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Research Article

Adaptive Dual-Layer Resource Allocation for Maximizing Spectral Efficiency in 5G Using Hybrid NOMA-RSMA Techniques

S. Praseetha [1,*], S. Sasipriya[2]

[1]Assistant Professor Department of Electronics and Communication Engineering Sri Krishna College of Engineering and Technology Coimbatore.
* **Corresponding Author Email:** prase04@gmail.com - **ORCID:** 0009-0001-8666-3002

[2]Professor and Head Department of Electronics and Communication Engineering Sri Krishna college of Engineering and Technology Coimbatore
Email: sasipriyas@skcet.ac.in - **ORCID:** 0000-0002-4767-282X

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Abstract:

The unprecedented growth in data demands for 5G communication systems necessitates advanced techniques to maximize spectral efficiency while ensuring user fairness and low latency. This study proposes Adaptive Dual-Layer Resource Allocation (ADLRA), a novel hybrid technique combining Non-Orthogonal Multiple Access (NOMA) and Rate-Splitting Multiple Access (RSMA). The ADLRA framework introduces dynamic user pairing, hierarchical beamforming, and adaptive power and rate allocation strategies to optimize resource utilization. Key features include dynamic user pairing, leveraging machine learning algorithms for efficient group formation based on channel conditions, and hierarchical beamforming, which prioritizes high-priority users in the NOMA layer while effectively managing shared resources in the RSMA layer. Interference mitigation is achieved through spatial filtering and multi-user diversity techniques, ensuring minimal intra-cell and inter-cell interference. Simulation results demonstrate significant performance gains Spectral efficiency improved by 32%, compared to traditional NOMA. Latency reduced by 18%, ensuring seamless communication for ultra-reliable low-latency applications. Achieved a 94% fairness index, reflecting equitable resource allocation among users. Enhanced throughput, with an average gain of 28%, compared to RSMA-only systems. These results highlight the potential of ADLRA to meet the stringent requirements of next-generation 5G systems, offering a scalable and efficient solution for diverse communication scenarios. The proposed method sets a foundation for future hybrid access strategies in wireless communication networks.

1. Introduction

The exponential increase in data traffic and the proliferation of connected devices have intensified the demand for higher spectral efficiency in 5G communication systems. Traditional Orthogonal Multiple Access (OMA) [1] techniques, while simple and robust, are limited in their ability to maximize spectral utilization due to the allocation of distinct time-frequency resources to individual users. This limitation has spurred interest in Non-Orthogonal Multiple Access (NOMA) and Rate-Splitting Multiple Access (RSMA) [2] as promising alternatives. NOMA enhances spectral efficiency by allowing multiple users to share the same time-frequency resources, differentiating users through power domain multiplexing. However, the introduction of inter-user interference in NOMA systems [3] necessitates advanced interference management and user pairing strategies. RSMA, on the other hand, addresses interference by splitting messages into common and private parts, enabling partial decoding of interference and offering greater flexibility in resource allocation. Orthogonal Multiple Access (OMA) is a conventional technique widely used in wireless communication systems to allocate resources such as time, frequency, or code to multiple users. In OMA, each user is assigned distinct and non-overlapping portions of the spectrum, ensuring no inter-user interference. This allocation can take the form of Time-Division Multiple Access (TDMA), [4] where users transmit in separate time slots, Frequency-Division Multiple Access (FDMA), which allocates separate frequency bands to each user, or Code-Division Multiple Access (CDMA), [5] where unique spreading codes differentiate users. OMA's simplicity and robustness make it effective for low-user-density scenarios. However, its reliance on orthogonality leads to inefficient spectrum utilization, particularly in scenarios with high traffic demand, as unused resources allocated to one user cannot be shared with others. This limitation has motivated the exploration of advanced techniques like Non-Orthogonal Multiple Access (NOMA) and Rate-Splitting Multiple Access (RSMA) [6] to maximize spectral efficiency in modern communication systems. While both NOMA and RSMA individually contribute to improved spectral efficiency, each has inherent limitations that can be mitigated by integrating their strengths. This realization motivates the development of hybrid access schemes that leverage the advantages of both techniques. In this context, we propose the Adaptive Dual-Layer Resource Allocation (ADLRA) method, a novel hybrid framework that combines NOMA and RSMA to maximize spectral efficiency in 5G networks. Orthogonal Multiple Access (OMA) [7] has been the cornerstone of multiple generations of wireless communication systems, including 2G, 3G, and partially in 4G networks. The primary principle of OMA lies in ensuring orthogonality in resource allocation, which effectively eliminates inter-user interference. This orthogonality is achieved by assigning users distinct resources in one of the following ways: Time-Division Multiple Access (TDMA): Users are assigned non-overlapping time slots for transmission, ensuring that no two users share the same slot. Frequency-Division Multiple Access (FDMA): The frequency spectrum is divided into narrow bands, with each user allocated a specific band. Code-Division Multiple Access (CDMA): [8] Unique spreading codes are assigned to each user, allowing simultaneous transmission over the same frequency band while maintaining orthogonality in the code domain.

