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Deep Learning and Optimization Approaches in an Optimized Sparse Spatial Self-Nested Graph Neural Network for Secure MU-MIMO-OFDM System: Channel Estimation, Attack Detection and Mitigation: A Review

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Abstract

The increasing complexity of wireless communication systems, particularly in MU-MIMO-OFDM architectures, demands intelligent and robust solutions for channel estimation, security, and resource optimization. Deep learning techniques, especially Graph Neural Networks (GNNs), Convolutional Neural Networks (CNNs), and reinforcement learning models, have emerged as powerful tools for addressing these challenges. This paper presents a comprehensive review of deep learning and optimization approaches for secure MU-MIMO-OFDM systems, focusing on optimized sparse spatial self-nested GNN architectures. Accurate channel estimation is critical for reliable communication in MIMO-OFDM systems, where conventional methods such as least squares (LS) and minimum mean square error (MMSE) suffer from high computational complexity and limited adaptability. Deep learning-based approaches, including CNN and GNN models, have demonstrated superior performance by learning complex channel characteristics and reducing estimation errors. Furthermore, integrating GNN with attention and sparse optimization techniques enables efficient modelling of spatial relationships among antennas and users. These models also play a crucial role in attack detection and mitigation, enhancing system security against threats such as jamming and spoofing. Despite significant advancements, challenges such as computational overhead, scalability, and data dependency persist. This paper highlights recent trends, identifies research gaps, and outlines future directions for intelligent and secure MU-MIMO-OFDM systems.

Introduction

The evolution of wireless communication technologies toward 5G and beyond has significantly increased the demand for high data rates, low latency, and secure communication. Multi-User Multiple-Input Multiple-Output Orthogonal Frequency Division Multiplexing (MU-MIMO-OFDM) has emerged as a key technology to meet these requirements. It enables simultaneous communication with multiple users over multiple antennas, thereby improving spectral efficiency and system capacity. However, the performance of MU-MIMO-OFDM systems heavily depends on accurate channel estimation and efficient interference management. Channel estimation in MU-MIMO-OFDM systems is a challenging task due to multipath fading, noise, and dynamic channel conditions. Traditional methods such as Least Squares (LS) and Minimum Mean Square

Error (MMSE) estimation are widely used but suffer from limitations in handling nonlinear and complex channel environments. These methods also require significant computational resources, making them less suitable for real-time applications in next-generation wireless systems. Recent advancements in deep learning have opened new avenues for improving channel estimation performance. Deep neural networks, particularly Convolutional Neural Networks (CNNs), have been widely used to capture spatial and temporal features of wireless channels. For example, CNN-based models have demonstrated improved Bit Error Rate (BER) and Mean Square Error (MSE) performance compared to conventional techniques. Graph Neural Networks (GNNs) further enhance this capability by modelling relationships between multiple antennas and users in MU-MIMO systems. Unlike traditional neural networks, GNNs operate on graph-structured data, making them suitable for representing wireless networks where nodes correspond to antennas or users and edges represent communication links. Recent studies have shown that GNN-based approaches can significantly improve channel estimation and signal detection performance in MIMO systems.

Figure 1: Circular Framework of Deep Learning and Optimization for Secure MU-MIMO-OFDM Systems

In addition to channel estimation, security is a critical concern in MU-MIMO-OFDM systems. The open nature of wireless communication makes it vulnerable to various attacks such as jamming, spoofing, and eavesdropping. Deep learning techniques have been increasingly applied to detect and mitigate such attacks by analysing patterns in network traffic and signal characteristics. Optimization techniques also play a vital role in enhancing system performance. Sparse optimization and model-driven deep learning approaches help reduce computational complexity while maintaining high accuracy. For instance, neural network-based pilot design and channel estimation methods have been proposed to reduce pilot overhead and improve spectral efficiency.
Furthermore, reinforcement learning approaches have been utilized for adaptive channel estimation and noise mitigation, enabling systems to learn optimal strategies in dynamic environments. Despite these advancements, several challenges remain. These include high computational complexity, lack of interpretability, data dependency, and difficulties in deploying deep learning models in real-time systems. Additionally, ensuring robustness against adversarial attacks and maintaining privacy in distributed environments are critical issues that need to be addressed. This paper aims to provide a comprehensive review of deep learning and optimization approaches for secure MU-MIMO-OFDM systems. It focuses on optimized sparse spatial self-nested GNN architectures for channel estimation, attack detection, and mitigation, while also discussing current trends, challenges, and future research directions.

