International Journal of
INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING
ISSN:2147-6799 www.ijisae.org Original Research Paper

An Attention based Spatial Temporal Graph Convolutional Networks for Traffic Flow Prediction

Sreenath Marimakalapalli Venkatarama Reddy*[1], Annapurna Dammur[2], Anand Narasimhamurthy[3]

Submitted: 05/12/2023 **Revised**: 26/01/2024 **Accepted**: 01/02/2024

Abstract: The accurate and timely prediction of traffic flow is crucial for a safe and stable Intelligent Transportation System (ITS). Because of the complexity and nonlinearity of traffic flow, the conventional techniques fail to capture global and local correlations. To overcome this issue, an Attention-based Spatial Temporal-Graph Convolutional Network (AST-GCN) is proposed for predicting traffic flows. This research utilized PEMS04 and PEMS08 datasets which are publicly available transport network datasets. In the spatial dimension, the various locations' traffic conditions are influenced by each other, and mutual influence is extremely dynamic. In the temporal dimension, the exists a correlation among traffic conditions and the correlations differ under various situations. The GCN is used for extracting spatial and temporal features that are applied to graph-structured data directly and it builds a graph between two neural network layers that is a graph edge weight. The obtained result shows that the proposed AST-GCN model achieves a better MAPE of 8% on the PEMS04 dataset and 5.67% on PEMS08 dataset which ensures accurate prediction compared with other existing methods like Spatial-Temporal Correlation Graph Convolutional Networks (STCGCN), Long-term Spatial-Temporal Graph Convolutional Fusion Network (LSTFGCN) and Attention-based Spatial-Temporal Graph Transformer (ASTGT).

Keywords: *Graph convolutional network, Graph neural network, Spatial dimension, Temporal dimension, Traffic flow prediction*

1. Introduction

Traffic flow prediction involves forecasting the conditions of traffic like vehicle volume and time of travel in a particular region or road [1]. The traffic flow prediction is significant for the optimization of transportation systems and minimizes the traffic crowd [2]. Traffic flow prediction is a global-ranging framework in human's everyday life, the prediction of traffic data tasks is learned widely by researchers [3]. The capability for accurate traffic flow prediction information can maximize effectiveness and safety especially huge traffic and speed on highways where crowds seriously affect its effectiveness [4] [5]. The accurate prediction of traffic flow gives support for the scheduling of vehicles and optimization of the bus system supports reducing the urban traffic crowd and maximizing the ability of urban traffic [6]. Based on the traffic flow prediction result, the departments of traffic flow perform timely traffic to reduce crowds formed through huge traffic [7]. The Intelligent Transportation System (ITS) handles serious traffic issues in cities like pollution of air and traffic jams [8].

The difficult technique in ITS is accurate and respectable prediction of traffic is a necessary element for the deliverance of traffic data, guidance of data, and optimization of traffic management [9]. The prediction of traffic flow in urban networks are important technique in ITS and is efficient for travelers and traffic managers [10]. The exact prediction of spatiotemporal traffic flow is needed to protect public transport crowd and allows decision-making for traffic management which includes temporary control of traffic and modification of traffic signal [11] [12]. Because of spatial dependency among adjacent road segments spatial prediction is performed by evaluating traffic flows from close roadways [13]. With the development of graph neural networks, concentrates on spatial-temporal graph model is maximized to attain huge efficient traffic flow predictions in long-term and complex spatial conditions [14]. Different types of sensor devices have been established on transportation networks due to the process of sensor technology. The sensors produce huge geographic-based traffic information that gives adequate traffic prediction [15]. The major contribution of this research is as follows:

- This paper proposed an Attention-based Spatial Temporal-Graph Convolutional Network (AST-GCN) to capture dynamic correlations of spatial and temporal traffic networks.
- The attention-based spatial and temporal mechanism was employed to calculate the attention weights for each time step in the input sequences.
- Then, the GCN is implemented according to spectral graphs to process signals directly and manipulate signal correlations on a network in spatial dimensions.

The remaining of this research is described as follows, the relative research in traffic flow prediction is given in section

[1] PESIT Bangalore South Campus, Bangalore 560100, India
[2] PESIT Bangalore South Campus, Bangalore 560100, India
[3] INSOFE, Bengaluru 560102, India
** Corresponding Author Email: sreenathmv@pes.edu*

2. The proposed method is explained in section 3. The results and comparative analysis of the proposed method are given in section 4 and section 5 is a conclusion of the paper.

2. Literature Review

In this section, the relevant existing papers are described in terms of methods, advantages, and limitations. It gives a better understanding of existing research and helps to build readers' knowledge in this field.

