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RESEARCH ARTICLE

EVHF-GCN: An Emergency Vehicle Priority Scheduling Model Based on Heterogeneous Feature Fusion With Graph Convolutional Networks

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ABSTRACT Traffic flow prediction is a crucial aspect of Intelligent Transport Systems, offering a scientific foundation for urban transport system management and planning. However, predicting traffic flow becomes challenging due to its susceptibility to diverse static and dynamic external factors, such as the presence of emergency vehicles that necessitate priority treatment in the road network. To tackle this issue, this paper introduces an Emergency Vehicle Priority Scheduling Model based on Heterogeneous Feature Fusion in Graph Convolutional Networks (EVHF-GCN). This model concurrently considers road network and emergency vehicle information, dynamically adjusting signal control strategies based on traffic flow prediction outcomes. This approach ensures the prioritized passage of emergency vehicles and mitigates traffic congestion. The model utilizes a heterogeneous feature fusion mechanism within a Graph Convolutional Network (GCN) to propagate features and aggregate information from intersection nodes. It also integrates a Gated Recurrent Unit (GRU) network to capture dynamic traffic flow features. Additionally, we propose a Dynamic Signal Control Strategy (DSCS) that determines intersection green light durations based on prediction results and selects different control strategies as per the situation. Experimental results demonstrate that the model enhances traffic flow prediction accuracy and improves traffic system efficiency and safety in scenarios with and without emergency vehicles.

INDEX TERMS Graph convolutional network, priority movement of emergency vehicles, spatiotemporal models, traffic flow forecasting.

I. INTRODUCTION

Traffic flow prediction constitutes a pivotal facet of Intelligent Transportation Systems (ITS), serving as a scientific foundation for urban transportation system management and planning [1], [2], [3], [4], [5]. Traffic flow prediction aims to estimate future traffic patterns based on historical data [6]. Nevertheless, achieving precise traffic flow prediction poses a formidable challenge, given its dependence on historical states and the influence of numerous external factors, both static and dynamic. Among the dynamic factors that impact traffic flow within a road network, the presence of emergency vehicles and their need for priority access stand out [7], [8]. Emergency vehicles, comprising ambulances, fire engines, and police vehicles, are required to reach their destinations quickly during emergencies. To expedite response and rescue times, priority is accorded to emergency vehicles when crossing intersections or road segments. These principles have been elucidated in previous studies [9], [10]. However, in current urban road situations, the effective implementation of priority measures for emergency vehicles may face difficulties due to traffic congestion, signal control, and interactions with other vehicles, potentially resulting in mission delays or disruptions.

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To address the limitation of traditional models that fail to integrate traffic flow prediction and emergency vehicle priority scheduling, we propose an Emergency Vehicle Priority Scheduling Model (EVHF-GCN) based on the fusion of GCN heterogeneous features. In contrast to existing approaches that depend on singular data sources or homogeneous networks, our approach manages both the nodes and relationships within the road network and emergency vehicles. Furthermore, it dynamically adapts the signal control strategy based on traffic flow prediction results to prioritize emergency vehicle scheduling and mitigate traffic congestion. The methodology not only enhances the accuracy of traffic flow prediction but also improves the efficiency and safety of the traffic network.

The paper's main outcomes include the following:

- In this paper, we introduce a new traffic scheduling model, named EVHF-GCN (Emergency Vehicle Priority Scheduling Model Based on Heterogeneous Feature Fusion in Graph Convolutional Networks). This model improves traffic flow prediction by integrating emergency vehicle-related factors into the prediction framework. Consequently, our system can provide more precise traffic congestion predictions and improve intersection efficiency.
- The EVHF-GCN model utilizes a graph convolutional network to leverage the features of both emergency vehicles and heterogeneous road network nodes. This integrated approach effectively addresses road network congestion and prioritizes emergency vehicle routes. By utilizing the GCN network to propagate features and aggregate information from intersection nodes, in addition to implementing the GRU network to model evolving traffic flow features, our model significantly improves traffic flow scheduling by seamlessly integrating congestion status information from road networks and emergency vehicle data.
- In this paper, we present a Dynamic Signal Control Strategy (DSCS) designed to calculate the most effective duration for green lights at intersections. Achieving this goal necessitates accurate traffic forecasting and the dynamic adjustment of signals to improve traffic flow and mitigate congestion.

We conducted comprehensive experimental assessments encompassing various scenarios. Our approach commenced by leveraging SUMO software for simulation, coupled with authentic traffic flow data to curate an exclusive dataset. Comparative analyses were performed against the baseline model. The outcomes of these experiments unequivocally establish the supremacy of our model in the domain of traffic prediction. Moreover, ablation experiments were diligently executed to validate the efficacy of the heterogeneous emergency vehicle fusion network. By seamlessly amalgamating diverse graph networks and incorporating emergency vehicle factors with a dynamic signal light control strategy, our model furnishes a precise and efficacious framework for traffic management. This framework optimizes both traffic flow and the efficacy of emergency vehicle passage.

II. RELATED WORKS

Traffic forecasting holds a pivotal role within the realm of intelligent transportation, playing a critical role in urban traffic management and advancement. Traffic prediction methods have traversed distinct stages of development. Traditional prediction models fall under the category of parametric models, predominantly relying on mathematical statistics to predict traffic conditions. Among them, the Historical Average model (HA) leverages historical average data for predictive outcomes. While the calculations are straightforward, their predictive accuracy remains suboptimal [11]. Time series models like ARIMA [12] and its various adaptations [13] utilize the interplay between current and historical data to anticipate future trends. While conventional parametric models deploy straightforward algorithms, they rest on the assumption of time series stability, limiting their ability to capture abrupt shifts in traffic flow. Non-parametric models offer a remedy to these constraints, with examples including Support Vector Regression (SVR) [14], Support Vector Machines (SVM) [15], Bayesian Networks [16], and Neural Network models.

