Spatial-temporal Dynamic Forecasting of EVs Charging Load Based on DCC-2D*

Shurong Peng[1], *Heng Zhang*[1*], *Yunhao Yang*[2], *Bin Li*[1], *Sheng Su*[1], *Shijun Huang*[1] *and Guodong Zheng*[1]

(1. School of Electrical & Information Engineering, Changsha University of Science & Technology, Changsha 410114, China;

2. College of Computer Science and Technology, Zhejiang University, Hangzhou 310058, China)

Abstract: The charging load of electric vehicles (EVs) has a strong spatiotemporal randomness. Predicting the dynamic spatiotemporal distribution of the charging load of EVs is of great significance for the grid to cope with the access of large-scale EVs. Existing studies lack a prediction model that can accurately describe the dual dynamic changes of EVs charging the load time and space. Therefore, a spatial-temporal dynamic load forecasting model, dilated causal convolution-2D neural network (DCC-2D), is proposed. First, a hole factor is added to the time dimension of the three-dimensional convolutional convolution kernel to form a two-dimensional hole convolution layer so that the model can learn the spatial dimension information. The entire network is then formed by stacking the layers, ensuring that the network can accept long-term historical input, enabling the model to learn time dimension information. The model is simulated with the actual data of the charging pile load in a certain area and compared with the ConvLSTM model. The results prove the validity of the proposed prediction model.

Keywords: Time and space dynamic prediction, dilated convolution, charging load, convolutional neural network

1 Introduction

In recent years, with energy crisis and increasing environmental pollution, electric vehicles (EVs), as a low-carbon and clean means of transportation, have attracted significant attention from governments all over the world. With the increase of the quantity of EVs, large-scale EVs connected to the power grid for charging have a significant impact on the operation and planning of the power system. The charging load prediction of EVs plays a significant role in power grid dispatching, charging station planning [1-2], power market transaction, convenient and economic travel of users, etc. [3-4]. The load prediction methods of EVs are mainly divided into two categories. The first kind of method uses a mathematical model to simulate the charging behavior of EVs to obtain the load prediction value of EVs. Ref. [5] proposes a mathematical model of the EVs charging demand for the rapid charging station, based on the fluid dynamic traffic model and multiple-server queuing model with Poisson arrival and exponential service times (M/M/S). The vehicle arrival rate of the charging station is predicted by the fluid dynamics model. The charging demand is predicted by the M/M/s queuing theory. Ref. [6] considered the charging demand of a single charging station, the charging decision-making process of the EVs' drivers, the traffic flow of EVs, the road system and other factors, and established the Baskett-Chandy-Muntz-Palacios (BCMP) queuing network model to describe the charging demand relationship of multiple charging stations. According to the classification of the EVs charging load in Ref. [7], a method for the EVs charging load prediction based on the Monte Carlo simulation was proposed, and the EVs charging load prediction in 2015, 2020, and 2030 in China was predicted respectively. In Ref. [8], origin-destination (OD) analysis was used to simulate the mobility of each EV. Moreover, Monte Carlo simulation was conducted

Manuscript received June 10, 2021; revised October 12, 2021; accepted November 20, 2021. Date of publication March 31, 2022; date of current version January 21, 2022.
* Corresponding Author, E-mail: 1326360169@qq.com
* Supported by the Research Foundation of Education Bureau of Hunan Province (20A021) and National Natural Science Foundation of China (51777015).
Digital Object Identifier: 10.23919/CJEE.2022.000005

to estimate the EVs' spatial-temporal charging load characteristics over a day. The simulation results show that the charging load of EVs is obviously regional and closely related to the characteristics of traffic network. In the above mathematical model-based modeling of the charging load prediction, there are many uncertain factors. When considering the spatial-temporal characteristics of the charging load, the model is not comprehensive, and the complex model is difficult to solve, which makes it difficult to guarantee its prediction accuracy.

The second method is using a statistical learning model for prediction based on historical data [9]. Traditional prediction methods include regression analysis and the similarity day method, whereas modern prediction methods include prediction methods based on neural networks, prediction methods based on wavelet analysis, and prediction methods based on the support vector machine [10] (SVM). Ref. [11] proposes a charging load prediction method for EVs based on big data. Ref. [12] proposed a short-term charging pile load prediction model based on the distance measurement method of time series. This method predicts the charging load according to the distance measurement of load and time series. In Ref. [13], the SVM is used for the short-term load prediction of EVs, and the final result is compared with the Monte Carlo method. The result of this method is obviously better than that of the Monte Carlo method. Ref. [14] proposes a planning and construction method for the quick charging station. First, the shared nearest neighbor clustering method (SNN) is used to determine the location and coverage of the charging station, and then the queuing theory is used to determine the capacity of the charging station. Ref. [15] proposed two algorithms: the modified pattern sequence forecasting (MPSF) and time weighted dot product nearest neighbor (TWDPNN) to predict the EVs charging load on smartphone applications. The MPSF algorithm was used to predict, and the TWDPNN algorithm was used to accelerate the prediction algorithm. In Ref. [16], the time series model is used to predict the load of electric vehicles. Ref. [17] proposed a combined prediction model based on data freshness and cross entropy. This method uses the model to learn the underlying law of historical data to achieve a better prediction effect. However, the existing electric vehicle charging load forecasting of statistical learning methods only considers the forecasting methods of the time dimension, and current research generally regards the charging load as a kind of fixed load with only time-varying characteristics, ignoring its mobility. The charging load of EVs also contains complex spatial characteristics. By comprehensively considering the dual dynamic changes of the load time and space, a better spatial-temporal dynamic prediction can be made.

