Electric Vehicle Charging Load Time-Series Prediction Based on Broad Learning System

1st Wang Sike
Marketing Service Center (Metering Center)
State Grid Hubei Electric Power Co., LTD
Wuhan, China
55855234@qq.com

2nd Yu Liansong†
State Grid Electric Power Research Institute Wuhan Nanrui Co., LTD
Wuhan, China
d202080754@hust.edu.cn

3rd Pang Bo
Marketing Service Center (Metering Center)
State Grid Hubei Electric Power Co., LTD
Wuhan, China

4th Zhu Xiaohu
State Grid Electric Power Research Institute Wuhan Nanrui Co., LTD
Wuhan, China

5th Cao Peng
Marketing Service Center (Metering Center)
State Grid Hubei Electric Power Co., LTD
Wuhan, China
1149843220@qq.com

6th Shen Yang
State Grid Electric Power Research Institute Wuhan Nanrui Co., LTD
Wuhan, China

Abstract—Accurate Electric Vehicle (EV) charging load time-series prediction is an important prerequisite for enhancing the safe and stable operation of charging stations. However, the EV charging load is strongly nonlinear, highly intermittent and random, which leads to the low accuracy of charging load time-series prediction. To this end, this paper proposes a broad learning system-based EV charging load time-series prediction method. First, the actual data of charging load of EV are analyzed and processed. Further, a charging load time-series prediction model is established using a broad learning system. Simulation experiments based on actual data indicate that the proposed charging load time-series prediction model based on the broad learning system has better prediction performance and also has less computing time compared to prediction models such as back propagation neural network and long-short term memory.

Index Terms—Electric Vehicle, charging load, time-series prediction, broad learning system

I. INTRODUCTION

As the global call for energy conservation, emission reduction and green manufacturing grows stronger, green and low-carbon development has become a major trend in global development. Due to the advantages of low carbon and environmental protection of Electric Vehicle (EV), more and more countries begin to promote the EV. However, the charging load prediction of the EV is the key to ensure the safety and stability of the grid. In addition, the charging load has the characteristics of nonlinear, random, intermittent, etc. How to establish an accurate EV charging load time-series prediction model is crucial.

† Corresponding Author: Yu Liansong (d202080754@hust.edu.cn)

Currently, the research on charging load prediction is mainly in traditional prediction methods and machine learning based methods. The traditional prediction methods mainly include: linear regression method, mathematical statistics method, etc. For example, a Monte Carlo simulation method was used to develop a charging station load prediction model [1]. Traditional modeling methods mostly rely on experience for modeling and are not accurate. Meanwhile, a large number of different types of data are needed for model verification, which may lead to poor generalization.

In recent years, machine learning methods have started to receive more and more attention from experts and scholars and are applied to numerous fields [2]–[4]. Machine learning-based charging load prediction methods have also become a hot topic in the field of smart grid. A prediction method based on a combination of improved random forest and density clustering was established to predict the short-term load frequency domain, but the model structure is complex [5]. Three temporal modeling methods, recurrent neural networks, long-short term memory (LSTM), and gated recurrent units, were used to predict the bus charging station load [6]. A hierarchical modeling-based EV charging load prediction method was proposed to perform day-ahead and hour-ahead forecasting for a region in the Netherlands [7]. An ultra-short-term EV charging load prediction model based on LSTM was developed [8]. The above machine learning-based modeling method can mine the time-series features in the load variation sequence without setting a large number of parameters manually, and the modeling is simple and effective.

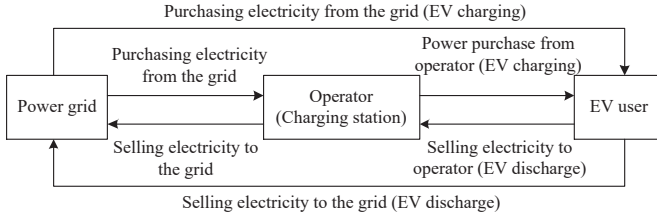In the above background, this paper establishes a time-

Fig. 1. EV charging and discharging relationship diagram.

series prediction model of EV charging load based on a broad learning system (BLS). This model is able to consider the effects of different factors on the charging load, as well as the time-series characteristics of the charging load. The efficiency of the proposed method is verified with actual data from a region of the UK.

