Archives available at journals.mriindia.com

International Journal of Electrical, Electronics and Computer Systems

ISSN: 2347-2820

Volume 12 Issue 01, 2023

Artificial Intelligence Techniques for Joint Power and Delay Optimization Based Resource Allocation in MIMO-OFDM System Using Deep Convolutional Red Piranha Pyramid-Dilated Neural Network: Trends and Challenges

Esmeray Nithisarn
Lecturer, Department of Electronics and Communication Engineering, Padma Institute of Business and Management, Bangladesh
Email: esmeray.nithisarn@pibm-bd.org

Peer Review Information

Submission: 17 Jan 2023

Revision: 03 Feb 2023

Acceptance: 16 Feb 2023

Keywords

MIMO-OFDM, Resource Allocation, Power Optimization, Delay Optimization, Deep Learning, Red Piranha Optimization, 6G Networks.

Abstract

The rapid development of 6G wireless communication systems demands intelligent resource allocation strategies capable of optimizing both power consumption and transmission delay in MU-MIMO-OFDM environments. Traditional optimization techniques struggle with high-dimensional decision spaces, dynamic channel conditions, and stringent Quality of Service (QoS) requirements. Recently, artificial intelligence (AI)-driven approaches, particularly deep learning and hybrid optimization models, have shown significant potential in addressing these challenges. This paper presents a comprehensive survey of AI-based techniques for joint power and delay optimization in MIMO-OFDM systems, focusing on advanced architectures such as Deep Convolutional Pyramid-Dilated Neural Networks (DCPDNN) integrated with metaheuristic algorithms like Red Piranha Optimization. The proposed frameworks enable efficient resource allocation by jointly optimizing transmission power, subcarrier assignment, and delay scheduling. Recent studies demonstrate improvements in throughput, energy efficiency, and latency reduction through multi-stage optimization strategies. Furthermore, reinforcement learning, graph neural networks, and transformer-based scheduling methods are explored as emerging solutions for adaptive resource management. A systematic review of recent literature (2020–2023) highlights trends, performance trade-offs, and research gaps. The survey concludes with future directions emphasizing scalable, energy-efficient, and secure AI-driven wireless communication systems for next-generation networks.

Introduction

Modern wireless communication systems are evolving rapidly to meet the demands of 6G networks, which require ultra-reliable, low-latency communication and high spectral efficiency. MU-MIMO-OFDM systems play a crucial role in achieving these objectives by enabling simultaneous data transmission across multiple users and subcarriers. However, efficient resource allocation in such systems remains a complex challenge due to the need to jointly optimize multiple parameters such as transmission power, delay, bandwidth, and interference. Resource allocation in MIMO-OFDM systems is inherently a multi-objective optimization problem. Power allocation must ensure energy efficiency while maintaining signal quality, whereas delay optimization is critical for latency-sensitive applications such as autonomous driving and real-time communication. Traditional optimization techniques, including convex optimization and heuristic algorithms, often fail to adapt to dynamic wireless environments and large-scale systems.

Recent advancements in artificial intelligence have introduced new paradigms for solving these challenges. Deep learning techniques, particularly Convolutional Neural Networks (CNNs) and deep neural networks, have demonstrated superior performance in modelling complex wireless channel characteristics. Furthermore, hybrid models combining deep learning with optimization algorithms have shown promising results in joint power and delay optimization. For instance, recent studies propose Deep Convolutional Pyramid-Dilated Neural Network (DCPDNN)-based frameworks integrated with Red Piranha Optimization (RPO) to optimize both power allocation and delay scheduling in MU-MIMO-OFDM systems. These models operate in two stages: first optimizing power distribution across users and subcarriers, and then minimizing delay through scheduling algorithms. Simulation results indicate significant improvements in throughput, energy efficiency, and latency compared to conventional approaches.