In summary, a two-dimensional dilated causal convolution neural network DCC-2D (Dilated causal convolution-2D neural network) is proposed in this study. This network can effectively learn the spatial-temporal dynamic law of the charging load to predict the overall load in spatial and temporal dimensions.

2 Spatial-temporal dynamic forecasting of EV charging load based on DCC-2D

2.1 One dimensional dilated causal convolution

Consider a one-dimensional wind power series $x=\{x(0),\cdots,x(N-1)\}$. Based on the past changing load series conditions, a model with parameter θ (in this paper, parameters are the weight and bias terms of the cavitation convolutional neural network) is used to predict the future values $\hat{x}(t+1)$. This is the concept of a causal system, where the output of the system is only related to the previous value, rather than the future value. The output is represented as Eq. (1). In this study, the dilated convolutional neural network is used to construct the charging load causal system.

$$p(x\mid\theta)=\prod_{t=0}^{N-1}p(x(t+1))\mid x(0),\cdots,x(t),\theta) \tag{1}$$

To predict the future charging load $x(t+1)$ via the previous wind power series $x(0),\cdots,x(t)$, we use $x(0),\cdots,x(t)$ as input and $x(t+1)$ as output to train the model. The charging load series often display the long-term autocorrelation. Therefore, to enable the network that learns these long-term dependencies, the structure of the stacked void convolutional layer is adopted, and the characteristics of the output layer of this structure are mapped as

$$(w_h^l *_d f^{l-1}) = \sum_{j=-\infty}^{\infty} \sum_{m=1}^{M_{l-1}} w_h^l(j,m) f^{l-1}(i - d \cdot j, m) \quad (2)$$

where d is the dilation factor. Consider the L layers of the dilated convolutions. To obtain a longer receptive field of the dilated convolution, the dilated factor for each layer should increase exponentially by 2. $d \in [2^0, 2^1, \cdots, 2^{L-1}]$. As shown in Fig. 1, the receptive field of the network is $r = 2^{L-1}k$, where k is the size of the convolution kernel.

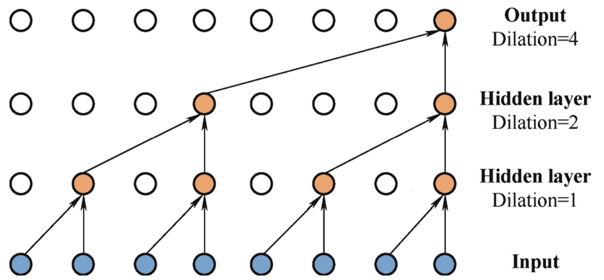


Fig. 1 Dilation convolutional-1D neural network

2.2 Three-dimensional convolution

Two-dimensional convolution is usually applied to two-dimensional data and the two-dimensional convolutional neural network is constructed by the layer-stacking method. Eq. (3) gives the convolution result of the j-th convolution kernel (x, y) in the i-th layer of the two-dimensional convolution network.

$$v_{ij}^{xy} = h(b_{ij} + \sum_m \sum_{p=0}^{P_i - 1} \sum_{q=0}^{Q_i - 1} w_{ijm}^{pqr} v_{(i-1)m}^{(x+p)(y+q)}) \quad (3)$$

where $h(\cdot)$ is a nonlinear activation function ReLU, $\mathrm{ReLU}(x) = \max(0, x)$; m is the number of convolution kernels, p and q are the height and width of the convolution kernel, respectively, b_{ij} is the bias term, and w_{ijm}^{pqr} is the parameter value of the convolution kernel.

The EVs charging load consists of the dual dynamic changes of space and time. However, the two-dimensional convolution can only capture the information of the spatial dimension, whereas the three-dimensional convolution can capture both the spatial information and the information of the time dimension. The three dimensional convolution kernel expands the two dimensional convolution kernel into three dimensions, and then conducts the convolution operation after stacking the data into three dimensions according to the time dimension. Eq. (4) gives the convolution result of the position (x, y, z) of the convolution kernel of j in the layer i of the three-dimensional convolution network.

$$v_{ij}^{xyz} = h(b_{ij} + \sum_m \sum_{r=0}^{R_i - 1} \sum_{p=0}^{P_i - 1} \sum_{q=0}^{Q_i - 1} w_{ijm}^{rpq} v_{(i-1)m}^{(x+r)(y+p)(z+q)}) \quad (4)$$

where R_i is the time dimension in the three-dimensional convolution kernel.

2.3 Spatial-temporal dynamic forecasting model of charging load based on DCC-2D

The randomness of the EVs' choice of the charging pile and charging time results in the dynamic change of the charging load space and time. First, according to the location of the charging station, the charging station load is represented by a two-dimensional matrix and arranged into a space-time sequence $D = \{D_1, D_2, \cdots, D_T\}, D \in \mathbf{R}^{T \times X \times Y}$. The space load matrix of the EVs at time t is shown in Eq. (5), where $d_t^{(x,y)}$ is the load at point (x, y).

$$\boldsymbol{D}_t = \begin{bmatrix} d_t^{(1,1)} & \cdots & d_t^{(1,Y)} \\ \cdots & & \cdots \\ d_t^{(X,1)} & \cdots & d_t^{(X,Y)} \end{bmatrix} \quad (5)$$

The coordinate distribution diagram of the 10 charging stations is constructed (Fig. 2), and a two-dimensional load matrix is established. According to the load matrix of the charging stations, the charging load at each moment is plotted as a heat diagram. The method of constructing the load heat map is as follows.

