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Research on the EV charging load estimation and mode optimization methods

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Abstract: With the increasing number of electric vehicles (EVs), the disordered charging of a large number of EVs will have a large influence on the power grid. The problems of charging and discharging optimization management for EVs are studied in this paper. The distribution of characteristic quantities of charging behaviour such as the starting time and charging duration are analysed. The results show that charging distribution is in line with a logarithmic normal distribution. An EV charging behaviour model is established, and error calibration is carried out. The result shows that the error is within its permitted scope. The daily EV charge load is obtained by using the Latin hypercube Monte Carlo statistical method. Genetic particle swarm optimization (PSO) is proposed to optimize the proportion of AC 1, AC 2 and DC charging equipment, and the optimal solution can not only meet the needs of users but also reduce equipment investment and the EV peak valley difference, so the effectiveness of the method is verified.

Key words: EVs, gap optimization, Latin hypercube sampling, Monte Carlo simulation

1. Introduction

EV charging stations not only provide an important energy guarantee for large-scale EV promotion but also improve power system operation and dispatch flexibility. For power systems, charging stations can be regarded as a kind of charging load. Due to the strong randomness of EV charging, it is an urgent problem to establish a probabilistic load model for EV charging stations that correctly and effectively reflects the randomness [1]. The large-scale popularization of EV must rely on the power grid, and EV charging behaviour has strong disorder and high simultaneity, so large-scale EV charging behaviour has greater impact on safe economic power grid operation. At present, EV charging behaviour research has made some achievements. Gao Ciwei *et al.* [2] review EV charging effects on charge facilities planning and construction of the transmission network, distribution network, power grid and grid harmonic. Ma Jinxiang *et al.* [3] collected the status, charging and discharging demand information for EVs and carried out the scheduling plan according to the system scheduling objective, successfully optimizing the charging and discharging scheduling for EVs. Zhang Weige *et al.* [4] predicted the daily load curve of electric buses by fuzzy clustering and a back propagation (BP) neural network. Li Yafang *et al.* [5] compared the charging behaviour of taxis with private cars and established a piecewise probability model for estimating the daily charging load of taxis, but he failed to do an accurate test of the model. Yuan Zhengping *et al.* [6] analysed the behavioural characteristics and charging methods of private cars, buses and taxis. Based on the development scale of Shanghai electric vehicles in 2015, the Monte Carlo method was used to predict the load of Shanghai electric vehicles in 2020. Wu Kuihua *et al.* [7] used the least squares method and obtained the bus charging load curve. Zhang Di *et al.* [8] used genetic intelligent optimization algorithms to rationally arrange the charging start time for battery packs and reduce the charging amount, realizing economic operation of substations, but the genetic algorithm itself could not make good use of feedback information, and the convergence speed was slow.

By calculating the skewness and kurtosis coefficients of EV behaviour characteristics, this paper draws Q-Q scatter plots and verifies that the charging start time and duration conform to the same skew-normal distribution; the resulting error is small, so the fitting curve is highly reliable. The daily load curve of EV charging power is established by the Latin hypercube-Monte Carlo statistical method, and the convergence speed is improved. By introducing a mutation operator, the PSO evolutionary formula is reconstructed. The mutation of genetic modified PSO has self-learning ability. The random mutation is improved to increase the individual adaptive ability mutation, and the search efficiency increases obviously. By reasonably arranging the proportion of AC class 1 and 2 and DC charging equipment, the disorderly EV charging behaviour is optimized to achieve the goal of load shifting and safe power grid operation.

2. Analysis of EV charging characteristics

EV charging start time and duration are random. EV charging behaviour can be analysed by using probability statistical models. In many charging behaviours, charging start time and duration are more important research directions. The original EV charging start time, duration and power data are described in detail in the literature [9].

2.1. Normal distribution test

The calculation of the skewness and the kurtosis coefficients [10] can measure the data distribution shape, and the skewness coefficient is calculated as shown in Equation (1).

$$P = \frac{n \sum_{i}^{n} (x_i - \bar{x})^2}{(n-1)(n-2)s^3}, \tag{1}$$

where n is the number of samples, x_i is the value of the i sample, $\bar{x}$ is the sample mean, and s is the sample standard deviation. The value of P is usually between −3 and 3 and is used to measure data symmetry. When the result is 0, the data set is symmetrical; when the result is negative, the left side is scattered; and when the result is positive, the right side is scattered.

