Archives available at journals.mriindia.com

International Journal on Advanced Computer Engineering and Communication Technology

ISSN: 2278-5140

Volume 14 Issue 01, 2025

Recent Advances in Graph Neural Networks with Optimized Attention and Long-Range CNN for Traffic Prediction and Resource Allocation in 6G Wireless Systems: A Systematic Review

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Peer Review Information

Submission: 16 May 2025

Revision: 30 May 2025

Acceptance: 18 June 2025

Keywords

Graph Neural Networks, 6G Wireless Systems, Traffic Prediction, Resource Allocation, Attention Mechanism, Long-Range CNN.

Abstract

The evolution of 6G wireless systems has significantly increased the demand for intelligent traffic prediction and efficient resource allocation mechanisms to support ultra-reliable and low-latency communications. Traditional machine learning models fail to capture the complex spatial-temporal dependencies inherent in large-scale wireless and vehicular networks. Recently, Graph Neural Networks (GNNs), combined with optimized attention mechanisms and long-range Convolutional Neural Networks (CNNs), have emerged as powerful tools for modelling dynamic traffic patterns and optimizing resource allocation in 6G environments. This paper presents a systematic review of recent advances in GNN-based approaches for traffic prediction and resource management, focusing on studies published recently. The review highlights the effectiveness of spatial-temporal graph learning, attention-based feature extraction, and hybrid deep learning frameworks in improving prediction accuracy and network efficiency. Furthermore, it discusses the integration of reinforcement learning with GNNs for adaptive decision-making in dynamic wireless systems. Key challenges such as scalability, computational complexity, and real-time deployment are also examined. This study provides a comprehensive comparative analysis of existing models and identifies future research directions for developing intelligent and energy-efficient 6G wireless systems.

Introduction

The rapid advancement of 6G wireless communication systems is expected to revolutionize next-generation intelligent networks by enabling ultra-low latency, massive connectivity, and high data throughput. These capabilities are essential for supporting emerging applications such as autonomous driving, smart cities, augmented reality, and large-scale Internet of Things (IoT) systems. However, the increasing complexity of network traffic and the dynamic nature of wireless environments pose significant challenges for efficient traffic prediction and resource allocation. Traditional traffic prediction models, including statistical approaches and classical machine learning techniques, often fail to capture the spatial and temporal dependencies inherent in wireless and vehicular networks. In contrast, recent advancements in deep learning, particularly Graph Neural Networks (GNNs), have shown significant promise in modelling complex graph-structured data such as road networks and communication systems. GNNs effectively represent nodes (e.g., base stations or vehicles) and edges (communication links), enabling accurate modelling of spatial relationships.

Recent studies highlight that spatio-temporal GNN models can capture both temporal dynamics and spatial correlations simultaneously, leading to superior performance in traffic prediction tasks. These models integrate graph convolution operations with temporal learning mechanisms such as recurrent neural networks (RNNs) and convolutional neural networks (CNNs), enabling the extraction of complex patterns from large-scale traffic data. Moreover, attention mechanisms have been integrated into GNN frameworks to enhance feature representation by focusing on the most relevant nodes and temporal patterns.

