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Real-Time Adaptive Traffic Flow Prediction Based on a GE-GRU-KNN Model

Xiangyu YI[1], Hongmei ZHOU[2], Shaopeng ZHONG[3]

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[1] xiangyuyi@mail.dlut.edu.cn, Dalian University of Technology, School of Transportation and Logistics
[2] Corresponding author, hzhou@dlut.edu.cn, Dalian University of Technology, School of Transportation and Logistics
[3] szhong@dlut.edu.cn, Dalian University of Technology, School of Transportation and Logistics; Centre for Urban Governance of Zhejiang, International Urbanology Research Centre

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ABSTRACT

Traffic flow prediction is an important part of urban intelligent transportation systems. However, due to strong nonlinear characteristics and spatiotemporal correlations of the traffic within the network, traffic flow prediction has been a challenging task. In order to capture the spatiotemporal correlation, and improve the traditional methods of using predefined adjacency matrices that cannot effectively characterise the dynamic correlation of traffic flow, a GE-GRU-KNN model for predicting the road traffic flow is proposed. Specifically, the spatial representation of the road network learned by GE is used to automatically extract the spatial features of the network; GRU is used to learn the nonlinear characteristics of the time series to capture the temporal correlation of the traffic flow; finally, the KNN algorithm is introduced to combine real-time traffic flow and historical data and adaptively update the fusion weights of predicted values for different road sections. The method enables the model to effectively characterise the dynamic correlation of traffic flow. An experiment using traffic flow data from 22 detectors on California freeways is conducted. The results show that compared with traditional methods, the prediction error of this method is reduced by 1.08%–14.71%, indicating that the hybrid GE-GRU-KNN model exhibits good performance.

KEYWORDS

traffic flow prediction; dynamic spatiotemporal correlation; graph embedding; gated recurrent unit; k-nearest neighbour.

1. INTRODUCTION

Traffic flow prediction is an important part of urban intelligent transportation systems. Accurate traffic flow plays an important role in alleviating traffic congestion, providing more reasonable travel routes for travellers, and improving road operation efficiency [1–2]. It refers to the prediction of the future traffic state of an urban road network by considering the spatiotemporal correlation of traffic flow, and based on the predicted results, corresponding traffic management and control can be carried out [3]. However, due to the complex temporal and spatial correlations of traffic flow in road networks, the prediction has been a challenging task.

Traditionally, linear regression models and autoregressive integrated moving average models (ARIMA) [4–6] have been widely used for traffic flow prediction. But these methods are more suitable for handling stable and linearly varying time series [7]. When used for the prediction of traffic flow with complex nonlinear spatiotemporal characteristics, the accuracy is relatively low. Machine learning methods have gradually been introduced into the field of traffic flow prediction due to their flexibility in handling nonlinear problems. For example, models such as Random Forest (RF), Support Vector Regression (SVR) [8–10], KNN [11] and Neural Network (NN) [12–13] can effectively capture the changing trends of traffic flow by learning from a large amount of historical data. However, most of them do not effectively extract the spatial correlation of traffic flow in the road networks.

In order to better characterise the spatiotemporal characteristics of traffic flow, deep learning methods have been widely applied in recent years. Recurrent Neural Network (RNN) and its variants long short-term memory neural network (LSTM) and GRU models [14–18] are utilised to process traffic time series data and mine the temporal dependencies among these data [19]; Convolutional Neural Network (CNN) [20–24] is utilised to extract the spatial correlation of traffic flow within the road network. As research deepens, scholars have also developed hybrid models [25–26] that comprehensively consider spatial and temporal dimensions to model data. Due to its combination of the advantages of two or more models, these models have better modelling capabilities of traffic data than a single model [27]. In early studies, researchers used prior knowledge to construct pre-defined graph structures representing spatial correlations. Spatiotemporal Graph Convolutional Networks (STGCN) [28] and Attention Based Spatiotemporal Graph Convolutional Networks (ASTGCN) [29] are representative models in recent years, which use the road connectivity and distance to characterise node similarity, thereby constructing an adjacency matrix representing a pre-defined graph structure. However, the adjacency matrix constructed from this type of prior knowledge is not directly related to the prediction task, resulting in limited spatial representation ability of the adjacency matrix. To address this issue, the Adaptive Graph Convolutional Recurrent Network (AGCRN) [30] uses an adaptive adjacency matrix to better extract spatial features. However, both pre-defined matrices and adaptive matrices have the disadvantage that the weights they use are static, meaning that the correlations between different road segments are fixed and invariant. The formation of traffic flow is a dynamic process, and the spatial correlations of traffic flow within the network may constantly change. Thus, establishing spatial relationships between different road segments through adjacency matrices cannot effectively represent spatial correlations dynamically.

In response to the above issues, this paper proposes a real-time adaptive traffic flow prediction model that combines the GE, GRU and KNN algorithms, aiming to more effectively characterise the dynamic changes of spatiotemporal characteristics in road networks. GE is used to automatically extract spatial features in the road network, overcoming the limitations of relying on pre-defined adjacency matrices. Then, GRU models for the target road segment and other road segments are trained and the temporal correlations are constructed. Finally, the KNN algorithm is introduced to combine real-time traffic flow with historical traffic data, adaptively updating the fusion weights of the predicted values of different road segments for the target road segment. The proposed method no longer relies on fixed adjacency matrices, but dynamically adjusts the correlations between road segments through the GE and KNN algorithms, better reflecting the dynamic spatiotemporal characteristics of traffic flow. The contributions of this paper can be summarised in the following three aspects:

1) This model integrates the methods of the GE and GRU, where the GE is used to learn the spatial representation information of the network, avoiding the limitation of pre-defined adjacency matrices and allowing the model to dynamically adapt to the changing spatial relationship in the road network. GRU is used to model time series data of traffic flow and extract temporal correlations. Independent GRU models are trained for the target road section and other road sections to capture the complex correlations.
2) The model specifically introduces the KNN algorithm, which adaptively adjusts the weight allocation during the prediction process by combining real-time traffic data and historical data, thereby improving the model's ability to handle dynamic traffic flow changes.
3) The study uses the real-world dataset to evaluate the model. Compared with other models, the proposed hybrid model exhibits good performance, indicating that incorporating dynamic spatiotemporal correlations of traffic flow will have a positive effect on improving the accuracy of traffic flow prediction.

The rest of the paper is organised as follows. The literature review section summarises previous research. The methodology section provides an overview of the modelling approach proposed in this paper. In the experiment section, an experiment is conducted to analyse the advantages and disadvantages of the model compared to other models. Conclusions are made in the conclusion section.

2. LITERATURE REVIEW

There are many literature on traffic flow prediction, and the prediction methods can be divided into two categories: parametric methods and non-parametric methods. Parametric methods include time series models, linear regression models, Kalman filter models, etc. ARIMA has been widely used for modelling traffic data in the past [31], but it is more suitable for handling stable time series data and is less accurate for capturing extreme values, making it unsuitable for processing nonlinear traffic flows [32]. The Kalman filter establishes the state space model of the sampled signal, and can model traffic data reasonably [33]. However, it utilises predefined states and error values of measurement noise, which limits its application in the real world. The key issue with these traditional parametric models lies in parameter calibration, and their algorithms are relatively simple. When there are abrupt changes in traffic flow, these models cannot respond well to the nonlinear characteristics and instability of traffic flow data.

With the acquisition of massive traffic data, it is possible to apply non-parametric models. These models can extract useful information from a large amount of historical data and learn the patterns. Many non-parametric methods based on machine learning have been proposed to model traffic data, including KNN, RF, SVR, NN, etc. Zhang et al. proposed a hybrid prediction model, which combines the RF, Genetic Algorithm (GA) and SVR to provide better performance compared to other methods [34]. Liu et al. applied the GA and Particle Swarm Optimisation (PSO) for the optimisation of parameters of the Back Propagation (BP) Neural Network, and proposed a GA-PSO-BP neural network model for traffic state estimation based on multi-source sensor data fusion [35]. Considering the varying accuracy of different models under different traffic conditions, Guo et al. applied three fusion strategies, including the average, weighted and KNN methods to three different machine learning models: NN, SVR and RF [36].

