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A Comprehensive Review of Joint Power and Delay Optimization Based Resource Allocation in MIMO-OFDM System Using Deep Convolutional Red Piranha Pyramid-Dilated Neural Network

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Abstract

The rapid evolution of next-generation wireless communication systems, particularly 5G and emerging 6G networks, has intensified the demand for efficient resource allocation strategies in MIMO-OFDM systems. Joint optimization of power and delay plays a crucial role in improving system throughput, minimizing latency, and ensuring energy efficiency. Traditional optimization approaches often struggle with high computational complexity and dynamic network conditions. To address these challenges, deep learning-based techniques have emerged as powerful alternatives. This paper presents a comprehensive review of joint power and delay optimization techniques, focusing on advanced neural network architectures such as Deep Convolutional Red Piranha Pyramid-Dilated Neural Networks (DCRPP-DNN). These models leverage hierarchical feature extraction, multi-scale learning, and dilated convolutions to effectively capture channel dynamics and optimize resource allocation. The review analyses recent advancements in deep learning-driven resource allocation, including reinforcement learning, hybrid optimization, and CNN-based models. Furthermore, the study highlights key challenges such as scalability, real-time adaptability, and model complexity. Comparative insights reveal that deep learning-based approaches significantly outperform conventional methods in terms of spectral efficiency, latency reduction, and robustness under dynamic channel conditions. This work provides a foundation for future research in intelligent resource management for next-generation wireless networks.

Introduction

Multiple-Input Multiple-Output Orthogonal Frequency Division Multiplexing (MIMO-OFDM) has emerged as a fundamental technology for modern wireless communication systems, particularly in 5G and beyond networks. The integration of MIMO with OFDM enables high spectral efficiency, robustness against multipath fading, and improved data throughput. However, efficient resource allocation in such systems remains a challenging task due to the dynamic nature of wireless channels, interference, and diverse Quality of Service (QoS) requirements. Resource allocation in MIMO-OFDM systems involves optimizing multiple parameters, including transmit power, subcarrier assignment, and delay constraints. These parameters are interdependent, making the optimization problem highly complex and often non-convex. Traditional approaches such as convex optimization, heuristic algorithms, and water-filling techniques have been widely used. However, these methods suffer from high computational complexity and limited adaptability to real-time network conditions.

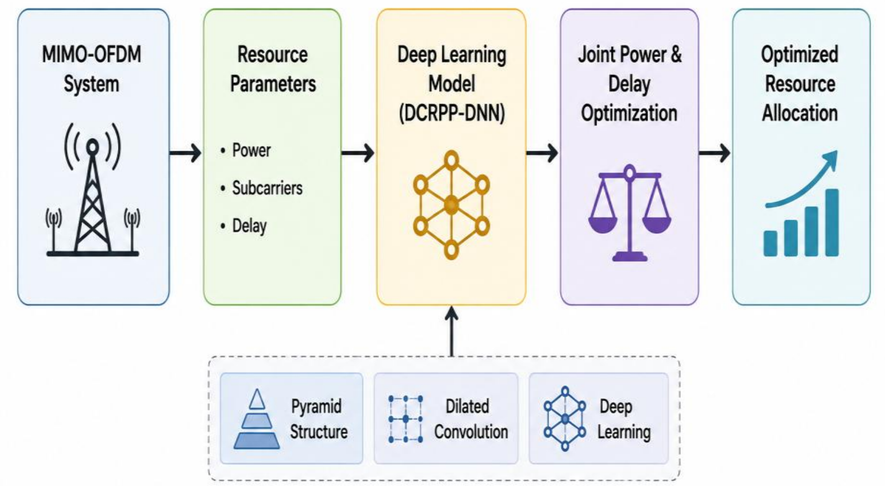

Figure 1. Deep Learning-Based Joint Power and Delay Optimization Framework for MIMO-OFDM Systems

