Calculation Method of Electric Vehicle Baseline Load Based on Classification

Yue Zhang¹*, Mingguang Liu¹, Dunnan Liu¹, Heping Jia¹, Shu Su², Xiaofeng Peng², Mengjiao Zou¹, Shanshan Shang¹ and Ye Yang²

¹School of economics and management, North China Electric Power University, Beijing, 102206, China
²State Grid Electric Vehicle Service Company, Beijing 100053, China
*Corresponding author’s e-mail: 120202206130@ncepu.edu.cn

Abstract. In the incentive based demand response project, the baseline load calculation of electric vehicle users can provide quantitative basis for evaluating the power demand response and the load adjustment degree of users. The charging load of electric vehicle is different from the traditional electric load, which has greater flexibility and is more affected by user’s behavior. This paper analyzes the characteristics and influencing factors of electric vehicle charging load. On the basis of summarizing the common calculation methods of user baseline load at home and abroad, this paper puts forward the calculation method of electric vehicle baseline load based on classification, and finally analyzes the accuracy and applicability of this method combined with specific examples.

1. Introduction

With the continuous development of energy transformation, the high proportion of new energy access, and the rapid development of flexible demand side resources represented by electric vehicles, the development of power demand response project has been promoted. Power demand response is considered to be an effective measure to absorb new energy and solve the problem of abandoning wind and light[1]. As an important part of demand side management, demand response takes the load resources on the user side as the alternative resources of energy supply. It can effectively guarantee the stability of the power grid by changing the electricity price or directly compensating the users to change the inherent power consumption mode. In the incentive based demand response project, user baseline load forecasting can provide quantitative basis for evaluating power demand response and adjusting user load. Baseline load is a load curve estimated according to the historical load data of users, which reflects the power demand of users when they do not participate in the demand response project. It is an important basis for the demand response project implementation agencies to compensate users[2]. Because the calculation method of benchmark load is simple, transparent and easy to understand, various calculation methods based on average value method and regression method are widely used in different projects. When there are further requirements for the accuracy of baseline load calculation, data mining methods such as artificial neural network and clustering appear[3]. These methods have achieved high prediction accuracy in suitable application scenarios. However, they only calculate the baseline load of a single user, which has poor generalization ability, and they do not choose suitable methods for different load characteristics.
On the basis of summarizing the common user baseline load calculation methods at home and abroad, aiming at the fact that the existing methods do not reflect different load characteristics[4], this paper proposes a classification based electric vehicle baseline load calculation method, and finally analyzes the accuracy and applicability of this method with a specific example.

2. Common baseline load calculation method
Many scholars abroad have studied the theory and method of load forecasting in power system. Because the domestic research on the response of starting power demand is relatively late and the coverage is small, so the relevant literature is less. In the foreign research, the calculation methods can be divided into three categories: average value method, regression method and data mining method[5].

2.1. Average value method
The average method takes the mean value of the corresponding hourly load value of N days before the demand response event date as the baseline load. It only makes statistics, analysis and calculation on the historical load data, but does not consider the influence of current information on the baseline load. Although the accuracy of the method is relatively low, it is widely used because of its ease of use and transparency.

2.2. Regression method
The average method is based on the historical load data of users, and the regression law considers the influence of external factors on the user baseline load. Because the change law of some users' power load has similar change trend with temperature change, temperature can be used as an independent variable of regression analysis to predict baseline load. In the case of sufficient external data, multiple regression analysis can be used to take time-sharing price, weather condition, other demand response project events and other factors as independent variables.

2.3. Data mining method
In recent years, the data mining methods represented by artificial neural network and clustering algorithm have been applied to the calculation of baseline load, and its prediction accuracy is usually high. Data mining methods can take into account many factors that affect the user's power load, such as historical load, weather, holiday, date type, etc., so the accuracy is often higher than the above two methods. In the research of artificial intelligence data mining method, domestic and foreign scholars are constantly proposing improved optimization model. In artificial intelligence algorithm, artificial neural network is a supervised learning algorithm which is simple and convenient to calculate, and can deal with complex nonlinear problems.

3. Calculation method of electric vehicle baseline load based on Classification
Firstly, the characteristics of electric vehicle charging load are analyzed and classified, and then the baseline load is calculated based on the classified data. Finally, the calculation error is compared and analyzed.

3.1. Load characteristics and classification of electric vehicles
The charging load of electric vehicle is different from the traditional electric load. The same characteristics are that both loads have periodicity and volatility, which are reflected in annual cycle, seasonal cycle and daily periodicity. Fluctuation is due to a series of external environment and internal conditions, which shows the characteristics of load curve fluctuation. Therefore, the classification of electric vehicle charging load can effectively improve the accuracy of the calculation of the baseline load. Before calculating the baseline load curve of electric vehicles, the load characteristics should be analyzed to facilitate the classification of the load.
3.1.1. Load characteristics

(1) Periodicity

The charging load has the characteristics of seasonal periodic variation. The weekly periodicity of charging load is mainly reflected by the date type. For example, the daily load variation of adjacent working days basically follows the same rule. According to the change characteristics of charging load, date types are divided into working days and weekend days, which are closely related to people's daily behavior. The daily periodicity of charging load is 24 hours a day, which reflects the load change trend in a day.

