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Review

Graph Neural Network for Traffic Forecasting: The Research Progress

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Abstract: Traffic forecasting has been regarded as the basis for many intelligent transportation system (ITS) applications, including but not limited to trip planning, road traffic control, and vehicle routing. Various forecasting methods have been proposed in the literature, including statistical models, shallow machine learning models, and deep learning models. Recently, graph neural networks (GNNs) have emerged as state-of-the-art traffic forecasting solutions because they are well suited for traffic systems with graph structures. This survey aims to introduce the research progress on graph neural networks for traffic forecasting and the research trends observed from the most recent studies. Furthermore, this survey summarizes the latest open-source datasets and code resources for sharing with the research community. Finally, research challenges and opportunities are proposed to inspire follow-up research.

Keywords: traffic forecasting; graph neural network; graph convolutional network; graph attention network

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1. Introduction

Traffic forecasting is the foundation of modern transportation infrastructures and intelligent transportation systems (ITSs). It has a wide range of applications in trip planning, road traffic control, and vehicle routing [1–6]. Traffic forecasting has drawn a great amount of attention from both academia and industry in recent decades [7–14]. However, the traffic forecasting problem has not been fully resolved due to the complex spatiotemporal dependencies of traffic activities. Furthermore, developments in the Internet of things (IoT), the Internet of vehicles (IoV) and artificial intelligence (AI) techniques [15] have helped to measure and model more diverse traffic-related characteristics, allowing the design of autonomous and efficient data-driven traffic forecasting methods [16–18]. To gain a comprehensive understanding of the opportunities and challenges in traffic forecasting, we summarize here the recent research progress in this vibrant field to facilitate future research.

Depending on the data format used, traffic forecasting problems can be classified into different types, including time series data, grid data, and graph data. Among them, the earliest and most common problem formulation is time series forecasting, where historical data points are used as model input to predict future conditions [19–21]. Furthermore, time series forecasting problems can be divided into univariate problems and multivariate problems. For univariate time series problems, only one traffic variable is considered, such as traffic flow or traffic speed. For multivariate time series problems, multiple traffic variables are considered simultaneously. In addition to univariate and multivariate settings, time series forecasting can also be formulated as single-step forecasting and multiple-step forecasting. In single-step forecasting problems, only one data point needs to be predicted in the next step. In multiple-step forecasting problems, there is more than one value to predict.

Some typical time series forecasting models include simple linear regression, autoregressive integrated moving average (ARIMA), and seasonal autoregressive integrated moving average (SARIMA). SARIMA outperforms ARIMA because it captures seasonal patterns. In the transportation domain, both daily and weekly patterns are observed and useful for forecasting. SARIMA was further improved using the Kalman filter in [19], and the improved model outperformed other time series models. Empirical mode decomposition (EMD) is often used together with time series models, where the time series is first decomposed into different components and each component is then modeled with a time series model. This combination has been shown to be effective for traffic forecasting [21].

Although time series data are the most commonly used data format in traffic-related studies, they are insufficient because they do not consider the spatial dependence of traffic activities. To overcome this problem, two data formats, grid data and graph data, are further used. For traffic forecasting with grid data, at each time step, the traffic data are aggregated by some regularly divided regions in the studied urban area. Each regularly divided region can be regarded as a grid. By aggregating the corresponding traffic variables in each grid, we obtain an intensity map that can be displayed in an image format, as shown in Figure 1. In single-step traffic forecasting problems with the grid-data format, the historical grid data in a predefined lookback window are formulated as image frames and used as the input feature. The frame in the next time step is used as the prediction target.

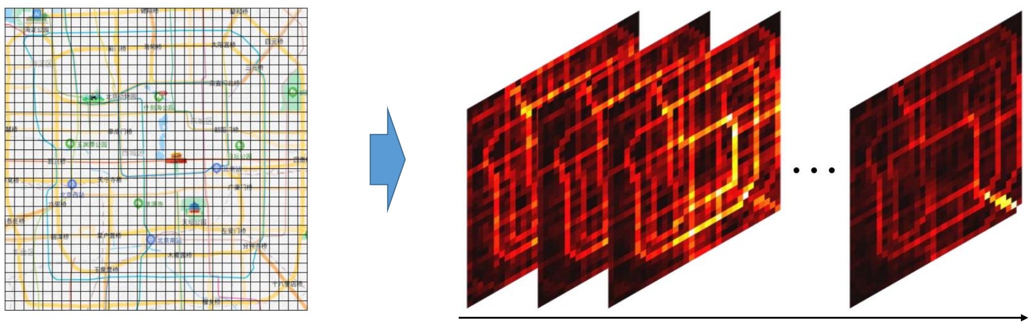

Figure 1. The grid-format traffic forecasting problem [22,23].

For traffic forecasting problems in graph format, traffic data are aggregated by specific locations or stations, which are regarded as nodes in a traffic graph. Node features are collected traffic variables such as traffic flow or speed. Edges can model road topological connections or spatial distances between different nodes. In single-step traffic forecasting problems with the graph format, the historical graph data in a predefined lookback window are used as the input feature. The graph in the next time step is used as the prediction target, as shown in Figure 2.

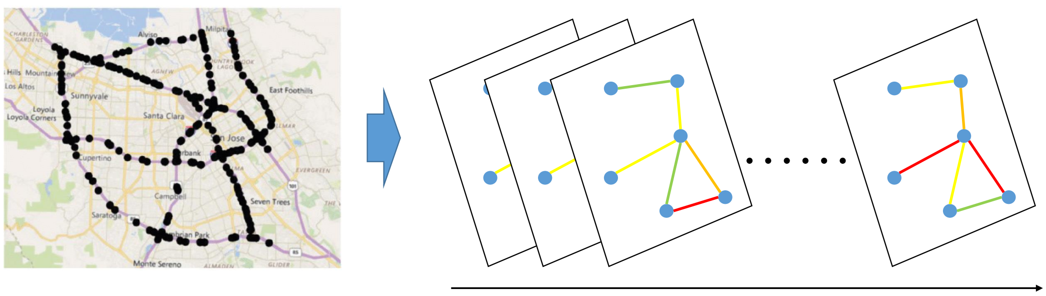

Figure 2. The graph-format traffic forecasting problem [24,25].

Existing traffic forecasting methods can also be divided into different categories according to the models used, including statistical models, shallow machine learning models, and deep learning models. Each has its own scope of applicable scenarios and can be adapted to different situations [26]. Statistical models are mainly linear models such as ARIMA and SARIMA. These models are advantageous due to their low computational cost and good interpretability. However, their predictive performance is inferior to that of machine learning and deep learning models, which are better at capturing nonlinear relationships. Shallow machine learning models are represented by tree-based models such as decision trees and random forests [27]. They were the first choice for early research until recently with the adoption of more intelligent and accurate deep learning models represented by modern neural networks such as convolutional neural networks (CNNs) [28] and recurrent neural networks (RNNs) [29].

These deep learning models have been proven effective for a variety of forecasting problems in the finance, energy and communications sectors [30–40]. Among various deep learning models, graph neural networks (GNNs) have become state-of-the-art solutions to various forecasting problems. In the financial field, a comprehensive survey of deep learning models for stock market forecasting showed that emerging GNN models received the most attention [30]. In the economic field, deep learning models have been proven effective for retail forecasting [37] and market demand forecasting [39], which are the basis of supply chain management. In the energy field, it has also been confirmed that deep learning models are becoming the main solution [31,33,34]. It is worth mentioning that external factors such as temperature and weather information have a great impact on the forecasting performance [32,38]. This observation is insightful for traffic forecasting problems, as transportation systems are also highly influenced by weather information, e.g., road traffic decreases during bad weather. For communication networks, various deep learning models have been proven to be more effective than statistical and machine learning models, such as the InceptionTime model adopted in [35] based on the time series data format and the convolutional LSTM model adopted in [36] based on the grid-data format. It is also observed that GNNs are gaining popularity in cellular traffic prediction [40]. GNNs utilize graph structures, which are common in transportation infrastructure, such as road networks and subway systems. GNNs can effectively capture interactions between nearby traffic sensors or stations, thereby improving prediction performance.

The research topic of this survey focuses on GNN-based solutions, and there are still many recent publications introducing CNN-based or decision-tree-based solutions [28,41–43]. As discussed in previous relevant studies [44,45], compared to CNN-based or decision-tree-based solutions, GNN-based solutions have a wide range of applicable scenarios and achieve state-of-the-art performance. GNN-based solutions can be applied when there is a natural graph structure (such as a road network) or when an artificial graph can be constructed (such as a neighborhood graph in grid data). However, GNN-based solutions are inapplicable when the above graphs are not available, e.g., traffic data collected in a single loop detector only. GNNs are mainly used to forecast speeds and volumes in urban networks and freeways. However, prediction in urban networks is far more challenging than that in freeways because of complex spatiotemporal traffic patterns caused by various reasons, such as complex road structures, different vehicle types, and time-varying user demands.

Although there have been some surveys of deep learning for traffic forecasting problems, most of them are not GNN-focused, with only a few exceptions [46–53]. This study serves as an extension of existing GNN-relevant surveys [44,45], summarizes the latest research progress in 2022, and aims to be the latest reference manual for researchers in related fields. In this survey, a total of 118 journal papers and 30 conference papers published in 2022 are reviewed, all of which are selected from prestigious journals and conferences in transportation, computer science, and multidisciplinary fields. Each paper is reviewed in a structured manner and lessons learned are discussed to reveal research trends. Based on the surveyed studies, the latest open datasets and code resources are also collected and organized in lists. Existing research challenges are identified, and corresponding research opportunities are further suggested.

