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Research on Urban Traffic Flow Prediction Based on Time Series Analysis

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Abstract

Urban traffic flow prediction is a core component of intelligent transportation systems. Accurate flow prediction is of great significance for alleviating traffic congestion and improving the operating efficiency of road networks. Traffic flow data have complex characteristics such as non-stationarity, seasonality, and spatiotemporal coupling, and time series analysis methods for traffic flow prediction have continuously evolved from statistical models to machine learning, deep learning, and hybrid models. Focusing on temporal dependence modeling, this paper systematically reviews the basic principles, temporal feature processing capabilities, and applicable scenarios of four types of methods, with emphasis on what problems each type of method has solved and what problems remain. The analysis shows that statistical models laid the theoretical foundation for temporal modeling, machine learning expanded nonlinear fitting capability, deep learning has become the current mainstream because of automatic feature extraction and long-range dependence modeling, and hybrid models show advantages in accuracy and robustness in some scenarios. Current research still faces challenges such as insufficient dynamic road network modeling, difficulty in fusing multi-source heterogeneous data, inadequate prediction of abnormal events, poor generalization with small samples, and insufficient model interpretability. Future research should continue to advance multi-source data fusion, dynamic spatiotemporal modeling, interpretability, and small-sample transfer, thereby promoting the transition of time series traffic flow prediction from academic research to reliable engineering applications.

Keywords

traffic flow prediction, time series analysis, deep learning, spatiotemporal modeling, hybrid model

1. Introduction

With the acceleration of urbanization and the growth of motor vehicle ownership, traffic congestion has become a common problem faced by large and medium-sized cities worldwide. Traffic congestion not only reduces travel efficiency but also causes energy waste, environmental pollution, and accident risks. Against this background, the Intelligent Transportation System (ITS) has become an important means of relieving traffic pressure, and traffic flow prediction is a core component of ITS. Accurate flow prediction can provide a basis for traffic management decisions and help travelers plan routes reasonably, thereby improving the operating efficiency of road networks.

Traffic flow data are essentially non-stationary time series recorded in chronological order. They have trends, seasonality, and random fluctuations and are also affected by weather, holidays, emergencies, and road

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network topology, thus showing complex spatiotemporal coupling characteristics. Time series analysis focuses on mining temporal dependencies within sequences and has continuously evolved over the past several decades from classical statistical models to machine learning and then to deep learning and hybrid models. Different methods have their own advantages and limitations in temporal feature capture, computational complexity, interpretability, and data requirements. Their evolution is essentially a process of continuously overcoming the insufficient ability of traditional models to model nonlinearity, long periods, and spatiotemporal coupling relationships [1].

Focusing on temporal dependence modeling, this paper reviews urban traffic flow prediction methods based on time series analysis. The methods are discussed in four categories: statistical models, machine learning, deep learning, and hybrid models. The internal logic of method evolution is examined in particular: statistical models address linearity and periodicity, machine learning addresses nonlinear fitting, deep learning addresses automatic feature extraction and spatiotemporal coupling, and hybrid models attempt to account for multiple component features.

2. Classification of Time Series Methods for Traffic Flow Prediction

The four types of methods do not simply replace one another; instead, they have evolved gradually to address specific gaps in the preceding type. They are discussed below according to this logic.

2.1 Statistical Model Methods

Statistical models were the earliest type of method applied to traffic flow prediction. Their core idea is to regard traffic flow as a random variable that changes over time and to describe the autocorrelation structure within the sequence through mathematical equations. A representative model is the Autoregressive Moving Average (ARMA) model, which makes predictions through a linear combination of historical observations and historical error terms. Because traffic flow has trends and non-stationary characteristics, researchers more often use the Autoregressive Integrated Moving Average (ARIMA) model and the Seasonal Autoregressive Integrated Moving Average (SARIMA) model to handle non-stationarity and periodic fluctuations, respectively [2, 3].