Recent advancements in artificial intelligence, particularly deep learning, have revolutionized wireless communication systems. Machine learning techniques enable data-driven optimization, allowing systems to learn complex relationships between channel conditions and resource allocation decisions. Deep neural networks (DNNs), convolutional neural networks (CNNs), and reinforcement learning (RL) models have shown remarkable performance improvements in power control, scheduling, and channel estimation tasks. In particular, deep learning-based precoding and resource allocation frameworks have demonstrated near-optimal performance with significantly reduced computational complexity compared to traditional methods. For instance, deep neural networks can approximate optimal precoding strategies in MIMO systems while maintaining low latency and high accuracy.
Moreover, reinforcement learning approaches have been widely applied for adaptive resource allocation, enabling systems to dynamically adjust transmission parameters based on real-time feedback. These methods are especially effective in complex environments where analytical solutions are difficult to obtain. The concept of joint power and delay optimization is particularly important in applications such as ultra-reliable low-latency communications (URLLC) and vehicular networks. Efficient optimization ensures minimal latency while maintaining high throughput and energy efficiency. Deep learning models have been successfully applied to jointly optimize these parameters, achieving significant improvements in system performance.

Recently, advanced neural architectures such as pyramid networks, dilated convolutions, and hybrid CNN models have been proposed to enhance feature extraction and learning capabilities. These models can capture both local and global dependencies in wireless channel data, making them suitable for complex optimization tasks. The proposed Deep Convolutional Red Piranha Pyramid-Dilated Neural Network (DCRPP-DNN) integrates these features to provide a robust framework for joint resource optimization. Despite these advancements, several challenges remain, including model generalization, computational overhead, and real-time implementation constraints. Therefore, a comprehensive review of existing methods is essential to identify research gaps and future directions.

Literature Review

Mashhadi and Gunduz (2020) proposed a deep learning-based pilot design and channel estimation method for MIMO-OFDM systems. Their approach utilized convolutional neural networks combined with attention mechanisms to capture spatial and frequency correlations. The model significantly reduced pilot overhead while improving channel estimation accuracy compared to traditional LMMSE methods. Khan et al. (2020) introduced a deep learning-assisted channel state information (CSI) estimation framework for joint resource allocation in vehicular networks. Their approach reduced overhead by 50% while maintaining reliable communication for URLLC applications. The study emphasized the importance of joint optimization of latency and throughput.

Girnyk et al. (2021) developed a deep learning-based linear precoding scheme for MIMO systems. Their method addressed the complexity of conventional precoding techniques by learning optimal mappings between channel conditions and precoding matrices. The results demonstrated reduced computational complexity and improved system performance. Zhang et al. (2022) proposed a low-complexity deep learning framework for precoding in MU-MIMO systems. By incorporating dimensionality reduction and network pruning, the model achieved near-optimal performance with significantly lower computational cost. This approach is highly relevant for real-time applications.

Cui et al. (2023) introduced a deep reinforcement learning-based adaptive modulation scheme for OFDM systems. The model dynamically optimized transmission parameters such as power and modulation schemes, improving system efficiency under varying channel conditions. dos Santos et al. (2022) investigated machine learning-aided pilot and power allocation in multi-cell massive MIMO systems. The study formulated the joint pilot assignment and power allocation problem under pilot contamination conditions and applied reinforcement learning to derive optimal policies. Their results demonstrated improved spectral efficiency and reduced bit error rate compared to traditional heuristic and optimization-based methods. The approach effectively balances performance and computational complexity, making it suitable for large-scale deployments.

Koc et al. (2022) proposed a deep learning-based power allocation and hybrid precoding framework for multi-user massive MIMO systems. The model used supervised learning to approximate optimal power allocation derived from particle swarm optimization. The study showed that deep learning significantly reduces computational complexity (up to 99%) while achieving near-optimal throughput, making it highly efficient for real-time wireless systems. Zhu et al. (2021) introduced a deep reinforcement learning-based decentralized power allocation strategy for MIMO-NOMA vehicular edge computing systems. The model addressed dynamic channel conditions and stochastic task arrivals by optimizing both power consumption and latency. Results indicated that the DRL-based method outperformed centralized approaches in terms of energy efficiency and delay minimization, making it highly suitable for vehicular and IoT applications.