II. EV CHARGING AND DISCHARGING PRINCIPLE

The main source of energy for the EVs is the power grid. Vehicle to Grid refers to the optimal management of the charging and discharging behavior of electric vehicles through rational strategies and advanced communication. In the process of interaction, there are three subjects: grid, operator (charging station) and EV user. EV user can either exchange electric energy with grid directly or choose charging and discharging agent service of operator, and the relationship between the three is shown in Fig. 1.

Achieving accurate time-series prediction of EV charging load can ensure safe and stable operation of the grid, and also provide security for Vehicle to Grid.

III. BLS-BASED EV CHARGING LOAD TIME-SERIES PREDICTION MODEL

This section ascribes how to build a BLS-based EV charging load time-series prediction model.

A. EV charging load related data processing and analysis

The actual charging load data is derived from real-time data from a regional charging station in the UK. These data mainly involve charging time, charging power, holidays, weather, temperature and other data. Obviously, these data are not of the same order of magnitude, and in order to reduce the impact of charging load modeling, all data need to be normalized.

$$\widetilde{X} = \frac{X - X_{\min}}{X_{\max} - X_{\min}}, \tag{1}$$

where X denotes the original data, $X_{\max}$ and $X_{\min}$ are the maximum and minimum values in the original data, respectively. Then, all EV charging load data values are between [0, 1], thus completing the normalization of the data.

After obtaining the normalized charging load data, a suitable modeling approach is needed to build its time-series prediction model. The BLS [9], [10] has a simple structure and is an efficient incremental learning system that does not require deep

structure. Therefore, it is feasible and meaningful to use BLS as an EV charging load time-series modeling method.

B. EV charging load time-series model using BLS

The BLS is proposed on the random vector function connectivity network, with the difference that the broad learning maps the input data, constructs the mapped features, and then activates the mapped features as augmented features, and inputs the two parts of features together to the top layer. The structure of the BLS is shown in Fig. 2.

In Fig. 2, BLS is assumed to include m groups of feature maps (each group contains f feature nodes) and n enhancement nodes. The input data $\widetilde{X}$ consists of the input factors required for EV charging load prediction at each time. A series of feature nodes can be obtained from $\widetilde{X}$ through feature mapping, among which the i-th group of feature nodes is as follows:

$$F_i = \psi\left(\widetilde{X}W_{e_i} + b_{e_i}\right), i = 1, 2, \ldots, m, \tag{2}$$

where ψ represents feature mapping incentive function, W_{e_i} and b_{e_i} are the weight and the bias associated with the feature node, respectively.

The combination of these feature nodes is recorded as

$$F^m = [F_1, F_2, \ldots, F_m]. \tag{3}$$

All feature nodes are extended to the enhancement layer by a nonlinear excitation function. The j-th enhancement node is denoted as

$$E_j = \xi\left(F^m W_{e_j} + b_{e_j}\right), j = 1, 2, \ldots, n, \tag{4}$$

where ξ is nonlinear excitation function (here, the Tansigmoid is used), W_{e_j} and b_{e_j} are the weight and bias associated with the enhancement node, respectively.

All enhancement nodes are represented as

$$E^n = [E_1, E_2, \ldots, E_n]. \tag{5}$$

The feature nodes layer and the enhancement nodes layer are connected by a matrix to finally form the BLS.

$$\begin{aligned} Y &= [F_1, F_2, \ldots, F_m | E_1, E_2, \ldots, E_n] W, \\ &= [F^m | E^n] W, \end{aligned} \tag{6}$$

where W is the weight of output, Y is the output of BLS.

The weight of output W can be computed by a pseudoinverse algorithm.

$$W = [F^m | E^n]^+ Y. \tag{7}$$

Let $\Omega = [F^m | E^n]$. The weight of output W is able to be computed approximately

$$W = \left(\Omega\Omega^T + \eta I\right)^{-1} \Omega^T Y, \tag{8}$$

$$\Omega^+ = \lim_{\eta \to 0} \left(\Omega\Omega^T + \eta I\right)^{-1} \Omega^T, \tag{9}$$