Zeng et al. [16] implemented a Long-term Spatial-Temporal Graph Convolutional Fusion Network (LSTFGCN) for the prediction of traffic flow. Initially, developed a synchronous spatial-temporal feature capture model that effectively extracts difficult local nodes dependency of spatial-temporal. Next, developed an Ordinary Differential Equation Graph Convolutional Network (ODEGCN) for capturing high spatial-temporal dependencies through the STGCN model. The integration of the gated convolution model and spatial-temporal graph convolution attention module (GCAM) efficiently learned long short-term spatiotemporal dependency however, this method failed to capture the spatial correlations.

Huang et al. [17] introduced a Spatial-Temporal Correlation Graph Convolutional Network (STCGCN) for traffic flow prediction. Initially, a merged graph structure was created to learn difficult spatiotemporal correlations that interrupt the drawbacks of the STCGCN model. Additionally, the STCGCN is established in a parallel way which incorporates a unified layer that allows to capture of both global and local dependencies concurrently. This model stacks numerous layer that learns several high-range spatial-temporal dependencies. This model is capable of handling sequential information and capturing short-term dependencies when losing a few data in high-term dependencies. However, this model causes huge computational complications and over-smoothing issues.

Zhang et al. [18] denoted an Attention-based Spatial-Temporal Graph Transformer (ASTGT) for traffic flow prediction. The developed model mainly contains two components a temporal encoder and a spatiotemporal decoder. In the first one, the traffic data of temporal dynamics are captured over the self-attention technique. The traffic flow information is incorporated through high-term dependencies. Furthermore, the spatial-temporal decoder overlays the gated spatial GCN block to obtain spatial and temporal relations. This model does not perform well due to the complex and nonlinearity of spatiotemporal dependencies.

Ma et al. [19] implemented a Spatio-Temporal Adaptive Graph Convolutional Network (STAGCN) for traffic flow forecasting. The developed technique utilized an adaptive graph formation block to capture the static and dynamic structure of network traffic. Additionally, the static and dynamic structures were incorporated to create adaptive network topology graphs. Then, these traffic flow features were captured through spatiotemporal convolutional blocks. This model can capture difficult spatial correlations and has better interpretability. However, this model required traffic information with traffic flow and speed features that were unable to be easily transported into other tasks dealing with spatiotemporal data.

Zhao et al. [20] suggested a Spatial-Temporal Position-aware Graph Convolutional Network (STPGCN) for the prediction of traffic flow. The suggested module was developed to represent the temporal and spatial nodes' position. Eventually, the suggested module flexibly reduces the weights of correlation for three significant relations of spatial-temporal. Depending on this produced relations of spatial-temporal were merged to graph convolution layer for measuring and adding features of node. The model captures temporal, spatial, and both correlations which make for faster performance. However, this model ignores spatiotemporal position factors when exhibiting spatiotemporal correlations.

Fang et al. [21] introduced a Multi-Source Spatio-Temporal Network through Automatic Neural Structure Search (AutoMSNet) for the prediction of traffic flow. The AutoMSNet has the structure of an encoder and decoder. The structure of the encoder takes the neighbor data as an input and the structure of the decoder captures the periodic patterns of long-term. The various functions of two temporal features were parallelly extracted and neural structure search space was developed for extraction of spatial features. The model was time-consuming and failed to capture correlations.

Xu et al. [22] presented a method of computing offloading for delay and energy trade-offs along traffic flow prediction in edge computing. Initially, developed a Graph Weighted Convolutional Network (GWCN) which fully removed connection and distance-related data between segments of the road for conducting the prediction of traffic flow. The short-term prediction outcomes were used as basic resource allocation adjustments of edge resources in various fields. The model reduces the overall time delay and energy consumption. The model does not take the complexity and variability into consideration.

Tang and Zeng [23] developed a Spatiotemporal Gated Graph Attention Network (STGGAT) for the prediction of traffic flow. The developed method merges a unit layer of gated recurrent, graph attention network layer along edge features, the gated approach depends on Bidirectional Long Short-Term (BiLSTM) Memory and residual architecture for extracting dependency of spatiotemporal and volumes of lane-level traffic. The model allows the nodes with less travel time and decides every significance of edge by their volume however, this model failed to capture the global and local correlations.

These existing methods have various applications and also suffer from limitations. The existing methods have issues like time consumption, failed to capture the spatial correlations, not perform well due to the complex and nonlinearity of spatiotemporal dependencies. Required traffic information with traffic flow and speed features that are unable to be easily transported into other tasks dealing with spatiotemporal data. Ignores spatiotemporal position factors when exhibiting spatiotemporal correlations. Hence, these limitations can be overcome in this manuscript by proposing an Attention based Spatial Temporal-Graph Convolutional Network (AST-GCN).