In recent years, deep learning has been applied in fields such as computer vision, speech recognition, etc. and has achieved great success. Compared with traditional machine learning models, deep learning models use a multiple-layer architectures to automatically extract inherent features from a large amount of raw data [37]. Many studies have also applied deep learning models to traffic data modelling and achieved good results. Mou et al. proposed a temporal information enhancing LSTM (T-LSTM) model for predicting traffic flow on individual road sections [38]. Cui et al. proposed a stacked bidirectional and unidirectional LSTM network architecture (SBU-LSTM) for traffic state prediction by utilising bidirectional LSTM (BDLSM) to capture forward and backward temporal dependencies in spatiotemporal data [39]. Mondal et al. proposed a short-term traffic flow prediction model based on the LSTM model by considering the spatiotemporal correlation of traffic flow and using the current as well as historical data of the target road and adjacent roads as input variables [40]. Chauhan et al. proposed a BiGRU-BiGRU model with two modules, which can distinctly capture the periodic and temporal characteristics of the traffic data. The proposed model is evaluated on the publicly available real-world dataset and achieved good performance [41].

The above models mainly consider the temporal correlation of traffic flow by exploring the characteristics of time series data, but most of them ignore the spatial correlation of traffic flow in the road network. Therefore, many hybrid prediction models have been developed to model the spatiotemporal correlations of traffic flow in road networks. Luo et al. proposed combining the KNN and the LSTM. The spatial stations were screened by the KNN model, and the screened station data were then used as input to the LSTM model for prediction. The experimental results show that the accuracy of the proposed traffic flow prediction model is better than other traditional methods [42]. Zhao et al. proposed a new temporal graph convolutional network (T-GCN) model that combines the GCN and the GRU for traffic state prediction to capture both spatial and temporal dependencies [43]. Zhou et al. raised a traffic flow prediction method based upon the k-order neighbour algorithm and gated recurrent unit, which obtains the temporal dependency of traffic flow by using the Euclidean distance to figure the spatial correlation between traffic networks and the gated recurrent neural network [44]. Zhuang et al. proposed a method to predict the spatio-temporal characteristics of short-term traffic flow by combining the k-nearest neighbour algorithm and the bidirectional long short term memory network model. This method can capture the spatial and temporal characteristics of traffic data. At the same time, the performance of this fusion method on real data sets is better than other methods [45]. The above research shows that the hybrid model has an excellent performance in traffic flow prediction. However, traffic flow in road networks has strong nonlinear characteristics and dynamic uncertainty. The traffic situation is a dynamic process and its spatial correlation is constantly changing. Therefore, it is necessary to adopt corresponding methods to identify the characteristics of dynamic changes in traffic flow.

In summary, most existing traffic flow prediction models are based on the temporal and/or spatial correlations of the traffic flow. When considering the spatial correlation, one approach is to manually select upstream/downstream roadway data, which does not fully take into account the complex spatial and temporal correlation of traffic flow data in the road network. Another way of modelling the spatial information of the roadway network is to use predefined adjacency matrices. However, this approach also has some limitations and cannot effectively characterise the dynamic correlation of traffic flow data. Therefore, this paper proposes a hybrid traffic flow prediction model that can automatically extract spatial features in the road network and combine historical data and real-time traffic flow to characterise the dynamic correlation of traffic flow.

3. METHODOLOGY

3.1 GE

Due to the fact that road networks can essentially be modelled as graphs as well, graph analysis has attracted increasing attention from researchers in the field of transportation. Graph Embedding (GE) allocates nodes in a network to a low dimensional representation and effectively preserves the network structure and properties, enabling functions such as node classification, node clustering and link prediction. Use a graph $G = (V, E, A)$ to represent the structure of the road network, where $V = \{v_1, v_2, \ldots, v_N\}$ is the set of nodes in the network, N is the number of the nodes; E is the set of edges connecting nodes in the network; The adjacency matrix $A \in R^{N\times N}$ is used to represent the connectivity between nodes, which contains only elements of 0 and 1. If two nodes i and j in the network are adjacent, $a_{ij} = 1$; otherwise, $a_{ij} = 0$; The traffic flow observed in the road network G at time t is denoted by $X^t \in R^{N\times M}$, where M is the dimensionality of the features of each node.

GE based on Deep-Walk is one of the typical graph embedding algorithms. It mainly consists of two parts: random walk and node representation learning. Firstly, a random walk sequence corresponding to each node is generated through a walk strategy to obtain local and global features in the graph. Then the Skip-Gram algorithm [46] is used to train the random walk sequence to obtain the corresponding representation vector for each node in the graph. Based on this method, the relationship among the nodes can be learned. The structure of graph embedding algorithm is shown in *Figure 1*.

In this study, the road network graph is extracted through the actual road network and then a series of random walk sequences are generated with each node as the root. $R_{v_i} = \{R^1_{v_i}, R^2_{v_i}, \ldots, R^l_{v_i}\}$ denotes the random walk with node v_i as the root. It is a stochastic process and the length of the random walk is specified as l. The random walk sequence is then trained using the Skip-Gram algorithm, the core idea of which is to maximise the probability of nodes in the walk sequence that are close to the target node. The optimisation objective is shown in *Equation 1*.

$$\underset{\Phi}{maximize}\ Pr\left(\{v_{i-s}, \ldots, v_{i-1}, v_{i+1}, \ldots, v_{i+s}\} \middle| \Phi(v_i)\right) \tag{1}$$

where s is the size of the selected window; $\Phi(v_i)$ is a mapping function that maps node v_i to an embedding vector.

Using the independence assumption, it can be rewritten as *Equation 2*.

$$minimise\ \ -\sum_{j=i-s, j\neq i}^{i+s} logPr\left(v_j \middle| \Phi(v_i)\right) \tag{2}$$

Firstly, each node is represented by a one-hot vector with elements of 0 and 1. Due to the fact that one-hot vectors cannot be used for vector similarity calculation, and a large number of nodes require a very large memory space and resources, a weight matrix to extract a new vector representation is designed. The matrix $W \in R^{N\times D}$ represents the embedding vector matrices of the central node and adjacent node; and D is the dimension of the node embedding vector $\Phi(v)$. Multiplying the one-hot vectors with the embedding vector matrices W realises the mapping of node v_i to the low-dimensional embedding vector $\Phi(v_i)$. Then, multiply the embedding vector $\Phi(v_i)$ with the matrix $\Phi(v_j)^T$ and input the result into the Softmax function to obtain the probability of node v_j. The calculation is shown in *Equation 3*.

$$Pr\left(v_j \middle| \Phi(v_i)\right) = \frac{exp\left(\Phi(v_j)^T . \Phi(v_i)\right)}{\sum_{v\in V} exp\left(\Phi(v). \Phi(v_i)\right)} \tag{3}$$

where V is the nodes in the graph; $\Phi(v_i)$ is the embedding vector of the center node v_i; and $\Phi(v_j)$ is the embedding vector of the adjacent node v_j.

Next, construct the loss function, as shown in *Equation 4*, and update the embedding vector $\Phi(v_i)$ of the centre node using the gradient descent algorithm, as defined in *Equation 5*.

$$logPr\left(v_j \middle| \Phi(v_i)\right) = \Phi(v_j).\Phi(v_i) - log\left(\sum\nolimits_{v \in V} exp\left(\Phi(v).\Phi(v_i)\right)\right) \tag{4}$$

$$\Phi(v_i)_{new} = \Phi(v_i)_{old} - \eta \nabla logPr\left(v_j \middle| \Phi(v_i)\right) \tag{5}$$

where $\Phi(v_i)_{old}$ and $\Phi(v_i)_{new}$ are the embedding vectors of node v_i before and after training; η is the learning rate; and ∇ is the gradient.

After model training is completed, the embedding matrix $W_{N \times D}$ corresponding to the road network nodes can be obtained. The embedding matrix $W_{N \times D}$ is shown in *Equation 6*.

$$W_{N \times D} = \begin{pmatrix} w_{11} & w_{12} & \cdots & w_{1D} \\ w_{21} & w_{22} & \cdots & w_{2D} \\ \cdots & \cdots & \cdots & \cdots \\ w_{N1} & w_{N2} & \cdots & w_{ND} \end{pmatrix} = \begin{pmatrix} e_1 \\ e_2 \\ \cdots \\ e_N \end{pmatrix} \tag{6}$$

where e_i is the embedding vector of the node i after training, with dimension D.