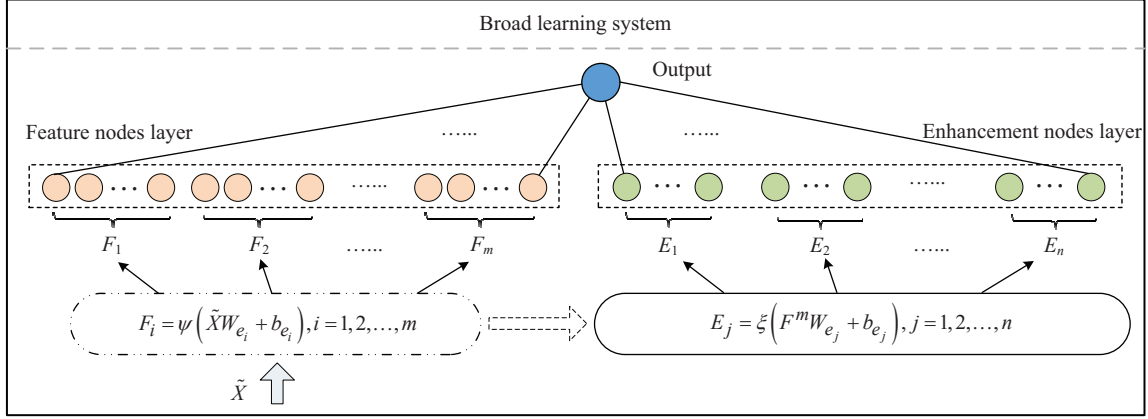where η represents the ridge coefficient.

Fig. 2. Structure of BLS.

TABLE I
HYPERPARAMETER OF DIFFERENT MODELS.

Model	Hyperparameter
LSTM	Number of memory cells: 10, learning rate: 10^{-6}
BPNN	Number of hidden nodes: 15
Our model	$f = 10$, $m = 10$, $n = 150$, $\eta = 2^{-30}$

Based on the above analysis, the BLS-based EV charging load time-series prediction model is developed. In addition, to evaluate the performance of the proposed model, root mean square error ($RMSE$), correlation coefficient (R^2), and mean absolute error (MAE) are considered as evaluation metrics.

$$RMSE = \sqrt{\frac{\sum_{t=1}^{M}\left[Y_r\left(t\right) - Y\left(t\right)\right]^2}{M}}, \qquad (10)$$

$$R^2 = 1 - \sum_{t=1}^{M}\left[Y\left(t\right) - \bar{Y}_r(t)\right]^2 \Big/ \sum_{t=1}^{M}\left[Y_r(t) - \bar{Y}_r(t)\right]^2, \qquad (11)$$

$$MAE = \frac{1}{M}\sum_{t=1}^{M}\left|Y_r\left(t\right) - Y\left(t\right)\right|, \qquad (12)$$

where M is the number of testing data, $Y_r\left(t\right)$ is the real value of EV charging load data, $Y(t)$ is the predicted value, and $\bar{Y}_r(t)$ is mean value of testing data.

IV. EXPERIMENT AND DISCUSSION

358 sets of actual EV charging load data are collected from a region of the UK, of which the first 258 sets are used for model training and the remaining 100 sets are used for model testing. To verify the effectiveness of the proposed model, we compare it with LSTM model [8] and back propagation neural network (BPNN) model [11]. Before conducting the model testing, the hyperparameters of the model are set as shown in Table I.
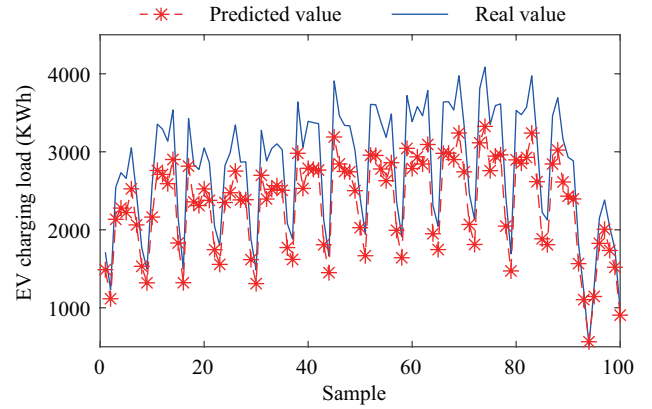

Fig. 3. Prediction results of LSTM.

The prediction results of LSTM model are shown in Fig. 3, and its prediction errors are shown in Fig. 4. The prediction errors of the LSTM model are in the range of [-800, 100] KWh. It is able to roughly follow the real value of EV charging load.

The prediction results of BPNN model are shown in Fig. 5, and its prediction errors are shown in Fig. 6. The prediction errors of the BPNN model are in the range of [-800, 600] KWh. It can also follow the real value of EV charging load.

The prediction results of our model are shown in Fig. 7, and its prediction errors are shown in Fig. 8. The prediction errors of the our model are in the range of [-80, 20] KWh. It can well follow the real value of EV charging load.