Traffic prediction is influenced by many factors, encompassing road network configuration, traffic regulations, driving behaviors, weather conditions, and the presence of emergency vehicles. Consequently, traffic data exhibit a marked degree of nonlinearity and complexity. In the pursuit of refining traffic prediction accuracy and real-time efficacy, GCN-based methodologies have emerged in recent years, classifiable into two primary paradigms: those predicated on spatial graph convolution. This category involves generating a spatial graph, leveraging traffic sensors or specific areas within the road network as nodes, while their interconnectivity or relative distances form the edges. The application of GCN facilitates the acquisition of spatial attributes of these nodes. These attributes are then harmonized with time-series models, such as recurrent neural networks (RNN) or long-short-term memory networks (LSTM) [17], including a variant known as the gated recurrent unit (GRU) [18]. These frameworks are adept at capturing the temporal nuances of the nodes. Subsequently, the synthesis of spatial and temporal attributes engenders traffic prediction outcomes. Representative methodologies within this class encompass STGCN [19], ASTGCN [20], ABSTGCN-EF [21], and T-GCN [22]. On the other hand, the spatiotemporal graph convolution-based techniques construct a spatiotemporal graph by aggregating observations from traffic sensors or different temporal snapshots of road network areas, with nodes symbolizing these instances and edges representing their spatiotemporal affiliations. The concurrent incorporation of GCN is instrumental in assimilating the spatial and temporal facets of nodes, culminating in the generation of traffic prediction outputs. Noteworthy approaches include ADST-GCN [23], STSGCN [24], and LSGCN [25].

All the aforementioned researchers have extensively investigated the spatiotemporal characteristics of traffic patterns.

Nevertheless, an excessive focus on these features can inadvertently overshadow other vital heterogeneous data aspects. For instance, the impact of emergency vehicles on traffic flow prediction has often been disregarded. Meanwhile, conventional GCN techniques primarily center around isomorphic graphs, characterized by uniform nodes and edges. Consequently, their efficacy diminishes when confronted with the intricacies of heterogeneous graphs. The latter exhibits a more intricate and extensive graph structure, encompassing multiple node and edge types, thereby offering an improved portrayal of intricate real-world relationships. In recent years, a plethora of strategies for managing heterogeneous graph data have arisen, encompassing Heterogeneous Graph Convolutional Network (HGCN) methodologies that leverage the power of attention mechanisms. This mechanism is designed to automatically assign significance weights among diverse inputs. Notably, R-GCN [26] hinges on a relationship type-based attention mechanism, assigning distinct weight matrices to individual relationship types, thus assigning weightage to features of various neighbor nodes. Meanwhile, HAN [27] employs a hierarchical attention mechanism. Initially, it gauges node similarity at the metapath level to compute node similarity. Subsequently, it determines the significance between a node and its neighbors at the node level.

In the domain of emergency vehicle prioritization, several intelligent technology approaches have emerged in recent years, predominantly centered on optimizing road networks. This optimization is achieved by reducing the travel time of emergency vehicles, either through meticulous trajectory planning or by adjusting the speed and direction of other vehicles to create temporary emergency lanes. For instance, the Emergency Vehicle Lane (EVL) [28] strategy is a proactive preclearance approach that grants priority to emergency vehicles on regular road segments through micro-cooperation with surrounding vehicles. The cooperative driving challenge is formulated as a mixed-integer nonlinear programming problem, with the primary objective of ensuring the desired speed of emergency vehicles while minimizing disruptions to surrounding traffic. Furthermore, the Emergency Vehicle Priority (EVP) [29] introduces an intelligent urban priority control strategy for emergency vehicle access. This strategy leverages IoT sensors and edge computing to reduce incident clearance time by assigning priority levels to emergency vehicles.

In conclusion, current methodologies inadequately address the intricate relationship between emergency vehicle planning, spatiotemporal traffic flow, and their impact on traffic prediction. To bridge this gap, we propose a novel traffic management approach, EVHF-GCN (Heterogeneous Emergency Vehicle Traffic Signal Control with Graph Convolutional Networks), employing a graph convolutional network with heterogeneous feature fusion. This model establishes a more efficient traffic scheduling framework. By integrating various nodes from the road network and emergency vehicle dynamics within a unified graph convolutional network, our model excels in precise traffic prediction and adeptly manages the priority scheduling dynamics associated with emergency vehicles.

III. METHOD

In the writing of this section, we have adhered to a linear logical progression. We initiate with a clear definition of the problem, ensuring the precise expression of the research framework and methods. Subsequently, we delve into the GCN module for spatial feature extraction, followed by an introduction to the attention mechanism for capturing emergency vehicle features and the temporal features within the GRU module. We then describe the GRU model for handling changes in dynamic traffic flow, introduce dynamic traffic signal control strategies, and conclude by presenting the model's loss function and optimization objectives.

A. PROBLEM DEFINITION

This study introduces emergency vehicles as a novel factor in the established traffic prediction framework, offering a fresh perspective and methodology to this task. By integrating the distinct characteristics of emergency vehicles into the congestion prediction model, our objective is to improve the accuracy and efficiency of traffic flow management, ultimately optimizing the operation of the transport system. In the subsequent sections, we provide a comprehensive explanation of traffic flow prediction and traffic signal control challenges, accompanied by the definition of relevant terminology and symbols. This approach ensures a transparent presentation of our research framework and methodology.

Definition 1: Road network G: We have selected a congested road network, consisting of multiple intersections, as the basis for our congestion prediction and control scenario. Each intersection is managed with traffic lights to regulate traffic flow, with directed lanes linking every two intersections together. To represent the data for each intersection, we use a node-indexed representation, wherein each intersection is assigned a distinct integer index value. We depict the road network's topology as an undirected weighted graph $G = (V, E)$, Where $V = \{v_1, v_2, \ldots, v_n\}$ represents the set of nodes and N represents the total number of nodes. The set E of linked lines indicates the connectivity between nodes. The adjacency matrix $A \in R^{N\times N}$ stores the overall connectivity details. The adjacency matrix is calculated according to (1). Each element in the matrix represents the connectivity between corresponding road segments. Where $d_{i,j}$ represents the

$$A_{i,j} = A_{j,i} = \{ \begin{matrix} \frac{1}{d_{i,j}}, d_{i,j} \neq 0 \\ 0, d_{i,j} = 0 \end{matrix} \tag{1}$$

distance between i and j, and matrix A encompasses only two distinct types of values: when two nodes lack a connection, the element's value is 0. However, in cases where a connection exists, the value becomes a non-negative number. This value signifies the degree of correlation (weight) between the two nodes. Thus, matrix A reveals that as the distance between two nodes decreases, the degree of correlation increases.