Then, the spatial features of the road network can be automatically obtained based on the similarity of the node embedding vectors e_i. Using the inner product of vectors to calculate similarity. The calculation is shown in *Equation 7*.

$$\partial_{ij} = e_i e_j^T \tag{7}$$

where ∂_{ij} is the similarity between node i and node j.

After obtaining the similarity between nodes, automatically select the most relevant road section to the target road section based on the similarity. Use historical traffic flow data of each selected road section as input data for the GRU model.

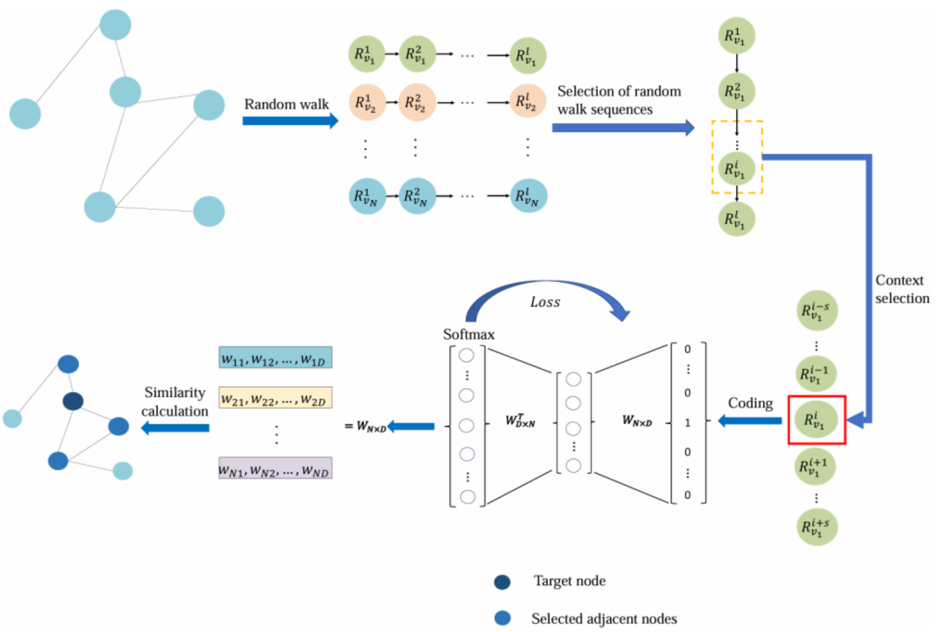


Figure 1 – Structure of the graph embedding algorithm based on the Deep-Walk

3.2 GRU

GRU is an improvement of the RNN [47] and is able to learn both long-term and short-term dependencies of time series data. Compared to the LSTM, the GRU has a simpler structure and is easier to train. The basic unit of the GRU model is shown in Figure 2. There are two gates in the unit, namely the reset gate and the update gate [48]. Through these defined gates, it is possible to retain and discard state information and mine the patterns of the time series data. Considering the dynamic instability and long-term dependence of traffic flow in the road network, this paper uses the GRU to extract the temporal pattern information of the traffic flow features.

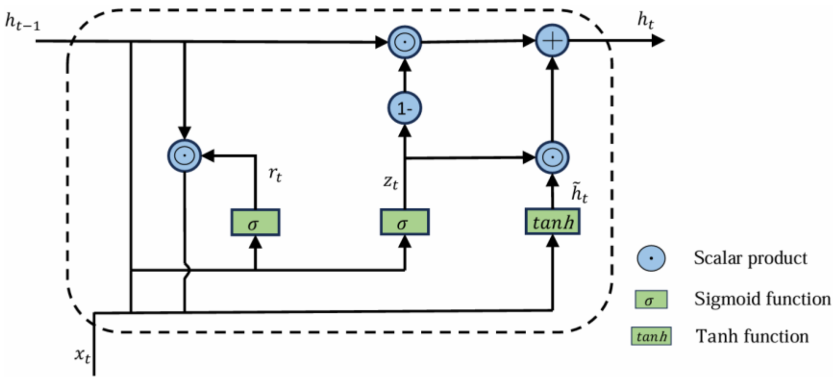


Figure 2 – Structure of the memory unit in the GRU model

In the GRU model, the reset gate r_t is used to determine how to combine new input with the previous memory by *Equation 8*:

$$r_t = \sigma(W_r[h_{t-1}, x_t] + b_r) \tag{8}$$

where r_t is a value between 0 and 1, with 0 representing complete discard and 1 representing complete retention; $\sigma(\cdot)$ is the activation function sigmoid; W_r is the weight of the reset gate; b_r is the bias of the reset gate; h_{t-1} is the output of the memory cell at moment $t-1$; and x_t is the input to the memory cell at moment t.

Then, a new candidate value vector $\tilde{h}_t$ is created through the $tanh$ function, as shown in *Equation 9*:

$$\tilde{h}_t = tanh\left(W_{\tilde{h}_t}[r_t \odot h_{t-1}, x_t] + b_h\right) \tag{9}$$

where $W_{\tilde{h}_t}$ is the weight of the candidate value vector; b_h is the bias of the candidate value vector; $\odot$ represents the scalar product of two matrices.

The update gate z_t determines the degree to which the previous state information is transmitted to the current state by *Equation 10*:

$$z_t = \sigma(W_z[h_{t-1}, x_t] + b_z) \tag{10}$$

where z_t is a value between 0 and 1, with 0 representing complete discard and 1 representing complete retention; W_z is the weight of the update gate; b_z is the bias of the update gate.

After obtaining the candidate hidden state information and the previous state information, update the unit state by *Equation 11*:

$$h_t = (1 - z_t) \odot h_{t-1} + z_t \odot \tilde{h}_t \tag{11}$$

According to the calculation formula above, the GRU stores and filters information through two gates, preserves important features through gate functions, captures dependencies through learning and obtains the optimal output value.

3.3 KNN

The traffic flow in the road network shows complex nonlinear characteristics and strong spatiotemporal correlations. Considering that the predefined adjacency matrices cannot effectively represent the dynamic correlation of traffic flow in the road network, this paper trains separate prediction models for different road sections, and then introduces the KNN algorithm to achieve adaptive weight updates based on real-time traffic flow and historical data. The basic idea is search for k nearest neighbours in the history database of each road section, calculate the prediction errors of the k neighbours, and determine the weights based on the error. The final output is obtained by weighting the results of different road sections. Specific steps are as follows.

Step 1: Neighbour search process. Given the current traffic flow state vector q_c, search for k nearest neighbours in the historical database of each adjacent road section based on the Euclidean distance. Here, $q_c$is a time series data of the traffic flow, which can be written as $q_c = [x_{t-p+1}, \dots, x_t]$. The k state vectors that are closest to the current state vector q_c found in the adjacent road section can be written as $Q_{q_c} \in R^{n\times k\times p}$, where n is the number of adjacent road sections, k is the number of neighbours searched from each adjacent road section, p is the size of the sliding window, i.e. the dimension of the selected traffic flow time series.

Step 2: Weight Determination. For each traffic flow feature vector q_i, input it into the trained model to obtain the predicted value $\hat{y}_i^j$ and then calculate the average absolute percentage error $MAPE_j$ of k state vectors of the j^{th} road section by *Equation 12*.

$$MAPE_j = \frac{1}{k}\sum_{i=1}^{k}\left|\frac{\hat{y}_i^j - y_i}{y_i}\right|, j = 1,2,\dots,n \tag{12}$$

where y_i is the actual value of the traffic flow of the target road section.

The weight coefficient for the j^{th} adjacent road section is determined by $wt_j = 1/MAPE_j$. Through the KNN, weights can be dynamically adjusted based on real-time traffic flow state, which effectively characterises the dynamic correlation of traffic flow data.

