# Electric Vehicle Charging Strategy based on User's Intention and Uncertain Charging Habits

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## Abstract

With the increasing number of electric cars, the studies of electric cars' charging strategies become more and more. This passage based on the large-scale electric vehicle orderly charging strategies, has taken uncertainty of charging habits of small-scale electric car users into account, and simulated the charging load in this model by Monte Carlo Simulation. Then, we use the minimum variance of the load of power grid as a goal, by means of controlling charging power and considered the limitation of energy demand and charging time, and set the model of charging load optimization by use of Particle Swarm Optimization. Compared with the curve of charging initial load based on MATLAB, this passage can reflect the superiority of Charging load optimization model.

## Keywords

Electric Cars, Uncertainty of Charging Habits, Monte Carlo Simulation, Particle Swarm Optimization, Load Regulation.

## 1. Introduction

The problems of energy shortages and environmental degradation which are caused by a lot of use of fossil fuels impel various countries in the world to develop the technology of electric cars positively and promote on a large scale. As a large energy consumption country in the world and the important power of environmental protection, China carries out the strategy of electric cars to upgrade the industrial structure and transform the electrification of power system positively. It can be anticipated that a number of electric cars will switch in power grid in not-too-distant future. Meanwhile, disordered charging of large-scale electric cars can cause the problems of power grid voltage dropping and grid loss increasing. Therefore, on the one hand, the government should lead and adjust the charging behaviors of electric cars users. On the other hand, for users, who do not participate in the deployment or who participate in the deployment but have special charging needs, it is essential to study the influence on the adjustment of charging load in the grid. It can protect the stability of grids and reduce the cost of power grid operation by considering and analyzing in two aspects.

Controlling the load effectively and the project of the charging system of electric cars are based on accurate demanding calculation of charging loads. The demanding calculation of charging loads is based on Monte Carlo Simulation to extract initiative state of loads and initiative charging time. This method classifies different charging behaviors of different cars. It gets charging load curve in according to the time of charging, the ways of charging, initiative state of loads, charging demand, and initiative charging time. Nowadays, the studies of the adjustment of charging loads mostly just take the strategy of orderly charging load adjustment into consideration, such as the way of smart charging and delayed charging and neglect the uncertainty of charging habits of those users who do not participate in the adjustment of charging. There are a few calculations that take uncertainty of charging habits into consideration while they do not make allowance for the limit of the frequency of charging of electric cars batteries.

This passage not only consider large-scale electric vehicle charging strategies, but also make allowance for uncertainty of charging habits of small-scale electric car users at the same time. It reflects on the cost of charging of every electric car, aging rate of every battery, and the variance of load of power grid in this project. It not only protects the stability of grids but also reduce the cost of power grid operation.

## 2. Electric Vehicle Charging Load Model

### 2.1 Uncertain charging habits model.

Charging load model of this paper is divided into two parts, the first part is uncertain charging habits model, the other part is orderly charging model which is based on user’s intention. One part sets up the weighted coefficient of 0.2 and the other is 0.8 which is the number of electric cars for a total of N, 0.2 N electric car charging situation belongs to the first part, 0.8 N electric car charging situation belongs to the second part.

When the electric vehicle users would not submit to the charging scheduling of the system, it will be thought in the "uncertain charging habits" model. Although the electric car charging user behavior has strong randomness and subjective, but it is not haphazard. Due to the electric vehicles operation scale is limited, we can get the electric car travel rule by researching the travel law of traditional fuel vehicle, and assume that users in the use of electric vehicles driving laws remain unchanged basically to obtain the regularity of the electric vehicles travel . Finally, the Monte Carlo simulation method is used to calculate the charging load. The steps are as follows:

1) Using Monte Carlo simulation method to obtain the charging situation of electric vehicle, charging time, starting state of charge, starting time charging, and set electric vehicle cluster charging power P.

2) Assume that when the SOC value reaches 0.98, the battery is full. Duration of charge:

$$t_s = (0.98 - S_t) * p_f / p \tag{1}$$

$$T_s = t_s / 0.25 \tag{2}$$

In the formula, $t_s$ is the expected duration of charge; $S_t$ is state of charge at the start of the battery for electric vehicle charging; P is electric vehicle cluster charging power; $p_f$ is electric vehicle battery capacity; $T_s$ is time accounted for the charging time, type (10) for the conversion of $T_s$ and $t_s$.