The contributions of this survey are summarized as follows:

- This survey summarizes the latest studies on the topic of traffic forecasting with graph neural networks.
- This survey provides the research community with up-to-date lists of open datasets and code resources.
- This survey identifies existing research challenges and suggests corresponding research opportunities to inspire follow-up research.

The remainder of this paper is organized as follows. Section 2 is a literature review of the latest relevant studies and a discussion of recent research trends. Then, the latest lists of open datasets and code resources for the research community are presented in Section 3. Section 4 discusses research challenges and opportunities when applying graph neural networks for traffic forecasting to inspire follow-up research. The conclusion is drawn in Section 5.

2. Literature Review and Research Trends

The studies covered in this survey were all selected from prestigious journals and conferences in transportation, computer science, and multidisciplinary fields. To share incremental knowledge and avoid repetition with existing similar surveys [44,45], this section only selected those published in 2022 for discussion, with a total of 118 journal papers and 30 conference papers. Source journals and conferences are listed in Tables A2 and A3, with the number of papers counted. The reviewed studies are summarized in Table 1. For each study, the specific traffic problem, graph type, dataset, model component (especially the GNN structures involved) and a summary of the main content are discussed. More relevant studies are tracked and updated in our GitHub repository (https://github.com/jwwthu/GNN4Traffic, accessed on 2 February 2023).

As discussed in the introduction, Section 1, we categorized traffic forecasting problems from two perspectives, namely, based on the data format or based on the model used. Furthermore, in Table 1, we provided another perspective based on transportation modes, such as road traffic, taxis, bikes, and subways. As shown in Table 1, we found that the road traffic flow and speed prediction problem was still the most popular traffic prediction problem in different traffic-related studies. There are two possible reasons for this trend. The first reason is that for the road traffic forecasting problem, open datasets and baseline models are more accessible with well-processed steps and instructions, which saves the workload of data collection and preprocessing. The second reason is that building graphs for road-network-related problems is more intuitive, making it more natural to use GNNs to solve road traffic flow and speed prediction problems, and thus more common in the scope of our investigation.

As shown in Table 1, there are two types of graphs listed in the graph column, static graphs and dynamic graphs. In the early research stages, static graphs were widely used because of their convenience. However, researchers realized that static graphs were insufficient to capture changes in network topology and traffic patterns. For example, traffic flow measurements and their correlations on road segments change dynamically in space and time, which is beyond the modeling capabilities of static graphs. Then, dynamic graphs were introduced. As the name implies, a dynamic graph is a graph that can evolve as new nodes or edges are added or removed. However, static graphs are still very useful when the traffic infrastructure remains unchanged for the time period considered. Therefore, some researchers use both dynamic and static graphs. The static graph is used to model the static road network, and the dynamic graph is used to consider the impact of dynamic traffic events and weather information.

Most of the collected datasets used in the surveyed studies are open datasets with only a few exceptions. Among those open datasets, some have made great contributions to support relevant studies, which can fairly evaluate and compare different models, e.g., PeMS-BAY and METR-LA. However, it also poses problems when existing datasets are overutilized and overfitted to GNN-based deep learning models and produce unreliable models for other traffic scenarios and datasets. To address this potential risk, new datasets were collected and are listed in Section 3 for further evaluation. Additionally, most of the surveyed studies used two or more datasets, a phenomenon worthy of further study.

For the model component part, the graph convolutional network (GCN) [54] and graph attention network (GAT) [55] are the two dominant networks used. It is difficult to go through all the GNN model details in the surveyed papers listed in Table 1. Interested readers are advised to read the original text of the surveyed papers.

A GCN is a pioneer in transferring the concept of convolution operations from Euclidean image data to non-Euclidean image data and has achieved great success in the past few years. The basic idea of a GCN is to aggregate the features from neighbors and then apply a linear transformation on the aggregated features. GCN layers can be stacked k times to capture k-hop neighbor information. However, a GCN requires the entire graph structure for training, which consumes a considerable amount of computer memory. In that case, GAT, based on the attention mechanism [56], was introduced as an alternative to GCN. The main difference between GAT and GCN is the introduction of importance scores for different neighbors based on the masked self-attention mechanism. Technical details about GCN and GAT are beyond the scope of this survey, which aims to identify research trends, and can be found in relevant surveys [57,58]. Designing more effective GCN or GAT variants is still a major research direction. Fundamental theoretical breakthroughs in the GNN research community will also help in the development of new traffic forecasting methods.

Both GCN and GAT are mainly used to capture spatial dependencies. To capture temporal dependencies, there are some classic models, e.g., temporal convolutional network (TCN), long short-term memory (LSTM), and gated recurrent unit (GRU). More recently, an attention-based model, i.e., the Transformer, has proven effective for capturing long-term dependency in time series [59]. Nevertheless, as indicated in Table 1, Transformer has only been used in a few surveyed studies, and there is still much room for research.

Table 1. Summary of the surveyed studies.

Study	Problem	Graph	Dataset	Model Component	Summary
[60]	Road traffic flow, road traffic speed	Dynamic graph	PeMS03, PeMS04, PeMS07, PeMS08, PeMS-BAY, METR-LA	GCN, TCN	Dual dynamic spatial–temporal graph convolution network (DDSTGCN) is featured with a dual graph structure of traffic flow graph and its dual hypergraph to reveal more complicated latent relations.
[61]	Road traffic flow	Dynamic graph, static graph	PeMS04, PeMS08	TCN, GCN	Spatiotemporal adaptive graph convolutional network (STAGCN) is featured with an adaptive graph generation block to capture both the learnable long-time static road graph and the learnable short-time dynamic graph.
[62]	Road traffic speed, regional bike flow	Dynamic graph	PeMS-BAY, METR-LA, BikeNYC	GAT, TCN	JointGraph is featured with a network reconstructor to reconstruct the traffic graph and the ability to handle a multidataset joint training task.
[63]	Metro traffic flow	Dynamic graph, static graph	BJMF15	GCN, TCN	Knowledge graph representation learning and spatiotemporal graph neural network (KGR-STGNN) is featured which better captures the influence of external factors.
[64]	Regional traffic flow	Static graph	HaikouTaxi, Chengdu-Taxi	GCN, TCN	Multiattribute graph convolutional network (MAGCN) is featured with the consideration for area attributes and a novel matrix whose values are the functional area-based origin–destination pairs.
[65]	Ride-hailing demand	Static graph	Ride-hailing datasets in Beijing and Shanghai	GCN	The proposed multilinear relationship GCN is characterized by multimodal coordinated representation learning and spatial feature extraction from different modalities.
[66]	Road traffic flow	Static graph	PeMS08, METR-LA	GCN, LSTM	A multiview Bayesian spatiotemporal graph neural network (MVB-STNet) is featured with a Bayesian neural network layer for handling data uncertainty with sparse and noisy data.
[67]	Road traffic flow	Static graph	PeMSD4, PeMSD7, PeMSD8	GraphSAGE, GRU	A transferable federated inductive spatial–temporal graph neural network (T-ISTGNN) is featured with the capability of cross-area traffic state forecasting when preserving the privacy of source areas.
[68]	Regional taxi usage	Static graph	TaxiNYC	GAT, GRU	A spatiotemporal heterogeneous graph attention network (STHAN) is featured with a spatiotemporal heterogeneous graph in which multiple spatial relationships and temporal relationships are modeled and metapaths are used to depict compound spatial relationships.
[69]	Road traffic flow	Dynamic graph, static graph	METR-LA, PEMS-BAY	GCN, GRU	A spatiotemporal prediction framework using high-order graph convolutional network (STHGCN) is featured with a dynamic adaptive spatial graph learning module to learn the high-order dependence.

Table 1. *Cont.*

Study	Problem	Graph	Dataset	Model Component	Summary
[70]	Road traffic flow	Dynamic graph	PeMS04, PeMS08	GCN	The proposed CTVI+ framework uses a temporal self-attention mechanism and a multiview graph neural network for learning temporal and spatial traffic patterns.
[71]	Origin–destination demand	Dynamic graph	TaxiNYC, BikeNYC, BikeDC	GAT, LSTM	A temporal graph autoencoder (TGAE) is featured with a temporal network embedding framework that utilizes node representations in latent space to capture the temporal evolution of traffic networks.
[72]	Regional ride-hailing demand	Dynamic graph	UberNYC, TaxiNYC	GAT, 1D-CNN, Transformer	A deep multiview spatiotemporal virtual graph neural network (DMVST-VGNN) is featured with an integrated structure of GAT, 1D-CNN, and Transformer networks.
[73]	Road traffic flow	Static graph	Private data	GCN, LSTM, GAN	A graph convolution and generative adversarial neural network [73] is featured with a GAN structure and parallel prediction ability for multiple steps.
[74]	Road traffic flow, road traffic speed	Dynamic graph	PeMS-Bay	GAT, GCN	A hierarchical mapping and interactive attention network (HMIAN) is featured with a hierarchical mapping structure for capturing functional zone relevance and long-distance dependence.
[75]	Road traffic flow	Static graph	PeMSD3, PeMSD4, PeMSD7, PeMSD8	GCN	The proposed forecasting framework uses an outlier detection strategy for a real-world IoV environment.
[76]	Metro passenger flow	Static graph	CDmetro2018	GCN, GRU	A spatial–temporal multigraph convolutional wavelet network (ST-MGCWN) is featured with a graph wavelet convolution with multigraph fusion.
[77]	Road traffic flow	Static graph	PeMSD4, PeMSD8	GCN, ConvLSTM	A multidimensional attention-based spatial–temporal network (MA-STN) is featured with a multidimensional attention mechanism to capture spatial and temporal patterns.
[78]	Road traffic speed	Static graph	METR-LA, PeMS-BAY	GCN, TCN	The proposed approach features a multimode spatial–temporal convolution of a mixed hop diffuse ordinary differential equation (MHODE).
[79]	Road traffic flow	Static graph	PeMSD4, PeMSD8	GCN	The proposed approach features a gated attention graph convolution model with multiple spatiotemporal channels.
[80]	Road traffic speed	Static graph	PeMS-BAY, METR-LA	GCN, GRU	The proposed approach features a combination of time classification and GCN models.
[81]	Road traffic flow, bike demand, taxi demand	Dynamic graph, static graph	PeMSD3, PeMSD4, PeMSD7, PeMSD8, BikeNYC, TaxiNYC	GCN, GRU	A dual graph gated recurrent neural network (DG^{2}RNN) is featured with a bidirectional GRU layer for learning temporal dependency and a spatial attention mechanism for learning spatial dependency.