The kurtosis coefficient is calculated as shown in Equation (2).

$$F = \frac{n(n-1) \sum_{i}^{n} (x_i - \bar{x})^4}{(n-1)(n-2)(n-3)s^3} \frac{3 \times (n-1)^2}{(n-2)(n-3)}, \tag{2}$$

where F is used to measure data dispersion. Negative values indicate that data are more concentrated, the data sets on both sides are less, and the positive values are opposite. When both the skewness and the kurtosis coefficients are 0, the data are subject to the standard normal distribution.

The initial data are calculated using Equations (1) and (2), and the results are shown in Table 1.

Table 1. The results of skewness and kurtosis coefficients

Charge characteristic	**Skewness coefficient *P***	**Kurtosis coefficient *F***
Charging start time	2	−0.26
Charge time	2.7	−0.1

It can be seen from Table 1 that the result of charging start time and the charging duration calculation all meet a skew-normal distribution.

The Q-Q scatter plot can be used to determine whether the two sets of data meet the same skew-normal distribution. It can be seen from Fig. 1 that the two sets of charging start time and

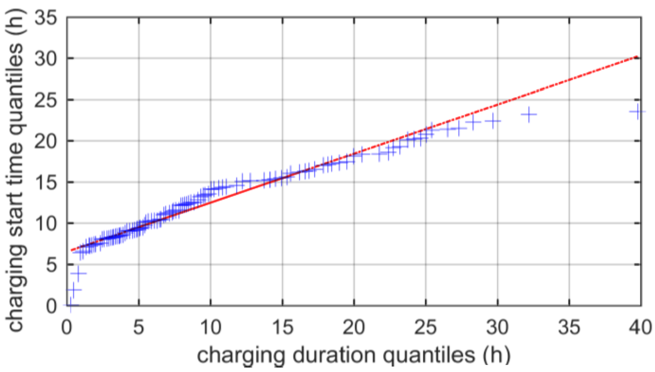

Fig. 1. Q-Q scatter plot of EV charging characteristics

duration data are in the vicinity of a straight line, and it can be judged that they satisfy the same kind of normal distribution. The histogram of the charging start time is made using the raw data of [9], as shown in Fig. 2.

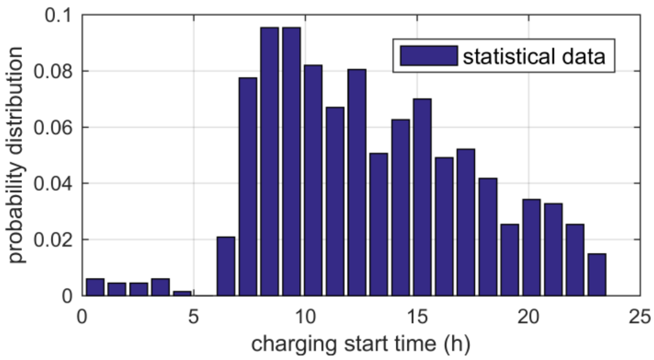

Fig. 2. Histogram of charging start time

It can be seen from Fig. 2 that the distribution peak shifts to the left, and the long tail extends to the right. Combined with the calculation of skewness and kurtosis coefficients, it is inferred that the distribution is consistent with the log-skew-normal distribution. According to the obtained skewness and kurtosis coefficients, the Jarque-Bera normal distribution test method is adopted, and it is assumed to be a log-skew-normal distribution. The test results are shown in Table 2.

Table 2. The results of normal distribution test

Charge characteristic	***h***	***P***
Charging start time	0	0.32
Charge time	0	0.09

The output result $\boldsymbol{h}$ is defined as assuming statistical sample N satisfies some normal distribution.

When the output $\boldsymbol{h}$ is 1, the original hypothesis is wrong; when the output $\boldsymbol{h}$ is 0, the original hypothesis is correct. The returned test p-value refers to the negative null hypothesis when the $\boldsymbol{p}$-value is less than a given significance level (typically 0.05). It can be seen from Table 2 that both the EV charging start time and the duration satisfy the log-skew-normal distribution.

2.2. Probability density histogram and fitting curve of charging characteristics

The probability density histogram and fitting curve for the charging start time and duration are shown in Figs. 3 and 4.

