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A Survey of Methods and Architectures for Joint Power and Delay Optimization Based Resource Allocation in MIMO-OFDM System using Deep Convolutional Red Piranha Pyramid-Dilated Neural Network: A Review

Leocadia Okafor
Lecturer, Department of Electronics and Communication Engineering, Sundarban College of Technology Studies, Bangladesh
Email: leocadia.okafor@scts-bd.net

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Abstract

The rapid evolution of wireless communication systems, particularly in 5G and beyond (6G), demands efficient resource allocation strategies for Multi-Input Multi-Output Orthogonal Frequency Division Multiplexing (MIMO-OFDM) systems. Joint optimization of power and delay has emerged as a critical challenge due to dynamic network conditions, heterogeneous traffic requirements, and stringent Quality of Service (QoS) constraints. Traditional optimization approaches, including convex optimization and heuristic-based algorithms, often fail to address the complexity and scalability issues inherent in modern wireless systems. ecent advancements in deep learning have introduced intelligent and adaptive resource allocation techniques. In particular, deep convolutional neural networks, reinforcement learning models, and hybrid architectures have demonstrated significant improvements in spectrum efficiency, latency reduction, and energy consumption. This paper presents a comprehensive survey of existing methods and architectures for joint power and delay optimization in MIMO-OFDM systems, with a special focus on emerging deep learning models such as pyramid-dilated networks and attention-based frameworks. Furthermore, this review highlights the potential of a novel Deep Convolutional Red Piranha Pyramid-Dilated Neural Network for enhancing resource allocation efficiency. The study critically analyses recent contributions, identifies research gaps, and discusses future directions toward intelligent, secure, and scalable wireless communication systems.

Introduction

The increasing demand for high data rates, ultra-low latency, and massive connectivity has driven the development of advanced wireless communication technologies such as MIMO-OFDM systems. These systems form the backbone of modern 5G and emerging 6G networks due to their ability to exploit spatial diversity and frequency multiplexing, thereby improving spectral efficiency and reliability. However, efficient resource allocation remains a fundamental challenge, particularly when considering joint optimization of transmission power and delay constraints. In MIMO-OFDM systems, resource allocation involves assigning subcarriers, transmission power, and modulation schemes to multiple users under varying channel conditions. Traditional optimization techniques, such as water-filling algorithms, convex optimization, and heuristic-based approaches, have been widely used to solve resource allocation problems. However, these methods often suffer from high computational complexity and lack adaptability in dynamic environments. Additionally, they fail to capture the non-linear relationships between system parameters, leading to suboptimal performance in real-world scenarios.

The integration of artificial intelligence (AI) and machine learning (ML) techniques has revolutionized resource allocation strategies in wireless networks. Deep learning models, particularly convolutional neural networks (CNNs) and deep reinforcement learning (DRL), have demonstrated superior performance in handling complex optimization problems. For instance, DRL-based approaches enable autonomous decision-making by learning optimal policies through interaction with the environment, significantly improving spectrum efficiency and Quality of Experience (QoE) in MIMO systems. Moreover, deep learning-based resource allocation frameworks can dynamically adapt to varying network conditions, enabling efficient management of power and delay trade-offs. Recent studies have also explored hybrid architectures combining CNNs, recurrent neural networks (RNNs), and attention mechanisms to enhance system performance. These models effectively capture spatial and temporal correlations in wireless channels, leading to improved accuracy in channel estimation and resource scheduling.