Definition 2: Identity matrix $X^{N\times P}$: We incorporate the count of vehicles within a specific road segment as a fundamental attribute of a network node, employing a feature matrix denoted as $X \in R^{N\times P}$. Here, P signifies the count of features characterizing the attribute of the node, reflecting the extent of the historical time series. X_t represents the traffic volume across all road segments at t instance.

Definition 3: Eigenvector matrix of emergency vehicles K. This paper introduces emergency vehicles as heterogeneous data, offering a comprehensive exposition of their essential attributes and behavioral characteristics within a traffic system. These feature vectors can be used to compose matrix $K = \{K_1, K_2, \ldots, K_l\}$ herein l designates the categorical index corresponding to the feature vector parameters of the emergency vehicle.

In summary, the emergency vehicle priority scheduling problem, contingent upon congestion prediction, can be formulated as the acquisition of upcoming-period traffic insights denoted by T. This pursuit is realized by devising function f, derived from the road network's topology denoted as G, the feature matrix represented by X, and the emergency vehicle feature vector matrix, denoted as K. The manifestation of this concept is depicted in (2):

$$f(G, X, K) = [x_{t-m}, \ldots, x_{t-1}, x_t] \tag{2}$$

B. GCN MODEL

As traffic information can be viewed as graphical signals, numerous researchers have leveraged graph neural networks in traffic flow prediction to capture the spatial features of road networks. To adapt standard convolution techniques for graph structures, researchers have employed the Fourier transform to convert the convolution operation into a spectral domain convolution, often referred to as spectral graph convolution. In this study, we use a spectral domain-based graph convolutional network to investigate profound spatial dependencies within neighborhood graphs. The spectral convolution can be defined as the product of the graph signal x and the convolution kernel θ. The constructive graph convolution operator is specified in the Fourier domain as follows:

$$\theta \times x = U\theta(\wedge)U^T x = \theta(U \wedge U^T)x = \theta(L)x \tag{3}$$

Here, L represents the normalized Laplace matrix, $L = I_n - D^{-1/2}WDD^{-1/2}$, while U signifies the Fourier basis matrix comprising the eigenvectors of L, where I_n is the unit matrix and D is the diagonal matrix. Λ is the diagonal matrix of the eigenvalues of L. Furthermore, we elevate the vector x to an eigenmatrix denoted as $X \in R^{N\times C}$, where C denotes the number of features.

Given a feature matrix X and an adjacency matrix A, GCN can capture the spatial characteristics of the graph by incorporating both the graph nodes and their first-order adjacency domains, enabling spectral convolution operations instead of the conventional convolution operations employed in CNNs.

The GCN model can be represented as:

$$H^{(l+1)} = \sigma(D^{*-(1/2)}A^* D^{*-(1/2)}H^{(l)}W^{(l)}) \tag{4}$$

Here, $A^* = A + I_N$ represents the adjacency matrix with a self-connected structure, I_N denotes the identity matrix, D^* stands for the degree matrix, $H^{(l)}$ signifies the output of the lth layer, $W^{(l)}$ represents the parameters of the lth layer, and $\sigma(\text{-})$ is the activation function employed for nonlinear modeling.

GCN captures spatial dependencies by encoding the road network based on the topological relationships among road segments and their associated attributes. The GCN model was previously explored and learned through the GCN model, as documented in prior research [30].

C. ATTENTION MODEL

1) HARD ATTENTION

This paper utilizes an attention module comprising both a hard attention mechanism and a soft attention mechanism as its fundamental components. Firstly, the hard attention mechanism selects and prioritizes emergency vehicles within the road network, aligning with the objective of granting priority passage to these vehicles in this study. The paper's fusion of GCN and heterogeneous emergency vehicle features is significantly influenced by the hard attention mechanism.

In our model, when emergency vehicles are detected, the system should automatically prioritize them by implementing an appropriate scheduling strategy. This objective is achieved by utilizing a hard attention mechanism within the model, explicitly selecting the focus of attention. This mechanism ensures that emergency vehicles receive preferential treatment and special consideration in traffic scheduling. Specifically, the hard attention mechanism adjusts the feature propagation and information aggregation of the GCN model within the road network based on the presence or absence of emergency vehicles and their associated characteristics. This enables the GCN to allocate greater attention to the status and requirements of emergency vehicles by assigning higher attention weights to the nodes representing these vehicles. In the decision-making process for traffic scheduling, the use of GCN and the diverse features of emergency vehicles through the hard attention mechanism ensures priority access for emergency vehicles. This mechanism effectively captures the correlation between emergency vehicles and the road network, incorporating this correlation information into the model's decision-making process to achieve priority scheduling for emergency vehicles.

In particular, the input feature matrix H combines both the road network features and the emergency vehicle features. Assuming we have the input feature matrix $H \in R^{N\times D}$ for the road network, where N signifies the number of nodes, and D represents the feature dimension for each node. The hard attention weights can be computed using the following expression:

$$\alpha_i = \begin{cases} 1, & if\ i = argmax(h_i^T W) \\ 0, & otherwise \end{cases} \tag{5}$$

In the given equation, h_i represents the feature vector of the ith node, while the weight matrix is denoted as W.

By calculating the dot product between the feature vector and weight matrix for each node, we can determine the node with the highest product value, which corresponds to the node representing emergency vehicles in the road network. This approach ensures that priority access is granted to emergency vehicles in traffic scheduling.

2) SOFT ATTENTION

In this study, we employ the soft attention mechanism to integrate dynamic features from traffic flow time series with other attributes, thereby enhancing the performance and accuracy of our traffic scheduling model. The amalgamation of the soft attention mechanism extends the expressiveness and flexibility of our model, resulting in an enhanced traffic scheduling solution. By dynamically adjusting feature weights, we can capture traffic flow changes and trends more accurately, thus improving the prediction and optimization of traffic congestion. The soft attention mechanism is particularly adept at flexibly handling inter-feature relationships, which enhances our model with a more comprehensive and precise information base.