Table 1. *Cont.*

Study	Problem	Graph	Dataset	Model Component	Summary
[82]	Road traffic flow	Static graph	Minnesota Department of Transportation Traffic Data	GCN, GRU	The proposed approach features an attribute feature unit to fuse external factors into a spatiotemporal GCN.
[83]	Road traffic speed	Dynamic graph	Seattle-Loop, METR-LA	GCN, GRU	A self-attention graph convolutional network with spatial, subspatial, and temporal blocks (SAGCN-SST) captures the dynamic spatial dependency with a self-attention mechanism and is robust against traffic congestion and accidents.
[84]	Taxi demand, bike demand	Dynamic graph	TaxiNYC, BikeNYC	DCNN, Transformer	A dynamical spatial–temporal graph neural network (DSTGNN) is featured with an inhomogeneous Poisson process to model the changing demand process and the spatial–temporal embedding network to infer the intensity.
[85]	Ride-hailing demand	Dynamic graph	TaxiNYC	GCN, GRU	A dynamic multigraph convolutional network with generative adversarial network (DMGC-GAN) is featured with a multigraph GCN module to learn from different dynamic OD graphs and a GAN structure to overcome the demand sparsity problem.
[86]	Road traffic speed	Static graph	Private data	GCN, GRU	The proposed approach features a GAN structure for robust data-driven traffic modeling.
[87]	Road traffic flow, road traffic speed	Static graph	Seattle-Loop, PeMS-BAY	GAT, GAN	The proposed GAT-GAN framework features a combination of first-order and high-order neighbors.
[88]	Road traffic flow	Dynamic graph	PeMSD4, PeMSD8	GCN, CNN	A graph and attentive multipath convolutional network (GAMCN) is featured with a novel GCN variant with road-network graph embedding and a multipath CNN module.
[89]	Road traffic accident	Dynamic graph	NYC Open Data, PeMS-Bay	GCN	A multiattention dynamic graph convolution network (MADGCN) is featured with multiple attention mechanisms for capturing spatial and temporal influences.
[90]	Road traffic flow	Static graph	Private data	GCN, GAT	The proposed approach leverages DRL to integrate and improve GCN and GAT results.
[91]	Road traffic flow	Static graph	PeMS (with 97 detectors)	GCN	The proposed approach features the combination of a GCN and six complex network properties.
[92]	Road traffic flow	Dynamic graph	PeMSD7, PeMSD11	GCN	The proposed approach features a GCN-based data imputation module and an adaptive approach of leveraging DRL for the dynamic graph's adjacency-matrix generation.
[93]	Road traffic flow	Dynamic graph	PeMSD4, PeMSD8	GCN	The proposed CRFAST-GCN features a conditional random field (CRF)-enhanced GCN to capture the semantic similarity globally.
[94]	Road traffic speed	Dynamic graph	PeMSD8, METR-LA	TCN, GCN	A universal framework is proposed to transform the existing one-step-ahead models to multistep-ahead models.
[95]	Road traffic speed	Static graph	METR-LA, PEMS-BAY	GNN	The proposed approach features a novel GNN layer with a location attention mechanism to aggregate traffic flow information from adjacent roads.

Table 1. *Cont.*

Study	Problem	Graph	Dataset	Model Component	Summary
[96]	Road traffic speed	Dynamic graph	METR-LA, PEMS-BAY	DCNN, TCN	Spatiotemporal sequence-to-sequence network (STSSN) is featured with an encoder-decoder structure with the joint modeling ability of spatial and temporal correlations.
[97]	Road traffic flow	Dynamic graph	PeMS, private data	GNN, LSTM	An attentive attributed recurrent graph neural network (AARGNN) is featured with the modeling of both static and dynamic factors.
[98]	Road traffic flow	Static graph	PeMSD4, PeMSD8	GCN	An adaptive graph learning algorithm (AdapGL) is proposed to learn the complex dependencies, and the model parameters are optimized with the expectation maximization algorithm.
[99]	Bike demand, taxi demand	Static graph	BikeNYC, TaxiNYC	GAT	A comodal graph attention network (CMGAT) is featured with a multiple-traffic-graph-based spatial attention mechanism and a multiple-time-period-based temporal attention mechanism.
[100]	Road traffic speed	Dynamic graph	METR-LA, PEMS-BAY	GCN, TCN	An adaptive spatiotemporal graph neural network (Ada-STNet) is featured with a dedicated spatiotemporal convolution architecture and a two-stage training strategy.
[101]	Road traffic speed	Static graph	PeMSD7, METR-LA, Seattle-Loop	GCN, Transformer	An attention-based graph convolution network and Transformer (AGCN-T) is featured with the combination of a GCN and temporal Transformer modules.
[102]	Road traffic speed	Dynamic graph	PeMSD4, PeMSD8	GCN, ConvGRU	An attention encoder–decoder dual graph convolution model with time-series correlation (AED-DGCN-TSC) is featured with the combination of a time series correlation analysis and deep learning modules.
[103]	Road traffic flow	Dynamic graph	PeMSD3, PeMSD4, PeMSD7, PeMSD8	GCN	An improved dynamic Chebyshev GCN is proposed with a novel Laplacian matrix update method, the attention mechanism, and a novel feature construction method.
[104]	Road traffic flow	Static graph	PeMSD4, PeMSD8	GCN, GLU	A causal gated low-pass graph convolution neural network (CGLGCN) is featured with a causal convolution gated linear unit with less computation time and a GCN with a self-designed low-pass filter.
[105]	Road traffic flow	Dynamic graph	PeMSD4, PeMSD8	GAT	An attention-based spatiotemporal graph attention network (ASTGAT) is featured with multiple residual convolution and a high–low feature concatenation.
[106]	Road traffic speed	Dynamic graph	METR-LA, PeMS-BAY, PeMS-S	GCN	An attention-based dynamic spatial–temporal graph convolutional network (ADST-GCN) is featured with the combination of a dynamic adjustment module, a gated dilated convolution module, and a spatial convolution module.
[107]	Road traffic flow	Static graph	PeMS-LA, PeMS-BAY	GCN	An attention-based spatiotemporal graph convolutional network considering external factors (ABSTGCN-EF) is featured with the combination of a GCN and attention encoder network modules and the consideration of external factors.

Table 1. *Cont.*

Study	Problem	Graph	Dataset	Model Component	Summary
[108]	Road traffic flow	Static graph	PeMSD4, PeMSD8	GCN, LSTM	An augmented multicomponent recurrent graph convolutional network (AM-RGCN) is featured with an LSTM-based temporal correlation learner that incorporates a one-dimensional convolution.
[109]	Road traffic speed	Static graph	TaxiSZ	GCN, GRU	A bidirectional-graph recurrent convolutional network (Bi-GRCN) is featured with the combination of a GCN and a bidirectional GRU.
[110]	Road traffic flow	Static graph	Private data	GraphSAGE, LSTM	The proposed approach features the combination of GraphSAGE, a global temporal block, and the self-attention mechanism.
[111]	Regional traffic flow	Static graph	Private data	GCN, CNN	The proposed ConvGCN-RF features a preprocessing-encoder–decoder framework and the combination of CNN, GCN, and random forest modules.
[112]	Bus demand	Static graph	Private data	GCN, LSTM	The proposed approach features the combination of a time-dependent geographically weighted regression and graph deep learning and the consideration of dynamic-built-environment influences.
[113]	Regional crowd flow	Static graph	TaxiNYC, BikeNYC	GAT, CNN, LSTM	The proposed approach features a semantic GAT module for learning dynamic inter-region correlations.
[114]	Road traffic speed	Static graph	A new open data of Seoul, South Korea	GCN	A distance, direction, and positional relationship graph convolutional network (DDP-GCN) is featured with the consideration of three spatial dependencies.
[115]	Road traffic flow	Static graph	PeMSD3, PeMSD7, private data	DGGP	The proposed approach features novel deep graph Gaussian processes (DGGPs), which consist of the aggregation of a Gaussian process, temporal convolutional Gaussian process, and Gaussian process with a linear kernel.
[116]	Road traffic flow, road traffic speed	Dynamic graph	PeMSD3, PeMSD4, PeMSD7, PeMSD8, METR-LA, PeMS-BAY	GCN	A dynamic spatial–temporal adjacent graph convolutional network (DSTAGCN) is featured with the construction of a spatial–temporal graph and the integration of fuzzy systems and neural networks for uncertain relationship representation.
[117]	Road traffic flow, road traffic speed	Dynamic graph	PeMS-BAY, TaxiBJ, PeMSD4, PeMSD8	GCN, GRU	A dynamic spatial–temporal graph convolutional network (DSTGCN) is featured with a dynamic graph generation module with geographical proximity and spatial heterogeneity.
[118]	Road traffic flow	Dynamic graph	PeMSD3, PeMSD4, PeMSD7, PeMSD8, PeMS-SAN	GCN	The proposed approach features a new temporal vector CNN module and a new dynamic correlation graph construction method.
[119]	Regional travel demand	Static graph	TaxiNYC	GCN, GRU	The proposed approach features a geographic similarity graph, functional similarity graph, and road similarity graph.