3. Proposed Methodology

In the proposed methodology, an Attention-based Spatial Temporal-Graph Convolutional Network (AST-GCN) is proposed for traffic flow prediction. The PEMS04 and PEMS08 datasets are utilized for this research which are public transport network datasets. The proposed AST-GCN is utilized for capturing dynamic correlations of spatiotemporal traffic networks. In the spatial dimension, the various locations' traffic conditions are influenced by each one. In the temporal dimension, the exists a correlation among traffic conditions at various times and the correlations differ under various situations. Then, the GCN is implemented according to spectral graphs to process signals directly and manipulate signal correlations on the network in spatial dimensions. Fig. 1 demonstrates the working process of the proposed methodology for traffic flow prediction.

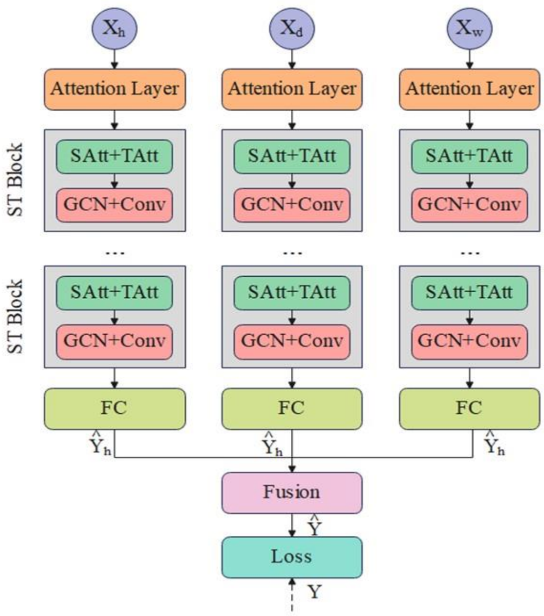

Fig. 1. The overall process of the proposed methodology

3.1. Dataset

The datasets utilized for the prediction of traffic flow are PEMS04 and PEMS08 which are public transport network datasets released by Caltrans Performance Measurement System (PeMS) [24]. For every dataset, a spatial adjacency network is developed from an actual distance-based road network. Every detector comprises per day 288 data samples and it includes 3D features such as traffic flow, speed, and time occupancy. Table 1 illustrates the dataset description.

Table 1. Dataset description

Dataset	PEMS04	PEMS08
Datatype	Traffic flow	Traffic flow
Time Range	1-1-2018 to 28-2-2018	1-7-2016 to 31-8-2016
Time Steps	16,992	17,856
Edges	340	295
Nodes	307	170

3.2. Spatial Temporal Attention

In this section, an attention based spatial-temporal mechanism is proposed to capture dynamic correlations of spatial and temporal traffic networks. It is a spatial network and these parameters and topologies are modified with time. These networks are significant because of numerous crucial applications like route finding and traffic planning services.

3.2.1.Spatial Attention

In the spatial dimension, various locations of traffic conditions are influenced by each one and mutual influence is extremely dynamic. This paper utilized an attention mechanism to capture dynamic correlation adaptively among nodes in spatial dimensions. Let's consider a recent component as an example of spatial attention which is shown in (1) and (2),

$$S = V_s \cdot \sigma((X_h^{(r-1)} W_1) W_2 (W_3 X_h^{(r-1)})^T + b_s) \quad (1)$$

$$S'_{i,j} = \frac{exp\,(S_{i,j})}{\sum_{j=1}^{N} exp\,(S_{i,j})} \quad (2)$$

Where, $X_h^{(r-1)} = (X_1, X_2, \ldots, X_{T_{r-1}}) \in \mathbb{R}^{N \times C_{r-1} \times T_{r-1}}$ is a r^{th} block of spatial temporal input. The C_{r-1} is an input data channel in r^{th} layer when $r = 1, C_0 = F$. The T_{r-1} is a temporal dimension length in a r^{th} layer when $r = 1, T_0 = T_h$. The $V_s, b_s \in \mathbb{R}^{N \times N}, W_1 \in \mathbb{R}^{T_{r-1}}, W_2 \in \mathbb{R}^{C_{r-1} \times T_{r-1}}, W_3 \in \mathbb{R}^{C_{r-1}}$ are parameters and σ is utilized for sigmoid function. This S denoted as the attention matrix which is estimated based on the present input layer. The element scores $S_{i,j}$ in S illustrates correlation strength among node i and j. Next, the SoftMax activation function is utilized to ensure nodes' attention weights. When accomplishing graph convolutions, an adjacent matrix A through spatial attention matrix $S' \in \mathbb{R}^{N \times N}$ for dynamically adjusting the weight among nodes.

