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Deep Learning and Optimization Approaches in Joint Power and Delay Optimization Based Resource Allocation in MIMO-OFDM System- Deep Convolutional Red Piranha Pyramid-Dilated Neural Network: A Review

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Abstract

The increasing demand for high data rates, low latency, and efficient spectrum utilization in 5G and emerging 6G networks has made resource allocation in MIMO-OFDM systems a critical research area. Joint optimization of power and delay is essential for achieving high spectral efficiency while satisfying Quality of Service (QoS) requirements. Traditional optimization techniques such as convex optimization and heuristic algorithms face limitations due to high computational complexity and inability to adapt to dynamic wireless environments. Recently, deep learning-based approaches have emerged as promising solutions for resource allocation problems. These methods leverage neural networks to learn complex relationships between channel conditions and resource allocation decisions. Advanced architectures such as convolutional neural networks (CNNs), reinforcement learning (RL), and hybrid models have demonstrated superior performance in optimizing power and delay simultaneously. Furthermore, pyramid and dilated convolution structures enable efficient multi-scale feature extraction, improving optimization accuracy. This paper provides a comprehensive review of deep learning and optimization approaches for joint power and delay optimization in MIMO-OFDM systems. It analyses recent advancements, identifies key challenges, and highlights future research directions. The study shows that deep learning-based methods significantly outperform conventional techniques in terms of efficiency, adaptability, and scalability, making them suitable for next-generation wireless communication systems.

Introduction

MIMO-OFDM technology has become a cornerstone of modern wireless communication systems due to its ability to enhance spectral efficiency and reliability. It combines the advantages of multiple antennas and multicarrier transmission, enabling efficient handling of multipath fading and interference. However, resource allocation in MIMO-OFDM systems remains a complex challenge due to the interdependence of parameters such as power, delay, subcarrier allocation, and channel conditions. Traditional optimization methods such as water-filling algorithms, convex optimization, and heuristic techniques have been widely used for resource allocation. While these approaches provide near-optimal solutions under certain conditions, they often suffer from high computational complexity and limited adaptability to dynamic network environments. The joint optimization of power and delay further increases the complexity, making real-time implementation difficult.

Recent advancements in artificial intelligence, particularly deep learning, have transformed wireless communication systems. Deep learning models can learn complex nonlinear relationships from large datasets, enabling efficient and adaptive resource allocation. Machine learning-based approaches have been widely applied in channel estimation, power control, and scheduling, showing significant improvements over conventional methods. Deep neural networks (DNNs) and convolutional neural networks (CNNs) are particularly effective in capturing spatial and temporal correlations in wireless channels. CNNs can extract hierarchical features from channel data, enabling accurate prediction of optimal resource allocation strategies. Furthermore, reinforcement learning (RL) approaches allow systems to dynamically adapt to changing network conditions by learning optimal policies through interaction with the environment.

In MIMO-OFDM systems, deep learning has been successfully applied to precoding and power allocation problems. For example, deep learning-based precoding methods can approximate optimal solutions with significantly lower computational complexity compared to traditional algorithms. Moreover, joint power and delay optimization is crucial for applications such as ultra-reliable low-latency communications (URLLC), autonomous driving, and IoT networks. Deep learning models can optimize multiple objectives simultaneously, making them suitable for such applications. Reinforcement learning-based approaches, in particular, have shown strong performance in dynamic environments where traditional methods fail.

Advanced neural architectures, including pyramid networks and dilated convolutional networks, further enhance feature extraction capabilities by capturing both local and global dependencies. These architectures form the foundation of the proposed Deep Convolutional Red Piranha Pyramid-Dilated Neural Network, which aims to improve resource allocation efficiency. Despite these advancements, challenges such as model complexity, training data requirements, and real-time deployment remain. Therefore, a comprehensive review of existing approaches is necessary to identify research gaps and guide future developments.

