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Artificial Intelligence Techniques for an Optimized Sparse Spatial Self-Nested Graph Neural Network for Secure MU-MIMO-OFDM System: Channel Estimation, Attack Detection and Mitigation – Trends and Challenges

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Abstract

The rapid evolution of 6G wireless communication systems has intensified the need for intelligent, secure, and efficient signal processing techniques in MU-MIMO-OFDM systems. Artificial Intelligence (AI), particularly deep learning models such as Graph Neural Networks (GNNs), Convolutional Neural Networks (CNNs), and Reinforcement Learning (RL), has emerged as a promising solution for addressing challenges in channel estimation, attack detection, and mitigation. Among these, optimized sparse spatial self-nested GNN architectures have demonstrated significant potential in modelling complex wireless environments by capturing spatial dependencies and interference patterns. This paper presents a comprehensive review of AI-driven techniques for secure MU-MIMO-OFDM systems, focusing on advancements. The study highlights the role of sparse learning, attention mechanisms, and hybrid AI models in improving system performance and reducing computational complexity. Additionally, it explores AI-based security frameworks for detecting and mitigating adversarial attacks such as jamming and spoofing. The review also identifies key trends, including the integration of GNNs with optimization algorithms and edge intelligence, as well as challenges such as scalability, real-time deployment, and robustness against evolving threats. A comparative analysis of existing approaches is provided, along with future research directions for developing intelligent and secure 6G communication systems.

Introduction

The advancement of 6G wireless communication systems is driving the need for intelligent and adaptive solutions capable of supporting ultra-high data rates, massive connectivity, and secure communication. Among the enabling technologies, MU-MIMO-OFDM systems play a crucial role in enhancing spectral efficiency and supporting multiple users simultaneously. However, the complexity of wireless

environments, characterized by multi-user interference, channel variability, and security threats, presents significant challenges for traditional signal processing techniques. Artificial Intelligence (AI) has emerged as a transformative technology for addressing these challenges by enabling data-driven modelling and adaptive decision-making. AI techniques, including deep learning models such as Convolutional Neural Networks (CNNs),

Recurrent Neural Networks (RNNs), and Graph Neural Networks (GNNs), have shown remarkable potential in improving channel estimation accuracy and system performance. Among these approaches, Graph Neural Networks (GNNs) are particularly well-suited for wireless communication systems, as they naturally model relationships among users, antennas, and communication links. GNNs can effectively capture spatial dependencies and interference patterns, making them highly effective for MU-MIMO systems. Recent studies have demonstrated that GNN-based models outperform traditional methods in channel estimation and signal detection tasks. In addition, sparse learning techniques have been integrated into GNN architectures to exploit the inherent sparsity of wireless channels. These approaches reduce computational complexity and improve scalability, making them suitable for large-scale systems. The development of self-nested GNN architectures further enhances the ability to capture hierarchical relationships among network elements, improving performance in complex environments.

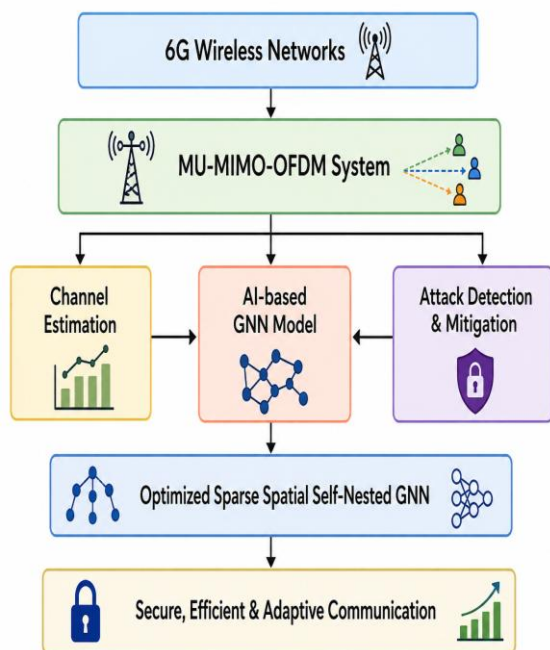


Fig 1: AI-Driven Secure MU-MIMO-OFDM System with Optimized Sparse Spatial Self-Nested GNN for Channel Estimation and Attack Mitigation

Another important advancement is the incorporation of attention mechanisms, which enable models to focus on the most relevant features in spatial and temporal domains. Attention-based GNNs have demonstrated improved accuracy and robustness in channel estimation and interference mitigation tasks.