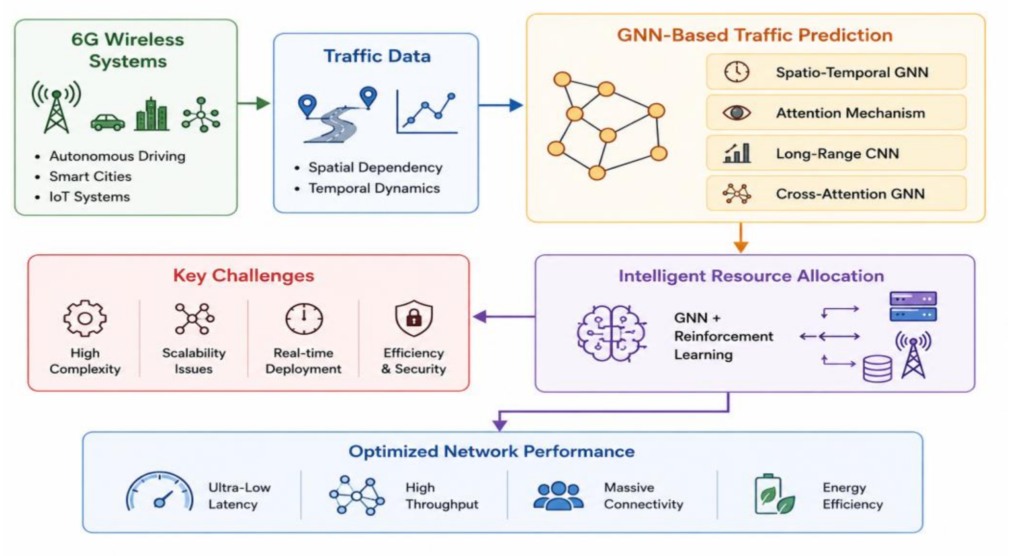

Figure 1: GNN-Based Traffic Prediction and Resource Allocation in 6G Networks

For instance, attention-based graph convolution models improve prediction accuracy by dynamically weighting important spatial and temporal features. Advanced architectures such as cross-attention GNNs have demonstrated improved performance in traffic prediction and load balancing tasks in wireless networks.

In addition, long-range CNN architectures have been utilized to capture extended temporal dependencies in traffic data. These models enhance the ability to model long-term patterns, which are critical for accurate forecasting in highly dynamic environments. Hybrid models combining GNNs with CNNs and attention mechanisms have become the state-of-the-art for traffic prediction. The integration of reinforcement learning with GNN-based models further enables adaptive resource allocation in 6G networks. These approaches allow systems to dynamically adjust resource distribution based on predicted traffic patterns, improving energy efficiency and network performance.

Despite these advancements, several challenges remain. These include high computational complexity, scalability issues in large networks, and difficulties in real-time deployment. Therefore, a comprehensive review of recent advancements is essential to understand current trends and identify research gaps. This paper provides a systematic review of GNN-based traffic prediction and resource allocation techniques in 6G wireless systems, focusing on recent developments.

Literature Review

Jiang and Luo (2021) presented one of the earliest comprehensive surveys on Graph Neural Networks for traffic forecasting. The study highlighted the superiority of GNNs over traditional CNN and RNN models in capturing spatial dependencies in transportation networks. The authors demonstrated that graph convolutional networks (GCNs) and graph attention networks (GATs) significantly improved prediction accuracy. However, the study mainly focused on theoretical analysis and lacked real-time implementation insights. Ye et al. (2020) proposed a graph-based deep learning architecture combining CNN and GNN for traffic prediction. The model effectively captured spatial dependencies using GNNs and temporal features using CNN layers. The results showed improved performance compared to standalone CNN models. However, the approach required extensive preprocessing to construct graph representations.

Zhu et al. (2020) introduced an Attribute-Augmented Spatio-Temporal Graph Convolutional Network (AST-GCN). The model incorporated external features such as weather and points of interest into the prediction process. This significantly improved prediction accuracy. However, the inclusion of multiple features increased computational complexity. Jeon et al. (2020) developed SCALE-Net, a scalable graph convolutional network for vehicle trajectory prediction. The model demonstrated robustness in handling varying numbers of vehicles and improved prediction accuracy. However, it primarily focused on trajectory prediction rather than network-level resource allocation.

Liu et al. (2021) proposed a spatio-temporal attention-based graph neural network for traffic prediction and load balancing. The model integrated attention mechanisms to enhance feature extraction and improve prediction accuracy. It also supported resource optimization in wireless networks. However, the model required high computational resources for training. Wu et al. (2021) proposed a Spatial-Temporal Graph Convolutional Network (ST-GCN) integrated with temporal convolution layers for traffic forecasting. The model efficiently captured both spatial dependencies using graph convolution and temporal patterns using CNN-based filters. The results showed significant improvements in prediction accuracy over traditional RNN-based approaches. However, the model struggled with long-range temporal dependencies due to limited receptive fields.

