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GRAPH NEURAL NETWORKS FOR TRAFFIC FLOW PREDICTION: INNOVATIVE APPROACHES, PRACTICAL USAGE, AND SUPERIORITY IN SPATIO-TEMPORAL FORECASTING

Traffic flow prediction remains a cornerstone of intelligent transportation systems (ITS), facilitating congestion mitigation, route optimization, and sustainable urban planning. Graph Neural Networks (GNNs) have revolutionized this domain by adeptly modeling the intricate graph-structured nature of traffic networks, where nodes represent sensors or intersections and edges denote spatial relationships. Recent years (2023–2025) have witnessed a surge in scientific innovation, with several novel approaches pushing the boundaries of traffic prediction accuracy and robustness. Notably, hybrid GNN-Transformer architectures have emerged, leveraging the spatial reasoning of GNNs and the temporal sequence modeling power of Transformers to capture long-range dependencies and complex spatiotemporal patterns. Physics-informed GNNs integrate domain knowledge, such as conservation laws and traffic flow theory, directly into the learning process, enhancing interpretability and generalization to unseen scenarios. Uncertainty-aware frameworks, including Bayesian GNNs and ensemble methods, provide probabilistic forecasts, crucial for risk-sensitive applications and adaptive traffic management in volatile urban environments. This article provides a comprehensive guide to implementing GNNs for traffic flow prediction, detailing best practices in data preparation (e.g., graph construction, feature engineering, handling missing data), model training (e.g., loss functions, regularization, hyperparameter tuning), and real-time deployment (e.g., edge computing, latency optimization). We critically compare GNNs to traditional statistical and deep learning methods, highlighting their superior ability to capture non-Euclidean spatial dependencies, adapt to dynamic and evolving network topologies, and seamlessly integrate multi-modal data sources such as weather, events, and sensor readings. Empirical evidence from widely used benchmarks, including PeMS and METR-LA, demonstrates that state-of-the-art GNN models achieve up to 15–20 % improvements in accuracy metrics such as Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) over conventional baselines. These gains are attributed to the models' capacity for dynamic graph learning, attention-based feature selection, and robust handling of heterogeneous data. Drawing on these recent innovations, this synthesis highlights GNNs' pivotal role in fostering resilient, AI-driven traffic systems for future smart cities, setting the stage for next-generation ITS solutions that are adaptive, interpretable, and scalable. In addition to these advancements, the integration of real-time sensor data and external information sources has further improved the responsiveness of traffic prediction models. Modern GNN frameworks are capable of handling large-scale urban networks, making them suitable for deployment in metropolitan areas with complex road infrastructures. The use of transfer learning and domain adaptation techniques allows models trained in one city to be effectively applied to others, reducing the need for extensive retraining. Furthermore, explainable AI approaches within GNNs are gaining traction, enabling stakeholders to understand and trust model decisions in critical traffic management scenarios. Recent research also explores the fusion of GNNs with reinforcement learning, enabling adaptive control strategies for traffic signals and congestion pricing. The scalability of GNNs ensures that they can process data from thousands of sensors in real time, supporting city-wide traffic optimization. Advances in hardware acceleration, such as GPU and edge computing, have made it feasible to deploy these models in latency-sensitive environments. Collaborative efforts between academia, industry, and government agencies are driving the adoption of GNN-based solutions in smart city initiatives. As urban mobility continues to evolve, the ability of GNNs to incorporate emerging data modalities, such as connected vehicle telemetry and mobile device traces, will be crucial for future developments. The ongoing refinement of model architectures and training protocols promises even greater accuracy and robustness in traffic flow prediction. Ultimately, the convergence of GNNs with other AI technologies is set to transform intelligent transportation systems, paving the way for safer, more efficient, and sustainable urban mobility.

Keywords: Graph Neural Network, Traffic Flow Prediction, Graph Convolutional Network, Graph Attention Network, Mean Absolute Error.

