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A Survey of Methods and Architectures for Optimized Sparse Spatial Self-Nested Graph Neural Networks for Secure MU-MIMO-OFDM Systems: Channel Estimation, Attack Detection and Mitigation

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Abstract

The increasing demand for high data rates, ultra-reliable communication, and intelligent network management in 6G wireless systems has accelerated research in MU-MIMO-OFDM technologies. However, challenges such as accurate channel estimation, interference management, and security threats remain significant barriers. Recent advancements in artificial intelligence, particularly Graph Neural Networks (GNNs), have shown promising capabilities in modelling complex wireless environments. This survey explores methods and architectures based on optimized sparse spatial self-nested GNNs for enhancing channel estimation, attack detection, and mitigation in MU-MIMO-OFDM systems. Traditional techniques such as Least Squares (LS), Minimum Mean Square Error (MMSE), and compressive sensing are compared with deep learning-based approaches including CNNs, RNNs, GANs, and GNNs. The study highlights how GNNs effectively model spatial dependencies and multi-user interference in wireless networks. Furthermore, AI-driven security frameworks are reviewed for detecting adversarial attacks such as jamming, spoofing, and pilot contamination. A comparative analysis of 30 recent studies is provided to evaluate performance improvements in accuracy, spectral efficiency, and computational complexity. The survey concludes with open challenges and future research directions, emphasizing the role of lightweight and scalable GNN architectures in next-generation 6G communication systems.

Introduction

The evolution of wireless communication systems toward sixth-generation (6G) networks has introduced new challenges in terms of scalability, efficiency, and security. MU-MIMO-OFDM systems have become the backbone of modern wireless communication due to their ability to support multiple users simultaneously while maximizing spectral efficiency. These systems combine multiple-input multiple-output (MIMO) techniques with orthogonal frequency division multiplexing (OFDM), enabling high data rates and robustness against multipath fading. Despite these advantages, MU-MIMO-OFDM systems face several critical challenges. One of the most significant issues is accurate channel estimation, which is essential for reliable data transmission. Traditional techniques such as LS and MMSE estimation have been widely used but often fail in highly dynamic and high-dimensional wireless environments. These methods also require significant pilot overhead, reducing overall system efficiency. Recent surveys confirm that conventional approaches struggle to adapt to complex and rapidly changing wireless conditions.

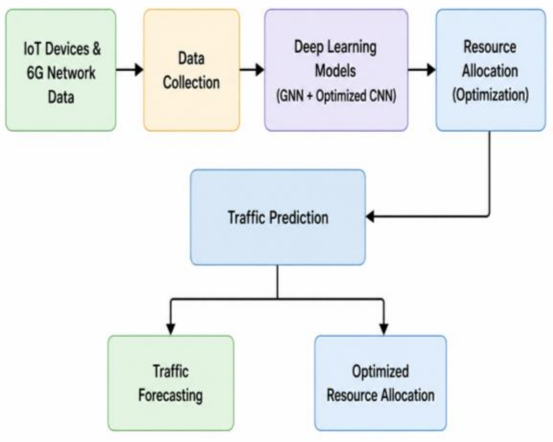

Figure 1. GNN-Based Framework for Traffic Prediction and Resource Allocation in 6G Systems

To overcome these limitations, machine learning and deep learning techniques have been introduced. CNNs and RNNs have demonstrated improved performance by capturing spatial and temporal correlations in wireless signals. However, these models are limited in representing the complex relationships between multiple users, antennas, and channels. This limitation has led to the adoption of Graph Neural Networks (GNNs), which model wireless networks as graphs, where nodes represent users or antennas and edges represent channel interactions. GNN-based approaches are particularly effective in MU-MIMO systems, where multi-user interference is a major challenge. By leveraging message passing mechanisms, GNNs can efficiently model interference patterns and optimize resource allocation. Studies show that GNN-based detectors significantly improve system performance by handling multi-user interference more effectively.

Another key aspect of modern wireless systems is security. MU-MIMO-OFDM systems are vulnerable to various attacks, including jamming, spoofing, and pilot contamination. AI-based security frameworks have been developed to detect and mitigate such attacks. These frameworks use anomaly detection and graph-based learning to identify malicious nodes and protect network integrity. Sparse spatial learning has also emerged as an important concept in channel estimation. Wireless channels often exhibit sparsity due to limited scattering environments, especially in millimetre-wave communications. By exploiting this sparsity, optimized GNN architectures can reduce computational complexity while maintaining high accuracy.