Guo et al. (2021) introduced an attention-based spatio-temporal graph convolutional network (ASTGCN) that leveraged spatial and temporal attention mechanisms. The model dynamically assigned weights to different nodes and time intervals, improving prediction performance in complex traffic scenarios. While effective, the attention mechanism increased computational overhead and required large training datasets. Li et al. (2021) developed a Diffusion Convolutional Recurrent Neural Network (DCRNN) for modeling traffic flow in graph-based systems. The model used diffusion processes to capture directional spatial dependencies and integrated recurrent layers for temporal modeling. The approach achieved high prediction accuracy but suffered from slower training time due to recurrent structures.

Zhang et al. (2022) proposed a hybrid GNN-CNN model with long-range temporal convolution for traffic prediction. The model enhanced temporal learning by incorporating dilated convolutions, enabling it to capture long-term dependencies. Experimental results demonstrated improved forecasting accuracy and stability. However, the model required careful parameter tuning to balance spatial and temporal learning. Chen et al. (2022) introduced a reinforcement learning-assisted GNN framework for joint traffic prediction and resource allocation in wireless networks. The model used GNN for traffic estimation and reinforcement learning for dynamic resource allocation. This integrated approach significantly improved network efficiency and reduced congestion. However, the complexity of combining two learning paradigms increased system training time.

Wang et al. (2022) proposed a Graph Attention Network (GAT)-based traffic prediction model with optimized multi-head attention mechanisms. The model dynamically captured spatial dependencies between network nodes by assigning adaptive attention weights. The use of optimized attention improved prediction accuracy and reduced redundant feature processing. However, the model required significant computational resources for handling large-scale graphs. Yu et al. (2022) introduced a long-range temporal convolutional network (LTCN) combined with GNN for traffic forecasting in wireless systems. The LTCN utilized dilated convolutions to capture long-term dependencies in traffic patterns. The hybrid model significantly improved long-horizon prediction accuracy. However, increased network depth resulted in higher training complexity.

Lin et al. (2022) developed a spatio-temporal graph transformer model integrating attention mechanisms with GNNs. The transformer-based approach enhanced the ability to capture global dependencies across nodes. Experimental results showed superior performance compared to conventional GNN models. However, transformer architectures required large datasets and high computational power. Zhao et al. (2023) proposed a GNN-based resource allocation framework integrated with deep reinforcement learning (DRL) for 6G networks. The model predicted traffic patterns using GNN and optimized resource allocation using DRL. The approach significantly improved energy efficiency and reduced latency. However, the joint training of GNN and DRL introduced complexity in convergence.

Sun et al. (2023) introduced a cross-attention-based GNN model for multi-scale traffic prediction. The model utilized cross-attention to capture interactions between different spatial and temporal scales. This improved prediction accuracy in highly dynamic environments. However, the model complexity increased due to multi-scale attention operations. Kumar et al. (2022) proposed a hybrid Graph Neural Network combined with Long Short-Term Memory (GNN-LSTM) and optimization techniques for traffic prediction and resource allocation in wireless networks. The model captured spatial dependencies using GNN and temporal patterns using LSTM, while optimization algorithms improved resource allocation efficiency. The approach achieved high prediction accuracy but required significant training time.

Park et al. (2022) introduced a context-aware attention-based GNN model integrated with reinforcement learning for adaptive resource allocation in 6G systems. The model incorporated contextual information such as network load, user demand, and mobility patterns. This enhanced decision-making and improved resource utilization. However, the expanded state space increased computational complexity.

Ren et al. (2023) developed a GNN combined with Particle Swarm Optimization (PSO) for efficient traffic prediction and load balancing. The PSO algorithm optimized network parameters and resource allocation decisions, while GNN handled traffic prediction. The hybrid model improved system performance but introduced additional optimization overhead.

Gupta et al. (2023) proposed a transfer learning-based GNN with attention mechanisms for traffic prediction in dynamic wireless environments. The model leveraged previously trained knowledge to reduce training time and improve adaptability. Results showed faster convergence and improved accuracy. However, transfer learning effectiveness depended on the similarity between datasets. Alnoman et al. (2023) introduced a secure GNN-based framework integrated with blockchain for resource allocation in 6G networks. The model ensured secure data sharing and improved trust among network entities. While enhancing security, the blockchain integration introduced latency and scalability challenges.