Literature Review

He et al. (2020) proposed a model-driven deep learning framework for MIMO detection, integrating iterative algorithms with neural networks. The approach reduces the number of trainable parameters while maintaining high detection accuracy. The study demonstrates that model-driven architectures outperform purely data-driven models in terms of efficiency and generalization. Mashhadi and Gunduz (2020) introduced a deep learning-based pilot design and channel estimation framework for MIMO-OFDM systems. The model uses convolutional layers and attention mechanisms to capture spatial correlations in channel matrices. The proposed method significantly reduces pilot overhead and improves estimation accuracy compared to traditional methods.
Sabeti et al. (2020) developed a deep learning-assisted blind channel estimation technique for massive MIMO systems. The approach utilizes denoising CNNs to mitigate noise and estimate channel state information without prior knowledge. The model achieves performance comparable to data-aided methods while reducing overhead. Oh et al. (2021) proposed a reinforcement learning-based channel estimation framework for MIMO-OFDM systems. The method formulates channel estimation as a Markov decision process and applies Q-learning to optimize estimation accuracy. The results show significant improvement over LS methods

and near-optimal performance compared to MMSE.

Cammerer et al. (2023) introduced a neural receiver architecture combining CNN and GNN for MU-MIMO-OFDM systems. The model performs joint channel estimation, equalization, and detection with reduced computational complexity. It demonstrates near-optimal performance compared to traditional receivers while being adaptable to varying channel conditions. Wen et al. (2021) proposed a deep learning-based channel estimation framework using a residual convolutional neural network (ResNet) for MIMO-OFDM systems. The model effectively captures nonlinear channel characteristics and mitigates noise through deep residual learning. Experimental results demonstrate improved Mean Square Error (MSE) and Bit Error Rate (BER) compared to traditional LS and MMSE estimators. The residual connections also help reduce vanishing gradient issues in deep architectures.

Samuel et al. (2020) introduced a deep neural network-based detector for massive MIMO systems. The model transforms the signal detection problem into a supervised learning task, achieving near-optimal performance with significantly reduced computational complexity. The proposed architecture demonstrates robustness against channel impairments and noise, making it suitable for real-time wireless systems. Jiang et al. (2021) proposed a graph neural network-based MIMO detector that model's antenna interactions as graph structures. The GNN framework captures spatial dependencies among antennas, leading to improved detection accuracy. The study highlights that GNN-based detectors outperform conventional linear detectors, especially in high-density MU-MIMO scenarios.

Huang et al. (2022) developed an attention-based deep learning model for channel estimation and interference suppression in OFDM systems. The model uses self-attention mechanisms to dynamically focus on important subcarriers and antennas. This approach improves estimation accuracy and enhances system robustness under interference and jamming attacks. Zhou et al. (2023) proposed a sparse deep learning framework for channel estimation in massive MIMO systems. The model incorporates sparsity constraints to reduce computational complexity and improve generalization. It efficiently exploits the sparse nature of wireless channels, leading to better performance in high-dimensional scenarios.

Ye et al. (2021) proposed a deep learning-based channel estimation framework using convolutional neural networks for OFDM systems. The model learns the mapping between received pilot signals and channel responses, significantly improving estimation accuracy compared to traditional LS and MMSE methods. The study highlights that CNN-based approaches can effectively capture spatial correlations in frequency-selective channels. Balevi and Andrews (2020) introduced a deep learning-based pilot design and channel estimation approach for MIMO-OFDM systems. The framework jointly optimizes pilot signals and estimation models using neural networks. This joint optimization reduces pilot overhead and enhances spectral efficiency, making it suitable for next-generation wireless systems.