Table 1. *Cont.*

Study	Problem	Graph	Dataset	Model Component	Summary
[120]	Road traffic speed	Dynamic graph	PeMS-BAY, METR-LA	GCN, LSTM	The proposed EnGS-DGR model features the ensemble learning of GCN, Seq2Seq, and dynamic graph reconfiguration algorithms.
[121]	Road traffic speed	Dynamic graph	PeMS-BAY, METR-LA	GCN, CNN, GRU	The embedded spatial–temporal network (ESTNet) combines multirange GCN and 3D-CNN modules for modeling spatial–temporal dependencies.
[122]	Passenger OD flow	Static graph	Private data	GCN, TCN	The proposed approach features a novel sharing-stop network to model relationships between bus passengers and various mobility patterns.
[123]	Road traffic speed	Static graph	Private data	GCN, GRU	The proposed approach features the incorporation of a wavelet transform and usage of the electronic toll collection (ETC) gantry transaction data.
[124]	Road traffic flow	Dynamic graph	PeMSD4, PeMSD8	GAT	A fully dynamic self-attention spatiotemporal graph network (Fdsa-STG) is featured with a spatial GAT, a temporal GAT, and fusion layers to extract recent, daily, and weekly periodicity patterns.
[125]	Regional traffic flow	Dynamic graph	TaxiNYC, TaxiBJ	GAT, GCN, LSTM	A federated deep learning based on the spatial–temporal long and short-term network (FedSTN) is featured with a recurrent long-term capture network module, attentive mechanism federated network module, and semantic capture network module to capture both spatial–temporal and semantic features.
[126]	Intersection turning traffic flow	Static graph	A new open data of Wuhan, China	GCN, GRU	The proposed approach features the modeling of turning traffic flow with a GCN and a GRU.
[127]	Metro ridership	Static graph	Private data	GCN, LSTM	An attention-weighted multiview graph to sequence learning approach (AW-MV-G2S) is featured that learns spatial correlations from geographic distance, functional similarity, and demand pattern views.
[128]	Regional traffic flow	Dynamic graph	TaxiNYC, TaxiBJ, BikeNYC	GAT	The proposed approach features the multiresolution transformer network, GAT, and channel-aware recalibration residual network modules.
[129]	Road traffic flow	Dynamic graph	PeMSD3, METRA-LA	GAT	The proposed GDFormer features a novel graph diffusing attention module to model the dynamically changing traffic flow.
[130]	Road traffic speed	Dynamic graph	PeMS-BAY, NavInfo Beijing, NavInfo Shanghai	GAT	The proposed approach features a novel data-driven graph construction method.
[131]	Road traffic flow	Dynamic graph	Metro Interstate Traffic Volume Data Set	GAT, LSTM	A graph correlated attention recurrent neural network (GCAR) is featured with a combination of GAT, multilevel attention, and parallel LSTM modules.

Table 1. *Cont.*

Study	Problem	Graph	Dataset	Model Component	Summary
[132]	Road traffic speed	Dynamic graph	Q-Traffic	GAT	A graph sequence neural network with an attention mechanism (GSeqAtt) is featured with two attention mechanisms to capture temporal correlations and graph structures.
[133]	Intersection traffic flow	Static graph	Qingdao Traffic Data	GCN	A spatial–temporal graph convolutional network (ST-GCN) is featured with an adjacent-similar algorithm and the ability to model both spatial and temporal dependencies of intersection traffic.
[134]	Regional traffic speed	Static graph	Private data	GCN, ConvLSTM	The proposed HDL4STP model features the combination of GCN, ConvLSTM, and fusion layers.
[135]	Road traffic flow	Dynamic graph, static graph	PeMSD4, PeMSD8	GCN, LSTM	An improved graph convolution res-recurrent network (IGCRRN) is featured with a combination of an origin graph matrix and a data-generated embedding node matrix for spatial dependency.
[136]	Bike flow	Static graph	Private data	Relation graph network	The proposed approach features a generalized attention mechanism to extract block features and make cross-city predictions.
[137]	Subway demand, ride-hailing demand	Static graph	SubwayNYC, TaxiNYC	GCN	A multirelational spatiotemporal graph neural network (ST-MRGNN) is featured with the multimodal demand prediction ability with multirelational GNNs.
[138]	Road traffic flow	Static graph	PeMSD3, PeMSD4, PeMSD7, PeMSD8, PeMS-BAY	GAT, TCN	A multirelational synchronous graph attention network (MS-GAT) considers multiaspect traffic data couplings and learns channel, temporal, and spatial relations with GATs.
[139]	Road traffic speed	Dynamic graph	Private data	GAT, CNN	The proposed HA-STGN model considers spatial–temporal heterogeneous features and contains a dynamic graph module, a time-sensitive attention mechanism, and an adaptive fusion module.
[140]	Road traffic flow	Static flow	PeMSD3, PeMSD4, PeMSD7, PeMSD8	GCN	An adaptive graph cross-strided convolution network (AGCSCN) is featured with temporal feature extraction with a cross-strided convolution network and spatial feature extraction with an adaptive GCN.
[141]	Road traffic flow	Static graph	PeMSD4, PeMSD8	GCN, LSTM	A long-short-term-memory-embedded graph convolution network (LST-GCN) is featured with an LSTM embedding into GCNs.
[142]	Road traffic speed	Dynamic graph	DidiChengdu, METR-LA	GCN, TCN	A spatiotemporal adaptive gated graph convolution network (STAG-GCN) is featured with the combination of a self-attention TCN, mix-hop adaptive gated GCN, and fusion layers.
[143]	Road traffic flow	Static graph	PEMS03, PEMS04, PEMS07, PEMS08	GCN, LSTM	A memory-attention-enhanced graph convolution long short-term memory network (MAEGCLSTM) is featured with the combination of a memory attention mechanism and LSTM.

Table 1. *Cont.*

Study	Problem	Graph	Dataset	Model Component	Summary
[144]	Road traffic speed	Dynamic graph, static graph	PeMS-BAY	GCN, TCN	A multistage spatiotemporal fusion diffusion graph convolutional network (MFDGCN) is featured with multiple static and dynamic spatiotemporal association graphs.
[145]	Road traffic flow	Static graph	PeMSD4, PeMSD8	GCN, TCN	A multihead self-attention spatiotemporal graph convolutional network (MSASGCN) is featured with the combination of a GCN, a TCN, and the multihead self-attention mechanism.
[146]	Metro passenger flow	Static graph	HZMF2019	GCN, GAT, CNN	A multitime multigraph neural network (MTMGNN) is featured with the combination of gated CNN, GCN, and GAT modules with multiple graphs.
[147]	Road traffic speed	Static graph	METR-LA	GCN, TCN	A gated temporal graph convolution network (GT-GCN) is featured with a multistep-ahead prediction ability with GCN and gated TCN modules.
[148]	Regional ride-hailing demand	Static graph	Private data	GCN, LSTM	Multigraph aggregation spatiotemporal graph convolutional network (MAST-GCN) is featured with a novel graph aggregation method.
[149]	Road traffic flow	Static graph	PeMSD4, PeMSD7, PeMSD8	GCN	The proposed approach features a multiscale traffic prediction ability with a cross-scale GCN and temporal networks.
[150]	Metro passenger flow	Dynamic graph	Private data	GCN, GRU	The proposed approach proposes multifeature spatial–temporal dynamic multigraph convolutional networks for spatial and temporal connections.
[151]	Road traffic speed	Static graph	Q-Traffic, private data	GCN, LSTM	The proposed approach features a multifold correlation attention network to model dynamic correlations.
[152]	Regional traffic flow	Dynamic graph	TaxiNYC, BikeNYC	GCN, GRU	A multimode dynamic residual graph convolution network (MDRGCN) is featured with multimode dynamic GCN, GRU, and residual modules for learning cross-mode relationships.
[153]	Metro passenger flow	Static graph	Private data	GCN, GAT, LSTM	A temporal graph attention convolutional neural network model (TGACN) is featured with a multigraph generation method and a new spatiotemporal feature fusion method.
[154]	Road traffic speed	Static graph	METR-LA, PeMS-BAY	GCN, Transformer	A multiview spatial–temporal graph neural network (MVST-GNN) is featured with multiview Transformer and GCN modules.
[155]	Metro flow, bus flow	Static graph	Private data	GCN	A multitask hypergraph convolutional neural network (MT-HGCN) models the correlation between different tasks with a feature-compressing unit.
[156]	Regional traffic flow	Static graph	TaxiSZ	GCN, GRU	The proposed TmS-GCN model features the combination of GCN and GRU modules.

