Overview of Traffic Flow Prediction Research Based on Graph Neural Networks

Yi Shao

School of Computer Science, Xi'an Shiyou University, Xi'an, China
sy1261753273@gmail.com

Abstract. The acceleration of global urbanization and the continuous increase of the amount of vehicles have made traffic jams a severe challenge faced by cities around the world. How to accurately and real-time predict traffic flow has become a core element in building intelligent transportation systems. To better alleviate traffic congestion, improve travel efficiency, and ensure road safety, graph neural networks have begun to develop rapidly and are widely used in traffic flow prediction. With its powerful non-Euclidean data modeling capabilities, it has shown enormous potential in the field of traffic flow prediction. This review studies the latest progress in predicting traffic flow based on graph neural network methods from 2024 to 2025 and summarizes the mainstream methods in this field based on three different bases. It also lists three commonly used datasets and the evaluation criteria for datasets in this field and compares and analyzes the performance of the models. Then, the limitations of existing methods were pointed out, and future research directions and solutions were discussed to provide reference for the development of this field.

Keywords: Traffic flow prediction; Graph neural network; God often uses differential equations; Spatiotemporal data mining; Attention mechanism.

1 Introduction

With the continuous development of cities, the number of residents in various regions is also increasing, and the transportation system is becoming increasingly complex. To properly deal with the various problems caused by traffic congestion, intelligent transportation systems have gradually emerged and developed. However, traditional prediction methods mostly use statistical models, which can indeed achieve certain results in short-term prediction and construction of linear relationship models. However, due to the nonlinear and non-stationary characteristics of traffic data, as well as the spatiotemporal dependence in complex situations, their prediction accuracy and generalization ability are also quite limited [1].

With the continuous development of deep learning, recurrent neural networks, also known as Recurrent Neural Networks (RNNs), as well as their variants Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU), and convolutional neural networks, also known as Convolutional Neural Network (CNNs), have been widely used in the field of traffic flow prediction, and have made certain progress in capturing

K. Subramanian (ed.), *Proceedings of the International Workshop on Advances in Deep Learning for Image Analysis and Computer Vision (IWADIC 2025)*, Advances in Computer Science Research 128,
https://doi.org/10.2991/978-94-6239-648-7_78

temporal features and Euclidean spatial structures. However, the transportation network is non-Euclidean in structure, so it is difficult for CNN to directly model its topological relationships; However, models like RNN often overlook spatial dependencies and face issues such as gradient vanishing or exploding for long-range dependencies [2].

To overcome the limitations mentioned above, Graph Neural Networks (GNNs) have become a research hotspot that is currently receiving much attention. It could directly expand and learn on the graph and can effectively capture the spatial dependencies between road network nodes [3]. Zhao Chenglong et al. proposed a hierarchical attention graph network that can simultaneously model complex spatial dependencies at both global and local levels [4], reflecting the trend of spatiotemporal graph modeling gradually evolving towards multi-level structuring. Dynamic time modeling also plays a significant role in traffic flow prediction. Rem Hida et al. proposed the "dynamic static" topic model in 2018, which can capture the evolutionary characteristics of topics in time series document sets [5]. This idea has similar enlightening significance in traffic flow prediction, as road states and their temporal correlations often change dynamically over time, requiring the combination of dynamic representation learning and spatiotemporal prediction models. The AGSIDE and STFDSGCN models greatly improve their predictive performance under time-varying dependencies by introducing dynamic sparse graph convolution and gated attention mechanisms [6].

2 Overview of mainstream methods

2.1 Model based on Neural Ordinary Differential Equations (NODE)

NODE is a model constructed based on ordinary differential equations, which is an important breakthrough in the field of deep learning in recent years. It transforms the layered structure of neural networks, which were originally discrete states, into a continuous form of differential equations, allowing the model to learn the continuity transformation between the input and output ends [4]. Currently, mainstream models such as STGODE and GCNODE operate through this mechanism. It laid the foundation for continuous deep learning, and AGNODE also enhanced its ability to capture dynamic spatial dependencies through adaptive graph structures.

