min} \leq U_j^t \leq U_j^{max} \quad (7)$$

Where, U_j^{min} and U_j^{max} represent the upper and lower voltage constraints of node j, respectively.

4 ADAPTIVE GENETIC ALGORITHM

Genetic algorithm (GA) is a kind of randomized search method based on the evolutionary law of the biological world. Through a series of operations such as selection, crossover and mutation, the individuals with the greatest fitness obtained in the evolutionary process are taken as the output of the optimal solution. However, simple genetic algorithm uses fixed crossover probability and mutation probability, ignoring the adaptive characteristics in the process of population evolution, which will affect the global search ability and premature convergence into local optimum. The adaptive genetic algorithm (AGA) uses the dynamic generation method to determine the adaptive crossover and mutation probability, so as to maintain the genetic diversity of individuals and prevent the genetic algorithm from premature convergence to local optimum. By comparing AGA with GA in dealing with some optimization problems, it is found that AGA can quickly converge to the global optimum. Therefore, this paper adopts adaptive genetic algorithm to study the intelligent charging strategy of electric vehicles.

Adaptive crossover probability Pc and mutation probability Pm can be obtained by the following formula:

$$P_c = \begin{cases} P_{c\_max} - \left(\frac{P_{c\_max} - P_{c\_min}}{M}\right) \times Gen & fit^t > fit_{avg} \\ P_{c\_max} & fit^t \leq fit_{avg} \end{cases} \quad (8)$$

In the formula, P_{c_max} is the maximum crossover probability; P_{c_min} is the minimum crossover probability; Gen is the current iteration number: M is the maximum number of iterations; fit^t is the larger fitness in a crossover operation; fit_{avg} is the average fitness of all individuals in the current iteration.

$$P_m = \begin{cases} P_{m\_min} - \left(\frac{P_{m\_max} - P_{m\_min}}{M}\right) \times Gen & fit > fit_{avg} \\ P_{m\_min} & fit \leq fit_{avg} \end{cases} \quad (9)$$

In the formula: P_{m_max} is the maximum mutation probability; P_{m_min} is the minimum mutation probability; Gen is the current iteration number; M is the maximum iteration number; fit represents the fitness of the individual in the current mutation operation. Fig. 1 is the flow chart of the adaptive genetic algorithm.

Before the operation starts, the environment variables of the adaptive genetic algorithm need to be set, such as the maximum number of iterations M, population size N, intersection and variation parameters Pc_max, Pc_min, Pm_max, Pc_min, The specific operation steps are as follows:

The first step is to initialize, generate effective population, and calculate the fitness of each individual;

The second step is to select and retain N individuals with better fitness. If the optimal fitness satisfies the set goal or reaches the maximum number of iterations, the optimal result is output and the operation is stopped, otherwise the next step will be taken.

The third step is crossover operation. When the random variable is less than the adaptive crossover probability, the single point crossover of parents and children is performed. Thus, 2N offspring individuals are generated from N parents, and the parents and offspring are combined to form a new population.

The fourth step is mutation operation. For new populations, mutation occurs when the random variable is less than the adaptive mutation probability.

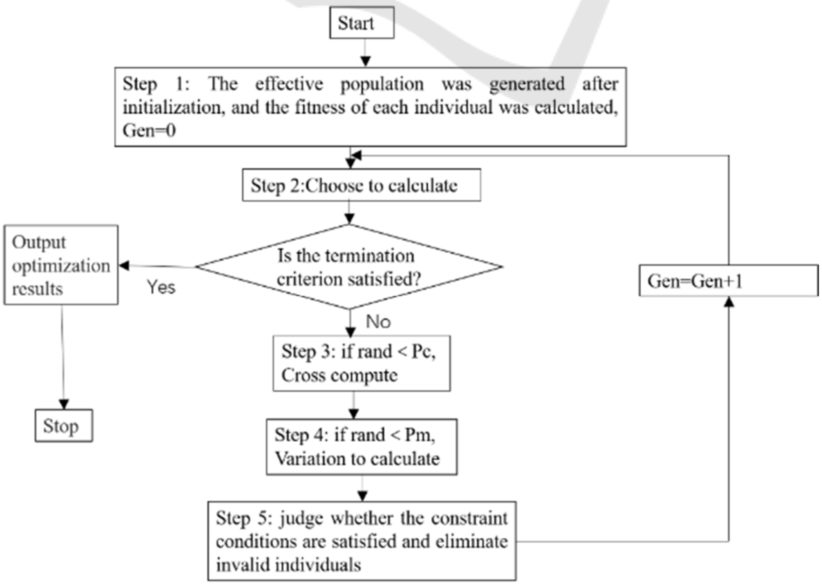

Fig 1. Operation flow chart of the adaptive genetic algorithm.