3.2.2.Temporal Attention

In the temporal dimension, the exists a correlation among traffic conditions and the correlations differ under various situations. This paper utilized an attention mechanism for attaching various significant data adaptively. Let's consider a recent component as an example for temporal attention which is shown in (3) and (4),

$$E = V_e \cdot \sigma((X_h^{(r-1)} U_1) U_2 (U_3 X_h^{(r-1)})^T + b_e) \quad (3)$$

$$E'_{i,j} = \frac{exp\ (E_{i,j})}{\sum_{j=1}^{T_{r-1}} exp\ (E_{i,j})} \quad (4)$$

Where, $V_e, b_e \in \mathbb{R}^{T_{r-1}}, U_1 \in \mathbb{R}^N, U_2 \in \mathbb{R}^{C_{r-1} \times N}, U_3 \in \mathbb{R}^{C_{r-1}}$ are parameters and E is denoted as a temporal correlation matrix which is defined through various inputs. The element value $E_{i,j}$ in E illustrates correlation strength among time i and j. Next, the SoftMax activation function is utilized to normalize the E. Apply directly to a standardized temporal matrix into an input and obtain $\hat{X}_h^{(r-1)} = (\hat{X}_1, \hat{X}_2, \dots, \hat{X}_{T_{r-1}}) = (X_1, X_2, \dots, X_{T_{r-1}})E' \in \mathbb{R}^{N \times C_{r-1} \times T_{r-1}}$ for adjusting an input dynamically through integrating appropriate features.

3.3. Graph Convolutional Network

The Graph Convolutional Network (GCN) is utilized for extracting spatial and temporal features. The GCN is applied to graph-structured data directly for extracting highly meaningful forms and features in a space domain. The spectral graph simplifies the convolution operation from the grid-based data into graph-structure data. In general, the traffic networks are graph structures and every node feature can be viewed as signals on a graph. This paper implements graph convolutions according to spectral graphs for processing the signals and manipulating signal correlations directly on the network in spatial dimensions. This spectral technique algebraically converts a graph to examine graph topological attributes like graph structure connectivity. Fig. 2 represents the architecture of GCN.

In spectral, the graph is presented through Laplacian Matrix (LM) and graph structure properties are attained through examining Laplacian Matrix and its eigenvalues. The LM of graph is determined as $L = D - A$ and the normalized form is $L = I_N - D^{-\frac{1}{2}} A D^{-\frac{1}{2}} \in \mathbb{R}^{N \times N}$, here I_N, A and $D \in \mathbb{R}^{N \times N}$ are a unit, adjacent and diagonal matrix respectively by considering node degree $D_{ii} = \sum_j A_{ij}$. The LM eigenvalue decomposition is $L = U \wedge U^T$, where U is Fourier basis and $\wedge = diag([\lambda_0, \dots, \lambda_{N-1}]) \in \mathbb{R}^{N \times N}$ is a diagonal matrix. Let consider, traffic at time t, every graph signal is $x = x_t^f \in \mathbb{R}^N$ and Fourier transform is determined as $\hat{x} = U^T x$. The GCN is a convolutional operation which is executed through linear operators that diagonalized in Fourier domain to change classical convolutional operators. The graph G of signal x is filtered through kerel $g\theta$ which is shown in (5),

$$g_\theta *_G x = g_\theta(L)x = g_\theta(U \wedge U^T)x = U g_\theta(\wedge) U^T x \quad (5)$$

Where, $*_G$ is the graph convolutional operation in that the signal is equivalent to the signal product which has been converted to spectral area through the graph Fourier transform technique. When the graph scale is high, the LM of eigenvalue decomposition is expensive to perform directly. Thus, the Chebyshev polynomials [25] are employed to tackle this issue accurately and effectively through (6),

$$g_\theta *_G x = g_\theta(L)x = \sum_{k=0}^{K-1} \theta_k T_k(\tilde{L})x \quad (6)$$

Where, parameter $\theta \in \mathbb{R}^K$ is a polynomial coefficient vector. The $\tilde{L} = \frac{2}{\lambda_{max}} L - I_N, \lambda_{max}$ is the highest eigenvalue of LM. The determination of Chebyshev polynomial is $T_k(x) = 2x T_{k-1}(x) - T_{k-2}(x)$ here, $T_0(x) = 1, T_1(x) = x$. Through estimated development of the Chebyshev polynomial is utilized to resolve corresponding formulations for extracting data of 0 to $(K-1)^{th}$ a neighbor which is located on every node graph with a conv kernel g_θ. The final activation function of GCN is a ReLU that is $ReLU\ (g_\theta *_G x)$. To adjust correlations dynamically among nodes, this paper accompanies $T_k(\tilde{L})$ by spatial-attention matrix $S' \in \mathbb{R}^{N \times N}$, then attain $T_k(\tilde{L}) \odot S'$, here, $\odot$ is a Hadamard product. Hence, the above GCN formula was modified as (7),

$$g_\theta *_G x = g_\theta(L)x = \sum_{k=0}^{K-1} \theta_k (T_k(\tilde{L}) \odot S')x \quad (7)$$

