Load Prediction of Multiple Electric Vehicle Charging Stations Based on T-GCN

1st Zeyuan Niu
Department of Electrical Engineering
Shanghai Jiao Tong University
Shanghai, China
nzy0720@sjtu.edu.cn

2nd Jiamei Li
Department of Electrical Engineering
Shanghai Jiao Tong University
Shanghai, China
lijiamei@sjtu.edu.cn

3rd Qian Ai
Department of Electrical Engineering
Shanghai Jiao Tong University
Shanghai, China
aiqian@sjtu.edu.cn

***Abstract*—As the number of electric vehicles (EVs) rises, together with the increasing load required to charge them, the stable and efficient operation of the grid is challenged. To consider the impact of electric vehicles on the power system, it is necessary to comprehensively understand the load and operation of electric vehicle charging station (EVCS). There is much literature concerned about load forecasting of EVCS's load in time dimension. However, the spatial and temporal correlation among multi-EVCSs in specific area also matters. To take that into account, this paper considers a load forecasting method for multi-EVCSs based on T-GCN (Temporal-Graph Convolution Network). The results of case study show that the considered model can predict the load of EVCSs timely and accurately.**

Keywords—electric vehicle; charging station; graph convolution network; load prediction

I. Introduction

As electric vehicles become more prevalent, their dynamic driving and charging behavior will interact with urban road networks and power grids. This interaction presents new challenges and opportunities for urban infrastructure planning and energy management. In the research field of microgrids and virtual power plants, EV charging stations are often considered as an adjustable load resource. Accurately predicting the load of electric vehicle charging stations is crucial to the healthy operation of the grid.

Previous research has made headway in the charging and discharging of electric vehicles. Different modes of charging and discharging EVs are explored in [1]-[3], offering detailed descriptions and analyses of battery behavior for individual EV. In [4]-[5], scheduling methods for EV charging station are discussed, and optimal approaches to guide and coordinate the charging processes of EVs in the charging station are proposed. Reference [6] presents a comprehensive overview of the current state of research on Graph Convolutional Networks (GCNs) in energy systems, including their various applications in prediction and optimization. Reference [7] demonstrates how the collective charging and discharging behavior of a group of EVs can be modelled and optimized by considering multiple EVs as an aggregator. By using Grey Theory and Neural Network, [8] proposes a load forecasting method of EVCSs based on a combination of multivariable residual correction grey model (EMGM) and long short-term memory (LSTM) network. A tool for load forecasting using gated GCN model is provided in [9], while the spatial-temporal dependencies among demand and load of EV charging is proposed in [10], which combines GCN with LSTM.

The literature above provides valuable insights into the charging patterns of EVs and the use of GCNs, some of which employ connectivity graph based on a fixed location topology. However, relying on geographic location does not fully extract correlations. Furthermore, the temporal features of the model undergo changes during the training phase, which impedes the ability to identify and utilize important information, thereby hindering the achievement of enhanced performance. This paper addresses this problem by proposing a Temporal-Graph Convolution Network, aiming at forecasting multi-EVCSs' load simultaneously. Chapter II analyses the spatial-temporal correlation of loads in EVCS. Chapter III presents a T-GCN based load forecasting model for EVCS. Chapter IV includes an arithmetic example analysis.

II. Correlation Analysis of EVCS Load

The correlation of EVCS load is studied to embody the rationality of using T-GCN and generate the Adjacency matrix which is used in training T-GCN.

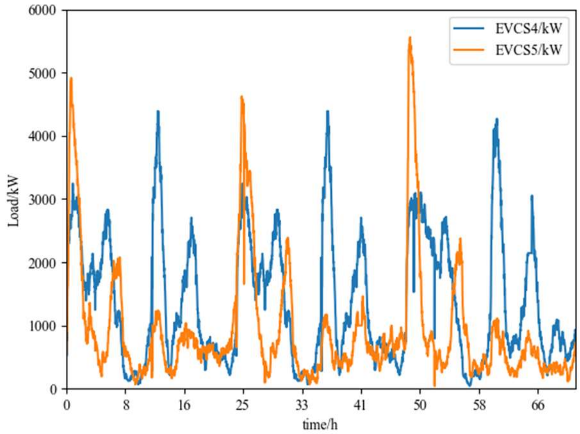

Fig. 1. Load curve of EVCS4 and EVCS5

From the visualization perspective, correlation analysis indicates a similar trend in the load fluctuation of each EVCS

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node, as demonstrated in Figure 1. To present the correlation more accurately, we use Grey correlation analysis method to quantify the degree of correlation among factors [11], which are load data sequences in this paper.