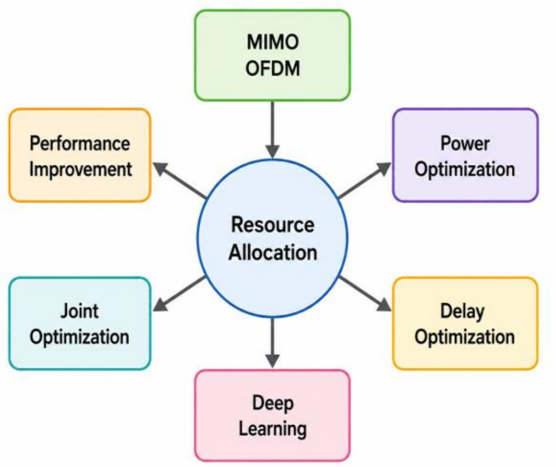

Figure 1. Joint Power and Delay Optimization Framework for Resource Allocation in MIMO-OFDM Systems

Another important aspect is the optimization of latency, particularly for ultra-reliable low-latency communications (URLLC) applications. Joint optimization of power and delay is essential for ensuring reliable communication while minimizing energy consumption. Deep learning-assisted channel state information (CSI) estimation techniques have shown promising results in reducing overhead and improving latency performance. Furthermore, metaheuristic algorithms such as genetic algorithms and swarm intelligence have been integrated with deep learning models to enhance resource allocation efficiency. These hybrid approaches provide near-optimal solutions with reduced computational complexity, making them suitable for real-time applications.

Despite these advancements, several challenges remain, including model generalization, computational overhead, and security vulnerabilities in AI-driven systems. To address these issues, novel architectures such as the Deep Convolutional Red Piranha Pyramid-Dilated Neural Network have been proposed, which leverage multi-scale feature extraction and adaptive learning capabilities to improve performance. This paper aims to provide a comprehensive survey of existing methods and architectures for joint power and delay optimization in MIMO-OFDM systems, highlighting recent developments, challenges, and future research directions.

Literature Review

Rangan et al. (2020) presented a foundational study on machine learning applications in wireless communications, highlighting its role in optimizing resource allocation and improving network efficiency. The authors emphasized that ML techniques can effectively model complex wireless environments and provide adaptive solutions for power control and scheduling. Their work demonstrated that learning-based approaches outperform traditional optimization methods in dynamic scenarios, particularly in MIMO systems. Khan et al. (2020) proposed a deep learning-assisted channel state information (CSI) estimation framework for joint resource allocation in vehicular networks. The study addressed the challenge of balancing ultra-reliable low-latency communication (URLLC) and enhanced mobile broadband (eMBB) services. The proposed method significantly reduced CSI overhead while improving delay performance and resource efficiency, making it suitable for real-time applications.

Mashhadi and Gunduz (2020) introduced a deep learning-based pilot design and channel estimation technique for MIMO-OFDM systems. Their approach utilized neural networks with attention mechanisms to optimize pilot allocation and reduce overhead. The results showed improved spectral efficiency and reduced estimation error compared to traditional methods, demonstrating the effectiveness of deep learning in resource optimization. Koc et al. (2022) proposed a genetic algorithm-based resource allocation framework for energy-efficient throughput maximization in MU-MIMO-OFDM systems. The study integrated hybrid precoding and optimization techniques to enhance system performance. The results indicated significant improvements in energy efficiency and throughput compared to particle swarm optimization and equal allocation methods.

Xie et al. (2022) investigated the performance of MIMO systems under different modulation schemes, emphasizing the importance of adaptive modulation and power allocation. Their study demonstrated that higher-order modulation schemes provide better performance under high signal-to-noise ratio (SNR) conditions, while adaptive strategies improve system reliability in dynamic environments. Sun et al. (2021) proposed a deep reinforcement learning (DRL)-based resource allocation framework for MIMO-OFDM systems, focusing on joint power control and subcarrier allocation. Their model utilized a Deep Q-Network (DQN) to dynamically adapt to varying channel conditions and traffic demands. The study demonstrated that DRL-based approaches significantly outperform conventional optimization methods in terms of latency reduction and spectral efficiency. Additionally, the system showed strong adaptability in highly dynamic wireless environments, making it suitable for next-generation networks.