3.4 GE-GRU-KNN

This paper proposes a hybrid traffic flow prediction model that combines the GE, the GRU and the KNN. Through the GE model, nodes in the graph can be represented as low-dimensional vectors, representing the spatial characteristics of each node in the road network. The GRU model shows good performance in mining the short-term and long-term dependence of time series data, and different GRU models are trained to characterised the temporal correlation of traffic flow for different road sections. The KNN is used to measure the contribution of relevant road sections to the target road section prediction based on real-time traffic flow state, achieving adaptive weight updates. The hybrid model combines the advantages of different models and can effectively capture the dynamic spatiotemporal correlation of traffic flow in the road network. The framework of the algorithm is shown in *Figure 3*. The specific steps of the GE-GRU-KNN model are shown below.

Step 1: Parameter Setting. Initialise various parameters in the GE, the GRU and the KNN models, including the size of sliding window p, the number of hidden units, the number of neighbours searched in each adjacent road section k and the number of epochs.

Step 2: Extract spatial features of the network. Utilise the GE algorithm to learn the spatial structure features of the network, the abstract expression of the process is shown in *Equation 13*. Then calculate the similarity between nodes based on *Equation 7* and select adjacent road sections $\{1, 2, \dots, n\}$ based on the similarity, n is the number of adjacent road sections (including the target road section itself), which is also the number of GRU models that need to be trained.

$$W_{N\times D} = GE(A) \tag{13}$$

where GE is the graph embedding algorithm.

Then, obtain raw traffic flow data for each selected road section. The raw traffic flow data is shown in *Equation 14*.

$$\begin{aligned} &x_{sim\_1}^{t-p+1}, x_{sim\_1}^{t-p+2}, \dots, x_{sim\_1}^{t} \\ &x_{sim\_2}^{t-p+1}, x_{sim\_2}^{t-p+2}, \dots, x_{sim\_2}^{t} \\ &\dots \\ &x_{tar}^{t-p+1}, x_{tar}^{t-p+2}, \dots, x_{tar}^{t} \end{aligned} \tag{14}$$

where $[x_i^{t-p+1}, x_i^{t-p+2}, \dots, x_i^t]$ is the historical traffic flow data of the i^{th} road section.

Step 3: Extract temporal correlation of traffic flow. Process the traffic flow data of selected different road sections separately and train n different GRU models to establish nonlinear relationships between different road sections and target road traffic flow. These road sections include neighbouring road sections and target road sections themselves. The abstract expression of the process is shown in *Equation 15*.

$$y_{tar} = GRU(y_i), i = 1, 2, \dots, n \tag{15}$$

where y_{tar} is the traffic flow of the target road section, y_i is the traffic flow of the i^{th} road section and GRU is the gated recurrent unit.

Step 4: Real-time prediction. In the prediction task, the traffic flow of the target road section at the moment $t+T$ is predicted based on the traffic flow of the target road section and neighbouring road sections in the time period $[t-p+1, t]$, where T is the prediction time step and p is the size of the sliding window. Substitute the real-time data of the target road section into GRU models of target road section and neighbouring road sections to obtain the predicted values. The process is shown in *Equation 16.*

$$y_{tar}^{i} = GRU(x_i^{t-p+1}, x_i^{t-p+2}, \dots, x_i^{t}), i = 1, 2, \dots, n \tag{16}$$

where y_{tar}^{i} is the predicted value of traffic flow for the target section of road i.

Step 5: Determine the degree of dynamic correlation. The spatiotemporal correlation of traffic flow in the network may change over time. To improve the accuracy, the degrees of correlation between the target road section and neighbouring road sections are measured and dynamically adjusted at different times. Use the KNN algorithm to find the k nearest neighbours from the historical database of different road sections based on real-time data of the target road section and determine the weight coefficients based on the MAPE values of the predictions. The method is described in Section 3.3.

Step 6: Fusion of predicted values. The final result is obtained by weighting the prediction values of different road sections on the target road section, as shown in *Equation 17.*The fusion result takes into account the complex spatial and temporal correlation of traffic flow in the road network, and at the same time dynamically adjusts the fusion weights according to the real-time traffic flow condition to improve the accuracy of the model.

$$\hat{y}_{tar} = \sum_{i=1}^{n} wt_i * y_{tar}^{i} \tag{17}$$

where $\hat{y}_{tar}$ is the predicted value of traffic flow on the target road section and wt_i is the fusion weight of road section i. The formula for weights is shown in *Equation 10.*

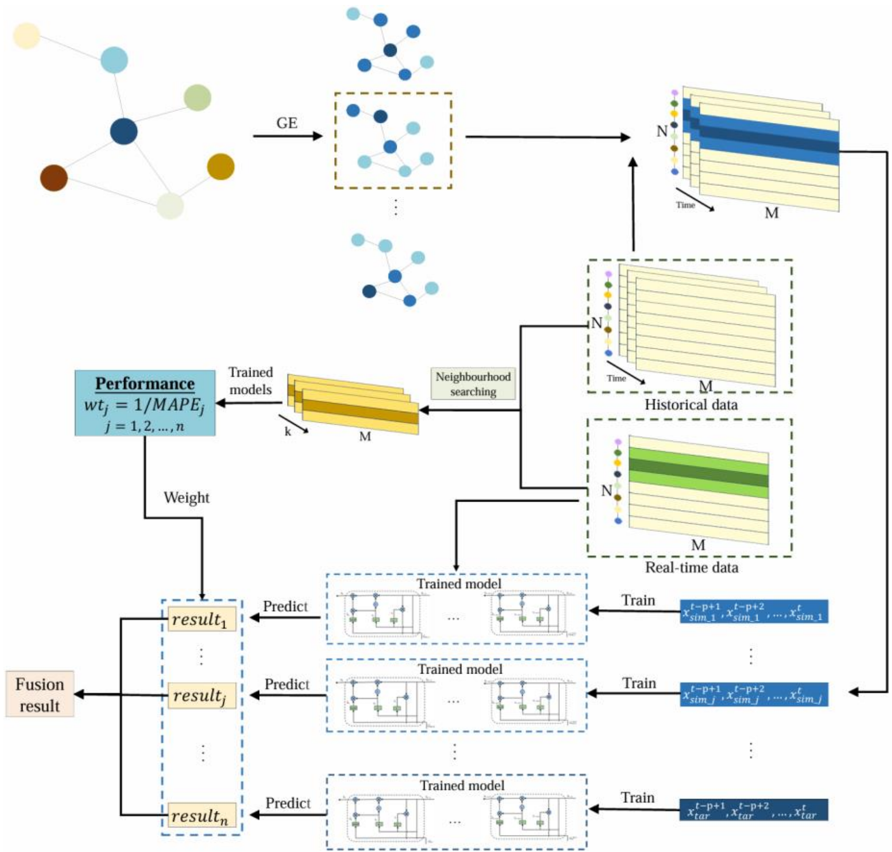


Figure 3 – The framework of the GE-GRU-KNN

4. EXPERIMENT

4.1 Data

The Caltrans Performance Measurement System (PeMS) provides a unified database of traffic data collected on freeways in California [49]. This study used weekend traffic data collected every 30 seconds from 22 freeway sections collected by detectors between 1 May and 30 June 2014. *Figure 4* shows the distribution of the traffic detectors along the freeway. After data cleaning, the data is aggregated into 5-minute traffic flow data.