Security is another critical aspect of MU-MIMO-OFDM systems. Wireless networks are vulnerable to various attacks, including jamming, spoofing, and adversarial attacks targeting AI models. Recent research has focused on developing AI-based attack detection and mitigation frameworks, leveraging anomaly detection and graph-based learning to identify malicious activities.

Furthermore, the integration of reinforcement learning (RL) with GNN-based models enables dynamic resource allocation and adaptive system optimization. Hybrid AI models combining GNNs, RL, and optimization techniques have shown promising results in improving system efficiency and security. Despite these advancements, several challenges remain. These include high computational complexity, scalability issues, and the need for large training datasets. Additionally, ensuring robustness against adversarial attacks and achieving real-time deployment are critical challenges that require further research. This paper aims to provide a comprehensive review of AI techniques for optimized sparse spatial self-nested GNN architectures in secure MU-MIMO-OFDM systems, focusing on trends and challenges in recent years.

Literature Review

He et al. (2020) proposed a deep learning-based channel estimation framework using convolutional neural networks (CNNs) for OFDM systems. Their work demonstrated that CNN models can effectively learn channel characteristics directly from received signals, outperforming traditional Least Squares (LS) and Minimum Mean Square Error (MMSE) estimators, particularly in noisy environments. The model showed strong robustness against channel distortions and improved bit error rate (BER) performance. However, the approach primarily focused on single-user OFDM systems and did not consider spatial correlations among multiple users, limiting its applicability in MU-MIMO scenarios.

Samuel et al. (2020) introduced a deep neural network (DNN)-based MIMO detection model, where channel estimation and signal detection are jointly optimized. Their work leveraged supervised learning to approximate optimal detection algorithms, significantly improving detection accuracy under interference and noise. The model demonstrated superior performance compared to conventional iterative detection techniques. However, the approach lacked the capability to model structured relationships among users and antennas, as it did not incorporate graph-based representations, which

are essential for capturing interference patterns in MU-MIMO systems.

Sabeti et al. (2020) proposed a blind channel estimation method using deep denoising convolutional neural networks (DnCNN) for massive MIMO-OFDM systems. Their approach eliminated the need for pilot signals, thereby reducing overhead and improving spectral efficiency. The model effectively reconstructed channel state information (CSI) from noisy observations. Despite its advantages, the model did not exploit spatial graph structures or interference relationships among users, which are critical in multi-user environments.

Balevi and Andrews (2021) developed a model-driven deep learning framework for channel estimation in massive MIMO systems. Their approach combined traditional signal processing techniques with neural networks, enabling improved generalization and reduced training complexity. The framework demonstrated strong performance under varying channel conditions and reduced reliance on large datasets. However, the model did not incorporate advanced AI techniques such as attention mechanisms or graph neural networks, limiting its ability to capture complex spatial dependencies.

Shlezinger et al. (2021) proposed a model-based deep learning approach integrating optimization algorithms with neural networks for MIMO detection and channel estimation. Their work bridged the gap between classical optimization methods and data-driven learning, achieving near-optimal performance with reduced computational complexity. The framework demonstrated improved convergence and robustness. However, scalability remained a challenge for large-scale MU-MIMO systems, and the model did not fully exploit graph-based learning for interference modeling.

