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RESEARCH ARTICLE

Traffic Flow Prediction Based on Information Aggregation and Comprehensive Temporal-Spatial Synchronous Graph Neural Network

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ABSTRACT It is extremely important to build a reasonable traffic network structure for traffic flow prediction. Owing to the complexity and dynamic of traffic networks, the graph neural network model has become one of the most effective methods for mining the spatial-temporal relationship between traffic flow data. However, most current methods use two components to extract the spatial dependence and time dependence separately and do not consider the auxiliary effect of additional traffic factors on the prediction target. Based on the above problems, this paper proposes a neural network prediction model for a comprehensive spatial-temporal synchronous graph based on information aggregation. The model is composed of a fusion feature attention module, an information aggregation module, and a comprehensive information integration framework. The fusion feature attention module considers the impact of each traffic factor on the traffic flow and strengthens the internal relationship of various traffic features; the information aggregation module synchronously extracts the temporal-spatial dependence of traffic flow; The multi-information combination module combines the traffic flow with the secondary information to mine the hidden relationship between the primary and secondary information. The experimental results on two real-world datasets show that the prediction effect of the model set out in the present paper is significantly better than that of the baseline.

INDEX TERMS Information aggregation, fusion feature attention, synchronous space-time map, multi-information, traffic flow prediction.

I. INTRODUCTION

In recent years, with the vigorous development of massive data analysis technology, the data of all walks of life have shown explosive growth [1]. The traffic data such as vehicle trajectory, vehicle flow, road sensor and so on increase geometrically compared with the previous. How to measure and process various traffic data has become one of the most concerned tasks in making planning decisions, designing traffic infrastructure, and building intelligent transportation systems [31]. An increasing number of researchers have introduced deep learning into intelligent transportation systems [2]. Significant success has been achieved in applications such as traffic signal control using reinforcement learning [3], traffic data collection based on computer vision [4], and mobile data analysis based on mobile modeling [5]. In recent years, under the COVID-19 epidemic, artificial intelligence combined with remote sensing and other technologies have also demonstrated outstanding ability in extracting traffic volume [32].In addition to the above applications, the prediction of

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traffic data is also a very important part of building an intelligent transportation system. Traffic flow prediction is a widely studied problem. Accurate and timely traffic flow prediction can not only alleviate traffic congestion and other problems but also save various resources [6]. Traffic flow data includes both temporal and spatial correlation, so how to effectively mine the spatial-temporal relationship between data is full of challenges. Early researchers focused on the development of time series, using statistical methods such as Autoregressive Integrated Moving Average model (ARIMA) [7] and Vector autoregressive model (VAR) [8]. Most of these methods consider only short-term information and accept linear input. When the data show a strong linear relationship, good prediction results can be achieved. However, most real-life data are long-term and nonlinear, and thus the prediction ability of statistical methods is greatly limited. The emergence of the Recurrent Neural Network (RNN) [18] and its variable:

Long Short-Term Memory (LSTM) and Gate Recurrent Unit (GRU) [19] has greatly improved the prediction accuracy of time series. By adding a hidden state and gate mechanism, the model has a memory function that effectively discards and retains information, thus realizing the processing of non-linear long-series data. Literature [9], [10] respectively built models based on LSTM and GRU to forecast traffic data, and the prediction accuracy was significantly improved compared with statistics and simple machine learning methods. However, traffic flow data is a set of spatial-temporal data, and it is far from enough to only consider the temporal correlation. How to mine its effective spatial relationship is the most critical problem in the research of traffic flow prediction methods in recent years. Some researchers model the traffic network as a grid and use a convolution neural network (CNN) [11] to learn the spatial interaction between different grids to capture spatial correlation. Before long, the shortcomings of mesh modeling began to emerge. There are local or global connections between roads, and grid modeling ignores the irregularity of real roads, thus losing topology information in the traffic network. As shown in Figure 1 (a), there is a direct or indirect spatial dependency between road monitoring points. For example, when the traffic flow of nodes M1 and M4 in a certain period is very large and will flow into M2, the traffic flow of the road where M2 is located will be directly affected; Although M3 is not directly connected with M1 and M4, it is also indirectly affected by M2. Therefore, modeling a traffic network as a grid cannot accurately reflect the spatial relationships between roads.

The traffic network has a strong spatial attribute, and real roads will interact with each other. Points, lines, and grids cannot accurately reflect the real situation in the traffic network. Therefore, it is more appropriate to model the traffic network problem as a graph [17], [22]. Each road segment was coded as a different node in the same graph. The space between the road segments affects the edges between the corresponding nodes, and the weight of edges reflects the strength of the interaction between nodes. Based on this idea, many new methods have been proposed to incorporate the graph structure into the model. Bai et al. [12] proposed an adaptive graph convolution recursive network (AGCRN) to capture the spatial-temporal correlation in traffic flow through an adaptive graph generation module and a GRU cyclic network. Diffusion Convolutional Recurrent Neural Network (DCRNN) [20], Sequence-to-Sequence Spatial-Temporal Attention Learning Model (STATF) [21], and other methods are used to combine graph convolution with a recurrent neural network. Yu et al. [13] proposed a spatial-temporal graph convolution network (STGCN) that uses graph convolution and gated time convolution to extract the spatial and temporal relationships of traffic flow. Attention Based Spatial-Temporal Graph Convolutional Networks (ASTGCN) [14], Spatiotemporal Adaptive Gated Graph Convolution Network (STAG-GCN) [15], and information enhanced propagation spatial-temporal graph neural network (STEGN) [16] use different attention mechanisms to extract temporal relationships, and then obtain spatial dependencies through corresponding graph convolution modules.