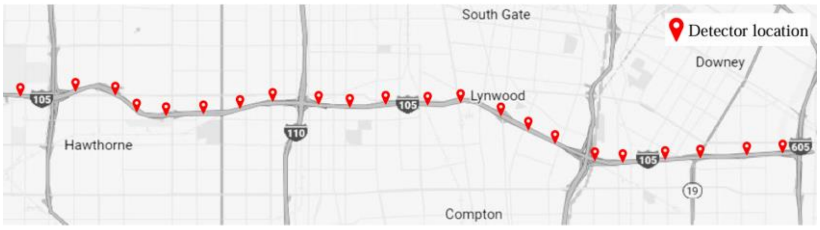
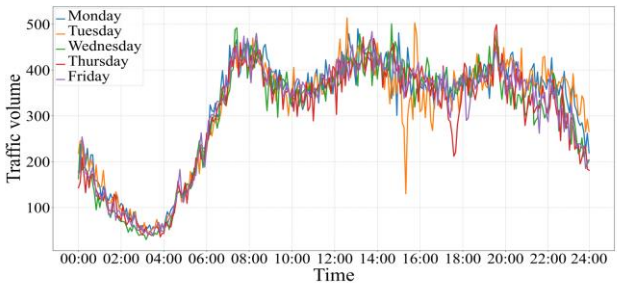
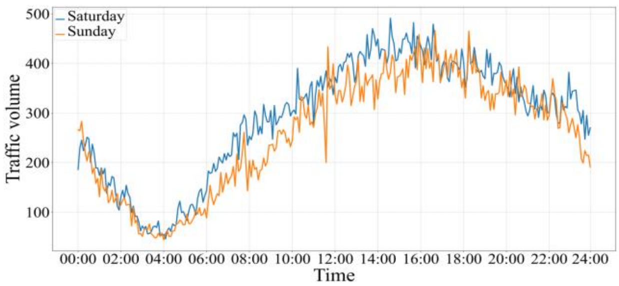


Figure 4 – The distribution of detectors along the freeway

Figure 5 displays traffic flow data for a week obtained by a randomly selected detector. There are periodic changes in traffic flow on the road, and the trend between weekdays and weekends shows significant differences. There are also temporal correlations of current traffic flow with traffic flow in the previous time periods.



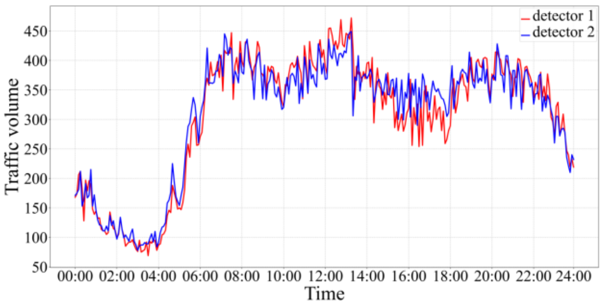
(a)



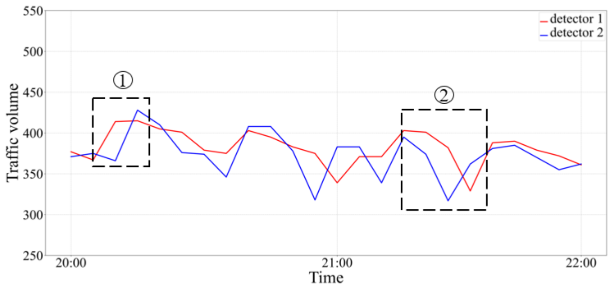
(b)

Figure 5 – a) Traffic volume on weekdays; b) Traffic volume on weekends

In terms of spatial correlation, there is mutual influence between the traffic flow of upstream and downstream road sections. The traffic conditions of the upstream section will be transmitted to downstream sections, while the traffic conditions of the downstream section will influence the upstream section through a feedback effect. *Figure 6* shows the traffic flow data measured by two consecutive detectors 1–2, representing the upstream and downstream detectors, respectively. It can be seen that the traffic flow data collected by two detectors shows similar trends. To observe in more detail, the figure is enlarged and the traffic flow data between 20:00 to 22:00 are shown in *Figure 6b*. Observing detectors 1 and 2, where detector 1 is the upstream detector and detector 2 is the downstream detector, it can be seen that in state ①, as the upstream traffic flow increases, the downstream traffic flow will increase in the later time period; In state ②, downstream road sections may experience congestion, resulting in a decrease in vehicles passing through detector 2 and a decrease in traffic flow. This congestion phenomenon is transmitted to upstream road sections and will have a certain impact on upstream traffic flow.



(a)



(b)

Figure 6 – a) Traffic volume measured by two adjacent detectors; b) Traffic volume from 20:00 to 22:00

4.2 Model settings

Evaluation indicators

Three commonly used performance indicators are used to evaluate the performance of the model, namely mean absolute error (MAE), mean absolute percentage error (MAPE) and root mean square error (RMSE).

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|\hat{y}_i - y_i| \tag{18}$$

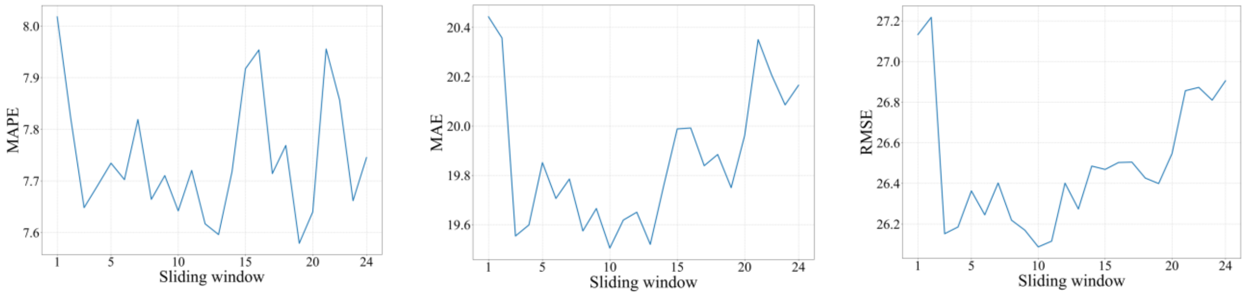
$$MAPE = \frac{1}{N}\sum_{i=1}^{N}\left|\frac{\hat{y}_i - y_i}{y_i}\right| \times 100\% \tag{19}$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{n}(\hat{y}_i - y_i)^2} \tag{20}$$

where N is the number of samples; y_i and $\hat{y}_i$ is the actual value and predicted value, respectively, corresponding to the i^{th} sample.

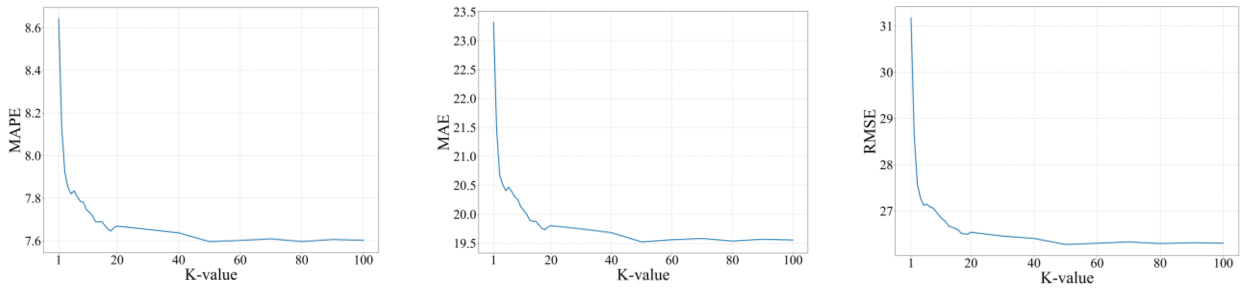
Model parameters

Model parameters have certain impacts on the performance of the model. *Figures 7–10* show the effect of parameters, including the size of sliding window p, the number of neighbours searched in each adjacent road section k, the number of epochs, the number of hidden units on the model performance. The performance of the model corresponding to different sizes of sliding windows is shown in *Figure 7*. It can be seen that the three curves have similar trends. As the size of sliding window increases, the error decreases at first. However, as the size of sliding window continues to increase, the error shows a certain upward trend, and from a comprehensive view of the three performance indicators, this paper finally determines the size of sliding window to be 13. *Figure 8* shows the model performance corresponding to different values of k. It can be seen that with the increase of the k value, there is a decreasing tendency in the errors. When the k value does not exceed 50, the magnitude of error reduction is significant. After that, as the value of k increases, the curve tends to flatten, indicating that increasing the value of k further does not have a significant impact on error reduction. Therefore, this paper sets the value of k in the model to 50 to achieve optimal performance while reducing computational complexity. According to *Figures 9–10*, this paper finally determines that the number of epochs of the model is 700 and the number of hidden units in GRU is 64. Considering the different impacts of traffic flows on adjacent road sections during the long and short-term prediction process, the number of adjacent road sections n in GE is set to 3 when predicting traffic flow for 5, 15 and 30 minutes, and 5 when predicting traffic flow for 60 minutes. For training, use 80% of the data for model training and the remaining data for testing.