The Equation (7) generalizes the determination of graph signals with numerous channels, considering in current component of input is $\hat{X}_h^{(r-1)} = (\hat{X}_1, \hat{X}_2, \dots, \hat{X}_{T_{r-1}}) \in \mathbb{R}^{N \times C_{r-1} \times T_{r-1}}$, here every node feature consumes C_{r-1} channels. Hence, every node is updated through the data of $0 \sim K-1$ neighbors' node. After capturing neighbor data for every node graph in the spatial dimension, a conv of temporal dimension is weighted to update node signals through integrating data at the neighboring time. Let's consider an example to take a process on r^{th} layer in the current component which is shown in (8),

$$X_h^{(r)} = ReLU\left(\Phi * \left(ReLU\left(g_\theta *_G \hat{X}_h^{(r-1)}\right)\right)\right) \in \mathbb{R}^{C_r \times N \times T_r} \quad (8)$$

Where, Φ is a temporal dimension conv kernel parameter, $*$ is the standard conv operation and $ReLU$ is an activation function. The spatial-temporal conv model is capable of capturing spatiotemporal features of traffic information. The spatiotemporal block is formed through its conv model and attention mechanism. Numerous spatiotemporal blocks are stacked to extract high-range dynamic spatiotemporal correlations. At last, the Fc layer is attached to ensure every component output has an equal shape and dimension by the predicting target. The final FC layer utilized the ReLU as an activation function.

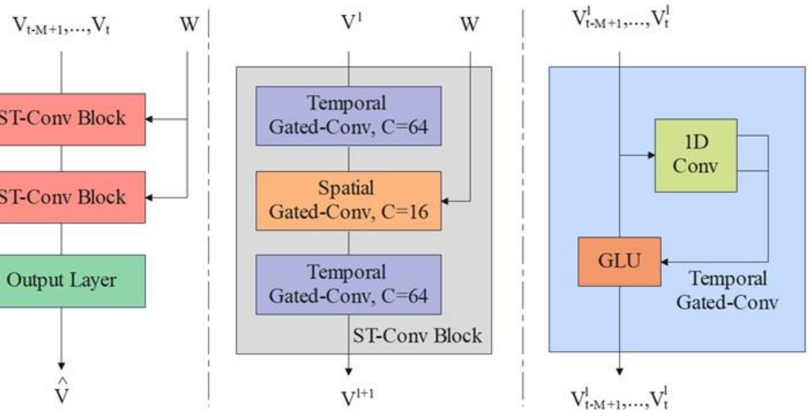

Fig. 2. Architecture of GCN

4. Experimental Result

In this paper, the proposed AST-GCN is stimulated by utilizing a Python environment with the system configuration: OS: Windows 10, processor: intel core i7 and RAM:16GB. Parameters like Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and Root Mean Square Error (RMSE) are utilized to estimate model performance. The mathematical representation of these parameters is shown in (9), (10) and (11),

$$MAE = \frac{1}{N}\left(\sum_{i=1}^{N} |(y_i - \widehat{y_i})|\right) \tag{9}$$

$$MAPE = \frac{100\%}{N}\sum_{i=1}^{N}\left|\frac{y_i - \widehat{y_i}}{y_i}\right| \tag{10}$$

$$RMSE = \sqrt{\frac{1}{N}\left(\sum_{i=1}^{N} |(y_i - \widehat{y_i})|\right)} \tag{11}$$

Where, N is the number of observations, y_i and $\widehat{y_i}$ is the actual and predicted value of ith observations.

4.1. Quantitative and Qualitative Analysis

This section shows the quantitative and qualitative analysis of the proposed AST-GCN model using MAE, MAPE and RMSE shown in Tables 2 and 3. Table 2 illustrates the performance of a proposed model on PEMS04 dataset and Table 3 illustrates the performance of the proposed model on PEMS08 dataset. The GNN required substantial memory and computation which makes them ineffective for large-scale networks. The GCN faces scalability issues, particularly dealing with large graphs which makes them less practical for real-world applications. The proposed AST-GCN model attains better prediction performance and decreases prediction errors.

Table 2. The performance of the proposed AST-GCN on PEMS04 dataset

Methods	MAE	MAPE (%)	RMSE
GNN	23.74	18.48	35.2
GCN	20.8	15.53	32.47
STPGCN	18.46	12.01	30.15
STPGNN	15.25	10.37	24.51
AST-GCN	12.8	8	19.33