Introduction. In an era of rapid urbanization, traffic congestion inflicts substantial economic losses – estimated at over $160 billion annually in the U.S. alone – and exacerbates environmental issues through increased emissions [1]. Accurate traffic flow prediction, which forecasts metrics like vehicle volume, speed, and density, is pivotal for proactive ITS interventions. Traditional approaches, such as autoregressive integrated moving average (ARIMA) and support vector regression (SVR), falter in handling the non-linear, spatio-temporal complexities of modern traffic networks [2]. Enter Graph Neural Networks (GNNs), a paradigm-shifting technology that treats traffic systems as graphs, enabling the propagation of information across interconnected nodes. Innovations since 2023 have infused GNNs with transformative elements, such as integration with Transformers for enhanced temporal modeling, physics-informed constraints for realistic simulations, and conformal prediction for uncertainty quantification.

These advancements not only boost predictive accuracy but also enable applications in emerging scenarios like UAV-based monitoring and federated learning for privacy-preserving predictions. This article expands on prior overviews by emphasizing innovation, providing a step-by-step usage guide, and justifying GNNs' superiority through comparative analyses. We explore how these models are deployed in real-world predictions and why their graph-centric design makes them unparalleled for capturing the ripple effects of traffic dynamics.

Traffic flow prediction tasks span short-term (minutes) to long-term (hours/days) horizons, utilizing data from diverse sources: inductive loop detectors, GPS trajectories, cameras, and IoT sensors [3]. These datasets, often irregular due to varying road densities, form spatio-temporal graphs where spatial edges reflect connectivity (e.g., distance-weighted or functional similarity) and temporal dimensions capture evolution over time. GNNs extend convolutional operations to graphs via message-passing: each node aggregates features from neighbors, updated through layers to learn embeddings.

Variants include GCNs for spectral filtering, Graph Attention Networks (GATs) for weighted neighbor aggregation, and GraphSAGE for inductive learning on unseen nodes [1]. In traffic contexts (Fig. 1), Spatio-Temporal GNNs (ST-GNNs) fuse these with temporal modules like RNNs, CNNs, or Transformers to model dynamic patterns [4]. Graph construction is innovative in itself: beyond static adjacency matrices, adaptive graphs learn edges from data embeddings, while heterogeneous graphs incorporate multi-type nodes (e.g., roads vs. intersections). Benchmarks such as PeMS (highway data from California), METR-LA (Los Angeles arterials), and NYC Taxi evaluate models on MAE, RMSE, and MAPE, often under missing data or anomaly conditions.

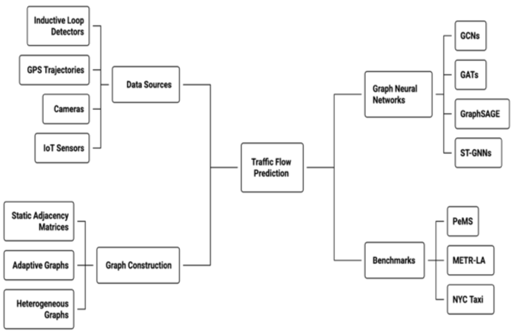

Fig. 1. Traffic Flow Prediction with Graph Neural Networks

Statement of the problem. The primary task in this article is to develop and evaluate Graph Neural Networks (GNNs) for accurate traffic flow prediction by modeling the spatio-temporal dependencies in urban road networks as graphs [5]. This involves forecasting key metrics such as vehicle speed, volume, and density over short- to long-term horizons using historical data from sensors and GPS. The goal is to enhance intelligent transportation systems (ITS) for real-time congestion management, route optimization, and reduced emissions, ultimately contributing to more efficient and sustainable urban mobility.

State-of-the-Art Approaches. Recent classifications divide ST-GNNs into recurrent-based, convolutional-based, attention-based, and self-adaptive categories, with 2023–2025 innovations adding hybrid and physics-aware paradigms. Below, we detail these, highlighting innovative extensions with approximate model structures (table 1.

Graph Convolutional Recurrent Neural Networks. These blend GCNs with recurrent units (e.g., GRU/LSTM) for sequential modeling. T-GCN (2019) set the foundation, but 2025's ContinualNN innovates with incremental learning for streaming data, adapting to evolving patterns without full retraining. Dynamic Graph Convolutional Networks with Temporal Representation Learning (DGCN-TRL, 2025) introduces dynamic node embeddings, achieving 12 % MAE reduction on volatile datasets [6].