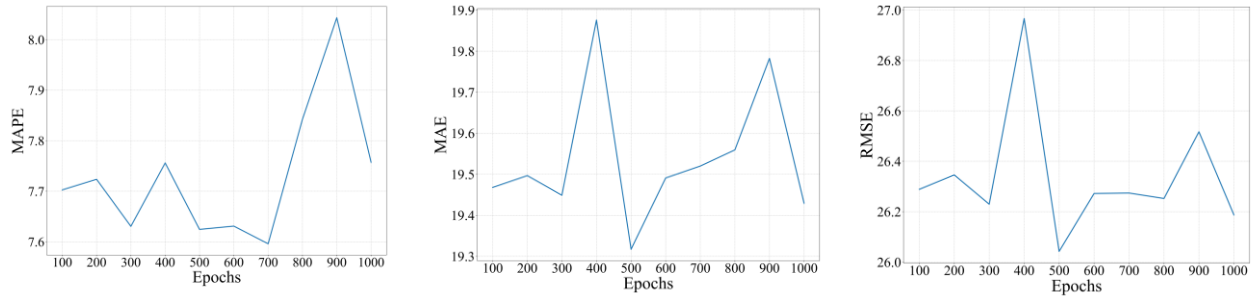
(a) *(b)* *(c)*

Figure 7 – Model performance under different sizes of sliding window



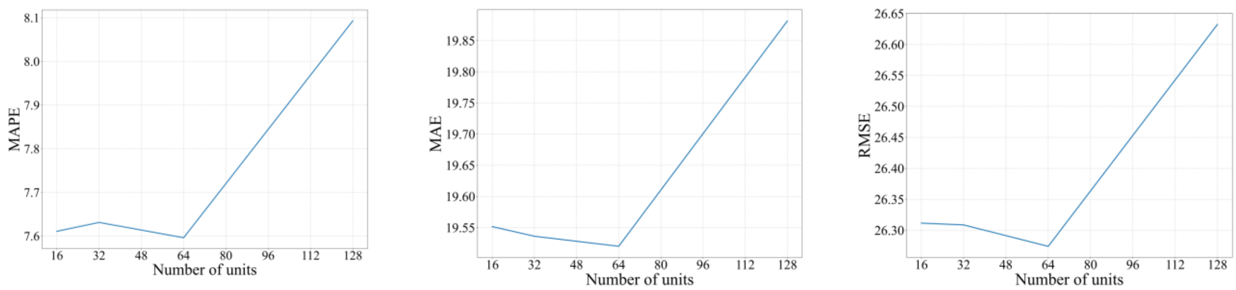
(a) *(b)* *(c)*

Figure 8 – Model performance under different k values



(a) *(b)* *(c)*

Figure 9 – Model performance under different epochs



(a) *(b)* *(c)*

Figure 10 – Model performance under different numbers of hidden units

4.3 Experimental results

Baseline models

To assess the performance of the proposed GE-GRU-KNN model, it is compared with the following baseline models.

— SVR: SVR is based on the theory of Kernel Function (KF), which maps high-dimensional samples to the feature space and then performs regression, which can effectively handle high-dimensional linear problems and improve prediction accuracy.
— RF: RF consists of multiple decision trees and is an integrated algorithm. The basic idea is to combine many weak classifiers into one strong classifier to improve the recognition accuracy.
— LSTM: LSTM is a variant of the RNN, which can learn long-term dependency information and overcome the shortcomings of the traditional RNN and has been widely used in the field of traffic flow prediction.
— GRU: GRU is also a variant of the RNN. Compared to the LSTM, it has a simple structure and is easy to train.
— T-GCN: The Temporal Graph Convolutional Network (T-GCN) model combines the GCN and the GRU. The GCN is used to learn complex topological structures and capture spatial dependencies, while the GRU is used to learn dynamic changes of traffic data and capture temporal dependencies.
— A3TGCN[50]: The Attention Temporal Graph Convolutional Network (A3TGCN) model introduces an attention mechanism based on the T-GCN to adjust the importance of different time points and integrate global temporal information.
— KNN-GRU[44]: The K-Nearest Neighbour-Gated Recurrent Unit (KNN-GRU) combines the KNN and the GRU, uses the Euclidean distance to figure out the spatial correlation between traffic networks, and the gated recurrent neural network obtains the temporal dependency of traffic flow.

Prediction results

To verify the accuracy and robustness of the proposed model, the prediction results of different models on different road sections are shown in the *Tables 1–2*. Due to space limitations, only the MAPE results of prediction time steps of 5 minutes and 60 minutes are shown in details. From the table, it can be observed that the GE-GRU-KNN model overall performs better in both short-term and long-term traffic flow prediction. The RMSE and the MAE of the model are also superior to other baseline models.

(1) When the prediction horizon is 5 minutes, the MAPE of the GE-GRU-KNN model for flow prediction is 8.096%. Compared to other models, it has the smallest error and the highest accuracy. Comparing the GE-GRU-KNN with SVR and RF models, it can be found that the MAPE of the GE-GRU-KNN model is reduced by 5.08% and 8.59%, respectively. This indicates that capturing the spatial features of the network is effective in improving the accuracy of the model, verifying the rationality of the proposed method in this paper. Comparing the GE-GRU-KNN with the LSTM and the GRU models, the MAPE of the proposed model is decreased by 2.6% and 2.34%, respectively. This shows that the hybrid model, in comparison to a single deep learning model that only captures temporal correlation, has better performance after considering the spatial correlation of the road network. Comparing the GE-GRU-KNN with the T-GCN, the A3T-GCN and the KNN-GRU models, the MAPE of the proposed model is decreased by 1.24%, 1.08%, and 1.89%, respectively. This paper separately processes data from different road sections to train different GRU models, and introduces the KNN to dynamically adjust fusion weights based on real-time traffic flow state. The results indicate that the model can effectively capture the dynamic spatiotemporal correlation of traffic flow.

(2) When the prediction horizon is 60 minutes, the MAPE of the GE-GRU-KNN model for traffic prediction is 10.725%. Compared to other models, it also has the highest accuracy, which indicates that the model can ensure the accuracy in the long-term traffic flow prediction. Compared to the T-GCN, the A3T-GCN and the KNN-GRU models, the MAPE of the GE-GRU-KNN model decreased by 14.71%, 3.43% and 2.59%, respectively. It can be observed that the deep learning models LSTM, GRU, and the hybrid models T-GCN, A3T-GCN, KNN-GRU perform well in short-term traffic flow prediction, but when conducting long-term traffic flow prediction, they exhibit certain instability and the performance decreases.

With further examination of the prediction for each road section, it can be found that the GE-GRU-KNN model shows better performance than baseline models in both short-term and long-term traffic flow predictions. In most road sections, the prediction errors using the GE-GRU-KNN model are lower. Meanwhile, it can be found that although the hybrid models T-GCN and A3T-GCN generally perform better in short-term traffic flow prediction compared to the LSTM, the GRU, the RF and the SVR, on some road sections, they perform worse than the LSTM and the GRU. This may be due to the fact that the adjacency matrices cannot extract the dynamic characteristics of the traffic flow. Observing the predictive performance of the KNN-GRU model, it can be found that although it selects n road sections based on the Euclidean distance between different traffic flows, its overall predictive performance is not as good as the model proposed in this paper due to the dynamic changes in traffic flow correlation in the road network over time.