Statistical models have the advantages of mature theory, strong interpretability, and low computational overhead, and they can be modeled with small samples. However, they essentially assume linear relationships in the data and have difficulty describing nonlinear dynamics in traffic flow; their accuracy often decreases during emergencies or severe weather. More specifically, ARIMA and SARIMA can handle non-stationarity and periodicity, but they have difficulty simultaneously handling nonlinear abrupt changes, spatial coupling, and multi-source exogenous variables. Statistical models solve linear and periodic problems but cannot handle nonlinear abrupt changes and spatial coupling, which directly motivates the introduction of machine learning. Through kernel mapping and ensemble strategies, machine learning specifically strengthens the ability to fit nonlinear relationships.

2.2 Machine Learning Methods

To compensate for the insufficient ability of statistical models to model nonlinear temporal relationships, researchers introduced machine learning methods. Support Vector Regression (SVR) handles nonlinear relationships through kernel function mapping and performs robustly on small-sample data [4]. Random Forest (RF) and Gradient Boosting Decision Tree (GBDT) improve generalization through ensembles of decision trees, can process multi-feature inputs, and can mine nonlinear associations between features and traffic flow [5, 6].

Machine learning methods break through linear limitations and improve prediction accuracy over statistical models in some scenarios, but they depend heavily on manual feature engineering. Researchers need to manually extract effective inputs such as time-lag features, periodic attributes, and external influencing factors, and feature quality directly affects model performance. At the same time, the computational complexity of some methods increases rapidly as the data scale grows, making them unsuitable for real-time prediction on large-scale road networks. In other words, machine learning solves the nonlinear fitting problem but does not

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solve automatic temporal feature extraction or spatial road network structure modeling. Deep learning specifically addresses this deficiency through end-to-end training and automatic feature extraction.

2.3 Deep Learning Methods

Because of its strong automatic feature extraction and deep nonlinear modeling capabilities, deep learning has become the mainstream direction of current time series traffic flow prediction. Its core breakthrough lies in alleviating the difficulties of traditional methods in capturing long-term temporal dependencies and complex spatiotemporal coupling. A Recurrent Neural Network (RNN) transmits temporal information through hidden states, but it has a vanishing-gradient problem. A Long Short-Term Memory (LSTM) network alleviates this problem through a gating mechanism and has been widely applied to traffic flow prediction [7]. As a simplified variant of LSTM, the Gated Recurrent Unit (GRU) reduces the number of parameters and training time while maintaining similar performance. Some comparative experiments show that GRU has a higher inference speed than LSTM at similar prediction accuracy and is more suitable for scenarios with high inference-speed requirements [8].

A Convolutional Neural Network (CNN) can extract local temporal features through one-dimensional convolution and capture traffic flow change patterns over short periods. Because traffic flow is also affected by the spatial structure of the road network, temporal dependence and spatial dependence are coupled with each other. Researchers have therefore proposed spatiotemporal hybrid models, such as convolutional LSTM, which combines the spatial feature extraction of CNN with the temporal modeling of LSTM.

In recent years, attention mechanisms and the Transformer architecture have directly calculated the associations between any time steps in a sequence through self-attention, breaking through the long-distance dependence bottleneck of recurrent structures. The Traffic Transformer proposed by Cai et al. models the periodic similarity of traffic flow through temporal attention and shows advantages in long-horizon prediction on multiple public datasets [9]. The dynamic adaptive attention graph learning-based spatiotemporal graph neural network Transformer (DASTGNN-Transformer) model proposed by Wang achieved a root mean square error (RMSE) of 0.072–0.085 and a mean absolute percentage error (MAPE) of 8.2%–9.5% on the PeMSD4 and PeMSD8 datasets [10].