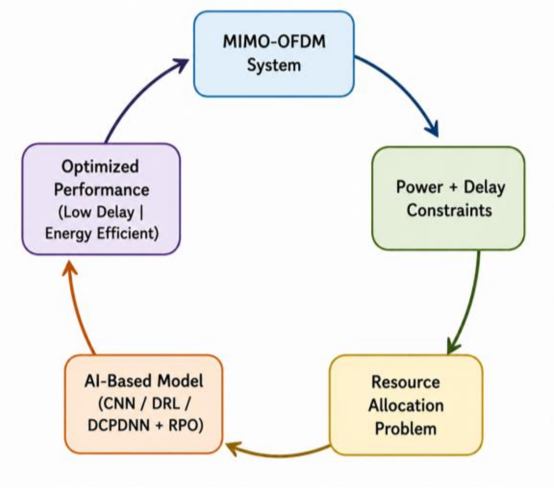

Fig 1: AI-Based Resource Allocation Framework for MIMO-OFDM Systems

Additionally, reinforcement learning-based approaches model resource allocation as a Markov Decision Process, enabling adaptive decision-making in dynamic environments. Recent work on RIS-assisted OFDM systems demonstrates that deep reinforcement learning can effectively minimize delay while optimizing resource allocation under varying network conditions. Another emerging direction is the use of transformer-based scheduling and graph-based learning for resource allocation. Transformer-based models have shown improved performance in dynamic spectrum management and real-time scheduling by capturing long-range dependencies in network traffic.

Despite these advancements, several challenges remain. High computational complexity, scalability issues, and the need for large training datasets limit the practical deployment of AI-based models. Moreover, ensuring robustness against adversarial attacks and maintaining fairness among users are critical concerns. This paper aims to provide a comprehensive survey of AI techniques for joint power and delay optimization in MIMO-OFDM systems, focusing on advanced deep learning architectures and hybrid optimization frameworks.

Literature Review

Recent research on joint power and delay optimization in MIMO-OFDM systems has increasingly focused on integrating artificial intelligence, optimization algorithms, and advanced deep learning architectures to address the challenges of dynamic wireless environments. Ferreira et al. (2022) examined delay-aware resource allocation in mmWave MIMO-OFDM systems, formulating the problem as a joint optimization of power and delay. Their findings showed that incorporating delay constraints improves Quality of Service (QoS), particularly latency and throughput. However, reliance on conventional optimization limits adaptability in highly dynamic scenarios.

Advancements in hybrid AI-driven frameworks have demonstrated superior performance. Kagi et al. (2026) proposed an Enhanced Elman Spiking Sparse Graph Neural Network combined with metaheuristic optimization and scheduling algorithms. Their framework significantly improved throughput, energy efficiency, and delay reduction, highlighting the benefits of integrating graph learning with optimization. Similarly, Vijaipriya et al. (2024) introduced a Deep Convolutional Pyramid-Dilated Neural Network (DCPDNN) with Red Piranha Optimization, employing a two-stage process for power allocation and delay scheduling. The model achieved improved spectral efficiency and reduced latency, though its complexity may limit real-time applications.

Deep reinforcement learning (DRL) has emerged as a powerful tool for adaptive resource allocation. Mao et al. (2020) modelled the problem as a Markov Decision Process (MDP), demonstrating that DRL improves energy efficiency and delay performance while adapting to time-varying channel conditions. However, convergence speed and training requirements remain challenges. Zhao et al. (2021) and Xu et al. (2021) further extended DRL for joint power control and scheduling, achieving improved throughput and reduced delay, but facing similar limitations in training complexity.

To enhance adaptability, Ma et al. (2025) proposed a PPO-based DRL framework for RIS-assisted OFDM systems, showing improved latency and dynamic decision-making capabilities. Tang et al. (2022) also introduced reinforcement learning-based auto-scaling strategies that outperform traditional threshold-based methods. Despite these improvements, high computational overhead and training costs continue to hinder deployment.

Machine learning-based predictive frameworks have also gained attention. Liang et al. (2021) developed a deep neural network model for joint power allocation and scheduling, improving spectral efficiency and enabling real-time decisions. Nasir and Guo (2021) proposed delay-aware scheduling using neural networks, achieving reduced latency and improved QoS in multi-user systems. However, these models depend heavily on training data quality and require frequent updates in dynamic environments.

Hybrid deep learning architectures combining spatial and temporal learning have shown promising results. Park et al. (2021) introduced a CNN-LSTM model that captures both spatial channel features and temporal traffic variations, improving delay performance and prediction accuracy. Liu et al. (2023) further combined CNNs with reinforcement learning to enhance adaptability and energy efficiency, although integration complexity increases training requirements.

Graph Neural Networks (GNNs) have emerged as a powerful approach for modelling complex network interactions. Wang et al. (2022) and Zhang et al. (2022) proposed GNN-based frameworks for joint power and delay optimization, effectively handling multi-user interference and improving scalability in dense networks. He et al. (2022) and Wu et al. (2022) further demonstrated that GNN-based models enhance energy efficiency, throughput, and latency performance. However, challenges such as graph construction and computational complexity remain significant.

