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An Improved Spatio-Temporal Network Traffic Flow Prediction Method Based on Impedance Matrix

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Abstract: Effective traffic management and congestion reduction heavily rely on accurate traffic flow prediction. Existing prediction methods, such as Markov, ARIMA, STANN, GLSTM, and DCRNN models, often face challenges because they rely on fixed spatial relationships, leading to limited long-term prediction accuracy. To address these shortcomings, this study proposes the Impedance-Spatio-Temporal Topological Network (Impedance-STTN) prediction model. The Impedance-STTN model integrates K-medoids clustering for data analysis, generating a real-time impedance matrix from impedance functions, traffic big data, and real-time flow data. This approach captures dynamic node relationships within the spatio-temporal network, enhancing prediction accuracy. Experimental results demonstrate the superior predictive performance of the Impedance-STTN model, achieving accuracies of 94.79%, 93.78%, and 93.11% in 5 min, 15 min, and 30 min predictions, respectively. These results outperform existing models, especially in long-term predictions. The findings underscore the model's high accuracy and effectiveness across varying prediction durations, marking a significant advancement in traffic flow prediction. This suggests promising avenues for future research and practical applications.

Key words: traffic engineering; traffic prediction; spatio-temporal correlation; real time impedance matrix; STTN network

1 Introduction

Traffic congestion and accidents have become increasingly prevalent in modern cities, posing significant challenges to urban transportation management[1]. These issues not only impact the efficiency of urban transportation but also affect the overall quality of life for city residents.

Traffic flow prediction plays a critical role in anticipating and managing traffic conditions for future periods, typically ranging from several minutes to hours ahead. The predicted outcomes can be directly integrated into traffic management systems and traffic information platforms, enabling traffic authorities to proactively address congestion and improve traffic flow efficiency. Therefore, the accuracy of traffic flow prediction is paramount in mitigating congestion and preventing accidents.

Despite the development of various traffic flow prediction methods in recent years, such as historical average models[2], time series models[3], wavelet theory[4], chaos theory models[5], support vector machines[6], and neural networks[7], challenges persist regarding efficiency and accuracy. For instance, historical average models often oversimplify by assuming future traffic flow will mirror historical averages, neglecting dynamic traffic patterns. Time series models capture temporal dependencies but may overlook complex spatial relationships among road segments. Machine learning techniques like support vector machines and neural networks require substantial data and can be prone to overfitting.

In this paper, we propose a novel traffic flow prediction approach that combines the impedance matrix and STTN model. The impedance matrix captures spatial relationships among road segments, while the STTN model effectively models temporal dependencies in traffic flow data. This integration aims to enhance the accuracy and efficiency of traffic flow prediction.

The structure of this paper is organized as follows:

Literature Review This: section delves into related works on traffic flow prediction and introduce the impedance matrix.

Methodology: This section details data processing, impedance matrix construction, and the new model pro-

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posed in this paper.

Experiment and Results: This section presents the experimental setup, evaluation metrics, and real-world traffic dataset results.

Conclusion: This will summarizes key findings and propose directions for future research.

2 Literature review

2.1 Traffic flow prediction

Numerous models have been employed for traffic flow prediction tasks, and with the advancements in computer technology, machine learning has emerged as a frontrunner due to its superior prediction accuracy[8]. Ma introduced the long short-term memory (LSTM) network, a type of recurrent neural network, for capturing long-term time correlations in traffic speed prediction[9]. This model demonstrated superior accuracy and stability compared to mainstream parameter and non-parameter algorithms. KE proposed the Fusion Convolutional Long Short-Term Memory Network (FCL-Net), a deep learning method, for short-term passenger demand prediction within an end-to-end learning framework[10]. Experimental results highlighted its superior performance over traditional methods and state-of-the-art machine learning algorithms like artificial neural networks, XGBoost, LSTM, and CNN.

MA presented the NN-ARIMA model, a hybrid machine learning and statistical time series model, for predicting traffic flow within a network[11]. This model not only captures the overall network coordinated traffic flow patterns but also identifies specific location traffic features and macro traffic variables. Additionally, research has shown that considering spatio-temporal correlations significantly enhances prediction accuracy, leading to the exploration of more methods incorporating these characteristics. CAI introduced the TAaDGCN model for air traffic flow prediction, incorporating time and space dependencies[12]. WANG proposed the KGR-STGNN method based on knowledge graph representation learning, expanding consideration of network factors[13]. SHAO combined an improved particle swarm optimization algorithm with LSTM and CEEMDAN to establish a hybrid model for network traffic flow prediction, reducing complexity[14]. CHEN proposed TGANet, a deep learning model integrating various modules for spatial information exploration and prediction[15]. GUO presented a spatio-temporal traffic flow prediction model based on dynamic graph convolutional network (DGCN), leveraging traffic data more comprehensively[16].