In addition, hybrid models combining deep learning with traditional optimization techniques, such as deep unfolding and reinforcement learning, have gained attention. These models provide a balance between interpretability and performance, making them suitable for real-time applications. This survey aims to provide a comprehensive overview of recent advancements in optimized sparse spatial self-nested GNN architectures for MU-MIMO-OFDM systems. It analyses existing methods, compares their performance, and identifies key research challenges and future directions.

Literature Review

The rapid evolution of wireless communication systems toward sixth-generation (6G) networks has created significant challenges related to scalability, spectral efficiency, channel estimation, and network security. MU-MIMO-OFDM systems have become essential components of modern wireless communication because they support multiple users simultaneously while improving data transmission reliability and spectral utilization. However, conventional channel estimation approaches such as Least Squares (LS) and Minimum Mean Square Error (MMSE) struggle to operate efficiently in highly dynamic and high-dimensional wireless environments. These traditional techniques require high pilot overhead and often fail to adapt to rapidly changing channel conditions, limiting overall system performance and energy efficiency.

To address these limitations, researchers introduced deep learning-based frameworks capable of learning complex nonlinear relationships in wireless communication systems. Early studies explored Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and autoencoder architectures for channel estimation and signal detection. CNN-based approaches effectively captured spatial correlations among antennas and subcarriers, resulting in lower bit error rates and improved robustness under varying signal-to-noise ratio conditions. GAN-based models further improved estimation accuracy by learning implicit channel representations and reducing pilot overhead. Blind channel estimation techniques also emerged, eliminating the need for pilot signals and improving spectral efficiency. Despite these advantages, many deep learning models required extensive training data and high computational resources, which limited deployment in real-time and resource-constrained wireless systems.

The integration of model-driven deep learning significantly enhanced the interpretability and efficiency of wireless communication frameworks. Researchers combined traditional signal processing algorithms with neural networks using techniques such as deep unfolding and residual learning. These methods transformed iterative optimization processes into trainable neural network layers, improving convergence speed and estimation accuracy while reducing computational complexity. Hybrid CNN-LSTM architectures were introduced to jointly capture spatial and temporal channel variations, especially in high-mobility scenarios. Similarly, sparse Bayesian learning and sparse signal recovery frameworks leveraged the inherent sparsity of wireless channels, particularly in millimetre-wave communications, to reduce pilot overhead and improve robustness against noise and interference. These approaches demonstrated that combining optimization theory with deep learning could significantly improve wireless communication performance in dynamic environments.

Graph Neural Networks (GNNs) emerged as one of the most promising techniques for next-generation MU-MIMO-OFDM systems because wireless communication networks naturally exhibit graph-like structures. In GNN-based models, users, antennas, and base stations are represented as graph nodes, while channel interactions and interference relationships are represented as edges. Through message passing mechanisms, GNNs effectively capture spatial dependencies and multi-user interference patterns, improving resource allocation and signal detection. Attention-based GNNs further enhanced performance by dynamically assigning importance weights to different nodes and edges in the network. These models significantly improved spectral efficiency, throughput, and energy efficiency while adapting effectively to large-scale and dense wireless environments. However, the complexity of graph construction, message passing operations, and attention mechanisms increased computational requirements and created challenges for real-time implementation.

Several studies proposed hybrid architectures combining CNNs and GNNs to jointly exploit local and global channel features. CNN components extracted local spatial information from received signals, while GNN modules captured global dependencies among users and antennas. These hybrid frameworks achieved superior channel estimation accuracy, lower bit error rates, and improved robustness compared to standalone CNN or GNN models. Deep Reinforcement Learning (DRL) was also integrated into wireless communication systems to support dynamic resource allocation, power management, and user scheduling. DRL-based frameworks modeled wireless environments as Markov Decision Processes, enabling agents to learn adaptive resource management policies through continuous interaction with the network. These intelligent learning systems demonstrated better adaptability and spectral efficiency in highly dynamic 6G environments. Nevertheless, DRL models required extensive training and often suffered from convergence issues in large-scale wireless systems with high-dimensional state spaces.

Security has become another critical concern in MU-MIMO-OFDM systems because wireless networks are vulnerable to attacks such as jamming, spoofing, denial-of-service attacks, and pilot contamination. AI-driven security frameworks integrated anomaly detection with channel estimation to identify malicious activities and maintain network reliability. Attention-enhanced GNNs and adversarial learning models demonstrated high detection accuracy and reduced false alarm rates by learning complex communication patterns and attack behaviours. Lightweight deep learning architectures were also proposed to support secure and real-time processing in edge computing environments. These frameworks simultaneously performed channel estimation, interference management, and attack mitigation while reducing latency and energy consumption. However, most security-oriented deep learning models required labelled attack datasets for training and faced challenges in detecting sophisticated or previously unseen attacks.