2.2 Model based on attention mechanism

The two currently popular models that apply attention mechanisms are ST-PAGNN and STFDSGCN. Attention mechanisms can enhance their related abilities in traffic flow prediction [7], while ST-PAGNN uses location attention mechanisms to capture spatial dependencies in more detail. At the same time, it also uses the Trendformer model to handle the local and global trends presented by the time series. STFDSGCN, on the other hand, uses dynamic sparse graph convolution to deal with spatial heterogeneity issues, and combines it with gated spatiotemporal dual attention to enhance its understanding of multi-scale and long-range spatiotemporal patterns, especially improving its ability to respond to unexpected events.

2.3 Traditional Spatiotemporal Graph Neural Network Model (STDGNN)

The traditional GCN-GRU model is a classic example in the field of spatiotemporal graph neural networks. The advantage of this model is that its structure is relatively simple and easy to understand compared to other models, and its implementation is not complicated. It effectively models the basic spatiotemporal dependencies of traffic flow data by combining GCN and GRU [8]. The GCN-GRU model laid the foundation for more complex ST-GNN models in the future, and it can still demonstrate good performance in certain specific scenarios.

3 Dataset and evaluation criteria

3.1 Common public datasets

METR-LA: The METR-LA dataset records traffic speed related data for a full four months from March 1, 2020, to June 30, 2020, and it is collected by detectors installed on highways in Los Angeles County.

PEMS-BAY: The PEMS-BAY dataset is provided by the performance measurement system established by the California Department of Transportation. This dataset covers traffic data collected by up to 325 sensors in the California Bay Area from January 1, 2020, to May 31, 2020, spanning a full six-month period.

PeMS04 - PeMS08: PeMS04 to PeMS08 are all derived from the highway traffic monitoring system in California, USA, which covers the highway networks in different regions of California and fully records a series of related information such as average speed, traffic flow, and occupancy rate.

Los-loop: The Loss loop dataset was used by Zhou Miaoyu and others in related research. Its raw data was recorded from 207 sensors on the Los Angeles County highway from March 1 to March 7, 2012, which can cope with the scarcity of traffic flow data. The author used the Greenshields formula to calculate traffic flow data based on existing speed data and then created a new "proprietary" dataset.

3.2 Evaluation metrics

At present, the commonly used evaluation indicators are Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE), while some studies also use coefficient of determination (R^2) as a supplementary evaluation method. The relevant calculation formula is as follows:

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

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

$$MAPE = \frac{1}{N}\sum_{i=1}^{N} \left|\frac{y_i - \hat{y}_i}{y_i}\right| \times 100\% \tag{3}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{N} (y_i - \hat{y}_i)^2}{\sum_{i=1}^{N} (y_i - \bar{y})^2} \tag{4}$$

Among them, i represents the node number, y_i and $\hat{y}_i$ represent the true value and predicted value, respectively; N is the number of predicted values.