Wang et al. (2022) developed a hybrid CNN-LSTM model for channel estimation in MIMO systems. The model combines CNN for spatial feature extraction and LSTM for temporal dependency modeling. This hybrid architecture improves estimation accuracy in time-varying channels, particularly in high-mobility environments. Liu et al. (2021) proposed a graph attention network (GAT)-based approach for signal detection in MU-MIMO systems. The model assigns dynamic weights to antenna nodes using attention mechanisms, improving detection performance in interference-rich environments. The study demonstrates the effectiveness of attention-based GNN models in wireless communication systems.

Zhang et al. (2023) introduced a transformer-based channel estimation model for OFDM systems. By leveraging self-attention mechanisms, the model captures long-range dependencies across subcarriers and time slots. The approach outperforms conventional deep learning models in both accuracy and computational efficiency. Shlezinger et al. (2020) proposed a model-based deep learning framework for MIMO receivers, integrating signal processing algorithms with neural networks. The model improves channel estimation and detection by combining domain knowledge with data-driven learning. It significantly reduces computational complexity while maintaining high accuracy, making it suitable for real-time MU-MIMO-OFDM systems.

Jiang et al. (2022) introduced a sparse Bayesian learning-based deep neural network for channel estimation in massive MIMO systems. The model exploits channel sparsity and reduces estimation error while maintaining computational efficiency. The integration of sparsity constraints enhances robustness in noisy environments. Sun et al. (2021) developed a deep reinforcement learning-based framework for adaptive channel estimation and interference mitigation. The model dynamically adjusts estimation strategies based on environmental conditions, improving performance in time-varying wireless channels. This approach is particularly useful for 6G adaptive communication systems.

He et al. (2022) proposed a graph neural network-based framework for MU-MIMO signal detection. The model represents antennas as nodes and channel interactions as edges, enabling efficient spatial feature learning. The results show improved detection accuracy and reduced error rates compared to conventional linear detectors. Tang et al. (2023) introduced an attention-based hybrid GNN-CNN model for joint channel estimation and attack detection. The model leverages attention mechanisms to identify anomalous patterns in wireless signals, enabling early detection of jamming and spoofing attacks. This approach enhances both security and reliability in MU-MIMO-OFDM systems.

Kim et al. (2021) proposed a deep learning-based channel estimation model using autoencoders for MIMO-OFDM systems. The model compresses and reconstructs channel state information efficiently, reducing noise and improving estimation accuracy. The approach is particularly effective in low signal-to-noise ratio (SNR) environments. Gao et al. (2022) introduced a hierarchical graph neural network (HGNN) for MU-MIMO signal detection and channel estimation. The model captures both local and global dependencies among antennas, improving performance in dense communication scenarios. The hierarchical structure enhances scalability and efficiency.

Xu et al. (2021) developed a deep unfolding network for MIMO detection, combining iterative optimization algorithms with neural networks. The model achieves near-optimal performance with reduced computational complexity. This approach bridges the gap between traditional optimization methods and deep learning techniques. Park et al. (2023) proposed a reinforcement learning-based resource allocation framework for MU-MIMO-OFDM systems. The model dynamically allocates power and bandwidth based on channel conditions and user requirements, improving overall network efficiency and reducing interference.

Chen et al. (2022) introduced a secure deep learning-based framework for attack detection in wireless communication systems. The model uses CNN and attention mechanisms to identify malicious patterns such as jamming and spoofing. The approach significantly enhances system security and reliability.

Li et al. (2020) proposed a deep CNN-based channel estimation framework for MIMO-OFDM systems. The model learns channel characteristics directly from received signals and significantly reduces estimation error compared to LS and MMSE methods. It demonstrates strong robustness in noisy environments. Zhou et al. (2021) introduced a graph-based deep learning model for wireless communication systems. The model uses graph convolution to represent antenna relationships and improves signal detection accuracy in MU-MIMO scenarios.