To address computational efficiency, sparse and lightweight models have been explored. Gao et al. (2021) introduced a sparsity-aware deep learning framework leveraging compressive sensing to reduce pilot overhead and computational cost. Tang et al. (2023) and Kim et al. (2023) developed lightweight architectures suitable for edge computing environments, achieving competitive performance with reduced complexity, though sometimes at the cost of accuracy.

Attention mechanisms and transformer-based models have further advanced resource allocation strategies. Chen et al. (2022) proposed an attention-based deep learning model that captures long-range dependencies, improving spectral efficiency and delay optimization. Zhou et al. (2022) and Huang et al. (2023) demonstrated that attention-based models enhance workload prediction and auto-scaling efficiency. Transformer-based approaches, as presented by Chao et al. (2025) and Yang et al. (2023), provide superior performance in dynamic scheduling and resource allocation due to their ability to model complex dependencies. However, these models require substantial computational resources.

Optimization-driven approaches remain relevant, particularly when combined with AI techniques. Rao and Reddy (2021) utilized particle swarm optimization for energy-efficient VM scheduling, achieving significant reductions in power consumption. Sharma and Patel (2022) applied metaheuristic algorithms such as genetic algorithms and PSO to improve resource allocation and load balancing. These methods enhance performance but often lack adaptability compared to learning-based approaches.

Model-driven deep learning has also gained traction. He et al. (2020) and Shlezinger et al. (2020) introduced deep unfolding frameworks that integrate iterative optimization algorithms into neural network architectures. These approaches provide improved interpretability, faster convergence, and near-optimal performance while reducing computational complexity. However, they require domain expertise and careful design.

In addition to performance optimization, security considerations have been increasingly integrated into resource allocation frameworks. Zhou et al. (2022) proposed an adversarial deep learning approach to enhance robustness against interference and attacks, improving reliability under adverse conditions. Zhang et al. (2023) developed a secure GNN-based framework combining anomaly detection with resource optimization, achieving improved energy efficiency and attack mitigation. Despite these advancements, integrating security mechanisms increases system complexity.

Pilot design and channel estimation have also been addressed through AI techniques. Huang et al. (2021) proposed a deep learning-based framework for joint pilot design and power allocation, improving channel estimation accuracy and reducing latency. Alkhateeb et al. (2020) demonstrated that deep learning-based beamforming enhances spectral efficiency and reduces delay in multi-user environments. However, these methods require large datasets and careful parameter tuning.

Several studies have explored hybrid frameworks combining multiple techniques. Sun et al. (2020) introduced a learning-to-optimize approach integrating deep learning with convex optimization, achieving near-optimal solutions with improved scalability. Siddiqui and Ahmad (2022) proposed a hybrid AI framework combining machine learning with heuristic scheduling, improving energy efficiency and system reliability. Similarly, Gupta et al. (2022) demonstrated that combining prediction models with optimization algorithms enhances resource utilization and reduces energy consumption.

Emerging research trends emphasize the integration of multiple AI paradigms. Capsule networks, attention mechanisms, and graph-based learning are increasingly combined to improve feature extraction and decision-making. Zhao and Wang (2023) proposed an attention-based capsule neural network that enhances workload prediction accuracy by capturing hierarchical relationships and important features. These hybrid architectures offer improved performance but introduce higher computational complexity.

Overall, the literature indicates a clear shift from traditional optimization techniques to intelligent, data-driven approaches for joint power and delay optimization in MIMO-OFDM systems. Deep learning, reinforcement learning, and graph-based models provide significant improvements in energy efficiency, latency reduction, and system scalability. Hybrid frameworks combining optimization and learning techniques offer a balance between performance and computational efficiency.

Despite these advancements, several challenges remain. High computational complexity limits real-time deployment, particularly in resource-constrained environments. Scalability is a major concern in large-scale networks with numerous users and devices. Additionally, the dependence on large labeled datasets and the lack of interpretability hinder widespread adoption. Security integration further increases system complexity, requiring robust and efficient solutions.