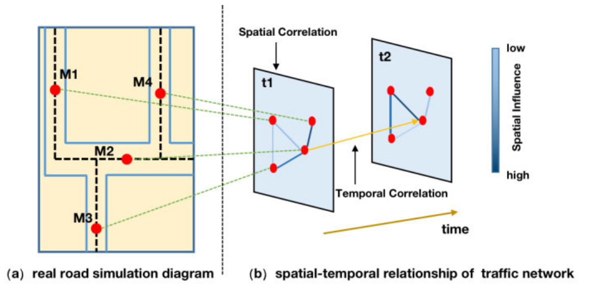

FIGURE 1. **(a) Is a road simulation diagram, and M1-M4 is a road sensor. (b) is the space-time diagram in (a). The blue line represents the impact of spatial dimensions between nodes, and the yellow line represents the impact of nodes on themselves in the next time step.t1 and t2 denote two continuous time steps.**

Because of the specific dynamics of the traffic network, some researchers have modeled the problem as a dynamic graph. Liu et al. [29] use the dynamic association between the historical traffic passenger flow and the transportation hub as the graph structure, and then convert the spatial structure information of the graph to construct the traffic network matrix and design a recursive depth convolution neural network to capture the space-time characteristics. In view of the possible data defects in practical applications, Peng et al. [30] propose to apply dynamic graph generation to the long-term prediction task of traffic flow and use the relevant algorithms in the graph strategy convolution network to generate dynamic graphs by strengthening learning, matching the Markov decision-making process with the traffic flow transfer graph.

Although traffic flow prediction has been extensively and deeply studied extensively and deeply, two important problems have been ignored. Currently, most methods [12], [13], [14], [15] use two independent components to capture temporal and spatial dependencies. As shown in Figure 1 (b), in the traffic network, different nodes at the same time will have a direct or indirect impact, and the same node will also have an impact on itself or other nodes at different times, so the spatial-temporal dependency in traffic flow exists at the same time. If the model can capture the space-time relationship of traffic flow synchronously, the prediction will be more reasonable. The second problem is to ignoring the complementary role of secondary information in prediction results. In addition to traffic flow, traffic data also includes traffic speed, traffic occupancy, etc. There are many problems associated with simply using historical information to predict the future. The lack, error, and abnormality of historical information are inevitable. Currently, the auxiliary role of secondary information is crucial. Based on the above two problems, this paper proposes a comprehensive spatiotemporal synchronous graph neural network based on the information aggregation (AC-STSGCN) model for traffic flow prediction. First, in Chapter II, traffic flow data is defined as primary information, and traffic speed and traffic occupancy are defined as secondary information; The first section of chapter III introduces the detailed process of feature attention module mining the hidden relationship between primary and secondary information; The second section of chapter III introduces how the information aggregation module synchronously extracts the spatiotemporal dependence between traffic flow data; The third section of chapter III introduces the combination process and principle of the multi-information combination module; The last section of Chapter III introduces the output layer; Chapter IV introduces relevant experiments and analysis; Chapter V is summary and prospect. The main contributions of this paper are as follows:

1) A special fusion feature attention mechanism is designed. This mechanism calculates the attention of each feature separately, and then combines the attention of secondary information with the main information to deeply mine the hidden relationships between different features.
2) An information aggregation module is designed. Starting from the time dimension, the nodes at adjacent times are aggregated and then the graph is convolved by segments to achieve synchronous extraction of the spatial-temporal relationship of traffic flow.
3) A multi-information combination module is designed to combine the secondary information with the primary information in time and space and mine the space-time dependency between the primary and secondary information. This module is applicable to all multi-feature spatial-temporal data.
4) The model in this paper has been repeated on two real-world datasets many times, and the experimental results are always better than the baseline.

II. PRELIMINARIES

A. NOTATIONS AND DEFINITIONS

Definition 1 (Primary Information): Traffic flow is the goal of this paper and is an important feature for describing traffic conditions. In this paper, the historical traffic flow is defined as $\boldsymbol{X}^{flow} = \left\{x^i_{f,t}, x^{i+1}_{f,t+1}, \ldots x^{i+m}_{f,t+m}\right\}$, hereinafter referred to as $\boldsymbol{X}^f$, $x^i_{f,t} \in \mathbb{R}^{N\times T}$ refers to the traffic flow of node at t time.

Definition 2 (Secondary Information): Traffic speed and occupancy are two important characteristics that reflect traffic conditions. There is a potential correlation between them and traffic flow, which is helpful for traffic flow prediction in some cases. This paper takes these two features as secondary information inputs. Respectively defined as $\boldsymbol{X}^{speed} = \left\{x^i_{s,t}, x^{i+1}_{s,t+1}, \ldots x^{i+m}_{s,t+m}\right\}$, $\boldsymbol{X}^{occupancy} = \left\{x^i_{o,t}, x^{i+1}_{o,t+1}, \ldots x^{i+m}_{o,t+m}\right\}$, hereinafter referred to as $\boldsymbol{X}^s$ and $\boldsymbol{X}^o$, $x^i_{s,t}$, $x^i_{o,t} \in \mathbb{R}^{N\times T}$ respectively represents the traffic speed and traffic occupancy of node A at t time.

Definition 3 (Spatial Graph): This paper uses $\mathcal{G} = (V, E, A)$ to represent the traffic network diagram, $|V| = N$ represents a collection of nodes, N is the number of nodes, E is the set of edges, $A \in \mathbb{R}^{N\times N}$ represents the adjacency matrix of nodes in the traffic network diagram and reflects the dependency between nodes. In this paper, $\mathcal{G}$ can be either a directed graph or an undirected graph.