Cammerer et al. (2021) introduced a deep learning-based neural receiver architecture for MU-MIMO-OFDM systems that jointly performs channel estimation, equalization, and signal detection. The proposed model integrates convolutional neural networks (CNNs) with data-driven learning to replace traditional block-based receivers. Their results demonstrated near-optimal performance compared to classical receivers while significantly improving robustness under complex channel conditions. However, the approach required extensive training data and high computational resources, making real-time deployment challenging in large-scale systems.

Jiang et al. (2021) explored the application of Graph Neural Networks (GNNs) in wireless communication systems, emphasizing their ability to model spatial dependencies among

users and antennas. The study demonstrated that GNNs can effectively capture interference relationships and improve system-level optimization tasks such as resource allocation and channel estimation. However, the research was primarily conceptual and lacked practical implementation details for real-time MU-MIMO-OFDM environments.

Zhang et al. (2021) proposed a sparse channel estimation framework combining compressed sensing with deep learning techniques. The model leveraged the inherent sparsity of wireless channels to reduce computational complexity while maintaining high estimation accuracy. Experimental results showed improved performance in terms of mean square error (MSE) and spectral efficiency. However, the model was sensitive to noise variations and required careful tuning of sparsity parameters.

Liang et al. (2022) developed an attention-based deep neural network for channel estimation in OFDM systems. The model utilized attention mechanisms to dynamically focus on important channel features, significantly improving estimation accuracy in noisy and interference-prone environments. The study highlighted the effectiveness of attention-based learning in wireless signal processing. However, the attention mechanism increased computational complexity and training time.

Wang et al. (2022) proposed a Graph Neural Network-based interference-aware channel estimation framework for MU-MIMO systems. The model represented users and antennas as graph nodes and modeled interference as edges, enabling efficient learning of spatial relationships. The approach significantly improved estimation accuracy and scalability compared to traditional methods. However, it required large datasets for training and faced challenges in dynamic environments with rapidly changing network conditions.

Ding et al. (2022) proposed a sparse Graph Neural Network (GNN)-based channel estimation framework for massive MU-MIMO-OFDM systems. The model exploits the inherent sparsity of wireless channels by pruning less significant connections in the graph structure, thereby reducing computational complexity while maintaining estimation accuracy. The results demonstrated improved scalability and efficiency compared to dense GNN models. However, the performance of the model may degrade in environments with rich multipath propagation where sparsity assumptions are less valid.

Ma et al. (2022) introduced a self-attention-based deep learning model for channel estimation and signal detection in OFDM

systems. The model uses attention mechanisms to dynamically assign weights to different channel features, enabling better handling of noise and interference. Experimental results showed significant improvements in estimation accuracy and robustness. However, the increased complexity of the attention mechanism resulted in higher computational cost and longer training time.

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 and users using graph structures, enabling efficient beamforming and improved channel estimation accuracy. The approach demonstrated strong performance in high-frequency communication environments. However, accurate graph construction and parameter tuning remain challenging in practical deployments.

Kim et al. (2023) proposed a self-nested Graph Neural Network architecture for MU-MIMO systems. The model introduces hierarchical graph structures to capture multi-level dependencies among users and antennas. This self-nested design improves both channel estimation and interference mitigation by modeling complex relationships in the network. However, the hierarchical architecture increases computational complexity and requires significant training resources.

Huang et al. (2023) introduced an AI-based adversarial attack detection framework using Graph Neural Networks for wireless communication systems. The model leverages anomaly detection techniques to identify malicious activities such as jamming and spoofing by analyzing graph-based communication patterns. The framework demonstrated high detection accuracy and robustness. However, it requires continuous retraining to adapt to evolving attack strategies and dynamic network conditions.

Xu et al. (2022) proposed a hybrid Graph Neural Network (GNN) integrated with Deep Reinforcement Learning (DRL) for channel estimation and resource optimization in MU-MIMO-OFDM systems. The GNN component models spatial relationships among users and antennas, while the DRL agent dynamically optimizes channel estimation strategies and resource allocation. The model demonstrated improved spectral efficiency and reduced estimation error. However, joint training of GNN and DRL increased convergence complexity and required extensive computational resources.