A Graph Neural Network (GNN) starts from road network topology and aggregates neighbor information through graph convolution to describe the coupling between the spatial propagation and temporal evolution of traffic flow. Models such as Graph WaveNet and the Graph Multi-Attention Network (GMAN) further improve spatiotemporal modeling capability through adaptive graph convolution and spatiotemporal attention mechanisms and have achieved good results in road-network-level prediction [11, 12].

Deep learning reduces dependence on manual feature engineering and shows accuracy advantages under some datasets and experimental conditions, but it has a large number of parameters, high training costs, poor interpretability, and unstable performance in scenarios with small samples or poor data quality. In addition, LSTM and GRU are weak in spatial structure modeling, CNN and convolutional LSTM depend on regular grids, GNN mostly depends on static graphs [13], and Transformer has high computational costs. Deep learning solves automatic feature extraction and spatiotemporal coupling problems, but still has shortcomings such as static graphs, high computational costs, and instability with small samples. Hybrid models combine different methods in an attempt to balance accuracy and robustness.

2.4 Hybrid Model Methods

A single model has inherent limitations when handling the complex temporal characteristics of traffic flow. Hybrid models combine different methods to complement one another. Their core logic is to decompose a traffic flow sequence into multiple parts, such as linear, nonlinear, and periodic components, model each part with an appropriate model, and then fuse the results. The combinations mainly fall into three categories: serial combination, parallel combination, and embedded combination.

The most common serial combination first uses ARIMA to capture the linear trend and periodic components of a sequence and then uses LSTM to model the nonlinear component in the residuals; the prediction results of the two parts are added together. Some studies also use the feature importance information of RF or GBDT to guide neural network input selection and reduce redundant computation in deep learning models through

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embedded combination. In addition, spatiotemporal hybrid models that combine GNN with Transformer use graph structures to encode spatial dependence and attention mechanisms to encode temporal dependence and have achieved good performance in large-scale road network traffic flow prediction.

Overall, under some experimental settings, hybrid models show higher accuracy or smaller error fluctuations than a single model. However, their advantages depend on the combination method, data conditions, and parameter tuning, and their complexity increases significantly. Their training and parameter tuning costs are high, and the collaborative design of components lacks unified theoretical guidance and mostly depends on empirical trial and error. Therefore, they are more suitable for scenarios with high prediction accuracy requirements and sufficient computational resources. Hybrid models attempt to account for multi-component features but do not fundamentally solve dynamic road network and multi-source data fusion problems, which directly motivates the subsequent introduction of dynamic spatiotemporal models and cross-source fusion methods.

3. Comparison and Discussion of Different Methods

3.1 Performance Comparison

The four types of methods have essential differences in theoretical foundations and temporal modeling ideas, and these differences are directly reflected in prediction performance. Because of their linear assumptions, statistical models can achieve acceptable accuracy during stable traffic flow periods, but their errors increase significantly during periods of drastic nonlinear changes, such as morning and evening peaks and sudden congestion. Machine learning methods break through linear limitations to some extent through kernel mapping and ensemble strategies, but their performance ceiling is restricted by the quality of manual feature engineering. Deep learning methods show accuracy advantages under some datasets and experimental conditions because of automatic feature extraction and deep nonlinear fitting capabilities. Hybrid models show accuracy improvements in some experiments through combination strategies, but the magnitude of improvement does not overwhelm a single deep model in all scenarios.

Representative models and differences among the methods are shown in Table 1.

Table 1: Comparison of Representative Models of Different Methods

Category	Representative Model	Main Advantages	Main Limitations	Data Requirement	Applicable Scenario
Statistical model	ARIMA, SARIMA	Mature theory, strong interpretability, and low computational overhead	Linear assumptions and difficulty handling nonlinear abrupt changes	Small	Stable traffic flow and limited data
Machine learning	SVR, RF, GBDT	Flexible nonlinear fitting and robust performance with small samples	Dependence on manual feature engineering and difficulty modeling road network spatial structure	Small to medium	Small- and medium-scale datasets with complete features
Deep learning	LSTM, GRU	Automatic temporal feature extraction and long-range dependence capture	Weak spatial structure modeling and poor interpretability	Large	Large-scale time series data and multi-step prediction
Deep learning	GNN, Transformer	Spatiotemporal coupling modeling and long-range	Mostly dependent on static graphs and high computational cost	Large	Road-network-level prediction and long-horizon prediction