The correlation degree ζ between the comparison sequence $x_i(k)$ and the reference sequence $y(k)$ is:

$$\zeta = \frac{1}{n}\sum_{i=1}^{n}\gamma_i(k) \tag{1}$$

$$\gamma_i(k) = \frac{\min_i \min_k \Delta_i(k) + \rho \max_i \max_k \Delta_i(k)}{\Delta_i(k) + \rho \max_i \max_k \Delta_i(k)} \tag{2}$$

$$\Delta_i(k) = | y(k) - x_i(k) | \tag{3}$$

where $\gamma_i(k)$ is the correlation coefficient between x and y; ρ is the resolution coefficient, which is generally 0.5; x_i and y are normalized values.

Figure 2 shows correlation between the loads at each node during the selected 72-hour period in this paper. The greater the value of correlation degree is, the more correlative the two EVCSs are.

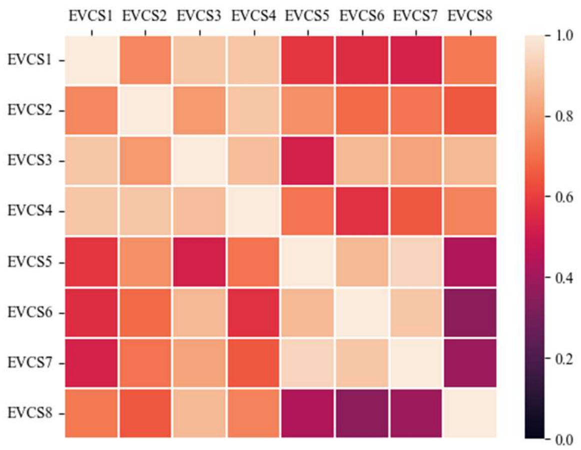


Fig. 2. Correlation between each node

III. EVCS Load Forecasting Based on T-GCN

To improve the prediction accuracy of EV charging station load, this paper considers a T-GCN method. The method's overall structure is illustrated in Figure 3.

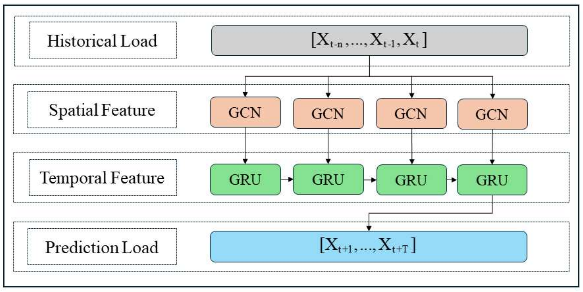


Fig. 3. Overall structure of T-GCN

A. Problem Statement

Construct and define network $G=(R,E)$, in which $R=\{r_1,r_2,...,r_N\}$ is the set of nodes representing EVCSs, N is the number of the nodes, and the edges connecting the nodes are represented by E. In the charging station problem, the weights of the edges are determined by the results of the correlation analysis discussed in chapter II. The feature matrix $X^{N\times P}$ is defined, with P representing the number of features of a node. This matrix is used to represent the load of each node.

Therefore, the problem of forecasting EVCSs' load can be seen as learning the mapping function f, given the network topology G and the feature matrix X, and then calculating the load information for the next T time intervals, as stated below:

$$[X_{t+1},...,X_{t+T}] = f(G,(X_{t-n},...,X_t)) \tag{4}$$

where n is the length of the historical time series and T is the length of the time series to be predicted. In our work, X_t is expressed as follow:

$$X_t = [P_{EVCS_{1,t}}, P_{EVCS_{2,t}}, ..., P_{EVCS_{i,t}}]^{\mathrm{T}} \tag{5}$$

where $P_{EVCS_{i,t}}$ is the load power of EVCS$_i$ at time t.

B. Model of Spatial Feature

To construct a GCN model, multiple convolutional layers can be stacked. In this paper, we utilize GCN models to acquire spatial features from data. A multi-layer GCN with the following layer-wise propagation rule is considered:

$$H^{(l+1)} = \sigma(\tilde{D}^{-1/2}\tilde{A}\tilde{D}^{-1/2}H^{(l)}W^{(l)}) \tag{6}$$

in which adjacency matrix with self-loop is:

$$\tilde{A} = A + I_N \tag{7}$$

A is the adjacency matrix representing connection between nodes, degree matrix is:

$$\tilde{D} = \sum_j \tilde{A}_{ij} \tag{8}$$

and $H^{(l)} \in \mathbb{R}^{N\times D}$ is the matrix of activations in the l^{th} layer, $H^{(0)} = X$. I_N is the identity matrix and $W^{(l)}$ is a layer-specific trainable weight matrix. The value of $\tilde{D}$ is calculated from Section II.