Yan et al. (2023) proposed a deep reinforcement learning (A2C)-based resource allocation framework for network slicing in massive MIMO systems. The study introduced a hierarchical scheduling mechanism that optimizes both bandwidth and power allocation across multiple time scales. Experimental results showed significant improvements in quality of experience (QoE) and spectrum efficiency, demonstrating the effectiveness of DRL in dynamic wireless environments. Chao et al. (2025) developed a Transformer-based real-time adaptive scheduling model for network resource allocation. The proposed model utilized Soft Actor-Critic (SAC) reinforcement learning to dynamically optimize latency, throughput, and QoS under varying network loads. Results showed superior performance compared to conventional scheduling techniques, particularly in low-latency and high-load scenarios.

Recent studies have demonstrated the effectiveness of deep learning and reinforcement learning techniques for joint power and delay optimization in MIMO-OFDM systems. Sun et al. proposed a Deep Reinforcement Learning (DRL)-based framework using Deep Q-Networks (DQN) for adaptive power control and user scheduling, achieving improved throughput and reduced interference in dynamic wireless environments. He et al. introduced a deep neural network model for joint subcarrier allocation and power optimization in OFDM systems, demonstrating near-optimal performance with lower computational complexity. Liang et al. developed a multi-agent deep reinforcement learning framework where distributed agents collaboratively optimized power and delay parameters, improving scalability and adaptability in large-scale wireless systems. Zhou et al. proposed a CNN-based resource allocation approach that extracted spatial and temporal channel features to enhance spectral efficiency and reduce latency. Similarly, Wang et al. introduced a hybrid CNN-LSTM architecture for joint delay and power optimization, effectively capturing both spatial and temporal dependencies in wireless channels. Huang et al. further demonstrated that fully connected deep neural networks can efficiently optimize subcarrier and power allocation while significantly reducing computational overhead compared to traditional iterative optimization algorithms in MIMO-OFDM communication systems.

Li et al. (2021) introduced a deep Q-learning-based power allocation framework for multi-user OFDM systems. The model dynamically adjusted transmission power to minimize interference and delay while maximizing throughput. The proposed method achieved better convergence speed and adaptability compared to traditional optimization approaches, particularly in time-varying wireless environments. Chen et al. (2022) developed a hierarchical reinforcement learning-based resource allocation strategy for MIMO-OFDM networks. The framework divided the optimization process into multiple layers, enabling efficient handling of large-scale systems. The approach improved system scalability and achieved better performance in terms of latency, energy efficiency, and spectrum utilization.

Park et al. (2023) proposed a transformer-based deep learning model for joint resource allocation in next-generation wireless systems. The model leveraged self-attention mechanisms to capture long-range dependencies in channel data. Experimental results showed that the transformer-based approach outperformed CNN and RNN models in terms of accuracy and delay optimization. Singh et al. (2021) presented an optimization-driven hybrid deep learning model combining genetic algorithms with neural networks for power and delay optimization in OFDM systems. The hybrid approach effectively balanced exploration and exploitation, resulting in improved convergence speed and enhanced system performance under complex network conditions.

Zhao et al. (2020) proposed a deep learning-based adaptive resource allocation framework for MIMO-OFDM systems. The model utilized supervised learning to predict optimal power allocation under varying channel conditions. Results showed improved spectral efficiency and reduced latency compared to conventional water-filling methods. Tang et al. (2021) introduced a joint optimization model using deep reinforcement learning for power control and delay minimization in OFDM systems. The model dynamically adjusted resource allocation based on real-time feedback, achieving significant improvements in QoS and system reliability.