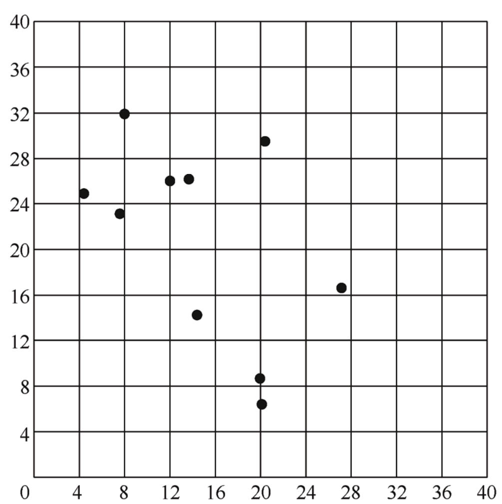


Fig. 2 Charging pile distribution map

(1) Coordinate axes were constructed to determine the coordinates of all the charging stations.

(2) The coverage area of each charging station [18] was determined. This study assumes that the coverage area of each charging station is a square with its own coordinate as the centre.

(3) The load amount of the charging stations is filled in at the time within the coverage of all the charging stations and added up to obtain the load matrix at that time.

(4) Step (3) is repeated at any time until a two-dimensional load matrix is constructed at all times.

The one dimensional dilated causal convolution can only be used in the one-dimensional time series, which is not applicable when we need to consider the time series of the spatial dimension, whereas the precise consideration of the EVs charging load needs to consider the spatial-temporal dynamic. Therefore, the three-dimensional convolution structure applied in the spatial dimension is combined with the one-dimensional dilated causal convolution structure, to form a two-dimensional dilated causal convolutional neural network. The model replaces the one-dimensional convolution of one-dimensional dilated causal convolution with three-dimensional convolution. The result of the convolution of j in the i-th layer with the position of (x, y, z) is shown in Eq. (6), and the size of the convolution kernel is $(2^{l-1} * w * h)$.

$$v_{ij}^{xyz} = h\Big(b_{ij} + \sum_{m}\sum_{r=0}^{R_i-1}\sum_{p=0}^{P_i-1}\sum_{q=0}^{Q_i-1} w_{ijm}^{rpq} v_{(i-1)m}^{(x+r\bullet d)(y+p)(z+q)}\Big) \tag{6}$$

where $d \in \left[2^0, 2^1, \cdots, 2^{L-1}\right]$, $R_i = 2$, r is the size of the receptive field, $h(\cdot)$ is a nonlinear activation function ReLU, and $\mathrm{ReLU}(x) = \max(0, x)$. Fig. 3 shows the structure when l=3. In the figure, the historical load heat data of the past eight moments are used to predict the load heat of the future one moment. It can be observed that this model constructs a causal system that uses the previous $D = (d_t)_{t=0}^{N-1}$ load heat conditions and a parametric model to predict the next $\hat{d}(N)$ load heat value.

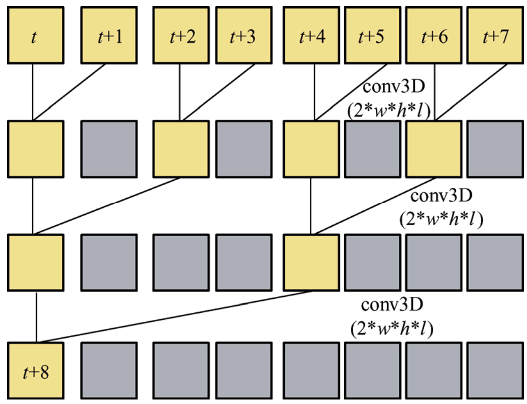


Fig. 3 Dilation convolutional-2D neural network

Fig. 4 shows the structure of the model network. Each layer has a residual connection from the input to the output convolution. The result of the previous layer is used as the input in the subsequent dilation convolution layer, and the total stack is the L layer two-dimensional dilation convolution residual connection layer [19]. Among the external macro factors, this study extracts the characteristics of weather conditions (sunny and rainy) and date types (days of the week, months, and holidays). Subsequently, they are fed into a two-layer fully connected neural network, integrating their results with the output of the convolution. Finally, the final prediction result is obtained through the output layer.