Table 1. *Cont.*

Study	Problem	Graph	Dataset	Model Component	Summary
[157]	Road traffic flow, road traffic speed	Static graph	Private data	GCN, LSTM	The proposed method features a Seq2seq GCN-LSTM framework and the usage of connected probe vehicle data.
[158]	Bus passenger flow	Static graph	Private data	GCN, LSTM	The proposed method features a bus network graph construction method and the combination of GCN and LSTM modules.
[159]	Road traffic flow	Static graph	PeMSD4, PeMSD8	GCN	The proposed approach features the combination of graph deep learning and federated learning.
[160]	Road traffic flow	Static graph	PeMSD4, PeMSD7	GCN, GRU	A spatial–temporal attention graph convolution network on edge cloud (STAGCN-EC) is featured with the edge training approach and deep learning modules designed for low-computational-power devices.
[161]	Road traffic flow	Static graph	PEMSD3, PEMSD4, PEMSD7, PEMSD8	GCN, TCN	The proposed approach features two semantic adjacency matrices and a dynamic aggregation method.
[162]	Road traffic speed	Static graph	METR-LA, PeMS-BAY	GCN, GRU	A spatial–temporal upsampling graph convolutional network (STUGCN) is featured with a novel upsampling method with virtual nodes to model the global spatial–temporal correlations.
[163]	Regional passenger demand	Static graph	DidiCD, TaxiNYC	GAT, ConvGRU	The proposed approach features the combination of GAT and ConvGRU modules.
[164]	Road traffic flow	Static graph	PeMSD4, PeMSD8	GCN, CNN	The proposed STGMN model features the combination of a 1D CNN with channel attention and interpretable multigraph GCN modules.
[165]	Metro passenger flow	Dynamic graph	Private data	GCN, TrellisNet	The proposed STP-TrellisNets+ incorporates TrellisNet with graph convolution in multistep traffic prediction for the first time.
[166]	Road traffic flow	Static graph	PeMSD4, PeMSD8	GCN, TCN	A spatial–temporal global semantic graph attention convolution network (STSGAN) is featured with the usage of global geographic contextual information for urban flow prediction.
[167]	Road traffic flow	Static graph	PeMSD4	GAT, GLU	A spatiotemporal multihead graph attention network (ST-MGAT) is featured with the combination of GAT and GLU structures.
[168]	Taxi demand	Static graph	Private data	MPNN	The proposed approach features multimodal message passing and attention mechanisms.
[169]	Road traffic congestion	Static graph	PeMSD4	GAT	The proposed TCP-BAST features bilateral alternation modules with GAT, a multihead masked attention network, and temporal and spatial embedding.

Table 1. *Cont.*

Study	Problem	Graph	Dataset	Model Component	Summary
[170]	Road traffic flow, road traffic speed, road travel time	Static graph	TaxiBJ, META-LA, PeMS-BAY, PeMSD4, PeMSD8	GCN, GAN, GRU	The proposed approach features the combination of multigraph GCN and GAN structures.
[171]	Road traffic flow	Dynamic graph	PeMSD4, PeMSD7	TCN, GCN	The proposed framework features the combination of dilated TCN, multiview GCN, and masked multihead attention modules.
[172]	Road traffic speed	Dynamic graph, static graph	METR-LA, PeMS-BAY	GCN, GRU	A time-evolving graph convolutional recurrent network (TEGCRN) is featured with the combination of time-evolving and predefined graphs.
[173]	Road traffic speed	Static graph	Seattle-Loop, TaxiSZ	GCN, GRU, GAN	The proposed approach features the combination of a GCN and a GAN with output distribution constraints.
[173]	Road traffic speed	Static graph	TaxiSZ, METR-LA, PeMS-BAY	MPNN, GRU	The proposed approach features a combination of bidirectional message passing, GRU, and self-attention mechanisms.
[174]	Road traffic speed	Dynamic graph	METR-LA, PeMS-BAY	GAT, TCN	The proposed TransGAT model features an attention-based node-embedding algorithm and a gated TCN module.
[175]	Regional ride-hailing demand	Static graph	DidiHaikou, Taxi-Wuhan	GCN, LSTM	A multiview deep spatiotemporal network (MVDSTN) is featured with the combination of both traffic and semantic views.
[176]	Road traffic flow, road traffic speed	Dynamic graph	METR-LA, PeMS-BAY, PeMSD4, PeMSD7	Transformer	An adaptive graph spatial–temporal Transformer network (ASTTN) is featured with adaptive spatial–temporal graph modeling and local multihead self-attention.
[177]	Road traffic flow, road traffic speed	Dynamic graph	METR-LA, PeMS-BAY, PeMSD3, PeMSD4, PeMSD7, PeMSD8	GCN, TCN	The proposed approach features the neural architecture search framework for GNN and CNN modules.
[178]	Road traffic speed	Static graph	METR-LA, PeMSD4	GCN, TCN	A spatial–temporal channel-attention-based graph convolutional network (STCAGCN) is featured with stacked dilated convolution for long-sequence modeling.
[179]	Road traffic flow	Dynamic graph, static graph	PeMSD3, PeMSD4, PeMSD7, PeMSD8	GCN	The proposed approach features a cascading structure to enhance interaction and capture heterogeneity.
[180]	Road traffic speed	Static graph	METR-LA, PeMS-BAY, PeMS-M, PeMSD4, PeMSD8	GAT	A spatiotemporal graph attention network (ST-GAT) is featured with an individual spatiotemporal graph for modeling individual dependencies.
[181]	Road traffic speed	Static graph	METR-LA, PeMS-BAY	GCN, TCN	The proposed approach features a novel residual estimation module.
[182]	Bike demand	Dynamic graph	BikeChicago, BikeLA	GNN	The approach features a novel graph generator and GNN with flow-based and attention-based aggregators.

Table 1. *Cont.*

Study	Problem	Graph	Dataset	Model Component	Summary
[183]	Road traffic speed	Dynamic graph	METR-LA, PeMS-Bay, TaxiSZ	GCN	The proposed approach features the decomposition of seasonal static and acyclic dynamic components for traffic prediction.
[184]	Road traffic flow	Dynamic graph	PeMSD3, PeMSD4, PeMSD7	GCN, GRU	An AdaBoost spatiotemporal network (Ada-STNet) is featured with the boosting approach of stacking base models.
[185]	Road traffic flow, road traffic speed	Dynamic graph	METR-LA, PeMS-BAY, PeMSD4, PeMSD8	GCN, GRU	A decoupled dynamic spatial–temporal graph neural network (D^2STGNN) is featured with a decoupled spatial–temporal framework and a dynamic graph learning module.
[186]	Road traffic flow	Dynamic graph	PeMSD3, PeMSD4, PeMSD7, PeMSD8	GCN, GTU	A dynamic spatial–temporal-aware graph neural network (DSTAGNN) is featured with a new dynamic spatial–temporal-aware graph and a novel GNN structure.
[187]	Road traffic flow	Static graph	PeMSD3, PeMSD4, PeMSD7, PeMSD8	GNN	The proposed approach features a first-order gradient supervision (FOGS) which uses first-order gradients for training the prediction model.
[188]	Road traffic flow	Dynamic graph	PeMSD3, PeMSD4, PeMSD7, PeMSD8	GCN	A spatiotemporal graph neural controlled differential equation (STG-NCDE) is featured with the incorporation of neural controlled differential equations in traffic forecasting for the first time.
[189]	Road traffic flow	Static graph	PeMSD4, PeMSD7	GNN	This study proposes a communication-efficient federated learning approach for graph-based traffic forecasting.
[190]	Road traffic flow, traffic demand	Static graph	PeMSD3, PeMSD8, BikeNYC, TaxiNYC	GCN, MSDR	The proposed approach is based on a graph-based multistep dependency relation (MSDR) model with the ability to learn from multiple historical time steps.
[191]	Road traffic speed	Static graph	DidiShenzhen, DidiChengdu, PeMS-BAY, METR-LA	GCN	The proposed ST-GFSL framework features the combination of spatiotemporal traffic prediction with few-shot learning and cross-city knowledge transfer.
[192]	Road traffic speed	Dynamic graph	METR-LA, PeMS-BAY	GAT, TCN	The proposed approach features the semantic closeness relationship and traffic dynamics.
[193]	Road traffic flow, road traffic speed	Dynamic graph	METR-LA, PeMS-BAY, PeMSD4	GNN	The proposed approach enhances the performance of spatiotemporal GNNs with a pretraining model trained with very long term history data.
[194]	Road traffic flow	Dynamic graph, static graph	PeMSD4, PeMSD8	GCN, GRU	Regularized graph structure learning (RGSL) is featured with an embedding-based implicit dense similarity matrix, a regularized graph generation method, and a Laplacian matrix mixed-up module to fuse the graphs.
[195]	Road traffic flow, road traffic speed	Dynamic graph	PeMSD8, METR-LA	GCN, TCN	Spatiotemporal latent graph structure learning network (ST-LGSL) is featured with a MLP-kNN-based graph generator and the combination of diffusion graph convolutions and gated TCN modules.