The representation of a two-layer GCN model is as follows:

$$f(A,X) = \sigma(\hat{A}\,\mathrm{ReLU}(\hat{A}XW_0)W_1) \tag{9}$$

$$\hat{A} = \tilde{D}^{-1/2}\tilde{A}\tilde{D}^{-1/2} \tag{10}$$

where W_0 and W_1 denote the weight matrices of the first and second layers, respectively, and $\sigma(\cdot)$ and $\mathrm{ReLU}(\cdot)$ denote the activation function.

C. Model of Temporal Feature

Acquiring temporal features is another key issue in EVCS load forecasting. LSTM and GRU are based on roughly the same fundamentals and are both used to solve the problems of gradient vanishing and gradient explosion that neural networks suffer from in long term forecasting. They both use gating mechanisms to remember information for as long as possible and are equally effective for a variety of tasks. However, due to its complex structure, the LSTM takes longer to train, whereas the GRU model has a relatively simple structure, fewer parameters, and faster training capability. Therefore, in this paper, GRU model is chosen to obtain the time dependence of load data.

The Gated Recurrent Unit (GRU) is a neural network structure designed for processing sequential data. It can predict and understand changes in the load state by analyzing historical data, including the hidden state at time t-1 and the current data, while taking into account temporal dependencies. The GRU model effectively reveals the load condition at time t by using the hidden layer state at time t-1 and the instantaneous load data. It not only monitors the load level in real-time but also retains insight into historical load dynamics by integrating previous data changes and demonstrates an understanding of time-series data dependency characteristics. The model is illustrated in Figure 4.

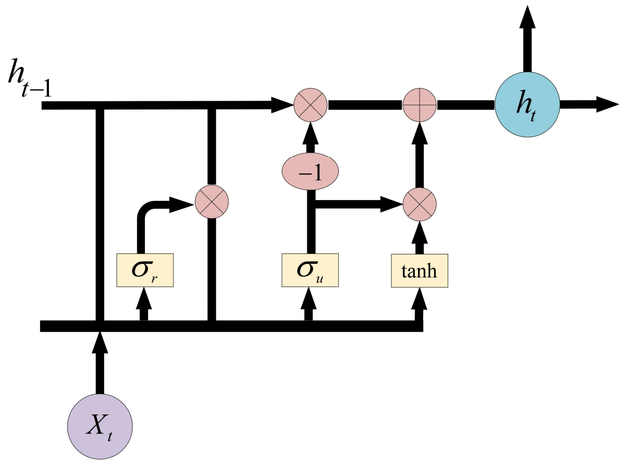


Fig. 4. Model of GRU

D. Model of T-GCN

In order to capture both spatial and temporal dependencies in the data, this paper considers a temporal graph convolutional network (T-GCN) model based on graph convolutional networks and gated cyclic cells. It is shown in the following equation:

$$u_t = \sigma(W_u\left[f(A, X_t), h_{t-1}\right] + b_u) \tag{11}$$

$$r_t = \sigma(W_r\left[f(A, X_t), h_{t-1}\right] + b_r) \tag{12}$$

$$\tilde{h}_t = \tanh(W_c[f(A, X_t), r_t * h_{t-1}] + b_c) \tag{13}$$

$$h_t = u_t * h_{t-1} + (1 - u_t) * \tilde{h}_t \tag{14}$$

where: $f(A, X_t)$ represents the graph convolution process and is defined in equation 9; h_t denotes the output at time t; W and b represent the weights and biases during training; u_t and r_t are update gate and reset gate at time t.

The loss function is represented as follows:

$$loss = \| L_t - \widehat{L_t} \| + \lambda L_{reg} \tag{15}$$

L_{reg} is the regularization term used to avoid overfitting problems [12]. λ is a hyperparameter to adjust the strength of the regularization. L_t and $\widehat{L_t}$ are used to denote the real load and the predicted load.