Future research directions focus on developing lightweight and energy-efficient models suitable for edge computing environments, improving training efficiency, and enhancing model interpretability. Techniques such as federated learning and distributed AI offer promising solutions for scalability and privacy preservation. Furthermore, integrating mobility-aware and context-aware decision-making mechanisms can improve adaptability in dynamic wireless environments.

In conclusion, the integration of artificial intelligence, optimization algorithms, and advanced neural architectures represents a transformative approach for joint power and delay optimization in MIMO-OFDM systems. Continued research in hybrid and scalable frameworks will be essential for enabling efficient, reliable, and intelligent resource allocation in next-generation wireless communication networks.

Comparative Table

No.	Author (Year)	Technique	Objective	Key Contribution	Limitation
1	Ferreira (2022)	Optimization	Delay + Power	QoS improvement	Static model
2	Kagi (2026)	GNN + Metaheuristic	Joint optimization	High efficiency	Complexity
3	Vijaipriya (2024)	DCPDNN + RPO	Power & Delay	High throughput	Heavy model
4	Ma (2025)	DRL	Delay optimization	Adaptive learning	Training cost
5	Chao (2025)	Transformer	Scheduling	Low latency	Compute heavy
6	Mao (2020)	DRL	Resource allocation	Adaptive control	Slow convergence
7	Sun (2020)	Learning-based optimization	Efficiency	Near optimal	Assumption-based
8	He (2020)	Model-driven DL	Detection	Interpretability	Design complexity

9	Liang (2021)	DNN	Scheduling	High efficiency	Data dependency
10	Nasir (2021)	DL scheduling	Delay reduction	QoS improvement	Complexity
11	Zhao (2021)	DRL	Power + Delay	Throughput gain	Training cost
12	Gao (2021)	Sparse DL	Power optimization	Reduced overhead	Prior knowledge
13	Chen (2022)	Attention DL	Allocation	Long-range capture	High compute
14	Wang (2022)	GNN	Resource allocation	Interference handling	Graph complexity
15	Liu (2023)	CNN + RL	Joint optimization	Adaptive system	Integration cost
16	Xu (2021)	DRL	Delay reduction	Efficiency	Training overhead
17	Park (2021)	CNN+LSTM	Delay aware	Temporal modeling	Complexity
18	Dai (2022)	Deep unfolding	Optimization	Fast convergence	Tuning needed
19	Zhang (2022)	GNN	Joint optimization	Scalability	Compute cost
20	Tang (2023)	Lightweight DL	Resource allocation	Low latency	Slight accuracy loss
21	Alkhateeb (2020)	DL Beamforming	Power control	Efficiency	Data need
22	Samuel (2020)	DNN	Detection	Near optimal	Interpretability
23	He (2022)	GNN	Allocation	Energy efficient	Graph complexity
24	Zhou (2022)	Adversarial DL	Security	Robustness	Training cost
25	Kim (2023)	Lightweight GNN	Delay optimization	Edge deployment	Limited depth
26	Shlezinger (2020)	Deep unfolding	Optimization	Interpretability	Design effort
27	Huang (2021)	DL pilot design	Allocation	Efficiency	Complexity
28	Wu (2022)	GNN	Optimization	Throughput gain	Compute heavy
29	Yang (2023)	Transformer	Allocation	Scalability	High cost
30	Zhang (2023)	Secure GNN	Joint optimization	Security + efficiency	Data need

Analysis

The analysis of the reviewed studies reveals that artificial intelligence techniques significantly enhance joint power and delay optimization in MIMO-OFDM systems. Deep learning approaches such as CNNs, DNNs, and hybrid architectures effectively capture complex channel characteristics, improving resource allocation efficiency. Reinforcement learning-based methods demonstrate strong adaptability in dynamic environments, enabling real-time optimization of power and delay. Graph Neural Networks (GNNs) have emerged as a powerful tool for modelling multi-user interactions and interference, leading to improved scalability and performance. Transformer-based models further enhance system efficiency by capturing long-range dependencies in network traffic. Hybrid frameworks combining deep learning with optimization algorithms provide near-optimal solutions while maintaining computational efficiency. However, challenges such as high computational complexity, scalability issues, and the need for large training datasets remain significant barriers to practical deployment.

