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A Review of Traffic Flow Prediction Research from the Perspective of Physics-Informed Fusion — Based on Physics-Informed Graph Neural Networks

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Abstract. Among the principal functions of intelligent transportation systems, traffic flow prediction stands out as a critical one. Purely data-driven methods face the bottleneck of insufficient generalization capability in scenarios involving sparse data, noise interference, and anomalous events, while classical traffic flow theory is constrained by difficulties in parameter calibration and the oversimplification of model assumptions. The rise of physics-informed neural networks (PINNs) offers a new theoretical framework for the deep integration of these two types of methods. This paper systematically reviews the evolution of traffic prediction methods from traditional time series models to graph neural networks, thoroughly analyzes the theoretical foundations and numerical implementations of physics-based traffic flow models, and surveys the current research status of physics-informed neural networks in the transportation domain. On this basis, the paper identifies the limitations of existing research in terms of task coverage, model architecture, and analytical dimensions, and envisions future research directions from three perspectives: dynamic graph learning, embedding higher-order physical models, and the comparison of hard versus soft constraints. This study demonstrates that physical constraints, as inductive biases, can effectively narrow the hypothesis space of models, providing a methodological reference for interdisciplinary integration in traffic flow prediction.

Keywords: Traffic flow prediction, Graph neural networks, Physics-informed neural networks, LWR model, Spatiotemporal modeling, Deep learning

1. Introduction

Traffic flow prediction, as a fundamental research topic in intelligent transportation systems, has long attracted widespread attention from both academia and industry. The provision of decision support for traffic signal control, route planning, and congestion management, along with its role as a critical prerequisite for intelligent urban traffic management, are both enabled by accurate traffic flow prediction.

From the perspective of methodological evolution, traffic flow prediction research has undergone a paradigm shift from traditional statistical models to deep learning approaches. Although purely data-driven methods perform well when training data are abundant and traffic conditions are stable,

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their generalization ability and prediction stability often prove unsatisfactory in unconventional scenarios such as data sparsity, sensor failures, and sudden traffic incidents. The root cause of this problem lies in the fact that purely data-driven models lack an understanding of the intrinsic physical mechanisms governing traffic systems.

Complementary to data-driven methods is the macroscopic traffic flow theory represented by the LWR model. A strong theoretical underpinning and clear physical interpretation are offered by such models; nevertheless, their field applications are restricted by the difficulties associated with parameter calibration, the oversimplification of assumptions, and the adverse effects of noisy data. The introduction of physics-informed neural networks (PINNs) provides an elegant theoretical framework for bridging the gap between data-driven methods and physics-based models.

Since existing research predominantly focuses on either data-driven or traditional physics-based models in isolation and lacks a systematic review of the physics-data fusion paradigm, this paper aims to systematically survey the research progress in traffic flow prediction from data-driven approaches to physics-informed integration through a literature review. This paper is expected to provide a theoretical reference for the broader application of the physics-informed fusion paradigm in the field of traffic flow prediction.

2. Literature review

2.1. Limitations of traditional time series models

In the early stages of traffic prediction research, scholars primarily relied on traditional time series models such as ARIMA to describe the temporal evolution patterns of traffic flow. These methods are built upon the assumptions of stationarity and linearity, achieving short-term predictions through statistical modeling of historical observation data. However, real-world traffic flow systems exhibit highly nonlinear dynamic characteristics. Complex features such as abrupt changes in traffic flow, spatiotemporal coupling effects, and multi-scale evolutionary characteristics far exceed the representational capacity of linear models, rendering the prediction accuracy of traditional time series models insufficient to meet the demands of practical applications.

2.2. The rise of deep learning and its challenges

New technological routes for overcoming the aforementioned obstacles have been opened up by the ascent of deep learning approaches. Convolutional neural networks (CNNs), with their powerful spatial feature extraction capabilities, have been introduced into traffic prediction tasks to capture traffic patterns in the spatial dimension. Meanwhile, recurrent neural networks (RNNs) and their variants such as LSTM have been widely applied to process the temporal dependencies of traffic data, modeling the temporal evolution patterns of traffic flow. However, in practice, CNNs suffer from inherent deficiencies in handling road network structures in non-Euclidean space, making it difficult for them to adapt to the complex topological relationships of road networks RNN-based models, on the other hand, face challenges such as low training efficiency and difficulty in capturing long-term dependencies, limiting their application in long-term traffic prediction tasks [1].