It can be seen from Fig. 3 that the charging start time peak is concentrated from 7:00 to 10:00, and the number of people charging after 10:00 is gradually reduced. It can be seen from Fig. 4 that during an EV charging the charging start time is kept at 0:00~10:00. After charging more than 10 hours, most electric vehicles will stop charging, and a few will continue charging for 40

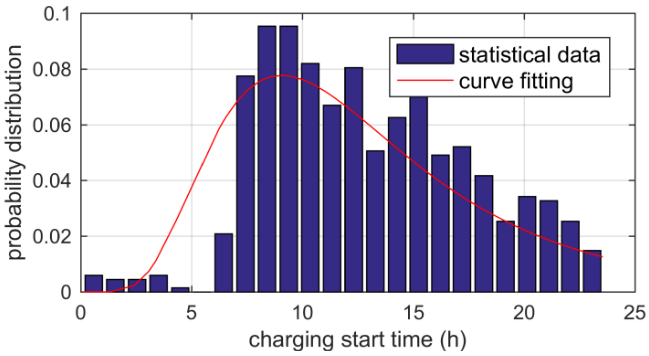

Fig. 3. Probability distribution of the EV charging start time

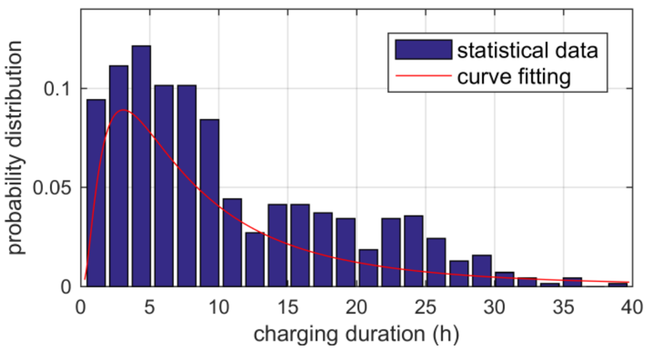

Fig. 4. Probability distribution of the EV charging duration

hours. This centralized charging behaviour will have a greater impact on the stable operation of the power grid.

2.3. Fitted curve error analysis

Figs. 3 and 4 show the log-skew-normal distribution of EV charging characteristics. The fitting results can be judged by three methods: mean square error (MSE), average absolute error (MAD), and the maximum absolute error (Max AE), and the error analysis results are shown in Table 3.

Table 3. The charging characteristic error analysis fitting curve

Charge characteristic	**MSE**	**MAD**	**Max AE**
Charging start time	0.21%	3.32%	10.12%
Charge time	0.27%	3.8%	11.14%

The mean square error and the average absolute error of the two charging feature quantities are close to 0, indicating that the fit is good; thus, it is feasible to use the log-skew-normal distribution.

3. Estimation of EV daily load curve

3.1. EV daily load curve model

Monte Carlo is a method to solve computational problems by generating pseudo-random numbers [11]. The ordinary Monte Carlo simulation method is random sampling, while the Latin hypercube-Monte Carlo statistical method is a multi-dimensional stratified sampling method. The standard error formulas of the two sampling methods are shown in Equations (3) and (4).

$$E_1 = \frac{1}{\sqrt{N}}\sigma_y^2, \tag{3}$$

$$E_2 = \frac{1}{N^3}\sigma_y^2, \tag{4}$$

where σ_y is the standard deviation, N is the number of data, and E_1 and E_2 are the standard Monte Carlo simulation method and the Latin Hypercube-Monte Carlo statistical standard error, respectively.

A comparative analysis of the standard error formulas of the two methods is shown in Equation (5).

$$\frac{E_2}{E_1} = \frac{1}{\sqrt{N^5}}\,. \tag{5}$$

It can be seen from Equation (5) that Latin hypercube sampling significantly saves the sample number N, to improve the Monte Carlo sampling method and give it better convergence.

The probability density functions of the charging start time and the duration are shown in Equations (6) and (7).

$$f_1(x) = \frac{1}{y\sigma_{s1}\sqrt{2\pi}}\, e^{\left(-\frac{(\ln(x)-\mu_{s1})^2}{2\sigma_{s1}^2}\right)}, \tag{6}$$

$$f_2(y) = \frac{1}{y\sigma_{s2}\sqrt{2\pi}}\, e^{\left(-\frac{(\ln(y)-\mu_{s2})^2}{2\sigma_{s2}^2}\right)}, \tag{7}$$

where μ_{s1} is the mean of the charging start time in the distribution, σ_{s1} is the standard deviation of the charging start time in the distribution; μ_{s2} is the mean of the charging duration in the distribution; and σ_{s2} is the standard deviation of the charging duration in the distribution.

