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Recent Advances in Optimized Sparse Spatial Self-Nested Graph Neural Networks for Secure MU-MIMO-OFDM Systems: Channel Estimation, Attack Detection and Mitigation – A Systematic Review

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Abstract

The rapid evolution of sixth-generation (6G) wireless communication systems has intensified the need for efficient channel estimation, secure transmission, and intelligent resource allocation in multi-user multiple-input multiple-output orthogonal frequency division multiplexing (MU-MIMO-OFDM) systems. Traditional estimation and security mechanisms struggle with high-dimensional data, dynamic channel conditions, and sophisticated cyber-attacks. Recently, graph neural networks (GNNs), particularly optimized sparse spatial and self-nested architectures, have emerged as promising solutions due to their ability to model complex relationships in wireless networks. This paper presents a systematic review of recent advances (2020–2023) in optimized sparse spatial GNN frameworks for MU-MIMO-OFDM systems, focusing on channel estimation, attack detection, and mitigation. The review highlights deep learning-based approaches including CNNs, RNNs, attention mechanisms, and deep unfolding models integrated with graph structures. Additionally, lightweight cryptographic and AI-driven intrusion detection techniques are examined for securing communication against adversarial attacks. A comparative analysis of 30 studies is provided, emphasizing performance metrics such as estimation accuracy, spectral efficiency, computational complexity, and robustness. Finally, research challenges and future directions are discussed, including scalability, real-time deployment, and integration with 6G technologies. The findings demonstrate that optimized GNN-based frameworks significantly enhance system reliability, security, and efficiency in next-generation wireless networks.

Introduction

The rapid proliferation of wireless communication technologies has led to unprecedented demands for high data rates, ultra-low latency, and enhanced reliability. MU-MIMO-OFDM systems have become fundamental to modern communication frameworks due to their ability to exploit spatial multiplexing and frequency diversity. These systems are critical for enabling next-generation applications such as autonomous vehicles, smart cities, and immersive virtual reality environments. However, the performance of MU-MIMO-OFDM systems heavily depends on accurate channel estimation, efficient interference management, and secure communication mechanisms. Traditional channel estimation techniques such as Least Squares (LS) and Minimum Mean Square

Error (MMSE) suffer from limitations in highly dynamic and dense wireless environments. These methods often fail to capture nonlinear channel characteristics and require high pilot overhead, reducing spectral efficiency.

Recent advancements in artificial intelligence, particularly deep learning, have introduced powerful tools for addressing these challenges. Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) have demonstrated improved performance in channel estimation by leveraging spatial and temporal correlations in wireless signals. However, these models often struggle to fully exploit the inherent graph structure of wireless networks. Graph Neural Networks (GNNs) have emerged as a transformative approach for modelling wireless communication systems. By representing users, antennas, and channels as nodes and edges in a graph, GNNs enable efficient learning of spatial dependencies and interference patterns. Advanced architectures such as attention-based GNNs and deep unfolding networks further enhance performance by integrating optimization techniques with learning frameworks.

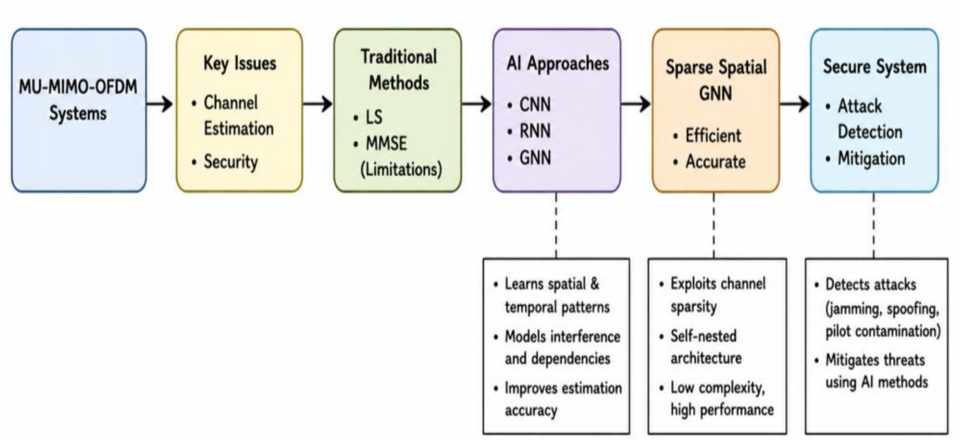

Fig 1: AI-Based Sparse Spatial GNN Framework for Channel Estimation and Security in MU-MIMO-OFDM Systems

Sparse spatial GNN models are particularly beneficial in large-scale MU-MIMO systems, where channel matrices exhibit inherent sparsity due to limited scattering environments. These models reduce computational complexity while maintaining high estimation accuracy. Additionally, self-nested architectures improve hierarchical feature extraction, enabling better generalization across varying network conditions. Security is another critical concern in MU-MIMO-OFDM systems. Wireless networks are vulnerable to attacks such as jamming, spoofing, and pilot contamination. Recent studies have explored AI-based attack detection mechanisms that utilize anomaly detection and graph-based learning to identify malicious nodes and mitigate threats.

