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Urban short-term traffic speed prediction with complicated information fusion on accidents

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ABSTRACT

Optimizing the traffic flow prediction system is crucial in developing intelligent transportation since it increases the road network's capacity. The system's overall prediction accuracy will be increased by taking into account the relationship between the temporal and spatial properties of the road network and different external elements affecting the traffic situation. The traffic state, which is still a largely unexplored area, is impacted by the complicated interaction between accident information and the spatiotemporal properties of the route. This paper proposes an Accident Information Graph Fusion Attention Convolutional Network(AI-GFACN). Firstly, a highly correlated global road network is created using a global spatial feature point-edge swapping method, a D-D algorithm fusing Dijkstra, and Depth-First Search, which resolves the issue where the spatial features of accident sections are challenging to capture the diffusion effects caused by spatial features of nearby and further sections. Following the data's incorporation, it is suggested to combine the Spatio-temporal features of accident information and embed them in the road network. In addition, an attention mechanism is introduced, effectively addressing the difficulty in capturing the Spatio-temporal features of accident information within the road network. By integrating and categorizing the regionally distributed and temporally sustained congestion effects of various categories of accidents concerning previous research on accident information, this paper enhances the semantic expressiveness of accident information within the road network. Ablation experiments confirm the effectiveness and robustness of the proposed method, and it is applied to the dataset of Hangzhou West Lake District (including accident information), which increases short-term traffic speed prediction accuracy by 0.2% overall.

Keywords: Traffic prediction Node embeddings Attention mechanism Trajectory planning Spatiotemporal dependency Multi-graph fusion

1. Introduction

1.1. Background

The field of traffic prediction has entered the era of big data due to the successful development of data capture technology and the rapid advancement of urbanization in China. This data includes vehicle speed monitoring, trajectory identification, and roadway sensor information (Zhang, Guo et al., 2021). Among them, the creation of an intelligent transportation system is crucial. One of its most crucial tasks is the accurate prediction of the conditions of the road network's traffic (such as traffic speed and flow), which not only aids the traffic department in optimizing the adjustment of road signals and reducing traffic congestion on urban roads but also aids in the integrated planning of the distribution of urban traffic routes (Zeng et al., 2019). Frequent traffic jams and non-periodic traffic jams brought on by accidents and other unforeseen events also seriously hinder the smooth operation of roads. Short-term road condition prediction and real-time accident information feedback can significantly assist drivers in avoiding congested roads. It can provide early warning alerts for congested roads, an effective remedy to increase road capacity and traffic efficiency (Liu, Zhang & Lv, 2021, Zhang, Zheng et al., 2018).

Due to the richness and diversity of traffic data, it is currently tough to get reliable data, weed out pointless variables, and create spatiotemporal feature functions linked to traffic data. The Spatio-temporal correlation of road networks is shown in Figure 1. As can be seen from the figure, $t+x1$, $t+x2$, and $t+x3$ are close in spatial proximity. However, their Spatio-temporal correlations could be more consistent due to numerous influencing factors (red and green signals, POI, geographic location, traffic accidents, etc.) on road sections. However, their traffic conditions are highly correlated with time variations. This paper's area of research focuses on creating a novel road network model that can efficiently collect spatial features while capturing highly linked Spatio-temporal data.

1.2. Development Lineage

Time series models frequently produce road forecasts through correlation and periodicity between historical and current data. Most conventional traffic forecasting techniques, including ARIMA and models derived from its variants (Lv, Lou et al., 2020, Williams, & Billy, 2003), use statistical analysis to integrate historical traffic data and make forecasts. Since, presumably, the historical data will have the same characteristic properties as the prediction results, the model's prediction accuracy will be significantly

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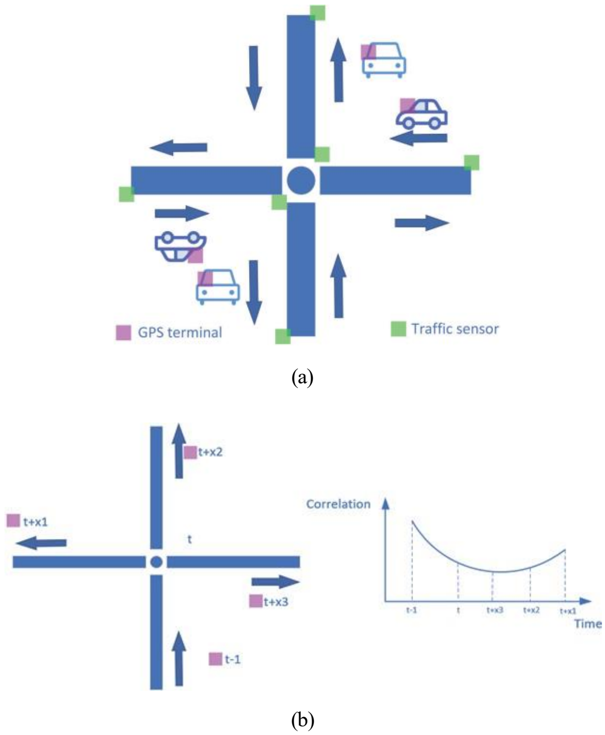

Figure 1: Space-time correlation of vehicle complexity: (a) The road network system's sensor integration devices, including GPS road information monitoring system, speed radar, video monitoring, and ground sensor coils, collect and aggregate data. (b) Despite the high location correlation, the road network speed in Figure b, the ambivalence of static territory and dynamic time, displays a non-linear Spatio-temporal correlation and does not demonstrate a positive connection.

decreased due to the vulnerability of the properties of the actual future data to the influence of complex factors inside and outside the traffic conditions. The modified VA (vector autoregressive model) by Hofleitner et al. (2012) helped improve the spatial correlation between the upstream and downstream sections of the model. However, it is also noted in the literature that the method, as mentioned above, cannot effectively capture the Spatio-temporal characteristics of road traffic to logically create the model due to the high spatial correlation and time dependence among road sections (Wang et al., 2019).

In recent years, deep learning has significantly advanced the subject of traffic speed prediction. The diffusion convolutional recurrent neural network (DCRNN) is described in the literature for the complex spatial characteristics and nonlinearly varying POI of road networks and multidimensional factors. Its bidirectional random wandering prop- erty is applied to capture the spatial dependence of road networks in the time frame of predefined encoder-decoder architecture as well as to employ recurrent neural networks to capture dynamic time series to jointly estimate the spatial dependence of the road networks (Li et al., 2017). The temporal graph convolutional network (T-GCN) model is a unique prediction technique that combines graph convolutional networks (GCNs) and gated recurrent units (GRUs) (Zhao et al., 2019). The graph convolutional network and gated circulation unit are used to learn the topological road network structure and the dynamic changes of traffic flow to capture the spatial and temporal dependencies, respectively. Yu, Yin & Zhu (2017) pointed out that precise and quick forecast messages are crucial for managing and control- ling urban traffic. By modelling multi-scale road networks, Spatio-temporal graph convolutional networks (STGCN) are proposed to capture Spatio-temporal feature correlations effectively. As a result, time series prediction accuracy is significantly increased.

A deep learning model called the graph convolutional recurrent network (GCRN), which is based on the recurrent neural network (RNN) to model arbitrarily structured data is proposed (Seo et al., 2018). This model can predict structured data sequences and provides theoretical support for modelling the capture of graph-structured data in the traffic domain. It is important to note that Lv, Hong et al. (2020) proposed the temporal multigraph convolutional network (T-MGCN). Additionally, Zhao, Han, & Xu, (2022) proposed the IMgruGcn model to simultaneously extract the spatiotemporal characteristics of the traffic flow by combining IMgru and graph convolutional network (GCN) modules. This network fuses Spatio-temporal correlation with global variables using fully connected neural networks, increasing traffic flow prediction precision. As the most fundamental time series prediction model, RNN, Li et al. (2017) creatively proposed the DCRNN model. This model learns the relationships between spatial node locations in dynamic time series by naturally fusing the graph with RNN to produce the spatially multiple nodes Spatio-temporal fusion. Additionally, Wu et al. (2019) suggested integrating Graph WaveNet into GCN to accommodate longer sequences by growing the sensation field through layered expansion. The capacity to convolve or aggregate node and edge attribute information based on graph theory and the accurate capture of spatial information in concealed non-Euclidean structured data were also accomplished. It is noted collectively that attention mechanisms have manifested exuberance in deep learning algorithms (Vaswani et al., 2017, Shen et al., 2018, Du et al., 2018). The core of the attention mechanism is to use the input data to recognize relevant aspects adaptively and effectively (Veličković et al., 2017). This would significantly improve the efficiency of capturing spatiotemporal features for traffic prediction.