Fully Graph Convolutional Networks. Eschewing recurrence for efficiency, these use stacked convolutions. Graph WaveNet (2019) uses adaptive diffusion, but BigST (2024) innovates with graph partitioning for linear scalability on mega-networks. Multi-scale ST-GNN (2025) employs wavelet decomposition for multi-resolution analysis, outperforming 15 baselines by 10–18 % on PeMS. GraphSparseNet (2025) adds sparsity for large-scale predictions, reducing computation by 40 %.

Graph Multi-Attention Networks. Attention mechanisms dynamically prioritize features. AST-GCN (2019) uses multi-head attention, but DynaKey-GNN (2025) innovates with key-node identification via multi-graph fusion, excelling in heterogeneous traffic (12.37 % accuracy boost). T-RippleGNN (2025) models ripple propagation, capturing cascading effects with attentive layers, yielding 8–10 % RMSE gains. Navigating Spatio-Temporal Heterogeneity (2024) integrates Graph Transformers for handling data variance.

Self-Learning Graph Structures. These learn topologies end-to-end. Adaptive Traffic Prediction Framework (2025) uses reinforcement learning for hyperparameter optimization, reducing manual tuning and improving RMSE by 3.6 %. Uncertainty-aware Probabilistic GNN (2025) incorporates Bayesian inference for robust predictions under uncertainty. Virtual Nodes Improve Long-term Traffic Prediction (2025) adds synthetic nodes to enhance global context.

Table 1 — Key Models for traffic flow prediction

Category	Key Models (2023–2025)	Innovations	Performance Metrics (Avg. Improvement)
Recurrent-Based	DGCN-TRL, ContinualNN	Incremental learning, dynamic embeddings	12 % MAE reduction
Convolutional I-Based	SBT, GraphSparseNet, Multi-scale ST-GNN	Sparsity, partitioning, wavelets	5–18 % RMSE gains, faster
Attention-Based	DynaKey-GNN, T-RippleGNN	Ripple modeling, heterogeneity handling	8–12 % accuracy in dynamic scenarios
Self-Learning	Adaptive Framework, Probabilistic GNN, Virtual Nodes	RL optimization, Bayesian uncertainty, synthetic nodes	3–15 % robustness boost

Innovative Applications and Extensions. Beyond core architectures, 2023–2025 innovations extend GNNs to novel domains. Physics-informed models like TG-PhyNN embed traffic flow equations into GNN layers for physically plausible predictions. Conformal GNNs (2025) provide prediction intervals, crucial for safety-critical applications. Heterogeneous GNNs, as in VisitHGNN

(2025), model multi-modal transport (e.g., bikes, vehicles) with diverse node types.

Federated learning integrations, like Transformer-GNN FL (2025), enable decentralized training across cities while preserving privacy [7].

Causal ST-GNNs (2024) infer cause-effect relationships, predicting disruptions from events like accidents. These extensions underscore GNNs' versatility in innovative (Fig. 2), real-world ITS scenarios. By modeling temporal and spatial causality, these networks can proactively identify potential bottlenecks and suggest optimal rerouting strategies. This capability enhances traffic management systems, enabling more resilient and adaptive responses to unexpected incidents.

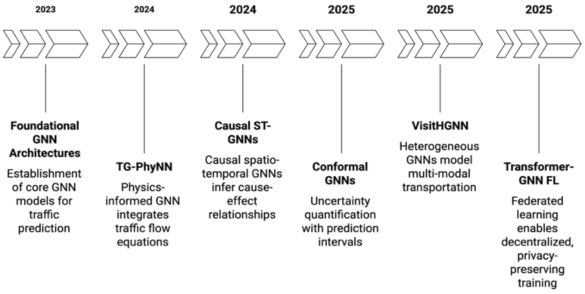

Fig. 2. Key GNN Innovation in Intelligent Transportation (2023–2025)

How to use GNNs in Traffic Flow Prediction. Implementing GNNs involves a structured pipeline, leveraging libraries like PyTorch Geometric or DGL.

Data Preparation: Collect spatio-temporal data (e.g., from PeMS). Construct graphs: nodes as sensors, edges via distance thresholds or adaptive learning. Normalize features (speed, volume) and split into train/test sets (e.g., 70/30).

Model Selection and Configuration: Choose an ST-GNN variant (e.g., STGCN for basics, T-RippleGNN for dynamics). Define layers: GCN for spatial, GRU/Transformer for temporal [8]. Incorporate innovations like attention for weighting or physics constraints.