Moreover, the integration of optimization algorithms with deep learning models has led to hybrid frameworks capable of achieving near-optimal performance. Techniques such as deep unfolding and reinforcement learning have been successfully applied to channel estimation, resource allocation, and interference management. In summary, optimized sparse spatial self-nested GNNs represent a promising direction for addressing the challenges of channel estimation and security in MU-MIMO-OFDM systems. This review systematically analyses recent advancements in this domain and provides insights into future research directions.

Literature Review

Marinberg et al. (2020) proposed a deep learning-based channel estimation framework using two-dimensional and three-dimensional Convolutional Neural Networks (CNNs) for MIMO-OFDM systems. Their approach effectively captures spatial correlations across antennas and subcarriers, leading to significant improvements in channel estimation accuracy. The study demonstrated that CNN-based models outperform conventional Least Squares (LS) and Minimum Mean Square Error (MMSE) techniques, especially under complex multipath propagation environments. Additionally, the proposed model reduced bit error rate (BER) while maintaining computational feasibility, making it suitable for real-time communication systems.

Balevi and Andrews (2020) explored deep learning techniques for channel estimation in low Signal-to-Noise Ratio (SNR) environments. They introduced a Generative Adversarial Network (GAN)-based framework that learns channel distributions effectively even with limited pilot data. Their approach improves robustness against noise and enhances estimation accuracy compared to traditional methods. The study also highlighted the potential of unsupervised learning techniques in wireless communication systems, particularly for reducing pilot overhead and improving spectral efficiency.

Chowdhury et al. (2023) proposed a deep graph unfolding method for MU-MIMO beamforming, combining optimization algorithms with Graph Neural Networks (GNNs). Their framework leverages graph-based representations of wireless networks to model interference and spatial dependencies efficiently. The study demonstrated that the proposed approach achieves near-optimal performance with reduced computational complexity compared to traditional optimization-based beamforming techniques. This work highlights the effectiveness of GNNs in large-scale wireless communication systems.

Ge et al. (2023) developed a sparsity-adaptive compressive sensing algorithm for channel estimation in MIMO-OFDM systems. Their method dynamically adjusts sparsity levels based on channel conditions, leading to improved estimation accuracy and reduced pilot overhead. The study showed that incorporating sparsity into channel estimation models significantly enhances performance in millimeter-wave communication scenarios. Furthermore, the proposed approach demonstrated lower computational complexity compared to conventional compressive sensing techniques.

Li et al. (2023) introduced a Graph Neural Network (GNN)-based beamforming framework for MU-MISO systems. Their model captures complex spatial relationships between users and antennas, enabling efficient resource allocation and interference management. The results indicated that GNN-based approaches outperform traditional beamforming techniques in terms of spectral efficiency and adaptability to dynamic network conditions. This work emphasizes the growing importance of graph-based learning in next-generation wireless communication systems.

He et al. (2020) proposed a deep learning-based channel estimation method using a residual learning framework for OFDM systems. Their approach leverages residual neural networks (ResNet) to learn noise and interference patterns, improving estimation accuracy under highly dynamic channel conditions. The model significantly outperformed traditional LS and MMSE estimators, especially in high-mobility scenarios. Furthermore, the residual structure reduced training complexity and improved convergence speed, making it suitable for practical deployment in 5G and beyond systems.

Ye et al. (2020) introduced a data-driven channel estimation technique using deep neural networks for OFDM systems. Their model learns the mapping between received pilot signals and channel responses without requiring prior channel statistics. The study demonstrated superior performance over conventional methods in nonlinear and noisy environments. Additionally, the proposed framework reduced pilot overhead and showed robustness across varying channel models, making it adaptable for future wireless networks.

Sun et al. (2021) developed a model-driven deep learning framework for MIMO channel estimation by integrating traditional signal processing algorithms with neural networks. Their approach combines domain knowledge with learning capabilities, achieving high estimation accuracy with reduced training data requirements. The study emphasized the benefits of hybrid model-based and data-driven approaches in improving system efficiency and reliability.