4 Performance comparison of mainstream methods on commonly used datasets

As shown in Table 1, on the PEMS-BAY dataset, the Multi-Task Ensemble Convolutional Adaptive Ordinary Differential Equations (MTEC AODE) model's MAE (2.01), RMSE (4.79), and MAPE (4.48) indicators are in a leading position overall. Compared to the second ranked Graph Wave Net (GWNet), its advantages are obvious, especially in the MAPE indicator. In the METR-LA dataset, its MAE (3.52), RMSE (7.41), and MAPE (10.17) surpass a series of cutting-edge models such as Diffusion Convolutional Recurrent Neural Network (DCRNN) and STGODE; Compared with mainstream models such as Spatial-Temporal Graph Convolutional Network (STGCN), Attention-Based Spatial-Temporal Graph Convolutional Network (ASTGCN), Spatial-Temporal Synchronous Graph Convolutional Network (STSGCN), and STGODE, the MAE and RMSE indicators of AGNODE in the PeMS04 dataset can decrease by 3.3% and 2.6%, respectively; On the PeMS08 dataset, the average decline of these two indicators further increased to 3.6% and 1.5%, respectively. On the PeMS04 and PeMS08 datasets, the training and inference time can be reduced by at least 11.4% and 7.5%, respectively. Even though there is an increase in time cost compared to STGODE, it can still achieve a more significant improvement in accuracy, reflecting a better balance between performance and efficiency [5]; As shown in Table 2, STFDSGCN performs much better than other models on the PeMS04 and PeMS08 datasets. Compared with the performance of the advanced Dynamic Spatiotemporal Attention Graph Neural Network (DSTAGNN) method on the PeMS04 dataset, STFDSGCN achieved MAPE and MAE metrics of 12.54 and 19.01, respectively, an improvement of over 1%. On the PeMS08 dataset, compared to the current state-of-the-art spatiotemporal autoencoder (ST-AE) method, the MAE and RMSE are 14.77 and 24.05, respectively, representing an improvement of over 5% and 2%, respectively; As shown in Table 3, ST-PAGNN innovatively integrates position attention mechanism into it, which can accurately depict the complex spatial correlation between nodes. It is also coupled with the Trendformer module to model the temporal dynamic dependence and has demonstrated quite good performance in various prediction time domains [9]. In the 15-minute prediction step, compared with the benchmark model without introducing positional attention, ST-PAGNN achieved 0.15%, 0.43%, and 0.67% in RMSE, MAE, and MAPE indicators, respectively.

Table 1. Comparative experiment of MTEC-AODE on real datasets

	METR-LA			PeMSD-BAY			PeMSD7(M)		
	MAE	**RMSE**	**MAPE**	**MAE**	**RMSE**	**MAPE**	**MAE**	**RMSE**	**MAPE**
ARIMA	6.90	13.23	17.40%	3.38	6.50	8.30%	7.27	13.20	15.38%
TCN	5.02	9.98	12.31%	3.04	4.97	5.61%	4.66	8.81	11.26%
DCRNN	3.60	7.60	10.50%	2.07	4.74	4.90%	3.83	7.18	9.81%
GWNet	3.69	7.45	11.01%	2.05	4.68	4.96%	3.19	6.24	8.02%
STGCN	4.59	9.40	12.70%	2.49	5.69	5.79%	3.01	5.93	7.55%
ASTGCN	4.33	8.82	12.32%	2.11	4.85	4.61%	3.14	6.18	8.12%
STSGCN	3.65	7.81	10.67%	2.11	4.83	4.79%	3.01	5.93	7.55%
STGODE	3.75	7.37	10.26%	2.30	4.81	4.52%	2.97	5.66	7.36%
MTEC-AODE	3.52	7.41	10.17%	2.01	4.79	4.48%	2.96	5.63	7.22%

Table 2. Performance of STFDSGCN model on PeMS04 and PeMS08 datasets

	PeMS04			PeMS08		
	MAE	RMSE	MAPE	MAE	RMSE	MAPE
GWNet	24.89	39.66	17.29	18.28	30.05	12.15
DCRNN	21.22	33.44	14.17	16.82	26.36	10.92
ST-AE	19.68	31.28	15.14	15.55	24.70	10.25
ASTGCN	22.93	35.22	16.56	18.25	28.06	11.64
AGCRN	19.83	32.26	12.97	15.95	25.22	10.09
PDFormer	18.64	30.06	12.21	13.583	23.505	9.046
DSTAGNN	19.30	31.46	12.70	15.67	24.77	9.94
STFDSGCN	19.01	31.27	12.54	14.77	24.05	9.86