Consider a matrix T composed of n time-steps of traffic flow attributes, where each row of the matrix denotes a feature vector for one time-step, resulting in a total of n rows. To model the traffic flow time series, we implement the GRU model, which yields a hidden state matrix H. The GRU model effectively captures both temporal information and traffic flow dynamics. The soft attention mechanism adjusts the significance of features by computing the attention weight vector A. The calculation of the attention weight vector A is presented by the following mathematical expression:

$$A = softmax(W * (H * U)\hat{\ }T) \tag{6}$$

Here, W is a matrix containing learnable attention weights, and U represents characteristics of flow. The transpose operation of the matrix is indicated with the symbol $\hat{\ }T$. The soft attention mechanism computes the attention weight vector A by performing matrix multiplication between the hidden state matrix H and the learnable parameter matrix U. This is followed by a linear transformation of the parameter matrix W and normalization using the softmax function.

Then, we can weigh and aggregate the hidden state matrix H using the attention weight vector A to derive the weighted feature representation Z:

$$Z = A * H \tag{7}$$

In the expression mentioned above, Z signifies the dynamic characteristic representation of the dynamic characteristic of the traffic flow time series, incorporating the attention weights. By employing the soft attention mechanism, we adjust the importance of features based on the dynamic properties of traffic flow, enabling us to discern changes and patterns in traffic flow with greater precision.

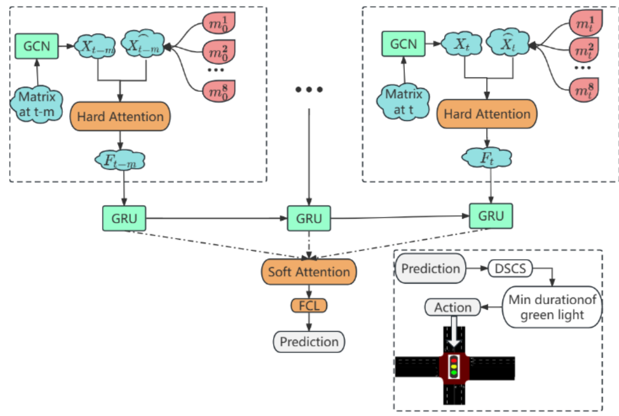

FIGURE 1. Overall framework.

D. FRAMEWORK

By amalgamating a spatiotemporal graph convolutional network with heterogeneous features and a dynamic signal control strategy, we introduce a novel traffic scheduling model (EVHF-GCN). This model enhances traffic flow scheduling by incorporating considerations for traffic congestion within the road network and emergency vehicle information.

The structure of our research is presented in Figure 1, comprising three key components: a network for fusing heterogeneous features using graph convolution, modeling of spatiotemporal dependencies and prediction through attention mechanisms, and a strategy for controlling dynamic signal lights.

E. DSCS

In this paper, we introduce a Dynamic Signalization Control Strategy (DSCS) that employs the EVHF-GCN model for predicting traffic flow and assessing the state of road network congestion. The predictive outcomes guide decisions regarding the duration of green lights at intersections, categorized according to the presence or absence of emergency vehicles. Distinct signalization control strategies are selected based on the prevailing circumstances and transmitted to the traffic signalization controllers.

When emergency vehicles are not present at an intersection, the projected duration of the green light using the expected number of incoming vehicles. Specifically, we utilize the expected number of incoming vehicles to compute the green light duration, ensuring that all upcoming vehicles in the specified direction can pass through the intersection, while also minimizing the green light duration to avoid traffic congestion. This approach empowers the traffic signal controller to adapt the current green light duration dynamically in response to the expected influx of vehicles, effectively addressing potential traffic congestion. Our control strategy efficiently clears the roadway and creates space for incoming vehicles by carefully selecting the green light duration.

As traffic approaches a congested state, we opt for longer green light durations in that direction to ease traffic flow, thereby preempting congestion. Additionally, we strive to minimize excessive durations as they would be ineffective and counterproductive.

The feature vector of an emergency vehicle serves as a critical numerical representation to depict its travel information. In this study, we treat emergency vehicles as heterogeneous data. When an emergency vehicle is present at an intersection, we introduce an eigenvalue to determine its passage status, assigning a value of 1 for presence and 0 for absence. Through the use of a hard attention mechanism, the allocation given to emergency vehicles is considerably boosted, ensuring appropriate prioritization. In situations involving multiple concurrent emergency vehicles, we introduce a ''priority'' attribute value and establish corresponding regulations. We adjust the signal phase based on the priority of each emergency vehicle to maintain order, safeguard traffic flow, and prevent chaotic situations. Please refer to Table 1 for the priority rules.

TABLE 1. Priority rule list.

Priority	Task Type	Vehicle Type	Priority Level
Low	Basic Processing, Observation, and Transport of Mild Patients	Ambulance	1
Low	Patrol, Dispute Resolution, Traffic Control Police	Police Car	2
Low	Fire Training	Fire Engine	3
Medium	Treatment, Monitoring, and Transport of Urgent Patients	Ambulance	4
Medium	Suspect Escort	Police Car	5
Medium	Handling Emergencies	Fire Engine	6
High	Treatment, Monitoring, and Transport of Critical Patients	Ambulance	7
High	Pursuit of Suspected Criminals and Rapid Response to Emergency Scenes	Police Car	8
High	Firefighting and Disaster Relief	Fire Engine	9

F. EVHF-GCN NETWORKS

The EVHF-GCN employs a graph convolution-based network that integrates heterogeneous features, incorporating data from emergency vehicles and information on traffic congestion to improve traffic flow scheduling.

We employ diverse emergency vehicle feature data to tackle the challenge of collecting emergency vehicle information features at intersections. We use SUMO simulation software to create a scenario that is consistent with a real street, define the behavior of the emergency vehicle in SUMO, run SUMO to produce additional pertinent data, including the emergency vehicle, and use the output function of SUMO to extract features such as the vehicle speed, position, route, timestamp, and set priority features (as shown in Table 1) from the data of the emergency vehicle as

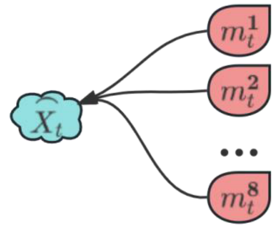

FIGURE 2. Heterogeneous emergency vehicle data fusion diagram.