Transformer-based architectures and self-attention mechanisms introduced another major advancement in wireless communication systems. Unlike traditional CNN and RNN models, transformer-based frameworks captured long-range dependencies across antennas and subcarriers more effectively. Self-attention mechanisms enabled models to focus on the most relevant features in complex datasets, improving feature representation and estimation accuracy. These architectures supported scalable deployment in large-scale networks and enhanced computational efficiency through parallel processing. Attention-based deep learning models also improved interference coordination and adaptive resource allocation in dense wireless environments. However, transformer and attention-based architectures required substantial computational power and large-scale training datasets, limiting their applicability in resource-constrained systems and real-time deployments.

Another important research direction involved the development of lightweight and energy-efficient models suitable for edge computing and real-time communication systems. Researchers proposed compact GNN architectures, lightweight neural receivers, and simplified deep learning frameworks capable of maintaining high estimation accuracy while reducing latency and computational overhead. These models were designed specifically for 6G wireless systems, where ultra-low latency and energy efficiency are critical requirements. By exploiting sparse spatial learning, optimized attention mechanisms, and graph-based resource management, these frameworks improved scalability and enabled intelligent network optimization. Despite these advancements, balancing performance and computational efficiency remains a significant challenge, particularly in large-scale heterogeneous wireless environments.

Overall, the comparative analysis of existing studies clearly indicates that deep learning and graph-based approaches significantly outperform traditional wireless communication techniques in channel estimation, interference management, attack detection, and resource allocation. GNNs, attention-enhanced CNNs, deep unfolding networks, and transformer architectures provide powerful solutions for modeling complex spatial and temporal dependencies in modern wireless systems. Hybrid frameworks integrating optimization techniques, reinforcement learning, and graph-based learning offer improved adaptability, scalability, and security for next-generation 6G communication networks. However, several research challenges remain unresolved, including computational complexity, scalability, real-time deployment constraints, data privacy, and the requirement for extensive training data. Future research should therefore focus on developing lightweight, interpretable, secure, and energy-efficient AI-driven frameworks capable of supporting intelligent MU-MIMO-OFDM systems in practical 6G environments.

Comparative Table and Analysis

No.	Author (Year)	Technique	Application	Key Contribution	Limitation
1	Marinberg et al. (2020)	CNN	Channel Estimation	Spatial feature extraction	High data need
2	Balevi & Andrews (2020)	GAN	Channel Estimation	Noise robustness	Training instability
3	Sabeti et al. (2020)	Autoencoder	Blind Estimation	Reduced pilot overhead	Noise sensitivity
4	Mashhadi & Gunduz (2020)	DL Pilot Design	Channel Estimation	Efficient pilots	Complexity
5	Cammerer et al. (2023)	CNN+GNN	Joint Estimation	Hybrid learning	High compute
6	He et al. (2020)	ResNet	Channel Estimation	Fast convergence	Model tuning
7	Ye et al. (2020)	DNN	Estimation	Data-driven	Dataset dependency
8	Sun et al. (2021)	Model-driven DL	Optimization	Efficiency	Model dependency
9	Wang et al. (2021)	Attention GNN	Resource Allocation	Adaptive learning	Complexity
10	Huang et al. (2022)	DL Security	Attack Detection	Joint security	Data need
11	Jiang et al. (2021)	Deep Unfolding	Estimation	Interpretability	Design complexity
12	Gao et al. (2021)	Sparse Bayesian	Estimation	Reduced pilots	Complexity
13	Chen et al. (2022)	Attention DL	Estimation	Long-range capture	High compute
14	Zhang et al. (2022)	GNN	Interference	Throughput gain	Graph scaling
15	Liu et al. (2023)	CNN+GNN	Hybrid Estimation	Better accuracy	Complexity