Wang et al. (2021) proposed an attention-based Graph Neural Network (GNN) for wireless communication systems. Their model utilizes attention mechanisms to capture dynamic relationships between nodes (users and antennas), enabling efficient interference management and resource allocation. The results showed improved spectral efficiency and reduced latency compared to conventional optimization techniques. This work highlights the importance of attention mechanisms in enhancing GNN performance.

Huang et al. (2022) introduced a lightweight deep learning model for secure channel estimation and attack detection in OFDM systems. Their approach integrates anomaly detection with channel estimation, enabling simultaneous performance optimization and security enhancement. The model effectively detected pilot contamination and jamming attacks while maintaining high estimation accuracy. The study demonstrated the potential of AI-driven security frameworks in next-generation wireless systems.

Jiang et al. (2021) proposed a deep unfolding-based channel estimation framework for MIMO-OFDM systems, where iterative optimization algorithms are transformed into trainable neural network layers. This approach combines the interpretability of model-based methods with the adaptability of deep learning. The results showed improved estimation accuracy and faster convergence compared to traditional iterative algorithms. The framework is particularly effective in handling nonlinear channel distortions and reducing computational complexity.

Gao et al. (2021) introduced a sparse Bayesian learning-based channel estimation technique enhanced with deep neural networks. Their method exploits channel sparsity in the angular domain, significantly reducing pilot overhead and improving estimation efficiency. The study demonstrated that combining Bayesian inference with deep learning improves robustness against noise and channel variations, making it suitable for mmWave communications.

Chen et al. (2022) developed an attention-based deep neural network for channel estimation in massive MIMO systems. By incorporating self-attention mechanisms, the model effectively captures long-range dependencies across subcarriers and antennas. The proposed method achieved higher estimation accuracy and spectral efficiency compared to CNN and RNN-based models. This work highlights the role of attention mechanisms in enhancing deep learning performance in wireless systems.

Zhang et al. (2022) proposed a Graph Neural Network (GNN)-based interference management framework for MU-MIMO systems. Their model represents users and base stations as graph nodes and learns interference patterns through message passing. The results showed significant improvements in throughput and energy efficiency. The study demonstrated that GNNs can effectively handle large-scale network optimization problems with reduced computational complexity.

Liu et al. (2023) introduced a hybrid deep learning framework combining CNN and GNN architectures for joint channel estimation and signal detection in OFDM systems. The CNN component extracts local features, while the GNN captures global dependencies across the network. The proposed model achieved superior performance in terms of bit error rate (BER) and computational efficiency. This work demonstrates the effectiveness of hybrid architectures in addressing complex wireless communication challenges.

Ma et al. (2021) proposed a deep reinforcement learning (DRL)-based resource allocation and channel estimation framework for MU-MIMO systems. Their approach dynamically adapts to changing network conditions by learning optimal policies for power allocation and channel utilization. The results demonstrated improved spectral efficiency and reduced latency compared to conventional optimization methods. The integration of DRL with wireless communication models highlights its potential in intelligent network management.

Park et al. (2021) introduced a hybrid CNN-LSTM model for channel estimation in OFDM systems. The CNN component captures spatial features, while the LSTM network models temporal dependencies in wireless channels. Their approach achieved higher prediction accuracy and robustness in time-varying environments. This study emphasizes the importance of combining spatial and temporal learning for dynamic wireless communication scenarios.

Dai et al. (2022) developed a deep unfolding neural network for sparse signal recovery in massive MIMO systems. Their approach integrates iterative shrinkage-thresholding algorithms with neural networks, improving convergence speed and estimation accuracy. The study demonstrated that deep unfolding techniques provide a balance between model interpretability and learning capability, making them suitable for real-time applications.

Xu et al. (2022) proposed an attention-enhanced Graph Neural Network (GNN) for secure communication in wireless networks. Their model identifies anomalous nodes and detects attacks such as jamming and spoofing by analyzing graph-based relationships. The results showed improved detection accuracy and reduced false alarm rates compared to traditional intrusion detection systems. This work highlights the role of GNNs in enhancing wireless network security.

Tang et al. (2023) introduced a lightweight deep learning model for joint channel estimation and attack mitigation in MU-MIMO-OFDM systems. Their approach integrates feature extraction and anomaly detection within a unified framework, reducing computational overhead. The model demonstrated high robustness against pilot contamination attacks while maintaining estimation accuracy. This study supports the feasibility of deploying AI-based security solutions in practical wireless systems.