B. PROBLEM FORMALIZATION

The purpose of traffic flow prediction is to predict the traffic flow of all sections in the future. The goal of this paper is to use a period of historical traffic flow data $X^f_{t-P+1:t}$ to predict the future traffic flow of T time slices. Therefore, the problem is defined as:

$$X^f_{t+1:t+T} = \mathcal{F}(X^f_{t-P+1:t}) \tag{1}$$

To accurately describe the spatial correlation between different traffic flow sequences, spatial graph G is introduced in this paper, and the problem is further defined as:

$$X^f_{t+1:t+T} = \mathcal{F}(X^f_{t-P+1:t}; \mathcal{G}) \tag{2}$$

This paper also considers the impact of secondary information on traffic flow, so the problem is finally defined as:

$$X^f_{t+1:t+T} = \mathcal{F}(X^f_{t-P+1:t}; X^s_{t-P+1:t}; X^o_{t-P+1:t}; \mathcal{G}) \tag{3}$$

III. PROPOSED MODEL

In this section, the proposed model in this paper will be introduced in detail. The detailed structure of this AC-STSGCN model is shown in Figure 2, which is composed of a fusion feature attention module, an information aggregation module, a multi-information combination module, and an output layer.

A. FUSION FEATURE ATTENTION

Communication information includes traffic flow, traffic speed and traffic occupancy. It is most common idea to use historical traffic flow data to predict future traffic flow data. However, real traffic networks are complex and changeable, and there are hidden relationships between different traffic information. For example, a low traffic speed and high traffic occupancy can reflect a large traffic flow. Therefore, in this paper, a fusion feature attention module is designed to mine the hidden time relationship between three types of traffic

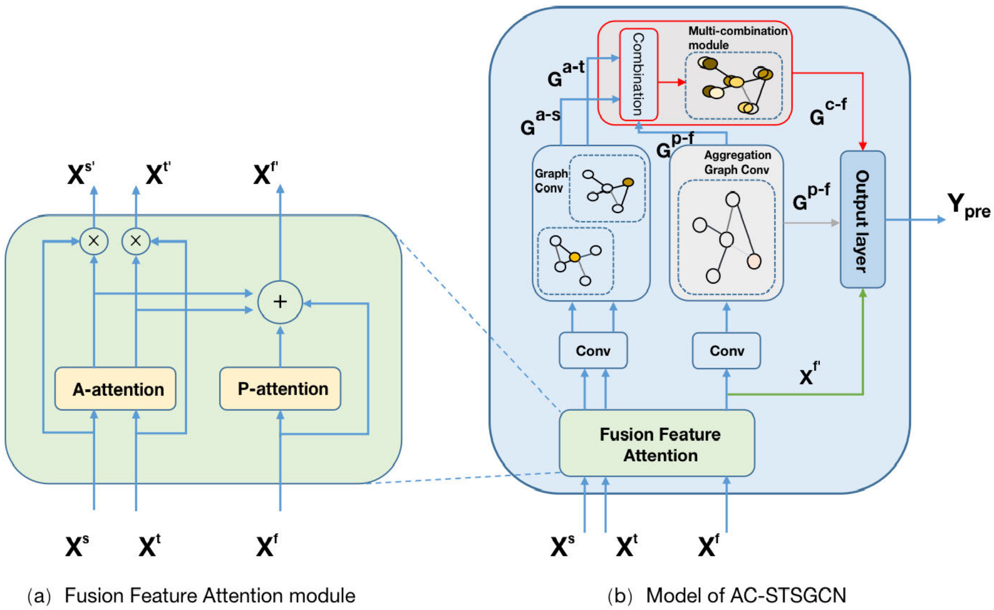

FIGURE 2. Architecture of AC-STSGCN. The model is a hierarchical structure: the fusion feature attention module receives primary and secondary information inputs at the same time. After that, different graph convolution strategies are adopted for primary and secondary information: the main information is convolved by the aggregation graph through the information aggregation module to synchronously extract the space-time dependency; The secondary information is extracted by common graph convolution. The multi-information combination module combines the primary and secondary information on the dynamic space-time map, and finally inputs it to the output layer to obtain the final prediction results.

information. Figure 2 (a) is the detailed diagram of the fusion feature attention module. First calculate the attention of the traffic flow, traffic speed, and traffic occupancy respectively, and then add attention to the traffic speed, traffic occupancy and traffic flow attention to obtain the fusion feature attention. The calculation formula for the fusion feature attention is

$$\alpha_t^f = W_\alpha^f \cdot \sigma(W_h^f h_{t-1}^f + b_\alpha^f) \tag{4}$$

$$\beta_t^{fj} = \frac{exp(\alpha_t^{fj})}{\sum_{i=1}^n exp(\alpha_t^{fi})} \tag{5}$$

$$\alpha_t^s = W_\alpha^s \cdot \sigma(W_h^s h_{t-1}^s + b_\alpha^s) \tag{6}$$

$$\beta_t^{sj} = \frac{\exp(\alpha_t^{sj})}{\sum_{i=1}^n \exp(\alpha_t^{si})} \tag{7}$$

$$\alpha_t^o = W_\alpha^o \cdot \sigma(W_h^o h_{t-1}^o + b_\alpha^o) \tag{8}$$

$$\beta_t^{oj} = \frac{\mathrm{EXP}(\alpha_t^{oj})}{\sum_{i=1}^n \mathrm{EXP}(\alpha_t^{oi})} \tag{9}$$

$$\beta_t^{Fj} = \beta_t^{fj} + \beta_t^{sj} + \beta_t^{oj} \tag{10}$$

where $\boldsymbol{W_\alpha} \in \boldsymbol{R^{n\times n}}$, $\boldsymbol{W_h} \in \boldsymbol{R^h}$, $\boldsymbol{b_\alpha} \in \boldsymbol{R^n}$ are all learnable parameters in the model; $\boldsymbol{\sigma}$ represents the activation function ***tanh***; h represents the number of hidden layer cells; $\boldsymbol{\beta_t^{fj}}$, $\boldsymbol{\beta_t^{sj}}$, $\boldsymbol{\beta_t^{oj}}$ are the attention weight values of the third node of traffic flow, traffic speed and traffic occupancy respectively; $\boldsymbol{\beta_t^{Fj}}$ is the fusion feature attention weight, and the final output of the fusion feature attention module is:

$$\boldsymbol{E^F} = X^f \boldsymbol{\beta_t^F} \tag{11}$$

In this paper, self-circulation is added to each attention division of the fusion feature attention module to consider the impact of the node's attention on itself in the process of circulation.