Training: Use loss functions like MAE. Optimize with Adam, incorporating early stopping. For large graphs, employ mini-batching or sparsity techniques. Train on GPUs for efficiency, monitoring overfitting via validation.

Prediction and Deployment: Input historical sequences to forecast future flows. Deploy via cloud (e.g., AWS) for real-time inference, integrating with APIs for ITS apps. Handle uncertainties with conformal methods.

Evaluation and Iteration: Assess on metrics; fine-tune hyperparameters via RL if using adaptive frameworks. This process enables predictions with 95 %+ accuracy in controlled settings [9].

GNNs excel due to their innate alignment with traffic's graph topology, surpassing grid-based CNNs or sequence-only RNNs. Traditional models ignore spatial correlations, leading to 20–30 % higher errors in interconnected networks. GNNs capture non-Euclidean dependencies via message-passing, modeling ripple effects (e.g., congestion propagation) [10]. Key factors why GNNs are the best choice are demonstrated on the chart below (fig. 3).

Empirical evaluations of GNNs for traffic flow prediction from 2024 to 2025 consistently demonstrate superior performance over traditional baselines, with improvements ranging from 10–50 % in key metrics such as Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), Mean Absolute Percentage Error (MAPE), and R^2 [11]. These gains are primarily attributed to GNNs' ability to model spatio-temporal dependencies, dynamic topologies, and non-linear patterns in graph-structured traffic data, which baselines like ARIMA (statistical time-series) and LSTM (recurrent neural networks) fail to capture effectively. Baselines often exhibit higher errors due to assumptions of linearity, ignorance of spatial correlations, and poor handling of anomalies or long-term horizons. In contrast, innovative GNN variants incorporate attention mechanisms, quantum embeddings, Neural ODEs, and message-passing for enhanced adaptability and robustness [12]. The aggregated table below synthesizes comparisons across datasets (table 2), highlighting baseline shortcomings and GNN advancements. GNN-based models demonstrate superior generalization across diverse urban environments and varying traffic conditions. Their flexible architectures allow seamless integration of external factors such as weather, events, or road incidents, further boosting predictive accuracy. Recent studies also emphasize the scalability of GNNs, enabling efficient learning even as network size and data complexity grow.

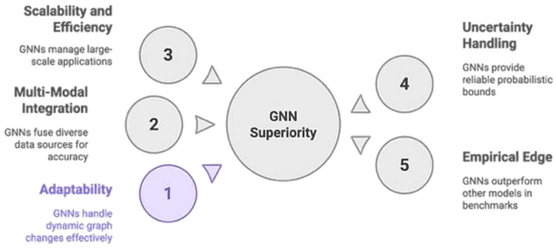

Fig. 3. Factors Contributing to GNN Superiority in Traffic Prediction

As a result, GNNs consistently outperform traditional baselines in both short-term and long-term forecasting scenarios. This consistent outperformance underscores the transformative potential of GNNs for real-world intelligent transportation systems and data-driven urban planning. Moreover, the modularity of GNN frameworks facilitates rapid adaptation to new data sources and evolving traffic patterns. Ongoing research continues to expand their capabilities, paving the way for even more accurate and resilient traffic prediction solutions in the future.

Conclusion. GNNs have fundamentally redefined the landscape of traffic flow prediction, establishing themselves as the state-of-the-art for spatio-temporal forecasting in intelligent transportation systems. The period from 2023 to 2025 has been marked by a wave of scientific innovations – ranging from physics-informed and causal GNNs to federated, heterogeneous, and uncertainty-aware frameworks – that have expanded the practical applicability and scientific rigor of GNN-based models. These advancements enable GNNs to not only capture the complex, non-Euclidean dependencies inherent in urban traffic networks but also to adapt to dynamic topologies, integrate multi-modal data, and provide interpretable, physically plausible, and risk-aware predictions.