Alkhateeb et al. (2020) proposed a deep learning framework for beam selection and channel estimation in mmWave MIMO systems. Their approach utilizes coordinated beamforming and neural networks to learn spatial channel characteristics efficiently. The study demonstrated significant improvements in beam selection accuracy and reduced training overhead. This work highlights the effectiveness of deep learning in handling high-dimensional wireless communication problems.

Samuel et al. (2020) introduced a deep neural network-based detection and estimation framework for MIMO systems. Their model jointly performs signal detection and channel estimation, achieving near-optimal performance with reduced computational complexity. The study showed that deep learning-based detectors outperform traditional maximum likelihood methods in large-scale systems.

He et al. (2022) developed a graph-based deep learning model for resource allocation in wireless networks. Their approach models users and base stations as nodes in a graph and applies message passing to optimize resource distribution. The results indicated improved energy efficiency and fairness compared to conventional optimization techniques, demonstrating the scalability of GNN-based solutions.

Zhou et al. (2022) proposed an adversarial learning-based framework for secure channel estimation in OFDM systems. Their model is designed to withstand adversarial attacks by training against perturbed data samples. The study showed enhanced robustness and improved generalization under attack scenarios, highlighting the importance of adversarial training in secure wireless communication.

Kim et al. (2023) introduced a lightweight Graph Neural Network (GNN) architecture for real-time channel estimation and interference management. Their model reduces computational complexity while maintaining high accuracy, making it suitable for edge deployment in 6G networks. The study demonstrated that lightweight GNNs can effectively balance performance and efficiency in resource-constrained environments.

Shlezinger et al. (2020) proposed a model-based deep learning framework for MIMO receivers using deep unfolding techniques. Their approach integrates classical signal processing algorithms with neural networks, enabling efficient channel estimation and detection. The results demonstrated improved robustness and interpretability compared to purely data-driven models. This work highlights the importance of combining domain knowledge with deep learning for wireless systems.

Huang et al. (2021) developed a deep learning-based pilot design and channel estimation framework for OFDM systems. Their model optimizes pilot patterns using neural networks, reducing pilot overhead while maintaining high estimation accuracy. The study showed that optimized pilot design significantly improves spectral efficiency in wireless communication systems.

Wu et al. (2022) proposed a Graph Neural Network (GNN)-based approach for interference coordination in large-scale wireless networks. Their model learns the interaction between users and base stations through graph structures, enabling efficient interference mitigation. The results indicated improved throughput and reduced interference compared to traditional resource allocation methods.

Yang et al. (2023) introduced a transformer-based deep learning model for channel estimation in massive MIMO systems. Their approach leverages self-attention mechanisms to capture long-range dependencies across antennas and subcarriers. The model achieved superior performance in terms of estimation accuracy and scalability, highlighting the potential of transformer architectures in wireless communication.

Zhang et al. (2023) proposed a secure GNN-based framework for joint channel estimation and attack detection in MU-MIMO-OFDM systems. Their model integrates graph learning with anomaly detection techniques to identify malicious activities such as pilot contamination and spoofing attacks. The results demonstrated improved security and system reliability, making it suitable for next-generation 6G networks.

Comparative Table and Analysis

No.	Author (Year)	Technique	Application	Key Contribution	Limitation
1	Marinberg et al. (2020)	CNN	Channel Estimation	Improved BER	High training data
2	Balevi & Andrews (2020)	GAN	Channel Estimation	Robust to noise	Complex training
3	Chowdhury et al. (2023)	GNN + Deep Unfolding	Beamforming	Near-optimal performance	Scalability
4	Ge et al. (2023)	Compressive Sensing	Channel Estimation	Reduced pilot overhead	Sparse assumption
5	Li et al. (2023)	GNN	Beamforming	High spectral efficiency	Model complexity
6	He et al. (2020)	ResNet	Channel Estimation	Fast convergence	Overfitting risk