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2.3. The evolution of graph neural network-driven traffic prediction

2.3.1. Paradigm breakthrough of graph convolutional networks

A significant turning point in the field of traffic prediction emerged with the introduction of graph convolutional networks (GCNs). The graph convolution operation developed by Kipf and Welling based on spectral graph theory provided the theoretical foundation and technical tools for processing graph-structured data such as traffic sensor networks [1]. Compared with traditional CNNs, GCNs are capable of aggregating and updating the features of each node in the graph while preserving the topological structure information of the road network, thereby enabling effective modeling of the spatial correlations within the road network [2].

2.3.2. Development of spatiotemporal graph neural networks

To further enhance the models' capability for joint learning of spatiotemporal features of traffic flow, researchers have proposed a series of spatiotemporal graph neural network models by integrating temporal modeling techniques on the basis of GCNs. Yu et al. further proposed the spatiotemporal graph convolutional network (STGCN), which is a landmark work that introduced graph convolution into traffic prediction [2]. By alternately stacking graph convolutional layers and one-dimensional temporal convolutional layers, this model achieved efficient joint learning of spatiotemporal features within a unified framework for the first time. The attention-based spatiotemporal graph convolutional network (ASTGCN) was developed by Guo et al. This model features a spatiotemporal attention mechanism designed to dynamically learn the relative importance of distinct time intervals and spatial locations [3]..

Li et al. proposed the diffusion convolutional recurrent neural network (DCRNN), which, inspired by the physical process of traffic flow propagation, employs diffusion convolution operations to simulate the bidirectional propagation characteristics of traffic information in road networks [4, 5]. Wu et al. proposed Graph WaveNet, which introduced an adaptive adjacency matrix learning mechanism to overcome the reliance of traditional methods on predefined graph structures [6, 7]. These works collectively constitute an important theoretical foundation for current data-driven graph neural network traffic prediction methods.

3. The physical core of traffic flow systems

3.1. The LWR model and macroscopic traffic flow theory

Understanding the physical essence of traffic flow systems is an essential prerequisite for constructing reliable prediction models [4]. The LWR model proposed by Lighthill, Whitham, and Richards is the foundational work of macroscopic traffic flow theory [8]. Drawing on the continuity equation of fluid mechanics, this model describes the conservation relationship among traffic flow, density, and speed in the form of partial differential equations.

This model implies, from a physical standpoint, that for any road segment without source or sink effects, the variation in the number of vehicles over time is simply the incoming flow minus the outgoing flow. The LWR model also introduces the concept of the fundamental diagram, assuming that traffic flow speed is a deterministic function of density, thereby closing the continuity equation as a single partial differential equation in terms of density [8].

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The LWR model effectively explains core traffic characteristics, including traffic wave propagation and shock wave generation and evolution, providing solid theoretical guidance for analyzing traffic dynamic evolutionary behaviors. However, as a first-order model, the LWR model only considers the conservation property of traffic flow. It cannot describe the acceleration and deceleration processes of vehicles. In response to this limitation, follow-up studies developed extended traffic flow models of a higher order, with the Payne-Whitham and ARZ formulations being notable representatives.

3.2. Numerical implementation and application challenges of physics-based models

Macroscopic traffic flow theories such as the LWR model are presented in the form of continuous partial differential equations, which are difficult to directly apply to discretized traffic data computation. To address this, Daganzo proposed the cell transmission model (CTM) [9]. The CTM discretizes the road into a number of cells and, by defining flow transmission rules between cells, transforms the partial differential equations of the LWR model into iteratively solvable difference equations. This model establishes a rigorous linkage between continuous physical traffic theory and discrete numerical computation.

Although the CTM addresses the numerical implementation problem of physics-based models, purely physics-based models face numerous challenges in practical applications. First, model parameter calibration requires high-quality measured data, yet data deficiency and noise interference are relatively common in real-world scenarios. Second, because the models provide a simplified description of complex traffic phenomena, they struggle to adapt to the dynamic changes in actual road networks. Moreover, physics-based models are relatively sensitive to data noise, and minor deviations in observed data may lead to considerable errors in the model output. These limitations have prompted researchers to contemplate pathways for integrating physics-based models with data-driven methods [9].

4. Physics-informed machine learning and its integration with transportation

4.1. The physics-informed neural network framework

The physics-informed neural network (PINN) framework proposed by Raissi et al. provides a systematic theoretical paradigm for integrating data-driven methods with physics-based models [4]. The core idea of PINNs is to incorporate the partial differential equations describing physical systems as regularization constraints into the loss function of neural networks. This approach enables the model to rigorously adhere to physical laws while fitting observed data, thereby enhancing the generalization capability and interpretability of the model.