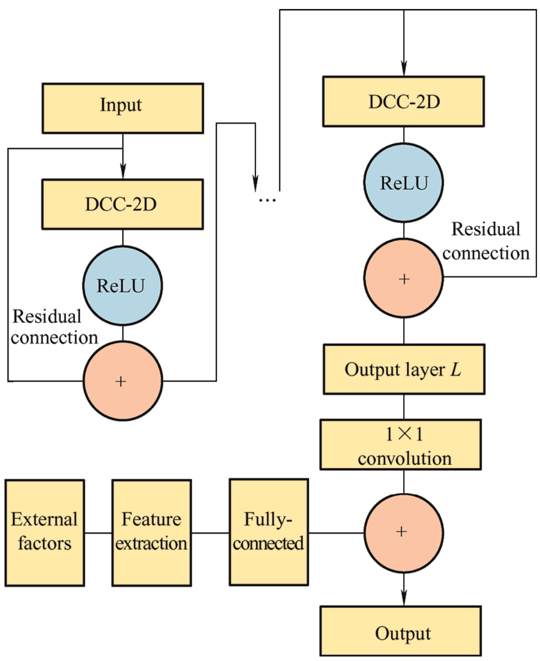


Fig. 4 Model network structure

The objective function of the prediction model is expressed in Eq. (7).

$$E(w)=\frac{1}{2N}\sum_{t=0}^{N-1}(y_{pre}-y_{ture})^2+\frac{\gamma}{2}(W)^2 \quad (7)$$

where W represents the parameters of the network structure, γ is the weight of the regularization term, and y_{pre} and y_{ture} are the predicted and true values, respectively.

The entire flow of the model is shown in Fig. 5. First, a planar distribution map of the charging stations is established according to the locations of the charging stations. The heat map is then constructed on the distribution map in the time sequence according to the historical load data. After normalizing the data of each picture, the data were input into the model for training, and the super parameters of the model were adjusted according to the training results, until the model training achieved satisfactory results. Finally, the image data was inversely normalized and output to obtain the final prediction result.

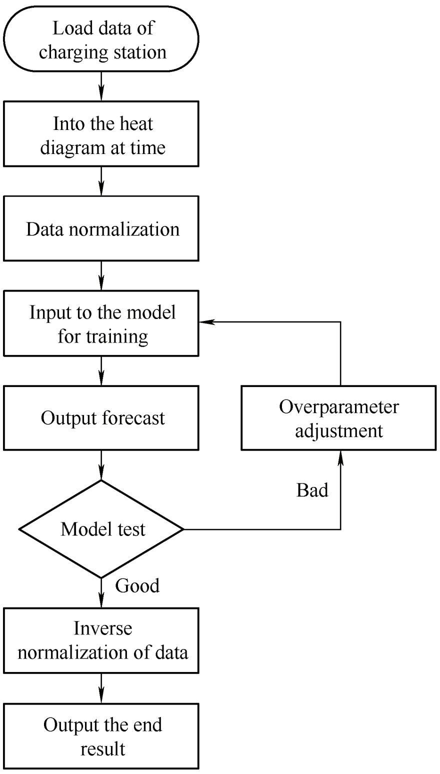


Fig. 5 Algorithm flowchart

3 Analysis of examples

The simulation is based on the charging load data of 10 charging stations in a certain region of China. There are four 320×10 pieces of data, which are composed of the charging load per hour for 180 days in the charging station. The load power of the charging stations is between 0-800 kW, and the average power is between 200-400 kW. The experimental platform was conducted on the Google company's deep learning framework — TensorFlow. The computer conditions were as follows: CPU: core i7-7700, Memory: 16 G, GPU: 1070 8G.

Fig. 6 shows an example of the heat diagram of the charging load at partial time. The lighter the color in the diagram, the higher the load.

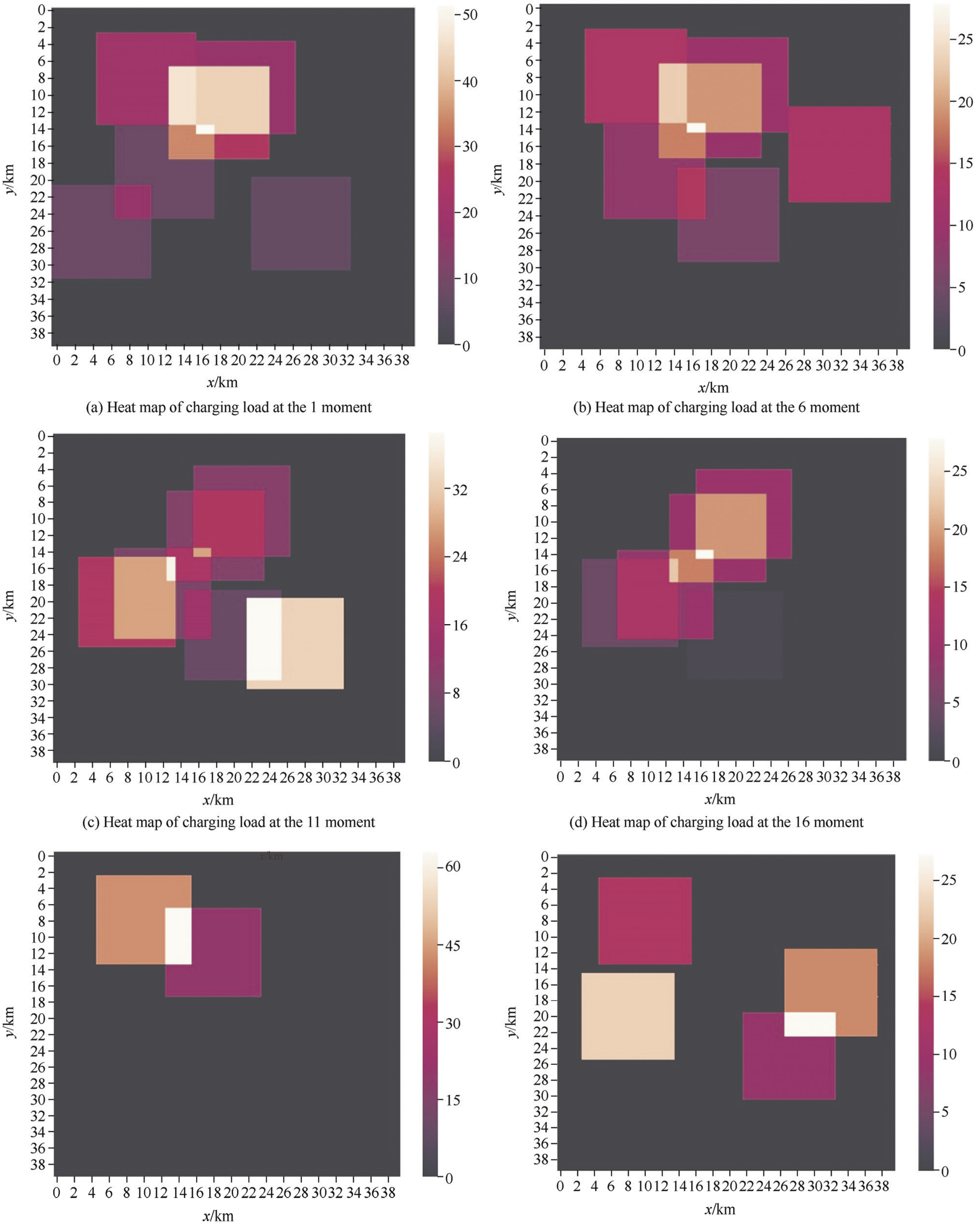
According to Eq. (8), the images were normalized, and the DCC-2D model was used for training and prediction. The heat load diagram of the past 200 moments was taken as the training set, and the heat load diagram of the next 4 h was predicted by rolling. The predicted results were inversely normalized according to Eq. (9) to process the output picture.