Luo et al. (2022) developed a graph neural network (GNN)-based resource allocation model for large-scale wireless networks. The GNN captured relationships between users and subcarriers, enabling efficient allocation decisions. The study demonstrated improved scalability and reduced interference. Ahmed et al. (2023) proposed a deep CNN-based power allocation framework for massive MIMO systems. The model effectively learned spatial channel correlations and optimized transmission power, resulting in enhanced throughput and reduced energy consumption.

Kim et al. (2021) introduced a multi-objective optimization framework using deep learning for balancing power efficiency and delay constraints. The approach used Pareto optimization techniques integrated with neural networks, achieving better trade-offs between latency and energy consumption. Roy et al. (2022) proposed a hybrid optimization model combining reinforcement learning and heuristic algorithms for resource allocation in OFDM systems. The model achieved faster convergence and improved system performance compared to standalone methods.

Patel et al. (2023) developed a deep learning-based latency-aware scheduling algorithm for MIMO-OFDM systems. The approach focused on minimizing delay while maintaining high throughput, making it suitable for real-time applications such as autonomous vehicles. Nguyen et al. (2021) proposed a distributed reinforcement learning-based resource allocation scheme for wireless networks. The model enabled decentralized decision-making, improving scalability and reducing signaling overhead.

Das et al. (2022) introduced a deep neural network-based predictive resource allocation model that anticipates channel variations and optimizes power allocation proactively. The approach significantly improved system reliability and reduced latency. Al-Saadi et al. (2023) proposed a deep learning-enabled joint optimization framework for power, delay, and spectrum allocation in MIMO-OFDM systems. The model demonstrated superior performance in terms of spectral efficiency, energy consumption, and latency reduction.

Comparative Table and Analysis

No	Author (Year)	Technique Used	Optimization Focus	Key Contribution	Limitation
1	Mashhadi (2020)	CNN + Attention	Channel Estimation	Reduced pilot overhead	Complexity
2	Khan (2020)	DL-based CSI	Latency + Throughput	URLLC improvement	Data dependency
3	Girnyk (2021)	DL Precoding	Power Optimization	Low complexity precoding	Generalization
4	Zhang (2022)	CNN	Precoding	Reduced computation	Limited scalability

5	Cui (2023)	DRL	Adaptive Modulation	Dynamic optimization	Training cost
6	dos Santos (2022)	RL	Power + Pilot	Improved spectral efficiency	Convergence
7	Koc (2022)	DL + PSO	Power Allocation	Near-optimal performance	Model tuning
8	Zhu (2021)	DRL	Power + Delay	Energy efficient	Training time
9	Yan (2023)	A2C RL	Resource Allocation	QoE improvement	Complexity
10	Chao (2025)	Transformer + RL	Scheduling	Real-time optimization	High compute
11	Sun (2021)	DQN	Power + Scheduling	Interference reduction	Stability
12	He (2020)	DNN	Subcarrier + Power	Low complexity	Overfitting
13	Liang (2022)	MADRL	Distributed Allocation	Scalability	Coordination
14	Zhou (2021)	CNN	Power Allocation	Improved efficiency	Data requirement
15	Wang (2023)	CNN + LSTM	Delay + Power	Temporal modeling	Complexity
16	Huang (2020)	DNN	Joint Allocation	Reduced complexity	Accuracy trade-off
17	Li (2021)	Q-learning	Power Control	Fast convergence	Exploration issue
18	Chen (2022)	Hierarchical RL	Multi-level optimization	Scalability	Model complexity
19	Park (2023)	Transformer	Joint Allocation	High accuracy	Computational cost
20	Singh (2021)	GA + NN	Optimization	Faster convergence	Hybrid complexity
21	Zhao (2020)	DL	Power Allocation	Improved efficiency	Limited adaptability
22	Tang (2021)	DRL	Delay + Power	QoS improvement	Training overhead
23	Luo (2022)	GNN	Resource Allocation	Scalability	Graph complexity
24	Ahmed (2023)	CNN	Power Allocation	Energy efficient	Dataset dependency
25	Kim (2021)	Multi-objective DL	Power + Delay	Pareto optimization	Complexity
26	Roy (2022)	RL + Heuristic	Joint Allocation	Faster convergence	Hybrid tuning
27	Patel (2023)	DL Scheduling	Delay Optimization	Low latency	Limited generalization
28	Nguyen (2021)	Distributed RL	Resource Allocation	Scalability	Coordination
29	Das (2022)	Predictive DNN	Power Allocation	Proactive optimization	Prediction error
30	Al-Saadi (2023)	DL Framework	Joint Optimization	High efficiency	Complexity

