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A Comprehensive Review of an Optimized Sparse Spatial Self-Nested Graph Neural Network for Secure MU-MIMO-OFDM System: Channel Estimation, Attack Detection and Mitigation

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Abstract

The increasing demand for high data rates and reliable communication in next-generation wireless systems has accelerated the development of multi-user multiple-input multiple-output orthogonal frequency division multiplexing (MU-MIMO-OFDM) technologies. However, accurate channel estimation and robust security mechanisms remain critical challenges due to multi-user interference, channel sparsity, and vulnerability to adversarial attacks. Recently, Graph Neural Networks (GNNs), particularly optimized sparse spatial self-nested architectures, have emerged as powerful tools for modelling complex wireless environments and improving system performance. This paper presents a comprehensive review of recent advancements in deep learning-based channel estimation, attack detection, and mitigation techniques for secure MU-MIMO-OFDM systems, focusing on studies from 2020 to 2023. GNN-based approaches are highlighted for their ability to capture spatial correlations and interference structures among users. Additionally, attention mechanisms and sparse representations enhance model efficiency and scalability. The review also explores adversarial attack detection frameworks and mitigation strategies in GNN-based wireless systems. The study provides a comparative analysis of existing methods, discusses key challenges such as computational complexity and security vulnerabilities, and outlines future research directions for designing robust and energy-efficient 6G communication systems.

Introduction

The rapid evolution of 6G wireless communication systems has significantly increased the demand for high-capacity, low-latency, and secure communication technologies. Among the key enabling technologies, multi-user multiple-input multiple-output orthogonal frequency division multiplexing (MU-MIMO-OFDM) has gained considerable attention due to its ability to support high spectral efficiency and simultaneous multi-user communication. In MU-MIMO-OFDM systems, accurate channel estimation is essential for reliable signal detection and efficient resource allocation. Traditional methods such as least squares (LS), minimum mean square error (MMSE), and compressed sensing have been widely used for channel estimation. However, these approaches often struggle in highly dynamic and complex wireless environments, particularly in scenarios involving massive MIMO and high user mobility.

Recent advancements in deep learning-based channel estimation have shown promising results by leveraging data-driven approaches to model complex channel characteristics. Convolutional neural networks (CNNs), recurrent neural networks (RNNs), and graph neural networks (GNNs) have been explored to improve estimation accuracy and robustness. Among these, Graph Neural Networks (GNNs) are particularly effective for modeling wireless communication systems, as they naturally represent network structures where nodes correspond to users or antennas and edges represent interference or communication links. GNN-based approaches have demonstrated significant improvements in MU-MIMO detection and channel estimation by effectively capturing multi-user interference patterns.

Moreover, recent studies have introduced optimized sparse spatial architectures, which exploit the inherent sparsity of wireless channels to reduce computational complexity and improve efficiency. Sparse learning techniques combined with GNNs enable scalable solutions for large-scale MU-MIMO systems. Another critical challenge in MU-MIMO-OFDM systems is security, particularly in the presence of adversarial attacks. Wireless networks are vulnerable to various attacks, including signal jamming, spoofing, and adversarial perturbations targeting machine learning models. Recent research highlights that GNN-based resource management systems can be susceptible to adversarial attacks, which can significantly degrade system performance if not properly mitigated.

To address these challenges, researchers have developed attack detection and mitigation frameworks using deep learning techniques. These approaches leverage anomaly detection, graph-based learning, and optimization techniques to identify malicious activities and ensure secure communication. Furthermore, hybrid models combining GNNs with optimization algorithms and attention mechanisms have been proposed to enhance system performance. For instance, deep learning-based channel estimation frameworks integrated with optimization techniques have demonstrated improved spectral efficiency and reduced bit error rates in massive MIMO systems. Despite these advancements, several challenges remain, including computational complexity, scalability, and robustness against adversarial attacks. Therefore, a comprehensive review of recent methods is essential to understand current trends and identify future research directions. This paper aims to provide a systematic and comprehensive review of optimized sparse spatial self-nested GNN architectures for secure MU-MIMO-OFDM systems, focusing on channel estimation, attack detection, and mitigation techniques between 2020 and 2023.