The dynamic graph convolution module in the proposed Spatio-temporal graph neural network (ASTGNN) by (Guo et al., 2021) uses a self-attention mechanism to dynamically compute the spatial correlation between nodes based on the global cycle sequence of the input traffic data and the local cycle sequences. In turn, spatial heterogeneity is captured. The method above will result in higher processing costs and is unsuitable for short-term traffic forecasting in road networks of crowded cities with highly complicated interactions between nodes. To put it another way, (Lan et al., 2022).

A data-driven dynamic spatial-temporal awareness map is intended to take the place of the conventional predefined static map. It does this by sorting the correlation properties between the probability distribution of each node and the spatial correlation degree between nodes using the dynamic traffic flow data over time. However, this needs to be revised in the topology of the road network. An attention-based Spatio-temporal graph attention network (ASTGAT) model was proposed by Wang, Jing ,Xu & Guo (2022), this model mines the deeper Spatio-temporal information of traffic data, and exhibits exceptionally superior Spatio-temporal feature capturing ability while reducing network degradation and resolving over-smoothing issues. In conclusion, the addition of an attention mechanism and the use of road networks as non-Euclidean structural data using graph modelling can better model their spatial features. It is also a popular research direction to combine the benefits of multi-class traffic flow models to achieve effective and thorough capture of Spatio-temporal features. To take into account the impact of external factors on the traffic state and spatial and temporal characteristics, such as weather, POI distribution, holidays, air quality, traffic accident information, and other external factors in the traffic flow prediction model to help improve the model accuracy is still a relatively new research direction (Lana et al., 2018). These outside variables and urban traffic conditions interact either directly or indirectly. In existing studies that take into account external factors, the interaction effects between traffic data and the corresponding external factors are disregarded (Liao et al., 2018, Zhang & Kabuka, 2018). The impact of harsh weather conditions, such as heavy rain and haze on the road, is also very low for the road portions lacking POI in the surrounding region. For instance, weather parameters fluctuate dynamically over time and can influence the traffic flow status to vary degrees. A Spatio-temporal graph convolutional network-based traffic prediction approach driven by knowledge representation is proposed by Zhu et al. (2022). A knowledge fusion cell (KF-Cell) is proposed to combine the knowledge and traffic features as the input of the Spatio-temporal graph convolutional network after first building a knowledge graph fusing two types of external factors, weather, and POI, to obtain the knowledge representation by the knowledge representation learning method.

As illustrated in Figure 2, we concentrate in this article on the effect of accident information as an external factor on traffic congestion. Therefore, it is crucial to introduce an attention mechanism to adaptively collect the temporal and geographical connection of accident information points. There are recommendations to train the temporal and spatial characteristics of traffic data in a hybrid model architecture and use stacked autoencoders to convert accident information into vectors for characterization among the few studies that currently take accident factors into account. According to the latitude and longitude of the sampling point, the road network is frequently divided into equal blocks. The entire road network is then divided into a regular grid as a two-dimensional image, and adjacent grids are combined for convolution operations. Due to Euclidean data limitations, flaws in the spatial feature capture, and one-sidedness in modeling the spatial features of the road network due to the influence of the diffusion of accident information, this type of approach is unable to accurately model the topology of the road network (Liyong W & Vateekul P, 2019). Zhang et al. (2021) developed a new graph neural architecture that separates the road network into a discontinuous grid that can learn global spatial semantics while capturing dependencies between subregions. Its ability to integrate the spatial correlation and global traffic dependence among different regional nodes is a vital reference for the effective fusion of accident information. Convolutional neural networks (CNNs) struggle to accurately describe the impact of accident information on road sections because of the complex and nonlinear Spatio-temporal correlations of traffic accidents, which are difficult to be captured by existing shallow models and may have ripple effects beyond a two-dimensional grid, which is noted in the literature (Wang et al., 2021). To model the road network and address the issue that the influence of accident section spread within the road network is challenging to capture, we adopt two methods in this paper: global space feature point-edge swapping and the D-D algorithm. A study also suggested using a fuzzy technique to characterize accident data and introduce a convolutional neural network (CNN) trained layer by layer to learn the properties of internal data, traffic accident data, and external data of traffic data to forecast future changes in traffic flow (An et al., 2019). This method, however, ignores the spatial solid dependence of accident dynamic time series on the pertinent road segments. In this paper, we propose to combine accident information as graph structure, embed global spatial features, and codify the dynamic distribution of accident time against each other. This can effectively address the difficulty in capturing Spatio-temporal features of highly complex accident information in the global road network. We also introduce temporal and spatial attention mechanisms to deal with the intricate Spatio-temporal correlations of the comprehensive traffic data. This significantly increases the effectiveness of capturing the Spatio-temporal features of the accident information in the global road network.

1.3. Important points of this article

In this paper, we consider the influence of external factors on road traffic status and propose a model structure, AI-GFACN, which can fuse temporal and spatial features of traffic accidents in a graph convolution framework and enable the capture of complex spatio-temporal features in a global context. The main contributions are as follows.

1) This paper proposes to model the global graph structure based on the distance information between each road section at the sampling points to achieve a strong correlation between the local space and the global space to address the high correlation between the global road network and the local space under the influence of accidents. Through

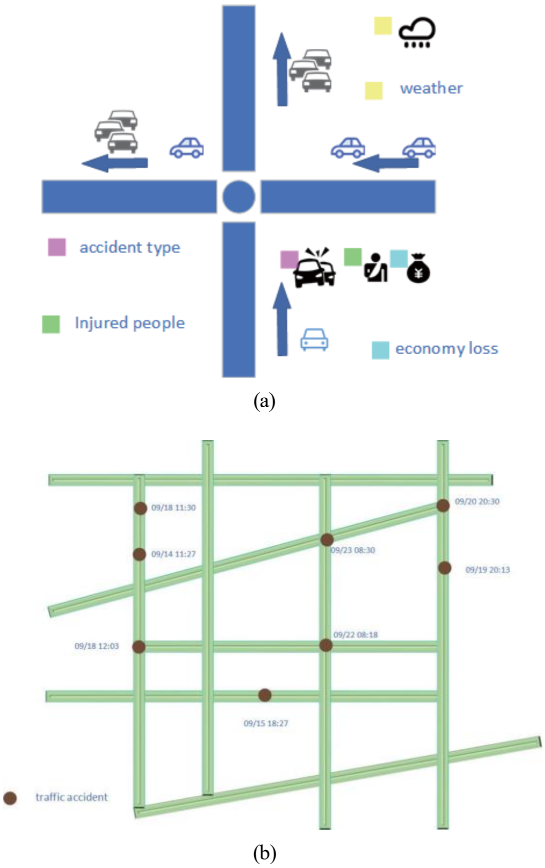

Figure 2: Impact of the accident on traffic conditions: (a) The temporal and spatial locations of various accident information vary noticeably at the time of occurrence, and the level of traffic congestion brought on by accidents as a result of various circumstances also differs significantly. The impact factors (such as weather, the number of injuries, economic loss, and accident content analysis, such as human-vehicle collision or vehicle-vehicle collision) can show the extent to which the accident affected the traffic conditions in the accident section and the surrounding areas. (b) The distribution of event data within the setting of smart cities typically presents a sparse and discrete scenario, and the Spatio-temporal correlation of this information is complex and non-linear, which makes it challenging to successfully represent using existing approaches.

the interaction influence of accident segments on each road segment and its neighbors in the global road network, we combine the spatial characteristics of accident information and capture the high dependency between road segment nodes and the global road network.

2) A traffic accident fine-grained analysis for traffic accident data is proposed to quantitatively analyze the level of traffic congestion on road sections and nearby neighborhoods based on intrinsic accident factors (e.g., accident contents, number of injuries, economic losses) and external accident factors (e.g., weather conditions) in spatial characteristics to assess the congestion impact of accident road sections on other neighborhoods.

3)The graph structure is modeled at the spatial level for the location information of each road section in the conventional state and each road section containing accident information, and the spatial attention mechanism is introduced to assign different weight values to each road section in the neighborhood adaptively, and finally, the two are a weighted fusion of the graph structure to obtain highly correlated spatial features; in the time series, the temporal attention mechanism is introduced to assign different weight values to each road section in the neighborhood.

4)The experimental results demonstrate that fusing accident data successfully enhances the model's prediction performance for short-term traffic speed prediction on urban road networks.

2. Method

2.1. Roadway network-based roadway point edge interchange

This paper first proposes the method of global spatial feature point edge swapping, which involves turning each road section in the traffic network into a node and connecting the connectivity between each intersection to obtain the spatial correlation of each road section node. This method will help to solve better the interaction correlation of geographic location information of each road section in the road network. For example, in Figure 3, the left map is a local geographic location information map - intersection (following the traffic regulations of driving on the right), clockwise marking a road section to h road section and its distance information, according to the left map a, b road section length 200m, c, d road section length 120m, e, f road section length 100m, g, h section length 180m, the section edge is converted to section node, in this process the distance between sections is also converted to the distance between nodes. Example: section node c to section node b, d, f1, h distance, take the average of the two section spacing. The distances from road segment node c to road segment nodes b, d, f, and h are 160m, 120m, 110m, and 150m, respectively. spatial feature modeling is performed by using the distance information between nodes. A weighted directed graph $G = (V, E, A)$ is constructed by the connection relationship between the nodes in the road network. $A \in R$ and $N \times N$ denotes the weighted adjacency matrix with the distance information of road segments as the weight.