Table 1. *Cont.*

Study	Problem	Graph	Dataset	Model Component	Summary
[196]	Road traffic flow	Static graph	Private data	GCN, GRU	A spatiotemporal differential equation network (STDEN) is featured with the combination of data-driven and physics-driven approaches and the differential equation network model for modeling the spatiotemporal dynamic process.
[197]	Road traffic flow	Dynamic graph	PeMSD3, PeMSD4, PeMSD8	GCN, CNN, GRU	Time-aware multipersistence spatio-supragraph convolutional network (TAMP-S2GCNets) is featured with the introduction of a time-aware multipersistence Euler-Poincaré surface and a supragraph convolution model for intra- and interdependencies.
[198]	Road traffic flow	Static graph	PeMSD8	GCN, GRU, GLU	A two-stage stacked graph convolution network (ED2GCN) is featured by the stacking of a GCN, a GLU, and the attention mechanism.
[199]	OD travel demand	Static graph	TaxiChicago, TaxiNYC	DCNN, TCN	A spatial–temporal zero-inflated negative binomial graph neural network (STZINB-GNN) is featured with the uncertainty quantification of the sparse travel demand with diffusion and temporal convolution networks.
[200]	Road traffic speed	Static graph	NAVER-Seoul, METR-LA	GCN	A pattern-matching memory network (PM-MemNet) is featured with a novel key–value memory structure and a pattern-matching framework.
[201]	Regional traffic flow	Static graph	NeurIPS Traffic4Cast Challenge Data	GNN	The proposed approach features the combination of U-Net with graph learning.
[202]	Road traffic speed	Static graph	PeMS-BAY, METR-LA	GCN, CNN	The proposed approach features a mix-hop GCN and stacked temporal attention mechanism.
[203]	Road traffic flow	Dynamic graph	PeMSD3, PeMSD4, PeMSD7, PeMSD8	GCN	The proposed approach features a graph construction method for cross-time and cross-space correlations.
[204]	Road traffic speed	Static graph	METR-LA, PeMS-BAY	GCN, GRU	The proposed approach features a novel local context-aware spatial attention mechanism.
[205]	Road traffic speed	Dynamic graph	PeMS-BAY, private data	GCN	The proposed approach features the combination of a GCN and attention mechanism for multidimensional information aggregation.

The problems considered in Table 1 were grouped into different transportation modes, e.g., road traffic, taxis, bikes, and subways. Previous studies have also shown that joint forecasting of multimode data is beneficial [206]. GNN-based solutions are applicable and have already been used for multimode forecasting cases. In [152], a multimode dynamic residual graph convolution network (MDRGCN) model was proposed for regional taxi and bike flow forecasting, in which cross-mode relationships were learned by multimode dynamic GCN, GRU, and residual modules. In [99], a comodal graph attention network (CMGAT) was proposed for bike and taxi demand forecasting, which was based on a multiple-traffic-graph-based spatial attention mechanism and a multiple-time-period-based temporal attention mechanism. In these studies, it was demonstrated that the GNN-based joint forecasting of multimode traffic data was more effective than individual forecasts.

We also noticed that the traffic occupancy prediction problem was not seen in the studies reviewed in this paper. Some possible reasons are discussed below. Traffic occupancy is often modeled as a decision variable rather than using continuous variables such as traffic speed or volume. While GNN-based solutions have been shown to be effective in predicting continuous variables, as described in this survey, decision-tree-based models are still powerful for making binary decisions, e.g., XGBoost and LightGBM [207–209]. Another possible reason is that traffic occupancy can be detected more efficiently with computer vision methods based on images or videos, in which case convolutional neural networks and Transformers still dominate [210]. A similar problem is lane-occupancy-rate prediction, which is also rare in the literature due to the high cost of collecting real-world lane-occupancy data, e.g., deploying loop detectors for each lane in large-scale road segments. For example, only simulated traffic data can be used for lane-occupancy measurement and prediction in [211].

For model evaluation and comparison, different evaluation metrics are used, e.g., root mean square error (RMSE), mean absolute error (MAE), and mean absolute percentage error (MAPE). Forecast horizons also differ per study, such as 5, 10, 30, or 60 min, and it was found that the larger the horizon, the harder the forecasting problem, and the greater the error observed with larger horizons. Due to the different evaluation metrics and forecast horizons, it is nearly impossible to fairly compare all surveyed studies and quantify the difficulty of the available datasets. It was also found that for some common baselines, e.g., DCRNN [212], STGCN [213], and Graph WaveNet [214], their reported performance in different studies could vary when the training variables were different.

3. New Dataset and Code Resources

This section provides up-to-date lists of open datasets and code resources for the research community.

3.1. New Datasets

Open datasets are the basis for evaluating and comparing different forecasting models [215]. As discussed in Section 2, several open datasets have been widely used in the surveyed studies, such as METR-LA, PeMS, and NYC Open Data. Despite the availability of these datasets, developing new datasets is still beneficial for the following two reasons. The first reason is the risk of overfitting of deep learning models on existing datasets, especially those that are relatively small compared to datasets in other domains, such as large collections of images and natural language corpora. The second reason is that models trained using datasets collected many years ago may suffer from data drift as traffic facilities change. The data-shift problem means that the traffic patterns in the historical training data could be totally different from those in the newly collected test data, and the performance of trained deep learning models can degrade significantly in unseen cases. Therefore, here, we update the community with new, publicly available traffic datasets in Table 2 to facilitate future research and encourage constant updates of high-quality traffic datasets.

Table 2. The list of new open traffic datasets.

Study	Traffic Attributes	Spatial Range	Temporal Range	Download Link (Accessed on 2 February 2023)
[114]	Aggregated taxi speed	Seoul, South Korea	1–30 April 2018	https://github.com/SNU-DRL/ddpgcn-dataset
[126]	Aggregated taxi flow	Wuhan, China	1–28 July 2015	http://ggssc.whu.edu.cn/ggsscAssets/download/AttentionModel/code_and_data.zip
HZMF2019 [146]	Aggregated metro passenger flow	Hangzhou, China	1–25 January 2019	https://github.com/lixus7/MTMGNN
TaxiBJ21 [23]	Aggregated taxi flow	Beijing, China	November 2012, November 2014, and November 2015	https://github.com/jwwthu/DL4Traffic/tree/main/TaxiBJ21
[216]	Aggregated traffic flow	Beijing, China	1 June–15 July 2009	https://github.com/gao0628/Dataset
[217]	Aggregated traffic flow	Six intersections in an urban area	56 days	https://zenodo.org/record/3653880#.Y20cPHZBzT6
XiAn Road Traffic [218]	Aggregated traffic flow, weather data	Xi'an, China	1 August–30 September 2019	https://github.com/FIGHTINGithub/Xi-an-Road-Traffic-Data
[219]	Aggregated traffic flow	Aveiro, Portugal	2019, 2020, and 2021	https://figshare.com/s/d324f5be912e7f7a0d21
[220]	Aggregated taxi and bike trips	New York City, USA	2019, 2020	https://github.com/Evens1sen/Deep-NYC-Taxi-Bike
[221]	Aggregated taxi and bike trips	Chicago, USA	2013 to 2020	https://github.com/iipr/mobility-demand
[222]	Citywide crowd flow	Tokyo and Osaka	1 April–9 July 2017	https://github.com/deepkashiwa20/DeepCrowd

3.2. New Code Resources

Open-code resources facilitate the replication of published results and migration of proposed models to new problems. We summarize here the new publicly available code resources in Table 3 and list the implementation frameworks, including TensorFlow (https://www.tensorflow.org, accessed on 2 February 2023) and PyTorch (https://pytorch.org/, accessed on 2 February 2023). It is observed from Table 3 that PyTorch is more popular than TensorFlow for developing new graph neural network models in traffic forecasting research.

There are also many off-the-shelf libraries available for implementing GNNs using PyTorch or TensorFlow, e.g., PyTorch Geometric (https://pytorch-geometric.readthedocs.io/, accessed on 2 February 2023), Deep Graph Library (https://www.dgl.ai/, accessed on 2 February 2023), TensorFlow Graph Neural Networks (https://blog.tensorflow.org/2021/11/introducing-tensorflow-gnn.html, accessed on 2 February 2023), and Spektral (https://graphneural.network/, accessed on 2 February 2023). These libraries have implemented some well-known GNN variants, such as GCN and GAT, and provide the ability to define new GNN models. However, they are not designed for traffic forecasting problems. It would be more convenient to replicate those existing GNN-based traffic forecasting models with the open-code resources listed in Table 3.

Table 3. The list of new open-code resources.

Study	Framework	Link (accessed on 2 February 2023)
DDSTGCN [60]	PyTorch	https://github.com/j1o2h3n/DDSTGCN
STAGCN [61]	PyTorch	https://github.com/QiweiMa-LL/STAGCN
CTVI+ [70]	PyTorch	https://github.com/dsj96/TKDD
TGAE [71]	PyTorch	https://github.com/wangqiang-codes/TGAE
GAMCN [88]	TensorFlow	https://github.com/alvinzhaowei/GAMCN
MADGCN [89]	TensorFlow, PyTorch	https://github.com/wumingyao/MADGCN
AdapGL [98]	PyTorch	https://github.com/goaheand/AdapGL-pytorch
Ada-STNet [100]	PyTorch	https://github.com/LiuZH-19/Ada-STNet
AM-RGCN [108]	PyTorch	https://github.com/ILoveStudying/AM-RGCN
DDP-GCN [114]	TensorFlow	https://github.com/SNU-DRL/DDP-GCN
GDFormer [129]	PyTorch	https://github.com/dublinsky/GDFormer
ST-GCN [133]	TensorFlow	https://github.com/Wautumn/ST-GCN
MTMGNN [146]	PyTorch	https://github.com/lixus7/MTMGNN2
TmS-GCN [156]	PyTorch	https://github.com/Joker-L0912/Tms-GCN-Py
STUGCN [161]	PyTorch	https://github.com/zsongsong/stugcn
D^2STGNN [185]	PyTorch	https://github.com/zezhishao/D2STGNN
DSTAGNN [186]	PyTorch	https://github.com/SYLan2019/DSTAGNN
FOGS [187]	PyTorch	https://github.com/kevin-xuan/FOGS
STG-NCDE [188]	PyTorch	https://github.com/jeongwhanchoi/STG-NCDE
ST-GFSL [191]	PyTorch	https://github.com/RobinLu1209/ST-GFSL
STEP [193]	PyTorch	https://github.com/zezhishao/STEP
RGSL [194]	PyTorch	https://github.com/alipay/RGSL
STDEN [196]	PyTorch	https://github.com/Echo-Ji/STDEN
TAMP-S2GCNets [197]	PyTorch	https://github.com/tamps2gcnets/TAMP_S2GCNets
PM-MemNet [200]	PyTorch	https://github.com/HyunWookL/PM-MemNet
[201]	TensorFlow	https://github.com/LucaHermes/graph-UNet-traffic-prediction
TraverseNet [223]	PyTorch	https://github.com/nnzhan/TraverseNet

4. Research Challenges and Opportunities

This section discusses research challenges and opportunities when applying GNNs to traffic forecasting problems in order to inspire follow-up research.