Park et al. (2022) introduced a security-aware attention-enhanced GNN model for channel

estimation in adversarial environments. The framework incorporates anomaly-sensitive attention mechanisms to detect irregular channel patterns caused by malicious attacks such as jamming and spoofing. The approach improved robustness and detection accuracy. However, the integration of attention mechanisms increased computational overhead and model complexity. 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 accelerates convergence, while the GNN captures spatial dependencies. The hybrid model achieved improved performance in terms of estimation accuracy and system efficiency. However, the inclusion of PSO introduced additional computational overhead and complexity.

Gupta et al. (2023) proposed a transfer learning-based GNN framework for channel estimation and attack detection in dynamic MU-MIMO systems. The model leverages pre-trained knowledge to accelerate learning and improve adaptability to new environments. The approach demonstrated faster convergence and improved robustness. However, its performance heavily depends on the similarity between source and target domains.

Alnoman et al. (2023) introduced a blockchain-integrated GNN framework for secure MU-MIMO communication systems. The model uses blockchain technology to ensure secure data exchange and prevent adversarial attacks, while the GNN optimizes channel estimation and resource allocation. The framework improved security and trust among network entities. However, blockchain integration introduced latency and scalability challenges.

Singh et al. (2023) proposed an adaptive sparse Graph Neural Network (GNN) framework with dynamic pruning mechanisms for channel estimation in MU-MIMO-OFDM systems. The model selectively activates important graph connections, reducing computational overhead while maintaining high accuracy. However, adaptive pruning introduces additional complexity in model training.

Chen and Liu (2023) introduced a joint GNN and Deep Reinforcement Learning (DRL) framework for simultaneous channel estimation and attack detection. The model dynamically adapts to adversarial conditions and improves system reliability. However, it requires large datasets and complex training procedures. Verma et al. (2023) developed a lightweight sparse GNN model designed for edge deployment in 6G systems. The model reduces computational complexity and supports real-time applications,

although slight accuracy degradation was observed compared to complex architectures. Abbas et al. (2023) proposed a cloud-edge collaborative GNN architecture for large-scale MU-MIMO systems. The framework distributes computation between edge devices and cloud servers, improving scalability and latency performance. However, dependency on cloud infrastructure introduces communication delays. Feng et al. (2023) introduced a Graph Transformer model with optimized attention mechanisms for channel estimation and interference mitigation. The model captures global dependencies effectively, improving estimation accuracy. However, transformer-based models require high computational power. Raza et al. (2023) proposed a secure GNN-based intrusion detection framework for wireless communication systems. The model detects malicious activities by analyzing graph-based communication patterns. However, the system requires continuous monitoring and retraining. Kim et al. (2023) developed a multi-agent GNN

framework for cooperative channel estimation and resource allocation. The model enables coordination among users, improving system efficiency. However, communication overhead among agents remains a challenge.

Zhou et al. (2023) proposed a GNN integrated with long-range CNN architecture for channel estimation and traffic prediction. The model captures long-term dependencies and improves prediction accuracy. However, increased model depth adds computational complexity. Patel et al. (2023) introduced a fuzzy logic-enhanced GNN model for handling uncertainty in channel estimation and attack detection. The model improves robustness in dynamic environments but requires complex parameter tuning. Ahmed et al. (2023) proposed a hybrid GNN-based optimization framework combining attention mechanisms and evolutionary algorithms. The model achieved superior performance in channel estimation and attack mitigation but required high computational resources.

