 DOI:10.30420/566414067

Prediction of Electric Vehicles Schedulable Capacity Based on Graph Convolution Network

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Abstract

Spatial-temporal prediction of the electric vehicles schedulable capacity is necessary for their integration into power grid management. This paper proposes a spatial-temporal prediction model based on graph convolution. Each charging station within a region is considered a node, the connection relationship is determined based on the spatial distance between charging stations, obtaining the charging station connectivity graph. Subsequently, using the graph convolution network to explore spatial features from the charging data, and the gate recurrent unit is used to mine temporal features, resulting in spatial-temporal predictions of the schedulable capacity of electric vehicles. Finally, the proposed method is validated and compared with other prediction methods.

1 Introduction

The rapid growth of clean and pollution-free new energy electric vehicles has been driven by the global climate change and the concept of green sustainable development[1]. According to statistics from relevant organizations, it is forecast that the total number of electric vehicles will reach 240 million by 2030[2]. However, the random integration of large number of electric vehicles into the power grid exacerbates the issue of supply-demand imbalance. Nevertheless, the electric vehicles can be seen as distributed energy storage devices and used to participate in various ancillary services in power system to improve its operation[3]. Ancillary services include frequency regulation and voltage regulation, etc. These different ancillary services have different response time requirements for electric vehicles[4]. And participation in ancillary services in different regions requires electric vehicles located in different positions. Therefore, accurately predicting the spatial and temporal distribution of the electric vehicle schedulable capacity (EVSC) can provide a data foundation for their participation in improving power system operation.

There are primarily two methods for spatial-temporal predictions of EVSC: data-driven and model-driven[5]. Model-driven method mainly combine electric vehicle travel behavior models with road networks to predict the spatial-temporal distribution of EVSC. For example, in [6], a city is divided into different functional zones using kernel density functions, and building a travel chain model for each functional zone. Then using the Monte Carlo to predict the charging behavior of electric vehicles in different functional zones. In [7], considering the impact of external environment and user preferences on charging station selection, and the charging station selection model integrating electric vehicles with the transportation network is established to obtain a spatial-temporal prediction model for electric vehicle loads. In [8], using the probability model as resident's travel model, combined with a transportation network to predict the spatial-temporal load of electric vehicles charging. In model-driven methods making assumptions about the probability of electric vehicle behavior, these may cause the problem that the model cannot match the spatial transportation network. Therefore, model-driven methods accuracy is relatively low.

Data-driven method use historical data to prediction future data, mainly using traditional machine learning algorithms, deep learning algorithms, etc. For example, in [9], charging stations are divided into industrial areas, residential areas, commercial areas, etc. The convolutional neural network-long short-term memory-attention (CNN-LSTM-Attention) model is used to predict the spatial-temporal distribution of EVSC in different functional areas. In [10], the parallel gradient boosting decision tree method is used to predict the EVSC at multiple time scales in a city. In sum up, in current spatial-temporal prediction methods for the EVSC, spatial predictions are mainly based on dividing a large area into different regions and then predicting the EVSC in different

ISBN 978-3-8007-6414-3

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regions. There is little consideration of region segmentation from the perspective of charging stations, and taking into account the spatial characteristics within each region and the mutual influences between different regions.

Therefore, this paper proposes a spatial-temporal prediction model for EVSC based on graph convolution network (GCN) and gate recurrent unit (GRU). It treats a charging station as a node and explores the spatial features in historical charging data through GCN, as well as the mutual influence between different nodes, then uses gate recurrent units to learn temporal features, obtaining a spatial-temporal distribution of EVSC for each charging station in the area.

The paper is structured as follows. In Section 2, the GCN GRU and spatial-temporal prediction model of EVSC is discussed. In Section 3, the prediction results based on proposed model and other predict models, such as CNN、LSTM, are compared, following conclusions in Section 4.

