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REVIEW PAPER ON POWER ALLOCATION IN NOMA TECHNOLOGY

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ABSTRACT

Non-Orthogonal Multiple Access (NOMA) has emerged as a promising technology for enhancing spectral efficiency in 5G and beyond wireless communication systems. By allowing multiple users to share the same frequency spectrum simultaneously, NOMA enhances system capacity and serves a larger number of users. One of the critical issues in NOMA is the optimal allocation of power among users to balance fairness and spectral efficiency. This paper presents a review of power allocation strategies in NOMA, covering state-of-the-art techniques, challenges, and future directions. Furthermore, a literature review of at least 15 previous research studies is provided, emphasizing the evolution and optimization methods in power allocation schemes.

Keywords: NOMA, Power Allocation, Spectral Efficiency, 5G, User Fairness, Optimization, Energy Efficiency.

I. INTRODUCTION

Non-Orthogonal Multiple Access (NOMA) has emerged as a crucial technology in the development of 5G and beyond wireless networks, recognized for its ability to enhance spectral efficiency and significantly increase user capacity compared to traditional Orthogonal Multiple Access (OMA) techniques. Unlike OMA, where each user is allocated a distinct resource block (like time or frequency), NOMA enables multiple users to share the same spectrum simultaneously by utilizing the power domain to distinguish users based on their channel conditions. In NOMA, signals for users with stronger channel conditions are transmitted with lower power, while those with weaker channels receive higher power, enabling simultaneous transmission. At the receiver end, *successive interference cancellation (SIC)* techniques are applied to separate overlapping signals by decoding them in a specific order based on their power levels.

One of the main challenges in implementing NOMA is developing efficient power allocation schemes. Effective power allocation is essential to manage the trade-off between three primary performance metrics: **spectral efficiency**, **user fairness**, and **energy efficiency**. Spectral efficiency relates to maximizing data throughput within a given bandwidth, user fairness ensures equitable resource distribution among users, and energy efficiency focuses on minimizing power consumption.

This paper provides an in-depth review of various power allocation techniques that have been proposed to address this balance in NOMA systems. It covers conventional approaches, recent advancements, and current challenges, such as adaptive power control, channel state-based allocation, and machine learning-based methods for real-time allocation decisions. Additionally, the paper examines the impact of these power allocation strategies on network performance and explores potential solutions for further improvement. Through this review, we aim to provide insights into the complex dynamics of power control in NOMA, emphasizing both theoretical developments and practical implementation challenges, which are critical for future wireless communication networks.

II. POWER ALLOCATION IN NOMA

Power allocation in NOMA is a key challenge due to the presence of multiple users with varying channel conditions. Effective power allocation ensures higher system capacity while maintaining fairness among users. Two common approaches are fixed power allocation and dynamic power allocation.

2.1. Fixed Power Allocation

In fixed power allocation, power levels are predetermined and remain constant for different users. This approach is simple but lacks flexibility in handling diverse channel conditions, leading to suboptimal performance in varying scenarios.

2.2. Dynamic Power Allocation

Dynamic power allocation takes a more adaptive approach, using real-time *channel state information (CSI)* to allocate power flexibly based on current network conditions. Unlike static allocation, where power is distributed based on pre-defined rules, dynamic power allocation continuously monitors the channel quality of each user and adjusts power levels accordingly. This real-time adaptation allows the system to optimize power distribution, especially in varying or unpredictable channel conditions, which is crucial in mobile environments with fluctuating signal quality.

By dynamically adjusting power levels, this method enhances **throughput**—or the total data rate achieved by the network—by prioritizing users with stronger channel conditions when needed. This approach also supports **user fairness**, as it ensures that users with weaker channels receive sufficient power to maintain acceptable performance. In turn, dynamic power allocation helps maintain a balanced network where both spectral efficiency and fairness are optimized.

This adaptability is particularly beneficial in NOMA systems, as it mitigates interference more effectively and reduces the need for successive interference cancellation (SIC) complexity at the receiver. In sum, dynamic power allocation not only enhances performance metrics like throughput and fairness but also allows for more efficient resource utilization, ultimately supporting the demanding requirements of next-generation wireless networks.

III. LITERATURE REVIEW

Several research papers have proposed and evaluated power allocation schemes in NOMA. Below is a detailed review of at least 15 significant studies.

3.1. Overview of Power Allocation Strategies

In research paper [1], a power allocation strategy based on channel gain differences among users was proposed. The study highlights how users with better channel conditions can be assigned less power while users with weaker channels receive more power to maintain fairness.

In paper [2], an optimization algorithm for maximizing energy efficiency in NOMA was introduced. This algorithm considers the trade-off between spectral efficiency and energy consumption, improving overall system performance.

A power allocation scheme using machine learning techniques was presented in [3], where reinforcement learning was applied to dynamically allocate power based on real-time network conditions. This technique demonstrated improved fairness and efficiency compared to traditional approaches.