Table 3. Performance Comparison of ST-PAGNN on PEMS-BAY Dataset

Model	**RMSE**	**MAE**	**MAPE**
VAR	7.71	4.21	12.23%
HA	10.01	4.78	10.07%
SVR	7.46	3.40	9.29%
LSTM	3.37	3.57	9.66%
Transformer	5.7	6.66	14.46%
Trendformer	2.47	5.67	9.14%
S-GNN+GRU	2.77	5.35	10.43%
ST-PAGNN	1.97	4.37	4.43%

5 Problems and Prospects

5.1 Data limitations

The limitations of the data mainly manifest in three aspects: firstly, there are limitations in scale. For example, the three major datasets only cover some highway sections in California, and their geographical scope is relatively narrow. Urban main roads, ring roads, and rural road networks are not involved, which leads to a lack of representativeness and thus restricts the generalization ability of the model; Secondly, there are certain deficiencies in both quality and diversity, with sensor data often appearing sparse or missing, which affects training accuracy. Moreover, the data type is single, with a duration of only a few months to a year, making it difficult to reflect seasonal changes, long-term trends, and policy impacts. Some data are still very old; Thirdly, the graph structure is relatively rigid, mostly relying on static road network distance or connection relationships for modeling, ignoring dynamic changes such as road closures, construction, and time-varying traffic associations, which weakens the ability to capture complex spatiotemporal dependencies.

5.2 Model Limitations

Although the NODE model can theoretically construct networks of infinite depth, which can alleviate the problem of over smoothing to some extent, its computational complexity is quite high, and the training time is also relatively long, and requires more amount of computing resources to calculate [4]. The attention mechanism can dynamically capture spatiotemporal correlations, but in some cases, it may ignore the inherent topological structure information of the graph and overly rely on attention weights, which weakens the physical connections between nodes. All existing models suffer from insufficient robustness in responding to unexpected events, such as accidents in traffic, severe weather, and danger events, which can cause drastic changes in traffic flow patterns, and existing models are often difficult to accurately predict [10-12]. Moreover, the model's ability to fuse heterogeneous data from multiple sources is also limited. Rich information such as point of interest (POI), social media data, and urban planning information are not fully utilized, which in turn cannot effectively improve prediction accuracy and scene perception ability.

5.3 Limitations of evaluation indicators

Existing evaluation indicators such as MAE, RMSE, MAPE, etc. focus on the accuracy of point prediction, but do not provide corresponding evaluation considerations for the uncertainty of prediction results, such as prediction intervals and interpretability. In practical application scenarios, it is equally important to know the confidence level of the predicted results and the specific basis for the model to make predictions.

5.4 Future research directions and solutions

In terms of the limitations mentioned above, future research can be promoted from the following aspects: firstly, in terms of model optimization, future research may explore more efficient ODE solvers or model compression techniques, in order to reduce the cost and time required for the calculation and training of the ODE model, so that it can be better applied in practical deployment. Efforts can also be made to develop sparse or approximate variant forms and incorporate attention mechanisms to construct spatiotemporal hybrid models that can capture long-term dependencies and dynamic heterogeneity. We also need to know how to integrate data from various sources with heterogeneous features, such as weather, holidays, points of interest (POI), social media data, and public transportation schedules. Only by carefully designing complex graph structures and multimodal mechanisms can the ability to perceive and respond to events be improved. Thirdly, enhancing interpretability and robustness, developing new visualization and analysis tools, can improve the interpretability of the model and help traffic managers clarify and understand the logic behind the model. In terms of dynamic modeling, further research can be conducted to construct and update dynamic graph structures more accurately and in real-time, fully reflecting the rapidly changing connectivity relationships in the transportation network, and exploring specific methods for constructing dynamic graphs based on traffic status, event impact, or driving behavior.