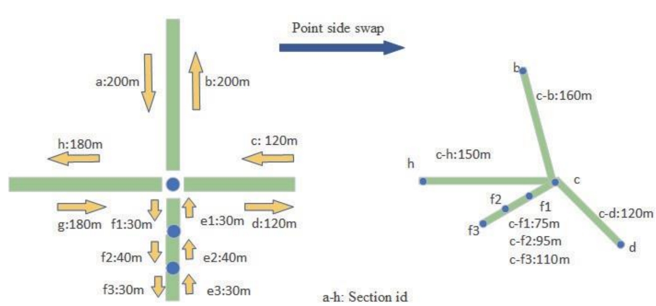

Figure 3: Point-side interchange of road networks.

The adjacency matrix is frequently built in earlier studies by choosing the distance between nearby nodes. However, the information thusly recorded frequently needs to include the interactive influence link between global information and local spatial properties. Based on those above global spatial feature point-edge interchange method, we propose the D-D algorithm, which combines the Dijkstra and depth-first search algorithms to obtain the distance information between each node under the global spatial information. This method best captures the degree to which local spatial features in urban traffic networks depend on global spatial information. For example, without taking into account other geographical location data, it can be seen from the connection relationship between road section node c and road section nodes f1, f2, and f3 that the distance relationship between non-adjacent road section nodes f2 and f3 is more significant than the spatial dependence between adjacent nodes c, b. As a result, the method suggested in this paper can effectively prevent the omission and neglect of local neighborhood spatial correlation by modeling adjacent nodes. However, this method of accurately capturing each node's spacing also significantly increases the computational cost. As a result, we propose a workable formula to convert the inter-node distance. We suggest a workable formula to weigh the distance data between nodes while removing the irrelevant data from an excessive distance. As follows.

$$A_{1vi,vj} = \begin{cases} \exp(-\frac{d_{vi,vj}^2}{\sigma^2 \times 1 \times 10^4}), if \exp(-\frac{d_{vi,vj}^2}{\sigma^2 \times 1 \times 10^4}) \geqslant \theta \\ 0, otherwise \end{cases} \quad (1) \quad 1)$$

Through the above formula, we can convert the distance information of each node in Figure 4 into weights. $d_{vi,vj}$ is the spacing value of each roadway node, σ is the standard deviation, and θ is the threshold value to control the sparsity of the adjacency matrix, assuming that σ is taken as 4 and θ is taken as 0.3, with three decimal places reserved. The following is the calculation of the weights between nodes c & d. node changes, at this time, the global spatial features

$$Roadweight = \exp(-\frac{120^2}{4^2 \times 1 \times 10^4}) = 0.914 > 0.3 \quad (2)$$

Table 1 shows the results of the weight transformation of the distance relationship of each road section in Figure 3(a). And Figure 4 shows the schematic diagram of each node, with the size of the circle indicating the degree of its influence on the origin, indicating the spatial correlation between the road section nodes.

2.2. Construction of adjacency matrix based on accident information under global road network

We then incorporate the accident information into the model to improve prediction accuracy. We incorporate the spatial features of the accident information into the completed adjacency matrix constructed above. However, the

Table 1
Connection relationship table of the partial node in the road network.

Inroadid	Outroadid	Roadlength(m)	Roadweight(0-1)
c	b	160	0.852
c	d	120	0.914
c	f1	75	0.965
c	f2	95	0.945
c	f3	110	0.927
c	h	150	0.869

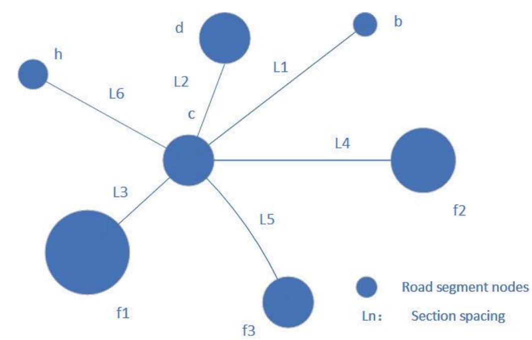

Figure 4: Partial node connection diagram.

accident information has a complex congestion effect on the roadway nodes and their neighborhoods, resulting in difficulty in capturing the spatial features of the roadway

pro- posed in the previous paper point-edge swap and the D-D algorithm, which are two methods that can effectively solve this problem, reflecting a solid superiority. We assume that any c, b, d, f1, f2, f3 six roadway nodes 16-time steps of road information, 3 minutes to sample the traffic speed of the node, assuming the sampling of 9:00 to 9:45 traffic speed conditions, such as the following table 2, part of the content presented.

Table 2
Speed of traffic at six road nodes (show the road conditions at some points in time).

time	c	b	d	f1	f2	f3	h
09:06	36.0	36.1	36.1	35.9	35.8	35.7	36.1
09:30	35.8	35.8	35.8	35.4	35.4	35.4	35.8
09:36	36.1	36.1	36.1	36.6	36.6	36.6	36.1

Using the aforementioned technique, we can arbitrarily select the historical H time steps of the time series in the data chain. X = $(X_{t1}, X_{t1}, \ldots, X_{tH}) \in R^{H\times N\times C}$. Our goal is to forecast the traffic for all vertices for the upcoming J time steps. denoted as Y = $(X_{tH+1}, X_{tH+2}, \ldots, X_{tH+J}) \in R^{J\times N\times C}$. The historical traffic speed data of six roadway nodes c, b, d, f1, f2, and f3 in the table are randomly grabbed from the time axis as shown in Figure 5 to predict the traffic speed for the next three time steps.

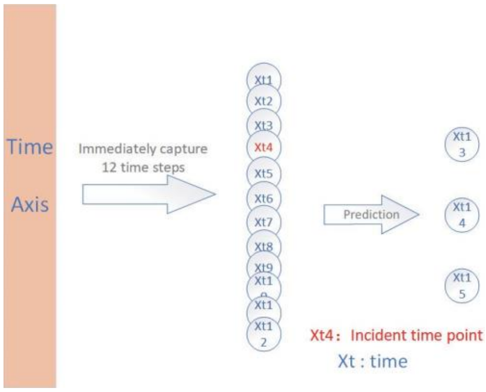

Figure 5: Randomly grabbing multiple time steps for prediction.

We propose to include traffic accident data, one of the external elements impacting the traffic condition, in the traffic flow parameters, in contrast to most prior studies on traffic flow prediction models. The impact of congestion on the spatial characteristics of the roadway node and its neighboring nodes is evaluated based on the intensity of the accident, i.e., accident content, number of injuries, economic loss, and weather conditions, and it is quantitatively analyzed in Table 3 (a_t : accident_type, i_p : injured_people, e_l : economy_loss, wea : weather, V-V_c : Vehicle-vehicle collision, H-V_c : Human-vehicle collision).

For example, in Table 2, three-time points 9:06, 9:30, and 9:36, traffic accidents occurred at point c, point f1, and point f3. We indicate in detail the intensity of the accidents at the relevant time points and locations in Table 4 (m_r : mapping_roadsect), and describe the impact of accident forms on the spatial characteristics of roadway nodes in Table 3 (accident content: 1 indicates a car-vehicle collision, 2 denotes human-vehicle collision; the number of injuries: numbers denote the number of injuries; economic loss: numbers from 1 to 4 denote increasing degree; weather: 1 denotes sunny day, 2 denotes cloudy day, and 3 denotes rainy day). Regarding the choice of parameters for accident information, we first refer to Tirtha et al. (2020)'s a meticulous examination of the length of impact time of traffic accident information as well as to the information network inspired by Li et al. (2022)'s design and structured by social relationships between vehicles, in which emergencies are able to feedback on this graph-structured network to obtain propagation breadth. Therefore the selection of the T-value should be in line with the range of influence of traffic accidents on surrounding sections of urban roads. We obtain the proper t value by combining it with the experimental data gathered for this paper. Concerning the study of Tirtha et al. (2020)., we can see that the impact of accidents on the surrounding congestion tends to diminish with increasing time, and we can derive an appropriate impact range (θ).

$$A_{2vi,vj} = \begin{cases} \exp\left(-\frac{d^2_{vi,vj}}{\sigma^2 \times t \times 10^4}\right), if \exp\left(-\frac{d^2_{vi,vj}}{\sigma^2 \times t \times 10^4}\right) \geq \theta \\ 0, otherwise \end{cases} \quad (3)$$

As above, $d_{vi,vj}$ is the spacing value of each roadway node, σ is the standard deviation, θ is the threshold to control the sparsity of the adjacency matrix, assuming that σ is taken as 4, θ is taken as 0.3, and three decimal places are retained. For example, 09:06 in node c accident, node c-d between the weights are calculated, as follows Table 5.

$$t_1 = 1.1,\ t_2 = 0,\ t_3 = 0,\ t = t_1 + t_2 + t_3 = 1.1 \quad (4)$$

$$Roadweight = \exp\left(-\frac{120^2}{4^2 \times 1.1 \times 10^4}\right) = 0.921 > 0.3 \quad (5)$$

Table 3

Quantitative analysis of the degree of impact of traffic accident information.