With the above results, it can be seen that our model has higher prediction accuracy and better performance, compared with BPNN model and LSTM model. The EV charging load curve shows a certain periodicity and stochasticity, and the three prediction models have enhanced their ability to track the actual charging load prediction curve in turn. However,
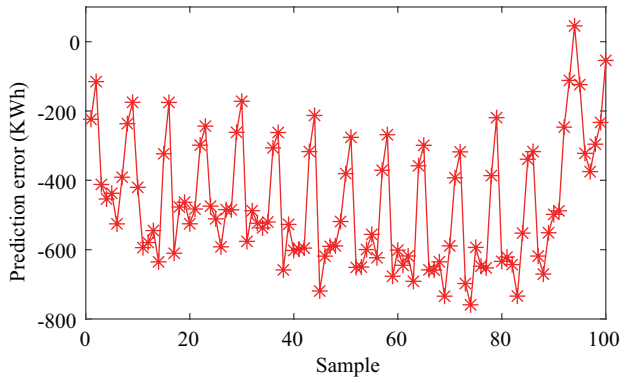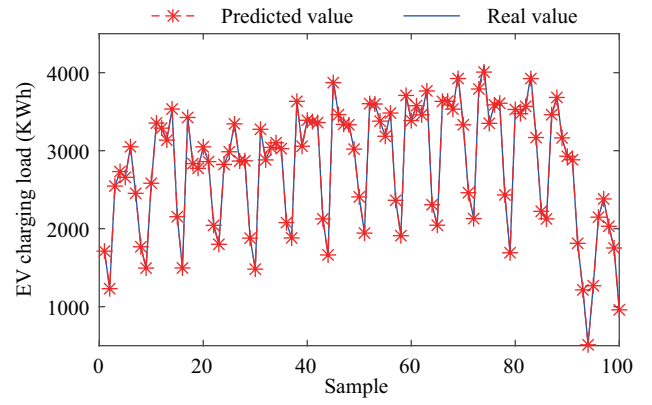
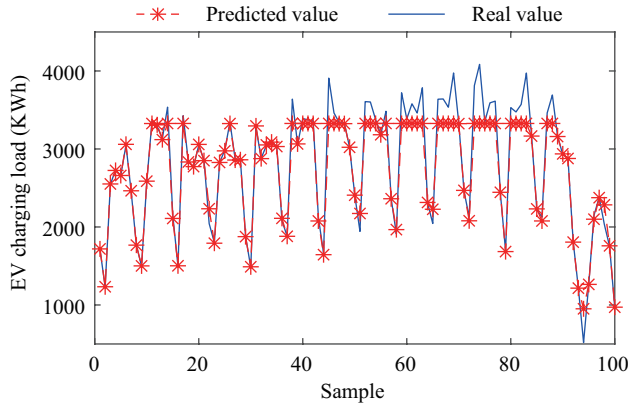Fig. 4. Prediction errors of LSTM.

Fig. 5. Prediction results of BPNN.

Fig. 6. Prediction errors of BPNN.

Fig. 7. Prediction results of our model.

Fig. 8. Prediction errors of our model.

TABLE II
PERFORMANCE COMPARISON OF EVALUATION METRICS FOR DIFFERENT
MODEL.

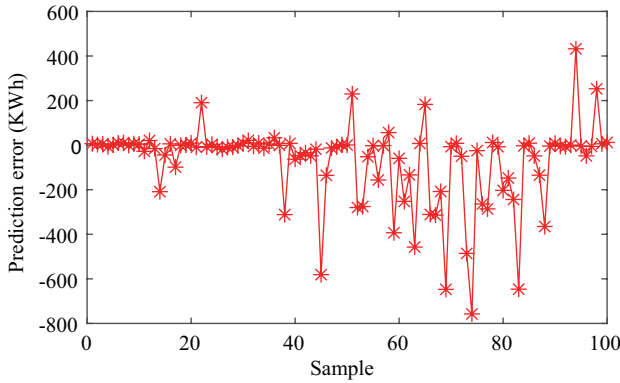| Model	$RMSE$ (KWh)	MAE (KWh)	R^2
LSTM	499.7542	467.7545	0.8135
BPNN	196.1845	106.2506	0.9614
Our model	11.6143	3.3416	0.9998

the BLS extracts features from the input data and can fit the relationship between parameters more accurately, so its prediction errors are significantly smaller than that of BPNN and LSTM.