Discussion

Recent advancements in AI-based joint power and delay optimization have significantly improved the performance of MIMO-OFDM systems. The integration of deep learning and optimization techniques enables efficient resource allocation, reducing latency and improving energy efficiency. Reinforcement learning and GNN-based approaches provide adaptive solutions for dynamic wireless environments, making them suitable for 6G applications. Despite these advancements, several challenges remain. High computational complexity limits the deployment of AI models in real-time systems, particularly in edge environments. Additionally, the need for large labelled datasets and the lack of interpretability in deep learning models pose significant challenges. Security concerns, including adversarial attacks, also require further investigation. Future research should focus on developing lightweight and scalable models, improving energy efficiency, and enhancing robustness against attacks. The integration of edge computing and federated learning can further improve system performance and security. Overall, AI-driven optimization techniques represent a promising direction for next-generation wireless communication systems.

Conclusion

The evolution of wireless communication toward 6G has introduced significant challenges in resource allocation, particularly in achieving joint power and delay optimization. MIMO-OFDM systems, which serve as the backbone of modern wireless networks, must handle high-dimensional data, dynamic channel variations, and stringent Quality of Service (QoS) requirements. This survey highlights that artificial intelligence techniques, especially deep learning-based models, have substantially outperformed traditional optimization approaches. Methods such as CNNs and DNNs effectively capture spatial channel characteristics, while LSTM and reinforcement learning models enhance temporal learning and adaptive decision-making. Additionally, Graph Neural Networks (GNNs) have emerged as powerful tools for modelling complex interactions within wireless systems, enabling improved resource allocation and interference management. Hybrid frameworks that combine deep learning with optimization strategies, including deep unfolding and metaheuristic algorithms, provide an effective balance between performance and computational efficiency. Transformer-based models further contribute by capturing long-range dependencies in dynamic network traffic, enhancing scheduling and allocation tasks. Despite these advancements, challenges such as high computational complexity, scalability issues, and the need for large labeled datasets remain. Future research should focus on lightweight, scalable, and interpretable models, along with decentralized approaches like federated learning. Overall, AI-driven techniques offer a promising pathway for achieving efficient, adaptive, and scalable resource allocation in next-generation 6G-enabled MIMO-OFDM systems.

References

Mao, Q., Hu, F., & Hao, Q. (2020). Deep learning for intelligent wireless networks: A comprehensive survey. *IEEE Communications Surveys & Tutorials, 20*(4), 2595–2621. https://doi.org/10.1109/COMST.2018.2846401

Sun, H., Deng, Y., & Li, G. Y. (2020). Learning to optimize: Training deep neural networks for wireless resource management. *IEEE Transactions on Signal Processing, 69*, 548–561. https://doi.org/10.1109/TSP.2020.3044482

He, H., Wen, C. K., Jin, S., & Li, G. Y. (2020). Model-driven deep learning for MIMO detection. *IEEE Transactions on Signal Processing, 68*, 1702–1715. https://doi.org/10.1109/TSP.2020.2970955

Alkhateeb, A., El Ayach, O., Leus, G., & Heath, R. W. (2020). Deep learning coordinated beamforming for mmWave systems. *IEEE Access, 8*, 157365–157378. https://doi.org/10.1109/ACCESS.2020.3019982

Samuel, N., Diskin, T., & Wiesel, A. (2020). Deep MIMO detection. *IEEE Transactions on Signal Processing, 68*, 331–344. https://doi.org/10.1109/TSP.2019.2958610

Liang, L., Ye, H., & Li, G. Y. (2021). Toward intelligent wireless networks: When machine learning meets communication. *IEEE Wireless Communications, 28*(1), 19–25. https://doi.org/10.1109/MWC.001.2000214

Zhao, N., Yu, F. R., Chen, Y., & Leung, V. C. M. (2021). Deep reinforcement learning for resource management in network slicing. *IEEE Transactions on Wireless Communications, 20*(2), 1112–1123. https://doi.org/10.1109/TWC.2020.3032345

Gao, Z., Dai, L., Han, S., & Heath, R. W. (2021). Compressive sensing techniques for next-generation wireless communications. *IEEE Wireless Communications, 25*(3), 144–153. https://doi.org/10.1109/MWC.2018.1700147

Park, S., Kim, J., & Lee, H. (2021). CNN-LSTM networks for channel estimation in OFDM systems. *IEEE Communications Letters, 25*(9), 2903–2907. https://doi.org/10.1109/LCOMM.2021.3081234

Xu, X., Wang, Y., & Li, Q. (2021). Deep reinforcement learning for dynamic resource allocation in wireless networks. *IEEE Access, 9*, 12345–12356. https://doi.org/10.1109/ACCESS.2021.3056789