In summary, literature encompasses a wide range of traffic flow prediction methods, from traditional statistical models to advanced machine learning techniques. However, due to the intricate nature of traffic flow, achieving accurate predictions remains challenging. In this paper, we propose a novel approach integrating impedance matrix and STTN model for traffic flow prediction, aiming to enhance prediction accuracy and efficiency.

2.2 Impedance function

Impedance function is a widely studied concept in transportation research, which quantifies the impact of road impedance on travelers' route choice, traffic allocation on the network, and spatial relationships among network nodes[17]. Many scholars in various countries have made significant progress in the study of impedance function. A series of impedance functions, represented by the Bureau of Public Roads (BPR) impedance function in the United States, have been widely used in transportation. In 1966, the Bureau of Public Roads summarized the relationship between travel time and traffic flow on road segments based on a large-scale traffic survey, which resulted in the BPR impedance function model. The BPR model accurately captures the essence of road impedance and has good mathematical properties, making it the most widely used impedance function internationally. The BPR formula is shown as follows:

$$t_t = t_0[1 + \alpha(\frac{v}{c})^{\beta}], \tag{1}$$

where, t_t is the travel time of vehicles passing through the road section; t_0 is the free flow travel time of vehicles passing through the road section; v is the traffic flow of the road section; c is the traffic capacity of the road section; α, β is the parameter.

The BPR model has a simple form, a small number of parameters, and a fast model-solving speed. Moreover, the parameters α and β can be recalibrated for different regions, making it widely applicable. However, there are also many shortcomings, including Problem 1: When the parameter β is too high, the accuracy is too low, and the travel time changes very little when the saturation rate (Q/C) is low. Problem 2: When Q/C tends to 1, the curve does not tend to infinity, resulting in the phenomenon that the road segment flow is greater than its capacity in the user equilibrium assignment. To address Problem 1, Spiess improved the parameter β and explored the relationship between travel time and distance and flow on road segments[18]. To address Problem 2, Davidson proposed the Davidson model based on queuing theory, which has a certain degree of popularity[19], but its parameter definition is inconsistent. Akcelik further corrected the function and derived the time-dependent form of the Davidson function using coordinate transformation to solve the problem of inconsistent parameter definition[20]. However, the accuracy of the impedance function is still affected by various factors, such as the heterogeneity of traffic flow, the nonlinearity of the relationship between traffic variables, and the spatial and temporal variation of traffic conditions. Therefore, there is still much room for improvement in the development of impedance functions for traffic modeling and management.

3 Methodology

The Impedance-STTN (Impedance-Spatio-Temporal Topological Network) model constructed in this paper is shown in Figure 1. Firstly, basic data cleaning is completed to remove missing, redundant, and erroneous data. Then, the data of each node is analyzed and clustered to generate free-flow travel time. After that, the impedance function is determined, and the real-time impedance matrix is generated by combining the free-flow travel time with real-time traffic flow. Finally, the impedance matrix is input as the graph adjacency matrix into the STTN network to generate the impedance-STTN model.