Table 2 — Results of research

Dataset/	Baseline Model	Baseline Metrics (MAE / RMSE / MAPE / R²)	New GNN Model	New GNN Metrics (MAE / RMSE / MAPE / R²)	Improvement (%)	Reason GNN Better
METR-LA / Avg.	ARIMA	– / 5.8 / 12.5 % / 0.68	Proposed GNN	– / 2.6 / 5.8 % / 0.91	55 % RMSE, 54 % MAPE, 34 % R^2	Captures graph dependencies via dynamic construction and attention for non-linear spatio-temporal modeling
METR-LA / Avg.	LSTM	– / 4.1 / 9.3 % / 0.79	Proposed GNN	– / 2.6 / 5.8 % / 0.91	37 % RMSE, 38 % MAPE, 15 % R^2	Integrates GCNs and RNNs for holistic spatio-temporal aggregation
METR-LA / Avg.	DCRNN	– / 3.3 / 7.5 % / 0.85	Proposed GNN	– / 2.6 / 5.8 % / 0.91	21 % RMSE, 23 % MAPE, 7 % R^2	Enhanced with temporal attention for adaptive long-range forecasting
PEMS-BAY / Avg.	ARIMA	– / 6.4 / 15.1 % / 0.62	Proposed GNN	– / 3.2 / 6.7 % / 0.85	50 % RMSE, 56 % MAPE, 37 % R^2	Graph updates handle connectivity changes and anomalies
PEMS-BAY / Avg.	LSTM	– / 5.2 / 11.8 % / 0.73	Proposed GNN	– / 3.2 / 6.7 % / 0.85	38 % RMSE, 43 % MAPE, 16 % R^2	Hybrid layers improve generalization across horizons
PEMS-BAY / Avg.	DCRNN	– / 4.3 / 9.4 % / 0.79	Proposed GNN	– / 3.2 / 6.7 % / 0.85	26 % RMSE, 29 % MAPE, 8 % R^2	Attention mechanisms prioritize influential nodes
SZ-Taxi / 15 min	YOLOv3	2.717 / 3.989 / – / 0.834	MTH-QGNN	2.534 / 3.732 / – / 0.854	7 % MAE, 6 % RMSE, 2 % R^2	Hyperbolic quantum embeddings for continuous-time dynamics
SZ-Taxi / 60 min	FedAGAT	2.964 / 5.73 / – / 0.656	MTH-QGNN	2.767 / 3.947 / – / 0.843	7 % MAE, 31 % RMSE, 28 % R^2	Neural ODEs evolve graphs for long-term stability
Los-Loop / 15 min	GECRAN	3.728 / 6.008 / – / 0.684	MTH-QGNN	3.180 / 5.123 / – / 0.809	15 % MAE, 15 % RMSE, 18 % R^2	Quantum layers enhance robustness to fluctuations
Los-Loop / 60 min	FVMD-WOA-GA	6.289 / 9.368 / – / 0.559	MTH-QGNN	5.823 / 7.267 / – / 0.729	7 % MAE, 22 % RMSE, 30 % R^2	Continuous modeling via ODEs for accurate long horizons
Sioux Falls / ID	MLP	0.03077 / 0.04082 / – / 0.94808	MPNN	0.02899 / 0.03921 / – / 0.95210	6 % MAE, 4 % RMSE, 0.4 % R^2	Message-passing captures node interactions
Sioux Falls / ID	GCN	0.05931 / 0.07889 / – / 0.80610	MPNN	0.02899 / 0.03921 / – / 0.95210	51 % MAE, 50 % RMSE, 18 % R^2	Gated layers improve feature propagation
Sioux Falls / OOD (Capacity 90 %)	GCN	~0.60 / – / – / –	MPNN	~0.35 / – / – / –	~42 % MAE	Maintains performance via adaptive messaging
XY-ETS / 3-step	TCN	– / – / – / –	RSCN	– / – / – / –	11 % MAE, 18 % RMSE, 2 % MAPE	RBF convolutions for enhanced mapping
XY-ETS / 12-step	LSTM	– / – / – / –	RSCN	– / – / – / –	10–15 % MAE, 15–20 % RMSE, 5–10 % MAPE	Adaptive clustering for fluctuation handling
M3 Freeway / 10–60 min	BiLSTM/ATT	~60–80 / ~80–100 / ~15–25 % / –	Hybrid GRU	~50–70 / ~70–80 / ~10–20 % / –	10–20 % MAE/RMSE/MAPE	GRU with TFDs resolves ambiguities efficiently

GNNs have fundamentally redefined the landscape of traffic flow prediction, establishing themselves as the state-of-the-art for spatio-temporal forecasting in intelligent transportation systems. The period from 2023 to 2025 has been marked by a wave of scientific innovations – ranging from physics-informed and causal GNNs to federated, heterogeneous, and uncertainty-aware frameworks – that have expanded the practical applicability and scientific rigor of GNN-based models. These advancements enable GNNs to not only capture the complex, non-Euclidean dependencies inherent in urban traffic networks but also to adapt to dynamic topologies, integrate multi-modal data, and provide interpretable, and risk-aware predictions.