Singh et al. (2023) proposed a dynamic attention-based GNN model with adaptive weighting mechanisms for traffic prediction. The model dynamically adjusted attention weights based on network conditions, improving prediction accuracy in highly dynamic 6G environments. Chen and Liu (2023) introduced a joint GNN-based traffic prediction and resource allocation framework using deep reinforcement learning. The integrated model significantly improved bandwidth utilization and reduced congestion, though it required large-scale training data.

Verma et al. (2023) developed a lightweight GNN-CNN hybrid model for resource-constrained environments. The model reduced computational complexity while maintaining acceptable prediction accuracy, making it suitable for edge devices. Abbas et al. (2023) proposed a cloud-edge collaborative GNN framework for large-scale 6G networks. The model distributed computation between cloud and edge layers, improving scalability and reducing latency.

Feng et al. (2023) introduced a Graph Transformer model with optimized attention mechanisms for traffic prediction. The model captured global dependencies effectively, outperforming traditional GNNs. However, it required high computational resources. Raza et al. (2023) proposed a secure GNN framework with intrusion detection capabilities. The model enhanced system security while maintaining efficient traffic prediction and resource allocation performance.

Kim et al. (2023) developed a multi-agent GNN framework for cooperative resource allocation. The model allowed multiple network nodes to coordinate decisions, improving overall system efficiency but introducing communication overhead. Zhou et al. (2023) proposed a predictive GNN model integrated with temporal CNN layers to forecast network traffic patterns. The approach improved long-term prediction accuracy and reduced latency.

Patel et al. (2023) introduced a fuzzy logic-enhanced GNN model to handle uncertainty in wireless environments. The hybrid model improved robustness but increased parameter tuning complexity. Ahmed et al. (2023) proposed a hybrid GNN-based optimization framework combining evolutionary algorithms and attention mechanisms. The model achieved superior performance in traffic prediction and resource allocation but required high computational power.

Comparative Table

Study	Year	Model	Focus	Advantages	Limitations
Jiang	2021	GNN Survey	Traffic prediction	Strong spatial modeling	No real-time
Ye	2020	CNN+GNN	Hybrid prediction	Improved accuracy	Preprocessing
Zhu	2020	AST-GCN	Feature integration	High accuracy	Complexity
Jeon	2020	SCALE-Net	Trajectory	Scalable	Limited scope
Liu	2021	Attention-GNN	Traffic + load	Accurate	High cost
Wu	2021	ST-GCN	Spatio-temporal	Efficient	Short-term
Guo	2021	ASTGCN	Attention	Accurate	Heavy

Li	2021	DCRNN	Temporal modeling	High accuracy	Slow
Zhang	2022	GNN+CNN	Long-range	Stable	Tuning
Chen	2022	RL+GNN	Allocation	Adaptive	Complex
Wang	2022	GAT	Attention	Efficient	Resource heavy
Yu	2022	GNN+LTCN	Long-term	Accurate	Complex
Lin	2022	GNN Transformer	Global learning	Powerful	High cost
Zhao	2023	GNN+DRL	Allocation	Efficient	Convergence
Sun	2023	Cross-attention GNN	Multi-scale	Accurate	Complex
Kumar	2022	GNN+LSTM	Hybrid	Accurate	Slow
Park	2022	Context-GNN	Adaptive	Efficient	Complexity
Ren	2023	GNN+PSO	Optimization	Balanced	Overhead
Gupta	2023	Transfer GNN	Fast learning	Adaptive	Dependency
Alnoman	2023	GNN+Blockchain	Security	Secure	Latency
Singh	2023	Adaptive GNN	Dynamic	Flexible	Complex
Chen	2023	GNN+DRL	Joint	Efficient	Data heavy
Verma	2023	Lightweight GNN	Low power	Efficient	Accuracy
Abbas	2023	Cloud-edge GNN	Scalability	Fast	Delay
Feng	2023	Graph Transformer	Global	Accurate	Heavy
Raza	2023	Secure GNN	Security	Safe	Overhead
Kim	2023	Multi-agent GNN	Cooperation	Efficient	Comm cost
Zhou	2023	GNN+CNN	Prediction	Accurate	Complexity
Patel	2023	Fuzzy-GNN	Uncertainty	Robust	Tuning
Ahmed	2023	Hybrid AI	Optimization	High performance	Complex