Fifth step: Constraint judgment is made on 3N individuals, invalid individuals are eliminated, and N individuals with better fitness are retained, then the second step is returned, and the number of iterations is increased once.

To study the intelligent charging problem of large-scale electric vehicles, this paper adopts adaptive genetic algorithm with binary coding, uses independent variable x_t^i to represent the charging state of ist electric vehicle at t-time, $x_t^i = 1$ to indicate charging: $x_t^i = 0$ to indicate not charging.

5 ANALYSIS OF EXAMPLES

Taking IEEE33 bus residential distribution network as an example, as shown in Figure 2, the impact of charging load on distribution network of large-scale electric vehicles under two charging strategies of disorderly charging and intelligent charging is studied. The routine daily load curve of the example system is shown in Figure 3 (KRISTIEN C, EDWIN H, JOHAN D, 2010).

Assuming that there are 600 electric vehicles in this area, the user chooses to merge them into the grid after the last trip, so the starting charging time of each electric vehicle is t0. The departure time td can be simulated by Markov chain.

Considering the actual situation, all electric vehicle loads are allocated to different nodes in geographic space according to the proportion of the conventional load of each node to the total load for charging (GARCIA-VALLE R, LOPES J A P, 2013), which is shown in the following formula:

$$N_j = \frac{P_{loadj}}{\sum_{j=1}^{M} P_{loadj}} \times N \qquad (10)$$

In the formula: N_j is the number of electric vehicles allocated by node j; N is the total number of electric vehicles; P_{loadj} is the normal load size of node j connection; $\sum_{j=1}^{M} P_{loadj}$ is the total amount of normal load in distribution network; M is the number of nodes in network.

In order to simplify the analysis, it is assumed that the rated battery capacity of each electric vehicle is Ci=60kWh; the rated charging power is PEvi=4kW; the charging efficiency is η=95%; and the initial power is SOC_{t0}^{i}. It obeys truncated Gauss distribution, with a mean of 40, a variance of 20, a minimum SOC_{t0}^{i} 20 and a maximum SO $_{t0}^{i}$ 50; the user's expected charge capacity obeys the uniform distribution between (80, 100).

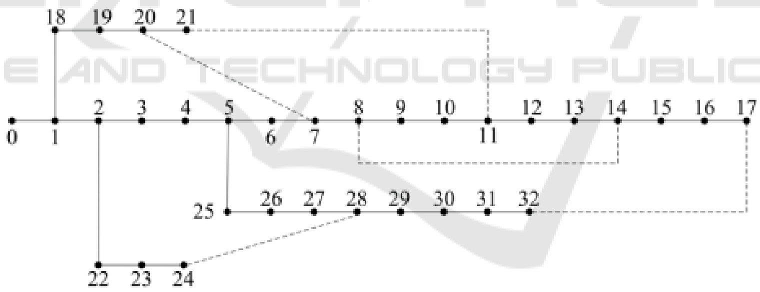

Fig 2. IEEE 33-nodes distribution system.

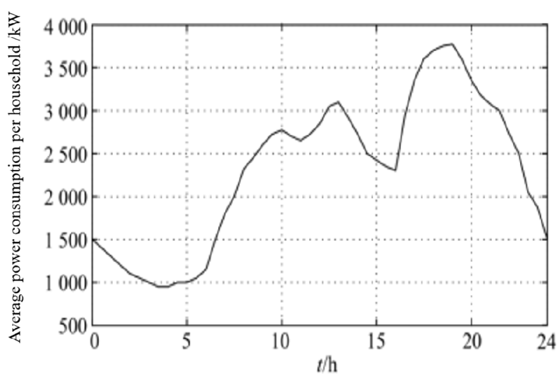

Fig 3. Daily load profile of the test system.