$$X_i' = X_i / X_{\max} \quad (8)$$

$$X_i = X_i' \times X_{\max} \quad (9)$$

The comparison between the predicted results and real values is shown in Fig. 7. The left side of the figure is the prediction graph, whereas the right side is the real graph. It can be observed from the figure that the true and predicted values have a high degree of similarity, which shows the effectiveness and practicability of the algorithm. However, it can be observed that the similarity between the predicted and real values will gradually decrease as the prediction time grows longer, thus, the long-term prediction still needs further research.

To reflect the advantages of this model, it is compared with the ConvLSTM prediction model in Ref. [20]. The comparison of the prediction error histogram of the two models is shown in Fig. 8. In the figure, the z-axis represents the absolute value error generated by each point of the two models. It can also be observed from the figure that the error of the DCC-2D model is mainly concentrated in the high-load area, and there is basically no error in the low-load area. The error of the ConvLSTM model was not only large in the high-load area, but also high in the low-load area or zero-load area. Moreover, the error of the ConvLSTM model was generally higher than that of the DCC-2D model, which fully demonstrated the superiority of the DCC-2D model.



(a) Heat map of charging load at the 1 moment

(b) Heat map of charging load at the 6 moment

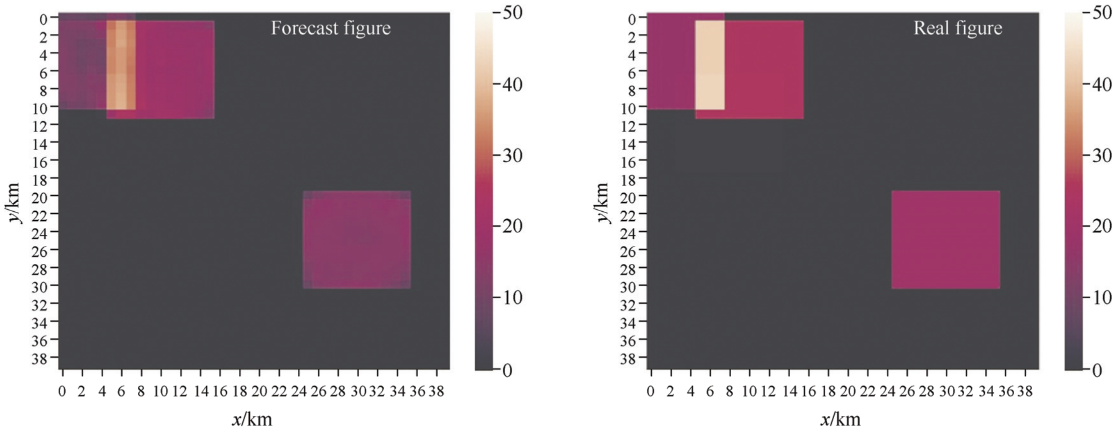
(c) Heat map of charging load at the 11 moment