2 Spatial-temporal prediction algorithms

2.1 Graph convolutional network

Convolutional neural network (CNN) can only operate on standard grid-structured data, while graph convolutional network (GCN) can perform convolution operations on irregular graph-structured data. A graph structure data is illustrated in Fig.1, in which comprises nodes and edges, and a graph can be represented as G = (*V*, *E*, A), where *V* represents the nodes, $V \in R^N$, N represents the number of nodes in the graph, *E* represents edges connecting two nodes, and *A* represents the adjacency matrix indicating the connectivity status between nodes. Specifically, $A_{ij}=0$ indicates no edge connection between nodes *i* and *j*, and $A_{ij}=1$ indicates an edge connection between nodes *i* and *j*.

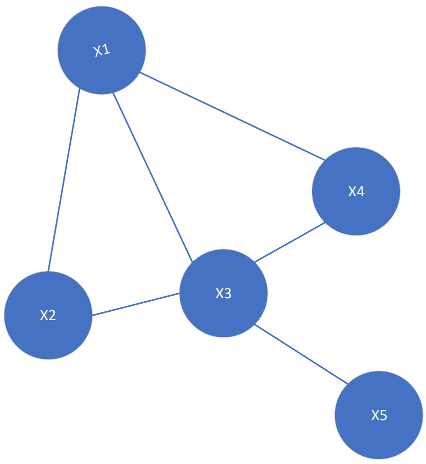

Fig. 1. Graph structure data

GCN are divided into spectral methods and spatial methods. Spectral methods extend convolution from traditional data to graph-structured data through the graph's Laplacian matrix. By using the degree matrix to transform the adjacency matrix into a normalized Laplacian matrix L, and the convolution kernel in a convolutional network is replaced by the graph's Laplacian matrix. After convolution, the feature vectors of nodes transform into combinations of their own feature vectors and those of adjacent nodes.

The Laplace matrix is show in (1):

$$L = I - D^{\frac{-1}{2}} A D^{\frac{-1}{2}} \tag{1}$$

where *D* is the degree matrix and *I* is the identity matrix.

The GCN formula can be expressed as in (2):

$$x_{GCN} = LxW = (I - D^{\frac{-1}{2}} AID^{\frac{-1}{2}})xW \tag{2}$$

Then, Chebyshev polynomials are used to replace the convolution kernel, as given by Equation (3), Chebyshev polynomial can be obtained by recursive formula (4):

$$L = \sum_{k=0}^{K-1} T_k(\tilde{L}) \tag{3}$$

$$T_k\left(\tilde{L}\right) = 2\tilde{L}T_{k-1}\left(\tilde{L}\right) - T_{k-2}\left(\tilde{L}\right) \tag{4}$$

where $\tilde{L} = \frac{2L}{\lambda_{\max}} - I$, $\lambda_{\max}$ is the maximum eigenvalue of L. $T_0 = 1, T_1 = \tilde{L}$

The GCN is performed by using the Chebyshev polynomial, so that the nodes of themselves combine the features of the surrounding K-1 neighbours, and finally the GCN output is show as in (5):

$$x_{GCN} = \sum_{k=0}^{K-1} T_k\left(\tilde{L}\right) x W_k \tag{5}$$

where *x* is the input matrix of the GCN, $X \in R^{N \times d}$, d is the dimension of the node vector, and W_k is the convolutional kernel weight matrix of the k-th order.

2.2 Gate recurrent unit

The gate recurrent unit (GRU) is a type of recurrent neural network (RNN) designed for processing sequential data and extracting temporal features from sequential data. The structure of GRU is illustrated in Fig.2, in which the cells and parameters are shown in the following equations.