B. INFORMATION AGGREGATION MODULE

The spatial-temporal relationship between nodes in a traffic network is complex and variable. Simultaneously, different nodes will have spatial dependence, and nodes at different times will also be affected by themselves and other nodes. For example, when a node has experienced traffic jams in historical times, the traffic flow of the node may increase in the future, while the traffic flow of adjacent nodes will also change significantly, and vice versa, Nodes are affected by their own time and space and other nodes at the same time. Therefore, it is important to capture the spatial-temporal dependence of the nodes for traffic flow prediction. Inspired by Spatial-temporal synchronous graph convolutional networks (STSGCN) [25], this paper designs an information aggregation module, that can synchronously mine the spatial-temporal relationship between nodes. The input of the information aggregation module is the main information (traffic flow), which is mainly divided into two operations: feature aggregation and aggregation extraction. As shown in Figure 4, the feature aggregation mechanism aggregates the current time features and adjacent time features of each main information node to form a new information node. The specific aggregation operation is as follows:

$$\boldsymbol{C_3{}' = Agg(C_1, C_2, C_3)} \tag{12}$$

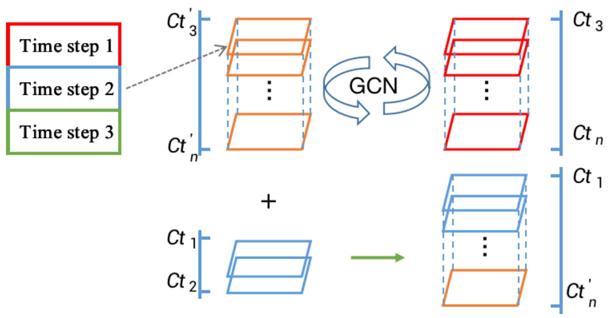

FIGURE 3. Information aggregation graph convolution. Each node in the aggregation contains the characteristic information of three adjacent time steps.

where $Agg(\cdot)$ represents the feature aggregation operation. The aggregation function selected in this paper is $SUM(\cdot)$,which directly adds the node features together. The original master information node feature $C \in R^1$, the aggregated feature $C' \in R^3$, and the length of the sequence with the time length of T becomes *T-2* after aggregation. Then, a connection layer is set to convert the node to a new dimension, and the converted output is $E_A^F = [V_3^{C'}, V_4^{C'}, \ldots, V_T^{C'}]$,where $V_i^{C'} \in R^{N\times 3}$ represents the *ith* time series after aggregation.

Dynamic graph: Next, the hidden state of features of graph convolution aggregation nodes in adjacent time periods is introduced to extract their spatial dependencies. In this paper, the graph convolution is defined in the vertex domain. Compared with [29] and [30], the dynamic graph defined in this paper has a simpler structure and only contains two variable parameters, namely, the number of vertices and the embedded dimension of vertices. In the first iteration of the model, the initial graph does not reflect the relationship between each station in the actual traffic network. As the number of iterations increases, each vertex in the adjacency matrix gets different weights, The strength of the connection with other vertices also changes with different weights. The graph structure consists of a set of learnable random parameters $E_a^p \in R^{3N\times d}$ Generated, $3N$ represents the number of master information nodes after aggregation, d represents the initial embedded dimension, and the generated dynamic adjacency matrix is defined as:

$$A_a^p = E_a^p E_a^{pT} \in R^{3N\times 3N} \tag{13}$$

A local graph convolution method is proposed in document [33] to learn the information and distance of the graph and describe the graph locally through the node and edge information of the graph. In this paper, the graph convolution is defined in the vertex domain, omitting the edge information, so it is not necessary to calculate the Laplace determinant of the graph, and each convolution is a global description of the graph. The input of the graph convolution operation is the graph signal matrix of the local spatial-temporal graph after feature aggregation. As shown in Figure 4, the whole graph convolution operation needs n-2 times, and then features are extracted through a full connection layer to restore the features of each node to N. The specific operation of a single time is described as follows:

$$V_G^{Fi} = \sigma(V_i^{C'} A_a^p W + b) \in R^{3N} \tag{14}$$
$$V_{G'}^{F} = Extract(V_G^{Fi}) \in R^{N} \tag{15}$$

where V_G^{Fi} represents the ith time series after convolution, $E_G^F = concat[V_{G'}^{F3}, V_{G'}^{F4}, \ldots, V_{G'}^{Fn}] \in R^{(T-2)\times N}$ represents the output after feature extraction. The length of the time dimension is *T-2*. To keep consistent with the subsequent operation dimensions, we select the first two-time node series V that are not processed V_1^C, V_2^C.If added to the output, the final output of the information aggregation module is:

$$E_G^F = concat[V_1^C, V_2^C, V_{G'}^{F3}, \ldots, V_{G'}^{Fn}] \in R^{T\times N} \tag{16}$$