	Content	t
a_t(t1)	V-V_c	1.15
	H-V_c	1.1
i_p+e_l(t2)	Total>4	0.1
	Othervise	0
wea(t3)	Rainy	0.05
	Othervise	0
	$t = t1 + t2 + t3$	t: [1.1, 1.3]

Table 4
Analysis of internal and external factors of accidents in six roadway nodes.

time	a_t	i_p	e_l	wea	m_r
09:06	2	1	2	1	c
09:30	2	1	2	1	f1
09:36	1	2	1	1	f3

Table 5
Connection relationship table between nodes (including accidents,09:06).

In_roadid	Out_roadid	Roadweight	Road_accweight
c	b	0.852	0.865
c	d	0.914	0.921
c	f1	0.965	0.969
c	f2	0.945	0.950
c	f3	0.927	0.934
c	h	0.869	0.880

As shown in Figure 6, assuming a traffic accident occurs at point C, it will directly or indirectly affect the traffic status of six roadway nodes at c, b, d, f1, f2, and f3, causing traffic congestion to some extent. If the accident occurs at point c at 09:06, we assume that the accident lasts for 8-time steps (24 minutes) because the impact time of the accident on the road will last for more than one time step. In this way, the accident information is successfully integrated into the spatial characteristics of the corresponding roadway road.

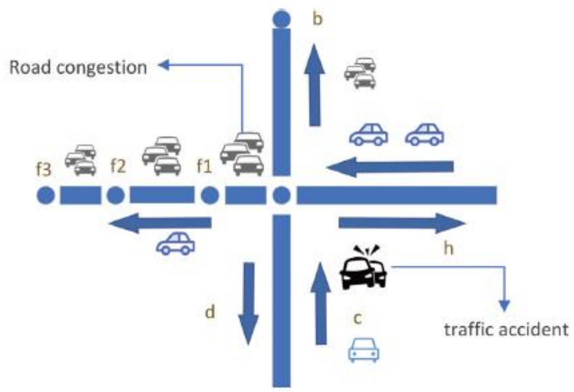

Fig. 6. Diagram of the impact of traffic accidents between adjacent nodes.

2.3. The overview of AI-GFACN

This study suggests that the AI-GFACN algorithm model complete traffic flow prediction in the subsequent steps based on the discussion above. First, the fully connected layer, which can lessen the impact of feature vectors and increase the robustness of the entire network, is used to pass historical traffic data into the GCN model. The distance information of each road node in the global road network that was gathered in the previous paper is first used to generate the adjacency matrix. Then, by storing the spatial characteristics of each node in the form of a certain type of vector information and maintaining the graph's structure, this research proposes to apply the Node2vec approach described by Grover and Leskovec (2016) to the adjacency matrix of road network graph construction. The spatial feature maps of the original road segment nodes (A2) and accident information (A1) are obtained, as illustrated in Fig. 7 respectively.

Meanwhile, since the form of spatial embedding characterizes the node properties in a static form only, we refer to the related literature

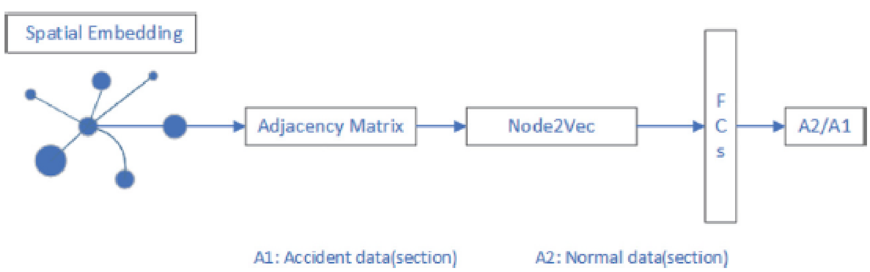

Fig. 7. Spatial Embedding of Accident data and Normal data. Furthermore, the form of A_1/A_2 : $E^S_{v_i} \in R^D$ represents the spatial embedding of the data.

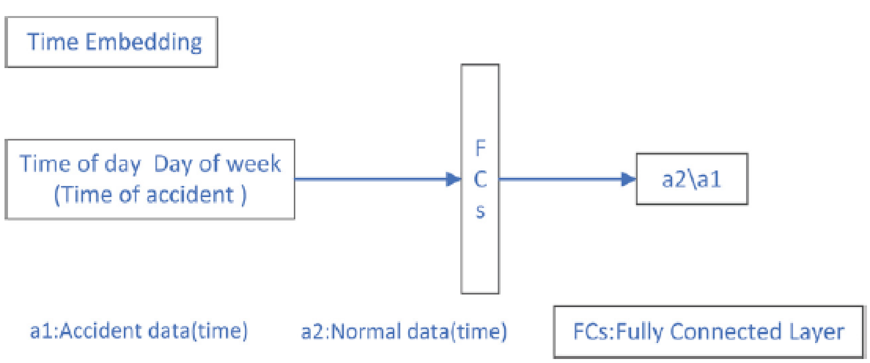

Fig. 8. Time Embedding of Accident data and Normal data. Moreover, the form of a_1/a_2 : $E^T_{t_x} \in R^D$ represents the spatial embedding of the data.

for dynamic time series to further analyze and propose to encode the accident occurrence time point and its ripple time range in the form of temporal embedding to represent each time step of the conventional time series as well as the accident time series in the form of vectors (Tang, Meng, & Liang, 2022). In the following Fig. 8, the conventional time series (a2), as well as the accident time series (a1), are obtained. And by the previous quantitative analysis of the time range of accident information ripple, it is assumed that an accident information ripple has 8-time steps (3 min is a time step, i.e., 480-time steps in a day), i.e., the accident information points are captured on the conventional dynamic time series with ripple periods.

To address the strong randomness and episodic nature of accident information, as shown in Fig. 9, we propose graph fusion of the spatial feature map (A2) of the original road segment node and the spatial feature map (A1) of accident information at the spatial embedding level. At the data screening level, we screen the accident-prone locations for feature extraction and graph fusion of accident information to reduce noise interference. As described in 2.2, the accident information is quantitatively analyzed to characterize the impact of accident road segments on their own and neighboring spatial features in the form of weight changes to achieve a weighted fusion of the two graph structures. At the temporal embedding level, due to the high dependence on accident information at the temporal level, to capture the impact of accident information on the spatial characteristics of roadway nodes, the accident period is reflected in the global dynamic time series level to capture the time series distribution of accidents (a1). Due to the high correlation between temporal and spatial features, we create a Spatio-temporal embedding module that contains accident information graph fusion to overcome the challenge of capturing Spatio-temporal features of accident information against one another. At the spatial level, spatial embedding takes the shape of a graph structure. Different road segments have various effects on each other's traffic, and non-periodic congestion brought on by accidents on the road might spread to the neighborhood. We therefore present a spatial attention mechanism that, while concentrating on the spatial properties of severely affected road segments and modeling these attributes, adaptively captures dynamic correlations between road segments. At the temporal level, time series are used for time embedding. A given road segment's traffic conditions and historical data are associated, and accident data is highly correlated with time. To achieve this, we introduce the temporal attention mechanism, which can adaptively describe the nonlinear temporal correlations. Finally, a gated fusion module adaptively regulates the dynamics of the individual nodes and time steps in spatial and temporal domains.

$$\text{STE: } E \in R^{(H+J)\times N\times D} \tag{6}$$

Here, the STE covers both graph structure and time information.It is defined as $e_{v_i,t_x} = E^S_{v_i} + E^T_{t_x}$. As was discussed above, this paper will combine the temporal and spatial characteristics of accident information and then take the Spatio-temporal fusion embedding, which significantly reduces the computational cost while also being able to enrich the Spatio-temporal characteristics of the road network by writing one of the external factors into the Spatio-temporal characteristics of the road network, complemented by a better prediction effect of the traffic flow.