Literature Review

Mashhadi and Gunduz (2020) proposed a deep learning-based pilot design and channel estimation framework for MIMO-OFDM systems. Their work addressed the challenge of pilot contamination and inefficient channel estimation, which directly impacts resource allocation and system performance. The authors employed convolutional neural networks (CNNs) combined with attention mechanisms to capture both spatial and frequency correlations of wireless channels. Unlike conventional least mean square error (LMMSE) estimators, their model learns channel characteristics directly from data, reducing the dependency on predefined statistical assumptions. The study demonstrated that the proposed approach significantly reduces pilot overhead while improving estimation accuracy. This improvement directly contributes to more efficient power allocation and delay minimization, as accurate channel state information (CSI) is crucial for optimal resource allocation. However, the model requires large training datasets and may face generalization issues in unseen environments.

Khan et al. (2020) introduced a deep learning-assisted CSI estimation and joint resource allocation framework for ultra-reliable low-latency communication (URLLC) and enhanced mobile broadband (eMBB) services. Their study focused on jointly optimizing latency and throughput, which are critical parameters in next-generation wireless systems. The authors utilized deep neural networks to predict CSI and assist in resource allocation decisions under strict delay constraints. The model effectively balances the trade-off between reliability and latency by dynamically allocating power and bandwidth resources. Their results showed that deep learning-based approaches can reduce latency while maintaining high throughput, outperforming traditional optimization techniques. This work highlights the importance of integrating deep learning into joint power and delay optimization problems. However, the approach depends heavily on training data quality and may require retraining in rapidly changing environments.

Girnyk et al. (2021) proposed a deep learning-based linear precoding strategy for multi-user MIMO systems. The study aimed to reduce the computational complexity associated with traditional precoding methods such as zero-forcing and minimum mean square error techniques. The authors designed a neural network that learns the mapping between channel conditions and optimal precoding matrices. By doing so, the model can quickly generate near-optimal solutions without solving complex optimization problems in real time. Their results demonstrated that the deep learning-based approach achieves comparable performance to conventional methods while significantly reducing computational overhead. This is particularly beneficial for real-time applications where low latency is required. The study also contributes to joint power optimization by enabling efficient signal transmission. However, scalability to large networks remains a challenge.

Zhang et al. (2022) developed a low-complexity deep learning-based precoding framework for multi-user MIMO-OFDM systems. Their approach incorporated dimensionality reduction and neural network pruning techniques to minimize computational requirements. The model used a deep neural network to approximate optimal precoding solutions, significantly reducing processing time compared to traditional optimization methods. The authors demonstrated that their approach achieves near-optimal spectral efficiency while maintaining low latency, making it suitable for real-time communication systems. Additionally, the model improves power allocation efficiency by optimizing transmission strategies across multiple users and subcarriers. This study highlights the effectiveness of deep learning in addressing the complexity of joint optimization problems. However, the model's performance may degrade under highly dynamic channel conditions.

dos Santos et al. (2022) investigated machine learning-based joint pilot and power allocation strategies in multi-cell massive MIMO systems. The study addressed the issue of pilot contamination, which negatively affects channel estimation and resource allocation. The authors employed reinforcement learning techniques to optimize pilot assignment and power allocation simultaneously. Their approach allows the system to learn optimal strategies through interaction with the environment, making it adaptable to changing network conditions. The results showed significant improvements in spectral efficiency and reduced interference compared to traditional heuristic methods. This work is particularly relevant for joint power and delay optimization, as efficient pilot allocation leads to better channel estimation and reduced transmission delays. However, reinforcement learning models may suffer from slow convergence and high training complexity.

Koc et al. (2022) proposed a deep learning-assisted power allocation and hybrid precoding framework for multi-user massive MIMO-OFDM systems. The authors aimed to overcome the high computational complexity associated with conventional optimization techniques such as particle swarm optimization (PSO) and water-filling algorithms. Their model utilized supervised learning to approximate optimal power allocation strategies derived from PSO-based solutions. By training a deep neural network on optimal datasets, the model was able to produce near-optimal results with significantly reduced computational time. The study demonstrated that the proposed approach achieves up to 99% reduction in complexity while maintaining comparable spectral efficiency. This is particularly beneficial for real-time applications where latency is critical. However, the model requires extensive training data and may not generalize well to unseen channel conditions without retraining.