C. MULTI-INFORMATION COMBINATION MODULE

The traffic network contains a variety of traffic information, each of which affects the others. The secondary information selected in this paper, traffic speed and traffic occupancy, can not only affect the traffic flow at the same location, but also help predict the traffic flow information of relevant time segments. For example, if the upstream traffic speed decreases or the traffic occupancy increases, traffic jams may occur, and the downstream traffic speed and traffic occupancy will also be affected; thus, the downstream traffic flow will also show a downward trend. In addition, in an actual traffic network, the main information that needs to be predicted may be recorded incorrectly, and the auxiliary prediction function of the secondary information is more obvious. Therefore, it is very important to model the spatial dependency relationship between the primary and secondary information nodes. This paper proposes a multi-information combination module, which combines primary and secondary information in space. Before combining the primary and secondary information, the spatial dependency of the secondary information nodes should also be considered. In this paper, two secondary information traffic speeds and traffic occupancy are assigned a space-time block respectively. The adjacency matrix is defined as $A^s \in R^{N\times N}$, $A^o \in R^{N\times N}$; after graph convolution, the hidden state of two secondary information features is obtained, and then the two hidden states are combined as the total hidden state output of secondary information. The specific calculation formula is:

$$E^{a-s} = \sigma(A^s E^s W_s + b_s) \in R^{T\times N} \tag{17}$$
$$E^{a-o} = \sigma(A^o E^o W_o + b_o) \in R^{T\times N} \tag{18}$$
$$E^{a-so} = Combine\left(E^{a-s}, E^{a-o}\right) = E^{a-s} + E^{a-o} \tag{19}$$

among σ is the activation function $ReLU$, W_s, W_o, b_s, b_o is the model learning parameter, and the secondary information combination function selected here is $SUM(\cdot)$. Then a dynamic graph is built to combine the hiding state of the main information and the secondary information in space. In this dynamic graph, the hiding state of their quired secondary information can be directly propagated to the main

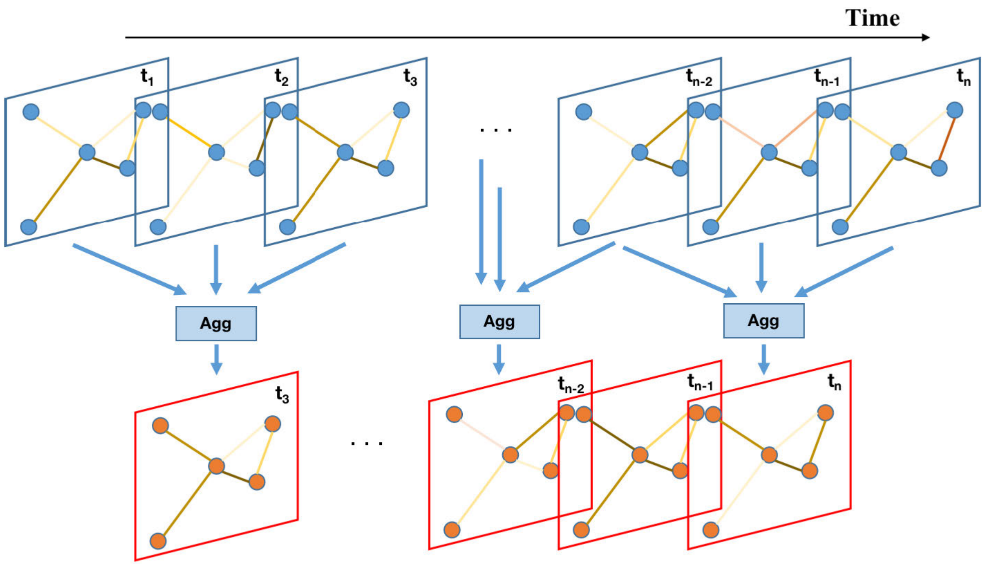

FIGURE 4. Feature aggregation mechanism.

information node. The specific operations are as follows:

$$E_f^{ap} = \sigma(A^g(E^{a-so} + E_G^F)W_g + b_g) \in R^{T\times N} \tag{20}$$

$$E_F^P = Combine(E_f^{ap}, E_G^F) \in R^{T\times 2N} \tag{21}$$

where E_f^{ap} indicates the influence of secondary information on primary information. Finally, $CONCAT(\cdot)$ is selected as the multi-information combination function to obtain the final output of the multi-information combination module.

The multi-information combination mechanism designed in this paper does not limit the types and dimensions of secondary information. Traffic speed, traffic occupancy and traffic flow are three types of traffic data contained in the same node, but there is still many information that affect traffic flow in real life. For example, when an office building is in the off-duty period, the traffic flow of nearby sections increases, which may cause traffic congestion and thus affect traffic flow. It is obviously unreasonable to directly connect the traffic flow information node with the traffic flow information node, The dynamic graph constructed in this paper integrates different types of node information into space and transfers the secondary information of the node to the primary node, which is more reasonable to help predict.

D. OUTPUT LAYER

At the end of the model is an output layer, which converts the output of the multi-information combination module into the prediction results. The output layer is composed of a set of convolution layers and a linear layer. At the same time, the residual connection is added to combine the outputs of each module. The calculation formula is:

$$E_{time} = Conv2d(E^F) \in R^{T\times N} \tag{22}$$

$$E_{combine} = Conv1d(E_F^P) \in R^{T\times N} \tag{23}$$

$$Output = \sigma(Linear(\alpha E_{time} + \beta E_{combine}) \in R^{N\times p} \tag{24}$$

TABLE 1. The details for the datasets.

Datasets	Samples	Nodes	Rate	Time Span
PeMSD4	16969	307	5 min	2 months
PeMSD8	17833	170	5 min	2 months

where $Conv2d(\cdot)$ and $Conv1d(\cdot)$ are two-dimensional and one-dimensional convolutional layers, and E_{time}, $E_{combine}$ is the output of the fusion feature attention and multi-information combination module respectively, σ Is the activation function $ReLU$, α and β are a learnable linear parameter, p is the number of prediction steps, and $Output$ is the final model prediction result.