4.1. Research Challenges

Several challenges can be observed from the surveyed studies, which can be categorized into data, model, and system perspectives. From a data perspective, challenges include data quality and cold-start issues. From a model perspective, challenges include complex graph structure and model robustness concerns. From a system perspective, the real-world deployment of GNNs in transportation systems is a challenge that cannot be ignored.

The first challenge is the training data quality. When utilizing graph neural networks, some issues related to data quality may arise. On the one hand, high-quality datasets are expensive to build, as the data collection process can be time-consuming and costly. As extreme or urgent traffic events such as traffic jams and accidents are rare, collecting comprehensive datasets is more difficult. On the other hand, data privacy is also nonnegligible if we want to create more comprehensive datasets, since most existing traffic datasets are collected from public transportation modes (e.g., taxis and shared bikes) or road sensors, rather than from private vehicles [224].

The second challenge is the cold-start problem [136] when initializing GNNs for traffic prediction. Deep learning models, including GNNs, usually require a large quantity of training data to efficiently train the model and obtain satisfactory predictions. However, data collection in the traffic field is often time-consuming and labor-intensive, for example, by installing loop detectors for traffic flow and speed information collection. The cold-start problem arises when the developed GNN models are to be used in a new area or station, especially for a growing urban network.

The third challenge is the diverse and complicated graph structures that exist in the real-world traffic infrastructure. Most surveyed studies consider only dense graphs, e.g., in downtown areas or on closely connected highways, when traffic activities are active. However, the complete traffic graph of a city may be sparse, with some nodes having no or few connections to other nodes. This real-world condition has received insufficient attention in the surveyed studies. Another limitation of the surveyed studies is that the graphs considered are relatively small, e.g., less than 1,000 nodes. For example, the most popular PeMS datasets are a collection of subsets from a large dataset collected from more than 40,000 individual detectors spread over a wider geographic area, since the size of the original dataset exceeds the computing abilities for some research groups.

The fourth challenge is the robustness of GNN models. Deep learning models have long been criticized for their black-box nature with little or no interpretation paired with predicted outcomes. This black-box problem exists for graph neural networks as well, and there are few systematic methods for interpreting GNNs in traffic forecasting settings. Many anomalies or outliers in the data are removed during processing steps or do not appear in the training dataset. When these anomalies are encountered during the testing or deployment phase, the performance of the trained GNN model degrades, leading to large deviations in model predictions. Given such risks, it is important to enhance the robustness and interpretability of GNN models to increase user confidence in the models.

The fifth challenge is the real-world deployment of GNNs in transportation systems. The real-world implementation of the surveyed GNN solutions requires substantial computing, communication, and storage resources. However, most of the surveyed studies only consider empirical evaluations based on offline datasets without testing their models on real-world transportation systems. Several obstacles arise in the real-world deployment of GNNs. To effectively utilize graph-based structures, a centralized deployment mode is required to collect global information and compute predictions in a single server. Although deep learning models, including GNNs, can be trained offline, the online inference process still requires considerable computing and storage resources when the considered traffic graph is very large. When the considered graph becomes larger, the communication overhead also increases. To achieve more efficient and safe transportation systems, complex GNN architectures may not be necessary for traffic-related tasks if their marginal performance improvement fails to cover the increased computational, communication, and storage costs.

4.2. Research Opportunities

Some promising research opportunities are discussed to address the above challenges and inspire future research.

The first research opportunity is the introduction of traffic simulation tools for creating unseen complex situations as training data. Two specific approaches, model-driven and data-driven approaches, can be further investigated. Model-driven approaches are based on macroscopic or microscopic traffic simulators, where macroscopic tools focus on the high-level deterministic relationships of flow, speed, and the density of traffic flows, while microscopic tools focus on individual details. On the other hand, data-driven methods do not rely on traffic domain knowledge but create more data samples from existing methods, e.g., generative adversarial network (GAN)-based studies [85–87,170,225]. Regarding the black-box nature of neural networks, the use of physics-informed neural network approaches is gaining popularity in research. These approaches combine both model-driven and data-driven methods and have been successfully applied in the transportation domain [226,227].

The second research opportunity is to introduce new learning schemes to traffic forecasting problems, e.g., transfer learning, meta learning, and federated learning. Transfer learning has been proven effective for transferring cross-city knowledge, which will help address the cold-start problem in new cities [191]. Furthermore, meta learning has been shown to be useful for building new graph structures through efficient structure-aware learning during cross-city knowledge transfer. Privacy-preserving schemes are further proposed to be combined with transfer learning, protecting the sensitive information from the source domain [67]. Federated learning is another effective learning approach for maintaining data privacy while training effective deep learning models [159,189].

The third research opportunity is the combination of knowledge graphs under different road conditions or transportation modes to establish connections among them [63]. More external data can be used when constructing traffic knowledge graphs, e.g., the activity calendar from social media for potential traffic demands. Additionally, the knowledge between different transportation modes, e.g., interchange hubs, would be useful for multimodal prediction [137,152,155].

The fourth research opportunity is a distributed learning approach for training large-scale graph neural networks for traffic forecasting [228,229]. When the application of GNNs for traffic prediction scales to larger graphs, a distributed training of graph neural networks is necessary. In those cases, improvements in training and runtime efficiency is even more beneficial and important. Another similar idea is to leverage cloud computing for model training and edge computing for runtime inference [160,230] to accelerate the distributed training and inference process.

The fifth research opportunity is the Bayesian learning approach for uncertainty quantification. Uncertainty in traffic forecasting may not be as critical as uncertainty in other domains, e.g., wireless communication problems. However, it is still important to account for uncertainty in the transportation domain when noisy or missing data could impair predictive capabilities and lead to unusual forecasts. Bayesian neural networks have been shown to be effective in dealing with data uncertainty caused by noisy or missing data in road traffic flow forecasting [66]. Another similar idea is to incorporate the physical mechanism of traffic flow dynamics as constraints, such as neural controlled differential equations [188] and Poisson processes [84], to avoid unreasonable predicted values [196] and help to improve the model interpretability.

The sixth research opportunity is the combination of graph neural networks and reinforcement learning, which is rarely considered in the surveyed studies, with only one exception [90]. The ensemble of these two models can sometimes produce brilliant sparks. For example, some relevant studies leverage reinforcement learning techniques for a more efficient graph neural network structure search [231]. On the other hand, reinforcement learning itself is useful for making optimal decisions in the traffic domain with properly designed rewards, e.g., traffic light control and autonomous driving. There is still a large research gap in applying reinforcement learning to graph data structures [232,233].

The last but not the least research opportunity is the deployment of GNNs based on cloud computing and B5G/6G communication techniques. Cloud computing can provide the required computing and storage resources. GNN models can be trained, deployed, and updated in the cloud with a scalable infrastructure. The B5G/6G communication technique is designed to have the ability to support massive machine-type communication scenarios and can be used for reliable and massive traffic data collection and transmission.

In summary, the first and second research opportunities are proposed to address the first and second research challenges. The third and fourth research opportunities are proposed to address the third research challenge. The fifth research opportunity is proposed to address the fourth research challenge. The last research opportunity is proposed to address the fifth research challenge.

5. Conclusions

In 2022, the number of studies on the topic of applying graph neural networks for traffic forecasting grew rapidly. In this survey, we summarized the progress made by these studies and listed their targeted problem, graph types, datasets, and neural networks used. We observed that the road traffic flow and speed prediction problem was still the most popular traffic forecasting problem. The GNN family, GCN and GAT, was one of the promising solutions to these problems. To further motivate follow-up research, new collections of datasets and code resources were presented. Research challenges and opportunities were further discussed in this study.

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Appendix A. Abbreviation List

The abbreviations used in this manuscript are listed in Table A1 with their full names.

Table A1. Abbreviations used in this manuscript.