Zhu et al. (2021) introduced a deep reinforcement learning (DRL)-based decentralized power allocation framework for MIMO-NOMA systems in vehicular edge computing environments. The proposed model addresses both energy efficiency and delay constraints by optimizing transmission power dynamically under time-varying channel conditions. The authors employed a multi-agent DRL approach where each user acts as an independent agent, learning optimal policies through interaction with the environment. This decentralized strategy significantly reduces signaling overhead and enhances scalability. Simulation results showed that the DRL-based model outperforms centralized optimization techniques in terms of latency reduction and energy efficiency. The study highlights the potential of reinforcement learning in joint power and delay optimization. However, issues such as training instability and convergence time remain key challenges.

Yan et al. (2023) proposed a deep reinforcement learning-based resource allocation framework using Advantage Actor-Critic (A2C) for network slicing in massive MIMO systems. Their work focused on optimizing multiple objectives, including power allocation, bandwidth distribution, and delay minimization across different service slices. The hierarchical framework operates at multiple time scales, enabling efficient resource management in dynamic network environments. The results demonstrated improved quality of experience (QoE), higher spectral efficiency, and reduced latency compared to traditional allocation methods. This study is particularly relevant for next-generation 6G systems where heterogeneous services require differentiated QoS. However, the model's complexity and training overhead can limit its real-time applicability.

Sun et al. (2021) developed a deep Q-network (DQN)-based joint power control and user scheduling scheme for multi-user MIMO systems. The proposed model integrates power allocation and scheduling decisions into a unified learning framework. By leveraging reinforcement learning, the system learns to minimize interference while maximizing throughput and reducing delay. The DQN agent observes channel states and user demands to make optimal decisions in real time. The results showed that the proposed approach significantly outperforms conventional heuristic and optimization-based methods, particularly in highly dynamic environments. This study demonstrates the effectiveness of reinforcement learning in solving complex joint optimization problems. However, the approach may suffer from stability issues and requires careful tuning of hyperparameters.

He et al. (2020) proposed a deep neural network-based joint subcarrier and power allocation framework for OFDM systems. The model learns optimal allocation policies by training on datasets generated from traditional optimization algorithms. This supervised learning approach enables the network to approximate complex optimization functions with high accuracy. The study showed that the proposed method achieves near-optimal performance while significantly reducing computational complexity and execution time. The framework is particularly suitable for real-time applications where fast decision-making is required. Additionally, the joint optimization of subcarriers and power contributes to improved delay performance and system efficiency. However, the model's dependence on training data limits its adaptability to rapidly changing network conditions.

Liang et al. (2022) proposed a multi-agent deep reinforcement learning (MADRL)-based resource allocation framework for large-scale wireless communication systems. The study addressed the scalability issues of centralized optimization approaches by distributing the decision-making process among multiple agents. Each agent independently optimizes power allocation and delay constraints while coordinating with other agents to achieve global optimization. The model uses deep Q-learning combined with policy gradient methods to improve convergence and stability. Simulation results demonstrated that the proposed MADRL framework significantly improves spectral efficiency and reduces latency in dense network scenarios. This approach is highly suitable for future 6G networks with massive connectivity. However, inter-agent coordination complexity and communication overhead remain key challenges.

Zhou et al. (2021) introduced a convolutional neural network (CNN)-based resource allocation model for MIMO-OFDM systems. The proposed model leverages CNN's ability to extract spatial features from channel matrices to optimize power distribution across subcarriers. By treating channel state information (CSI) as a structured input, the model captures correlations between subcarriers and antennas effectively. The results showed improved spectral efficiency and reduced delay compared to traditional heuristic methods. The study highlights the importance of feature extraction in resource allocation problems. However, CNN models require large datasets and may struggle with generalization in highly dynamic environments.

Wang et al. (2023) proposed a hybrid deep learning framework combining CNN and Long Short-Term Memory (LSTM) networks for joint power and delay optimization in OFDM systems. The CNN component extracts spatial features from channel data, while the LSTM captures temporal dependencies in time-varying channels. This hybrid architecture enables the model to adapt to dynamic network conditions effectively. The study demonstrated significant improvements in delay reduction and reliability, particularly in real-time applications such as autonomous vehicles and IoT systems. However, the increased model complexity leads to higher computational requirements and longer training times.

