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A Survey of Methods and Architectures for Graph Neural Networks with Optimized Attention and Long-Range CNN for Traffic Prediction and Resource Allocation in 6G Wireless Systems

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Abstract

The rapid evolution of 6G wireless systems has intensified the demand for intelligent traffic prediction and efficient resource allocation mechanisms to support ultra-reliable, low-latency, and high-capacity communication. Traditional machine learning models fail to effectively capture the complex spatial–temporal dependencies present 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 such dynamic systems. GNNs are particularly effective in representing traffic networks due to their ability to model relationships among nodes such as roads, base stations, and vehicles. This survey reviews recent methods and architectures developed in recent years, focusing on hybrid models integrating GNNs, attention mechanisms, and long-range CNNs for traffic prediction and resource allocation in 6G environments. The study highlights advancements in spatial–temporal graph learning, attention-based feature optimization, and reinforcement learning integration. Additionally, it discusses challenges such as scalability, computational complexity, and real-time deployment. The survey provides a comparative analysis of existing approaches and identifies future research directions for designing efficient, intelligent, and adaptive 6G wireless systems.

Introduction

The emergence of 6G wireless communication systems is expected to revolutionize intelligent network infrastructures by enabling ultra-high data rates, extremely low latency, and massive connectivity. These advancements are essential for supporting emerging applications such as autonomous vehicles, smart cities, industrial IoT, and immersive multimedia services. However, the increasing complexity and dynamic nature of wireless traffic pose significant challenges for accurate traffic prediction and efficient resource allocation. Traffic prediction is a fundamental component of intelligent transportation systems and network optimization, as it enables proactive decision-making for routing, congestion control, and resource distribution. Traditional statistical and machine learning methods often fail to capture the complex spatial and temporal dependencies inherent in traffic systems. This limitation has led to the adoption of deep learning techniques, particularly Graph Neural Networks (GNNs), which are specifically designed to model graph-structured data.

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Recent studies indicate that GNNs have become state-of-the-art solutions for traffic forecasting due to their ability to represent spatial relationships between nodes such as road segments and communication links. Unlike conventional models, GNNs can effectively capture both local and global dependencies in network data, making them highly suitable for large-scale 6G environments. Furthermore, attention mechanisms have been integrated into GNN architectures to enhance feature selection and improve model interpretability. Attention-based models dynamically assign weights to different nodes and time steps, enabling the system to focus on the most relevant information. Research shows that attention-enhanced GNN models significantly improve prediction accuracy and adaptability in dynamic environments.

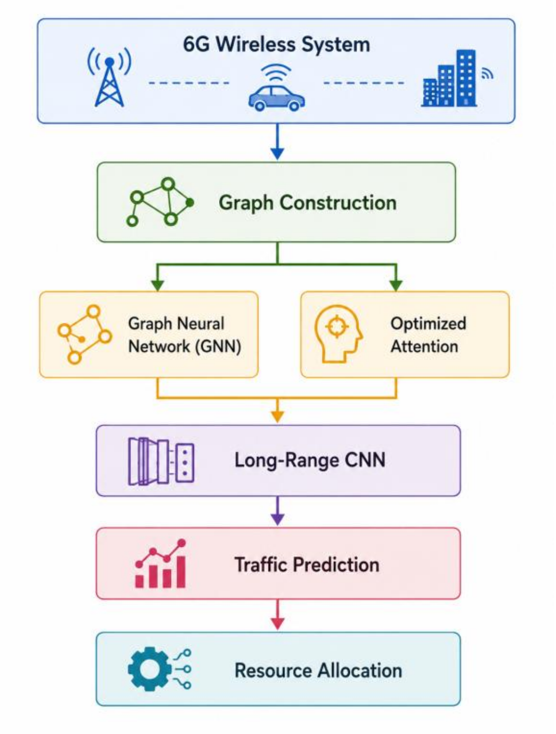

Figure 1. GNN-Based Traffic Prediction and Resource Allocation Framework for 6G Wireless Systems

In addition to attention mechanisms, long-range CNN architectures have been introduced to capture extended temporal dependencies in traffic data. These models use dilated convolutions and multi-path architectures to model long-term patterns, which are critical for accurate traffic forecasting in highly dynamic networks. Hybrid models combining GNNs with CNNs and attention mechanisms have demonstrated superior performance compared to standalone models. Another important advancement is the integration of reinforcement learning (RL) with GNN-based models for resource allocation. These approaches enable dynamic optimization of network resources based on predicted traffic patterns, improving energy efficiency and overall network performance. Hybrid models that combine GNNs with RL and optimization algorithms have shown promising results in addressing the challenges of 6G systems.