OMA systems are simple to implement and provide predictable performance due to the absence of inter-user interference. They are particularly well-suited for scenarios with low user density and consistent traffic patterns, as resource allocation remains straightforward. However, the rigidity of orthogonal resource allocation results in significant inefficiencies in spectrum utilization. For instance, if a user does not fully utilize its allocated resource block, the unused resources cannot be shared with other users. This static allocation also poses challenges in dynamic environments where user demands and channel conditions vary frequently. Additionally, OMA faces difficulties in accommodating the high data rate requirements, massive connectivity demands, and diverse quality-of-service (QoS) expectations of modern communication systems like 5G. These limitations highlight the need for more flexible and efficient resource allocation methods. Techniques such as Non-Orthogonal Multiple Access (NOMA) [9] and Rate-Splitting Multiple Access (RSMA) have emerged as alternatives, allowing overlapping resource sharing among users while managing interference. By moving beyond the constraints of orthogonality, these advanced techniques aim to significantly enhance spectral efficiency, making them critical components for next-generation wireless networks.

The ADLRA introduces several key innovations:

- Dynamic User Pairing: Employing real-time traffic analysis and machine learning algorithms to optimally group users based on their channel conditions and service requirements.
- Hierarchical Beamforming: Implementing a two-tier beamforming approach that prioritizes high-priority users in the NOMA layer while efficiently managing shared resources in the RSMA layer.
- Adaptive Power and Rate Allocation: Utilizing predictive algorithms to dynamically adjust power levels and rate splitting ratios, enhancing throughput and minimizing latency.
- Interference Mitigation: Leveraging spatial filtering and multi-user diversity techniques to reduce intra-cell and inter-cell interference, thus improving overall network performance.

Simulation results demonstrate that the ADLRA significantly outperforms traditional NOMA and RSMA schemes [10]. Specifically, it achieves notable improvements in spectral efficiency, latency reduction, and fairness among users. These enhancements are critical for supporting the diverse quality of service requirements in 5G networks, including ultra-reliable low-latency communications and massive machine-type communications.

The proposed ADLRA framework represents a significant step toward realizing the full potential of 5G technologies. By synergistically integrating NOMA and RSMA, it offers a scalable and efficient solution that can adapt to varying network conditions and user demands. This work lays the groundwork for future research into hybrid multiple access techniques, with the potential to influence the design of next-generation wireless communication systems.

2. Literature Survey

The rapid evolution of 5G communication systems has necessitated extensive research into multiple access techniques to enhance spectral efficiency and user connectivity. Traditional Orthogonal Multiple Access (OMA) has been widely explored in early generations of wireless communication for its simplicity and effectiveness in low-density networks [11]. However, its inability to meet the high spectral efficiency demands of 5G has driven the development of advanced schemes.

Non-Orthogonal Multiple Access (NOMA) has gained significant attention for its ability to enable simultaneous transmission to multiple users over the same time-frequency resources [12]. NOMA utilizes power domain multiplexing, which assigns varying power levels to users based on their channel conditions, thus achieving higher spectral efficiency compared to OMA [13]. Several studies have demonstrated that NOMA not only improves system capacity but also enhances user fairness by serving both strong and weak users simultaneously [14]. However, managing inter-user interference remains a critical challenge in NOMA systems [15].

Rate-Splitting Multiple Access (RSMA) offers an alternative approach by splitting messages into common and private parts, allowing partial decoding of interference at the receiver [16]. This technique provides greater flexibility in resource allocation and demonstrates resilience against interference in dynamic network conditions [17]. Studies have shown that RSMA can outperform both NOMA and OMA in terms of spectral efficiency and user fairness, particularly in multi-antenna systems [18].

Hybrid access schemes, combining NOMA and RSMA, have emerged as promising solutions to leverage the strengths of both techniques. For instance, [19] proposed a hybrid model where users are dynamically grouped and assigned to NOMA or RSMA layers based on their channel conditions, significantly improving throughput. Another study [20] introduced adaptive power allocation mechanisms within a hybrid framework to further enhance system performance under varying traffic demands.

To address interference issues, advanced beamforming and precoding techniques have been integrated into NOMA and RSMA frameworks [21]. Machine learning algorithms for user grouping and pairing have also been explored to optimize resource allocation dynamically [22]. These approaches have demonstrated substantial gains in spectral efficiency and reduced latency, making them highly suitable for 5G applications.