Huang et al. (2020) proposed a deep neural network-based joint subcarrier and power allocation scheme for MIMO-OFDM systems. The model learns optimal allocation policies from data generated by traditional optimization techniques such as convex optimization. By approximating complex optimization functions, the model reduces computational complexity while maintaining high performance. The results showed improved system throughput and reduced delay compared to baseline methods. This approach demonstrates the potential of supervised learning in solving joint optimization problems. However, its performance is highly dependent on the quality and diversity of training data.

Li et al. (2021) developed a deep Q-learning-based power control algorithm for multi-user OFDM systems. The proposed method dynamically adjusts transmission power to minimize interference and delay while maximizing throughput. The reinforcement learning agent learns optimal policies through interaction with the environment, making it adaptable to changing network conditions. The study showed faster convergence and better performance compared to traditional optimization techniques. This work highlights the effectiveness of reinforcement learning in real-time resource allocation. However, issues such as exploration-exploitation trade-off and convergence stability need further improvement.

Chen et al. (2022) proposed a hierarchical reinforcement learning (HRL)-based resource allocation framework for MIMO-OFDM systems. The key contribution of this work lies in decomposing the complex joint optimization problem into multiple hierarchical levels. At the higher level, the model determines global resource allocation strategies such as bandwidth and power distribution, while the lower level focuses on fine-grained optimization of subcarriers and delay constraints. This hierarchical approach significantly reduces computational complexity and improves scalability in large-scale networks. The results demonstrated enhanced spectral efficiency and reduced latency compared to flat reinforcement learning models. However, the multi-level training process introduces additional complexity and requires careful coordination between hierarchical layers.

Park et al. (2023) introduced a transformer-based deep learning model for joint power and delay optimization in next-generation wireless systems. Unlike CNN and RNN models, the transformer architecture utilizes self-attention mechanisms to capture long-range dependencies in channel state information. This allows the model to effectively learn complex relationships between users, subcarriers, and time slots. The study demonstrated that the transformer-based approach outperforms conventional deep learning models in terms of prediction accuracy, spectral efficiency, and delay reduction. This makes it particularly suitable for large-scale and highly dynamic 6G networks. However, the high computational cost and memory requirements of transformer models remain a limitation.

Singh et al. (2021) proposed a hybrid optimization framework combining genetic algorithms (GA) with deep neural networks (DNNs) for joint power and delay optimization in OFDM systems. The genetic algorithm is used to explore the solution space and generate near-optimal solutions, which are then used to train the neural network. This hybrid approach leverages the strengths of both evolutionary algorithms and deep learning, resulting in faster convergence and improved optimization performance. The results showed significant improvements in throughput, delay reduction, and energy efficiency compared to standalone methods. However, the integration of GA and DNN increases computational complexity and requires careful parameter tuning.

Zhao et al. (2020) developed a supervised deep learning-based power allocation framework for MIMO-OFDM systems. The model was trained using datasets generated from traditional optimization algorithms such as water-filling and convex optimization. By learning the mapping between channel conditions and optimal power allocation, the model can provide near-optimal solutions in real time. The study demonstrated improved spectral efficiency and reduced latency compared to conventional methods. This approach highlights the effectiveness of supervised learning in solving complex optimization problems. However, its performance is limited by the quality of training data and may not adapt well to unseen scenarios.

Tang et al. (2021) proposed a deep reinforcement learning-based joint power and delay optimization framework for OFDM systems. The model dynamically adjusts transmission power and scheduling decisions based on real-time channel conditions and user requirements. The reinforcement learning agent learns optimal policies through continuous interaction with the environment, enabling adaptive and efficient resource allocation. The results showed significant improvements in QoS, latency reduction, and system reliability compared to traditional approaches. This study demonstrates the potential of reinforcement learning in addressing dynamic optimization problems. However, challenges such as slow convergence and training instability remain.

Luo et al. (2022) proposed a graph neural network (GNN)-based resource allocation framework for large-scale MIMO-OFDM systems. The model represents users and subcarriers as nodes in a graph and learns the relationships between them using message-passing mechanisms. This enables efficient modelling of interference and channel dependencies. The study demonstrated that GNN-based approaches significantly improve scalability and resource utilization compared to conventional deep learning models. Additionally, the framework effectively optimizes power allocation and delay by capturing complex interactions among network entities. However, graph construction and computational overhead remain challenges for large-scale implementations.

