Multi-Objective Optimization Charging Strategy for Electric Vehicles Based on Genetic Algorithm

Tianyi Qu [1, a]

[1] School of Management, XuZhou University of Technology, Xuzhou, Jiangsu, China 221008

[a]jdbh2001@163.com

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Abstract. On the basis of analyzing the factors affecting the charging load of electric vehicles, from the perspective of user and grid game, the minimum load fluctuation of distribution network and the minimum charging cost of users are taken as the goal. A multi-objective optimization charging strategy based on genetic algorithm is proposed. The example verifies the effectiveness and feasibility of the strategy. The example shows that the multi-objective optimization charging strategy can effectively guide the orderly charging of electric vehicles, effectively ensuring the safe operation of the grid and the economic benefits of users.

1. Introduction

In recent years, with the continuous development of science and technology, energy and pollution problems have become increasingly serious. The energy crisis caused by the excessive use of primary energy such as fossil energy has forced people to think about how to use clean energy instead of primary energy. In the transportation industry, electric vehicles began to flourish, which eased the pressure on China's energy crisis and contributed to the cause of environmental protection. However, the increased power load of large-scale electric vehicles connected to the power grid also has a negative impact on the stable operation of the power grid. For example, during peak charging period, the load “peaks up”, and the charging low period makes the utilization rate of charging equipment lower.

The traditional research is based on the demand side response theory to describe the response mechanism of electric vehicle charging behavior. The electric vehicle user layer and the grid layer economic benefit are the optimization objectives, and the optimal time-of-use electricity price and real-time electricity price are measured. The research results show that the real-time electricity price is for electric vehicles. Ordered charging has better optimization effect; in recent years, using game theory to describe the economic interests of various subjects in the electric vehicle charging network, so as to obtain more accurate electric vehicle charging demand response behavior, and develop an optimized electricity price strategy. It has become a hot spot to study the charging price of electric vehicles. Literature studies show that the grid considers the economic income including network loss, peak-to-valley difference and charging revenue when formulating the electricity price strategy, while electric vehicle users want to obtain the most including charging time, short queue time and low charging cost. Good charging experience.

In this paper, in the orderly charging system, the intelligent charging and discharging system solves the optimal charging arrangement, aiming at the minimum load fluctuation of the distribution network and the minimum user charging cost, and proposes a multi-objective ordered charging strategy for electric vehicles, using genetic algorithm to seek the optimal solution.

2. Genetic Algorithm

The genetic algorithm (GA) is inspired by the biological evolution theory proposed by Mr. Darwin. It is an intelligent search algorithm based on natural selection and population genetic mechanism. It simulates the genetic selectivity of organisms in nature and is in the process of genetics. Simulations of reproduction, hybridization, and mutation occurred. Firstly, the problem to be studied needs to be modeled, and each feasible solution is regarded as an individual through the

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coding operation, and a series of feasible solutions are randomly generated as the initial population. Secondly, each individual is given an evaluation according to the set objective function. Determine the standard of evaluation, that is, the fitness function; then, the genes with high fitness will be retained, the genes with low fitness will be eliminated, and the individuals selected through this will undergo cross-over and mutation operations to create new ones. In the first generation, the quality of the population has continuously improved. After a certain number of algebras, the population that meets the expected requirements will be obtained, and the final optimization result will be obtained by decoding the chromosome.

The genetic algorithm mainly involves coding, initial population generation, fitness function setting, genetic evolution operation, termination condition judgment and so on.

Coding is the basic work of genetic algorithms. First, we must determine the objective function and variables of the problem, and encode the variables.

The initial population is usually randomly generated in the space of the feasible solution. The selection of the initial population is related to the complexity of the research problem and the scale of the solution, and needs to be determined according to the specific situation.

Fitness function is used as an index to evaluate the quality of chromosomes. The value of fitness function reflects the degree of fitness of individuals to objective function. Usually, the reciprocal of objective function or objective function can be chosen directly as fitness function. The larger the value, the better the result of the proof solution.