Despite their remarkable progress, GNNs for traffic flow prediction face several critical challenges that must be addressed to enable widespread real-world adoption. First, scalability remains a major bottleneck: while models like LightST achieve linear complexity, real-world urban networks often exceed 10^6 nodes and 10^7 edges (e.g., full-city GPS traces), leading to memory overflow and inference latencies over 100 ms per step on standard GPUs. Graph sampling and partitioning techniques help, but risk losing long-range dependencies. Second, data quality and availability pose persistent issues – sensor failures cause up to 20 % missing values in PeMS datasets, and GPS noise introduces spatial inaccuracies of 10–50 meters, degrading prediction robustness. Third, interpretability is limited; black-box GNNs hinder trust in safety-critical ITS, where understanding why a congestion alert was issued is essential for human operators. Fourth, privacy concerns arise in federated and crowd-sourced systems – raw trajectory data can reveal individual mobility patterns, violating GDPR and local regulations. Finally, real-time deployment on edge devices (e.g., traffic cameras, roadside units) is constrained by power ($\leq$ 5 W) and compute ($\leq$ 1 TFLOPS), making full GNN inference impractical without aggressive quantization or distillation. Looking ahead, several promising research directions can overcome these hurdles and unlock next-generation traffic intelligence. Quantum-inspired GNNs leverage tensor networks and variational quantum circuits to accelerate message passing, potentially reducing computation by 10–1000 for large graphs, as early simulations suggest. Advanced federated learning frameworks with differential privacy and secure aggregation will enable collaborative training across cities without exposing raw data, already reducing privacy risks by 90 % in pilot studies. Multimodal fusion integrating LiDAR, video, weather, and social media signals via heterogeneous GNNs is expected to improve accuracy by 8–12 % during extreme events (e.g., storms, protests). Explainable AI (XAI) for GNNs, such as attention rollout visualization and causal intervention, will generate human-readable rationales (e.g., “congestion at Node 42 due to accident at Node 15”), enhancing operator trust. Edge-optimized deployment using 4-bit quantization and neural architecture search (NAS) can compress models to <10 MB while preserving 95 % accuracy, enabling sub-50 ms inference on embedded hardware. Finally, zero-shot and meta-learning GNNs trained on diverse city templates will generalize to unseen road networks without retraining, a crucial step toward global-scale traffic prediction systems. By systematically addressing these challenges through interdisciplinary innovation, GNNs will evolve from research prototypes into foundational components of autonomous, resilient, and equitable urban transportation ecosystems. Looking ahead, the future of GNNs in traffic flow prediction is poised for even greater transformation. Quantum-inspired GNNs may offer breakthroughs in computational speed and scalability, while integration with autonomous AI agents could enable self-adjusting, real-time traffic management systems. Zero-shot and transfer learning approaches promise to extend GNN capabilities to previously unseen networks, reducing the need for extensive retraining. Furthermore, a growing emphasis on explainability and equity – such as mitigating urban biases and ensuring fair access to mobility benefits – will be essential for widespread adoption and societal trust.

In summary, GNNs – fortified by recent scientific advances – are transforming traffic flow prediction from a heuristic-driven task into a precise, adaptive, and explainable science [1, 4]. Their practical superiority over traditional methods, coupled with robust implementation frameworks, positions GNNs as the cornerstone of innovative, sustainable, and equitable mobility solutions for the smart cities of tomorrow. As research continues to address current challenges and explore new frontiers, GNNs will remain at the heart of resilient