In this paper, the specific parameters of the adaptive genetic algorithm are set as follows: the number of genetic iterations is 80, the total number of individuals in the population is 200, the maximum crossover probability Pc_max = 0.9, the minimum crossover probability Pc_min = 0.4, the maximum mutation probability Pm_max = 0.1, and the minimum mutation probability Pm_max = 0.01. The specific operation flow is shown in Figure 4.

The intelligent optimal charging strategy proposed in this paper is compared with disordered charging, and the results are shown in Fig. 5.

The peak-valley difference rate in Table 1 is the ratio of peak-valley difference to peak load. From Fig. 5 and Table 1, it can be seen that under the disordered charging strategy, users access the power grid after the last trip and start charging immediately. Therefore, in the evening, the overlap between the electric vehicle load and the original load presents a "peak" phenomenon, which increases the peak-valley difference of the system, and reduces the utilization rate of power resources, and will have a negative impact on the power grid. Under the intelligent charging strategy, the charging load of most electric vehicles is transferred to the low valley period of the original load. Compared with the disordered charging, it can reduce the peak-valley difference and make the total load curve more flat, which is conducive to reducing the number of unit start-up and shutdown, and improving the security and economy of the system operation.

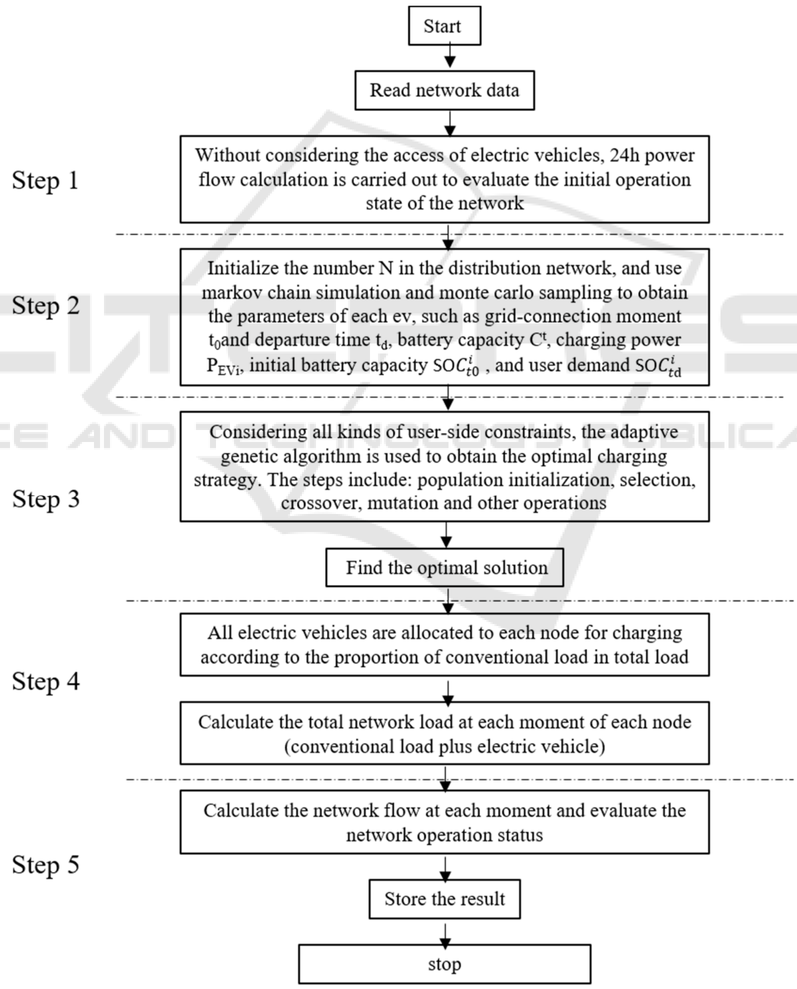

Fig 4. Flow chart intelligent algorithm.