(2) Volatility

The charging load is affected by various factors such as temperature, date type and user behavior. In this paper, the daily average load, daily maximum load, daily minimum load, instantaneous average daily load rate of change and average change rate of adjacent daily load are introduced to analyze the fluctuation characteristics of charging load of electric vehicles.

3.1.2. Load classification

Electric vehicles can be classified according to different standards, among which classification according to vehicle use is a common method. Different types of electric vehicles charging load characteristics are different naturally. According to the classification of traditional fuel vehicles, electric vehicles can also be divided into public transport and private vehicles. Electric buses, electric environmental protection vehicles, electric commercial vehicles and electric intercity vehicles are all public transport vehicles, which mainly provide transportation services for public utilities, usually with relatively stable driving distance and charging time and place, and their load characteristics are also well mastered. Private vehicles are mainly electric private vehicles, which play the role of personal step by step and transportation. It is flexible in operation, and the driving distance and charging time place are greatly affected by users' habits, and the charging power is random, and the load characteristics are not different from public transport.

3.2. Electric vehicle baseline load calculation

3.2.1. Algorithm Introduction

Artificial intelligence prediction has become the mainstream prediction method at present. Compared with traditional prediction methods, it can better deal with high-dimensional and nonlinear problems, and can effectively use power big data to fully explore historical information. It has the advantages of high prediction accuracy and wide application range, which improves the problem of limited improvement of prediction accuracy of traditional methods.

The traditional baseline load calculation model is described by explicit mathematical expression, which determines the limitations of the traditional calculation model. In fact, the change of electric vehicle charging load is strongly affected by weather conditions and people's social activities, and there are a lot of nonlinear relationships, so it is difficult to express its development law with an explicit mathematical formula.

LS-SVM is an improved method of traditional SVM. It can be used as function approximation method in the field of prediction. It replaces the inequality constraint of SVM with equality constraint, transforms the quadratic programming problem into linear problem solving, and reduces the complexity of calculation. LS SVM is based on statistical theory and can solve the problems of small sample, nonlinear and local minimum by minimizing structural risk.

3.2.2. Calculation steps

(1) Data preprocessing

In the process of collecting charging load data, the existence of abnormal data will make the general law of load change not really appear, and the reliability of baseline load calculation results will be affected by it. In addition, the influence factors and the dimension and unit of load data will also have
different effects on the calculation results. In order to eliminate the interference of the magnitude of these data on the analysis of load change rules, the original load data needs to be preprocessed.

(2) Establish LS-SVM model

Given the training sample set \( \{ (x_i, y_i) \} \), \( i = 1, 2, ..., n \), \( x_i \) is the input load value and \( y_i \) is the corresponding output value, and the regression function is constructed:

\[
f(x) = \omega^T \phi(x) + b
\]  

(1)

Where: \( \omega \) is the weight vector; \( \phi(x) \) is the mapping function from low dimensional space to high dimensional space; \( b \) is the offset term. In this case, the objective function and constraints are as follows:

\[
\begin{align*}
\min J(\omega, e) &= \frac{1}{2} \| \omega \|^2 + \frac{1}{2} C \sum_{l=1}^{l} e_l^2 \\
y_i &= \omega^T \phi(x_i) + b + e_i, \quad i = 1, 2, ..., l
\end{align*}
\]  

(2)

(3)

Where: \( e_i \) is the error, \( C \) is the penalty parameter, and Lagrange multiplier is introduced \( \lambda \), \( \lambda \in \mathbb{R}^{|l|} \), then the constrained optimization problem is transformed into an unconstrained optimization problem:

\[
L(\omega, b, e, \lambda) = \frac{1}{2} \| \omega \|^2 + \frac{1}{2} C \sum_{l=1}^{l} e_l^2 - \sum_{l=1}^{l} \lambda_i [\omega^T \phi(x_i) + b + e_i] - y_i
\]  

(4)

According to the Karolin Kuhn Tucker (KKT) optimization conditions, the following results are obtained:

\[
\frac{\partial L}{\partial \omega} = 0 \rightarrow \omega = \sum_{i=1}^{l} \lambda_i \phi(x_i)
\]  

\[
\frac{\partial L}{\partial b} = 0 \rightarrow \sum_{i=1}^{l} \lambda_i = 0, \quad i = 1, 2, ..., l
\]  

\[
\frac{\partial L}{\partial \lambda_i} = 0 \rightarrow \lambda_i = C e_l, \quad i = 1, 2, ..., l
\]  

\[
\frac{\partial L}{\partial \lambda_i} = 0 \rightarrow \omega^T \phi(x_i) + b + e_i - y_i = 0, \quad i = 1, 2, ..., l
\]  

(5)

With the \( \omega \) and \( e_i \) removed, the solution of equation (13) is as follows:

\[
\begin{bmatrix} 0 & E^T \\ E & K + C^{-1}I \end{bmatrix} \begin{bmatrix} b \\ \lambda \end{bmatrix} = \begin{bmatrix} 0 \\ Y \end{bmatrix}
\]  