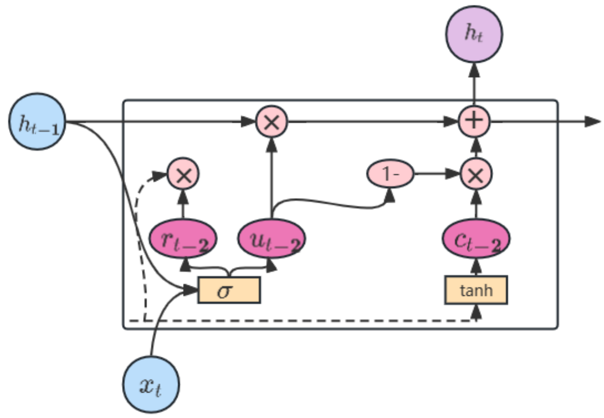

FIGURE 3. The architecture of GRU model.

heterogeneous feature data. The composition of heterogeneous emergency vehicle features is illustrated in Figure 2. To harmonize the feature matrix through GCN, we integrate a hard attention mechanism. By leveraging the fusion output of the hard attention mechanism, we feed it into the GRU to enable the model to capture temporal dependencies.

A spatiotemporal congestion prediction model is developed by integrating Graph Convolutional Networks (GCNs) and Gated Recurrent Units (GRUs). The design receives m historical time series traffic data as input and generates m hidden states (h), which capture the spatiotemporal features and are known as $\{h_{t-m}, \ldots, h_{t-1}, h_t\}$. The GRU model is comprised of a reset gate and an update gate, as depicted in Figure 3. Specifically, let's consider the gate at time t. The reset gate (r_t) combines the previous traffic state (h_{t-1}) with the representation of the road segment at time t to compute the candidate hidden state (c_t). Conversely, the update gate (u_t) determines the relevance of the previous traffic states (h_{t-1}) to discard and incorporates new information about c_t to derive the final hidden traffic state (h_t). In this process, W and b represent the weights and biases, respectively, involved in the training process, while GCsignifies the graph convolution process. The mathematical formulation of this process can be represented as (8), (9), (10), (11):

$$u_t = \sigma(W_u \times [GC(A, X_t, h_{t-1})] + b_u) \tag{8}$$

$$r_t = \sigma(W_r \times [GC(A, X_t, h_{t-1})] + b_r) \tag{9}$$

$$c_t = tanh(W_c \times [GC(A, X_t, (r_t \times h_{t-1}))] + b_c) \tag{10}$$

$$h_t = u_t \times h_{t-1} + (1 - u_t) \times c_t \tag{11}$$

Subsequently, the hidden states are utilized as inputs for the soft attention model to incorporate the dynamic characteristics of the traffic flow time series and integrate them with other features, thereby enhancing the performance and accuracy of the traffic scheduling model. Specifically, the weight assigned to each hidden state, denoted as $\{a_{t-n}, \ldots, a_{t-1}, a_t\}$, is computed using the Softmax function. The significance of global traffic features is determined by a weighted sum. Finally, the prediction results are acquired by employing a fully connected layer. These prediction results are then utilized to determine the current duration of the green light at the junction and select appropriate signal control strategies based on the prevailing conditions.

In summary, we introduce EVHF-GCN, a framework designed to forecast and schedule the movement of emergency vehicles. The urban roadway system is represented as a graph network, capturing the topological properties of the road network using GCN to account for spatial dependencies. Additionally, distinct feature vectors are employed to characterize the attributes of emergency vehicles. GRUs are used to capture real-time variations in node features, enabling the acquisition of temporal dependencies. Furthermore, an attention model is incorporated to capture the overall trend of traffic state changes, thereby facilitating accurate traffic forecasting.

G. LOSS FUNCTION

We used the following loss function. Firstly, we employ the mean square error (MSE) loss function, as defined in (12), to measure the disparity between the predicted (P) and actual (A) number of vehicles present at an intersection. To assess the prioritization of emergency vehicles, we introduce the time error as a metric, as expressed in (13). Here, T_{actual} represents the time taken for actual emergency vehicles to traverse the junction, while $T_{predicted}$ signifies the time required for the model-predicted emergency vehicles to do the same. To strike a balance between these two aspects, we combine them and introduce the hyperparameters λ in (14). Adjusting the hyperparameter λ allows for control over the model's focus on traffic flow prediction accuracy and the priority of emergency vehicles. During optimization of this loss function, the model accurately predicts the duration of green lights at intersections and selects appropriate signal control strategies based on real-world conditions.

$$L_{traffic} = (A - P)^2 \tag{12}$$

$$L_{priority} = (T_{actual} - T_{predicted})^2 \tag{13}$$

$$L_{total} = \lambda \cdot L_{traffic} + (1 - \lambda) \cdot L_{priority} \tag{14}$$

IV. EXPERIMENTS

A. DATASETS

For dynamic analysis, prediction tests on diverse data (comprising traffic flow data and information about emergency vehicles) by utilizing the subsequent sets of data:

- Traffic Data: The real dataset utilized in our study was taken from the Caltrans Performance Measurement System (PeMS) [31], specifically the PEMSD4 dataset. This dataset comprises raw detector data obtained from more than 18,000 vehicle inspection stations located across the motorway system, encompassing major metropolitan areas of California, spanning the period from 2001 to 2019. The data collection involved diverse sensors such as induction loops, side-shot radar, and magnetometers. Samples were recorded at a frequency of every 30 seconds and aggregated into 5-minute intervals. Specifically, the PEMSD4 dataset was collected from the San Francisco Bay area and consists of data from 307 sensors, covering the period from January 1st, 2018, to February 28th, 2018.
- Emergency Vehicle Information: A dedicated dataset encompassing emergency vehicle factors for traffic flow predictions is not readily available. Therefore, we employed the SUMO simulation software to generate our dataset by integrating the aforementioned traffic flow characteristics. SUMO (Simulation of Urban Mobility) is an open-source microscopic traffic simulation software extensively used for modeling and analyzing urban transportation systems. It accurately replicates the movements and interactions of vehicles, pedestrians, and other entities within road networks. Furthermore, SUMO incorporates various aspects such as traffic signal control, vehicle travel patterns, traffic flow dynamics, and emergency vehicle deployments, among others, enabling comprehensive simulations of real-world scenarios. By leveraging SUMO, we were capable of mode-ling and capturing the intricate details necessary to account for emergency vehicle considerations in our research. We employed SUMO's output functionalities to extract data related to emergency vehicles, encompassing information such as vehicle speed, position, route, timestamps, and designated priority features. We subsequently integrated this emergency vehicle data, generated by SUMO, with the PeMSD4 dataset. Ensuring temporal alignment between the two datasets was of utmost importance, as it allowed for the seamless integration of emergency vehicle data with actual traffic flow data. This alignment significantly contributes to the universality of our model.