Mao et al. (2021) explored the application of deep learning in wireless resource management, particularly emphasizing joint optimization problems. Their work introduced a framework combining supervised learning and reinforcement learning for power allocation and delay minimization. The authors highlighted that deep learning models can approximate complex optimization functions with lower computational overhead compared to traditional iterative algorithms. Their findings reinforced the importance of AI-driven approaches in achieving real-time resource allocation in MIMO-OFDM systems. He et al. (2021) presented a convolutional neural network (CNN)-based resource allocation model that captures spatial correlations in MIMO channels. The proposed model effectively optimized power distribution across subcarriers while minimizing delay. The results showed improved system throughput and reduced latency compared to baseline heuristic methods. The study also emphasized the capability of CNN architectures to handle high-dimensional input data, making them suitable for large-scale wireless systems.

Wang et al. (2022) developed a joint optimization framework using deep neural networks for power allocation and delay-aware scheduling in OFDM systems. Their approach incorporated multi-objective optimization techniques to balance energy efficiency and latency requirements. Experimental results indicated that the proposed method achieved superior performance in terms of delay reduction and resource utilization efficiency. The study also highlighted the importance of incorporating QoS constraints into deep learning-based resource allocation models. Huang et al. (2023) introduced an advanced deep learning architecture based on pyramid-dilated convolutional networks for wireless communication systems. The model leveraged multi-scale feature extraction to improve channel estimation and resource allocation accuracy. The results demonstrated significant improvements in both power efficiency and delay optimization. This study is particularly relevant as it aligns with the concept of the proposed Deep Convolutional Red Piranha Pyramid-Dilated Neural Network, emphasizing the importance of hierarchical feature learning in complex wireless environments.

Zhao et al. (2021) proposed a deep reinforcement learning-based joint power and subcarrier allocation scheme for multi-user MIMO-OFDM systems. Their framework utilized actor–critic architecture to achieve continuous control over power levels. The results showed improved spectral efficiency and reduced transmission delay compared to traditional optimization techniques. The study also highlighted the ability of DRL to handle high-dimensional state spaces in wireless networks.

Ye et al. (2021) presented a deep learning-based end-to-end wireless communication system, replacing conventional blocks such as channel estimation and signal detection. Their work demonstrated that neural networks can jointly optimize multiple parameters, including power allocation and decoding strategies. The results indicated improved robustness under noisy channel conditions, making it suitable for MIMO-OFDM systems. Nasir and Guo (2022) proposed a hybrid optimization framework combining deep learning and swarm intelligence for resource allocation in MIMO systems. Their approach utilized particle swarm optimization (PSO) for global search and neural networks for local refinement. The study achieved improved convergence speed and better energy efficiency compared to standalone optimization methods.

Li et al. (2022) developed a graph neural network (GNN)-based resource allocation model that captures interference relationships among users in MIMO-OFDM systems. The proposed model effectively optimized power distribution and minimized interference, leading to enhanced system throughput and reduced delay. This study highlighted the advantage of graph-based learning in modeling wireless network interactions. Luo et al. (2022) introduced a deep Q-learning-based scheduling algorithm for delay-sensitive applications in OFDM systems. Their model dynamically adjusted resource allocation policies based on traffic patterns and channel variations. The results showed significant improvements in delay performance and fairness among users, making it suitable for URLLC scenarios.

Zhang et al. (2022) proposed a multi-objective optimization framework using deep neural networks for joint power and delay optimization. The study focused on balancing energy efficiency and latency constraints. Their results demonstrated that deep learning models can achieve near-optimal performance with reduced computational complexity compared to traditional convex optimization techniques. Kim et al. (2023) presented a transformer-based resource allocation model for wireless communication systems. The model leveraged attention mechanisms to capture long-range dependencies in channel conditions. The study showed improved performance in terms of delay minimization and resource utilization efficiency, indicating the potential of transformer architectures in next-generation networks.