(6)

Where \( E \in \{1, 1, ..., 1\}^T \); \( I \) is the identity matrix; \( \lambda = [\lambda_1, \lambda_2, ..., \lambda_l]^T \); \( Y = [y_1, y_2, y_3, ..., y_l]^T \); \( K \) is the kernel function mapped to the high dimensional space by nonlinear mapping, and the optimal linear regression function of LS-SVM is as follows:

\[
f(x) = \sum_{i=1}^{l} \lambda_i K(x_i, x) + b
\]  

(7)

(3) Error analysis

The average absolute percentage error is selected for error analysis, and the calculation formula is as follows:

\[
\lambda_{mae} = \frac{1}{N} \sum_{i=1}^{N} \left| \frac{x_i - \hat{x}_i}{x_i} \right| \times 100\%
\]  

(8)

Where: \( N \) is the sampling point; \( i \) is the sampling point, \( x_i \) is the actual load value of \( i \) sampling point, and \( \hat{x}_i \) is the calculation value of baseline load of \( i \) sampling point.

4. Example analysis

4.1. Example overview

In this paper, the user charging load data of electric vehicles in a certain region is used for the test, and the charging load data of electric vehicles in this region from November 16, 2019 to April 30, 2020 is selected for the simulation experiment. Since the 11:00 to 13:00 on the non working day in April 2020 does not participate in the demand response, the load forecast value of this period is selected as the baseline load value. Electric vehicles are divided into four categories: public electric vehicles, public
electric vehicles, unit electric vehicles and other electric vehicles according to their functions and uses. The total load is the sum of all loads, and the loads of each category are calculated respectively. Figure 1 is the daily load curve and total charging load curve of public transport, public transport and unit electric vehicles formed by the original electric vehicle charging load data of the region from December 12, 2019 to February 1, 2020.

The peak values of the four types of loads are concentrated in the daytime and afternoon, and the valley values are all in the period of 2:00-7:00. The peak valley value and load value at each time point of the charging load curve of different types of electric vehicles are different. In addition, the shape of the curve also shows great differences. The load curve and total load curve of public and bus electric vehicles are similar, but the charging load value of unit electric vehicle is generally low due to the difference of user behavior, the peak value is less than 8MW, and the shape is also different. It can be seen that the unified forecasting of them will affect the forecasting effect.

Considering the influence of temperature and date type, the maximum temperature, minimum temperature and date type of the predicted area are input into the prediction model as influence variables. BP neural network and LS-SVM are used for prediction, and comparative analysis is carried out.

4.2. Result analysis
The mean absolute percentage error (MAPE) is selected for error analysis. The prediction errors of the two methods are shown in Table 1:

![Figure 1. load curve of various electric vehicles.](image-url)
Table 1. Comparison of different algorithms for predicting MAPE

| Types of EVs      | BP neural network | LS-SVM |
|------------------|-------------------|--------|
| Public EVs       | 26.22%            | 1.59%  |
| Transit EVs      | 25.19%            | 1.79%  |
| Company EVs      | 19.91%            | 1.33%  |
| Other EVs        | 27.34%            | 1.65%  |
| Total load       | 27.81%            | 1.54%  |

Since BP neural network has high sensitivity to initial value and randomness of initial value and threshold value at the beginning of each training, the results and errors of convergence to local optimal solution obtained by different initial values will be different. Therefore, this paper takes the MAPE average value of multiple real tests as the evaluation index of this method. In the non working day load forecast of April 2020, the MAPE predicted by BP neural network is more than 20%, while LS-SVM has no more than 2% MAPE, which fully reflects the advantages of LS-SVM algorithm.

5. Conclusion

In the incentive based demand response project, the baseline load calculation of EV users can provide quantitative basis for evaluating the response of electric demand and the load adjustment degree of users. The charging load of electric vehicle is different from the traditional electric load, which has greater flexibility and is more affected by user’s behavior. In view of the fact that the existing methods do not reflect different load characteristics of electric vehicles, this paper analyzes the charging load characteristics and influencing factors of electric vehicles. Based on the summary of the calculation methods of baseline load of domestic and foreign users, a classification based calculation method of baseline load of electric vehicles is proposed. Finally, the accuracy and applicability of the baseline load calculation method proposed in this paper are analyzed by a specific example.

References

[1] Huang, S.J., Abedinia, O. (2021) Investigation in economic analysis of microgrids based on renewable energy uncertainty and demand response in the electricity market. Energy, 225.
[2] Lee, E.J., Lee, K., Lee, H., Kim, E., Rhee, W.J. (2019) Defining virtual control group to improve customer baseline load calculation of residential demand response. Applied Energy, 250.
[3] Zhang, Y.F., Ai, Q., Li, Z.y. (2020) Improving aggregated baseline load estimation by Gaussian mixture model. Energy Reports, 6:59.
[4] Wang, X.F., Su, H.L., Song, T.L., Huang, Q.F. (2018) Differentiated user baseline load forecasting based on load subdivision. Power engineering technology, 37:33-38.
[5] Meng, Y.Y. (2020) Calculation method of user base load considering demand response. Automation application, 8:110-111.