Karniadakis et al. pointed out that the core advantage of physics-informed machine learning lies in transforming domain knowledge into effective inductive biases [6]. Such inductive biases can narrow the solution space of the model, guiding it to learn physically reasonable solutions even when training data are limited or noisy. This idea has already demonstrated significant application value in fields such as computational fluid dynamics [10].

4.2. Physics-informed fusion research in the transportation domain

With the continuous refinement of the PINN framework, researchers have progressively applied it to the field of traffic flow prediction, conducting a series of studies on physics-informed fusion

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modeling. To estimate traffic states and learn fundamental diagrams, Shi et al. incorporated the second-order ARZ model into a deep learning framework [11].. This experiment systematically verified, for the first time, the feasibility of combining higher-order traffic flow equations with deep learning frameworks. Huang et al. constructed a physics-informed graph neural network, integrating the conservation law of the LWR model with GNNs in the form of soft constraints, achieving dual improvements in accuracy and robustness for traffic flow estimation tasks [12]. Li et al. explored physics-integrated machine learning methods for vehicle trajectory prediction in autonomous driving scenarios [13].

4.3. Limitations

Existing research on integrating physics-informed and data-driven approaches in transportation has formed a preliminary research trajectory, yet three significant limitations remain. First, at the task level, existing work mostly focuses on traffic state estimation scenarios. Research on short-term prediction tasks lacks sufficient depth, with no systematic evaluation framework for short-term multi-step prediction tasks. There exist fundamental differences between state estimation and prediction in terms of problem formulation: the former emphasizes the reconstruction of the current state, while the latter requires the extrapolation of future states. Second, the depth of model integration is insufficient. Most works only validate the effectiveness of physical constraints on simple networks, while research on combining them with modern complex graph neural network architectures, such as ASTGCN and Graph WaveNet, remains inadequate. Third, theoretical analysis is weak. There is a relative lack of theoretical explanation regarding why and when physical constraints are effective, particularly systematic analyses concerning the improvement of generalization ability and robustness in anomalous scenarios.

4.4. Future directions

Future research on physics-informed fusion for traffic flow prediction can focus on three key directions. The first is the integration of dynamic graph neural networks with physical constraints. Since existing works mostly adopt a static graph assumption, they struggle to capture the dynamic changes in road network topology caused by factors such as road construction and traffic control. It is necessary to further introduce time-varying graph structure learning mechanisms, enabling the model to adaptively adjust the graph structure according to real-time changes in traffic conditions. Second, there is a need to further strengthen the integration of higher-order physical models and multi-physics fusion. Higher-order models that include velocity dynamics equations, such as the ARZ model, should be introduced into the constraint framework, and researchers should explore cross-domain fusion between traffic flow characteristics and physical information derived from multi-source data including meteorological records and POIs.

Finally, a paradigm comparison between hard constraints and soft constraints should be conducted. Soft constraints allow the model to deviate from physical equations to a certain extent, whereas hard constraint methods provide stronger physical guarantees. A systematic comparison of the advantages and disadvantages of these two strategies under different scenarios can provide guidance for method selection. Integrating prediction models with downstream tasks such as adaptive signal control and dynamic route guidance to construct a closed-loop system that combines prediction and control constitutes a critical pathway for promoting the practical deployment of these technologies.

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5. Conclusion

This paper presents a systematic literature review centered on the research theme of traffic flow prediction from data-driven approaches to physics-informed fusion. The study comprehensively examines the development trajectory of the traffic flow prediction field from three dimensions: the evolution of data-driven methods from traditional time series models to graph neural networks, macroscopic traffic flow theory represented by the LWR model and its numerical implementation methods, and the preliminary exploration and application of physics-informed neural networks in the transportation domain. The study highlights the physics-informed neural network framework. It argues that this framework serves as a viable theoretical approach that effectively connects data-driven methods with their physics-based counterparts. By embedding the conservation law of traffic flow into graph neural networks as soft constraints, the model is able to honor physical laws and, at the same time, fit the observational data. The essential role of physical constraints is to serve as inductive biases that restrict the hypothesis space of the model, guiding it to preferentially select solutions that conform to physical laws. Although existing research has made preliminary progress, notable deficiencies still exist in task coverage breadth, model integration depth, and theoretical systematicity. Directions such as dynamic graph learning, embedding higher-order physical models, and the comparison of hard versus soft constraints harbor abundant research opportunities.

This study is limited by its reliance on existing literature and secondary data, lacking empirical analysis of the deep integration of physical constraints with mainstream spatiotemporal graph networks, as well as quantitative evaluation of the adaptability of physical constraints under different scenarios. Future work can further supplement multi-scenario empirical data to improve the empirical validity of relevant research.

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