The genetic evolution operation is the core part of the genetic algorithm. Through this process, the fitness of the population is continuously improved to achieve the expected optimization goal. Genetic evolution operations usually include three parts: selection, intersection, and variation. The selection process is to select the individual as the parent for follow-up genetic operation according to the probability of individual fitness, so as to ensure that the individuals with high fitness are retained; the cross process is the main way to generate the offspring, through the two male parents. Genes are combined to produce new progeny, and the high fitness of the male parent is easy to produce better offspring, so that the fitness of the population is continuously improved. The crossover operation greatly improves the search efficiency of the genetic algorithm, usually the crossover probability. The selection is 0.4-0.9; the mutation process is to mutate part of the gene of the father to produce new offspring. This process is beneficial to break through the limitations of the original search space, avoid falling into local optimum, and increase the diversity of the population. The probability is low, and the probability of variation is usually chosen to be 0.01-0.1.

The termination condition is judged, and the maximum evolution algebra T is set. When the evolution algebra t>T, the individual with the greatest fitness obtained in the evolution process is used as the optimal solution output, and the operation is terminated [29]-[31].

3. Multi-objective Optimization of Electric Vehicle Charging Based on Genetic Algorithm

The large-scale electric vehicle network connection relationship involves the interests of both the power grid and the user. The peak-to-valley electricity price is used to guide the orderly charging behavior of electric vehicles, which can suppress load fluctuations and reduce peak-to-valley difference, which is conducive to the safety, stability and economic operation of the distribution network. At the same time, electric vehicle users can reduce the charging cost by independently selecting the charging period in combination with their own needs. Therefore, this paper chooses distribution network load fluctuation and user charging cost as the objective function of multi-objective optimization model to achieve a win-win situation between power grid and electric vehicle.

3.1 The Objective Function.

(1) Targeting the minimum fluctuation of distribution network load

$$f_1 = \min \sum_{t=1}^{24} (P_{Lt} + P_t - P_{av})^2 \tag{1}$$

Among them, P_{Lt} represents the original load at each moment, P_t represents the total charging power of the electric vehicle at each moment, and P_{av} represents the average load of the day.

(2) Aiming at the minimum user charging cost

$$f_2 = \min \sum_{j=1}^{24} (p_a * pr_j * \Delta t * C_{i-j}) \tag{2}$$

Among them, p_a is analyzed as 8kW, pr_j represents the price of electricity at each moment, Δt represents the time interval, this paper takes 1h, $C_{i\text{-}j}$ represents the state of charge of the i^{th} car at j.

$$C_{i-j} = \begin{cases} 1\text{，The i car is charging at j} \\ 0\text{，The i car is not charging at j} \end{cases} \tag{3}$$

Since the dimensions of the two objective functions are different, normalization is necessary.

$$f = \frac{f - f_{min}}{f_{max} - f_{min}} \tag{4}$$

There are many Pareto optimal solutions for multi-objective optimization problems based on genetic algorithm. In this paper, the weight coefficient transformation method is chosen to solve the problem, and a new objective function is obtained.

$$\min f = \lambda_1 f_1 + \lambda_2 f_2 \tag{5}$$

λ_1 and λ_2 are the weight coefficients corresponding to the load fluctuation of the distribution network and the user's charging cost. This paper considers that the grid side and the user side are equally important, so both λ_1 and λ_2 take 0.5.

3.2 Constraints.

(1) Power constraints of charging stations

The charging power in each period should not exceed the maximum allowable capacity of the power station.

$$0 < P_t < P_{tmax} \tag{6}$$

(2) Electric Vehicle Capacity Constraints

In order to ensure the daily running of electric vehicles, the charging capacity of each electric vehicle should not be too low, and at the same time, it should not exceed the charging plan, so as to avoid waste.

$$Q_{imin} < \sum_{j=1}^{24} (p_a * C_{i-j}) < Q_{imax} \tag{7}$$

Among them, $Q_{i\min}$ denotes the minimum charging capacity required by the first electric vehicle, and $Q_{i\max}$ denotes the maximum charging capacity required by the second electric vehicle.