$$r_t = \sigma\left(W_r[X_t, U_r] + b_r\right) \tag{6}$$

$$u_t = \sigma\left(W_u\left[X_t, h_{t-1}\right] + b_u\right) \tag{7}$$

ISBN 978-3-8007-6414-3

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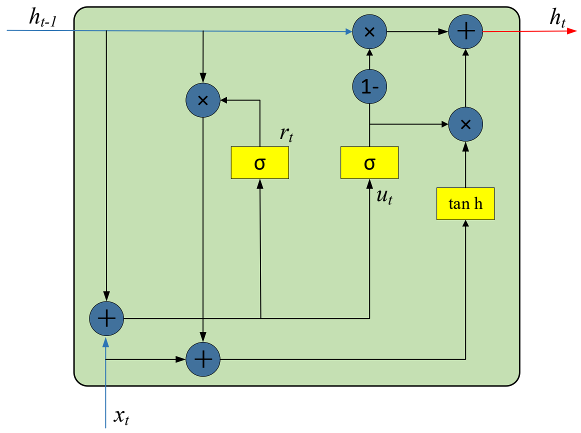
$$c_t = \tanh\left(W_c\left[X_t,\left(r_t^* h_{t-1}\right)\right]+b_c\right) \quad (8)$$

$$h_t = u_t * h_{t-1} + \left(1-u_t\right) * c_t \quad (9)$$



where x_t is the data at time t, and it is used along with the hidden state h_{t-1} from the previous time step as the input to the GRU. This process results in the computation of the next hidden state h_t. Through the recurrent operation of multiple GRU, temporal features are extracted from sequential data. Here, r_t represents the reset gate, indicating the extent to which the previous state h_{t-1} is to be ignored, and u_t represents the update gate, indicating the extent to which the previous state h_{t-1} is to be retained. $\sigma()$、 $tanh()$ as an activation function. GRU can learn the data features of the current moment while retaining the change law of the data at the past moment, so as to extract the temporal features in the sequence data.

2.3 Spatial-temporal prediction model of EVSC

The proposed spatial-temporal prediction model for EVSC, as illustrated in Fig.3, consists of GCN, GRU, and fully connected layers. The GCN treating each charging station as a node. The interconnection relationships among charging stations are determined based on geographical locations, forming a graph G=(V, E, A). By applying GCN learns the spatial features of each charging station, including its own position and potential relationships with neighbouring stations, thereby extracting spatial characteristics of each charging station node. The temporal layer utilizes gate recurrent unit (GRU), taking the output of the spatial layer's GCN as input for extracting temporal features. The GRU captures the inherent trends and variations in historical sequential data, extracting the temporal characteristics of the data sequence. Finally, the model's output is obtained through a fully connected layer, serving as the prediction result for the model.

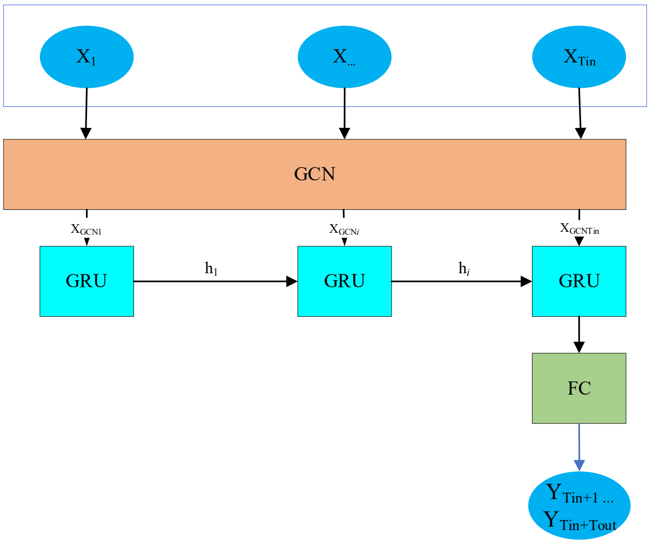


Fig. 3. Spatial-temporal prediction model based on graph convolution

The input of the model is the historical data of the charging station. The input in Fig.3 represents the historical data of T_{in} time points, with each time point's historical data representing the features of each charging station. The inputs denoted as $X_{in}ЄR^{N\times Tin\times F}$, where N represents the number of charging stations, T_{in} represents the time step of the input data, F represents the characteristic dimension of the data and the input data is the historical EVSC data, therefore F=1, and the output is the EVSC of the charging station at the next moment denoted as $Y_{out}ЄR^{N\times Tout\times F}$, where T_{out} represents the time step of the output data.