To facilitate congestion prediction in EVHF-GCN, we performed data preprocessing. Initially, we categorized the data based on the presence of emergency vehicles. Subsequently, we extracted significant characteristics such as the average speed per five-minute interval, total traffic flow, and average lane occupancy. Data points that were not associated with the prevailing road conditions were eliminated from the analysis. This preprocessing step ensured that the input data for the EVHF-GCN model captured relevant information and focused solely on factors that directly influenced congestion.

B. FORECASTING TASKS

We conducted dataset processing by capturing data on traffic flow and emergency vehicles at five-minute intervals. Our research aims to forecast the sixth data point using the preceding five records. More specifically, we predict the traffic flow data for the next five minutes based on a comprehensive

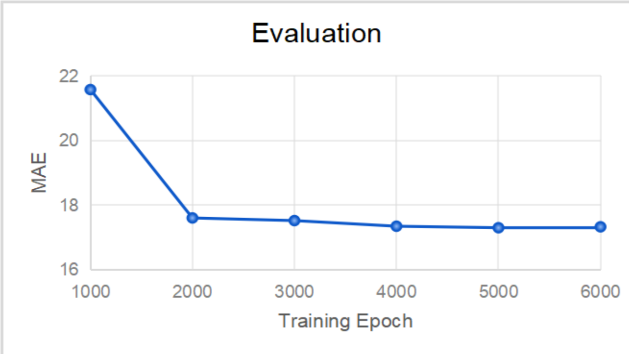

FIGURE 4. The influence of the selection of epochs on the MAE.

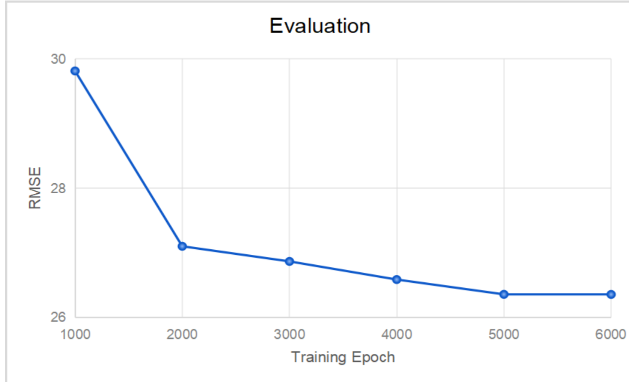

FIGURE 5. The influence of the selection of epochs on the RMSE.

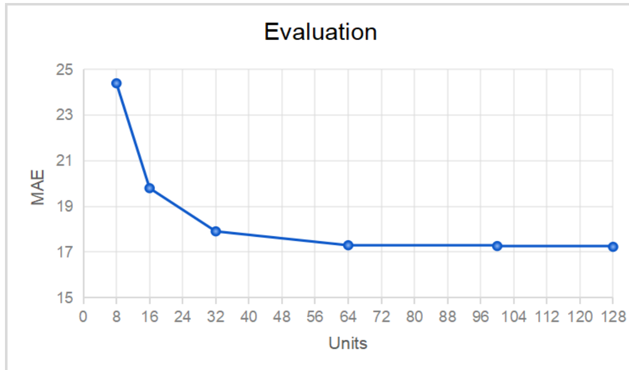

FIGURE 6. The influence of the selection of units on the MAE.

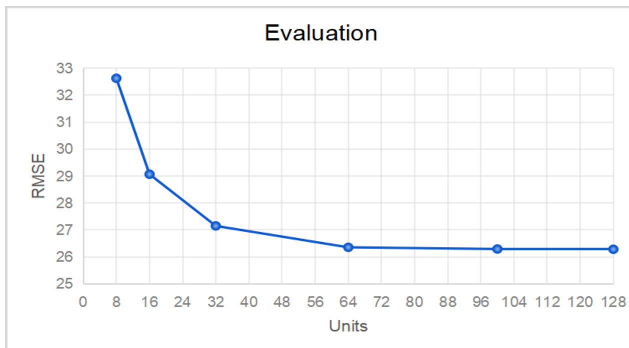

FIGURE 7. The influence of the selection of units on the RMSE.

analysis of the preceding sixty minutes' data. To handle the historical data, we calculate the maximum number of vehicles in each lane every minute, which we use as input for our model. The model generates the projected maximum number of vehicles for the following five minutes, establishing the optimal duration of the green light. Finally, we evaluated the effectiveness of our proposed traffic flow prediction module by comparing the real and forecasted information, specifically in the presence of emergency vehicles.

C. EVALUATION METRICS

To evaluate the forecasting ability of the model put forward, the subsequent metrics are employed.

1) RMSE

$$REMS = [(1/n)\sum_{t=1}^{n}(y_t - \hat{y}_t)^2]^{\frac{1}{2}} \tag{15}$$

A smaller RMSE value indicates a smaller prediction error, reflecting improved model performance.

2) MAE

$$MAE = \frac{\sum_{i=1}^{n}|y_t - \hat{y}_t|}{n} \tag{16}$$

A smaller RMSE value indicates a smaller prediction error, reflecting improved model performance.

3) MAPE

$$MAPE = ({}^{100}/_{n})\sum_{i=1}^{n}|y_t - \hat{y}_t/y_t| \tag{17}$$

MAPE is utilized for evaluating prediction error, which denotes the mean percentage variance between predicted and actual outcomes. It is a frequently employed indicator of performance, ideally suited for evaluating the efficiency of predictive models in datasets of varying sizes.