E. Evaluation Metrics

The calculation of the prediction accuracy is given by the following equation:

(1) Accuracy:

$$Accuracy = 1 - \frac{\| L - \hat{L} \|_F}{\| L \|_F} \tag{16}$$

(2) Root Mean Squared Error (RMSE):

$$RMSE = \sqrt{\frac{1}{mn}\sum_{j=1}^{m}\sum_{i=1}^{n}(l_i^j - \widehat{l_i^j})^2} \tag{17}$$

(3) Mean Absolute Error (MAE):

$$MAE = \frac{1}{mn}\sum_{j=1}^{m}\sum_{i=1}^{n}\left| l_i^j - \widehat{l_i^j} \right| \tag{18}$$

where l_i^j and $\widehat{l_i^j}$ represent the real load and predicted load of EVCS$_i$ at time j; m is number of time samples; n is number of modes. L and $\hat{L}$ represent the set of l_i^j and $\widehat{l_i^j}$ respectively.

The root mean square error (RMSE) and the mean absolute error (MAE) are employed to assess the predictive accuracy. A smaller value indicates a more accurate prediction. The accuracy of the prediction is gauged by the magnitude of the value, with a larger value indicating a more precise prediction.

The T-GCN model is capable of handling complex spatial dependencies and temporal dynamics. On the one hand, the graph convolutional network is employed to capture the topology of the network, thereby enabling the extraction of spatial dependencies. On the other hand, the gated loop unit is utilized to capture the dynamics of the load, thus facilitating the acquisition of temporal dependencies and ultimately the task of EVCS load forecasting.

IV. Case Study

A. Parameter Design and Data Set Introduction

The data set utilized in this study comprises load data from nine neighboring charging stations in the Shenzhen region, collected over a three-day period. Figure 5 shows the load curve of EVCSs within 72 hours.

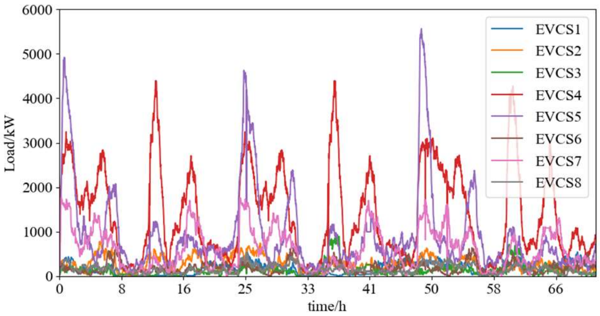


Fig. 5. EVCSs' load curve

Table I shows the parameters chosen in neural network's training and testing.

TABLE I. NEURAL NETWORK PARAMETER DESIGN

Parameters	Value
Number of Hidden Units	32
Learning Rate	0.001
Batch Size	64
Training Epoch	2000
Train Set Proportion	0.8
T (predicted time length)/min	15/30/60
t (historical time length)/min	60

When choosing the number of hidden units, tests are deployed to achieve the model's best performance, seen in Figure 6.

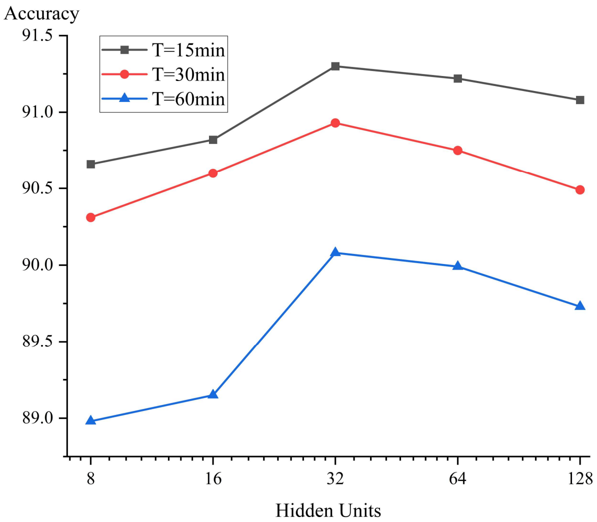


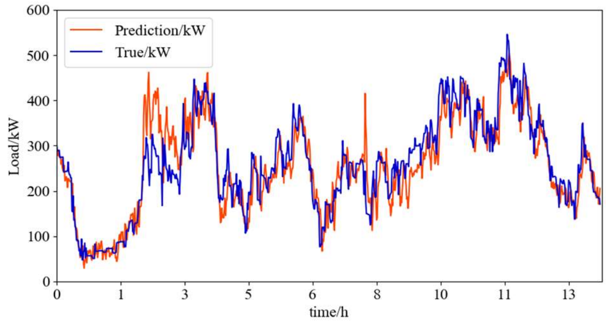
Fig. 6. Tests on the number of hidden units

As the results shown in Figure 6 indicates, the number of 32 hidden units is chosen to train the model.