After obtaining the probability and statistical model of the EV charging characteristics, the daily load curve is estimated by the Latin Hypercube-Monte Carlo statistical method.

3.2. Example of the charging daily load curve

After establishing the probability density function of the charging start time and duration, according to Monte Carlo, the number of charging EVs at each moment and the power used by each EV at that moment are estimated. The daily charging load curve of 10 000 EVs is calculated through the Latin hypercube sampling method, and the results are shown in Fig. 5.

It can be seen from Fig. 5 that the charging power gradually increases from 0 to 8 o'clock, reaching a maximum at 9 o'clock, and it starts to gradually decrease after 9 o'clock. Fig. 5 shows that the daily load curve trend is basically consistent with the charging start time probability

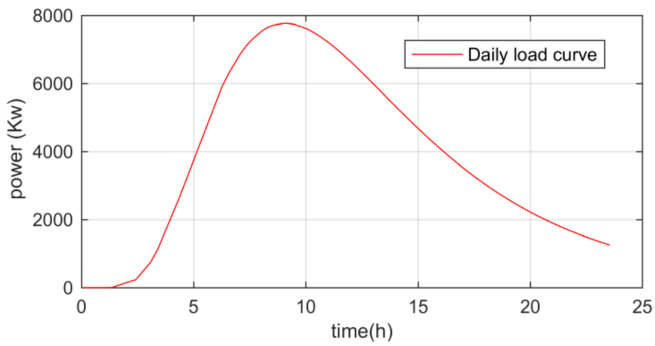

Fig. 5. Daily load curve for 10 000 electric vehicles

density curve trend, but due to the charging duration, the probability density curve of the daily load curve relative to the charging start time has a certain hysteresis. Therefore, the power grid needs to achieve a reduction in load peak-to-valley difference, and a guiding strategy can be adopted from charging start time and duration.

4. Optimizing charging mode based on a genetic particle swarm optimization algorithm

4.1. Establishment of objective functions

Three charging devices with different power levels are shown in Table 4. By optimizing the amount of charging equipment purchased, one can meet the charging demand of large-scale electric vehicles and also simultaneously reduce capital investment in charging station construction as well as the disorderly EV charging load peak-valley difference and load shifting. First, a multi-objective optimization model for charging stations is established, and the decision variables are AC $1(x_1)$, AC $2(x_2)$ and DC(x_3). The objective function is the total equipment investment and the EV disorderly charging load peak-valley difference. The constraint is that the expected user charging capacity is satisfied within the connecting time.

Table 4. EV charging power level

	AC 1	**AC 2**	**DC**
Power (kW)	1.4~1.9	7.7~25.6	40~100
Cost per unit (yuan)	3 000	15 000	50 000

Let $Y_1\,(x_1,\ x_2,\ x_3)$ be the total investment function of the equipment, which is composed of the product of the proportion and cost of each piece of equipment in the charging station. $Y_2\,(x_1,\ x_2,\ x_3)$ is the peak-valley difference function of the disorderly EV charging load, composed of the sum of the proportion of each device in the charging station and the maximum power product of each charging device, minus the sum of the proportion of each device in the charging station and the minimum power product of each charging device. Here, the objective function is established:

$$Y_1(x_1, x_2, x_3) = 3\,000x_1 + 15\,000x_2 + 5\,0000x_3, \tag{8}$$

$$Y_2(x_1, x_2, x_3) = 1.9x_1 + 25.6x_2 + 100x_3 - 1.4x_1 - 7.7x_2 - 40x_3\,. \tag{9}$$

The charging station must meet user expectations of charging power within the connecting time. To meet customer demand, the lower limit of the total charging power at the lowest charging power for each charging station is set as the daily charging load, and the constraint function is shown as follows:

$$1.4x_1 + 7.7x_2 + 40x_3 \geq 39.06. \tag{10}$$

4.2. Realization of genetic particle swarm optimization algorithm

Charging equipment models for charging stations are complex with nonlinear multi-objective functions. Their optimization methods can be solved by intelligent algorithms. A genetic particle swarm optimization algorithm is proposed to solve a charging equipment optimization model for charging stations. Genetic particle swarm optimization introduces the crossover operator into particle swarm optimization (PSO). After crossover operation of two operators, two new operators are obtained that improve the algorithm search performance and avoid falling into local optima [12]. For the population, the algorithm uses the concept of multi-population and the strategy of ranking selection in the genetic algorithm for reference. By comparing the optimal solutions among different groups, the algorithm determines whether the global or local is the optimal solution. While guaranteeing the optimality of the group, the algorithm prevents all individuals from approaching extremes in evolution, which is conducive to expanding the search space. On mutation of the operator, the mutation algorithm reconstructs the PSO evolution formula, as shown in Equation (11):

$$V_{\max\_i,j}(t) = \frac{\sum_{k=2}^{t} x_{\max\_i,j}(k) - x_{\max\_i,j}(k-1)}{t}\,. \tag{11}$$