In addition, to further verify the prediction performance of the models, we statistically analyze the prediction results of different models. The results of the statistical analysis are shown in Table II. As far as the $RMSE$ is concerned, the result of the LSTM model is 499.7542 KWh, the result of the

BPNN model is 196.1845 KWh, and the result of our model is only 11.6143 KWh. In terms of MAE, the results for the LSTM model are 467.7545 KWh, the results for the BPNN model are 106.2506 KWh, and the results for our model are only 3.3416 KWh. Specifically, with respect to R^2, the result of the LSTM model is 0.8135, the result of the BPNN model is 0.9614, and the result of our model is only 3.3416.

Based on the above discussion, the proposed model in this paper demonstrates higher prediction accuracy and better prediction performance in EV charging load time-series prediction.

V. CONCLUSION

In this paper, a BLS-based EV charging load time-series prediction model is constructed for the time-series data of EV charging load with temporal characteristics and influenced by multiple factors. It is compared with back propagation

neural network model and long-short term memory model. The simulation experiments based on the actual data show that the proposed model can explore the intrinsic relationship between EV charging load, thus improving the prediction performance and verifying the superiority and effectiveness of the model. This model can be used to predict the charging load of EVs in a realistic environment, which can provide a strong reference for the optimal scheduling of EVs.

In the future research, we will study the large-scale electric vehicle grid-connected performance monitoring and scheduling decision optimization methods.

REFERENCES

[1] Q. Dai, T. Cai, S. Duan, and F. Zhao. "Stochastic modeling and forecasting of load demand for electric bus battery-swap station," *IEEE Transactions on Power Delivery*, vol. 29, no. 4, pp. 1909-1917, 2014.

[2] J. Hu, M. Wu, L. Chen, K. Zhou, P. Zhang, and W. Pedrycz, "Weighted kernel fuzzy c-means-based broad learning model for time-series prediction of carbon efficiency in iron ore sintering process," *IEEE Transactions on Cybernetics*, vol. 52, no. 6, pp. 4751-4763, 2022.

[3] J. Hu, M. Wu, L. Chen, W. Cao, and W. Pedrycz, "Real-time dynamic prediction model of carbon efficiency with working condition identification in sintering process," *Journal of Process Control*, vol. 111, pp. 97-105, 2022.

[4] J. Hu, M. Wu, L. Chen, and W. Pedrycz, "A novel modeling framework based on customized kernel-based fuzzy c-means clustering in iron ore sintering process," *IEEE/ASME Transactions Mechatronics*, vol. 27, no. 2, pp. 950-961, 2022.

[5] J. Zhang, Q. Zhang, Y. Ma, and Z. Li, "Short-term load frequency domain prediction method based on improved random forest and density-based spatial clustering of applications with noise," *Control Theory & Applications*, vol. 37, no. 10, pp. 2257-2265, 2020.

[6] J. Zhu, Z. Yang, Y. Guo, J. Zhang, and H. Yang, "Short-term load forecasting for electric vehicle charging stations based on deep learning approaches," *Applied Sciences*, vol. 9, no. 9, pp. 1723, 2019.

[7] L. Buzna, P. D. Falco, G. Ferruzzi, S. Khormali, and G. V. D. Poel, "An ensemble methodology for hierarchical probabilistic electric vehicle load forecasting at regular charging stations," *Applied Energy*, vol. 283, pp. 116337, 2021.

[8] J. Zhu, Z. Yang, M. Mourshed, Y. Guo, Y. Zhou, Y. Chang, Y. Wei, and S. Feng, "Electric vehicle charging load forecasting: A comparative study of deep learning approaches," *Energies*, vol. 12, pp. 2692, 2019.

[9] C. L. P. Chen and Z. Liu, "Broad learning system: An effective and efficient incremental learning system without the need for deep architecture," *IEEE Transactions on Neural Networks and Learning Systems*, vol. 29, no. 1, pp. 10-24, 2018.

[10] C. L. P. Chen, Z. Liu, and S. Feng, "Universal approximation capability of broad learning system and its structural variations," *IEEE Transactions on Neural Networks and Learning Systems*, vol. 30, no. 4, pp. 1191-1204, 2019.

[11] Q. Ge , H. Qiao , C. Li, Q. Yang , and H. Jiang, "Real-time charging risk assessment for electric vehicles based on improved broad BP-AH," *IEEE Transactions on Industrial Electronics*, vol. 69, no. 9, pp. 9472-9482, 2022.