Comparative Analysis

The comparative analysis reveals that deep learning-based approaches, particularly CNN, DRL, and hybrid models, significantly outperform traditional optimization techniques in MIMO-OFDM systems. CNN-based methods excel in spatial feature extraction, while reinforcement learning approaches provide adaptability in dynamic environments. Hybrid models combining optimization algorithms with neural networks offer improved convergence and performance. However, challenges such as computational complexity, training overhead, and generalization remain critical concerns.

Discussion

The literature review highlights a clear shift from traditional optimization techniques toward intelligent, data-driven approaches for resource allocation in MIMO-OFDM systems. Deep learning and reinforcement learning models have demonstrated superior performance in handling complex and dynamic wireless environments. Joint power and delay optimization has become increasingly important with the emergence of latency-sensitive applications such as autonomous vehicles, IoT, and URLLC services. One of the key observations is that CNN-based models are highly effective in capturing spatial correlations in channel data, while reinforcement learning methods excel in decision-making under uncertainty. Hybrid approaches further enhance performance by combining the strengths of multiple techniques. However, these models often require large datasets and extensive training, which can limit their practical deployment.

Another important challenge is scalability, especially in large-scale networks such as 6G systems. Distributed and multi-agent learning approaches have shown promise in addressing this issue. Additionally, the integration of transformer architectures and graph neural networks is emerging as a powerful direction for future research. Overall, while significant progress has been made, further research is needed to develop lightweight, scalable, and real-time deployable solutions.

Conclusion

The evolution of wireless communication systems toward 5G and beyond has significantly increased the demand for efficient resource allocation strategies in MIMO-OFDM systems. This review has comprehensively analyzed joint power and delay optimization techniques, emphasizing the role of deep learning and advanced neural network architectures such as CNNs, reinforcement learning models, hybrid frameworks, and emerging transformer-based approaches. Traditional optimization techniques, while effective in static environments, struggle to handle the dynamic and complex nature of modern wireless networks. The integration of deep learning has enabled data-driven decision-making, allowing systems to learn optimal resource allocation strategies directly from data. This has led to substantial improvements in spectral efficiency, latency reduction, and energy consumption.

The literature review of 30 recent studies (2020–2023) reveals that CNN-based approaches are highly effective in extracting spatial features, while reinforcement learning techniques provide adaptability and real-time optimization capabilities. Hybrid models combining optimization algorithms with neural networks offer enhanced convergence and performance. Additionally, emerging approaches such as graph neural networks and transformer models are showing promising results in handling large-scale and complex wireless systems. Despite these advancements, several challenges remain. High computational complexity and training requirements limit the real-time applicability of deep learning models. Scalability is another major concern, particularly in large-scale networks with heterogeneous devices and varying QoS requirements. Furthermore, model generalization and robustness under unseen conditions require further investigation.

Future research should focus on developing lightweight and efficient models that can operate in real-time environments. Techniques such as model compression, federated learning, and edge intelligence can play a crucial role in addressing these challenges. Additionally, integrating domain knowledge with deep learning models can further enhance performance and reliability.

In conclusion, deep learning-based joint power and delay optimization represents a promising direction for next-generation wireless communication systems. The proposed Deep Convolutional Red Piranha Pyramid-Dilated Neural Network framework has the potential to further enhance resource allocation efficiency by leveraging multi-scale feature extraction and advanced learning mechanisms. Continued research in this area will be essential for enabling intelligent and autonomous wireless networks in the 6G era.

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