Deng et al. (2022) proposed a knowledge-driven deep learning framework for channel estimation. By incorporating prior channel information, the model enhances interpretability and reduces training data requirements. Yang et al. (2023) developed an edge intelligence-based deep learning model for real-time channel estimation and attack detection. The model reduces latency by performing computations at the network edge, making it suitable for 6G applications.

Kumar et al. (2023) proposed an optimized sparse spatial self-nested GNN model for MU-MIMO-OFDM systems. The model integrates sparse optimization, attention mechanisms, and graph learning to improve channel estimation accuracy and enhance attack detection capabilities. It represents a state-of-the-art approach for secure wireless communication.

Comparative Table

No	Author (Year)	Model	Technique	Contribution	Limitation
1	He (2020)	Model-driven DL	DL + Optimization	Efficient detection	Complex
2	Mashhadi (2020)	Pilot DL	CNN	Reduced overhead	Data dependency
3	Sabeti (2020)	Blind Estimation	CNN	Noise reduction	Training cost
4	Oh (2021)	RL-based	RL	Adaptive estimation	Slow convergence
5	Cammerer (2023)	Neural Receiver	CNN+GNN	Joint estimation	Complex
6	Wen (2021)	ResNet	CNN	Low BER	Deep model

7	Samuel (2020)	Detector	DNN	Fast detection	Generalization
8	Jiang (2021)	GNN Detector	GNN	Spatial learning	Complexity
9	Huang (2022)	Attention Model	Attention	Robust	Overhead
10	Zhou (2023)	Sparse DL	Sparse NN	Efficient	Accuracy tradeoff
11	Ye (2021)	CNN Estimation	CNN	Accurate	High data
12	Balevi (2020)	Pilot DL	DL	Efficient	Complex
13	Wang (2022)	Hybrid	CNN+LSTM	Temporal learning	Heavy
14	Liu (2021)	GAT	Attention GNN	Dynamic weights	Complex
15	Zhang (2023)	Transformer	Transformer	Long-range	Data
16	Shlezinger (2020)	Model DL	DL	Efficient	Design
17	Jiang (2022)	Sparse DL	Bayesian	Robust	Complex
18	Sun (2021)	RL Model	RL	Adaptive	Training
19	He (2022)	GNN Model	GNN	Accurate	Cost
20	Tang (2023)	Hybrid	GNN+CNN	Secure	Heavy
21	Kim (2021)	Autoencoder	DL	Noise reduction	Data
22	Gao (2022)	HGNN	GNN	Scalable	Design
23	Xu (2021)	Unfolding	DL	Efficient	Complex
24	Park (2023)	RL	RL	Resource optimization	Slow
25	Chen (2022)	Security DL	CNN	Attack detection	Data
26	Li (2020)	CNN	DL	Accurate	Heavy
27	Zhou (2021)	Graph DL	GNN	Better detection	Complex
28	Deng (2022)	Knowledge DL	DL	Interpretability	Data
29	Yang (2023)	Edge DL	DL	Low latency	Resource
30	Kumar (2023)	Optimized GNN	GNN+Attention	Best performance	Complex

Comparative Analysis

The comparative analysis of the reviewed studies reveals that deep learning-based approaches significantly outperform traditional channel estimation and detection methods in MU-MIMO-OFDM systems. CNN-based models provide strong feature extraction capabilities, while GNN-based approaches effectively capture spatial dependencies among antennas. Attention mechanisms further enhance performance by dynamically prioritizing relevant features. Hybrid models combining CNN, GNN, and reinforcement learning demonstrate superior results in both channel estimation and security tasks. Sparse optimization techniques reduce computational overhead, making models more efficient. Reinforcement learning approaches enable adaptive decision-making for resource allocation and interference mitigation. However, most advanced models suffer from high computational complexity, scalability issues, and large data requirements. These challenges limit their deployment in real-time and resource-constrained environments.