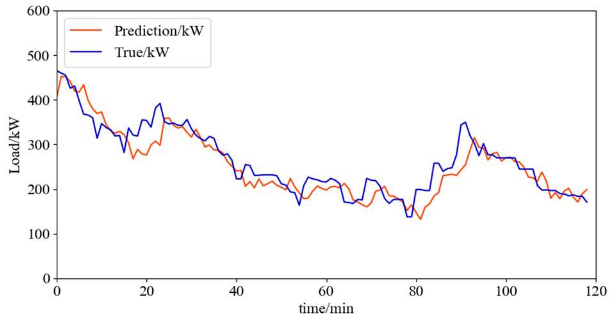
With regard to the cleansing of the data, the methodology employed in this paper is as follows: any instances of missing data are filled in with the mean values observed both before and after the missing data; any instances of anomalous data are removed or replaced with the mean values of the time series observed both before and after.

B. T-GCN Prediction Results

The load of EVCS1 is employed as an illustrative case. Figure 7 demonstrates the predicted outcomes for EVCS1 over 14.4 hours (20% of 72 hours) and 2 hours, in comparison to the actual loading, at T=15 min.



(a)

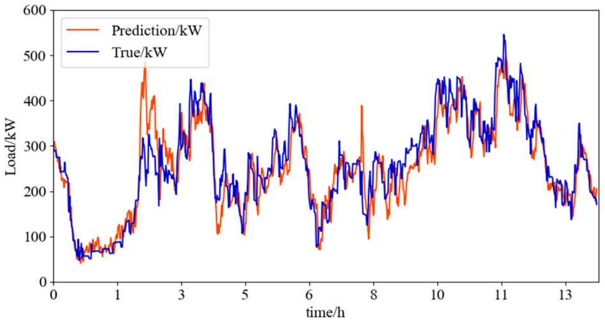


(b)

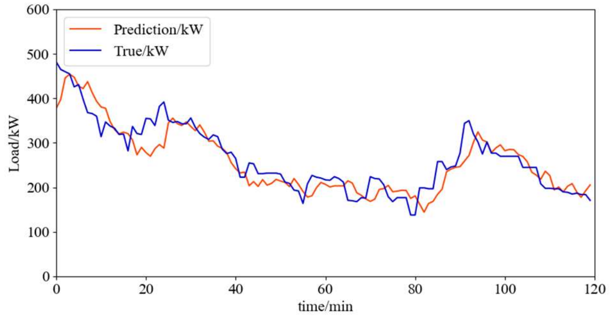
Fig. 7. T=15 EVCS1 load prediction results: (a) 14.4h and (b) 2h

The predicted load line exhibits considerable volatility, which is attributable to the daily usage patterns. These include increased charging demand during the morning and evening peak hours. The forecast model demonstrates a satisfactory fit, although there are some intervals, for instance within the 100-200 minute range of the time series, where there is a notable discrepancy between the forecast and actual values. The model exhibits a degree of lag or over-smoothing in the capture of peaks and troughs. This may be attributed to the model's lack of sensitivity to the treatment of extreme values or to overfitting of the data in smooth intervals. The predicted values typically exhibit a slight increase prior to reaching the peak and subsequently decline only after the actual values have declined. This phenomenon indicates that the model is not responsive enough to unexpected events or that the training data lacks sufficient mutation information to enable the model to more accurately predict such rapid changes.

Figure 8 and Figure 9 show the predicting results of EVCS1 at T=30 and 60 min.

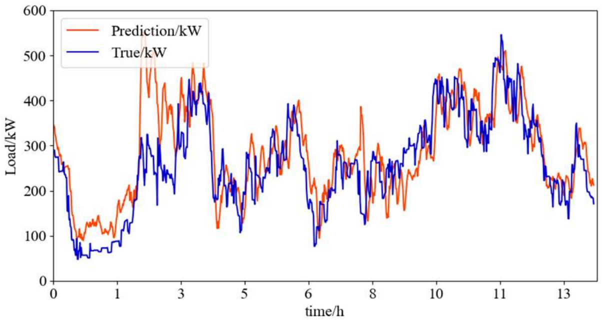


(a)