Ahmed et al. (2023) introduced a deep convolutional neural network (CNN)-based power allocation scheme for massive MIMO systems. The model utilizes convolutional layers to extract spatial features from channel state information and optimize power distribution across users and subcarriers. The results showed improved spectral efficiency and reduced energy consumption compared to traditional optimization techniques. The study highlights the effectiveness of CNNs in capturing spatial dependencies for resource allocation. However, the model requires large training datasets and may face challenges in highly dynamic environments.

Kim et al. (2021) proposed a multi-objective deep learning-based optimization framework that simultaneously considers power efficiency, delay minimization, and throughput maximization. The model integrates Pareto optimization techniques with neural networks to achieve an optimal trade-off among conflicting objectives. The study demonstrated that the proposed approach outperforms traditional single-objective optimization methods in terms of overall system performance. This work is particularly relevant for applications requiring balanced QoS metrics. However, the complexity of multi-objective optimization increases computational requirements.

Roy et al. (2022) developed a hybrid reinforcement learning and heuristic-based resource allocation model for OFDM systems. The approach combines the adaptability of reinforcement learning with the efficiency of heuristic algorithms to achieve faster convergence and improved performance. The study showed that the hybrid model significantly reduces latency and enhances throughput compared to standalone methods. This approach is suitable for real-time systems where both speed and accuracy are critical. However, tuning hybrid models can be complex and requires careful parameter selection.

Patel et al. (2023) proposed a deep learning-based latency-aware scheduling algorithm for MIMO-OFDM systems. The model focuses on minimizing delay while maintaining high throughput by prioritizing time-sensitive data packets. The approach leverages neural networks to predict optimal scheduling decisions based on channel conditions and traffic patterns. The results demonstrated significant improvements in delay performance, making the model suitable for URLLC applications. However, the model may require continuous retraining to adapt to changing network conditions.

Nguyen et al. (2021) introduced a distributed reinforcement learning-based resource allocation framework for wireless communication systems. The model allows multiple agents to independently optimize resource allocation decisions while sharing limited information. This decentralized approach improves scalability and reduces communication overhead. The results showed enhanced system performance in terms of latency reduction and energy efficiency. However, coordination among agents remains a challenge in highly dense networks.

Das et al. (2022) proposed a predictive deep neural network-based resource allocation model that anticipates channel variations and optimizes power allocation proactively. By predicting future channel conditions, the model reduces delay and improves reliability in dynamic environments. The study demonstrated that predictive models can outperform reactive approaches in terms of performance and efficiency. However, prediction errors may affect system performance, especially in highly unpredictable environments.

Al-Saadi et al. (2023) developed a deep learning-based joint optimization framework for power, delay, and spectrum allocation in MIMO-OFDM systems. The model integrates multiple optimization objectives into a unified learning framework, achieving significant improvements in spectral efficiency and latency reduction. The study highlights the potential of deep learning in solving complex multi-objective optimization problems. However, the model's complexity and training requirements remain significant challenges.

Xie et al. (2022) proposed a deep reinforcement learning-based adaptive resource allocation model for dynamic wireless environments. The model continuously learns optimal allocation strategies by interacting with the environment, enabling real-time adaptation to changing channel conditions. The results showed improved system performance in terms of delay, throughput, and energy efficiency. However, reinforcement learning models require extensive training and may suffer from slow convergence.

Johnson et al. (2023) introduced a deep learning-based dynamic modulation and resource allocation framework for MIMO-OFDM systems. The model jointly optimizes modulation schemes, power allocation, and delay constraints to achieve optimal system performance. The study demonstrated that integrating multiple optimization parameters into a single deep learning framework significantly enhances system efficiency. However, the complexity of joint optimization increases computational requirements and implementation challenges.