In addition, to better solve the problem of high dependency on temporal and spatial features of accidents, the study of He, Zhang, Ren, and Sun (2016) on Attentional Mechanisms was referred to and based on the previous Spatio-temporal embedding module (STE), the Spatial Attention Mechanism is introduced to adaptively capture the correlation between individual sensor systems within the road network, and the Temporal Attention is introduced to adaptively capture the correlation of temporal features of individual nodes. Finally, a gated fusion block (ST-Attention blocks) is designed to achieve adaptive control capture of Spatio-temporal feature information. In addition, to facilitate the capture of time series by the model, we further integrate the time points into individual time nodes, i.e., encode them into individual time steps for subsequent prediction processing, where the activation function is expressed through the following equation (Nair & Hinton, 2010).

$$\mathrm{f(x) = ReLU(xW + b)} \tag{7}$$

Here, W and b are the parameters that can be learned. $ReLU$ is used as the activation function. As in Fig. 10, the calculation of different nodes v_i or v_j in each time step (X), i.e., the weights of different traffic

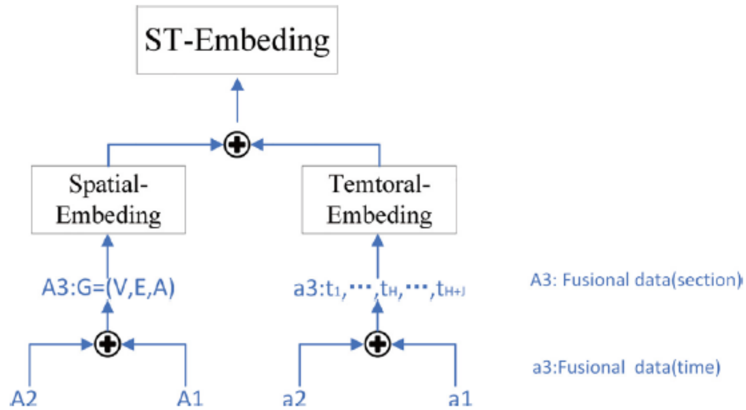

Fig. 9. Spatio-temporal embedding schematic exploded view.

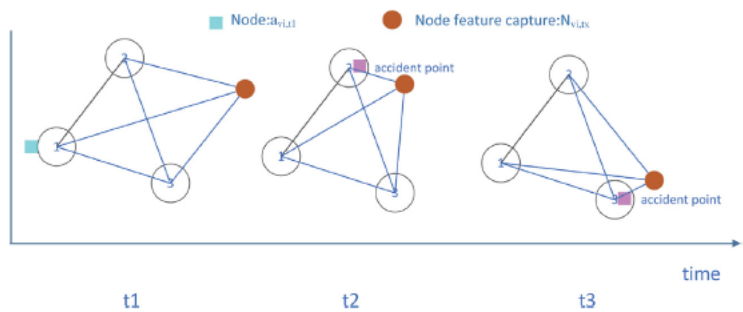

Fig. 10. Time-variant pair-wise correlations between nodes are captured by the spatial attention mechanism.

conditions within the nodes, within different time steps:

$$N_{v_i,t_x} = \sum_{v\epsilon V} a_{vi,t_x} \tag{8}$$

Here, N_{vi}, t_x denotes the weighted summation over individual nodes, V denotes the set of all nodes, and a_{vi}, t_x denotes the weight assignment value for a time step.And the total of the attention scores is 1.

The spatial attention mechanism captures the spatial features of each node. It can be seen that within each time step, its current traffic condition is closely related to the road network and dynamic time variables. For example, congestion at a road segment node or a traffic accident will most likely have a significant impact on the traffic state of that node and the roads in its associated domain. Therefore, we need to consider that some road segments' spatial characteristics also change with time dynamics. Here we use the scaled dot-product approach (the scaled dot-product approach) (Vaswani et al., 2017).

$$s_{v_i,v} = \frac{\left\langle h^{(q-1)}_{v_i,t_x} \middle\| e_{v_i,t_x}, h^{(q-1)}_{v,t_x} \middle\| e_{v,t_x} \right\rangle}{\sqrt{2D}} \tag{9}$$

Here, we denote the input of the q^{th} block as H^{q-1}, where he hidden state of vertex v_i at time step t_x is represented as $h^{(q-1)}_{v_i,t_x}$. p denotes the tandem operation, $\langle\rangle$ denotes the inner product processing, $2D$ refers to the dimensionality of $h^{(q-1)}_{v_i,t_{xj}} \| e_{v_i,t_x}$, and $S_{vi,v}$ refers to the normalization process by the softmax function, and again here the attention mechanism is extended by a multi-headed mechanism (Vaswani et al., 2017).

$$s^{(p)}_{v_i,v} = \frac{\left\langle f^{(p)}_{s,1}\left(h^{(q-1)}_{v_i,t_j} \| e_{v_i,t_j}\right), f^{(p)}_{s,2}\left(h^{(q-1)}_{v,t_j} \| e_{v,t_j}\right)\right\rangle}{\sqrt{2D}} \tag{10}$$

Since road section nodes have a significant relationship with the outcomes of their historical observation moments, this relationship exhibits the property of non-linearly changing with the forward or backward time steps. Since accident information may have an ongoing congested effect on the roadway nodes and their neighbors, a temporal attention mechanism is introduced to better model these temporal characteristics. This mechanism also improves the ability to analyze and capture the traffic state characteristics of the preceding and following time steps. In Fig. 11, the enhanced capture of accident node information, with global information training, helps to improve the model to make a more sensitive prediction effect on accident occurrence points or frequent accident points. Here, the spatial correlation between the integrated nodes V_i, the time correlation between each time step, i.e., t_x and t. As follows.

$$M^{(p)}_{t_x,t} = \frac{\left\langle f^{(p)}_{t,1}\left(h^{(q-1)}_{v_i,t_x} \| e_{v_i,t_x}\right), f^{(p)}_{t,2}\left(h^{(q-1)}_{v_i,t} \| e_{v_i,t}\right)\right\rangle}{\sqrt{2D}} \tag{11}$$

Here, $M_{tx,t}$ denotes the correlation between t_x and t time steps. $\langle\rangle$ denotes the inner product, $\|$ represents the concatenation operation, p denotes the tandem operation, and $f_{t,1}$ denotes the temporal distribution case of what category the relevant time step is in, $f^{(p)}_{s,1}(\bullet)$ and $f^{(p)}_{s,2}(\bullet)$ stand for two distinct nonlinear projections (in Eq. (7)) in the pth head attention.

Finally, using a gated fusion component, we combine temporal and spatial attention methods to efficiently capture the intricate Spatio-temporal correlations present in the traffic prediction environment. The essential framework of (a) the accident information graph fusion attention convolutional network is displayed in Fig. 12. (AI-GFACN). A Spatio-temporal embedding module containing accident information is designed, and the input history H moment step X $\in R^{H\times N\times C}$ is further transformed into data through feature extraction in the fully connected layers (FCs), N(0)$R^{H\times N\times D}$, through the encoder–decoder

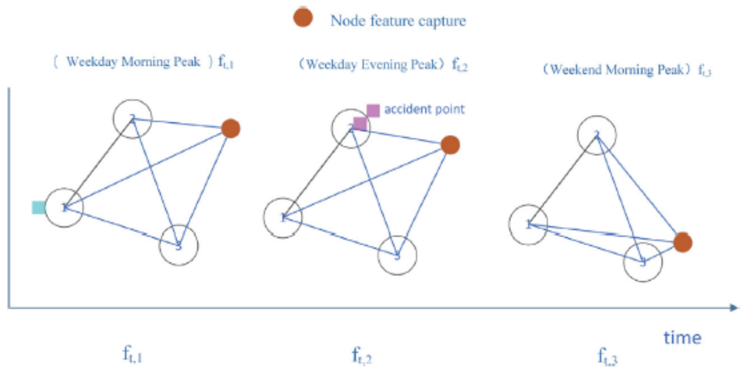

Fig. 11. Time-variant pair-wise correlations between nodes are captured by the temporal attention mechanism.

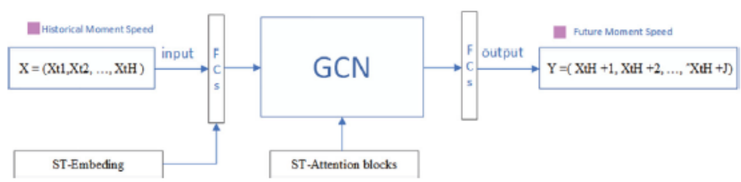

Fig. 12. The architecture of AI-GFACN.

structure of the GCN model, and then through the ST-Attention Blocks borrowed from the application to participate in the adaptive encoding of the features after Spatio-temporal embedding extraction, deriving $N(t_x)R^{H\times N\times D}$. Finally, the predicted velocity results for the J moment step, $Y \in R^{J\times N\times C}$ are derived after the fully connected layers (FCs), resulting in the predicted traffic flow data results.

3. Data

3.1. Data selection

Smart transportation is highly valued in the development of smart cities, so the dataset used in this study comes from the West Lake District of Hangzhou, which is a smart city. The dataset gathered this time has the following distinguishing and helpful characteristics. Fig. 13, shows the data sampling area — part of the Hangzhou road section.