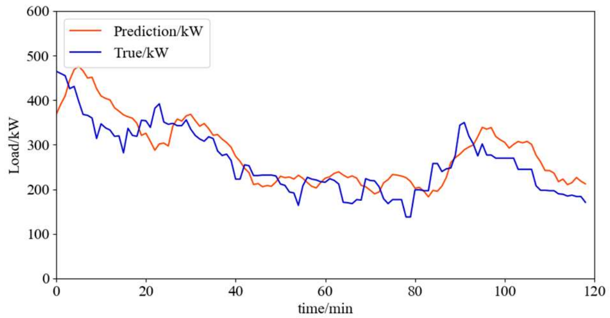


(b)

Fig. 8. T=30 EVCS1 load prediction results: (a) 14.4h and (b) 2h



(a)



(b)

Fig. 9. T=60 EVCS1 load prediction results: (a) 14.4h and (b) 2h

As T increases, the discrepancy between the predicted and actual loads widens. Additionally, the lag between the two lines becomes more pronounced due to the longer prediction period. Nevertheless, the outcomes demonstrate that the prediction efficacy remains intact even when T reaches 60 minutes.

C. Nerual Network Comparison

The experiment results of T-GCN, GCN, and GRU are shown in Table II. GCN model: see [13] for details. GRU model: see [14] for details.

TABLE II. THE PREDICTION RESULTS OF T-GCN AND OTHER METHODS

T	Metric	T-GCN	GCN	GRU
15min	Accuracy	**0.9130**	0.8081	0.9064
	RMSE	**56.02**	80.75	57.06
	MAE	38.56	60.25	**36.91**
30min	Accuracy	**0.9093**	0.7897	0.8958
	RMSE	**58.87**	84.48	60.77
	MAE	40.29	62.69	**39.55**
60min	Accuracy	**0.9008**	0.7815	0.8896
	RMSE	**70.32**	100.55	71.55
	MAE	47.21	72.84	**46.91**

The preceding table indicates that the T-GCN model exhibits the most favorable prediction performance across a range of evaluation metrics for all prediction horizons. This evidence supports the efficacy of T-GCN in forecasting the load of multi-EVCSs. The accuracy of the predictions exceeds 0.9, which ensures the reliability of the data derived from these predictions. Although GRU exhibits slightly better performance in terms of mean absolute error (MAE) compared to T-GCN, T-GCN demonstrates superior overall performance.

Figure 10 highlights the method's capability for long-term prediction. It shows that as the prediction interval extends from 15 to 60 minutes, the accuracy slightly decreases by only 1.22%. Concurrently, the Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE) increase by 14.30 and 8.65, respectively. This demonstrates the method's robustness in maintaining prediction reliability over longer periods.

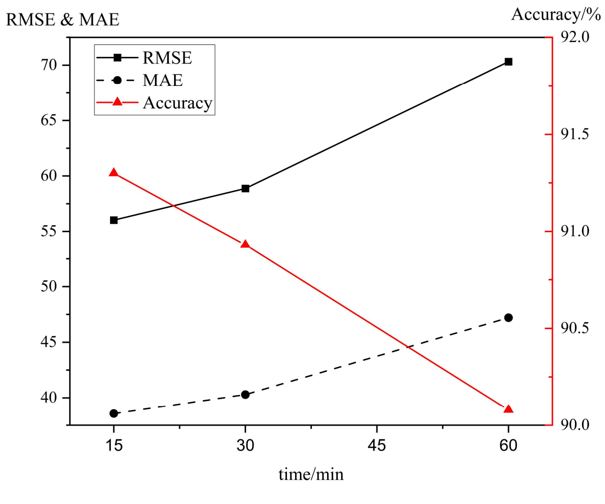


Fig. 10. Visulization of T-GCN's long-term prediction ability

V. CONCLUSION

The study underscores the significance of integrating both network topology (spatial features) and sequential data analysis (temporal features) to enhance the prediction accuracy of EVCS loads by employing T-GCN method. This dual approach not only aids in better grid management but also supports the strategic placement and operational scheduling of EV charging stations. Future research could explore the scalability of the model across larger networks of EVCSs and integrate more dynamic real-time data sources to further refine its predictive capabilities.

In conclusion, the model for multiple EVCSs' load prediction based on T-GCN considered in this paper represents a significant advancement in the field of load forecasting for electric vehicle charging stations, with potential implications for energy management systems and urban infrastructure planning. The model's ability to handle complex spatial-temporal data efficiently could be a promising tool in solving the problems in the electric vehicle ecosystem field.

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