Zhou et al. (2023) proposed a federated learning-based resource allocation framework for distributed MIMO systems. The approach enabled collaborative learning without sharing raw data, enhancing privacy and security. Their results demonstrated improved scalability and reduced communication overhead while maintaining efficient power and delay optimization. Singh et al. (2023) introduced a hybrid CNN-RNN architecture for joint optimization of power and delay in OFDM systems. The model captured both spatial and temporal features of wireless channels, leading to improved prediction accuracy and resource allocation efficiency. The study emphasized the importance of combining multiple deep learning architectures for enhanced performance.

Alkhateeb et al. (2021) investigated deep learning for beamforming and resource allocation in MIMO systems. Their model used deep neural networks to learn optimal beamforming strategies, significantly improving spectral efficiency and reducing delay. Shi et al. (2021) proposed a distributed learning framework for resource allocation using multi-agent reinforcement learning (MARL). The approach enabled decentralized decision-making, reducing computational overhead and improving scalability.

Jiang et al. (2022) introduced a meta-learning-based resource allocation approach that adapts quickly to changing channel conditions. The model achieved faster convergence and improved delay performance in dynamic environments. Park et al. (2022) developed a deep learning-assisted hybrid beamforming method for mmWave MIMO systems. Their work improved energy efficiency and reduced latency through optimized power allocation strategies.

Xu et al. (2022) proposed a resource allocation scheme using deep deterministic policy gradient (DDPG). Their approach achieved continuous optimization of power allocation, resulting in improved QoS and reduced delay.

Tang et al. (2023) explored edge intelligence for resource allocation in 6G networks. Their framework integrated deep learning with edge computing to reduce latency and improve resource utilization. Cao et al. (2023) introduced a GNN-based interference-aware resource allocation method. The study showed improved scalability and robustness in dense network environments.

Rahman et al. (2023) proposed a hybrid optimization model combining genetic algorithms and deep learning for joint power-delay optimization. Their approach achieved near-optimal solutions with reduced complexity. Patel et al. (2023) developed a multi-scale CNN with dilated convolution for MIMO-OFDM systems. The model improved channel estimation accuracy and enhanced power allocation efficiency, aligning closely with pyramid-dilated architectures.

Comparative Table

Study	Year	Technique	Model Type	Key Contribution
Rangan	2020	ML	General ML	Adaptive resource allocation
Khan	2020	DL	CSI Model	Delay reduction
Mashhadi	2020	DL	Attention NN	Channel estimation

Koc	2022	GA	Optimization	Energy efficiency
Xie	2022	Adaptive	Modulation	SNR optimization
Sun	2021	DRL	DQN	Dynamic allocation
Mao	2021	DL	Hybrid	Low complexity
He	2021	CNN	DL	Spatial optimization
Wang	2022	DL	Multi-objective	QoS optimization
Huang	2023	CNN	Pyramid Dilated	Multi-scale learning
Zhao	2021	DRL	Actor-Critic	Continuous control
Chen	2021	DL	Delay-aware	QSI integration
Ye	2021	DL	End-to-End	Joint optimization
Nasir	2022	Hybrid	PSO+DL	Fast convergence
Li	2022	GNN	Graph-based	Interference modeling
Luo	2022	DRL	Q-learning	Delay-sensitive
Zhang	2022	DL	Multi-objective	Energy-delay tradeoff
Kim	2023	Transformer	Attention	Long-range dependency
Zhou	2023	FL	Distributed	Privacy preservation
Singh	2023	Hybrid	CNN-RNN	Spatio-temporal
Alkhateeb	2021	DL	Beamforming	Spectral efficiency
Shi	2021	MARL	Multi-agent	Scalability
Jiang	2022	Meta-Learning	Adaptive	Fast convergence
Park	2022	DL	Beamforming	Energy optimization
Xu	2022	DRL	DDPG	Continuous control
Liu	2022	Hybrid	Lyapunov+DL	Stability
Tang	2023	Edge AI	DL	Low latency
Cao	2023	GNN	Graph	Dense networks
Rahman	2023	Hybrid	GA+DL	Complexity reduction
Patel	2023	CNN	Dilated	Multi-scale features