IV. EXPERIMENT

A. DATASETS

This paper conducts experiments on two real road datasets, PeMSD4 and PeMSD8. Both data sets are from the performance test system of the California Automobile Transportation Agency [26], which includes three characteristics: traffic flow, traffic speed, and traffic occupancy. In this paper, traffic flow is taken as the main feature of prediction, and traffic speed and traffic occupancy are taken as secondary features. See Table 1 for detailed data set information. The following is the supplementary information of the dataset:

- **PeMSD4**: The traffic data of the San Francisco Bay Area collected by the performance test system of the California Automobile Transportation Agency, including three characteristics of traffic flow, traffic speed and traffic occupancy, selected 307 detectors, each detector collected data every 30 seconds, and then aggregated into data with a time interval of 5 minutes. The time span was from January 1, 2018, to February 28, 2018, and was published in ASTGCN [14].
- **PeMSD8**: The traffic data of San Bernardino Area also collected by the performance test system of the California

Automobile Transportation Agency, including three characteristics of traffic flow, traffic speed and traffic occupancy, were selected from 170 detectors, and each detector collected data every 30 seconds, and then aggregated into data with a time interval of 5 minutes. The time span was from July 1, 2016, to August 31, 2016, and was published in ASTGCN [14].

• **Preprocessing**: The missing values in the data set are filled with linear interpolation, and the data is aggregated every 5 minutes to get 288 data points every day. In addition, the data are converted through zero mean normalization $x' = x - mean(x)$ to make the average value 0, speed up the gradient descent of the optimal solution, and improve the prediction accuracy. Then, the data set is cut into three data segments with the same length: week, day, and the last three segments. The initial step size of each data segment is set to 12.

B. BASELINE

To verify the prediction performance of the AC-STSGCN model proposed in this paper, the following 12 baselines were selected for comparative experiments:

• VAR: a statistical model that captures the paired relationship of time series.

• Historical Average (HA): Considering the periodicity of traffic flow, the historical average value is taken as the prediction result.

• SVR: Support vector regression, a supervised learning algorithm.

• LSTM: Long- and short-term memory neural network, a variant of RNN, is used to predict time series.

• Dual self-attention network (DSANet) [28]: Two parallel modules, the global attention module, and the local attention module are used. Finally, the prediction results are input into the self-attention module.

• Diffusion convolutional recurrent neural network (DCRNN) [20] : Diffusion convolution recurrent neural network uses diffusion graph convolution and sequence to sequence to encode spatial information and temporal information respectively.

• Graph wavenet for deep spatial-temporal graph modeling (Graph WaveNet) [24]: Adaptive diffusion convolution and void causality convolution are introduced to capture spatial dependence and temporal dependence respectively.

• STGCN [13]: Spatiotemporal graph convolution network uses temporal convolution block and spatial convolution block to capture temporal and spatial dependencies respectively.

• ASTGCN [14]: Based on the spatiotemporal graph convolution network of attention, spatial attention and temporal attention mechanisms are designed respectively to capture spatial and temporal dependencies.

• Spatial-temporal graph to sequence model (STG2Seq) [27]: The multi-step prediction spatial-temporal graph sequence model uses gated convolution and attention mechanisms to make a multi-step prediction.

• STSGCN [25]: The spatiotemporal synchronous graph convolution network is used to construct a local spatiotemporal graph and capture the spatiotemporal dependency at the same time.

• Long Short-Term Traffic Prediction with Graph Convolutional Networks (LSGCN) [23]: Long-term short-term graph convolution network integrates a new attention mechanism and graph convolution network into a spatial gating block to capture spatial-temporal dependencies.

C. SETUP OF EXPERIMENTS

All data sets in this paper are divided into training data, validation data and test data according to the ratio of 6:2:2. The test data is the result of the experimental results. The history window of the main informatio traffic flow is set to H = 12 (1 hour). The initial history window and the characteristic dimension of the two secondary information, traffic speed and traffic occupancy are consistent with the main information. The size of the prediction target window is P = 12 (1 hour). MSELoss is selected as the loss function. The learning rate of PeMSD4 is set to 0.003, and the learning rate of PeMSD8 is set to 0.01. The performance of the model in this paper is evaluated by selecting three indicators: root means square error (RMSE), mean absolute error (MAE) and mean absolute percentage error (MAPE).

In this paper, all baselines were repeated for 5 times under the appropriate environment. The parameter settings of all baselines are as follows:

• VAR: The degree of hysteresis selected is set to 1.

• HA: The data of the first week will not be involved in the forecast. From the eighth day, the average value of the same time of the previous week on the same day will be taken as the forecast.

• SVR: The initial value of the penalty coefficient C is set to 1, the kernel function selects the Gaussian function, and the initial value of the kernel function coefficient is set to 0.001.

• LSTM: The number of LSTM layer is set to 1. The number of LSTM hidden dim is set to 10. The history window is set to 12. The learning rate is set to 0.01. The batch size is set to 64.

• DSANet: The number of Mutil-head is set to 16. The number of layers in encoder is set to 12. The learning rate is set to 0. 005.The batch size is set to 64.

• DCRNN: The number of DCRNN layer is set to 1. The number of DCRNN units is set to 5.

• Graph WaveNet: The layers of Graph WaveNet is set to 8. The sequence of dilation factors is set to [1, 2, 1, 2, 1, 2, 1, 2]. The learning rate is set to 0. 001.Dropout is 0.1.

• STGCN: The channels of three layers in ST-Conv block is set to 64, 32, 64. The initial learning rate is set to 0.001 with a decay rate of 0.8 after every 5 epochs.

• ASTGCN: The number of all graph convolution layers is set to 64. To ensure the fairness of the experiment, the length of the three-time segments is set to 12. The batch size is set to 64 and the learning rate is set to 0.0001.

• STG2Seq: The number of GCN units is set to 10. The number of GGCM is set to 5. The learning rate is set to 0. 001.The batch size is set to 64.

• STSGCN: The number of STSGLCs is set to 4. The filters of all graph convolutional operations are set to 64. The batch size is set to 64.

• LSGCN: The channels of the GLU are set to 32. The channels of GCN are set to 32. The channels of cosAtt are set to 32. The batch size of PeMSD4 is set to 32. The batch size of PeMSD8 is set to 16. The learning rate is set to 0.001.