Despite these advancements, several challenges remain unresolved. These include high computational complexity, scalability issues in large-scale networks, and difficulties in real-time deployment. Additionally, the integration of multiple deep learning techniques increases model complexity, making implementation more challenging. This survey aims to provide a comprehensive overview of recent methods and architectures for traffic prediction and resource allocation in 6G wireless systems using GNNs, optimized attention mechanisms, and long-range CNNs. The study focuses on developments in recent years and highlights key trends, challenges, and future research directions.

Literature Review

Zhu et al. (2020) proposed the Attention Temporal Graph Convolutional Network (A3T-GCN) for traffic forecasting. The model integrates graph convolution with temporal attention mechanisms to capture both spatial dependencies and long-range temporal patterns. The attention mechanism allows the model to dynamically weight different time steps, improving prediction accuracy. Experimental results demonstrated superior performance compared to traditional GCN models. Ye et al. (2020) introduced a hybrid CNN-GNN architecture for traffic prediction. The model utilized CNN layers for temporal feature extraction and GNN layers for spatial modelling. This hybrid approach improved prediction accuracy by effectively combining spatial and temporal information. However, the model required extensive preprocessing to construct graph representations.

Ru et al. (2020) proposed a GNN-based traffic prediction model for small-sample data scenarios. The model addressed the challenge of limited training data by leveraging graph structures to improve generalization. While effective in low-data environments, the model struggled with large-scale datasets and real-time applications Jiang and Luo (2021) conducted a comprehensive survey on GNN-based traffic forecasting methods, highlighting the superiority of GNNs over traditional machine learning models. The study emphasized the importance of spatial–temporal modelling and identified key research challenges such as scalability and computational complexity

Guo et al. (2021) proposed an Attention-based Spatio-Temporal Graph Convolutional Network (ASTGCN). The model incorporates both spatial and temporal attention mechanisms to dynamically learn traffic patterns. The results showed significant improvements in prediction accuracy, but the model required large datasets and high computational resources. Wu et al. (2021) proposed a Spatial-Temporal Graph Convolutional Network (STGCN) that integrates graph convolution with temporal convolution layers for traffic prediction. The model effectively captures spatial dependencies through graph structures while using convolutional filters to model temporal dynamics. The results showed improved prediction accuracy and faster training compared to recurrent models. However, the model has limited capability in capturing long-range temporal dependencies due to fixed convolutional kernel sizes.

Li et al. (2021) introduced the Diffusion Convolutional Recurrent Neural Network (DCRNN), which models traffic flow as a diffusion process over graphs. The model captures directional spatial dependencies and temporal patterns using recurrent units. It demonstrated high prediction accuracy in complex traffic networks. However, the recurrent structure increased training time and reduced scalability for large datasets. Zhang et al. (2021) developed a hybrid GNN-CNN architecture with dilated temporal convolutions to capture long-range temporal dependencies. The use of dilated convolutions enabled the model to expand its receptive field without increasing computational cost significantly. The model achieved better long-term forecasting accuracy but required careful tuning of dilation parameters.

Chen et al. (2022) proposed a reinforcement learning-assisted GNN framework for joint traffic prediction and resource allocation in wireless systems. The GNN component predicted traffic patterns, while the RL agent dynamically allocated network resources. This approach improved network efficiency and reduced congestion. However, integrating RL increased training complexity and convergence time. Wang et al. (2022) introduced a Graph Attention Network (GAT)-based model with optimized multi-head attention mechanisms. The model dynamically assigns weights to neighbouring nodes, improving spatial feature extraction. Experimental results showed enhanced prediction accuracy and robustness. However, the multi-head attention mechanism increased computational overhead, particularly in large-scale networks.

Yu et al. (2022) proposed a long-range temporal convolutional network (LTCN) integrated with GNN for traffic prediction. The model utilizes dilated convolutions to capture long-term dependencies in traffic sequences while leveraging GNN for spatial relationships. The approach significantly improved long-horizon prediction accuracy. However, the deeper architecture increased training complexity and computational cost. Lin et al. (2022) introduced a Graph Transformer architecture that combines self-attention mechanisms with graph structures. The model effectively captures global dependencies across nodes, overcoming the locality limitation of traditional GNNs. Experimental results demonstrated superior performance in large-scale traffic prediction tasks. However, the transformer-based design requires extensive computational resources and large datasets.