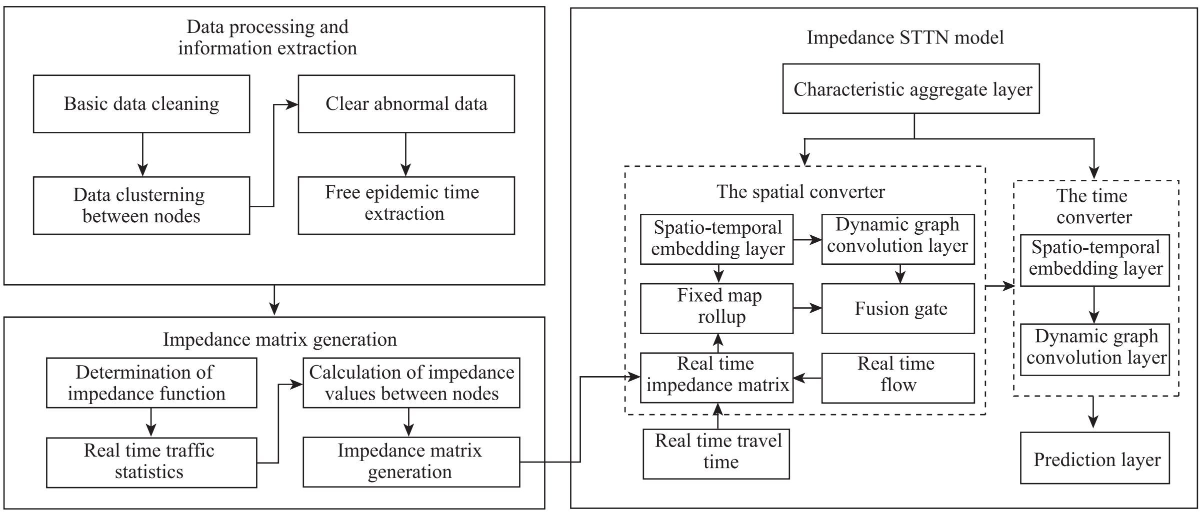


Fig. 1 The impedance-STTN model

3.1 Data processing and information extraction

The first part of this section is Data Processing and Information Extraction. The main objective is to extract the spatiotemporal relationships between nodes from the data. Therefore, the data should provide at least the entry and exit time of the vehicles and the basic information of the vehicles. After ensuring the quality of the data, the steps for information extraction are as follows.

3.1.1 Calculation of travel time

Firstly, relevant calculations are performed on each data to obtain the travel time between the corresponding nodes.

$$t_{ij} = T_{\mathrm{E}} - T_{\mathrm{R}} \in T_{\mathrm{R}} V_{ij} \tag{2}$$

where, t_{ij} is the travel time from toll station i to toll station j; T_{E} is the time to leave the toll station; T_{R} is the time to enter the toll station, and several t constitute t_{ij} set $T_R V_{ij}$.

3.1.2 Clustering of travel time

There is some interference data in the travel time data, such as accidents or rest periods during the driver's journey. These data should not be included in the subsequent calculation of free-flow travel time. Therefore, relevant cleaning is performed on these data.

Kmeans clustering is employed to perform data cleansing by systematically categorizing the sets of travel times, referred to as $T_R V$, among individual nodes. Throughout this clustering operation, we concurrently monitor several key metrics-the Sum of Squared Errors (S_{SE}), the Davies-Bouldin (I_{DB}) Index, and the Silhouette Coefficient (S)-as reliable indicators to ascertain the optimal number of clusters.

S_{SE} is the sum of squares of all residuals. In this study, the ability to accomplish effective clustering with the current number of clusters is evaluated based on whether there are drastic changes in the S_{SE}.

$$S_{SE}(k) = \sum_{i=1}^{k} \sum_{X \in C_i} | d(X, C_i) |^2, \tag{3}$$

where, k is the number of clusters; C_i is the ith cluster; X is the divided sample, $d(X, C_i)$ is the Euclidean distance from the sample to its corresponding cluster center.

The Silhouette Coefficient (S) is an indicator used to evaluate the effectiveness of clustering. In this study, whether the current number of clusters can achieve effective clustering is determined by the value of the Silhouette Coefficient.

$$S(k) = \sum_{i=1}^{k} \sum_{X \in C_i} \frac{b(x) - a(x)}{\max[a(x), b(x)]} / \sum_{i=1}^{k} \sum_{X \in C_i} 1 \tag{4}$$

where, $a(x)$ represents the average distance from sample x to all other samples within its own cluster; $b(x)$ is the minimum value among the average distances from sample x to all samples from all other clusters.

The I_{DB} index describes the intra-class scatter of the sample and the distance between the cluster centers. The optimal number of clusters is determined by the I_{DB} index.

$$I_{DB}(k) = \sum_{i=1}^{k} \max_{j=1 \sim k, j \neq i} \left[\frac{W_i + W_j}{d(X, C_i)} \right], \tag{5}$$

where, W_i represents the average distance from all samples in the class to the center of the class; W_j represents the average distance from all samples in to the class center; $d(X, C_i)$ represents the Euclidean distance between the class center and the class.