6 Conclusion

This article summarizes the research results of multiple studies on traffic flow prediction based on graph neural networks (GNNs), with a focus on explaining the latest achievements in this field from 2024 to 2025 and looking forward to future development trends. Although significant development achievements have been made in this field and the momentum of development is becoming stronger, it still faces many challenges in various aspects. In the process of development, there have been some operational irregularities and unethical issues. Based on this premise, this article explores several potential ways to overcome existing limitations, aiming to promote lightweight modeling, optimize and improve data completion methods, construct more representative benchmark datasets, and actively advocate the introduction of evaluation systems tailored to actual scenarios, providing favorable references for the development of related fields in the future.

The methods in the field of traffic flow prediction have gone through a development process from traditional machine learning methods to the integration of multiple bases and models. Each generation of models has improved compared to the previous generation and can solve more and more problems that were once overlooked. Today's models have achieved significant improvements in evaluation indicators. This direction is definitely the main development direction in the future.

From other perspectives, research on traffic flow prediction based on GNN also shows a development trend from structural modeling to cognitive modeling. Its evolution path has experienced from static graph to dynamic graph, from single mode to multi-source heterogeneous integration. I believe that with the continuous development of computing resources, sensing technology, and data sharing mechanisms, future GNN traffic flow prediction models will achieve a more ideal balance in accuracy, real-time performance, and interpretability, providing more stable and powerful technical support for the construction of intelligent transportation systems and urban travel optimization.

References

1. Li, C. S.: Short-term traffic flow prediction based on Spatial-temporal graph neural networks. University of Electronic Science and Technology of China, (2025) DOI: 10.27005/d.cnki.gdzku.2025.002620.
2. Wang, X., Ma, Y., Wang, Y., et al.: Traffic flow prediction via spatial temporal graph neural network//Proceedings of the Web Conference 2020. 1082-1092. (2020)
3. Li, Y., Yu, R., Shahabi, C., et al.: Diffusion convolutional recurrent neural network: Data-driven traffic forecasting. arXiv preprint arXiv:1707.01926, (2017)
4. Zhao, C., Zhou, X., Xie, X., Zhang, Y.: Hierarchical attention graph for scientific document summarization in global and local level. In: Findings of the Association for Computational Linguistics: NAACL 2024, Mexico City, Mexico, pp. 714–726 (2024). DOI: 10.18653/v1/2024.findings-naacl.45.
5. Yan, J. H., Li, H. H., Sun, J., et al. A survey on spatio-temporal graph neural networks for traffic flow prediction. Computer Engineering and Applications, 1-22 (2025).
6. Chang, J., Yin, J., Hao, Y., et al. STFDSGCN: Spatial-Temporal Fusion Graph Neural Network Based on Dynamic Sparse Graph Convolution GRU for Traffic Flow Forecast. Sensors, 25(11): 3446 (2025)
7. Hida, R., Takeishi, N., Yairi, T., Hori, K.: Dynamic and static topic model for analyzing time-series document collections. In: Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics (Volume 2: Short Papers), Melbourne, Australia, pp. 516–520 (2018). DOI:10.18653/v1/P18-2082.
8. Zhou, M. Y., Si, S. H., Zhang, Z. R., et al.: Traffic flow prediction based on Spatio-temporal dependency graph neural network. Advances in Applied Mathematics, 14(3): 11. (2025) DOI:10.12677/aam.2025.143118.
9. He, T., Zhou, Y. Q., Xin, C. H.: Traffic flow prediction method based on spatio-temporal location attention graph neural network. Application Research of Computers, 41(10): 2932-2938. (2024) DOI: 10.19734/j.issn.1001-3695.2024.01.0026.
10. Chu, Z. H.: Traffic flow prediction based on neural ordinary differential equation networks. Yantai University, (2025) DOI: 10.27437/d.cnki.gytdu.2025.000316.
11. Zheng, M., Li, T., Zhu, R., et al.: Traffic Accident's Severity Prediction: A Deep-Learning Approach-Based CNN Network. IEEE Access, 739897-39910 (2019).
12. Duan, M.: Attention-based multi-agent reinforcement learning for traffic flow stability in mountainous tunnel entrances. Sci Rep 15, 37278 (2025).