(d) Heat map of charging load at the 16 moment

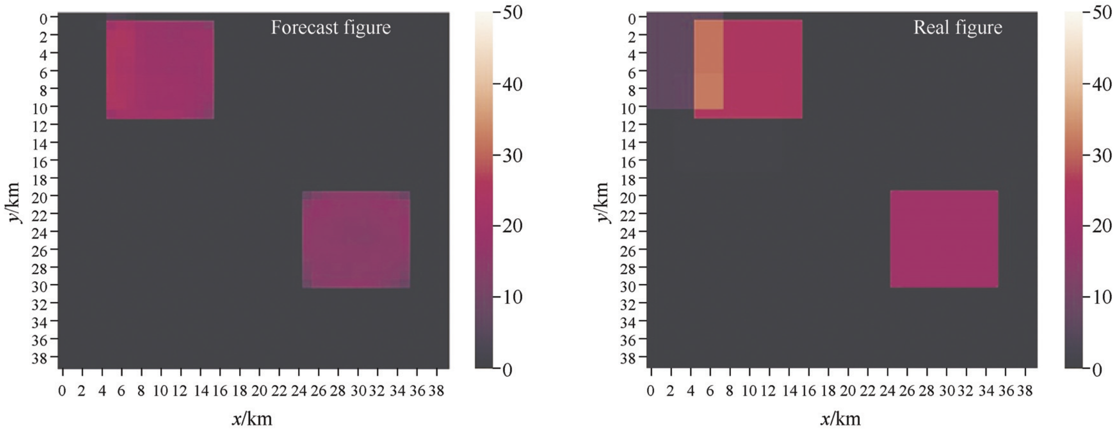
(e) Heat map of charging load at the 21 moment