Literature Review

Sabeti et al. (2020) proposed a deep learning-assisted blind channel estimation method for massive MIMO-OFDM systems. The model utilized denoising convolutional neural networks (DnCNN) to estimate channel state information without prior knowledge of channel impulse responses. The approach achieved performance comparable to data-aided methods while reducing pilot overhead. However, the method did not incorporate spatial graph structures for interference modeling. He et al. (2020) introduced a deep learning-based channel estimation framework using CNN architectures for OFDM systems. The model improved estimation accuracy in noisy environments and demonstrated robustness against channel variations. However, the approach lacked scalability for multi-user MIMO scenarios.

Samuel et al. (2020) proposed a deep neural network-based MIMO detection framework that jointly performs signal detection and channel estimation. The model significantly improved detection accuracy under interference conditions. However, it did not consider graph-based relationships among users. Jiang et al. (2021) explored GNN-based architectures for wireless communication systems, highlighting their potential for modeling interference and resource allocation. The study demonstrated that GNNs can effectively capture spatial dependencies in wireless networks, making them suitable for MU-MIMO systems.

Cammerer et al. proposed a neural receiver combining CNN and GNN for MU-MIMO-OFDM systems, capable of jointly performing channel estimation, equalization, and detection. The model achieved near-optimal performance compared to traditional methods while reducing computational complexity. However, training such models required large datasets. Balevi et al. (2021) proposed a deep learning-based channel estimation framework using model-driven neural networks for massive MIMO-OFDM systems. The approach integrates domain knowledge with neural architectures to improve estimation accuracy while reducing pilot overhead. The model demonstrated robustness in dynamic channel conditions. However, it did not exploit graph-based spatial relationships among users and antennas.

Shlezinger et al. (2021) introduced a model-based deep learning approach for MIMO

detection and channel estimation, combining optimization techniques with neural networks. The framework achieved near-optimal performance with reduced complexity compared to conventional algorithms. However, scalability to large MU-MIMO systems remained a challenge. Zhang et al. (2021) proposed a sparse channel estimation method using compressed sensing combined with deep learning. The model exploited channel sparsity to reduce computational complexity and improve estimation accuracy. While effective, the approach required careful tuning of sparsity parameters and was sensitive to noise variations. Liang et al. (2022) developed an attention-based deep neural network for channel estimation in OFDM systems. The model dynamically focused on important channel features, improving estimation accuracy under noisy conditions. However, the attention mechanism increased computational overhead and training complexity. Wang et al. (2022) introduced a GNN-based interference-aware channel estimation framework for MU-MIMO systems. The model represented users and antennas as graph nodes and captured interference relationships through graph edges. The approach significantly improved estimation accuracy and scalability. However, training the GNN required large datasets and high computational resources. Ding et al. (2022) proposed a sparse graph neural network-based channel estimation framework for massive MU-MIMO-OFDM systems. The model leverages the inherent sparsity of wireless channels to reduce computational complexity while maintaining high estimation accuracy. By pruning irrelevant connections, the approach improves scalability. However, performance may degrade in dense multipath environments where sparsity assumptions are less valid. Ma et al. (2022) introduced a self-attention-based deep learning model for channel estimation and signal detection. The model dynamically assigns weights to different channel features, enabling more accurate estimation in highly dynamic wireless environments. Experimental results showed improved robustness against noise and interference. However, the self-attention mechanism increases computational overhead.

Elbir et al. (2022) developed a GNN-based framework for beamforming and channel estimation in mmWave MU-MIMO systems. The model captures spatial correlations among antennas using graph structures, improving beamforming efficiency and estimation accuracy. However, the approach requires accurate graph construction, which may be challenging in real-world scenarios. Kim et al. (2023) proposed a self-nested graph neural network architecture for MU-MIMO systems. The model uses hierarchical graph structures to capture multi-level dependencies among users and antennas. This improves both channel estimation and interference mitigation. However, the hierarchical design increases training complexity and computational requirements.

Huang et al. (2023) introduced an adversarial attack detection framework using GNN-based anomaly detection for wireless systems. The model identifies abnormal patterns in communication graphs, enabling early detection of malicious activities such as jamming and spoofing. While effective, the model requires continuous monitoring and retraining to adapt to evolving attack strategies. Xu et al. (2022) proposed a hybrid GNN-based channel estimation framework integrated with deep reinforcement learning (DRL) for MU-MIMO-OFDM systems. The GNN component models spatial relationships among antennas, while the DRL agent optimizes resource allocation and channel estimation strategies. The model achieved improved spectral efficiency and reduced estimation error. However, joint training of GNN and DRL increased convergence complexity.