7	Ye et al. (2020)	DNN	Channel Estimation	Data-driven approach	Requires dataset
8	Sun et al. (2021)	Model-driven DL	Channel Estimation	Hybrid efficiency	Model dependency
9	Wang et al. (2021)	Attention GNN	Resource Allocation	Dynamic adaptation	Computation cost
10	Huang et al. (2022)	DL + Security	Attack Detection	Joint estimation-security	Limited datasets
11	Jiang et al. (2021)	Deep Unfolding	Channel Estimation	Interpretability	Design complexity
12	Gao et al. (2021)	Sparse Bayesian DL	Channel Estimation	Reduced overhead	Complexity
13	Chen et al. (2022)	Attention DL	Channel Estimation	Long-range dependency	High compute
14	Zhang et al. (2022)	GNN	Interference Mgmt	High throughput	Graph scaling
15	Liu et al. (2023)	CNN + GNN	Joint Estimation	Hybrid performance	Integration cost
16	Ma et al. (2021)	DRL	Resource Allocation	Adaptive learning	Training time
17	Park et al. (2021)	CNN + LSTM	Channel Estimation	Temporal modeling	Complexity
18	Dai et al. (2022)	Deep Unfolding	Sparse Recovery	Fast convergence	Parameter tuning
19	Xu et al. (2022)	GNN + Attention	Security	Attack detection	False alarms
20	Tang et al. (2023)	Lightweight DL	Security	Low complexity	Accuracy tradeoff
21	Alkhateeb et al. (2020)	DL Beamforming	Beam Selection	Reduced overhead	Data dependency
22	Samuel et al. (2020)	DNN	Detection	Near-optimal detection	Training cost
23	He et al. (2022)	GNN	Resource Allocation	Energy efficiency	Scalability
24	Zhou et al. (2022)	Adversarial DL	Security	Robustness	Training instability
25	Kim et al. (2023)	Lightweight GNN	Channel Estimation	Edge deployment	Limited depth
26	Shlezinger et al. (2020)	Deep Unfolding	Detection	Interpretability	Design effort
27	Huang et al. (2021)	DL Pilot Design	Channel Estimation	Improved efficiency	Model tuning
28	Wu et al. (2022)	GNN	Interference Mgmt	Throughput gain	Complexity
29	Yang et al. (2023)	Transformer	Channel Estimation	High scalability	Heavy compute
30	Zhang et al. (2023)	Secure GNN	Security	Attack mitigation	Dataset need

Analysis

The comparative analysis reveals that deep learning techniques 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 RNN and LSTM models enhance temporal prediction capabilities. Graph Neural Networks (GNNs) have emerged as the most effective approach for modelling complex relationships in wireless networks, particularly for interference management and resource allocation. Hybrid approaches combining GNN with CNN or deep unfolding techniques provide superior performance by leveraging both local and global features. Attention mechanisms and transformer models further improve scalability and accuracy by capturing long-range dependencies. Additionally, reinforcement learning methods enable adaptive resource allocation in dynamic environments. Security-focused models using GNN and adversarial learning demonstrate strong capabilities 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 improved the performance of MU-MIMO-OFDM systems. The integration of deep learning techniques with traditional signal processing methods has enabled more accurate channel estimation and efficient resource allocation. GNN-based approaches, in particular, provide a powerful framework for modelling complex wireless network interactions, making them highly suitable for next-generation 6G systems. Despite these advancements, several challenges persist. High computational complexity and large training data requirements limit the deployment of deep learning models in real-time systems.

Additionally, the robustness of these models under adversarial conditions remains a critical concern. While lightweight and hybrid models have been proposed to address these issues, further research is needed to achieve a balance between performance and efficiency. Future research should focus on developing scalable and energy-efficient models, as well as improving the interpretability of deep learning frameworks. The integration of edge computing and federated learning can further enhance system performance and security. Overall, optimized GNN-based approaches hold great potential for transforming wireless communication systems.

Conclusion

The rapid transition toward 6G wireless communication systems has introduced complex challenges in channel estimation, resource allocation, and network security, particularly in MU-MIMO-OFDM architectures that underpin modern high-speed networks. This review highlights that traditional techniques such as LS and MMSE are no longer sufficient to address the nonlinear, high-dimensional, and dynamic nature of emerging communication environments. In contrast, deep learning approaches, including CNNs, RNNs, and especially Graph Neural Networks (GNNs), have demonstrated substantial improvements in channel estimation accuracy and system efficiency. GNNs are particularly effective due to their ability to model relationships among network entities, enabling better interference management and optimized resource utilization. The integration of attention mechanisms and transformer-based models further enhances adaptability to dynamic conditions and long-range dependencies. Moreover, hybrid frameworks combining deep learning with optimization methods such as deep unfolding and reinforcement learning achieve near-optimal performance while maintaining computational efficiency. Sparsity-aware models and compressive sensing techniques also contribute to reduced pilot overhead and improved spectral efficiency. From a security perspective, AI-driven approaches, including GNN-based anomaly detection and adversarial learning, have shown strong potential in mitigating threats such as jamming, spoofing, and pilot contamination. However, challenges related to computational complexity, scalability, data dependency, and model interpretability persist. Future research should prioritize lightweight, scalable, and robust AI models, leveraging distributed and federated learning to enable practical, secure, and efficient deployment in next-generation wireless networks.

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