The formula of particle swarm optimization with mutation operator is updated to:

$$\begin{cases} V_{\max\_i,j}(t+1) = V_{\max\_i,j} + c_1 r_1 \left[p_{i,j} - x_{i,j}(t)\right] + c_2 r_2 \left[p_{i,j} - x_{i,j}(t)\right] \\ x_{i,j}(t+1) = x_{i,j}(t) + V_{\max\_i,j}(t+1) \end{cases}, \tag{12}$$

where $x_{\max\_i,j}$ is the particle position of historical optimal individuals; $V_{\max\_i,j}$ is the update speed; $v_{i,j}$ and $x_{i,j}$ are the velocity and position of the first individual particle, $j = 1, 2, 3, \ldots, d$; d is the dimension; c_1 and c_2 are positive learning factors; r_1 and r_2 are the random numbers with uniform distribution from 0 to 1; $p_{i,j}$ is the optimal solution positions of sub-populations; and $p_{g,j}$ is the locations of global optimal solutions.

Equation (12) predicts the mutation prior to the one that enables mutation operation self-learning and replaces random mutation with improving individual adaptive ability mutations. The genetic particle swarm optimization overcomes the premature particle swarm optimization, improves the ability of local searching and jumping out of local minimum, and has high efficiency and fast convergence speed [13]. Genetic particle swarm optimization is shown in Fig. 6.