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Category	Representative Model	Main Advantages	Main Limitations	Data Requirement	Applicable Scenario
		dependence capture			
Hybrid model	ARIMA-LSTM, GNN-Transformer	Accounts for linear and nonlinear features	High complexity and lack of a unified theory for component coordination	Medium to large	High accuracy requirements and sufficient computational resources

To further show differences at the level of specific studies, Table 2 lists the year, method, dataset, prediction target, prediction horizon, and main advantages and disadvantages of representative studies in recent years.

Table 2: Comparison of Representative Studies

Year	Representative Study	Method	Dataset	Prediction Target	Prediction Horizon	Main Advantages	Main Limitations
2003	Williams et al. [3]	SARIMA	Actual traffic flow data	Traffic flow	Short term	Solid theoretical foundation and clear periodic modeling	Linear assumptions and difficulty handling nonlinear abrupt changes
2004	Wu et al. [4]	SVR	Travel-time data	Travel time/traffic flow	Short term	Robust with small samples and nonlinear fitting	Depends on manual features
2005	Guo et al. [2]	ARIMA	Urban road data	Traffic flow	Short term	Simple computation and strong interpretability	Applicable only to stable periods
2015	Ma et al. [7]	LSTM	Microwave sensor data	Traffic speed	Multi-step	Long-range dependence modeling and automatic feature extraction	Weak spatial modeling and poor interpretability
2016	Fu et al. [8]	LSTM/GRU	Traffic flow data	Traffic flow	Short term	Fast GRU inference	Weak spatial modeling
2017	Zhang et al. [5]	Random forest	Expressway data	Traffic flow	Short term	Multi-feature processing and good generalization	Weak spatial structure modeling
2019	Wu et al. [11]	Graph WaveNet	METR-LA, PEMS-BAY	Traffic speed	Multi-step	Adaptive graph convolution and long-sequence modeling	Static graph and limited scalability
2020	Zheng et al. [12]	GMAN	Public road network dataset	Traffic flow	1 hour	Spatiotemporal attention and long-range modeling	High computational cost
2021	Cai et al. [9]	Traffic Transformer	Multiple public datasets	Traffic flow	Long horizon	Strong long-range dependence and good periodic modeling	High computational cost
2025	Chalkiadakis et al. [6]	GBDT	Crowdsourced travel-time data	Lane-level flow	Hourly	Good interpretability	Weak spatial modeling

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Year	Representative Study	Method	Dataset	Prediction Target	Prediction Horizon	Main Advantages	Main Limitations
						and high accuracy	
2025	Yuan et al. [14]	FME-GCN	SZ-taxi, PEMS04, PEMS08	Traffic flow	Short term	Multi-source data fusion and improved accuracy	Complex data alignment
2025	Zhang et al. [15]	Interpretable dynamic spatiotemporal graph convolution	Four real datasets	Traffic flow	Short term	Strong interpretability and dynamic graph	High complexity
2025	Zhang et al. [16]	Two-way heterogeneous dynamic graph convolution	Public datasets	Traffic flow	Short term	Robust in abnormal scenarios	Immature real-time sensing
2025	Cheng et al. [17]	Transfer-Mamba	Four traffic speed datasets	Traffic speed	Few-shot	Cross-city transfer and good few-shot performance	Risk of negative transfer
2026	Wang [10]	DASTGNN-Transformer	PeMSD4, PeMSD8	Traffic flow	Multi-step	Dynamic graph learning and high accuracy	Computationally complex