3.3 Multi-objective Optimization. The specific flow chart is simulated by genetic algorithm as shown in Figure 1.

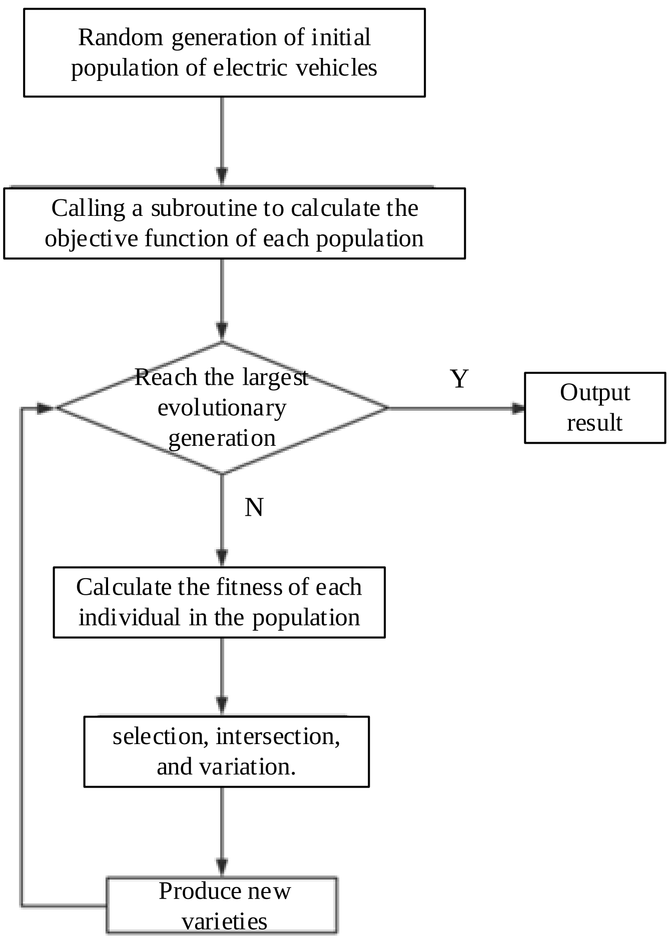

Figure 1. Flow chart of genetic algorithm

Referring to the relevant literature and aiming at the problems studied in this paper, when programming genetic algorithm, the parameters are selected as follows: population size N = 20, iteration times 300, crossover probability 0.7, mutation probability 0.04. As the number of iterations increases, the normalized objective function decreases gradually. After 150 iterations, the objective function begins to converge and finally tends to be stable. The convergence process is shown in Figure 2.

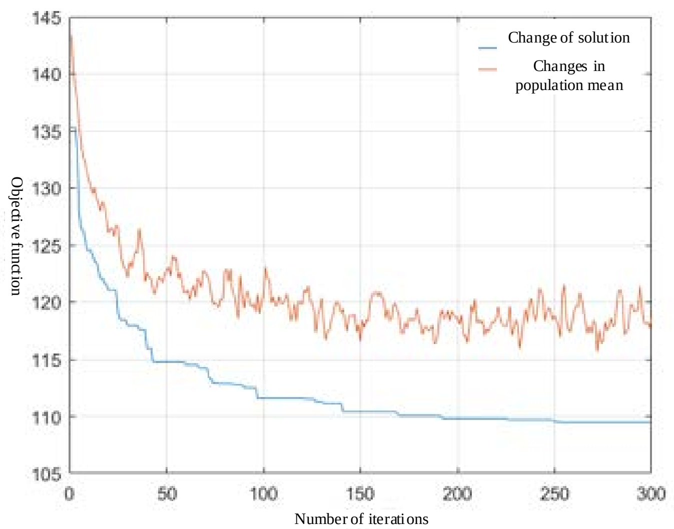

Figure 2. Variety of object function in iterative process

According to the optimal solution obtained by genetic algorithm, the distribution of charging power at each time of orderly charging can be obtained, as shown in Table 1.