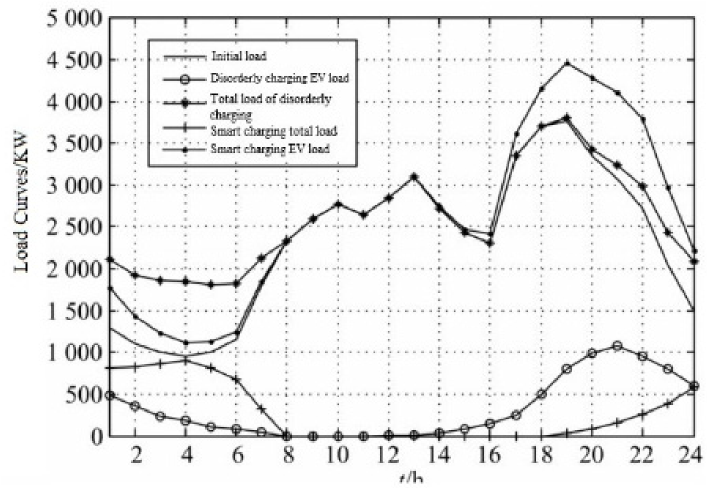

Fig 5. Load curves under two control strategies.

Table 1. Comparisons of system load level indexes.

The charging strategy	Load value/kW		The peak valley rate/%	Standard deviation of total load
	Max load	Min load		
The original load	3775	958	74,6	627,3
Intelligent charging	4467	1122	74,8	983,5
Disordered charge	3811	1816	52,3	339

In this model, the voltage offset of node 17 is the largest, which can reflect the impact of electric vehicle access on the node voltage, and is representative. Therefore, this point is taken as the research object to study the voltage offset of the node. Figure 6 shows the voltage offset at each time of node 17. As can be seen from the figure, intelligent charging can effectively reduce voltage offset.

Table 2. Comparisons of system losses.

The charging strategy	Network loss/%
Intelligent charging	3,27
Disordered charge	3,47

As can be seen from Table 2, the network loss of intelligent charging is less than that of disorderly charging, because when the total load is fixed in a day, The flatter the daily load curve, the smaller the loss; conversely, the greater the difference between peak and valley, the greater the loss.

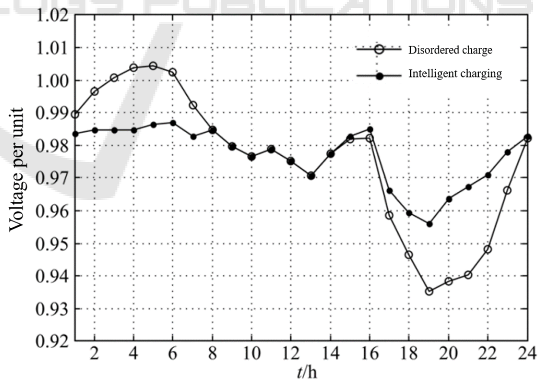

Fig 6. Comparisons of voltage deviation of bus 17.

Figure 7 shows the convergence curve of the optimization algorithm. When the iteration is about 60 times, the optimal solution is obtained, which proves that the optimization algorithm has good convergence.

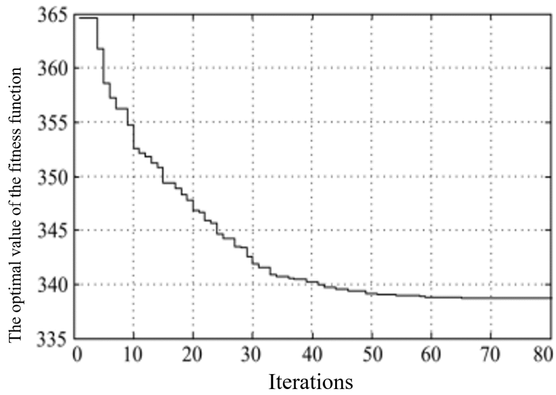

Fig 7. Convergence of the optimization algorithm.

6 SUMMARY

This paper presents a solution model and method of intelligent charging control strategy for large-scale electric vehicles. The key of this model is to consider the user's charging demand and grid side constraints, and to minimize the standard deviation of total load as the optimization objective. An example is given to study the intelligent charging with each charging plan as the control variable. The effectiveness of the proposed model and method is verified by comparing the effect of the disorderly charging mode on the load of the electric vehicle. Based on this model and method, other types of objective functions can also be considered, such as maximum absorption of renewable energy generation, and so on. In addition, based on Monte Carlo scenario random simulation and distribution network power flow calculation, the model can also be used to evaluate the impact of a given scale of electric vehicle access on distribution network and the maximum penetration level of electric vehicles in distribution network.

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