(f) Heat map of charging load at the 26 moment

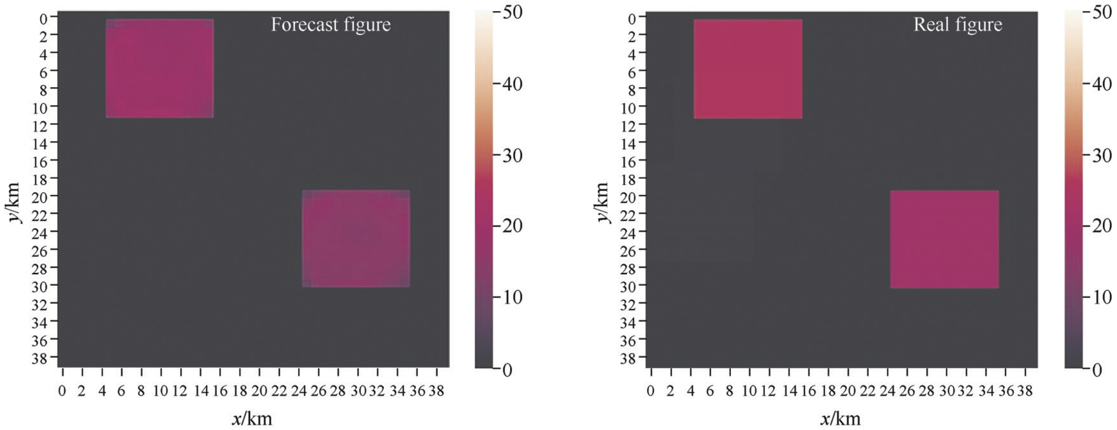
Fig. 6 Charging load heat figure



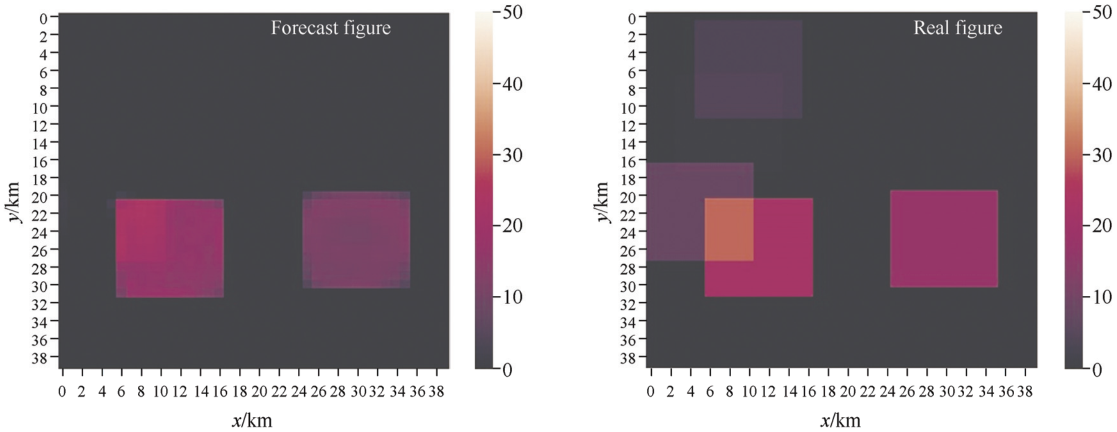
(a) The first prediction moment



(b) The second prediction moment

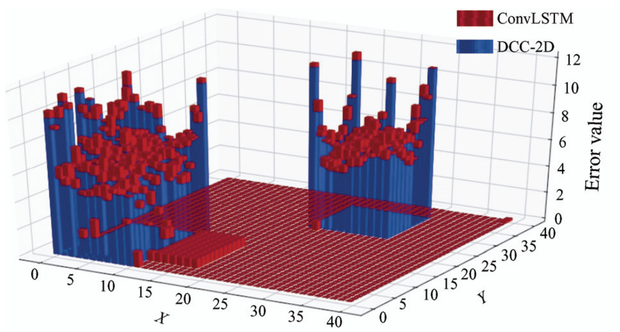


(c) The third prediction moment

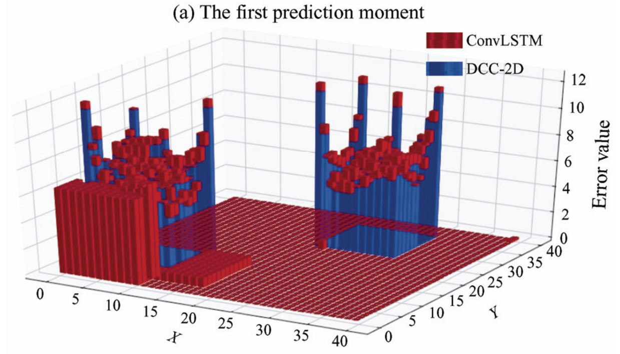


(d) The fourth prediction moment

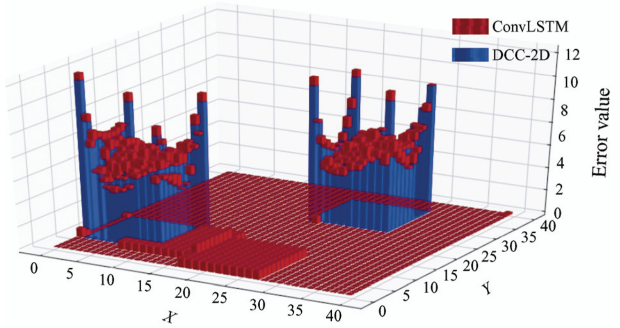
Fig. 7 Forecast result figure



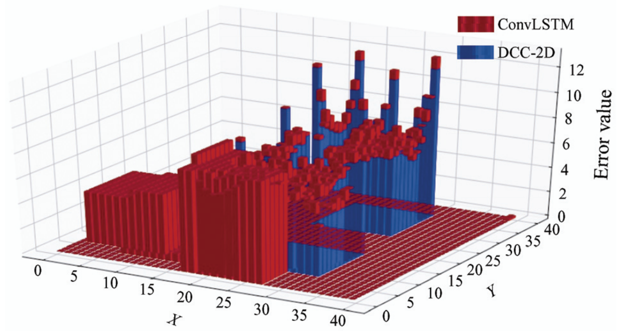
(a) The first prediction moment



(b) The second prediction moment



(c) The third prediction moment



(d) The forth prediction moment

Fig. 8 Error comparison of prediction results

Tab. 1 lists the MAE (Mean absolute error), RMSE (Root mean squared error), and R^2 (R-square) of the five experiments of the two models, as well as the corresponding mean values. From the average value of the above three indexes, the DCC-2D model has a better effect, thus, it can be observed that the DCC-2D model has a higher prediction accuracy.

Tab. 1 Comparison between DCC-2D and ConvLSTM algorithm

Algorithm	Number of experiments	MAE	RMSE	R^2
DCC-2D	1	1.23	8.18	0.81
	2	1.24	8.21	0.82
	3	1.07	6.56	0.89
	4	1.79	10.30	0.73
	5	1.50	10.14	0.78
	Mean	1.37	8.68	0.81
ConvLSTM	1	1.32	9.44	0.80
	2	1.32	9.22	0.80
	3	1.34	7.63	0.80
	4	1.87	12.96	0.72
	5	1.58	11.36	0.76
	Mean	1.49	10.12	0.78

4 Conclusions

(1) In this study, a DCC-2D neural network model was proposed to solve the problem of the short-term spatiotemporal dynamic load of electric vehicles and achieved certain results.

(2) Compared with the ConvLSTM model, it has a higher accuracy rate. The average errors of the MAE and RMSE of the DCC-2D model are 8.16% and 14.23%, respectively, which are lower than those of ConvLSTM. The score of DCC-2D was 3.84%, higher than that of ConvLSTM. It can be observed that the prediction accuracy of the DCC-2D model is significantly improved.

(3) This method not only improves the prediction accuracy, but also dynamically predicts the charging load of the EVs in time and space. The DCC-2D model can bring the load information of time and space to the power grid and help to reasonably plan the layout and capacity configuration of the charging facilities, which will provide a more specific reference for the planning of urban charging facilities.

References

[1] Y Cao, Y Liu, L Que, et al. Multi-objective bi-level real-time charging/discharging dispatch with coordination of BSS and grid. *Electric Power Automation Equipment*, 2015, 35(4): 1-7.

[2] B Qian, D Shi, P Xie, et al. Simulation analysis on zigzag

transformer-based AC-DC combined distribution network. *Automation of Electric Power Systems*, 2014, 38(2): 64-69, 84.

[3] P Chen, Q Meng, Y Zhao. The electric vehicle charging load calculation based on the Monte Carlo method. *Journal of Electrical Engineering*, 2016, 11(11): 40-46.

[4] R Chen, Y He, F Chen, et al. Long-term daily load forecast of electric vehicle based on system dynamics and Monte Carlo simulation. *Electric Power*, 2018, 51(9): 126-134.

[5] S Bae, A Kwasinski. Spatial and temporal model of electric vehicle charging demand. *IEEE Trans on Smart Grid*, 2012, 3(1): 394-403.

[6] H Liang, I Sharma, W Zhuang, et al. Plug-in electric vehicle charging demand estimation based on queueing network analysis. *2014 IEEE PES General Meeting | Conference & Exposition*, *National Harbor*, 2014: 1-5.