Table 1 Orderly charging power distribution of electric vehicles

Time	1	2	3	4	5	6	7	8	9	10	11	12
Power\kW	9806	9510	9390	9441	2375	7976	444	5113	1153	2630	518	1471
Time	13	14	15	16	17	18	19	20	21	22	23	24
Power\kW	1353	384	30	1779	225	315	654	53	247	5	1544	9458

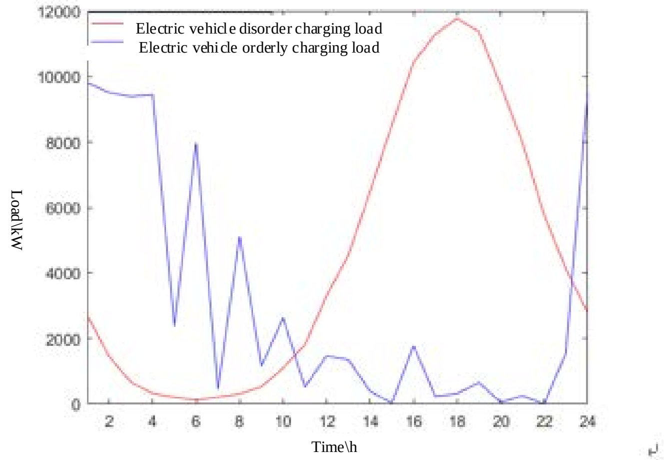

Figure 3. Comparison of orderly charging load curve and disorderly charging load curve

Comparing the orderly charging load with the disorderly charging load of electric vehicles, as shown in Figure 3, it can be seen that the charging load of electric vehicles has shifted from 16:00 to 21:00 in the peak period to 24:00 at night to 6:00 in the morning. The corresponding equivalent load curves are obtained by superimposing the disordered charging load and the ordered charging load with the original daily load, respectively, as shown in Figure 4.

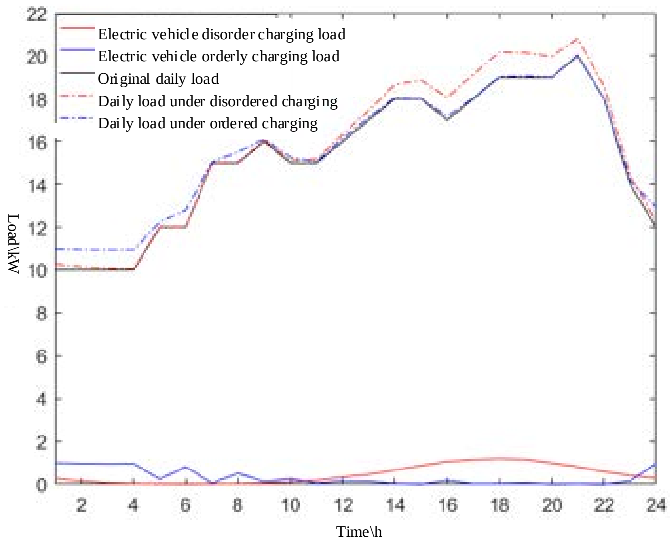

Figure 4. Load curve

It can be seen from this that under the orderly charging mode, the load of electric vehicles has basically shifted to the low night time, staggered the peak time of the original residential power consumption, and filled the low night load. Compared with the "peak-to-peak" situation of disordered charging, it has played a very good improvement, and the daily load curve tends to be stable compared with the original.

4. Conclusion

Aiming at minimizing load fluctuation and charging cost of distribution network, genetic algorithm is used to find the optimal charging strategy. The experimental results show that, under the guidance of multi-objective ordered charging strategy, the fluctuation of power grid load decreases significantly, and the daily load curve tends to be stable, which is conducive to the safe and stable operation of power grid, and the ordered charging strategy has a significant effect.

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