Compared to the PeMS California highway dataset, this dataset is based on a joint aggregation of road traffic sensor records and GPS data collection from rental cars and is more compatible with traffic flow prediction models in the context of smart cities in terms of spatial complexity of the sampled area and traffic data (Wang, Fan, Liu, Zheng, Chen, Wang, & Li, 2017). The road network data, traffic data, and other external factors – in this case, traffic accident data, which includes information collection on accident contents, accident sections, accident casualties, accident weather, etc. – of the same area at the same time are also difficult to satisfy, even though there are many open traffic flow datasets. Although the dataset used in this study is specific to the Hangzhou West Lake area, our experimental design is highly generalizable and simple to replicate in other locales.

The information collected in this dataset records traffic speeds for 307 roadway nodes spanning up to 5 consecutive months, with a date range of 2021.04.20 to 2021.09.30 (164 days). As shown in Fig. 14, after visualizing the speed information, it can be seen that the information has a certain regularity and reference significance in terms of forecasting. In terms of time breadth, it is consistent with the training feasibility of the traffic prediction model.

Fig. 13. Hangzhou main city roads live map.

3.2. Data preprocessing

Within the dataset, data cleaning, data filtering, and delineation of 3 min as a time step. We can obtain the traffic speed information of 307 road sections in the region at 3-minute intervals for 164 days. Each actual road section in the road network is transformed into a road node using the Global Spatial Feature Point Edge Swapping method suggested in the previous paper, and the connectivity of each road node can be determined using the details of the actual road sections and the associated intersections in the road network. A graph structure model of each road segment node is created to see the relationship between each surrounding node. Then, to capture the firm reliance of local features within the urban road network on the global information, the

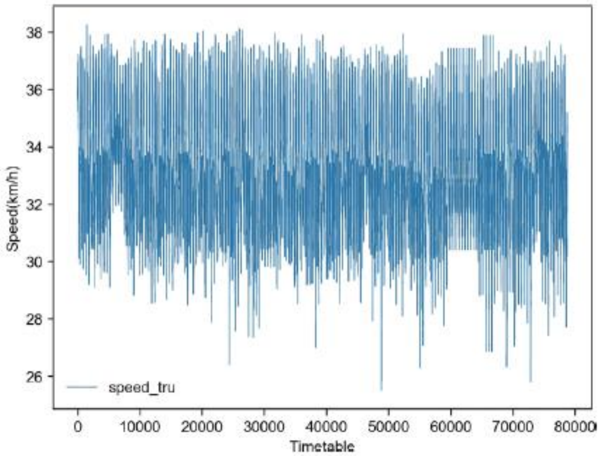

Fig. 14. Average traffic speed of 307 road nodes in Hangzhou for 164 days.

Table 6
Connection relationship table of each node in the road network.

In_roadid	Out_roadid	Roadlength (m)
100	100	0
100	0	398.5
100	197	454.5
52	290	6545
52	297	3317.5

Table 7
Weight analysis among nodes.

In_roadid	Out_roadid	Roadlength
100	100	1
100	0	0.590
100	197	0.502
52	290	0
52	297	0

D–D Algorithm developed in the earlier paper is utilized to extract the spatial distance information between each node under the global spatial information. The graph structure is then modeled using this inter-node location relationship, and a traffic road network information map based on spatial correlation is initially obtained. Table 6 shows a partial list of the 307 road segments for which distance information between the individual segment nodes was obtained.

With the distance information between nodes, we can apply the previous Eq. (1) to calculate the corresponding weights.

Here, $A_{1vi,vj}$ is the adjacency matrix about the spatial correlation of each roadway node without introducing accident information, $d_{vi,vj}$ is the spacing value of each roadway node, σ is the standard deviation, and θ is the threshold value to control the sparsity of the adjacency matrix, which is assigned to 0.2 based on the Foregoing research method.

As in Table 7, in addition to accident information, some research works have pointed out that the impact range of a road traffic accident on its accident section and its neighbors can be delineated with reference to the average speed of the section (Li et al., 2022). In this way, we calculate the weights of the adjacency matrix by the incident coding process in method 2, using Eq. (3).

Here, $A_{2vi,vj}$ is the adjacency matrix of the spatial correlation of each roadway node without introducing accident information and with accident information, respectively, and the other selected parameters are kept constant. For the value of t, the accident coding treatment in Method 2 can be based on the research work of Tirtha et al. (2020),

Table 8
Weight analysis among nodes involved in the accident information.

In_roadid	Out_roadid	Accident_Roadlength
100	100	1
100	0	0.590
100	197	0.549
52	290	0
52	297	0

and correlate the traffic dataset used in this paper according to the local context, and the results are presented in Table 8.

The paper uses the traffic speed information of H historical moments to predict the traffic speed of the last J future moments in one time step of 3 min. Here H is taken as 12, i.e., 36 min, and J is taken as 3, i.e., 9 min, to achieve a short-time speed prediction model with accident information points. Here we use the Adam optimizer proposed by Kingma and Ba (2014) and set the initial learning rate to 0.001 to train our model. This paper uses 70% of the data (55,090) for training, 10% (7858) for validation, and 20% (15,730) for testing after normalizing the data information by the allocation ratios for training, validation and testing of a wide range of traffic prediction models. The samples used for training are selected at random. Additionally, it can capture accident occurrence time series based on dynamic time variation and use it to achieve the best possible prediction of future events during the data training phase. In addition, for the Experimental Settings, the following models, which are widely used in traffic prediction, are used to evaluate the final performance of this model.

3.3. *Baseline model comparison*

We do this by comparing other excellent baseline methods of recent years. As follows: the autoregressive integrated moving average model (ARIMA) is a classical time forecasting model, the distribution forms the data chain over time as a random series, and the future values are predicted by learning the model to approximate the series, which consists of an AR model (autoregressive model), an MA model (moving average model) with the order of difference (Lv, Wu, & Zhang, 2021). Support Vector Regression (SVR) achieves good linear regression characteristics of the independent and dependent variables in the high-dimensional data feature space by mapping the nonlinear data into the high-dimensional feature space and outputting back to the original address space after fitting the data within this (Castro-Neto, Jeong, Jeong, & Han, 2009). For the ARIMA and the SVR in the above model, we used the observations made by Li et for the rationalization of the settings (Li et al., 2017). Spatio-temporal graph convolutional network (STGCN) incorporates a graph convolutional layer for modeling multi-scale traffic networks (Yu et al., 2017).

4. Experimental results

By processing the data above we can get two adjacency matrices and then perform spatial embedding to integrate the high correlation of the global space, and finally, here we use the weighted fusion of the information of the spatial variables after these two spatial embeddings as the input terminal of the model. We use the following three metrics to evaluate the performance of the model.

(1) Mean Absolute Error (MAE):

$$MAE = \frac{1}{mn}\sum_{x=1}^{m}\sum_{i=1}^{m}\left|Y_i^x - \widehat{Y}_i^x\right| \quad (12)$$

(2) Root Mean Squared Error (RMSE):

$$RMSE = \sqrt{\frac{1}{mn}\sum_{x=1}^{m}\sum_{i=1}^{n}\left(Y_i^x - \widehat{Y}_i^x\right)^2} \quad (13)$$

Table 9
Comparison of the prediction performance of different prediction models on the Hangzhou dataset.

Time	Metric	ARIMA	SVR	ST-GCN	AI-GFACN
3 min	MAE	3.53	3.11	2.80	2.74
	RMS	4.88	4.18	3.88	3.80
	MAPE	10.96%	10.00%	9.07%	8.86%
6 min	MAE	4.76	3.96	3.34	3.04
	RMSE	6.53	5.20	4.60	4.23
	MAPE	14.52%	12.88%	10.71%	9.91%
9 min	MAE	6.46	5.03	3.85	3.11
	RMSE	8.30	6.43	5.27	4.33
	MAPE	19.85%	16.93%	12.04%	10.22%

Table 10
Comparison of prediction performance between models with and without accident data.

Metric	no_accident	θ=0.2	AI-GFACN accident θ=0.3	θ=0.4
MAE	2.96	2.95	**2.91**	3.04
RMSE	4.12	4.12	**4.08**	4.32
MAPE	9.66%	9.63%	**9.40%**	9.82%

(3) Mean Absolute Percentage Error (MAPE):

$$MAPE = \frac{100\%}{mn}\sum_{x=1}^{m}\sum_{i=1}^{n}\left|\frac{Y_i^x - \widehat{Y_i^x}}{\widehat{Y_i^x}}\right| \tag{14}$$

Where Y_i^x and $\widehat{Y_i^x}$ represent actual traffic data and a forecast for the xth time sample in the ith road section, respectively. Besides, m is the number of time samples. n is the number of roads. RMSE may accurately represent the difference between the model prediction value and the actual value; the lower the value, the higher the accuracy of the forecast. MAPE is used to detect the prediction precision: the closer the result is to 0%, the better the prediction effect is.