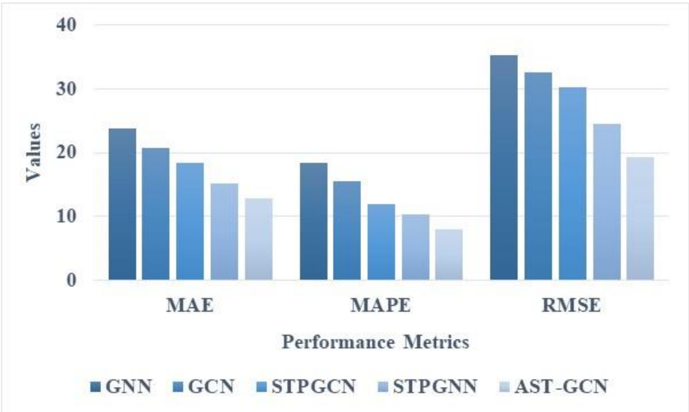

Fig. 3. Performance of proposed AST-GCN on PEMS04 dataset

Table 2 and Fig. 3 show the performance of the proposed AST-GCN model on the PEMS04 dataset. The performance of Graph Neural Network (GNN), Graph Convolutional Network (GCN), Spatial-Temporal Position-aware Graph Convolutional Networks (STPGCN), and Spatial-Temporal Position-aware Graph Neural Networks (STPGNN) are measured and matched with the proposed AST-GCN model. The obtained result shows that the proposed AST-GCN model achieves better results by utilizing performance metrics like MAE, MAPE, and RMSE values of about 12.8, 8% and 19.33 correspondingly while comparing other models.

Table 3. The performance of the proposed AST-GCN on PEMS08 dataset

Methods	MAE	MAPE (%)	RMSE
GNN	22.44	17.45	32.15
GCN	19.3	13.72	27.43
STPGCN	13.81	9.06	23.58
STPGNN	11.25	7.391	19.71
AST-GCN	8.67	5.67	15.23

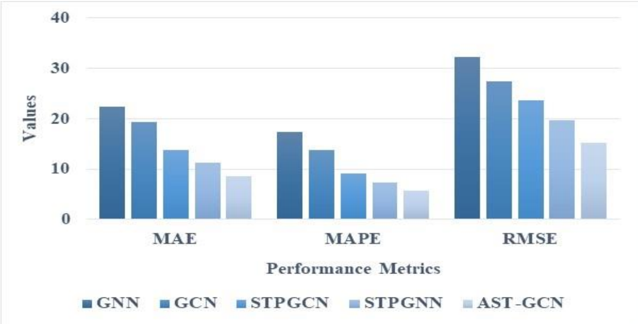

Fig. 4. Performance of proposed AST-GCN on PEMS08 dataset

Table 3 and Fig. 4 show the performance of the proposed AST-GCN model on PEMS08 dataset. The performance of GNN, GCN, STPGCN, and STPGNN are measured and matched with the proposed AST-GCN model. The obtained result shows that the proposed AST-GCN model achieves better results by utilizing performance metrics like MAE, MAPE and RMSE values of about 8.67, 5.67%, and 15.23 correspondingly while comparing other models.

4.2. Comparative Analysis

This section demonstrates the comparative analysis of the proposed AST-GCN model with performance metrics like MAE, MAPE and RMSE as shown in Tables 4 and 5. The existing result such as [16], [17], [18], [19], and [20] are utilized to evaluate the ability of the model. The proposed model is trained, tested, and validated using PEMS04 and PEMS08 datasets. The results obtained from Tables 4 and 5 show that the proposed model attains better performance when compared with the existing methods. In the PEMS04 dataset, the proposed model attains MAE, MAPE and RMSE values of 12.8, 8% and 19.33. In the PEMS08 dataset, the proposed model attains MAE, MAPE and RMSE values of 8.67, 5.67% and 15.23 correspondingly.

Table 4. Comparative analysis of the proposed method on PEMS04 dataset

Methods	MAE	MAPE (%)	RMSE
LSTFGCN [16]	19.71	13.01	31.39
STCGCN [17]	13.53	8.71	20.54
ASTGT [18]	20.58	12.89	32.74
STAGCN [19]	19.65	13.20	31.53
STPGCN [20]	18.46	12.01	30.15
Proposed AST-GCN	12.8	8	19.33

Table 5. Comparative analysis of proposed method on PEMS08 dataset

Methods	MAE	MAPE (%)	RMSE
LSTFGCN [16]	16.03	10.15	25.18
STCGCN [17]	9.83	6.71	18.68
ASTGT [18]	15.56	9.05	25.04
STAGCN [19]	15.85	10.21	25.08
STPGCN [20]	13.81	9.06	23.58
Proposed AST-GCN	8.67	5.67	15.23

4.2.1.Discussion

In this section, the advantages of the proposed method and the limitations of existing methods are discussed. The existing method has some limitations such as the LSTFGCN [16] model failed to capture the spatial correlations. The STCGCN [17] technique causes huge computational complications and over-smoothing issues. The ASTGT [18] model does not perform well due to the complex and nonlinearity of spatiotemporal dependencies. The STAGCN [19] model required traffic information with traffic flow and speed features that were unable to be easily transported into other tasks dealing with spatiotemporal data. The STPGCN [20] model ignores spatiotemporal position factors when exhibiting spatiotemporal correlations. The proposed AST-GCN model overcomes these existing model limitations. Additionally, the AST-GCN model attains better prediction performance and decreases prediction errors.