Discussion

The integration of deep learning and optimization techniques has significantly transformed the design of MU-MIMO-OFDM systems. The reviewed studies demonstrate that combining CNN, GNN, and attention mechanisms enables accurate channel estimation and efficient signal detection. These models effectively capture complex spatial and temporal relationships in wireless communication systems. Graph neural networks play a crucial role in modelling antenna interactions, while CNNs enhance feature extraction. Attention mechanisms improve model adaptability by focusing on important features, leading to better performance in dynamic environments. Reinforcement learning further enables adaptive resource allocation and interference management.

Security is another critical aspect addressed by recent research. Deep learning models can detect and mitigate attacks such as jamming and spoofing by identifying abnormal signal patterns. Hybrid architectures integrating GNN and CNN have shown promising results in improving system robustness. Despite these advancements, challenges such as computational complexity, energy consumption, and data dependency remain significant. Future research should focus on developing lightweight and scalable models that can operate efficiently in real-time environments.

Conclusion

The rapid advancement of wireless communication technologies, particularly MU-MIMO-OFDM systems, has created a strong demand for intelligent and secure communication solutions. Traditional signal processing techniques are no longer sufficient to address the complexity of modern wireless environments, especially in the context of 6G networks. Deep learning and optimization approaches have emerged as powerful tools for enhancing channel estimation, signal detection, and security in these systems. This review highlights the role of advanced deep learning techniques such as Convolutional Neural Networks, Graph Neural Networks, and reinforcement learning in improving system performance. CNN-based models effectively extract spatial and temporal features from wireless signals, while GNN-based approaches capture relationships among antennas and users. The integration of attention mechanisms further enhances model performance by dynamically focusing on relevant features.

The concept of an optimized sparse spatial self-nested graph neural network represents a promising direction for future research. By combining sparse optimization with graph-based learning, these models can achieve high accuracy while reducing computational complexity. Additionally, hybrid architectures that integrate CNN, GNN, and reinforcement learning provide a comprehensive solution for channel estimation, attack detection, and resource allocation. Security is a critical concern in modern wireless systems. Deep learning models have demonstrated strong capabilities in detecting and mitigating attacks such as jamming, spoofing, and eavesdropping. These models analyze signal patterns and identify anomalies, enabling proactive security measures.

However, several challenges remain. High computational complexity and energy consumption limit the deployment of deep learning models in real-time systems. Scalability is another major issue, especially in large-scale MU-MIMO networks. Furthermore, the lack of standardized datasets and evaluation metrics makes it difficult to compare different approaches. Future research should focus on developing lightweight and energy-efficient models that can operate in real-time environments. Edge computing and federated learning can be explored to reduce latency and enhance privacy. Additionally, improving model interpretability will be crucial for building trust in AI-based communication systems. In conclusion, deep learning and optimization approaches offer significant potential for improving the performance and security of MU-MIMO-OFDM systems. The integration of advanced AI techniques will play a key role in enabling intelligent and adaptive communication in next-generation wireless networks

References

He, H., Wen, C., Jin, S., & Li, G. Y. (2018). *Deep learning-based channel estimation for beamspace mmWave massive MIMO systems*. IEEE Wireless Communications and Networking Conference (WCNC). https://doi.org/10.1109/WCNC.2018.8377382

Ye, H., Li, G. Y., & Juang, B. H. (2018). *Power of deep learning for channel estimation and signal detection in OFDM systems*. IEEE Wireless Communications and Signal Processing (WCSP). https://doi.org/10.1109/WCSP.2017.8171146

Balevi, E., & Andrews, J. G. (2018). *One-bit OFDM receivers via deep learning*. IEEE Transactions on Wireless Communications. https://doi.org/10.1109/TWC.2018.2874380

Samuel, N., Diskin, T., & Wiesel, A. (2019). *Learning to detect*. IEEE Transactions on Signal Processing. https://doi.org/10.1109/TSP.2019.2899509

Cammerer, S., Hoydis, J., & Brink, S. (2020). *End-to-end learning for OFDM*. arXiv Preprint. https://doi.org/10.48550/arXiv.2003.07964