Table 1 – Model performance for each road section with the prediction horizon of 5 minutes

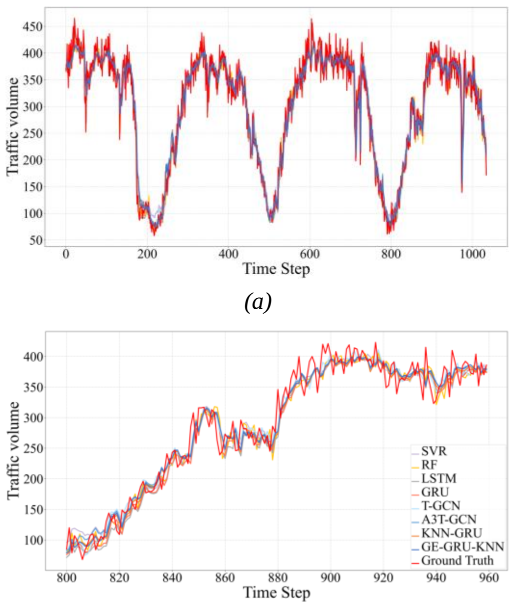
Road section	MAPE (%)							
	SVR	**RF**	**LSTM**	**GRU**	**T-GCN**	**A3T-GCN**	**KNN-GRU**	**GE-GRU-KNN**
1	10.548	10.757	10.152	10.502	10.598	10.486	10.776	**10.086**
2	10.375	10.220	10.297	10.287	10.582	9.740	9.848	**9.280**
3	9.563	10.507	**9.027**	9.773	9.998	9.583	9.595	9.067
4	12.787	12.996	13.405	**12.551**	12.642	12.681	12.724	12.747
5	6.721	8.410	6.648	6.577	6.581	6.575	6.743	**6.553**
6	8.073	7.728	7.197	7.143	6.966	7.234	7.582	**6.839**
7	6.295	7.572	6.952	6.861	6.959	6.283	6.682	**6.272**
8	6.919	7.370	6.788	6.887	6.676	6.367	6.573	**6.361**
9	6.714	7.865	6.538	6.567	**6.382**	6.488	6.393	6.493
10	7.257	8.440	7.126	7.219	**7.057**	7.449	7.342	7.541
11	8.845	9.792	8.745	8.677	8.550	**8.064**	8.588	9.186
12	8.905	9.155	8.764	8.728	**8.673**	10.085	8.750	9.287
13	10.773	9.969	10.488	10.048	10.498	10.289	10.844	**9.956**
14	7.987	**7.103**	7.965	7.995	7.510	7.556	7.694	8.573
15	7.395	7.403	7.440	7.438	7.523	7.442	7.440	**7.384**
16	7.692	8.804	7.600	8.114	7.620	7.602	7.981	**7.585**
17	9.751	10.046	7.930	7.877	7.780	7.791	7.724	**7.696**
18	6.094	6.385	6.385	6.248	6.268	6.299	6.258	**6.078**
19	8.561	8.467	8.937	8.478	**7.981**	8.275	8.024	8.246
20	7.801	7.868	7.617	7.919	7.805	7.789	7.852	**7.607**
21	7.889	7.983	7.489	7.326	7.071	7.490	7.475	**7.048**
22	10.724	10.033	9.398	9.165	8.651	8.503	8.661	**8.235**
Mean	8.530	8.857	8.313	8.290	8.198	8.185	8.252	**8.096**

Table 2 – Model performance for each road section with the prediction horizon of 60 minutes

Road section	MAPE (%)							
	SVR	**RF**	**LSTM**	**GRU**	**T-GCN**	**A3T-GCN**	**KNN-GRU**	**GE-GRU-KNN**
1	15.368	14.617	13.948	12.711	16.309	12.345	12.956	**12.250**
2	14.763	14.202	14.597	12.548	13.900	12.416	12.583	**11.669**
3	14.826	14.409	14.595	13.739	12.811	11.956	13.213	**10.925**
4	19.528	18.710	17.435	18.343	16.394	16.455	**16.374**	18.981

Road section	**MAPE (%)**							
	SVR	**RF**	**LSTM**	**GRU**	**T-GCN**	**A3T-GCN**	**KNN-GRU**	**GE-GRU-KNN**
5	11.075	9.761	12.517	14.075	10.490	9.924	9.932	**9.401**
6	11.632	10.240	11.876	11.840	11.991	10.194	10.288	**8.777**
7	10.524	9.637	8.459	9.862	10.812	8.339	8.831	**8.117**
8	11.116	9.609	8.342	8.332	10.825	8.725	9.061	**8.292**
9	10.929	9.554	8.233	8.255	10.427	9.100	8.878	**8.199**
10	11.521	10.773	9.321	**8.581**	11.310	9.876	9.848	9.728
11	14.904	13.636	10.443	10.782	14.410	10.895	10.434	**10.237**
12	13.379	11.890	12.166	**10.772**	13.311	12.936	12.218	11.364
13	13.766	12.349	11.139	10.524	14.425	10.982	**10.398**	11.567
14	9.594	9.036	8.215	7.880	9.014	**7.411**	7.663	10.006
15	12.194	11.228	11.373	9.860	10.905	10.392	10.299	**9.797**
16	13.371	12.621	11.256	10.493	12.248	10.815	10.400	**10.301**
17	14.536	14.323	12.814	13.182	12.632	12.642	12.610	**12.578**
18	12.424	12.417	9.862	10.258	11.421	10.435	9.282	**8.747**
19	15.412	14.389	11.636	11.760	13.411	11.806	12.046	**11.567**
20	14.498	13.206	12.258	11.328	12.862	11.907	11.912	**11.038**
21	14.273	12.783	12.941	11.830	12.141	12.147	11.723	**11.363**
22	14.328	13.351	11.083	11.137	14.604	12.659	11.288	**11.060**
Mean	13.361	12.397	11.568	11.276	12.575	11.107	11.011	**10.725**

Figure 11 shows the prediction results of different models visually on the test set. It can be seen that the GE-GRU-KNN model proposed in this paper can fit the changing trends of real-world datasets due to the fact that the model is able to effectively capture dynamic correlations of traffic flow in the road network.



(b)

Figure 11 – Visualisation results of different models

Analysis of prediction horizons

Table 3 shows the performance of the GE-GRU-KNN model and the baseline models under different prediction horizons for a randomly selected road section. It can be seen that as the prediction horizon increases, the accuracy of the models gradually decreases. Meanwhile, the GE-GRU-KNN model proposed in this paper always achieves optimal performance regardless of the change of predicted horizons. Compared to the GE-GRU-KNN model, the traditional machine-learning methods SVR and RF perform weaker with the complex and unstable time series data. The GRU model only considers the temporal characteristics of traffic flow, while ignoring its spatial correlation characteristics. Furthermore, the reason for the lower accuracy of the T-GCN and A3T-GCN models is probably because the predefined adjacency matrix cannot effectively characterise the dynamic correlation of traffic flow which fluctuates over time and space. Although the KNN-GRU captures the spatial correlation between road sections in the road network based on the Euclidean distance of traffic flow, its correlation is constantly changing due to the dynamic nature of traffic flow, resulting in lower predictive performance of the model.

Table 3 – Prediction results of different prediction horizons

Time	Metric	Value							
		SVR	RF	LSTM	GRU	T-GCN	A3T-GCN	KNN-GRU	GE-GRU-KNN
5 min	RMSE	27.759	28.631	26.692	26.704	26.672	26.612	26.624	**26.574**
	MAPE (%)	9.751	10.046	7.930	7.877	7.780	7.791	7.724	**7.696**
	MAE	22.317	21.976	20.055	19.855	19.570	19.565	19.641	**19.520**
15 min	RMSE	32.406	32.705	29.640	30.589	29.948	30.064	30.351	**29.940**
	MAPE (%)	9.989	9.510	8.867	9.426	8.625	8.602	8.726	**8.566**
	MAE	23.581	22.996	21.566	22.290	21.482	21.593	22.068	**21.471**
30 min	RMSE	37.459	37.661	34.149	33.573	36.220	34.369	33.763	**32.977**
	MAPE (%)	11.704	10.863	9.910	10.055	10.024	9.931	9.596	**9.488**
	MAE	27.622	27.060	24.044	23.781	26.399	24.983	24.064	**23.545**
60 min	RMSE	45.459	46.525	38.782	40.869	42.946	38.701	38.938	**38.501**
	MAPE (%)	14.536	14.323	12.814	13.182	12.632	12.642	12.610	**12.578**
	MAE	33.737	33.592	28.290	28.249	31.004	28.456	28.520	**28.228**