As shown comprehensively in Table 2, different methods have clear differences in four dimensions. In terms of prediction horizon, statistical and machine learning methods are mostly used for short-term prediction, whereas LSTM, Transformer, and GNN models are used more often for multi-step and long-horizon prediction; this trend is reflected in the existing literature [7, 9, 10]. In terms of data scale, small-sample-friendly methods such as statistical models and SVR are suitable for scenarios with limited data, whereas deep learning models usually require large-scale data to show their advantages. This judgment comes partly from the descriptions of experimental settings in the literature [4, 7] and partly from the summary in this paper based on method characteristics. In terms of spatiotemporal modeling capability, ARIMA and traditional machine learning methods do not have explicit spatial modeling capability, whereas GNN and Transformer models achieve spatiotemporal coupling modeling through graph convolution and attention mechanisms [11, 12]. In terms of computational cost, computational complexity generally increases from statistical models to deep learning and then to hybrid models, but the specific cost depends on model scale and road network size. This summary comes from the analysis of method limitations in the preceding sections.

3.2 Analysis of Applicable Scenarios

Method selection is highly dependent on the specific application scenario. There is no universally optimal model, and a comprehensive judgment must be made by combining temporal data characteristics with business requirements.

From the perspective of data conditions, when little historical data are available, small-sample-friendly methods such as statistical models and SVR are more practical, whereas deep learning has difficulty showing its advantages because of insufficient data. When data are sufficient and include multi-source information accumulated over a long period, deep learning and hybrid models are preferred. From the perspective of prediction timeliness, scenarios with high real-time requirements need models with fast inference. Because GRU has fewer parameters and high computational efficiency, it has deployment advantages over LSTM and Transformer in some scenarios with high real-time requirements. For scenarios that are not sensitive to timeliness, such as offline analysis or transportation planning decisions, complex hybrid models with higher accuracy can be given priority. From the perspective of interpretability requirements, transportation management departments often need to understand the basis of predictions when formulating policies. In this case, the transparent mechanisms of ARIMA and SVR are superior to the black-box characteristics of deep

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learning; in real-time guidance applications that only require prediction results, interpretability can be secondary to accuracy.

3.3 Main Gaps in Existing Research

Based on the preceding analysis and recent review studies, current research still has the following specific gaps.

First, dynamic road network modeling is insufficient. Most GNN models use static road network graphs and cannot reflect the dynamic changes in road capacity over time or with events. Wang proposed a dynamic adaptive attention graph learning method specifically to address the problem that fixed graph structures cannot adapt to dynamic traffic conditions [10]. This method achieved good accuracy on PeMSD4 and PeMSD8, but the computational cost and scalability of dynamic graph construction remain unresolved.

Second, multi-source heterogeneous data fusion is insufficient. Existing studies mostly depend on a single data source, and factors such as weather, emergencies, and large events have inconsistent temporal granularities [18]. The FME-GCN method proposed by Yuan et al. fuses multi-source heterogeneous external data, including weather, temperature, points of interest (POIs), holidays, and traffic peak and off-peak periods, and achieved a 1% to 8.1% improvement in prediction accuracy on the SZ-taxi, PEMS04, and PEMS08 datasets [14]. However, the temporal alignment mechanisms of different data sources have not been unified, and a general framework for cross-granularity fusion has yet to be established.

Third, abnormal event prediction is insufficient. Traffic flow shows strong nonlinear abrupt changes during abnormal periods such as accidents, severe weather, and holidays. Existing models are mostly trained for normal traffic flow, and their errors increase significantly in abnormal scenarios [16].

Fourth, small-sample generalization is insufficient. Deep models are difficult to train directly for newly built roads or road sections without long-term historical data accumulation. Cheng et al. proposed Transfer-Mamba, a cross-city spatiotemporal knowledge transfer framework that outperformed baseline models in few-shot prediction [17], but the generality of cross-city transfer and the risk of negative transfer still require further verification.