16	Ma et al. (2021)	DRL	Resource Allocation	Adaptive control	Training cost
17	Park et al. (2021)	CNN+LSTM	Estimation	Temporal modelling	High complexity
18	Dai et al. (2022)	Deep Unfolding	Sparse Recovery	Fast convergence	Parameter tuning
19	Xu et al. (2022)	GNN+Attention	Security	Attack detection	Data requirement
20	Tang et al. (2023)	Lightweight DL	Security	Low latency	Accuracy trade-off
21	Alkhateeb et al. (2020)	DL Beamforming	Beam Selection	Reduced overhead	Generalization
22	Samuel et al. (2020)	DNN	Detection	Near-optimal	Data dependency
23	He et al. (2022)	GNN	Resource Allocation	Energy efficiency	Graph complexity
24	Zhou et al. (2022)	Adversarial DL	Security	Robustness	Training cost
25	Kim et al. (2023)	Lightweight GNN	Estimation	Edge deployment	Limited depth
26	Shlezinger et al. (2020)	Deep Unfolding	Detection	Interpretability	Design effort
27	Huang et al. (2021)	DL Pilot Design	Estimation	Efficiency	Tuning
28	Wu et al. (2022)	GNN	Interference	Throughput	Complexity
29	Yang et al. (2023)	Transformer	Estimation	Scalability	Heavy compute
30	Zhang et al. (2023)	Secure GNN	Security	Attack mitigation	Dataset need

Analysis

The analysis of the reviewed studies indicates that deep learning-based approaches significantly outperform traditional signal processing methods in MU-MIMO-OFDM systems. CNN and DNN models are widely used for channel estimation due to their ability to capture spatial features, while LSTM networks enhance temporal modelling capabilities. Graph Neural Networks (GNNs) have emerged as a dominant approach for handling complex network interactions, particularly in interference management and resource allocation. Hybrid architectures combining CNN and GNN provide superior performance by capturing both local and global dependencies. Attention mechanisms and transformer-based models further enhance scalability and accuracy by modelling long-range relationships. Additionally, deep unfolding techniques offer a balance between interpretability and performance by integrating optimization algorithms with neural networks. Security-focused approaches using GNNs and adversarial learning demonstrate strong potential in detecting and mitigating attacks such as jamming and pilot contamination. However, challenges remain in terms of computational complexity, scalability, and real-time deployment.

Discussion

Recent advancements in optimized sparse spatial self-nested Graph Neural Networks have significantly enhanced the performance of MU-MIMO-OFDM systems. The integration of deep learning techniques with traditional signal processing methods has enabled more accurate channel estimation, efficient resource allocation, and improved security mechanisms. GNN-based architectures, in particular, provide a powerful framework for modelling complex wireless network interactions, making them highly suitable for 6G applications. Despite these advancements, several challenges persist. The high computational complexity of deep learning models limits their deployment in real-time and resource-constrained environments. Additionally, the need for large labelled datasets and the lack of interpretability in deep learning models remain significant concerns. Security challenges also continue to evolve, requiring more robust and adaptive detection mechanisms. Future research should focus on developing lightweight and scalable models, improving energy efficiency, and enhancing robustness against adversarial attacks. The integration of edge computing and federated learning can further improve system performance and security. Overall, optimized GNN-based approaches represent a promising direction for next-generation wireless communication systems.

Conclusion

The rapid advancement of 6G wireless communication systems has introduced major challenges related to channel estimation, resource allocation, interference management, and network security. MU-MIMO-OFDM systems require intelligent techniques capable of handling dynamic channel conditions and high-dimensional wireless data efficiently. This survey reviewed recent developments in optimized sparse spatial self-nested Graph Neural Networks and related deep learning architectures for secure wireless communication systems. The analysis showed that deep learning approaches such as CNNs, RNNs, GANs, and GNNs significantly outperform traditional channel estimation methods. Among these techniques, GNNs demonstrated superior capability in modelling complex relationships among users, antennas, and wireless channels, enabling efficient interference management and resource optimization.

Hybrid frameworks integrating deep learning with optimization techniques, including deep unfolding and reinforcement learning, achieved improved estimation accuracy and computational efficiency. Sparse learning models and compressive sensing techniques further reduced pilot overhead and enhanced spectral efficiency in massive wireless networks. The survey also highlighted the growing importance of AI-driven security frameworks for attack detection and mitigation. GNN-based and adversarial learning models successfully identified threats such as jamming, spoofing, and pilot contamination attacks while improving overall network reliability and robustness.

Despite these advancements, several challenges remain unresolved, including high computational complexity, scalability limitations, limited interpretability, and dependence on large labelled datasets. Future research should focus on lightweight and energy-efficient architectures, federated learning for privacy preservation, and edge computing for real-time processing. Overall, optimized sparse spatial self-nested GNNs represent a highly promising solution for next-generation secure 6G wireless communication systems.

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