3 Case analysis

In this paper, the historical charging data of 20 electric vehicle charging stations in February, March and April 2021 are used as a dataset, and the charging power of the charging stations per minute is recorded in the dataset, and the EVSC per minute can be obtained according to the charging power data. The past hourly historical EVSC data with the resolution of one minute is used to predict the next one-minute EVSC. Therefore, T_{in}=60, T_{out}=1.

Comparing the proposed GCN-GRU prediction model with three other algorithms, namely CNN, LSTM, CNN-LSTM, we obtain the predicted results for each charging station based on each prediction model. Among them, the adjacency matrix of GCN is obtained by using the difference in longitude and latitude, and the mean square error is used as the loss function for the training of each model.

The Fig.4 below shows the predictions for station 1 from different models for one day, and the average absolute error and average relative error for 20 charging stations under different models are obtained as the evaluation metrics, as shown below Fig.5 and Fig.6.

ISBN 978-3-8007-6414-3

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From Fig.4, it can be observed that the EVSC of charging stations varies significantly within a day. Under single-step prediction, the results of various models are close to the real values. The proposed GCN-GRU model can capture the spatial-temporal features of charging stations, and the predicted results closely follow the trend and magnitude of the real values. However, there is still some different in areas with drastic changes. Other prediction models exhibit insufficient feature learning, resulting in similar trends but with certain discrepancies in magnitude compared with the real values.

From Fig.5 and Fig.6, it can be observed that due to different spatial locations and features of each charging station, the prediction errors fluctuate significantly for different models. The proposed GCN-GRU prediction model explores the spatial features of each charging station. As a result, it has the higher prediction accuracy than other prediction model, with the smallest average relative error and average absolute error for most charging station. Only a few charging stations have similar prediction error. In contrast, LSTM and CNN-LSTM only capture the time features of each charging station, resulting in higher prediction errors compared to GCN-GRU. From the perspective of charging station 1, compared with LSTM, the MAE and MAPE by GCN-GRU are decreased by 27.66% and 1% respectively.

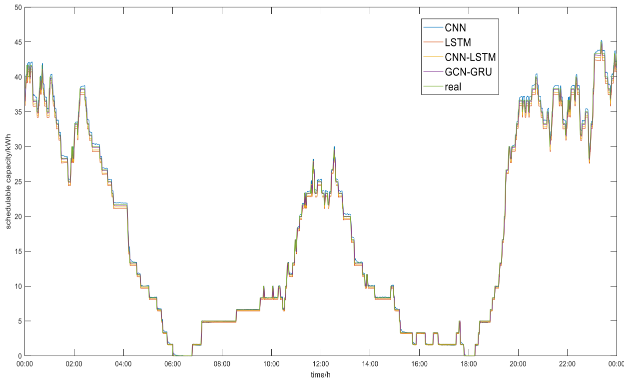


Fig. 4. Comparison of the prediction results of charging station 1 in one day by different models