3) The total charge load is obtained by superimposing the charging load of all charged electric vehicles at one time a day

$$P_a = \sum_{t=1}^{T} \sum_{j=1}^{N} P_{t,j} \tag{3}$$

Among them, $P_a$ is the total charging load when the electric cars access to the grid ; T is the total number of hours required for charging; N presents the total number of charged electric vehicles; $P_{t,j}$ represents charging load of the jth electric vehicle at the t moment.

### 2.2 Orderly charging model which based on intention of users

At first, Electric Power Companies would study the law of electric car trip, then make out an orderly charging scheme for electric cars users who want to obey the dispatch, for the purpose of reducing the charging fees of each electric car, reducing the battery aging rate and reducing the variance of load of power grid. Then they can find out the daily charging load distribution of electric cars, which would like to obey the dispatch.

This model will divide one day into 96 times, which means every 15 minutes is a period of time. It will calculate the number of electric vehicles that connected to the electricity grid and the load data of each period of one day, and it will optimize the scheme in time.

Firstly, this model will read the original data, then it will begin to plan the dispatch schedule, which includes reducing the charge fees of total electric cars, reducing the number of charging and dropping the variance of load of power grid. And then determine whether the charging users want to obey schedule, and discussed in 2.2 if the answer is no, and make out an reasonable scheduling command for another answer, and form a new charging load curve of electric car.

The purposes of the charging optimization model are the least electric car charging fees, the fewest charging times and the smallest fluctuations in variance of daily load of power grid. The objective function of fees is

$$\min C=\sum_{t=1}^{T}\sum_{n=1}^{N} S_{n,t}\, P p_i \Delta t, \tag{4}$$

In this function, $C$ represents charging fees, $S_{n,t}$ represents the current electric vehicle charging status, it means it is charging when $S_{n,t}$ shows num.1, and it is not charging when $S_{n,t}$ shows num.0, T represents the expected time needed for electric vehicle charging, N represents the total number of electric vehicle which is obeying the dispatch and is connected to the electricity grid, P represents charging power of the electric car, $p_i$ represents the price of electricity during this time period, $\Delta t$ means 15 minutes.The objective function of charging times is

$$\min P=\sum_{n=1}^{N}\sum_{t=1}^{T}|X_{n,t}-X_{n,t-1}| \tag{5}$$

In this function, P represents times of battery charge, N represents the total number of electric vehicle which is obeying the dispatch, T represents 96 time frame, $X_{n,t}$ represents charging state of the nth vehicle at time t, it means the vehicle is charging if $X_{n,t}$ is equal to 1 and is not charging if $X_{n,t}$ is equal to 0. $X_{n,t-1}$ represents charging state of the nth vehicle at time t-1.The objective function of variance is

$$\min L=\frac{1}{T-1}\sum_{t=1}^{T}(P_t-P_{av}) \tag{6}$$

In this function, L represents the daily load variance of power grid, T represents the total time frame, $P_t$ represents load value of the electric cars which are charged, $P_{av}$ represents average of load ,that electric vehicle charging in the total times, computational formula is

$$P_{av}=\frac{1}{T}\sum_{t=1}^{T}P_t \tag{7}$$

1)Demand Constraint Of Charging Energy

$$S_{j,n}\le\sum_{\Delta t=1}^{T}\frac{\mathrm{Pt}\,\Delta\mathrm{t}}{P_f}+S_{j,s}\le 0.98 \tag{8}$$

In this function, $S_{j,n}$ represents eventually charged state of the ith charging electric car that set at the beginning, $P_t$ represents charging power provided by the moment charging pile, $P_f$ represents the total capacity of the electric car battery. Assume that, SOC is defined as 0.98 when the state of the electric car is charged, so it will stop charging when SOC exceeds 0.98.