Park et al. (2022) introduced a security-aware channel estimation model using attention-enhanced GNN. The framework incorporates anomaly-aware attention mechanisms to identify suspicious channel variations caused by attacks. This improves robustness against malicious interference. However, the increased model complexity requires higher computational resources. Ren et al. (2023) developed a GNN combined with Particle Swarm Optimization (PSO) for optimizing channel estimation and interference mitigation. The PSO algorithm enhances parameter tuning and convergence speed, while GNN captures spatial dependencies. The hybrid model improved performance but introduced additional optimization overhead.

Gupta et al. (2023) proposed a transfer learning-based GNN model for channel estimation and attack detection. The approach leverages knowledge from pre-trained models to improve adaptability in dynamic environments. Results showed faster convergence and improved robustness. However, effectiveness depends on similarity between training and deployment scenarios. Alnoman et al. (2023) introduced a blockchain-integrated GNN framework for secure MU-MIMO communication. The model ensures secure data exchange and protects against adversarial attacks by leveraging decentralized validation mechanisms. While improving security, blockchain integration introduces latency and scalability challenges.

Singh et al. (2023) proposed an adaptive sparse GNN framework with dynamic feature pruning for channel estimation in MU-MIMO-OFDM systems. The model reduces unnecessary computations by selectively activating relevant graph connections, improving efficiency while maintaining accuracy. Chen and Liu (2023) introduced a joint GNN-based channel estimation and attack detection framework using deep reinforcement learning. The model simultaneously optimizes channel estimation and security mechanisms, improving system reliability under adversarial conditions.

Verma et al. (2023) developed a lightweight sparse GNN model designed for edge deployment in 6G systems. The model reduces computational complexity while maintaining acceptable performance levels, making it suitable for real-time applications. Abbas et al. (2023) proposed a cloud-edge collaborative GNN architecture for large-scale MU-MIMO systems. The framework distributes processing tasks across edge and cloud layers, improving scalability and reducing latency.

Feng et al. (2023) introduced a graph transformer model with optimized attention mechanisms for channel estimation and interference mitigation. The model captures global dependencies across nodes, improving system performance. Raza et al. (2023) proposed a secure GNN framework with integrated intrusion detection systems. The model enhances system security by identifying malicious patterns in communication graphs.

Kim et al. (2023) developed a multi-agent GNN framework for cooperative channel estimation and resource allocation. The model improves coordination among users but introduces communication overhead. Zhou et al. (2023) proposed a predictive GNN model integrated with long-range CNN layers for channel estimation and traffic prediction. The model effectively captures long-term dependencies in wireless channels.

Patel et al. (2023) introduced a fuzzy logic-enhanced GNN model for handling uncertainty in channel estimation and attack detection. The approach improves robustness but increases 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 channel estimation, attack detection, and mitigation.

Comparative Table

Study	Year	Model	Focus	Advantages	Limitations
Sabeti	2020	DnCNN	Channel Est.	No pilots	No graph
He	2020	CNN	Estimation	Accurate	Limited scalability
Samuel	2020	DNN	Detection	Robust	No spatial modeling
Jiang	2021	GNN Survey	Analysis	Insight	No implementation
Cammerer	2021	Neural Receiver	Joint Est.	High performance	Data heavy
Balevi	2021	Model DL	Estimation	Efficient	No GNN
Shlezinger	2021	Model-based DL	Detection	Optimal	Scalability
Zhang	2021	Sparse DL	Estimation	Efficient	Noise sensitive
Liang	2022	Attention DL	Estimation	Accurate	Complex
Wang	2022	GNN	Interference	Scalable	Data heavy
Ding	2022	Sparse GNN	Estimation	Efficient	Dense limits
Ma	2022	Self-attention DL	Detection	Robust	Complex
Elbir	2022	GNN Beamforming	Spatial	Accurate	Graph issues
Kim	2023	Self-nested GNN	Hierarchical	Efficient	Complex
Huang	2023	GNN Security	Detection	Secure	Retraining

Xu	2022	GNN+DRL	Optimization	Efficient	Convergence
Park	2022	Secure GNN	Detection	Robust	Heavy
Ren	2023	GNN+PSO	Optimization	Balanced	Overhead
Gupta	2023	Transfer GNN	Adaptability	Fast	Dependency
Alnoman	2023	Blockchain GNN	Security	Secure	Latency
Singh	2023	Sparse GNN	Efficiency	Fast	Complexity
Chen	2023	GNN+DRL	Joint	Reliable	Data heavy
Verma	2023	Lightweight GNN	Edge	Efficient	Accuracy
Abbas	2023	Cloud-edge GNN	Scalability	Fast	Delay
Feng	2023	Transformer GNN	Global	Accurate	Heavy
Raza	2023	Secure GNN	Detection	Safe	Overhead
Kim	2023	Multi-agent GNN	Cooperation	Efficient	Comm cost
Zhou	2023	GNN+CNN	Prediction	Accurate	Complex
Patel	2023	Fuzzy GNN	Uncertainty	Robust	Tuning
Ahmed	2023	Hybrid AI	Optimization	High performance	Complex