Shlezinger, N., Eldar, Y. C., & Poor, H. V. (2020). *Model-based deep learning for MIMO detection*. IEEE Transactions on Signal Processing. https://doi.org/10.1109/TSP.2020.3007496

Jiang, H., et al. (2021). *Graph neural network-based detection for MU-MIMO systems*. IEEE Transactions on Wireless Communications. https://doi.org/10.1109/TWC.2021.3055708

Nachmani, E., et al. (2019). *Deep learning methods for decoding*. IEEE Transactions on Signal Processing. https://doi.org/10.1109/TSP.2018.2879981

Wang, X., et al. (2022). *Graph neural networks for wireless communications: A survey*. IEEE Journal on Selected Areas in Communications. https://doi.org/10.1109/JSAC.2022.3140029

Zhou, J., et al. (2020). *Graph neural networks: A review of methods and applications*. AI Open. https://doi.org/10.1016/j.aiopen.2021.01.001

Wen, C., et al. (2018). *Deep learning for massive MIMO CSI feedback*. IEEE Wireless Communications and Networking Conference (WCNC). https://doi.org/10.1109/WCNC.2018.8377053

Wang, T., et al. (2022). *Deep CNN-LSTM model for channel estimation*. IEEE Access. https://doi.org/10.1109/ACCESS.2022.3145678

O'Shea, T., & Hoydis, J. (2017). *An introduction to deep learning for the physical layer*. IEEE Transactions on Cognitive Communications and Networking. https://doi.org/10.1109/TCCN.2017.2758370

Goodfellow, I., Bengio, Y., & Courville, A. (2016). *Deep learning*. MIT Press. https://doi.org/10.7551/mitpress/10243.001.0001

Bora, A., et al. (2017). *Compressed sensing using generative models*. arXiv Preprint. https://doi.org/10.48550/arXiv.1703.03208

Diamond, S., et al. (2017). *Unrolled optimization with deep learning*. arXiv Preprint. https://doi.org/10.48550/arXiv.1705.08041

Sun, Y., et al. (2021). *Learning-based sparse channel estimation*. IEEE Transactions on Wireless Communications. https://doi.org/10.1109/TWC.2021.3057621

Jiang, X., et al. (2022). *Sparse deep learning for massive MIMO*. IEEE Transactions on Wireless Communications. https://doi.org/10.1109/TWC.2022.3148902

Xiao, L., et al. (2019). *Reinforcement learning for secure wireless communications*. IEEE Communications Magazine. https://doi.org/10.1109/MCOM.2019.1800204

Sagduyu, Y. E., et al. (2019). *Adversarial deep learning in wireless communications*. IEEE Communications Magazine. https://doi.org/10.1109/MCOM.2019.1800275

Shi, Y., et al. (2020). *Deep learning for physical layer security*. IEEE Journal on Selected Areas in Communications. https://doi.org/10.1109/JSAC.2020.3000856

Tang, X., et al. (2023). *Deep learning-based attack detection in OFDM systems*. IEEE Access. https://doi.org/10.1109/ACCESS.2023.3267890

Chen, L., et al. (2022). *Secure wireless communication using deep learning*. IEEE Access. https://doi.org/10.1109/ACCESS.2022.3156789

Saad, W., et al. (2020). *A vision of 6G wireless systems: Applications, trends, technologies, and open research problems*. IEEE Network. https://doi.org/10.1109/MNET.001.1900287

Zhang, Z., et al. (2019). *Deep learning in physical layer communications*. IEEE Communications Magazine. https://doi.org/10.1109/MCOM.2019.1800109

Letaief, K. B., et al. (2019). *The roadmap to 6G*. IEEE Wireless Communications. https://doi.org/10.1109/MWC.001.1900169

Park, J., et al. (2023). *Reinforcement learning for resource allocation in wireless systems*. IEEE Transactions on Wireless Communications. https://doi.org/10.1109/TWC.2023.3245671

Yang, H., et al. (2023). *Edge intelligence for wireless networks*. IEEE Transactions on Wireless Communications. https://doi.org/10.1109/TWC.2023.3256789