Fifth, interpretability is insufficient. Deep learning models have high accuracy, but their decision-making processes are opaque, making it difficult for traffic managers to trust and adopt their prediction results. The multi-scale adaptive interpretable dynamic spatiotemporal graph convolutional network proposed by Zhang et al. reduced the mean absolute error by approximately 16.65% compared with the best baseline on four real datasets and improved model interpretability by analyzing graph convolution node weight parameters [15]. However, existing interpretability methods mostly remain at the post hoc analysis level and lack an in-depth explanation of the causal mechanisms of prediction.

4. Challenges and Prospects

The preceding analysis shows that current research still has specific gaps, including insufficient dynamic road network modeling, difficulty in fusing multi-source heterogeneous data, insufficient abnormal event prediction, poor small-sample generalization, and insufficient model interpretability. To address these problems, future research can proceed in the following three core directions.

First, dynamic spatiotemporal modeling and multi-source data fusion should be jointly deepened. This direction addresses the insufficient dynamic road network modeling and multi-source heterogeneous data fusion identified above. The two are highly coupled in actual scenarios: dynamic changes in road network topology are often accompanied by changes in the temporal granularity of data sources. Existing studies mostly treat them as independent problems and lack a unified modeling framework. Future research can incorporate dynamic graph construction and cross-granularity data alignment into the same system, resolving the temporal alignment of multi-source heterogeneous data while modeling the dynamic evolution of spatial topology, thereby improving model adaptability in complex scenarios.

Second, robust prediction in abnormal scenarios should be studied. This direction addresses the insufficient abnormal event prediction identified above. Traffic flow shows strong nonlinear abrupt changes during abnormal periods such as accidents, severe weather, and holidays, whereas existing models are mostly trained

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for normal traffic flow. Their errors increase significantly in abnormal scenarios, and real-time sensing and online update mechanisms for abnormal events are not yet mature. Future research can study event-driven spatiotemporal time series modeling methods, introduce event information into models as exogenous variables, and design robust loss functions and online update mechanisms to improve prediction stability in abrupt-change scenarios.

Third, small-sample generalization and interpretability should be improved. This direction addresses the insufficient small-sample generalization and interpretability identified above. Deep models are difficult to train directly for newly built roads or road sections without long-term historical data accumulation, and the generality of cross-city transfer and the risk of negative transfer still need verification. At the same time, deep learning decision-making processes are opaque, and existing interpretability methods mostly remain at the post hoc analysis level. Future research can use transfer learning and meta-learning to improve the rapid adaptability of models in new scenarios and introduce explainable artificial intelligence techniques to reveal the basis of model prediction from both temporal and spatial dimensions, thereby improving model acceptance in traffic management decisions.

5. Conclusion

This paper systematically reviews urban traffic flow prediction methods based on time series analysis and discusses four categories: statistical models, machine learning, deep learning, and hybrid models. Focusing on temporal dependence modeling, it analyzes the basic principles of each type of method, their capability to process different temporal features, their advantages and disadvantages, and their applicable scenarios. Overall, the evolution of the four types of methods is not a simple replacement relationship but progresses gradually according to the logic of what problem has been solved, what shortcomings remain, and why further development is needed. Traditional statistical models solve linear and periodic problems, machine learning strengthens nonlinear fitting capability, deep learning further solves complex temporal dependence and spatiotemporal coupling problems, and hybrid models attempt to account for different feature components. This evolutionary process shows that the internal driving force of method iteration comes from specific gaps in the preceding type of method rather than from merely pursuing model complexity.

Method selection should comprehensively consider data conditions, timeliness requirements, and interpretability requirements, and there is no universal optimal solution. The issues that currently truly deserve attention have shifted from which model to choose to three more specific challenges: dynamic road network modeling, multi-source heterogeneous data fusion, and robust prediction in abnormal scenarios. Future research should continue to advance these three directions and promote the transition of time series traffic flow prediction from academic research to reliable engineering applications.

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Conflicts of Interest

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