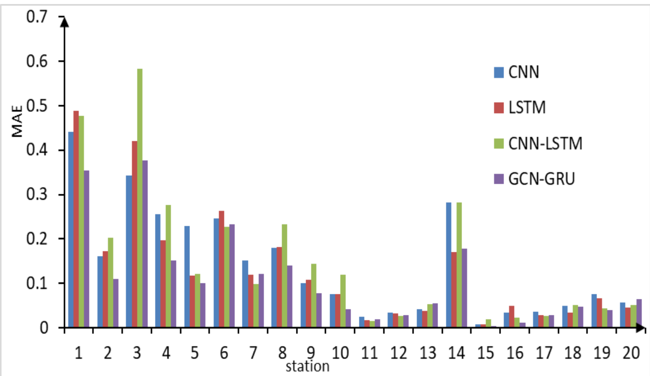


Fig. 5. Comparison of MAE of each charging station by different models

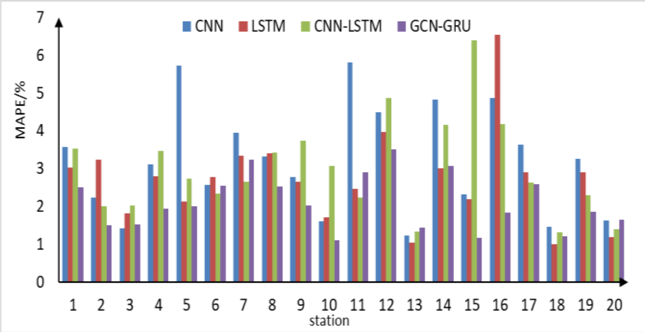
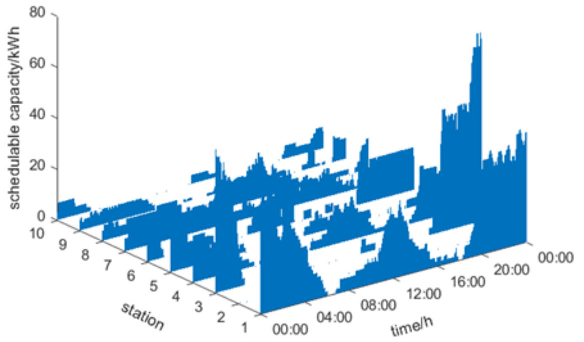
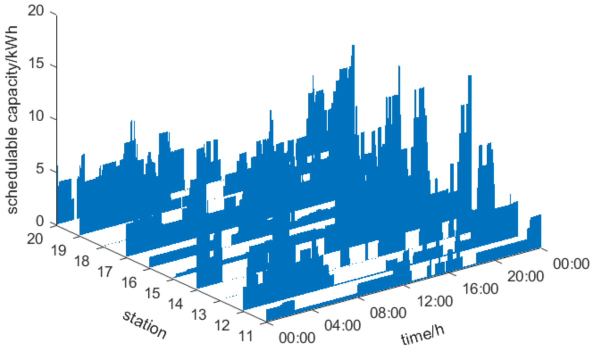


Fig. 6. Comparison of MAPE of each charging station by different models



(a)



(b)

Fig. 7. One day prediction results for 20 charging stations: (a)the first 10 stations charging prediction result (b) the last 10 stations charging prediction results

Fig. 7. displays the one-day predicted results of the EVSC for 20 charging stations. It can be observed that the trends and magnitudes of EVSC vary among different charging stations. Charging stations 1 and 3 exhibit a wide range of power variations, and their trends are approximately similar. In contrast, the EVSC of other charging stations has a smaller energy range, but with different trend patterns. Therefore, the spatial-temporal prediction model based on the GCN-GRU can effectively capture the spatial-temporal features of different charging stations.

4 Summary

This paper proposes a spatial-temporal prediction model of EVSC based on the GCN-GRU algorithm. The

ISBN 978-3-8007-6414-3

effectiveness of the proposed model is validated using data from selected charging stations at city level. From the prediction results and comparisons with other prediction models, it is evident that GCN can effectively explore the spatial features of historical data, significantly improving the accuracy of spatial-temporal predictions of EVSC. However, there is still error between the prediction results and real values, and this study primarily focuses on forecasting the EVSC for one-minute ahead, catering to specific scenarios in grid management, such as voltage regulation. Future work will involve improving prediction accuracy and analysing the prediction of EVSC over multiple time steps to meet the requirements of various power system ancillary services at multi-time scales.

5 Acknowledge

This work was partially supported by Anhui Province Natural Science Foundation Energy Internet Key Project (No. 2108085UD02) and 111 Project [No. BP0719039].

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