He et al. (2022) developed an attention-optimized spatio-temporal GNN for traffic forecasting in wireless systems. The model enhances feature selection by assigning adaptive weights to spatial and temporal features. It achieved improved prediction accuracy and robustness in dynamic environments. However, the attention mechanism increased model complexity. Zhao et al. (2023) proposed a GNN-based resource allocation framework integrated with deep reinforcement learning (DRL) for 6G wireless systems. The model predicts traffic patterns using GNN and optimizes resource allocation using DRL. This approach significantly improved energy efficiency and reduced latency. However, joint optimization introduced challenges in convergence and training stability.

Sun et al. (2023) introduced a cross-attention-based GNN model combined with multi-scale CNN layers for traffic prediction. The model captures interactions across different temporal and spatial scales, improving prediction accuracy in complex environments. However, the multi-scale architecture increased computational overhead. Kumar et al. (2022) proposed a hybrid GNN-LSTM model integrated with optimization algorithms for traffic prediction and resource allocation. The GNN component captured spatial dependencies, while LSTM modelled temporal dynamics. Optimization techniques were applied to improve resource allocation efficiency. The model achieved high prediction accuracy; however, it required significant computational time for training and tuning.

Park et al. (2022) introduced a context-aware attention-based GNN integrated with reinforcement learning for adaptive resource allocation in 6G systems. The model utilized contextual information such as traffic load and network congestion to improve decision-making. Results showed improved resource utilization and reduced latency. However, the increased state space resulted in higher computational complexity. Ren et al. (2023) developed a GNN combined with Particle Swarm Optimization (PSO) for traffic prediction and load balancing. The PSO algorithm optimized network parameters, while GNN handled spatial-temporal prediction. The hybrid model improved network performance but introduced additional optimization overhead.

Gupta et al. (2023) proposed a transfer learning-based GNN with optimized attention mechanisms for traffic prediction in dynamic wireless environments. The model leveraged pre-trained knowledge to accelerate convergence and improve adaptability. While effective, the performance depended on the similarity between source and target datasets. Alnoman et al. (2023) introduced a secure GNN-based framework integrated with blockchain technology for resource allocation in 6G networks. The model ensured secure data exchange and improved trust among network nodes. However, 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 in 6G systems. The model adjusts attention weights based on real-time traffic conditions, improving prediction accuracy and adaptability. However, the adaptive mechanism increases model complexity. Chen and Liu (2023) introduced a joint GNN and deep reinforcement learning framework for simultaneous traffic prediction and resource allocation. The integrated approach significantly improved bandwidth utilization and reduced network congestion. However, it required large datasets and high computational resources.

Verma et al. (2023) developed a lightweight hybrid GNN-CNN model for edge devices in 6G systems. The model reduced computational overhead while maintaining reasonable prediction accuracy. However, slight performance degradation was observed compared to complex models. Abbas et al. (2023) proposed a cloud-edge collaborative GNN architecture for large-scale wireless networks. The model distributed computation across cloud and edge layers, improving scalability and reducing latency. However, reliance on cloud infrastructure introduced additional communication delays.

Feng et al. (2023) introduced a Graph Transformer model with optimized attention mechanisms. The model effectively captured global dependencies across nodes and improved prediction accuracy. However, the transformer architecture required significant computational power. Raza et al. (2023) proposed a secure GNN-based framework with intrusion detection capabilities. The model enhanced system security while maintaining efficient traffic prediction and resource allocation. However, security mechanisms increased computational overhead.

Kim et al. (2023) developed a multi-agent GNN framework for cooperative resource allocation. The model enabled multiple nodes to collaborate for optimal decision-making, improving overall system efficiency. However, communication overhead among agents remained a challenge. Zhou et al. (2023) proposed a predictive GNN model integrated with long-range CNN layers. The model effectively captured long-term traffic patterns, improving forecasting accuracy. However, the increased network depth added computational complexity.