Abbreviation	Full Name
AARGNN [97]	Attentive attributed recurrent graph neural network
ABSTGCN-EF [107]	Attention-based spatiotemporal graph convolutional network considering external factors
ADSTGCN [106]	Attention-based dynamic spatial–temporal graph convolutional network
AED-DGCN-TSC [102]	Attention encoder–decoder dual-graph convolutional network with time series correlation
AGCN-T [101]	Attention-based graph convolution network and transformer
AGCSCN [140]	Adaptive graph cross-strided convolution network
AM-RGCN [108]	Augmented multicomponent recurrent graph convolutional network
ARIMA	Autoregressive integrated moving average
ASTGAT [105]	Attention-based spatiotemporal graph attention network
ASTTN [176]	Adaptive graph spatial–temporal transformer network
AW-MV-G2S [127]	Attention-weighted multiview graph-to-sequence learning
Ada-STNet [184]	AdaBoost spatiotemporal network
Ada-STNet [100]	Adaptive spatiotemporal graph neural network
AdapGL [98]	Adaptive graph learning
Bi-GRCN [109]	Bidirectional-graph recurrent convolutional network

Table A1. *Cont.*

Abbreviation	Full Name
CGLGCN [104]	Causal gated low-pass graph convolution neural network
CMGAT [99]	Comodal graph attention network
CNN	Convolutional neural network
CRF	Conditional random field
ConvGRU	Convolutional GRU
ConvLSTM	Convolutional LSTM
D^2STGNN [185]	Decoupled dynamic spatial–temporal graph neural network
DCNN [234]	Diffusion convolutional neural network
DDP-GCN [114]	Distance, direction, and positional relationship graph convolutional network
DDSTGCN [60]	Dual dynamic spatial–temporal graph convolution network
DG^2RNN [81]	Dual-graph gated recurrent neural network
DGGP [115]	Deep graph Gaussian process
DMGC-GAN [85]	Dynamic multigraph convolutional network with generative adversarial network
DMVST-VGNN [72]	Deep multiview spatiotemporal virtual graph neural network
DRL	Deep reinforcement learning
DSTAGCN [116]	Dynamic spatial–temporal adjacent graph convolutional network
DSTAGNN [186]	Dynamic spatial–temporal aware graph neural network
DSTGCN [117]	Dynamic spatial–temporal graph convolutional network
DSTGNN [84]	Dynamical spatial–temporal graph neural network
ED2GCN [198]	Two-stage stacked graph convolution network
EMD	Empirical mode decomposition
ESTNet [121]	Embedded spatial-temporal network
ETC	Electronic toll collection
FOGS [187]	First-order gradient supervision
Fdsa-STG [124]	Fully dynamic self-attention spatiotemporal graph network
FedSTN [125]	Federated-deep-learning-based on the spatial–temporal long and short-term network
GAMCN [88]	Graph and attentive multipath convolutional network
GAN	Generative adversarial network
GAT	Graph attention network
GCAR [131]	Graph correlated attention recurrent neural network
GCN	Graph Convolutional Network
GCN-GAN [73]	Graph convolution and generative adversarial neural network
GDFormer [129]	Graph diffusing Transformer
GLU	Gated linear unit
GRU	Gated recurrent unit
GSeqAtt [132]	Graph sequence neural network with an attention mechanism
GT-GCN [147]	Gated temporal graph convolution network
GTU	Gated tanh unit
HMIAN [74]	Hierarchical mapping and interactive attention network
IGCRRN [135]	Improved graph convolution res-recurrent network
ITS	Intelligent transportation systems
IoT	Internet of things
IoV	Internet of vehicles
KGR-STGNN [63]	Knowledge graph representation learning and spatiotemporal graph neural network
kNN	K-Nearest Neighbor
LST-GCN [141]	Long-short-term-memory-embedded graph convolution network
LSTM	Long short-term memory
MA-STN [77]	Multidimensional attention-based spatial-temporal network
MADGCN [89]	Multiattention dynamic graph convolution network
MAEGCLSTM [143]	Memory attention enhanced graph convolution long short-term memory network
MAGCN [64]	Multiattribute graph convolutional network
MAST-GCN [148]	Multigraph aggregation spatiotemporal graph convolutional network
MDRGCN [152]	Multimode dynamic residual graph convolution network

Table A1. *Cont.*

Abbreviation	Full Name
MFDGCN [144]	Multistage spatiotemporal fusion diffusion graph convolutional network
MG-GAN [225]	Multiple-graph-based generative adversarial network
MHODE [78]	Mixed hop diffuse ordinary differential equation
MLP	Multilayer perceptron
MPNN	Message-passing neural network
MS-GAT [138]	Multirelational synchronous graph attention network
MSASGCN [145]	Multihead self-attention spatiotemporal graph convolutional network
MSDR [190]	Multistep dependency relation network
MT-HGCN [155]	Multitask hypergraph convolutional neural network
MTMGNN [146]	Multitime multigraph neural network
MVB-STNet [66]	Multiview Bayesian spatiotemporal graph neural network
MVDSTN [175]	Multiview deep spatiotemporal network
MVST-GNN [154]	Multiview spatial–temporal graph neural network
PM-MemNet [200]	Pattern-matching memory network
RGSL [194]	Regularized graph structure learning
SAGCN-SST [83]	Self-attention graph convolutional network with spatial, subspatial, and temporal blocks
SARIMA	Seasonal autoregressive integrated moving average
ST-GAT [180]	Spatiotemporal graph attention network
ST-GCN [133]	Spatial–temporal graph convolutional network
ST-LGSL [195]	Spatiotemporal latent graph structure learning
ST-MGAT [167]	Spatiotemporal multi-head graph attention network
ST-MRGNN [137]	Multirelational spatiotemporal graph neural network
STAG-GCN [142]	Spatiotemporal adaptive gated graph convolution network
STAGCN-EC [160]	Spatial–temporal attention graph convolution network on edge cloud
STAGCN [61]	Spatiotemporal adaptive graph convolutional network
STCAGCN [178]	Spatial–temporal channel-attention-based graph convolutional network
STDEN [196]	Spatiotemporal differential equation network
STG-NCDE [188]	Spatiotemporal graph neural controlled differential equation
STHAN [68]	Spatiotemporal heterogeneous graph attention network
STHGCN [69]	Spatiotemporal prediction framework using high-order graph convolutional network
STSGAN [166]	Spatial–temporal global semantic graph attention convolution network
STSSN [96]	Spatiotemporal sequence-to-sequence network
STUGCN [161]	Spatial–temporal upsampling graph convolutional network
STZINBGNN [199]	Spatial–temporal zero-inflated negative binomial graph neural network
Seq2Seq	Sequence to sequence
T-ISTGNN [67]	Transferable federated inductive spatial-temporal graph neural network
TAMP-S2GCNets [197]	Time-aware multipersistence spatio-supragraph convolutional network
TCN	Temporal convolutional network
TEGCRN [172]	Time-evolving graph convolutional recurrent network
TGACN [64]	Temporal graph attention convolutional neural network
TGAE [71]	Temporal graph autoencoder

Appendix B. The Source Journal list

The source of the journals for the surveyed studies are listed in Table A2 with the number of papers counted.

Table A2. Source journals for the surveyed papers.

Journal Name	Number of Surveyed Papers
IEEE Transactions on Intelligent Transportation Systems	23
Information Sciences	7
Applied Intelligence	6
Journal of Advanced Transportation	6
Electronics	5
Physica A: Statistical Mechanics and its Applications	5
ACM Transactions on Intelligent Systems and Technology	4
Applied Sciences	4
Knowledge-Based Systems	4
Transportation Research Part C: Emerging Technologies	4
Expert Systems with Applications	3
ACM Transactions on Knowledge Discovery from Data	2
GeoInformatica	2
IEEE Internet of Things Journal	2
IEEE Transactions on Knowledge and Data Engineering	2
IET Intelligent Transport Systems	2
ISPRS International Journal of Geo-Information	2
Neural Computing and Applications	2
Wireless Communications and Mobile Computing	2
World Wide Web	1
Applied Soft Computing	1
Big Data	1
Computer Communications	1
Computers, Environment and Urban Systems	1
Connection Science	1
Digital Communications and Networks	1
Digital Signal Processing	1
Engineering Applications of Artificial Intelligence	1
Environment, Development and Sustainability	1
Future Generation Computer Systems	1
IEEE Access	1
IEEE Sensors Journal	1
IEEE Transactions on Big Data	1
IEEE Transactions on Neural Networks and Learning Systems	1
IEEE Transactions on Vehicular Technology	1
International Journal of Intelligent Systems	1
International Journal of Machine Learning and Cybernetics	1
Journal of King Saud University-Computer and Information Sciences	1
Journal of Rail Transport Planning & Management	1
Mathematics	1
Neural Processing Letters	1
Neurocomputing	1
Pattern Recognition Letters	1
Remote Sensing	1
Sustainability	1
Sustainable Computing: Informatics and Systems	1
The Computer Journal	1
Transportation Research Record	1
Transportmetrica B: Transport Dynamics	1
Transportmetrica B: transport dynamics	1

Appendix C. The Source Conference List

The source conferences for the surveyed papers are listed in Table A3 with the number of papers counted.

Table A3. The source conferences for the surveyed papers.

Conference Name	Number of Surveyed Papers
International Joint Conference on Neural Networks (IJCNN)	6
ACM International Conference on Information and Knowledge Management (CIKM)	4
ACM SIGKDD Conference on Knowledge Discovery and Data Mining (KDD)	4
International Joint Conference on Artificial Intelligence (IJCAI)	2
AAAI Conference on Artificial Intelligence (AAAI)	2
International Conference on Learning Representations (ICLR)	2
IEEE Symposium on Computers and Communications (ISCC)	1
International Conference on Artificial Neural Networks (ICANN)	1
IEEE International Conference on Data Engineering (ICDE)	1
Pacific-Asia Conference on Knowledge Discovery and Data Mining (PAKDD)	1
IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)	1
International Conference on Very Large Databases (VLDB)	1
International Conference on Machine Learning (ICML)	1
IEEE Wireless Communications and Networking Conference (WCNC)	1
International Conference on Database Systems for Advanced Applications (DASFAA)	1
IEEE International Conference on Computer Supported Cooperative Work in Design (CSCWD)	1

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