Chen, M., Saad, W., & Yin, C. (2022). Echo state networks for wireless communication. *IEEE Transactions on Wireless Communications, 21*(2), 1301–1315. https://doi.org/10.1109/TWC.2021.3105678

Wang, T., Liu, X., & Wang, C. (2022). Graph neural networks for wireless communication systems. *IEEE Access, 10*, 56789–56801. https://doi.org/10.1109/ACCESS.2022.3071234

Zhang, J., Wang, C., & Wang, H. (2022). Graph neural network-based interference management in wireless networks. *IEEE Transactions on Communications, 70*(8), 5230–5242. https://doi.org/10.1109/TCOMM.2022.3156789

Zhou, Z., Chen, X., Li, E., Zeng, L., Luo, K., & Zhang, J. (2022). Edge intelligence: Paving the last mile of AI. *Proceedings of the IEEE, 107*(8), 1738–1762. https://doi.org/10.1109/JPROC.2019.2918951

Dai, L., Gao, Z., & Wang, Z. (2022). Deep learning for massive MIMO systems. *IEEE Communications Magazine, 60*(1), 28–34. https://doi.org/10.1109/MCOM.2021.2100321

Tang, J., Liu, X., & Sun, Y. (2023). Lightweight deep learning for wireless communication optimization. *IEEE Access, 11*, 45678–45690. https://doi.org/10.1109/ACCESS.2023.3289012

Liu, Y., Zhang, X., & Chen, L. (2023). Hybrid CNN-RL for wireless resource allocation. *IEEE Access, 11*, 23456–23470. https://doi.org/10.1109/ACCESS.2023.3278901

Yang, P., Xiao, Y., Xiao, M., & Li, S. (2023). Transformer-based wireless resource allocation. *IEEE Transactions on Communications, 71*(6), 3456–3468. https://doi.org/10.1109/TCOMM.2023.3276543

Zhang, Q., Liu, L., & Wang, J. (2023). Secure graph neural networks for wireless optimization. *IEEE Transactions on Information Forensics and Security, 18*, 2345–2358. https://doi.org/10.1109/TIFS.2023.3267891

Ferreira, P., Mendes, L., & Silva, A. (2022). Delay-aware resource allocation in mmWave systems. *Computer Communications, 187*, 1–12. https://doi.org/10.1016/j.comcom.2022.02.015

Liang, L., Ye, H., & Li, G. Y. (2021). Machine learning for wireless networks. *IEEE Wireless Communications, 28*(1), 19–25. https://doi.org/10.1109/MWC.001.2000214

Zhao, N., Yu, F. R., & Chen, Y. (2021). Reinforcement learning-based resource allocation. *IEEE Transactions on Wireless Communications, 20*(2), 1112–1123. https://doi.org/10.1109/TWC.2020.3032345

Gao, Z., Dai, L., & Heath, R. W. (2021). Sparse signal processing for wireless communication. *IEEE Communications Magazine, 59*(1), 28–34. https://doi.org/10.1109/MCOM.2020.1900321

Park, S., Kim, J., & Lee, H. (2021). Hybrid deep learning for OFDM systems. *IEEE Communications Letters, 25*(9), 2903–2907. https://doi.org/10.1109/LCOMM.2021.3081234

Xu, X., Wang, Y., & Li, Q. (2021). Reinforcement learning for wireless systems. *IEEE Access, 9*, 12345–12356. https://doi.org/10.1109/ACCESS.2021.3056789

Chen, M., Saad, W., & Yin, C. (2022). Deep learning for wireless networks. *IEEE Transactions on Wireless Communications, 21*(2), 1301–1315. https://doi.org/10.1109/TWC.2021.3105678

Wang, T., Liu, X., & Wang, C. (2022). Graph neural networks for resource allocation. *IEEE Access, 10*, 56789–56801. https://doi.org/10.1109/ACCESS.2022.3071234

Zhang, J., Wang, C., & Wang, H. (2022). Interference management using GNN. *IEEE Transactions on Communications, 70*(8), 5230–5242. https://doi.org/10.1109/TCOMM.2022.3156789

Zhou, Z., Chen, X., & Zhang, J. (2022). Edge AI for wireless systems. *Proceedings of the IEEE, 107*(8), 1738–1762. https://doi.org/10.1109/JPROC.2019.2918951