2)Peak-valley Load Constraint

This model emphasizes the economic benefits of charging users, but the economic benefit of ascension may make the peak valley increase, which leads to bad influence on power grid, so we make the following constraints for peak-valley. The objective function of peak-valley load constraint is:

$$|L_{max}-L_{min}|<\Delta L_{min} \tag{9}$$

In this function, $L_{max}$ represents the maximum of system load from 00.00 to the recharge time, $L_{min}$ represents the minimum of system load from 00.00 to the recharge time, $\Delta L_{min}$represents minimum peak valley differentials in the past 14 days. In the actual system, Δ Lmin would increase 0.5% until find out solutions.

3)Charging Time Constraints

$$\mathrm{T}\le T_{end} \tag{10}$$

$$T_{end}=\min\{T_{end1},T_{end2}\} \tag{11}$$

In this function, T represents number of periods that electric vehicle are charged, $T_{end1}$ represents number of periods that predicted by the laws of its travel, $T_{end2}$ represents number of periods that electric vehicle are needed to meet the demand of the charge, $T_{end}$ represents the minimum between $T_{end1}$ and $T_{end2}$.

## 3. Optimization of charging load model

The method of load adjustment is changing charging power and delaying time of charging, due to the delay of charging is the special case of the charging power is 0, so in this model, adjusting the charging load only by the method of changing the charging power. The load regulation of electric vehicle needs to consider the dynamic and real-time adjustment, so the particle swarm optimization algorithm is used to solve the problem. The charging power of the electric vehicle is constructed by a one dimensional particle $X_p$, namely the power particle.

1) The fitness function of PSO is determined by the objective function formula (4), formula (5), formula (6), and the function is the sum of the three objective function multiplied by 0.5, 0.3,0.2, as shown in formula (11):

$$\text{Fitness}=\sum_{t=1}^{T}\sum_{n=1}^{N} S_{n,t}\, Pp_i \Delta t,*0.5+\sum_{n=1}^{N}\sum_{t=1}^{T}|X_{n,t}-X_{n,t-1}|*0.3+\frac{1}{T-1}\sum_{t=1}^{T}(P_t-P_{av})*0.2 \quad (12)$$

2) The update expression of particle is expressed by formula (13) and formula (14)

$$v_i^{n+1}=wv_i^n+c_1 * rand(x)*(pbest-x_i^n)+c_2*rand(x)*(gbest-x_i^n) \quad (13)$$

$$x_i^{n+1}=x_i^n+\mathrm{a}v_i^{n+1} \quad (14)$$

Among them, $v_i^n$ said in the nth iteration, the velocity of the ith power particle; $v_i^{n+1}$ said that the velocity of the latest power particle or the (n+1)th power particle after the correction of recurrence formula ; $x_i^n$ represents the vector of the ith power particle in the nth iteration; $x_i^{n+1}$ said that the vector of the (n+1)th power particle after the correction of recurrence formula ; a is a coefficient of speed when updating, which is called constraint factor, usually set to 1; $w$ is inertia weight, reflects the proportion coefficient of particles to maintain the original speed, when the system needs the global search, $w$ select high value, when the system needs the local search, $w$ select smaller value. With the increase of the number of iterations, the inertia weight decreases gradually, and the variation formula is formula(12)

$$\mathrm{w}=w_{max}-\frac{n*(w_{max}-w_{min})}{n_{max}} \quad (15)$$

Among them, $w_{max}$ and $w_{min}$ are respectively the maximum and minimum values of the inertia weight; n represents the number of iterations, and $n_{max}$ represents the maximum number of iterations.

## 4. Example simulation

1)POS parameter setting

The population size of power particle is m=20 ;particle number is N=500, the particle number N can be decided according to the complexity of the problem, the more complex the problem ,the higher the the value of N; learning factors$c_1$=2, $c_2$=2, learning factor is to make the particle have self-summary ability and learn from the excellent individuals in the group, and approach to the optimum point in the group or the field ; $w_{max}$=0.98, $w_{min}$=3.7; power; the maximum and minimum value of particle power velocity is that $v_{max}$=5, $v_{min}$=-5, $n_{max}$=1000.

2) Parameter Setting of Charging Load Model

Through the analysis of the traditional fuel vehicle data, the probability distribution of the traditional fuel vehicles travel law is obtained, shown in Table 1,supposing that, compared to it , the electric car travel rules basically unchanged, and the original charging power is 6.6KW/h.