D. EXPERIMENTAL SETTINGS

All experiments were performed on a computer with 32 GB of memory, an Intel Core i7 CPU, and an NVIDIA GeForce RTX 3060 GPU. The hyperparameters were set as follows: a learning rate of 0.0001, a batch size of 128, and a range of epochs evaluated on the test set, spanning from the options [1000, 2000, 3000, 4000, 5000, 6000], to analyze the variability in the model's performance. The evaluation results for Figure 4 and Figure 5 under different training configurations are shown. With the increasing duration of the training period, the assessment metrics gradually stabilize and exhibit an inflection point around the 5000th epoch. Subsequently, for a fixed training period of 5000, we select the number of candidate GRU hidden units from the options [8, 16, 32, 64, 100, 128]. As depicted in Figure 6 and Figure 7, the model demonstrates consistent performance when the number of units reaches 100. Consequently, we have decided to maintain the training period at 5000 and the number of hidden units at 100.

To exhibit the superiority of the model, we compared it to six other algorithms:

- HA (Historical Average): This statistically-based method calculates traffic flow parameter averages to generate a forecast.
- ARIMA (Autoregressive Integrated Moving Average) is a conventional time series forecasting technique that includes an autoregressive element and a moving average element.
- GRU [18] (Gate Recurrent Unit) is a model that removes the forgetting gates from LSTM and is comprised solely of update and reset gates. It requires fewer parameters and converges more easily than LSTM.
- T-GCN [22]: This model is a time series neural network with a GRU-GCN structure, where GCN deals with spatial dependence and GRU deals with temporal dependence.
- Bi-LSTM [32]: This study introduces a novel hybrid deep learning framework that incorporates GCN to capture the spatiotemporal dependency and periodicity of traffic data. The proposed model partitions the time series into recent, daily cycle, and weekly cycle components.
- PDFormer [33]: This article presents PDFormer, a novel deep learning model that utilizes a time series neural network with a Propagation Delay-aware dynamic long-range transformer structure. The model incorporates a spatial self-attention module specifically designed to capture dynamic spatial dependencies.

E. PERFORMANCE COMPARISON

Initially, we conducted a comparative analysis between our proposed algorithm and six other prediction algorithms to assess its accuracy. Upon confirming the effectiveness of our algorithm, we proceeded with ablation experiments to investigate the impact of the heterogeneous emergency vehicle data fusion network within the algorithm. Subsequently, we validated the secondary development of the dynamic signal control strategy for SUMO-simulated junctions and developed a simulation program for emergency vehicle prioritization at junctions to substantiate the effectiveness of the strategy.

1) OVERALL COMPARISON

Table 2 presents the results of the overall performance comparison. The RMSE, MAE, and MAPE do not differ in this study regarding their ordering. For consistency, we will maintain an ordered structure throughout the paper. This statement is to prevent any reader misunderstanding. Lower values of RMSE and MAE indicate higher prediction accuracy. While the traditional method based on historical averages is more practical than other approaches, its evaluation metrics do not surpass those of the other methods. This simplistic algorithm, however, fails to handle complex, variable, and real-time traffic flow data. The ARIMA method focuses on the regularity and stability of traffic flow data in the temporal dimension, leading to outperformance over traditional machine learning methods, albeit with limited accuracy. GRU exhibits improved performance compared to ARIMA. However, neither GRU nor ARIMA accounts for spatial dependency. Conversely, T-GCN effectively addresses both spatial and temporal relationships, resulting in superior overall performance. Although both Bi-LSTM and PDFormer take into account the spatiotemporal characteristics of the data, further improvement can be made as they do not consider emergency vehicles. The study highlights that the proposed heterogeneous graph convolutional network achieves the most comprehensive performance, with MAE, RMSE, and MAPE measuring at 17.2961, 26.3557, and 13.2429%, respectively.

To visualize the performance differences among various methods, we constructed bar charts based on Table 2, as depicted in Figure 8. The horizontal axis represents the model names, while the vertical axis displays the values of the evaluation metrics RMSE, MAE, and MAPE (%). From Figure 8, it is evident that neural network models, such as GRU, T-GCN, Bi-LSTM, PDFormer, and our proposed model, exhibit higher prediction accuracy compared to traditional models like HA and ARIMA. HA displays significantly higher RMSE, MAE, and MAPE values of approximately 107.44%, 117.19% and 103.16%, respectively, compared to our model. Similarly, ARIMA displays approximately 72.50% higher RMSE, 121.39% higher MAE, and 62.07% higher MAPE than our model. These results primarily stem from the suboptimal non-linear fitting capabilities of HA and ARIMA when dealing with complex and dynamic traffic data. The utilization of ARIMA is challenging for long-term non-stationary data. Additionally, ARIMA leverages the averaging of errors across different segments, which may result in significant fluctuations in data for specific segments, leading to increased overall errors and lower predictive accuracy.

Compared to our model, GRU exhibits higher RMSE, MAE, and MAPE by approximately 64.63%, 73.75%, and 49.93%, respectively. The reason our model maintains lower predictive errors than GRU is that GRU considers only temporal features. Given the complexity of traffic situations at intersections, this can lead to a decrease in predictive accuracy. Our model's advantage lies in its consideration of spatial features in addition to temporal features. T-GCN displays RMSE, MAE, and MAPE approximately 27.49%, 68.23%, and 18.20% higher than our model. T-GCN has been a classic spatiotemporal traffic flow prediction model in recent years, as it incorporates both temporal and spatial features through the GRU-GCN architecture. Bi-LSTM exhibits RMSE, MAE, and MAPE approximately 28.15%, 26.23%, and 9.89% higher than our model. Bi-LSTM is a hybrid deep learning model that combines GCN and Bidirectional LSTM. It considers both spatiotemporal features and places a particular emphasis on capturing periodic features. Our model outperforms PDFormer with an approximately 16.14% higher RMSE, 8.28% higher MAE, and 0.57% higher MAPE.

TABLE 2. Performance comparison of different models.

Model	RMSE	MAE	MAPE
HA	54.6716	36.6999	26.9039%
ARIMA	45.4646	38.2920	21.4634%
GRU	43.3894	30.0535	19.8559%
T-GCN	33.6018	29.0979	15.6526%
Bi-LSTM	33.7772	21.8323	14.5522%
PDFormer	36.9	27.9555	16.4076%
Ours	30.6095	18.7274	13.3179%

PDFormer can capture long-range spatial dependencies and explicitly models the temporal delay in spatial information propagation, improving predictive accuracy. However, PDFormer requires substantial computational resources and a large amount of historical traffic data for training, which may limit its performance in emerging or data-limited areas. T-GCN, Bi-LSTM, and PDFormer have demonstrated excellent performance in prior research, making their performance more closely comparable to our model. Nonetheless, these models possess unique strengths and may be better suited to specific scenarios. However, none of these models consider the influence of other factors on traffic prediction accuracy, which can affect their generalizability. In contrast, our model exhibits uniqueness, particularly in considering factors such as emergency vehicle-related features and spatiotemporal characteristics. A detailed analysis of experimental results and graphical representations confirms that the newly proposed algorithm outperforms the other six methods in overall predictive performance.