Firstly, we use 3 min as a time step to predict the traffic speed for the next three time steps. The prediction results of different models are compared. It is shown in Table 9. We can observe that the AI-GFACN model backbone (without incorporating accident information) has better prediction performance. A single intersection's traffic conditions are frequently influenced by nearby intersections (dynamically changing over time) and highly associated with previous traffic data (non-linearly changing over time). The spatial attention mechanism developed in this study allows for assigning weights to various nodes at various time steps, and the suggested temporal attention mechanism can also adaptively model the pertinent variables. In contrast to other approaches, AI-GFACN employs a lightweight way to represent spatial qualities while considering spatial topological links. Additionally, it senses and collects Spatio-temporal data by stacking attention modules, considerably enhancing overall efficiency. The ARIMA model performs the worst because it cannot handle complex Spatio-temporal data, and deep learning techniques can produce more accurate prediction outcomes than machine learning algorithms. As a result, AI-GFACN displays advanced and efficient prediction ability in comparison. And in terms of fault tolerance (e.g., partial packet loss in data transmission, sensor failure in some road sections, etc.), we randomly discarded a portion of historical data for testing, and the short-time prediction performance was not greatly affected.

Second, we perform ablation experiments to analyze the impact of incorporating incident information on the overall road network traffic speed prediction task. The results are shown in Table 10, θ is the threshold to control the accident impact area.We compared this parameter's impact on prediction accuracy. And it can be seen that the AI-GFACN model can more accurately reflect a semantic correlation between roads and traffic accidents after the incorporation of accident information,

Table 11
Data comparison between the true and predicted values in Figs. 15 and 16.

T-table	tru (km/h)	pre(15)	D-V1	pre(16)	D-V2
511–520	32.38	32.06	0.32	32.19	0.19
531–540	32.07	32.15	0.08	32.08	0.01
551–560	31.81	31.95	0.14	31.92	0.11
571–580	32.11	31.74	0.37	31.90	0.21

and to a certain extent, assist in improving the model's prediction accuracy. The Spatio-temporal attention mechanism effectively captures the complex Spatio-temporal correlation of urban roads and accurately predicts the speed variation trend in the sampling area. In addition, referring to Fig. 19, the presentation of the one-week traffic speed prediction results (with accident information) verifies that the negative impact of the error propagation response can be effectively controlled as the time step advances. As shown in Fig. 16, the results show that the AI-GFACN model captures the impact of accident information on traffic speed in the road network well, comparing Fig. 15(a) with Fig. 16(a), the latter presents a smoother prediction curve that fits the actual value better. Non-periodic congestion causes a significant reduction in vehicle traffic speed, while traffic accidents can trigger a certain degree of non-periodic congestion. Comparing Fig. 15(b) with Fig. 16(b), the incorporation of accident information can help the model predict the speed change at the turning point more smoothly to a certain extent, confirming the effectiveness and stability of incorporating external factors in the Spatio-temporal graph convolutional network(Similarly, Figs. 17 and 18 also show the comparison). In Table 11 (Table 12), we see more intuitively through the numerical indicators: the accident information is coded to take into account the impact of the traffic accident on the roadway in question over a certain period. Thus making the predicted data more relevant to the actual data. (T-table:time step, tru:true velocity, pre:predicted velocity, D–V:difference between true and predicted velocity). However, the model's prediction is significantly biased at the turning point, probably because the peak variation is not only influenced by the accident information but also depends on the combination of various aspects such as POI and weather. Overall the accident information can assist the prediction model to a certain extent and improve the prediction accuracy. In the experiments of this paper, the average prediction performance was improved by about 0.2%.

Computation time: this paper's training time and derivation time on the experimental dataset. ST-GCN:training time is 166.5 s/epoch, inference time is 187.2 s. AI-GFACN:training time is 699.7 s/epoch, inference time is 17.9 s. Although the ST-GCN model is better trained and the overall prediction is practical and viable, the prediction is comparatively inaccurate and less efficient in derivation since iterative computing is needed to produce the prediction results. AI-GFACN can significantly shorten the inference time because it can produce findings for a 12-step prediction process in a single run.Computation time: this paper's training time and derivation time on the experimental dataset. ST-GCN:training time is 166.5s/epoch, inference time is 187.2s. AI-GFACN:training time is 699.7s/epoch, inference time is 17.9s. Although the ST-GCN model is better trained and the overall prediction is practical and viable, the prediction is comparatively inaccurate and less efficient in derivation since iterative computing is needed to produce the prediction results. AI-GFACN can significantly shorten the inference time because it can produce findings for a 12-step prediction process in a single run. A Windows workstation with two Intel Xeon Silver 4210 10Core @ 2.20 GHz CPUs, 128 GB of RAM, and an NVIDIA RTX 2080ti GPU with 11 GB of video memory was used for the experiment.

5. Discuss

(1) The model in this paper can improve the prediction accuracy of the model for future traffic data by combining the accident location and time with the existing road network traffic data. However, due to the high spatial and temporal randomness of accident occurrence

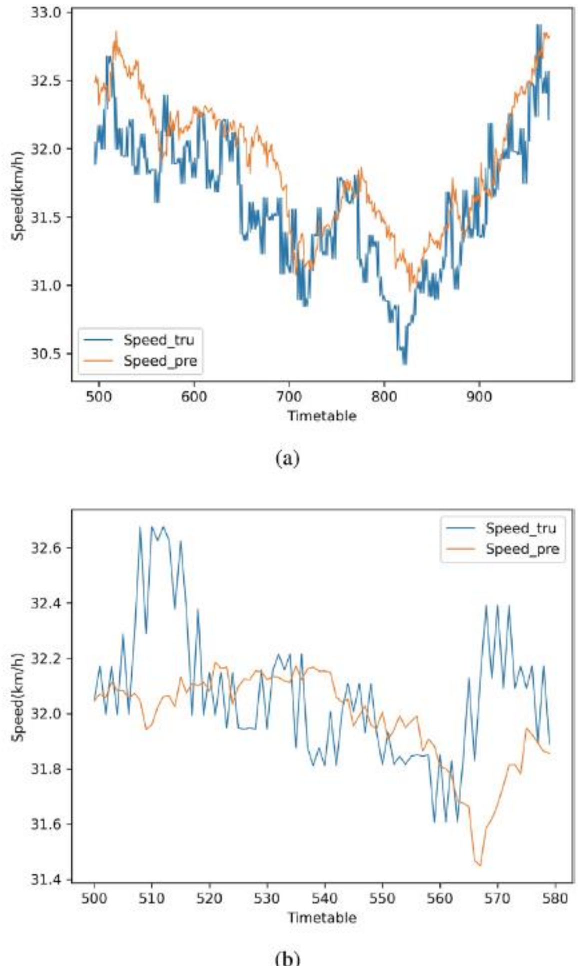

Fig. 15. Traffic speed prediction results: (a) Forecast result of traffic speed in one day. (b) Traffic speed forecast results for a portion of the day.

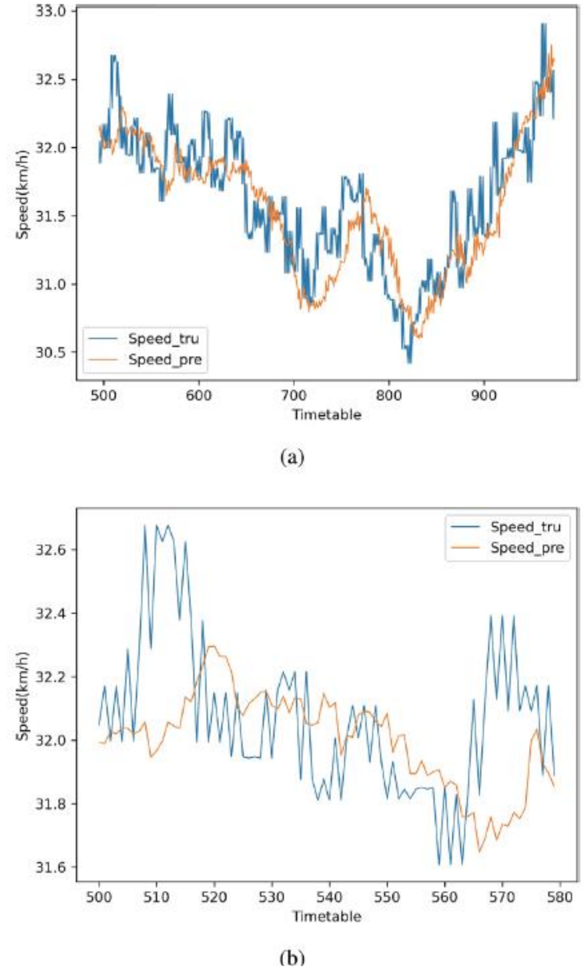

Fig. 16. Traffic speed prediction results (Incorporated accident information): (a) Forecast result of traffic speed in one day. (b) Traffic speed forecast results for a portion of the day.

Table 12
Data comparison between the true and predicted values in Figs. 17 and 18.