The S_{SE} with the change of the number of classifications, the I_{DB} and the S with the change of the number of classifications are calculated and generated. When the decrease of S_{SE} slows down, the optimal number of clusters is selected to make both I_{DB} and S reach their minimum values. If the optimal numbers of clusters determined by different methods are not the same, a more appropriate number of clusters is selected after consideration.

After determining the number of clusters, the classes with a proportion of less than 5% are removed.

3.1.3 Calculation of free-flow travel time

The average value of the minimum travel time of the cleaned data is taken as the free-flow travel time. According to the "Evaluation Norm for Urban Traffic Operation", 1/9 is taken to calculate the free-flow travel time between each node.

Thus, the free-flow travel time between nodes in the road network is extracted.

3.2 Impedance matrix

In the traffic prediction process, spatiotemporal correlation is a necessary factor that must be considered[21]. Temporal correlation can often be characterized by time series models, while spatial correlation is more difficult to characterize. In order to better utilize the spatial correlation within the road network, this paper uses the OD impedance matrix to define the spatial correlation between different observation points[22]. Assuming there are m nodes in the target road network, the size of the impedance matrix is a $m \times m$ matrix. The impedance matrix is as follows:

$$\boldsymbol{A} = \begin{bmatrix} z_{11} & \cdots & z_{1m} \\ \vdots & \ddots & \vdots \\ z_{m1} & \cdots & z_{mm} \end{bmatrix}, \tag{6}$$

where, m is the total number of nodes in the road network; z_{ij} is the impedance value between node i and node j; $\boldsymbol{A}$ is the traffic impedance matrix containing m nodes. This paper adjusts the BPR function appropriately based on the actual situation to complete the calculation of the corresponding impedance values. The corresponding calculation function is as follows:

$$t_{tij} = t_{0ij} \left[1 + \alpha_2 \left(\frac{V_i + V_j}{8C_{ij}} \right)^{\beta} \right], \tag{7}$$

where, t_{tij} is the direct impedance value between node i

and node j; and V_i is the hourly traffic flow of node i; C_{ij} refers to the traffic capacity from node i to node j, with a high speed of 2 200 pcu/h/ln; α_2, β are system parameters, $\alpha_2 = 0.15, \beta = 4$. The resulting impedance matrix is input into the STTNS network as a graph adjacency matrix $\boldsymbol{A}$.

3.3 The STTN model

The full name of the STTN model is Spatial Temporal Transformer. The overall structure of the STTN model is shown in Figure 2, which can be divided into three parts: the feature aggregation layer, the spatio-temporal block, and the prediction layer. The feature aggregation layer is used for basic feature extraction. The spatio-temporal block contains multiple spatio-temporal blocks, and each spatio-temporal block jointly models the spatio-temporal dependency relationship through a spatial transformer and a temporal transformer, and connects the spatio-temporal features at each level through skip connections. The prediction layer uses two 1×1 convolutional layers to aggregate these spatio-temporal features for traffic prediction[23].