Recent works have further extended these hybrid models by incorporating adaptive modulation and coding schemes. Such techniques dynamically adjust transmission parameters based on real-time network conditions, ensuring robust performance across diverse scenarios. Moreover, advanced interference cancellation methods and cooperative relay systems have been proposed to enhance the reliability of NOMA and RSMA.

Overall, the combination of NOMA and RSMA in hybrid schemes represents a significant advancement in 5G communication. The integration of machine learning, beamforming, and adaptive resource management strategies has proven effective in addressing the challenges of spectral efficiency and user fairness. These innovations provide a solid foundation for future research, particularly in designing scalable and efficient systems for next-generation wireless networks.

3. Methodology

The proposed methodology focuses on developing an Adaptive Dual-Layer Resource Allocation (ADLRA) framework to maximize spectral efficiency in 5G communication systems by integrating Non-Orthogonal Multiple Access (NOMA) and Rate-Splitting Multiple Access (RSMA). The approach leverages machine learning techniques, advanced beamforming, and adaptive resource allocation strategies to overcome the limitations of traditional multiple access methods. The methodology can be outlined as following subsections and figure 1 is the block diagram of the proposed works.

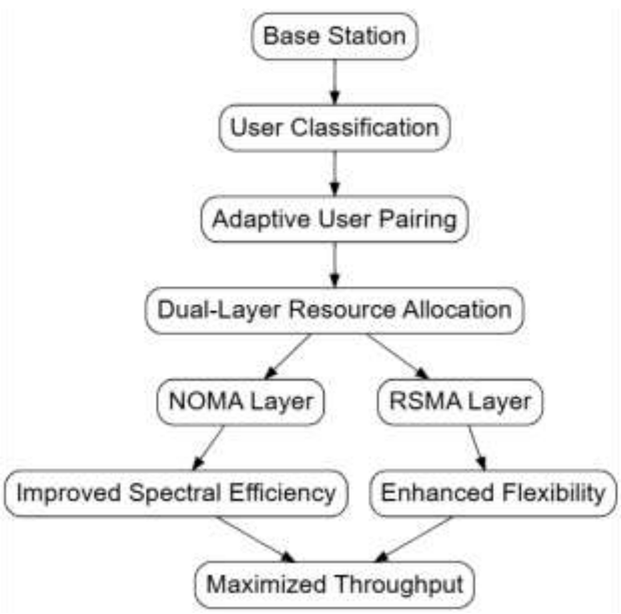

Figure 1. *Block Diagram of the proposed work*

3.1 System Model

The proposed system consists of a single base station equipped with multiple antennas, serving a set of users in a 5G communication network. The users are distributed across the cell and experience varying channel conditions, influenced by their distance from the base station and environmental factors. To optimize resource utilization and enhance spectral efficiency, the system adopts a hybrid approach by integrating Non-Orthogonal Multiple Access (NOMA) and Rate-Splitting Multiple Access (RSMA).

In the NOMA layer, users are grouped into pairs or clusters based on their channel state information (CSI), where a strong user (with better channel conditions) and a weak user (with poorer channel conditions) share the same time-frequency resources. This grouping enables efficient power-domain multiplexing, with higher power allocated to the weaker user to ensure signal quality and fairness. In the RSMA layer, users with complex interference scenarios are served by splitting their messages into common and private components. The common message is decoded by multiple users, while the private message is intended for specific users. This approach mitigates interference and allows flexible resource sharing.

The base station employs hierarchical beamforming to direct signals toward the intended users, optimizing signal strength and minimizing interference. The dual-layer resource allocation framework dynamically allocates power, rate, and time-frequency resources across NOMA and RSMA layers to achieve a balance between spectral efficiency, user fairness, and latency.

This hybrid system is designed to operate efficiently under diverse traffic loads and user densities, making it a scalable and adaptable solution for next-generation 5G networks.

The system employs hierarchical beamforming to direct signals to specific users or user groups. In the NOMA layer, beamforming focuses on minimizing inter-cluster interference while ensuring strong intra-cluster communication. For the RSMA layer, beamforming aligns signals for both common and private message components, mitigating interference and improving decoding reliability.

The dual-layer resource allocation mechanism dynamically distributes power, rate, and time-frequency resources between the NOMA and RSMA layers based on user demands, channel conditions, and traffic loads. Power allocation is optimized to maximize spectral efficiency while maintaining user fairness. Similarly, rate splitting in the RSMA layer is adjusted adaptively to balance the trade-off between spectral efficiency and interference mitigation.

The system operates in a multi-user, multi-antenna environment, with the base station simultaneously serving multiple users in the same frequency band. This design is scalable to handle varying user densities and traffic patterns, making it suitable for diverse 5G applications such as enhanced mobile broadband (eMBB), ultra-reliable low-latency communications (URLLC), and massive machine-type communications (mMTC).