5. Conclusion

In this paper, an Attention-based Spatial Temporal-Graph Convolutional Network (AST-GCN) model is proposed for predicting traffic flows. This research utilized PEMS04 and PEMS08 datasets which are publicly available transport network datasets. In the spatial dimension, the various locations' traffic conditions are influenced by each other and mutual influence is extremely dynamic. In the temporal dimension, the exists a correlation among traffic conditions and the correlations are differ under various situations. The GCN is used for extracting spatial and temporal features that are applied to graph-structured data directly for extracting highly meaningful forms and features in a space domain. The GCN builds a graph between two neural network layers that is a graph edge weight. The obtained result shows that the proposed model achieves 12.8 of MAE, 8% of MAPE, and 19.33 of RMSE on PEMS04 dataset and 8.67 of MAE, 5.67% of MAPE, and 15.23 of RMSE on PEMS08 dataset correspondingly. The future work is to integrate the AST-GCN with deep learning models for better learning of spatiotemporal features in hidden traffic data.

Author contributions

Sreenath Marimakalapalli Venkatarama Reddy: Conceptualization, Methodology, Software, Field study **Annapurna Dammur:** Data curation, Writing-Original draft preparation, Software, Validation., Field study **Anand Narasimhamurthy:** Visualization, Investigation, Writing-Reviewing and Editing.

Conflicts of interest

The authors declare no conflicts of interest.

References

[1] X. Huang, Y. Ye, C. Wang, X. Yang, and L. Xiong, "A multi-mode traffic flow prediction method with clustering based attention convolution LSTM," *Appl. Intell.*, vol. 52, no. 13, pp. 14773–14786, Oct. 2022. https://doi.org/10.1007/s10489-021-02770-z

[2] S. Wang, C. Shao, J. Zhang, Y. Zheng, and M. Meng, "Traffic flow prediction using bi-directional gated recurrent unit method," *Urban Inf.*, vol. 1, p. 16, Dec. 2022. https://doi.org/10.1007/s44212-022-00015-z

[3] B. Wang and J. Wang, "ST-MGAT: Spatio-temporal multi-head graph attention network for Traffic prediction," *Physica A*, vol. 603, p. 127762, Oct. 2022. https://doi.org/10.1016/j.physa.2022.127762

[4] R. Kumar, J. M. Moreira, and J. Chandra, "DyGCN-LSTM: A dynamic GCN-LSTM based encoder-decoder framework for multistep traffic prediction," *Appl. Intell.*, vol. 53, no. 21, pp. 25388–25411, Nov. 2023. https://doi.org/10.1007/s10489-023-04871-3

[5] J. Dai, J. Huang, Q. Shen, Q. Shi, S. Feng, and Z. Shi, "SDSCNN: A Hybrid Model Integrating Static and Dynamic Spatial Correlation Neural Network for Traffic Prediction," *IEEE Access*, vol. 10, pp. 121159–121172, Nov. 2022. doi: 10.1109/ACCESS.2022.3222561

[6] J. Lu, "An efficient and intelligent traffic flow prediction method based on LSTM and variational modal decomposition," *Meas.: Sens.*, vol. 28, p. 100843, Aug. 2023. https://doi.org/10.1016/j.measen.2023.100843

[7] A. R. Sattarzadeh, R. J. Kutadinata, P. N. Pathirana, and V. T. Huynh, "A novel hybrid deep learning model with ARIMA Conv-LSTM networks and shuffle attention layer for short-term traffic flow prediction," *Transportmetrica A: Transport Sci.*, Jul. 2023. https://doi.org/10.1080/23249935.2023.2236724

[8] D. Xia, Y. Chen, W. Zhang, Y. Hu, Y. Li, and H. Li, "RSAB-ConvGRU: A hybrid deep-learning method for traffic flow prediction," *Multimedia Tools Appl.*, Aug. 2023. https://doi.org/10.1007/s11042-023-15877-x

[9] M. Xia, D. Jin, and J. Chen, "Short-Term Traffic Flow Prediction Based on Graph Convolutional Networks and Federated Learning," *IEEE Trans. Intell. Transp. Syst.*, vol. 24, no. 1, pp. 1191–1203, Jan. 2023. doi: 10.1109/TITS.2022.3179391

[10] Q. Zhang, M. Tan, C. Li, H. Xia, W. Chang, and M. Li, "Spatio-Temporal Residual Graph Convolutional Network for Short-Term Traffic Flow Prediction," *IEEE Access*, vol. 11, pp. 84187–84199, Jul. 2023. doi: 10.1109/ACCESS.2023.3300232.