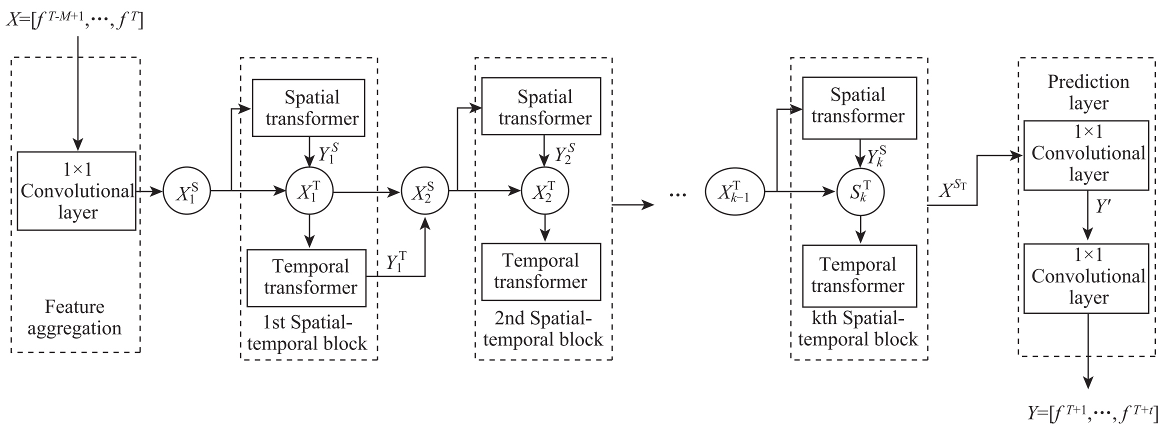


Fig. 2 The STTN model

The feature aggregation layer extracts d_G-dimensional features from M consecutive time series of N nodes and aggregates them into a three-dimensional tensor of size $M \times N \times d_G$. The three-dimensional tensor is then input into the spatio-temporal block. In each spatio-temporal block, the spatial transformer S and the temporal transformer τ are used to generate a three-dimensional output tensor by superimposing. The output tensor is then passed to the next spatio-temporal block. In the i-th spatio-temporal block, the spatial transformer S receives the node features combined with the real-time impedance matrix A to extract the spatial features.

$$Y_l^S = S(X_l^S, A). \tag{8}$$

X_l^S will be combined with Y_l^S to generate input for subsequent time changers.

$$X_l^\tau = X_l^S + Y_l^S. \tag{9}$$

X_l^τ generates Y_l^τ through the time changer.

$$Y_l^\tau = \tau(X_l^\tau). \tag{10}$$

Y_l^τ will combine with X_l^τ to generate X_{l+1}^S into $l+1$ space time block.

$$X_{l+1}^S = X_l^\tau + Y_l^\tau. \tag{11}$$

In the last spatio-temporal block, the $\mathrm{d}S^{\mathrm{T}}$-dimensional features of N nodes are extracted and aggregated into a two-dimensional tensor of size $N \times \mathrm{d}S^{\mathrm{T}}$. The prediction layer performs a second convolution to generate the prediction results for the N nodes in the future T time.

$$Y = \mathrm{Conv}[\mathrm{Conv}(X^{S\tau})]. \tag{12}$$

The model is trained with average absolute loss.

$$L = \| Y - Y_{\mathrm{gt}} \|, \tag{13}$$

where Y_{gt} is the true value of the corresponding result.

4 Experiment

In this section, we apply the improved spatiotemporal network based on the impedance matrix to predict the overall traffic flow of the Beijing-Tianjin-Hebei expressway network, which includes 22 expressway sections such as the Beijing-Shanghai Expressway and the Tianjin-Hebei Expressway. We compare and analyze the predicted values obtained with the actual values, and finally compare the prediction results with those of similar models to verify the reliability of the method.

4.1 Dataset description

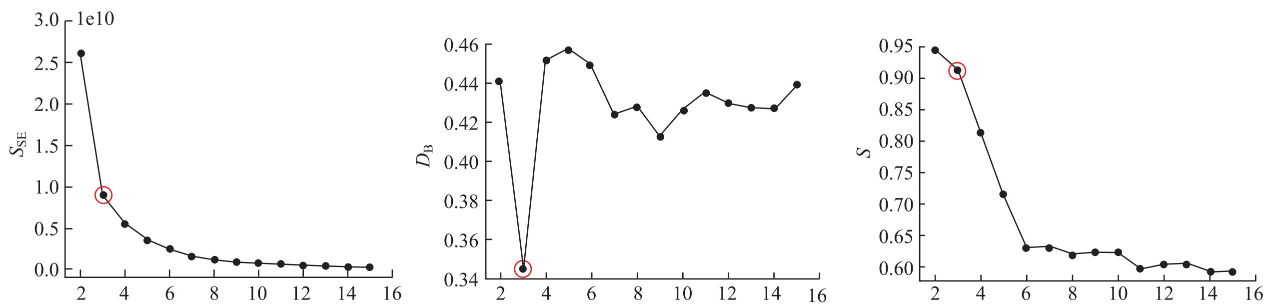
The dataset used in this research pertains to the related data of the expressway network in the Beijing-Tianjin-Hebei region in China, specifically focusing on data from the period of May to June 2018 for detailed analysis. This network comprises 22 expressway sections, including the Beijing-Shanghai Expressway, the Beijing-Tianjin Expressway, among others, and encompasses traffic data from 113 ETC gantries within these expressways. The key fields of the ETC data utilized in this study are shown in Table 1, with a principal requirement for data identifiers, vehicle pass-through node information at entrances and exits, as well as vehicle attribute information.