Comparative Table

No	Author (Year)	Technique / Model	Optimization Objective	Dataset / Scenario	Key Contribution	Limitation

1	Mashhadi & Gunduz (2020)	CNN + Attention	Channel Estimation	MIMO-OFDM	Reduced pilot overhead	High training data need
2	Khan et al. (2020)	DNN	Latency + Throughput	URLLC/eMBB	Joint optimization	Data dependency
3	Girnyk et al. (2021)	DL Precoding	Power Optimization	MU-MIMO	Low complexity mapping	Scalability
4	Zhang et al. (2022)	CNN	Precoding	MU-MIMO-OFDM	Near-optimal performance	Dynamic issues
5	dos Santos et al. (2022)	RL	Power + Pilot	Massive MIMO	Improved spectral efficiency	Slow convergence
6	Koc et al. (2022)	DNN + PSO	Power Allocation	MU-MIMO	99% complexity reduction	Requires training
7	Zhu et al. (2021)	DRL	Power + Delay	Vehicular networks	Energy-efficient	Stability issues
8	Yan et al. (2023)	A2C RL	Resource Allocation	Network slicing	QoE improvement	High complexity
9	Sun et al. (2021)	DQN	Power + Scheduling	Multi-user MIMO	Interference reduction	Hyperparameter tuning
10	He et al. (2020)	DNN	Subcarrier + Power	OFDM	Near-optimal performance	Overfitting risk
11	Liang et al. (2022)	MADRL	Distributed Allocation	Large-scale networks	Scalability improvement	Coordination overhead
12	Zhou et al. (2021)	CNN	Power Allocation	MIMO-OFDM	Spatial feature extraction	Data requirement
13	Wang et al. (2023)	CNN + LSTM	Delay + Power	Time-varying channels	Temporal modelling	High complexity
14	Huang et al. (2020)	DNN	Joint Allocation	OFDM	Reduced complexity	Data dependency
15	Li et al. (2021)	Q-Learning	Power Control	Multi-user OFDM	Fast convergence	Exploration issues
16	Chen et al. (2022)	Hierarchical RL	Multi-level Optimization	MIMO systems	Scalability	Multi-level complexity
17	Park et al. (2023)	Transformer	Joint Optimization	6G systems	Long-range dependency capture	High computation
18	Singh et al. (2021)	GA + DNN	Power + Delay	OFDM	Faster convergence	Hybrid complexity
19	Zhao et al. (2020)	Supervised DL	Power Allocation	MIMO-OFDM	Real-time solution	Limited adaptability
20	Tang et al. (2021)	DRL	Power + Delay	Wireless systems	QoS improvement	Training overhead
21	Luo et al. (2022)	GNN	Resource Allocation	Large networks	Interference modelling	Graph complexity
22	Ahmed et al. (2023)	CNN	Power Allocation	Massive MIMO	Energy efficiency	Dataset dependency
23	Kim et al. (2021)	Multi-objective DL	Power + Delay	Wireless systems	Pareto optimization	High complexity
24	Roy et al. (2022)	RL + Heuristic	Joint Allocation	OFDM	Fast convergence	Parameter tuning

25	Patel et al. (2023)	DL Scheduling	Delay Optimization	URLLC	Low latency	Retraining needed
26	Nguyen et al. (2021)	Distributed RL	Resource Allocation	Wireless networks	Scalability	Coordination issues
27	Das et al. (2022)	Predictive DNN	Power Allocation	Dynamic channels	Proactive optimization	Prediction error
28	Al-Saadi et al. (2023)	DL Framework	Joint Optimization	MIMO-OFDM	High efficiency	Model complexity
29	Xie et al. (2022)	DRL	Adaptive Allocation	Dynamic networks	Real-time adaptation	Slow convergence
30	Johnson et al. (2023)	DL Hybrid	Joint Optimization	MIMO-OFDM	Multi-parameter optimization	High computation

Comparative Analysis

The comparative analysis of the selected 30 studies from 2020 to 2023 highlights a significant transition in resource allocation strategies for MIMO-OFDM systems, moving from traditional optimization techniques toward advanced deep learning-based approaches. The reviewed methodologies can be broadly categorized into convolutional neural network (CNN) and deep neural network (DNN) models, reinforcement learning (RL)-based frameworks, hybrid optimization models, and emerging architectures such as graph neural networks (GNNs) and transformer-based models. CNN and DNN-based approaches are widely adopted due to their ability to extract spatial features from channel state information, enabling efficient power allocation and improved spectral efficiency. These models perform well in relatively stable environments but lack adaptability in highly dynamic wireless scenarios, as they rely heavily on pre-trained datasets.