It is important to emphasize that the consistent linear descent observed in Figure 8 from the HA model to the model proposed in this paper does not imply a mere enhancement of its predecessor. On the contrary, this consistent trend reflects a standardized metric employed in the performance comparison of different models to facilitate a more comprehensive evaluation of their performance. The improvement and development of each subsequent model are driven by distinct objectives and improvement points.

2) ABLATION COMPARISON

To examine the crucial role of a heterogeneous emergency vehicle data fusion network in enhancing accuracy, we conducted ablation experiments by systematically removing specific components from our proposed network. We have opted to validate models T-GCN, Bi-LSTM, and PDFormer, as they have demonstrated outstanding performance in previous research and utilize similar evaluation metrics. To maintain conciseness in the paper, we have selected a few high-performing models for validation. We have presented the findings of these experiments in Table 3, where 'Ours$*$' denotes the prognostication outcomes of the emergency vehicle data fusion network absent the heterogeneous structure. It is evident that the accuracy of Ours$*$ is significantly lower compared to the full structure, indicating the substantial impact of this structure on the overall framework and its essential role in enhancing accuracy.

FIGURE 8. Performance comparison charts.

TABLE 3. Performance comparison for ablation experiment.

Model	RMSE	MAE	MAPE
Ours*	44.6189	27.9886	15.4713%
T-GCN	33.6018	29.0979	15.6526%
Bi-LSTM	33.7772	21.8323	14.5522%
PDFormer	30.6095	18.7274	13.3179%
Ours	26.3557	17.2961	13.2429%

3) SIMULATION VERIFICATION

In this paper, we employ SUMO's TraCI (Traffic Control Interface) interface to extract simulated object data and dynamically modify their behavior based on real-time access to the ongoing road traffic simulation. Furthermore, we establish control over SUMO through a client/server architecture implemented using TCP (Transmission Control Protocol). The control mechanism is also TCP-based. By utilizing a collaborative control methodology implemented in Python, we can effectively manipulate SUMO to exert command over the traffic simulation.

In the simulation model, social and emergency vehicles are defined and utilized in the construction of an intersection to display the efficiency of the proposed model. By analyzing the delay time of emergency vehicles at the intersection when implementing the proposed model versus not implementing it, the effectiveness of the model for improving emergency vehicle passing is demonstrated in this paper.

The proposed dynamic signal control strategy and method for granting priority access to emergency vehicles at intersections were implemented and simulated using SUMO. To uphold the simulation's credibility, emergency traffic flow was set at 20 pcu/h. Comprehensive operational data was collected from all vehicles, and the average output value was calculated. The average delay experienced by emergency vehicles was compared under various flow conditions, as illustrated in Figure 9, where the x-axis represents the traffic volume (pcu/h) and the y-axis represents the average

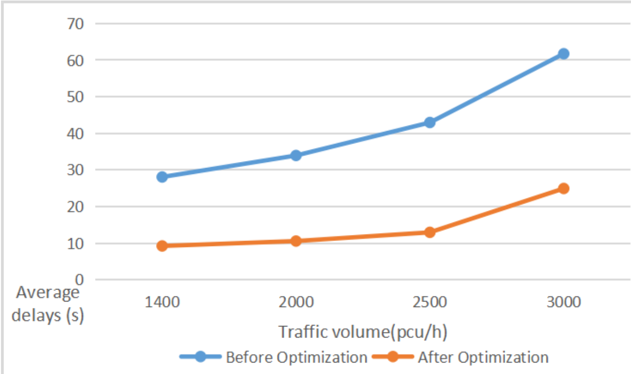

FIGURE 9. **Comparison of Average Delay at Emergency Vehicle Intersections.**

duration of delay (s) experienced by emergency vehicles at the intersection.

As shown in Figure 9, the implementation of the prioritization strategy has resulted in a significant reduction in the average delays for emergency vehicles. Specifically, the strategy achieves reductions of 67.1501%, 68.8939%, 69.8711%, and 59.6321% for intersection flows of 1400 pcu/h, 2000 pcu/h, 2500 pcu/h, and 3000 pcu/h, respectively. Notably, the delays for emergency vehicles remain relatively consistent until the intersection flow reaches 2500 pcu/h. However, beyond this flow threshold, the effectiveness of the optimization benefits diminishes significantly. This phenomenon occurs due to increased traffic volume, resulting in heightened interference between vehicles and a rise in factors influencing priority control.

V. CONCLUSION

In summary, the introduction of the EVHF-GCN model opens up new possibilities for addressing the limitations of traditional traffic flow prediction models in the context of emergency vehicle prioritization. Through the synergistic integration of heterogeneous feature fusion, graph convolutional networks, and dynamic traffic signal control strategies, this model not only achieves more accurate traffic flow predictions but also caters to the needs of emergency vehicle prioritization. Comparative evaluations with other methods in this study demonstrate the significant advantages of the EVHF-GCN model in enhancing traffic efficiency and providing priority access for emergency vehicles. The introduction of this model offers novel insights and methods for improving intelligent transportation systems, providing substantial support for urban traffic management and planning. Our future work will focus on additional real-world scenario validations, further refinement, and enhancement of the model to boost its performance and applicability continually. Building upon this study, we intend to integrate emergency vehicle route planning with graph neural networks, add an emergency vehicle prioritization module, consider the impact of other factors on traffic flow prediction to enhance prediction accuracy and explore the incorporation of algorithms like DQN for more intelligent traffic signal control to optimize green signal resource utilization.

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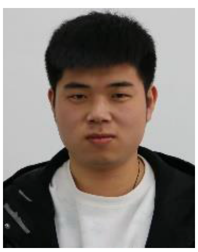

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