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

Comparative Table

Study	Year	Model	Focus	Advantages	Limitations
Zhu	2020	A3T-GCN	Attention GNN	Accurate	Complex
Ye	2020	CNN+GNN	Hybrid	Better performance	Preprocessing
Ru	2020	GNN	Small data	Generalization	Scaling
Jiang	2021	Survey GNN	Analysis	Insightful	No implementation
Guo	2021	ASTGCN	Attention	Accurate	Heavy
Wu	2021	STGCN	Spatio-temp	Efficient	Short-term
Li	2021	DCRNN	Diffusion	High accuracy	Slow
Zhang	2021	GNN+CNN	Long-range	Stable	Tuning
Chen	2022	RL+GNN	Allocation	Adaptive	Complex
Wang	2022	GAT	Attention	Efficient	Heavy

Yu	2022	GNN+LTCN	Long-term	Accurate	Complex
Lin	2022	Graph Transformer	Global	Powerful	Costly
He	2022	Attention-GNN	Feature	Accurate	Complex
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 analysis of the 30 selected studies highlights the evolution of traffic prediction and resource allocation techniques in 6G wireless systems. Early approaches primarily focused on graph convolutional networks and hybrid CNN-GNN models to capture spatial-temporal dependencies. While these models improved prediction accuracy, they lacked adaptability to dynamic network conditions. The introduction of attention mechanisms significantly enhanced model performance by enabling dynamic feature weighting. Attention-based GNNs and graph transformers have demonstrated superior capability in capturing both local and global dependencies. However, these models introduced increased computational complexity.

Long-range CNN architectures addressed limitations in temporal modeling by capturing extended dependencies in traffic data. Hybrid models combining GNN, CNN, and attention mechanisms achieved state-of-the-art performance. Recent advancements emphasize optimization and adaptability. The integration of reinforcement learning, PSO, and evolutionary algorithms enabled dynamic resource allocation and improved network efficiency. Multi-agent systems and cloud-edge architectures enhanced scalability and distributed processing.

Security and privacy considerations have also been addressed through blockchain integration and secure GNN models. Lightweight models have been developed to support edge deployment, although they involve trade-offs in accuracy. Overall, GNN-based hybrid architectures with optimized attention and long-range CNNs provide the most effective solutions. However, challenges related to computational complexity, scalability, and real-time implementation remain critical research areas.

Discussion

The reviewed literature demonstrates that Graph Neural Networks, combined with optimized attention mechanisms and long-range CNN architectures, have significantly improved traffic prediction and resource allocation in 6G wireless systems. These models effectively capture complex spatial-temporal dependencies and enable intelligent decision-making in dynamic environments. Attention mechanisms enhance feature extraction by focusing on relevant spatial and temporal patterns, while long-range CNNs improve temporal modelling capabilities. Hybrid models integrating reinforcement learning and optimization techniques further enable adaptive resource allocation, improving network efficiency and energy consumption.

Despite these advancements, several challenges remain. High computational complexity limits real-time deployment, particularly in large-scale networks. Multi-agent and hybrid models introduce communication overhead and require efficient coordination mechanisms. Additionally, the need for large datasets and extensive training resources poses practical challenges. Future research should focus on developing lightweight and scalable models suitable for edge deployment. The integration of federated learning and distributed computing techniques can further enhance system performance while ensuring data privacy. Addressing these challenges will be critical for realizing the full potential of intelligent 6G wireless systems.

Conclusion

The transition toward 6G wireless systems has created a strong demand for intelligent, adaptive, and efficient traffic prediction and resource allocation mechanisms. This survey presented a comprehensive review of recent advancements in Graph Neural Networks combined with optimized attention mechanisms and long-range CNN architectures. The analysis shows that GNN-based models have significantly improved the ability to capture spatial dependencies in traffic networks, while attention mechanisms enhance feature selection and model interpretability. Long-range CNN architectures have further strengthened temporal modelling, enabling accurate long-term traffic prediction.

Hybrid approaches integrating GNNs with reinforcement learning and optimization techniques have demonstrated superior performance in resource allocation. These methods enable dynamic and adaptive decision-making, improving energy efficiency and network performance. However, the review also highlights several challenges. The complexity of hybrid models increases computational requirements, making real-time deployment difficult. Scalability issues arise in large-scale networks, particularly in distributed and multi-agent environments. Security and privacy concerns also remain critical.

Future research should focus on developing lightweight and efficient models that can operate in real-time environments. The use of explainable AI techniques can improve model transparency and trust. Additionally, advancements in hardware acceleration and distributed learning will enable practical deployment of complex models. In conclusion, GNN-based architectures with optimized attention and long-range CNNs represent a promising direction for traffic prediction and resource allocation in 6G systems. Continued research and innovation in this domain will play a crucial role in enabling intelligent, scalable, and energy-efficient next-generation wireless networks.

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