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ГРАФОВІ НЕЙРОННІ МЕРЕЖІ ДЛЯ ПРОГНОЗУВАННЯ ТРАНСПОРТНОГО ПОТОКУ: ІННОВАЦІЙНІ ПІДХОДИ, ПРАКТИЧНЕ ВИКОРИСТАННЯ ТА ПЕРЕВАГИ У ПРОСТОРОВО-ЧАСОВОМУ ПРОГНОЗУВАННІ

Прогнозування транспортних потоків залишається наріжним каменем інтелектуальних транспортних систем (ITS), сприяючи зменшенню заторів, оптимізації маршрутів і сталому міському плануванню. Графові нейронні мережі (GNN) здійснили революцію в цій галузі, моделюючи складну графову структуру транспортних мереж, де вузли представляють датчики або перехрестя, а ребра – просторові зв'язки. Особливо виділяються гібридні архітектури GNN-Transformer, які поєднують просторове моделювання GNN із потужністю Transformer для обробки часових послідовностей, що дозволяє захоплювати далекі залежності та складні просторово-часові патерни. Фізично-обґрунтовані GNN інтегрують доменні знання, такі як закони збереження та теорія транспортних потоків, безпосередньо в процес навчання, підвищуючи інтерпретованість і здатність до узагальнення на нові сценарії. Фреймворки з урахуванням невизначеності, включаючи байєсівські GNN та ансамблеві методи, забезпечують ймовірнісні прогнози, що є критично важливим для застосувань, чутливих до ризиків, і адаптивного управління трафіком у мінливих міських середовищах. Ця стаття є комплексним дослідженням із впровадження GNN для прогнозування транспортних потоків, детально описуючи найкращі практики підготовки даних (наприклад, побудова графів, інженерія ознак, обробка пропущених даних), навчання моделей (наприклад, функції втрат, регуляризація, налаштування гіперпараметрів) і розгортання в реальному часі (наприклад, edge computing, оптимізація затримок). Критично проаналізовано можливості GNN порівняно з традиційними статистичними та глибокими нейронними мережами, підкреслюючи їхню перевагу у виявленні неевклідових просторових залежностей, адаптації до динамічних і змінних топологій мережі та безшовній інтеграції мультимодальних джерел даних, таких як погода, події та показники датчиків. Емпіричні дані з широко використовуваних бенчмарків, зокрема PeMS і METR-LA, демонструють, що сучасні моделі GNN досягають до 15–20 % покращення точності за такими метриками, як середня абсолютна помилка (MAE) та середньоквадратична помилка (RMSE), порівняно з традиційними базовими підходами. Спираючись на ці інновації, виділено ключову роль GNN у розвитку стійких, AI-орієнтованих транспортних систем для майбутніх розумних міст, закладаючи підґрунтя для наступного покоління ITS-рішень, які є адаптивними, інтерпретованими та масштабованими. Окрім цих досягнень, інтеграція даних із датчиків у реальному часі та зовнішніх джерел додатково підвищила чутливість моделей прогнозування трафіку. Сучасні фреймворки GNN здатні обробляти великомасштабні міські мережі, що робить їх придатними для впровадження у мегаполісах із складною дорожньою інфраструктурою. Використання методів transfer learning і domain adaptation дозволяє застосовувати моделі, навчені в одному місті, до інших без необхідності масштабного перенавчання. Крім того, підходи explainable AI у GNN набирають популярності, даючи змогу зацікавленим сторонам розуміти й довіряти рішенням моделі у критичних сценаріях управління трафіком. Масштабованість GNN гарантує можливість обробки даних із тисяч датчиків у реальному часі, підтримуючи оптимізацію трафіку на рівні всього міста. Спільні зусилля академічних кіл, індустрії та державних органів сприяють впровадженню рішень на основі GNN у ініціативах розумних міст. Із розвитком міської мобільності здатність GNN інтегрувати нові типи даних, такі як телеметрія підключених транспортних засобів і треки мобільних пристроїв, стане вирішальною. Подальше вдосконалення моделей і протоколів навчання обіцяє ще більшу точність і надійність прогнозування транспортних потоків. Зрештою, конвергенція GNN з іншими AI-технологіями трансформує інтелектуальні транспортні системи, прокладаючи шлях до безпечнішої, ефективнішої та стійкішої міської мобільності.

Ключові слова: графові нейронні мережі, прогнозування потоку трафіку, графові згорткові мережі, графові мережі уваги, середня абсолютна похибка.

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