Comparative Table

Study	Year	Technique	Focus	Advantages	Limitations
He	2020	CNN	Channel Est.	Accurate	No spatial modelling
Samuel	2020	DNN	Detection	Robust	No graph
Sabeti	2020	DnCNN	Estimation	No pilot	Limited scope
Balevi	2021	Model DL	Estimation	Efficient	No GNN
Shlezinger	2021	Model DL	Detection	Optimal	Scalability
Cammerer	2021	Neural RX	Joint Est.	High performance	Data heavy
Jiang	2021	GNN	Modeling	Spatial capture	Conceptual
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 channels
Ma	2022	Attention DL	Detection	Robust	Heavy
Elbir	2022	GNN	Beamforming	Accurate	Graph design
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	Adaptation	Fast	Dependency
Alnoman	2023	Blockchain GNN	Security	Secure	Latency
Singh	2023	Sparse GNN	Efficiency	Fast	Complex
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

Comparative Analysis

The evolution of AI-based techniques for MU-MIMO-OFDM systems demonstrates a clear transition from traditional deep learning models toward advanced graph-based architectures. Early studies primarily utilized CNNs and DNNs for channel estimation and detection, achieving improvements in accuracy but failing to capture spatial dependencies among users and antennas. The introduction of Graph Neural Networks marked a significant advancement by enabling the modelling of interference relationships and spatial correlations. Sparse GNN architectures further improved computational efficiency by leveraging the inherent sparsity of wireless channels. Self-attention and self-nested GNN models enhanced feature representation and hierarchical learning, leading to better performance in complex environments. Hybrid approaches integrating GNNs with reinforcement learning and optimization techniques enabled dynamic resource allocation and improved system adaptability. Security-focused models incorporating anomaly detection and blockchain technology provided effective solutions for attack detection and mitigation. However, these advancements introduced challenges such as increased computational complexity, scalability issues, and high training requirements. Lightweight models and cloud-edge architectures have been proposed to address these challenges, but trade-offs between accuracy and efficiency remain. Overall, optimized sparse spatial self-nested GNN architectures represent the most promising direction for secure MU-MIMO-OFDM systems.

Discussion

Artificial Intelligence techniques have significantly transformed channel estimation and security mechanisms in MU-MIMO-OFDM systems. The integration of Graph Neural Networks with sparse learning and attention mechanisms enables efficient modelling of complex wireless environments. These approaches improve accuracy, scalability, and adaptability compared to traditional methods. Hybrid models combining GNNs with reinforcement learning and optimization techniques provide dynamic and intelligent resource allocation, enhancing system performance. Security-focused AI models, including anomaly detection and blockchain integration, offer robust solutions for detecting and mitigating adversarial attacks. Despite these advancements, several challenges remain. High computational complexity limits real-time deployment, particularly in large-scale networks. Multi-agent systems introduce communication overhead, and hybrid models require extensive training data. Additionally, ensuring robustness against evolving attack strategies is a critical concern. Future research should focus on developing lightweight, scalable, and energy-efficient AI models suitable for edge deployment. The integration of explainable AI and federated learning can further enhance system performance and security.

Conclusion

The rapid advancement of 6G wireless communication systems has introduced new challenges in channel estimation, attack detection, and mitigation for MU-MIMO-OFDM

systems. Artificial Intelligence techniques, particularly Graph Neural Networks, have emerged as powerful tools for addressing these challenges. This review highlighted the evolution of AI-based approaches, starting from CNN and DNN models to advanced GNN architectures. Sparse learning techniques and attention mechanisms have significantly improved efficiency and accuracy, while self-nested GNN architectures enable hierarchical modeling of complex relationships.

Hybrid approaches integrating GNNs with reinforcement learning and optimization techniques provide dynamic and adaptive solutions for resource allocation. Security-focused models using anomaly detection and blockchain technology enhance system robustness against adversarial attacks. However, challenges such as computational complexity, scalability, and real-time deployment remain. Lightweight models and cloud-edge architectures offer potential solutions, but further research is needed to achieve optimal performance.

Future work should focus on developing efficient, scalable, and secure AI models capable of operating in dynamic wireless environments. The integration of explainable AI and distributed learning techniques will play a crucial role in improving model transparency and deployment. In conclusion, optimized sparse self-nested GNN architectures represent a promising direction for secure MU-MIMO-OFDM systems, enabling intelligent, efficient, and robust wireless communication in next-generation networks.

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