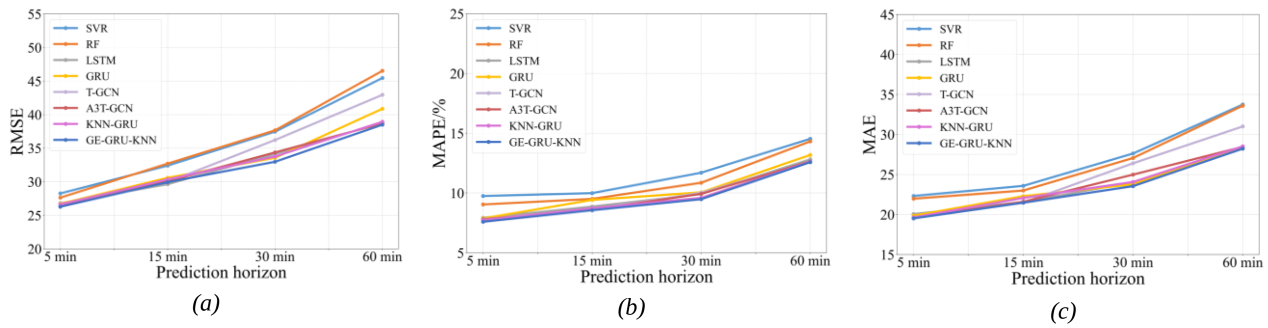


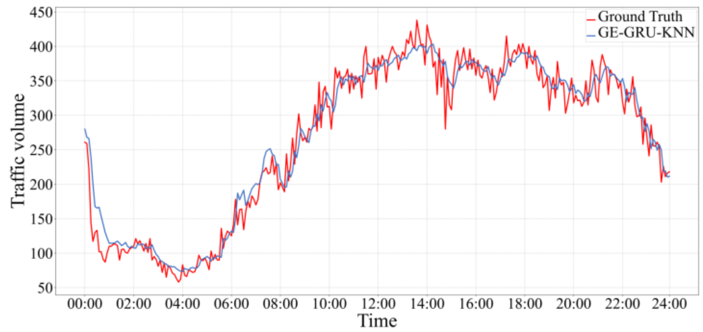
Figure 12 – RMSE, MAPE and MAE of different models

Analysis of time periods

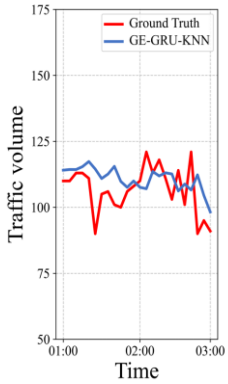
Traffic flow changes regularly over time. At specific times of the day, traffic flow may experience sudden changes. From the visualisation of the data presented earlier, it can be seen that the traffic flow on the freeway section is lower from 01:00 to 03:00, the traffic flow changes significantly from 10:00 to 12:00 and the traffic flow is higher from 20:00 to 22:00, representing three typical traffic flow states.

To better demonstrate the prediction performance of the GE-GRU-KNN model in different time periods, the predicted traffic flow of a randomly selected road section for different time periods of the day is shown in

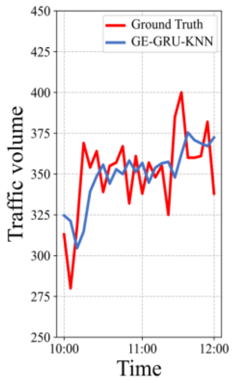
Figure 13. From the figure, it can be seen that the model proposed in this paper always performs well at different time periods. When there are significant fluctuations in traffic flow, it can capture the sudden changes in traffic flow, making the predicted results of traffic flow closer to the real traffic flow state.



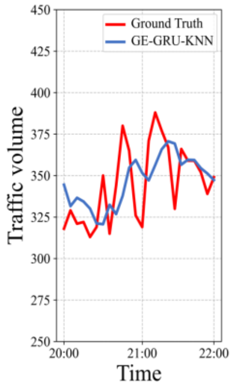
(a)



(b)



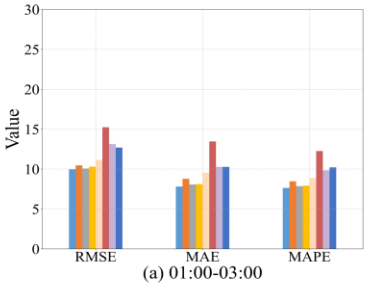
(c)



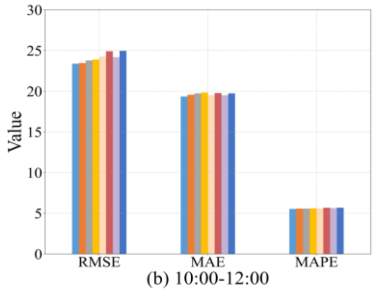
(d)

Figure 13 – Visualisation results of typical time periods with the prediction horizon of 5 minutes

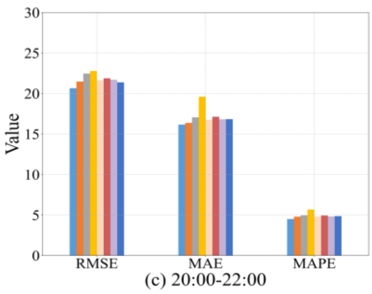
The prediction accuracy of the selected road section in three time periods is shown in *Figure 14*. It can be seen that the model has relatively high accuracy in predicting traffic flow during the three typical periods. It indicates that the model can effectively characterise the dynamic correlation of traffic flow by combining real-time traffic flow and historical traffic flow data, thereby improving the prediction accuracy of the model.



(a)



(b)



(c)

Figure 14 – Model performance of typical time periods with the prediction horizon of 5 minutes

5. CONCLUSIONS

Traffic flow prediction is an important component of urban intelligent transportation systems. This paper proposes a real-time adaptive traffic flow prediction model that combines the GE, the GRU and the KNN to address the issues of insufficient consideration of spatiotemporal correlation in road networks and the inability of predefined adjacency matrices to effectively represent the dynamic correlation of traffic flow. The model utilises the GE to automatically extract spatial features of the network and combines the advantages of the GRU in mining temporal patterns in time series data to capture the temporal correlation of traffic flow. In order to effectively characterise the dynamic correlation of traffic flow and adjust the fusion weights of predicted values for each relevant road section based on real-time traffic flow states, this paper introduces the KNN to mine information from historical data. The experimental results show that the proposed model provides more accurate predictions that match the actual traffic flow. Compared with the model that does not model the spatial characteristics of the network, and the model that does not characterise the dynamic correlation of the traffic flow by mining the historical data based on real-time traffic flow states, the accuracy of the proposed model has been improved, verifying the rationality of the proposed method.

In this study, the parameters used to predict traffic flow are relatively single. In future research, more parameters that characterise traffic conditions can be considered to obtain more accurate traffic conditions. The model can also consider more factors such as weather and special events to improve the accuracy of predicting traffic flow on road sections. Meanwhile, when the prediction time is 60 minutes, the performance of the model deteriorates faster, so improving the long-term prediction ability of the model is also a major task in the future.

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易翔宇，周红媚（通讯作者），钟绍鹏

基于 GE-GRU-KNN 模型的实时自适应交通流预测

摘要：
交通流预测是城市智能交通系统的重要组成部分。然而，由于道路网络内交通流的强非线性特征和时空相关性，交通流量预测一直是一项具有挑战性的任务。为了捕捉时空相关性，并改进使用预定义邻接矩阵无法有效地表征交通流的动态相关性的传统方法，提出了一种用于预测道路交通流的 GE-GRU-KNN 模型。具体来说，GE 学习到的道路网络的空间表示用于自动提取网络的空间特征；GRU 用于学习时间序列的非线性特征，以捕捉交通流的时间相关性；最后，引入 KNN 算法，将实时交通流状况和历史数据相结合，自适应地更新不同路段预测值的融合权重。该方法使模型能够有效地表征交通流的动态相关性。利用加利福尼亚州高速公路上 22 个检测器的交通流量数据进行实验。结果表明，与传统方法相比，该方法的预测误差降低了 1.08%-14.71%，表明 GE-GRU-KNN 模型具有良好的性能。

关键词：
交通流预测；动态时空相关性；图嵌入；门控递归单元；k-近邻