• LSGCN: The channels of the GLU are set to 32. The channels of GCN are set to 32. The channels of cosAtt are set to 32. The batch size of PeMSD4 is set to 32. The batch size of PeMSD8 is set to 16. The learning rate is set to 0.001.

D. EXPERIMENTS RESULT

The prediction results of this model and each baseline on the two data sets are shown in Table 2. On the PeMSD4 and PeMSD8 datasets, the three indicators of this model are obviously better than each baseline.

In this paper, traditional statistical methods, traditional machine learning methods and deep learning methods are selected as the baseline for comparison. As shown in Table 2, VAR and HA are both traditional statistical methods. Except for PeMSD8, which is slightly better than STG2Seq, the performance of the three indicators on the two data sets is far worse than that of other methods. VAR and HA can only accept linear input and only consider time correlation, which is not good for forecasting traffic flow, a non-linear spatial-temporal data. Compared with traditional statistical methods, SVR, which is based on traditional machine learning, can deal with nonlinear input, but also can only consider time dependence. The method LSTM based on deep learning is improved based on RNN [18]. It realizes the memory of longer historical information through cell state and different gate mechanisms and reduces the possibility of gradient disappearance and gradient explosion. Therefore, the length of temporal information that can be processed is greatly increased, but its disadvantage is that spatial correlation is not considered. DSANet also only considers time dependence, but it adds bidirectional attention to capture the time dependence between nodes from both global and local perspectives of the entire timing information, and finally integrates it into a self-attention module output. Compared with LSTM, the processing ability of timing information is further improve; For the traffic data, it is not enough to only consider the time dependence. DCRNN uses the coding and decoding architecture to model, bidirectional graph convolution to capture spatial dependence, and GRU [19] to capture time dependence, while considering the space-time relationship of the traffic data. Both ASTGCN and LSGCN us attention mechanisms to capture spatial relationships, which is much better than traditional statistical methods and most methods that only consider temporal relationships. However, Table 2 shows that the three indicators of LSGCN are far better than ASTGCN, indicating that attention mechanisms have different abilities to mine information spatial-temporal dependencies. Graph WaveNet and STGCN respectively use two modules to capture temporal and spatial relationships, ignoring the spatial-temporal synchronization of traffic data, so the prediction effect needs to be improved. STG2Seq and STSGCN both try to build models to capture spatial-temporal dependencies at the same time. Unlike the model in this paper, STG2Seq simply connects adjacent time node information through graph convolution, while STSGCN only processes local spatial-temporal graph information, while the model in this paper adds a linear layer after local graph convolution to further aggregate adjacent features, and simultaneously processes global spatial-temporal graph information in the multi-information integration module, The spatial-temporal dependency of synchronous capture is greatly improved. It can be seen from Table 2 that the prediction result of STG2Seq is poor, and the thre indicators of the model in this paper on the two data sets are better than each baseline.

To further compare the prediction performance of this model and each baseline, we selected three models, STGCN, ASTGCN and STSGCN, to make a shorter prediction comparison on the data set PeMSD8, using two evaluation indicators, MAE and RMSE, and the results are shown in Table 3. It can be seen from Table 3 that the prediction performance of the two indicators of the model AC-STSGCN in the three short time steps is significantly better than the three comparison baselines. Among the baselines, STSGCN has the best prediction performance, and the synchronous extraction mechanism shows a good effec; STGCN performance takes the second plac; ASTGCN has the worst prediction performance, and the use of attention mechanism alone cannot extract the space-time relationship of traffic flow well. In a word, the prediction performance of the model in this paper is better than that of the baseline in a shorter time.

E. COMPONENT ANALYSIS

To analyze the impact of each module of this model on the overall prediction performance, this paper designs four variants of the model after removing different modules respectively:

(1) One secondary information in the fusion feature attention module is removed, and the model is named AC-STSGCN/f1.
(2) Remove both kinds of secondary information in the fusion feature attention module and name the model AC-STSGCN/f2.
(3) Remove the information aggregation module, and directly convolve the whole time series. The model is named AC-STSGCN/a.
(4) Remove the multi-information combination module, and directly send the output after information aggregation to the output layer to get the prediction results. The model is named AC-STSGCN/c.

The experimental results of 12 step prediction of four variant models on PeMSD8 are shown in Figure 6.

TABLE 2. Performance evaluation of AC-STSGCN and baselines on two real-world datasets.

Model	PeMSD4			PeMSD8		
	MAE	RMSE	MAPE(%)	MAE	RMSE	MAPE(%)
HA	36.76	54.14	21.83	29.52	44.03	16.59
VAR	33.63	51.62	19.73	23.46	36.33	15.42
SVR	28.71	44.57	19.21	23.26	36.18	14.75
LSTM	27.34	41.82	18.61	22.38	34.38	14.69
DSANet	22.79	35.77	16.03	17.14	26.96	11.32
DCRNN	24.92	38.38	17.49	17.89	27.88	11.48
Graph WaveNet	25.48	39.74	17.63	19.21	31.12	13.25
STGCN	23.34	36.30	14.80	18.16	28.03	11.50
ASTGCN	24.22	37.12	17.92	19.01	28.64	14.08
STG2Seq	25.20	38.48	18.77	20.17	30.71	17.32
STSGCN	22.19	33.85	13.95	17.22	26.98	11.03
LSGCN	21.53	33.86	13.18	17.73	26.76	11.20
AC-STSGCN	**19.74**	**32.11**	**12.65**	**15.12**	**23.69**	**10.43**

TABLE 3. Performance evaluation of AC-STSGCN and baselines on two real-world datasets.