[7] Y Luo, Z Song, Z Hu, et al. Forecasting charging load of plug-in electric vehicles in China. *2011 IEEE Power and Energy Society General Meeting*, Detroit, MI, USA, 2011: 1-8.

[8] Y Shao, Y Mu, X Yu, et al. A spatial-temporal charging load forecast and impact analysis method for distribution network using EVs-traffic-distribution model. *Proceedings of the CSEE*, 2017, 37(18): 5207-5219, 5519.

[9] Q Zhu, J Chen, D Shi, et al. Learning temporal and spatial correlations jointly: A unified framework for wind speed prediction. *IEEE Transactions on Sustainable Energy*, 2020, 11(1): 509-523.

[10] L Liu, Y Li, Y Cao, et al. Transient rotor angle stability prediction method based on SVM and LSTM network. *Electric Power Automation Equipment*, 2020, 40(2): 129-139.

[11] M B Arias, S Bae. Electric vehicle charging demand forecasting model based on big data technologies. *Applied Energy*, 2016(183): 327-339.

[12] S Xin, Q Lei, T Li, et al. Short-term load forecasting for electric vehicle charging stations based on time series distance measuring. *2017 IEEE 13th International Conference on Electronic Measurement & Instruments*, 2017: 417-423.

[13] E S Xydas, C E Marmaras, L M Cipcigan, et al. Forecasting electric vehicle charging demand using support vector machines. *2013 48th International Universities' Power Engineering Conference (UPEC)*, Dublin, 2013: 1-6.

[14] X Dong, Y Mu, H Jia, et al. Planning of fast EV charging stations on a round freeway. *IEEE Transactions on Sustainable Energy*, 2016, 7(4): 1452-1461.

[15] M Majidpour, C Qiu, P Chu, et al. Modified pattern sequence-based forecasting for electric vehicle charging stations. *2014 IEEE International Conference on Smart Grid Communications (Smart Grid Comm)*, Venice, 2014: 710-715.

[16] M Mostafa. Time series prediction for electric vehicle charging load and solar power generation in the context of smart grid. Los Angeles: University of California, 2016.

[17] W Liu, R Long, X Xu, et al. Forecasting model of short-term EV charging load based on data freshness and cross entropy. *Automation of Electric Power Systems*, 2015, 32(10): 2951-2954.

[18] Z Wang. Optimization of charging infrastructure siting for electric taxis in Beijing. Beijing: Beijing Jiaotong University, 2017.

[19] J Zhang, Y Zheng, D Qi. Deep spatio-temporal residual networks for citywide crowd flows prediction. *Proceedings of the Thirty-First AAAI Conference on Artificial Intelligence (AAAI'17)*. AAAI Press, 2017: 1655-1661.

[20] X Shi, Z Chen, H Wang, et al. Convolutional LSTM network: A machine learning approach for precipitation nowcasting. *Proceedings of the 28th International Conference on Neural Information Processing Systems*, 2015(1): 802-810.

Shurong Peng, doctor, Assistant Professor. She received the B.S. degree in Industrial Automation in 1996, the M.S. degree in Control Theory and Control Engineering in 2004, the Ph.D. degree in Control Science and Engineering respectively from Hunan University, Changsha, China, in 2009 respectively from Hunan University, Changsha, China.

She joined CSUST, Changsha, China, in 2004. From 2012 to 2013, she was a Research Assistant in Darmstadt TU in Germany. Her research interests include the information processing in intelligent grid and big data application in power system.

Heng Zhang received the B.S. degree in Electrical Engineering from the Jiangsu University of Science and Technology, Zhenjiang, China, in 2018.

He is currently pursuing the M.S. degree in Electrical Engineering at Changsha University of Science and Technology (CSUST), Changsha, China. His research interest is information processing in smart grids.

Yunhao Yang, undergraduate from College of Computer Science and Technology, Zhejiang University, Hangzhou, China. His research interest includes the application of deep learning algorithm in data digging field.

Bin Li received the master's degree from Changsha University of Science & Technology, China, in 2019. He is working in the School of Mechanical and Electrical Engineering, Hunan City University. His current research fields include power system informatization, planning and new energy.

Sheng Su (M'05-SM'19) received the B.S. degree in Electrical Engineering from Wuhan University of Hydraulic & Electrical Engineering, Wuhan, China, in 1998, the M.S. degree in Electrical Engineering from Wuhan University, Wuhan, China, in 2002, and Ph.D. degree from HUST, Wuhan, China in 2009, respectively.

He joined CSUST, Changsha, China, in 2002. From 2004 to 2007, he was a Research Assistant with the Hong Kong Polytechnic University, Hong Kong, China. From 2009 to 2012, he is a Postdoctoral with the Department of Automatic control Engineering, HUST, Wuhan, China. He is currently a Professor with CSUST, Changsha, China. His research interests include the cyber security defense of power system and application of power system big data.

Shijun Huang received the B.S. degree in Electrical Engineering from the Hunan Institute of Engineering, Xiangtan, China, in 2016.

He is currently pursuing the M.S. degree in Electrical Engineering at Changsha University of Science and Technology (CSUST), Changsha, China. His research interest is information processing in smart grids.

Guodong Zheng received the B.S. degree in Electrical Engineering from the Tongling University, Tongling, China, in 2017.

He is currently pursuing the M.S. degree in Electrical Engineering at Changsha University of Science and Technology (CSUST), Changsha, China. His research interest is information processing in smart grids.