Table 1 Main fields and meanings of ETC gantry data

Field name	Attribute meaning
ID	Data number, a unique number corresponding to each data
EXSTATIONID	Corresponding number of exit toll station
PASSTIME	Time when the vehicle passes the exit toll station
RSTATIONID	Corresponding number of entrance toll station
RPASSTIME	Time for vehicles to pass the entrance toll station
TOTALWEIGHT	Total weight
VEHICLECLASS	vehicle type

4.2 Free-flow travel time

Initially, fundamental data cleaning is performed to eliminate redundant and erroneous data. After the basic data cleansing process, the K-means algorithm is employed based on the existing data to cluster the travel times between each node. The detailed clustering process is as follows: Firstly, the number of clusters is determined by collectively considering the Sum of Squared Errors (S_{SE}), Davies-Bouldin (D_B) index, and Silhouette Coefficient (S). Taking the travel time between node 1 181 801 and node 1 090 905 as an example, Figure 3 illustrates the variations in S_{SE}(left), D_B(middle), and S (right) under different cluster quantities. From the S_{SE} change graph, it can be seen that the S_{SE} decreases as the number of clusters increases. After the number of clusters reaches 3, the S_{SE} basically stabilizes and can be maintained at a low error rate. Therefore, for this node pair, the optimal number of clusters is chosen to be 3 or more. From the variations observed in the D_B and the S graphs, we note that both the D_B and S indices reach their optimal values when the number of clusters is 3. Consequently, the optimal number of clusters is established to be 3.



(a) S_{SE} chang (b) D_B chang (c) S chang

Fig. 3 Graph of parameters changing with the number of clusters

Table 2 Clustering results

Cluster category		Cluster center (min)	Data volume	Proportion (%)
Cluster	1	8 783.77	1 804	96.68
	2	60 501.28	9	0.48
	3	81 706.64	53	2.84
Altogether			1 866	100

Upon determining the optimal number of clusters, clusters with proportions less than 5% are removed. For instance, between node 1181 801 and node 1 090 905, data are clustered into three classes, with classes 2 and 3 possessing extremely small proportions and hence, are not considered in calculations. After eliminating outliers, the average of the smallest one-ninth of the travel time data is taken as the free-flow travel time for each road segment. The free-flow propagation time between node 1 181 801 and node 1 090 905 is found to be 146.40 minutes (any impedance value between disconnected nodes is filled with the maximum value). By combining the free-flow travel time with real-time traffic flow, the corresponding impedance values between nodes are generated.

These values then constitute the impedance matrix, which is input into the STTN.

4.3 Model training

The STTN model has many hyperparameters, and the settings and combinations of these parameters can significantly impact the model's performance. Therefore, it is essential to optimize the model's hyperparameters to enhance its predictive capabilities. Through cross experiments and error comparison analysis, the main parameter-related fields and their final determined values in this study are shown in Table 3.

Table 3 Model parameter settings

Parameter name	Parameter meaning	Short-cut process
In_channels	Number of input channels	1
Embed_size	Number of transformer channels	64
Num_layers	Spatial-temporary block stacking layers	3
T_dim	Enter a time dimension	12
Output_T_dim	Output Time Dimension	6
Heads	Number of transformer heads	2
cheb_K	Order of Chebyshev polynomial	2
Forward_expansion	Dimensions of feedforward networks	4

4.4 Results and analysis

This paper evaluates the model with the following parameters: mean squared error (M_{SE}), root mean squared error (R_{MSE}), mean absolute error (M_{AE}), mean absolute percentage error (M_{APE}), and r-square (R_2). Taking the data between node 1 181 801 and node 1 090 905 on the expressway as an example, the prediction curve of STTN is observed by predicting the traffic flow for different time intervals in the future. The prediction results are shown in Figure 4.

Figures 4 show the comparison between the predicted values and the actual values for different time intervals between node 1 181 801 and node 1 090 905 on the expressway based on the STTN algorithm. It can be seen from the figure that the STTN model can predict the trend and direction of the data well, and the overall prediction accuracy of STTN is maintained at a good level. Table 4 shows the traffic flow prediction errors for different time intervals. It can be observed that the STTN model has good prediction accuracy for short time intervals and also has relatively good prediction accuracy for long-term predictions, which can complete the task of traffic flow prediction.