3) Simulation Of MATLAB and Result Analysis

According to the electric vehicle charging model, apply Monte Carlo simulation method to simulate the load curve of the model in MATLAB. The distribution of the curve is in the two-dimensional plane, the abscissa represents time, the vertical axis represents the charging load, in the simulation, 24h was evenly divided into 96 time periods, random numbers generated by the rand function, the judgment of the random number range and generate the corresponding starting battery state of charge and the starting time, superimpose the charging load of N cars in the loop structure and generate the charging load curve of electric vehicle, the original load curve is shown in Figure 1.

Table 1.Travel rules of traditional fuel vehicles

| Charge situation | Daily charge Power frequency | Charging period | Whether the charge time limit | Charging probability | The initial of charge distribution | Start time distribution |
|---|---|---|---|---|---|---|
| Private Car Working day | 1.0 | 8:00-17:00 | no | 0.2 | N(0.6, 0.01) | N(18.5,0.25) |
| | | 16:00-6:00 | no | 0.6 | | N(21.0,0.25) |
| | | 19:00-22:00 | 80min | 0.2 | | Uniform distribution |
| Private Car holidays | 0.8 | 20:00-6:00 | no | 0.5 | N(0.6, 0.01) | Uniform distribution |
| | | 0:00-8:00 | no | 0.1 | | N(0.5, 0.25) |
| | | 12:00-23:00 | 80min | 0.2 | | Uniform distribution |

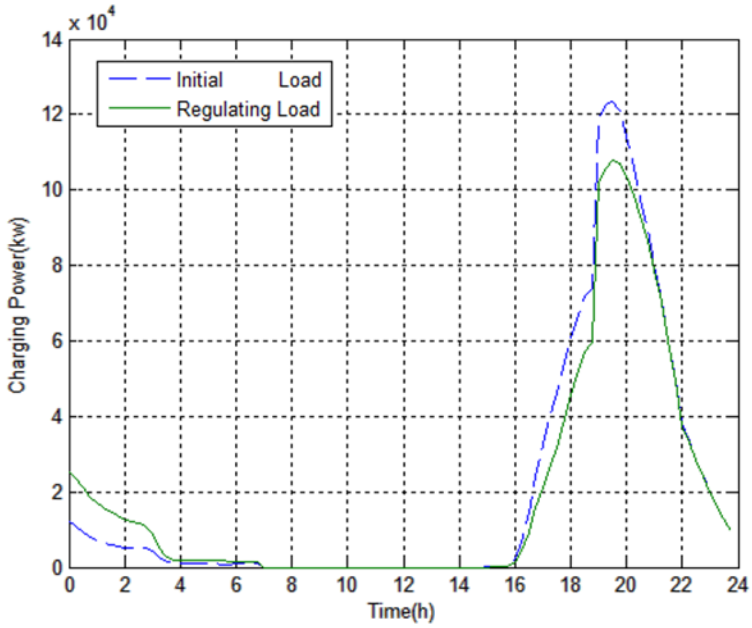


Fig.(1) Load curve for regulating charging power

On the basis of the original charging load, in accordance with the above particle swarm optimization algorithm, and in accordance with the above parameters set, in the MATLAB optimization, optimization of the curve as shown in Figure 1 of the regulated load is shown. Optimization model improves the peak and valley value of charging load curve, relative to the original load. Charging power is adjusted appropriately reduced at the peak and appropriately enhanced in the valley. Optimization model has smoothed the fluctuation of original charging load in the valley , so that the peak value after adjustment is smaller than the original peak value., and the value in the valley after adjustment is higher than the original ones .

## 5. Conclusion

By considering the majority of users willing to submit to the charge allocation, a small part of the user's uncertain charging habits, we have apply the method of Monte Carlo to establish the load model on the above charging habits. Based on some research, in order to reduce network loss and reduce user charging fees and the number of charging, by the means of changing the charging power, we apply the particle swarm optimization algorithm to optimize the initial charging load , by MATLAB simulation, verified the superiority of the proposed charging load regulation strategy.

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