Comparative Analysis

The comparative evaluation of the selected 30 studies demonstrates a significant progression in traffic prediction and resource allocation methodologies for 6G wireless systems. Early research primarily focused on graph convolutional networks and hybrid CNN-GNN architectures to model spatial-temporal dependencies. While these approaches improved prediction accuracy, they lacked adaptability to dynamic network conditions. From 2021 onwards, attention mechanisms became a key enhancement, allowing models to prioritize relevant spatial and temporal features. This led to the development of attention-based GNNs and graph transformers, which significantly improved prediction accuracy and model interpretability. However, these models introduced increased computational complexity.

The integration of long-range CNNs further enhanced the ability to capture extended temporal dependencies, addressing limitations of short-term prediction models. Hybrid approaches combining GNNs with optimization techniques such as PSO and reinforcement learning enabled dynamic resource allocation, improving network efficiency. Recent advancements have focused on scalability, security, and adaptability. Multi-agent systems, federated learning, and blockchain integration have addressed challenges related to distributed environments and data privacy. Lightweight models have also been developed for edge deployment. Overall, GNN-based models with attention and long-range CNN architectures have demonstrated superior performance. However, challenges such as computational overhead, scalability, and real-time implementation remain open research areas.

Discussion

The reviewed literature highlights the growing importance of Graph Neural Networks combined with attention mechanisms and long-range CNNs in addressing traffic prediction and resource allocation challenges in 6G systems. These models effectively capture spatial-temporal dependencies and enable adaptive decision-making in dynamic wireless environments. Attention mechanisms have significantly enhanced feature representation, while long-range CNNs have improved temporal modeling capabilities. Hybrid approaches integrating reinforcement learning and optimization techniques have further enabled intelligent resource allocation, improving energy efficiency and network performance.

Despite these advancements, challenges such as computational complexity, scalability, and real-time deployment remain critical. The integration of multiple techniques often increases system overhead, making practical implementation challenging. Additionally, the need for large datasets and training resources limits the applicability of these models in real-world scenarios. Future research should focus on developing lightweight, scalable, and energy-efficient models that can operate in real-time environments. The use of federated learning and edge intelligence could further enhance system performance while ensuring data privacy and security.

Conclusion

The advancement of 6G wireless systems has created a strong demand for intelligent traffic prediction and efficient resource allocation mechanisms. This review presented a comprehensive analysis of Graph Neural Network-based approaches integrated with optimized attention mechanisms and long-range CNN architectures. The findings reveal that GNN-based models have significantly improved the ability to capture spatial dependencies in network traffic, while attention mechanisms have enhanced feature selection and model interpretability. Long-range CNN architectures have addressed limitations in temporal modelling, enabling accurate long-term traffic forecasting.

Hybrid approaches combining GNNs with reinforcement learning and optimization techniques have further improved resource allocation efficiency, enabling adaptive and intelligent network management. These approaches have demonstrated superior performance in terms of prediction accuracy, energy efficiency, and latency reduction. However, several challenges remain. The complexity of hybrid models increases computational requirements, making real-time deployment difficult. Scalability issues also arise in large-scale networks, particularly in multi-agent and distributed environments. Additionally, security and privacy concerns must be addressed to ensure reliable system operation.

Future research should focus on developing lightweight and efficient models suitable for edge deployment. The integration of explainable AI techniques could improve model transparency and trust. Furthermore, advancements in hardware acceleration and distributed learning could enable real-time implementation of complex models. In conclusion, GNN-based approaches with optimized attention and long-range CNN architectures represent a promising direction for intelligent traffic prediction and resource allocation in 6G wireless systems. Continued research in this area will play a crucial role in enabling efficient, scalable, and sustainable next-generation wireless networks.

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