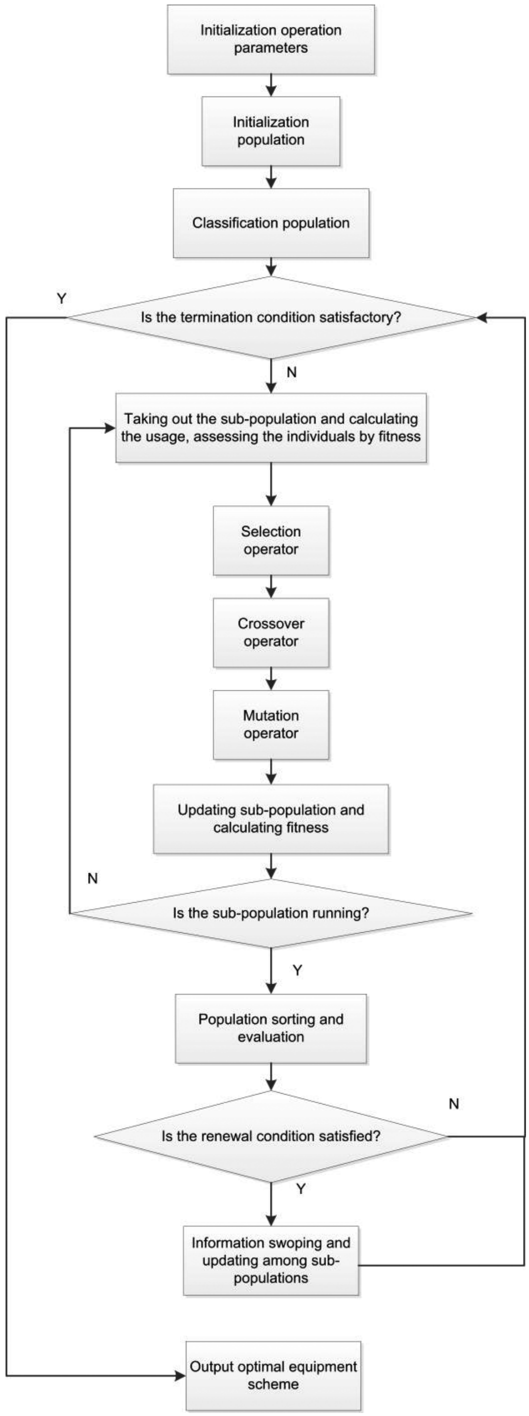

Fig. 6. Genetic particle flow chart

The total number of electric vehicles is 10 000, the maximum iteration is 50 generations, the population size is 40, and each operator is an individual and corresponds to a certain solution of a set of variables. Before using genetic particle swarm optimization to find the optimal solution, the fitness functions $\min Y_1(x_1, x_2, x_3)$ and $\min Y_2(x_1, x_2, x_3)$ and the proportion of three kinds of charging power devices x_1, x_2, and x_3 are determined according to the requirements of meeting user needs, reducing equipment investment and decreasing peak-valley difference of EV disorderly charging load and, furthermore, to determine whether the fitness function meets the requirements. Based on the genetic particle swarm optimization algorithm, the inertia weight, cross coefficient, learning factor and other related parameters are set, and the optimal solution is obtained. The X_1 data of AC level 1 charging equipment are taken out, and the iteration situation is shown in Fig. 7. The solution methods of AC Level 2 charging equipment X_2 and DC level equipment X_3 are the same. Genetic particle swarm optimization is used to optimize charging. When the optimal solution is obtained by genetic particle swarm optimization, the proportion of charging equipment is shown in Fig. 8.

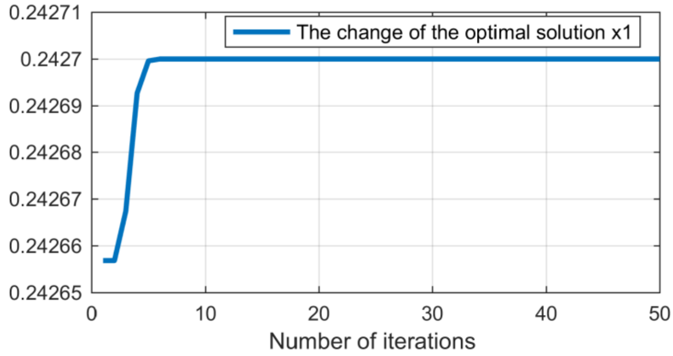

Fig. 7. Running results

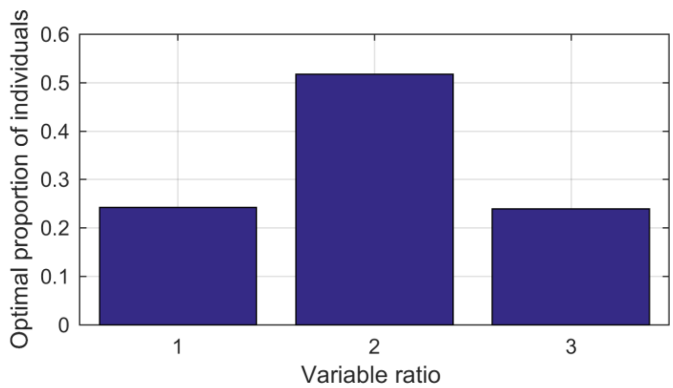

Fig. 8. Iterative results

As seen from Fig. 8, the best charging station operating conditions are the AC 1 level accounting for 24.27%, the AC 2 level accounting for 51.79%, DC accounting for 23.94% and the AC 2 level equipment with the largest AC power accounting for the largest proportion, while DC equipment with the largest power accounted for a relatively small proportion.

5. Conclusions

With more and more government policies encouraging EV development, EVs are bound to replace traditional internal combustion engine vehicles on a large scale. EVs are frequently connected to the power grid to charge, and the pressure on the power grid will be further increased.

First, EV charging characteristics are analysed, and the Jarque-Bera normal distribution test is used to verify that the charging behaviour conforms to a logarithmic deviated normal distribution. By using probability and statistics, the probability density curves of charging start time and duration are obtained, and the mean square error (MSE), mean absolute error (MAD) and maximum absolute error (Max AE) are calculated. Compared with the fit probability density curves, satisfactory results are obtained. The results show that the model has less error with the actual values and high credibility. The daily load curve for large scale EV is estimated using Latin hypercube Monte Carlo statistics.

By analysing the charging behaviour of EV users, objective functions are established with the lowest charging cost, lowest charging station investment, lowest power grid operation peak-valley difference, and optimal ratios for AC-1, AC-2 and DC charging equipment. The objective functions are satisfied using a genetic particle swarm optimization algorithm. The results show that AC and DC charging equipment should be built to meet the rapid charging needs of some users. Users can be divided into fast charging and slow charging users according to connection time. Users with long connection time can use low-power charging equipment to charge during the peak period and then switch to high-power equipment to charge quickly after the peak period. Small-scale power grid upgrading achieves load shifting and reduces the power grid operation pressure while accommodating more EV charging.

Acknowledgements

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