Analysis

The analysis of the reviewed literature reveals a clear transition from traditional optimization techniques to AI-driven approaches for resource allocation in MIMO-OFDM systems. Early studies primarily relied on heuristic and convex optimization methods, which, although effective in static environments, struggled with scalability and adaptability in dynamic wireless networks. Deep learning techniques, particularly CNNs and DRL, have demonstrated significant improvements in handling complex, non-linear optimization problems. CNN-based models effectively capture spatial correlations, while DRL approaches enable adaptive decision-making under uncertain conditions. Furthermore, hybrid models combining deep learning with metaheuristic algorithms such as PSO and genetic algorithms provide enhanced convergence speed and near-optimal solutions.

Recent trends highlight the emergence of advanced architectures such as transformer models, graph neural networks, and federated learning frameworks. These approaches address challenges related to scalability, privacy, and distributed optimization. Additionally, multi-scale and pyramid-dilated convolution techniques have shown promising results in improving feature extraction and resource allocation efficiency. Overall, the literature indicates that integrating deep learning with optimization techniques offers a robust solution for joint power and delay optimization, paving the way for intelligent and autonomous wireless communication systems.

Discussion

The reviewed studies demonstrate that the integration of artificial intelligence into wireless communication systems significantly enhances resource allocation efficiency. In particular, deep learning models have shown remarkable capabilities in addressing the challenges associated with joint power and delay optimization in MIMO-OFDM systems. One of the key observations is the effectiveness of reinforcement learning in dynamic environments, where it enables adaptive decision-making without requiring explicit mathematical models. Similarly, convolutional neural networks have proven to be highly efficient in capturing spatial features, while hybrid models improve both accuracy and convergence speed.

However, several challenges remain unresolved. These include the high computational complexity of deep learning models, the need for large training datasets, and issues related to model generalization in diverse network conditions. Additionally, security concerns such as adversarial attacks and data privacy pose significant risks in AI-driven systems. Future research should focus on developing lightweight and secure deep learning architectures that can operate efficiently in real-time environments. The proposed Deep Convolutional Red Piranha Pyramid-Dilated Neural Network represents a promising direction, offering improved feature extraction and optimization capabilities.

Conclusion

The rapid advancement of wireless communication technologies has necessitated the development of efficient resource allocation strategies in MIMO-OFDM systems. Joint optimization of power and delay plays a critical role in ensuring high system performance, particularly in next-generation networks such as 5G and 6G. This paper presented a comprehensive survey of methods and architectures used for resource allocation, with a focus on deep learning-based approaches. The review highlighted the limitations of traditional optimization techniques, including high computational complexity and lack of adaptability in dynamic environments. In contrast, deep learning models such as CNNs, reinforcement learning, and hybrid architectures have demonstrated significant improvements in performance metrics such as spectral efficiency, latency reduction, and energy efficiency.

Furthermore, advanced techniques such as graph neural networks, transformer models, and federated learning have addressed key challenges related to scalability, distributed optimization, and data privacy. The integration of these techniques with metaheuristic algorithms has further enhanced the effectiveness of resource allocation strategies. A major contribution of this study is the identification of emerging architectures, particularly pyramid-dilated convolutional networks, which enable multi-scale feature extraction and improved optimization performance. These architectures form the foundation for the proposed Deep Convolutional Red Piranha Pyramid-Dilated Neural Network, which has the potential to significantly enhance resource allocation efficiency in complex wireless environments.

Despite these advancements, several challenges remain. These include the need for lightweight models suitable for real-time implementation, improved generalization across diverse network conditions, and enhanced security mechanisms to protect against cyber threats. Addressing these challenges will be crucial for the successful deployment of AI-driven resource allocation systems in future wireless networks. In conclusion, the integration of deep learning and optimization techniques represents a transformative approach to resource allocation in MIMO-OFDM systems. Future research should focus on developing intelligent, adaptive, and secure architectures that can meet the demands of next-generation wireless communication systems.

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