Model	PeMSD8					
	P=1		P=3		P=6	
	MAE	RMSE	MAE	RMSE	MAE	RMSE
STGCN	16.45	24.69	17.22	26.13	17.75	27.11
ASTGCN	17.47	25.65	18.12	26.69	18.94	28.10
STSGCN	16.01	23.14	16.76	24.57	17.03	25.33
AC-STSGCN	**12.14**	**20.76**	**13.28**	**21.50**	**13.94**	**22.45**

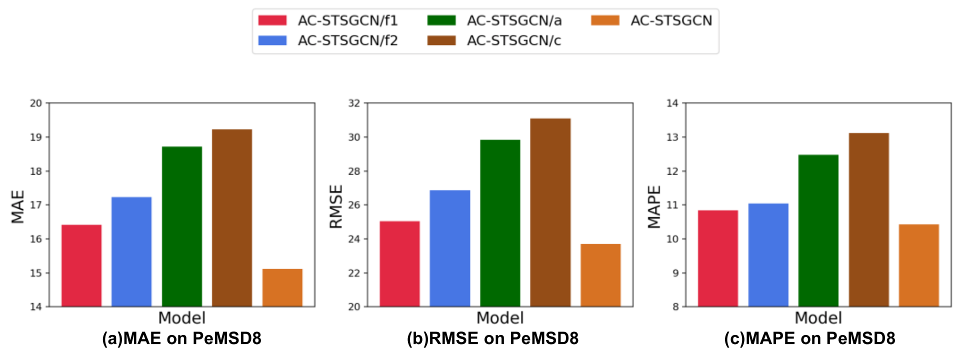

FIGURE 5. Component analysis of AC-STSGCN.

It can be seen from Figure 6 that the removal of one secondary information in the fusion feature attention module has little impact on the prediction of the model, while the model's prediction ability decreases significantly when both secondary information is removed, indicating that the secondary information can improve the prediction accuracy of the main information, and the auxiliary effect of adding multiple secondary information is better; The information aggregation module and multi-information combination module have a greater impact on the model than the fusion feature attention module. The information aggregation module enhances the connection of main information in different historical periods, which can greatly improve the prediction performance; The multi-information combination module includes the combination of primary and secondary information on the spatial-temporal graph. By modeling a good spatial-temporal dependency between nodes on the dynamic graph, the prediction performance of the model is improved most. To sum up, each module designed in this paper can well capture the temporal and spatial dependence between traffic data and improve the prediction performance of the model.

F. SECONDARY INFORMATION ANALYSIS

The traffic system contains a variety of traffic information, and different traffic information is different from each other and affects each other. This paper has conducted the following analysis experiments on PeMSD8 on how the secondary information affects the main information, taking the historical

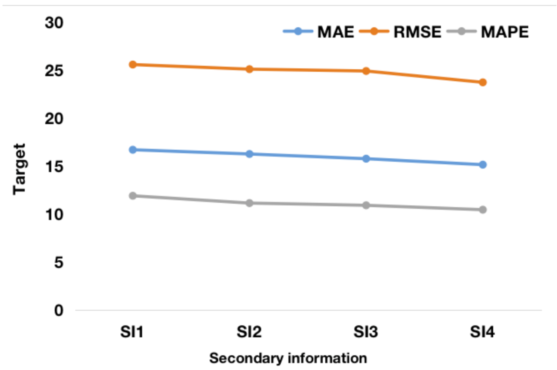

FIGURE 6. Secondary information analysis.

TABLE 4. Secondary information details.

Secondary information	Historical time step	Nodes
S I 1	3	170
S I 2	6	170
S I 3	9	170
S I 4	12	170

time step of the secondary information as the experimental variable. The specific data of the secondary information is shown in Table 3.

It can be seen from Figure 7 that with the increase of the historical time step of secondary information, the prediction effect of the model is getting better and better, which indicates that the secondary information added in this paper has a good auxiliary effect on the prediction of primary information. At the same time, the more secondary information, the more obvious the auxiliary effect.

V. CONCLUSION

Aiming at the complex and changeable traffic flow prediction problem, this paper proposes a comprehensive time-space synchronous graph neural network prediction model based on information aggregation. This model not only fully aggregates the historical information of traffic flow data, but also effectively combines the traffic flow and other secondary information in time and space. The fusion feature attention module excavates the time dependence between the traffic flow itself and the secondary information; The information aggregation module and the multi-information integration module realize the synchronous capture of spatial-temporal dependency. In addition, the combination mode of the multi-information combination framework is to build a space-time map to connect primary and secondary information, so it is not limited to primary and secondary information with the same dimension, type, and number of nodes. The experimental results on two real datasets show that the performance of our model is better than that of each baseline; The module analysis experiment also verified the different effects of each module on the model; At the same time, the influence of secondary information on traffic flow is analyzed. The more secondary information, the more obvious the auxiliary effect. In the actual traffic flow prediction, compared with other models, this model ensures the stability of the prediction. When one information is missing or seriously deviated, other information can assist the prediction.

There are three main advantages of the model proposed in this paper. First, it can accept multiple information inputs related to the prediction target at the same time, and integrate relevant auxiliary information through different modules to improve the prediction accuracy of the main targe; Second, multiple related information can be freely transformed between main information and auxiliary information as long as simple dimensional transformation is carried ou; Thirdly, in addition to the prediction of traffic data, the model in this paper is also applicable to weather, electricity, stock and other forecasts, with wide applicability. However, the model proposed in this paper also has shortcomings. For example, when severe weather events and traffic accidents occur, these factors cannot be quickly converted into the impact on traffic for subsequent prediction, which may lead to inaccurate prediction.

In the future work, we will try to use different loss functions, such as marginal loss function [34], to optimize our model, and carry out multi-step prediction research for a longer time. At the same time, we will add more types of secondary information, deeply explore the impact relationship between different information, and take traffic accidents, weather events and other factors into account to achieve more accurate prediction and apply this model to the prediction work in a broader field.

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