[11] Z. Su, T. Liu, X. Hao, and X. Hu, "Spatial-temporal

graph convolutional networks for traffic flow prediction considering multiple traffic parameters," *J. Supercomput.*, vol. 79, no. 16, pp. 18293–18312, Nov. 2023. https://doi.org/10.1007/s11227-023-05383-0

[12] J. Wang, J. Ji, Z. Jiang, and L. Sun, "Traffic Flow Prediction Based on Spatiotemporal Potential Energy Fields," *IEEE Trans. Knowl. Data Eng.*, vol. 35, no. 9, pp. 9073–9087, Sep. 2023. doi: 10.1109/TKDE.2022.3221183

[13] V. B. Getanda, P. K. Kihato, P. K. Hinga, and H. Oya, "Data grouping and modified initial condition in grey model improvement for short-term traffic flow forecasting," *Automatika*, vol. 64, no. 1, pp. 178–188, 2023. https://doi.org/10.1080/00051144.2022.2119500

[14] M. A. Mondal and Z. Rehena, "Stacked LSTM for Short-Term Traffic Flow Prediction using Multivariate Time Series Dataset," *Arabian J. Sci. Eng.*, vol. 47, no. 8, pp. 10515–10529, Aug. 2022. https://doi.org/10.1007/s13369-022-06575-1

[15] X. Yu, Y. -X. Bao, and Q. Shi, "STHSGCN: Spatial-Temporal Heterogeneous and Synchronous Graph Convolution Network for Traffic Flow Prediction," *Heliyon*, vol. 9, no. 9, p. E19927, Sep. 2023. DOI: https://doi.org/10.1016/j.heliyon.2023.e19927

[16] H. Zeng, C. Jiang, Y. Lan, X. Huang, J. Wang, and X. Yuan, "Long Short-Term Fusion Spatial-Temporal Graph Convolutional Networks for Traffic Flow Forecasting," *Electronics*, vol. 12, no. 1, p. 238, Jan. 2023. doi: 10.3390/electronics12010238.

[17] R. Huang, Z. Chen, G. Zhai, J. He, and X. Chu, "Spatial-temporal correlation graph convolutional networks for traffic forecasting," *IET Intel. Transport Syst.*, vol. 17, no. 7, pp. 1380–1394, Jul. 2023. https://doi.org/10.1049/itr2.12330

[18] Q. Zhang, W. Chang, C. Li, C. Yin, Y. Su, and P. Xiao, "Attention-based spatial-temporal graph transformer for traffic flow forecasting," *Neural Comput. Appl.*, vol. 35, no. 29, pp. 21827–21839, Oct. 2023. https://doi.org/10.1007/s00521-023-08951-w

[19] Q. Ma, W. Sun, J. Gao, P. Ma, and M. Shi, "Spatio-temporal adaptive graph convolutional networks for traffic flow forecasting," *IET Intel. Transport Syst.*, vol. 17, no. 4, pp. 691–703, Apr. 2023. https://doi.org/10.1049/itr2.12296

[20] Y. Zhao, Y. Lin, H. Wen, T. Wei, X. Jin, and H. Wan, "Spatial-Temporal Position-Aware Graph Convolution Networks for Traffic Flow Forecasting," *IEEE Trans. Intell. Transp. Syst.*, vol. 24, no. 8, pp. 8650–8666, Aug. 2023. doi: 10.1109/TITS.2022.3220089

[21] S. Fang, C. Zhang, S. Xiang, and C. Pan, "AutoMSNet: Multi-Source Spatio-Temporal Network via Automatic Neural Architecture Search for Traffic Flow Prediction," *IEEE Trans. Intell. Transp. Syst.*, vol. 24, no. 3, pp. 2827–2841, Mar. 2023. doi: 10.1109/TITS.2022.3225553

[22] X. Xu, C. Yang, M. Bilal, W. Li, and H. Wang, "Computation Offloading for Energy and Delay Trade-Offs With Traffic Flow Prediction in Edge Computing-Enabled IoV," *IEEE Trans. Intell. Transp. Syst.*, Nov. 2022. doi: 10.1109/TITS.2022.3221975

[23] J. Tang and J. Zeng, "Spatiotemporal gated graph attention network for urban traffic flow prediction based on license plate recognition data," *Computer-Aided Civil and Infrastructure Engineering*, vol. 37, no. 1, pp. 3–23, Jan. 2022. https://doi.org/10.1111/mice.12688

[24] Dataset Link: https://www.kaggle.com/datasets/elmahy/pems-dataset (accessed on 16 October 2023).

[25] L. Liao, Z. Hu, Y. Zheng, S. Bi, F. Zou, H. Qiu, and M. Zhang, "An improved dynamic Chebyshev graph convolution network for traffic flow prediction with spatial-temporal attention," *Appl. Intell.*, vol. 52, no. 14, pp. 16104–16116, Nov. 2022. https://doi.org/10.1007/s10489-021-03022-w