T-table	tru (km/h)	pre(17)	D-V1	pre(18)	D-V2
1581–1590	33.89	33.55	0.34	33.73	0.16
1601–1610	33.58	33.39	0.19	33.45	0.13
1621–1630	33.28	33.40	0.12	33.24	0.01
1641–1650	33.25	33.43	0.18	33.28	0.03
1661–1670	32.89	32.82	0.36	33.08	0.24

and the impact of congestion caused by different levels of accidents, the time scale of the impact and the diffusion impact of road sections are significantly different. Therefore, the model in this paper still has a strong plasticity for the time series processing of accident information and the ability to capture spatial characteristics attributes. In addition, it is foreseen that using the model in this paper to learn to train the sampling area of the dataset with poor road condition information and more accident information, it is more evident that the accident information can help the prediction accuracy of traffic speed with positive feedback.

(2) Through the results and analysis of the historical traffic data of 12 moments to predict the traffic speed of 3 moments in the future, it can be inferred that the model proposed in this paper has excellent performance for short-time traffic speed prediction, and the participation of accident information really assists to improve the learning training ability of the model for the whole traffic data, and its prediction results can roughly feedback the future traffic state of the relevant road sections and neighborhoods. The model can also horizontally delineate the speed range to label the congestion of the road in the sampled area. For example, 30 km/h can be regarded as smooth, 20–30 km/h as light congestion, 10–20 km/h as congestion, etc. This quantitative and qualitative analysis of the traffic conditions in the area can help traffic management departments improve the capacity of the relevant roads effectively, and jointly plan road traffic rationing with signal management systems to improve the operational efficiency of the road network jointly.

(3) Accident information has a good application prospect in enriching the prediction model and in early warning of short-time traffic. The model can produce better prediction outcomes and requires less computation time and memory. For instance, it enables networked vehicles to avoid congested road segments in advance, informs drivers of a more accurate analysis of the state of the roads, and also help traffic management departments to schedule traffic more logically and increase traffic efficiency on the entire road network. As a result, this model has a fair chance of accurately predicting short-term traffic flow, including accident information.

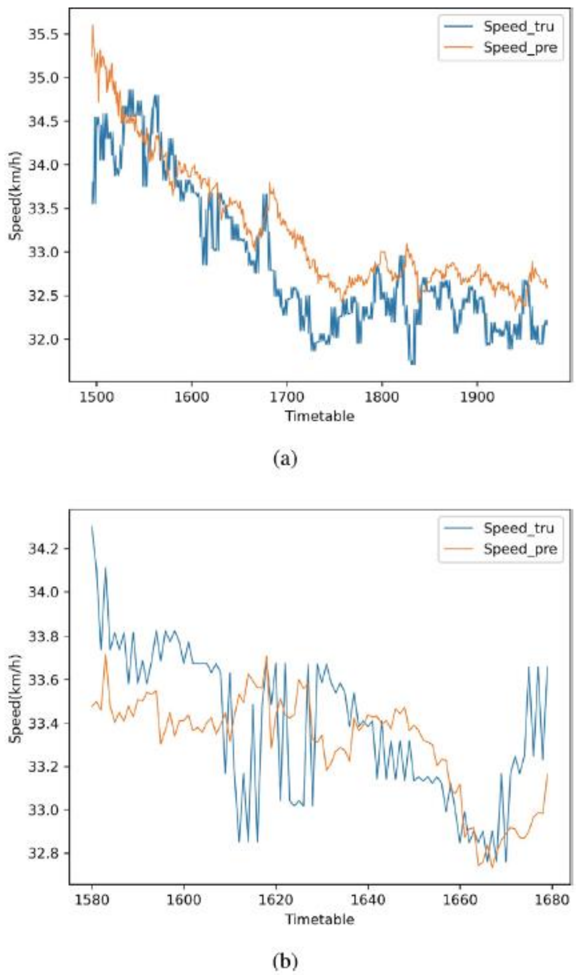

Fig. 17. Traffic speed prediction results: (a) Forecast result of traffic speed in one day. (b) Traffic speed forecast results for a portion of the day.

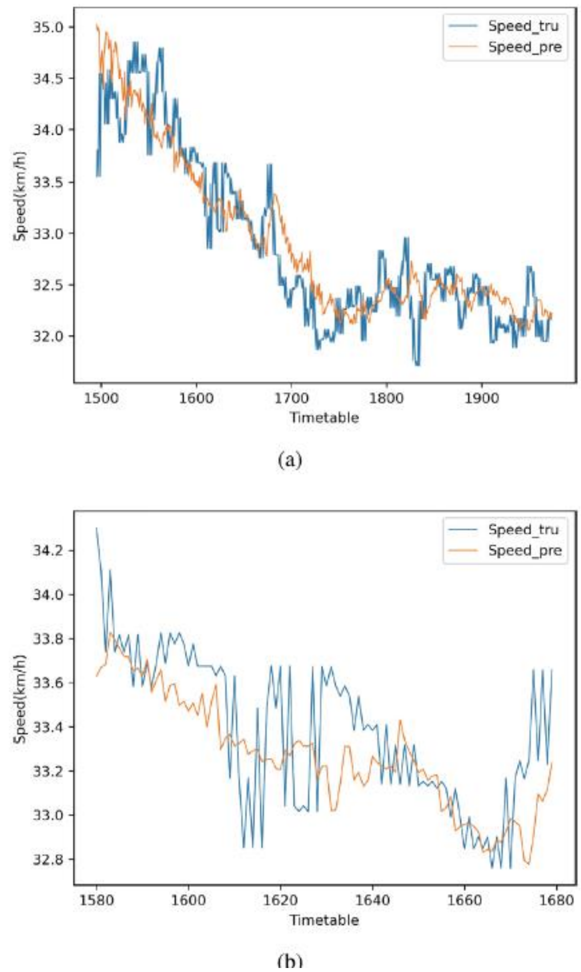

Fig. 18. Traffic speed prediction results (Incorporated accident information): (a) Forecast result of traffic speed in one day. (b) Traffic speed forecast results for a portion of the day.

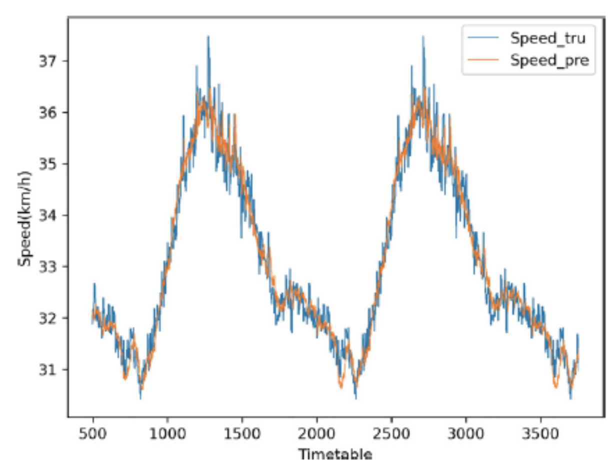

Fig. 19. Forecast results of weekly traffic speed (Incorporated accident information).

6. Conclusion

This paper proposes an Accident Information Graph Fusion Attention Convolutional Network (AI-GFACN). Firstly, we use two methods to model the road network, namely, global spatial feature point-edge swapping and D–D algorithm fusing Dijkstra (Dijkstra algorithm) and DFS (depth-first search algorithm), which solves the problem that the spatial features of each road node change due to the spreading influence of accident sections within the road network and are not easily captured. Then we propose embedding the spatial features of fused accident information into the global spatial features and the accident time into the overall time series. Through a gated fusion module, we realize the combination of the two Spatio-temporal information and successfully integrate the accident information into the Spatio-temporal features of the global road network in a clear and organized way. In addition, we introduce a temporal and spatial attention mechanism to deal with the complex Spatio-temporal correlations in traffic data, which effectively solves the problem that the Spatio-temporal features become highly complex due to the embedding of accident information are difficult to be captured effectively. In this paper, recent traffic datasets are used, which are more in line with the actual road conditions of today. Experiments prove that the model and method in this paper achieve superior prediction results, with an overall improvement of 0.2%. However, our method is a preliminary attempt, as the overall traffic conditions in the sampling area of this dataset are good, the accident information is less and the impact of accidents is less, so for the sampling area with poor traffic conditions or frequent accidents, the model in this paper will show more significant improvement in the prediction effect. In addition, this paper only considers the influence of external factors on traffic status, which has Limited semantic expressiveness and limits the performance of the model. AI-GFACN will perform better when more abundant data information is integrated.

CRediT authorship contribution statement

Xing Xu: Methodology, Writing – original draft. Xianqi Hu: Writing– original draft. Yun Zhao: Conceptualization, Methodology, Supervision. Xiaoshu Lü: Conceptualization, Investigation, Data curation. Aki Aapaoja: Conceptualization, Investigation, Data curation.

Declaration of competing interest

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Data availability

The data that has been used is confidential.

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