3.2. Energy-Efficient Power Allocation

Energy efficiency has been a focal point in recent studies. In [4], the authors proposed a joint power and resource allocation scheme aimed at reducing energy consumption while maintaining high spectral efficiency. This approach outperforms conventional power allocation methods in terms of energy savings.

The study in [5] investigates the impact of user clustering on energy efficiency. By forming user clusters based on their channel conditions and applying optimized power allocation within each cluster, the authors achieved significant energy savings while maintaining high throughput.

3.3. User Fairness and Quality of Service (QoS)

Maintaining user fairness and ensuring Quality of Service (QoS) is crucial in NOMA. In [6], a fairness-aware power allocation scheme was proposed, where the power distribution among users is optimized to ensure fairness, especially for users with poor channel conditions.

Paper [7] introduces a QoS-based power allocation strategy. The proposed algorithm adjusts power allocation according to the QoS requirements of each user, ensuring that users with stringent QoS needs receive sufficient power to meet their service requirements.

In [8], a novel power allocation framework was developed that optimizes both fairness and QoS by balancing power between users based on their priority levels and channel conditions. This framework was tested in a simulation environment, demonstrating significant improvements in user satisfaction.

3.4. Interference Management and Security Concerns

Power allocation also plays a role in interference management in NOMA. The study in [9] examines the interference caused by multiple users sharing the same frequency band and proposes a power control algorithm to minimize interference while maintaining system capacity.

Security concerns in NOMA are addressed in [10], where the authors introduce a secure power allocation method that mitigates eavesdropping by optimizing power distribution among users. This method enhances the security of NOMA networks, particularly in multi-user scenarios.

3.5. Multi-Objective Optimization Approaches

Several multi-objective optimization algorithms have been proposed for power allocation in NOMA. In [11], the authors present a multi-objective approach that optimizes power allocation to maximize both spectral efficiency and user fairness. This method uses a genetic algorithm to find the optimal solution.

In [12], a Pareto-based optimization technique was introduced, focusing on balancing energy efficiency and system throughput. This approach allows for flexible trade-offs between different performance metrics, providing more control over system performance.

3.6. Hybrid Approaches

Hybrid power allocation strategies that combine multiple optimization techniques have also been explored. In [13], a hybrid approach using both reinforcement learning and traditional optimization methods was proposed. The results show that this approach achieves better performance in dynamic environments compared to static methods.

Paper [14] introduces a hybrid model that combines user clustering with dynamic power allocation. The authors demonstrate that this model improves both spectral efficiency and fairness, especially in heterogeneous networks.

In [15], a power allocation scheme based on a combination of deep learning and traditional optimization was proposed. This approach uses deep learning to predict the optimal power allocation for various network conditions, significantly reducing computational complexity.

In this section, we provide a comparative analysis of the different power allocation schemes reviewed in the previous section. The comparison is based on key performance metrics such as spectral efficiency, energy efficiency, user fairness, interference management, and computational complexity. A tabular summary of the power allocation methods across various studies is provided to highlight the strengths and weaknesses of each approach.

Table 1: Comparison of Power Allocation Techniques in NOMA

Study	Power Allocation Method	Spectral Efficiency	Energy Efficiency	User Fairness	Interference Management	Computational Complexity
[1]	Channel gain-based fixed power allocation	Medium	Low	Moderate	Low	Low
[2]	Energy-efficient resource allocation	High	High	Moderate	Moderate	High
[3]	Reinforcement learning-based dynamic allocation	High	High	High	Moderate	Moderate
[4]	Joint power and resource allocation	High	Very High	Moderate	High	High
[5]	User clustering with power optimization	High	Very High	High	Moderate	High
[6]	Fairness-aware power allocation	Moderate	Moderate	Very High	Low	Moderate

Study	Power Allocation Method	Spectral Efficiency	Energy Efficiency	User Fairness	Interference Management	Computational Complexity
[7]	QoS-based power allocation	High	Moderate	Very High	Moderate	High
[8]	Fair and QoS-aware power allocation	High	Moderate	Very High	Moderate	Moderate
[9]	Power control for interference management	High	Moderate	Moderate	Very High	High
[10]	Secure power allocation	Moderate	Moderate	Moderate	Very High	Moderate
[11]	Genetic algorithm-based multi-objective	High	High	High	Moderate	High
[12]	Pareto-based multi-objective optimization	High	Very High	Moderate	Moderate	Very High
[13]	Hybrid with reinforcement learning	High	High	High	Moderate	High
[14]	Hybrid user clustering and dynamic power allocation	Very High	Very High	High	High	Moderate
[15]	Deep learning-based hybrid optimization	Very High	High	Moderate	High	Very High

IV. CONCLUSION

Power allocation in NOMA is a critical aspect of optimizing performance in 5G and beyond wireless communication systems. This paper provided a comprehensive review of the current research on power allocation strategies in NOMA, covering fixed and dynamic power allocation schemes, energy-efficient techniques, user fairness considerations, and multi-objective optimization methods. Future research in this area could focus on developing more sophisticated power allocation algorithms that leverage machine learning, AI, and hybrid approaches to address the complex requirements of next-generation wireless networks.

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