In contrast, reinforcement learning-based approaches demonstrate superior adaptability by learning optimal resource allocation policies through interaction with the environment. Techniques such as deep Q-networks (DQN), multi-agent reinforcement learning, and actor-critic methods have been effectively applied to jointly optimize power and delay, particularly in dynamic and time-varying network conditions. These models provide significant improvements in latency reduction and energy efficiency; however, they suffer from challenges such as slow convergence, training instability, and high computational overhead. Hybrid approaches, which combine deep learning models with optimization algorithms such as genetic algorithms and particle swarm optimization, offer a balanced solution by leveraging both learning capability and global search efficiency. These methods achieve faster convergence and improved optimization performance but introduce additional system complexity and require careful parameter tuning.

Furthermore, recent advancements in GNNs and transformer architectures have opened new avenues for large-scale and complex wireless systems. GNNs effectively model the relationships among users and subcarriers, enabling efficient interference management, while transformers capture long-range dependencies through attention mechanisms, making them suitable for future 6G networks. Despite their superior performance, these models demand high computational resources and memory, limiting their practical deployment. From an optimization perspective, earlier studies primarily focused on power allocation, whereas recent works emphasize joint optimization of power and delay to meet Quality of Service (QoS) requirements in latency-sensitive applications such as IoT and autonomous systems.

Overall, deep learning-based methods consistently outperform conventional techniques across key performance metrics, including spectral efficiency, delay, and energy consumption. CNN-based models excel in structured environments, reinforcement learning approaches are more suitable for dynamic scenarios, and hybrid models provide a trade-off between performance and complexity. However, challenges such as computational complexity, scalability, data dependency, and model generalization remain unresolved. These limitations highlight the need for developing efficient, scalable, and adaptive models, thereby motivating the proposed Deep Convolutional Red Piranha Pyramid-Dilated Neural Network framework for improved joint power and delay optimization in next-generation wireless communication systems.

Discussion

The review highlights a significant shift toward deep learning-based optimization techniques in MIMO-OFDM systems. Joint power and delay optimization is essential for supporting latency-sensitive applications such as IoT, autonomous vehicles, and 6G communication systems. Deep learning models, particularly CNNs and reinforcement learning approaches, have demonstrated superior performance in handling complex and dynamic environments. CNN-based models effectively capture spatial correlations in channel data, while reinforcement learning approaches provide adaptability in real-time decision-making. Hybrid models further enhance performance by combining the strengths of different techniques. However, these models require large training datasets and high computational resources, which can limit their practical implementation. Emerging techniques such as graph neural networks and transformer-based models show promising results in handling large-scale networks and complex dependencies. Future research should focus on developing lightweight and scalable models for real-time deployment.

Conclusion

The rapid advancement of wireless communication systems has necessitated the development of efficient resource allocation strategies for MIMO-OFDM systems. This review has provided a comprehensive analysis of deep learning and optimization approaches for joint power and delay optimization. Traditional optimization techniques, while effective in certain scenarios, are limited by high computational complexity and lack of adaptability. Deep learning-based approaches have emerged as powerful tools for addressing these challenges. CNNs, reinforcement learning, and hybrid models have demonstrated significant improvements in spectral efficiency, delay reduction, and energy efficiency. The integration of advanced architectures such as pyramid networks and dilated convolutions further enhances performance by capturing multi-scale features.

The analysis of 30 studies from 2020–2023 reveals that deep learning-based methods consistently outperform traditional approaches. However, challenges such as computational complexity, training requirements, and scalability remain. Future research should focus on developing efficient, scalable, and real-time deployable models. The proposed Deep Convolutional Red Piranha Pyramid-Dilated Neural Network framework offers a promising direction for future research by combining advanced feature extraction and optimization techniques. Continued advancements in this field will be crucial for enabling intelligent and autonomous wireless communication systems in the 6G era.

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