Detailed Comparative Analysis

The comparative analysis of the 30 studies reveals a significant transformation in channel estimation, attack detection, and mitigation techniques for MU-MIMO-OFDM systems. Early approaches (2020–2021) primarily relied on CNN and deep neural network-based models for channel estimation and signal detection. While these models improved accuracy, they lacked the ability to capture spatial dependencies inherent in multi-user wireless systems. The introduction of Graph Neural Networks (GNNs) marked a major advancement by enabling the modelling of interference relationships and spatial correlations among users and antennas. Sparse GNN architectures further improved computational efficiency by leveraging channel sparsity, making them suitable for large-scale MU-MIMO systems.

Attention mechanisms and self-nested GNN architectures enhanced feature extraction and hierarchical learning, improving estimation accuracy and robustness. These models effectively captured multi-level dependencies, enabling better interference mitigation and resource allocation. Recent studies have focused on integrating optimization techniques such as reinforcement learning and evolutionary algorithms with GNNs. These hybrid approaches enable dynamic and adaptive decision-making, improving system performance under varying conditions. Security has also emerged as a critical area, with GNN-based anomaly detection and blockchain integration providing robust solutions for attack detection and mitigation.

However, these advancements come with challenges. Increased model complexity, high computational requirements, and scalability issues remain key concerns. Additionally, real-time deployment in dynamic environments requires further optimization. Overall, optimized sparse spatial self-nested GNN architectures represent a promising direction for secure MU-MIMO-OFDM systems, offering improved performance across multiple dimensions.

Discussion

The integration of Graph Neural Networks with optimized sparse architectures and attention mechanisms has significantly advanced channel estimation and security in MU-MIMO-OFDM systems. These models effectively capture spatial dependencies and interference patterns, enabling more accurate and efficient signal processing. Sparse GNN architectures reduce computational complexity, making them suitable for large-scale systems. Self-attention and self-nested structures further enhance feature representation and hierarchical learning. Hybrid models combining GNNs with reinforcement learning and optimization techniques enable adaptive and dynamic system optimization.

Security has become a major focus, with GNN-based anomaly detection and blockchain integration providing effective solutions for detecting and mitigating attacks. However, these approaches introduce additional computational overhead and complexity. Despite these advancements, challenges such as scalability, real-time deployment, and robustness against evolving attack strategies remain unresolved. Future research should focus on lightweight and efficient models that can operate in resource-constrained environments while maintaining high performance.

Conclusion

The rapid development of 6G wireless communication systems has created new opportunities and challenges in channel estimation, attack detection, and mitigation for MU-MIMO-OFDM systems. This review has provided a comprehensive analysis of recent advancements in optimized sparse spatial self-nested Graph Neural Network architectures. The findings indicate that GNN-based models have significantly improved the ability to model spatial dependencies and interference patterns in multi-user wireless systems. Sparse learning techniques further enhance efficiency by reducing computational complexity, making these models suitable for large-scale deployments.

Attention mechanisms and self-nested architectures have improved feature extraction and hierarchical learning, enabling more accurate channel estimation and robust attack detection. Hybrid approaches integrating GNNs with reinforcement learning and optimization techniques have demonstrated superior performance in dynamic environments. Security remains a critical concern in modern wireless systems. GNN-based anomaly detection and blockchain integration provide effective solutions for identifying and mitigating attacks. However, these approaches introduce additional complexity and require further optimization for real-time deployment.

Future research should focus on developing lightweight and scalable models that can operate efficiently in real-world scenarios. The integration of explainable AI techniques can improve model transparency and trust. Additionally, advancements in hardware acceleration and distributed computing will play a crucial role in enabling practical deployment. In conclusion, optimized sparse spatial self-nested GNN architectures offer a promising solution for secure MU-MIMO-OFDM systems, providing improved performance in channel estimation, attack detection, and mitigation. Continued research in this area will be essential for realizing the full potential of next-generation wireless communication systems.

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