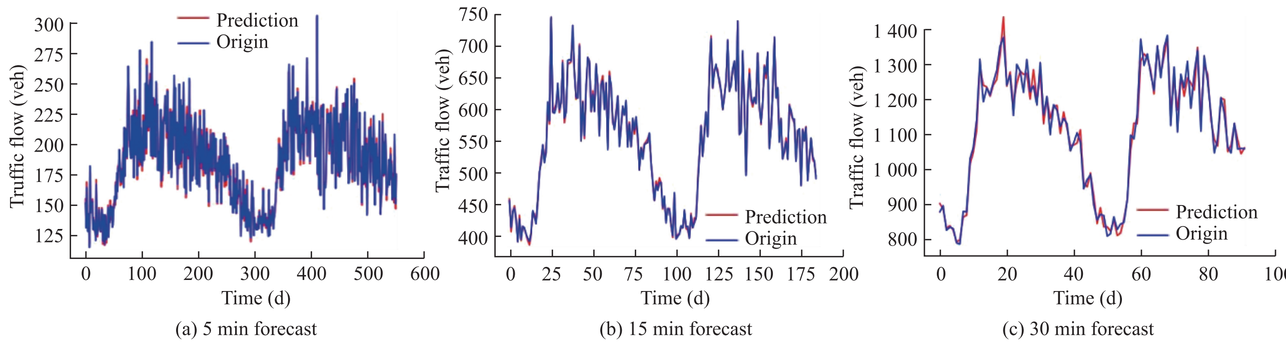


Fig. 4 Traffic prediction under different M_{RSE} lengths

Table 4 STTN model different time horizon flow prediction

Forecast duration	M_{SE}	M_{RSE}	M_{AE}	M_{APE}(%)	R_2
5 min	192.65	13.88	1.96	4.15	0.99
15 min	441.84	21.02	14.26	7.12	0.97
30 min	1 577.68	39.72	29.62	6.37	0.98

To further demonstrate the prediction performance of the model, this paper compares the prediction accuracy of different models including Markov, ARIMA, STANN, GLSTM, DCRNN, and STTN for different time intervals. The evaluation is conducted using three evaluation indicators, RMSE, M_{AE}, and M_{APE}. The traffic flow between all nodes is predicted for error calculation, and the average error between all nodes is taken. The results are shown in Table 5.

Table 5 shows the error of the predicted values and the actual values for all nodes by different models. The three values represent the error results for the future 5 minutes, 15 minutes, and 30 minutes, respectively. It can be seen from the table that the M_{RSE}, M_{AE}, and M_{APE}

of the STTN model are lower than those of other machine learning models, and the STTN model shows good prediction accuracy for traffic flow prediction at different time intervals.

Table 5 Comparison of model prediction performance

Model	M_{RSE}	M_{AE}	M_{APE}(%)
Markov	10.51/32.78/78.21	9.91/26.11/55.21	16.21/21.98/24.67
ARIMA	13.12/28.21/50.86	7.21/23.25/45.12	18.89/23.21/25.32
STANN	9.23/29.75/60.18	7.15/25.30/44.74	21.23/26.98/24.74
GLSTM	12.21/29.31/72.67	9.34/23.52/51.43	17.62/23.60/25.49
DCRNN	6.31/21.15/36.71	6.52/21.02/29.86	8.75/11.89/14.19
STTN	4.62/18.15/38.21	5.21/15.43/28.23	5.21/6.22/6.89

5 Conclusions

In this paper, a method for generating an impedance matrix using traffic big data and real-time traffic flow is proposed to address the shortcomings of existing prediction methods. The method is illustrated using data from the expressway network in the Beijing-Tianjin-Hebei region. The conclusions are as follows:

(1) Compared with traditional methods for characterizing spatial relationships, the impedance matrix used in this study to extract the spatial relationships of the road network overcomes challenges such as high costs, lengthy investigation cycles, and susceptibility to traffic flow interference. This makes it more suitable for predicting traffic flow in the expressway network.

(2) The proposed prediction model can enhance the predictive capability and stability of the entire prediction system.

(3) The proposed model demonstrates significant advantages in accuracy compared to other models, particularly in long-term prediction.

This paper proposes a method for generating an impedance matrix using traffic big data and real-time traffic flow, and the prediction results are highly reliable. In future research, we will further analyze and utilize the data to improve prediction accuracy and apply it to more complex road network prediction tasks.

Declaration of competing interest

The authors have no competing interests to declare that are relevant to the content of this article.

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