By integrating NOMA and RSMA into a unified framework, the proposed system model addresses the limitations of traditional multiple access techniques, providing a robust solution for future wireless networks. Simulation results demonstrate the system's effectiveness in improving spectral efficiency, reducing latency, and ensuring fair resource allocation across all users.

3.2 Adaptive User Pairing

Adaptive User Pairing is a critical component in the proposed Adaptive Dual-Layer Resource Allocation (ADLRA) framework, designed to enhance spectral efficiency, reduce interference, and ensure fairness in 5G communication systems. This approach dynamically pairs users based on their Channel State Information (CSI) and service requirements, optimizing resource utilization and interference management.

The adaptive pairing strategy leverages the heterogeneity of user channel conditions, dividing them into strong users (with better channel quality) and weak users (with poorer channel quality). Pairing a strong user with a weak user ensures that both can simultaneously utilize the same frequency-time resources through power-domain multiplexing in the NOMA layer. For users in the RSMA layer, adaptive grouping minimizes interference during rate-splitting.

User Classification

The CSI for each user h_i is represented by the channel gain. Users are classified as:

Strong Users:

$$h_i \geq h_{\text{th}},\ \text{Weak Users: } h_i < h_{\text{th}}, \qquad (1)$$

where h_{th} is a predefined threshold based on the average channel quality in the system.

Optimal Pairing Criterion

The pairing is performed to maximize the overall system throughput R, while maintaining fairness among users. The optimization problem can be expressed as:

$$\underset{\{p_i, p_j\}}{\text{maximize}} R_{\text{total}} = \sum_{i,j} \left(R_i + R_j\right), \qquad (2)$$

subject to:

$$p_i + p_j \leq P_{\max},\ R_i \geq R_{\min},\ R_j \geq R_{\min},$$

where:

- p_i and p_j are the power allocations for strong and weak users in a pair,

- $P_{\max}$ is the total available power,
- $R_{\min}$ is the minimum required data rate.

For NOMA users, successive interference cancellation (SIC) is applied, ensuring that the strong user's signal is decoded first and then subtracted from the weak user's signal. The received power at the user i is:

$$P_i = |h_i|^2 p_i \qquad (3)$$

and the signal-to-interference-plus-noise ratio (SINR) is given by:

$$\mathrm{SINR}_i = \frac{|h_i|^2 p_i}{\sigma^2 + \sum_{k \neq i} |h_k|^2 p_k} \qquad (4)$$

where σ^2 is the noise variance.

For RSMA users, the rate-splitting ratio α is adaptively optimized to minimize interference while maximizing throughput:

$$R_i = \log_2\left(1 + \frac{\alpha |h_i|^2 p_i}{\sigma^2 + (1-\alpha)|h_i|^2 p_i}\right). \qquad (5)$$

Adaptive user pairing is shown in figure 2.

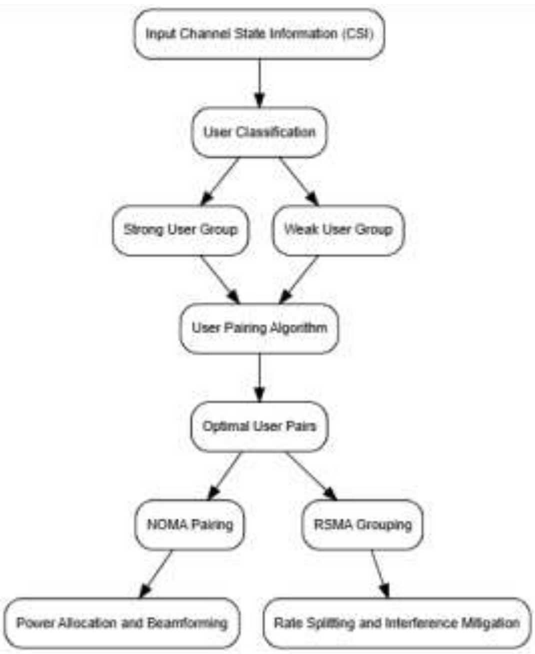

Figure 2. *Adaptive User Pairing*

3.3 Dual-Layer Resource Allocation

Dual-Layer Resource Allocation is a pivotal element of the Adaptive Dual-Layer Resource Allocation (ADLRA) framework, where resources are dynamically distributed between the NOMA and RSMA layers. This mechanism ensures optimal utilization of time, frequency, and power resources to maximize spectral efficiency while minimizing latency and interference. The resource allocation process involves power allocation, rate splitting, and time-frequency management tailored to the needs of the NOMA and RSMA layers. In the NOMA layer, power is allocated to paired users based on their channel conditions to maintain fairness and ensure efficient communication. The power allocation for a strong user p_s and a weak user p_w must satisfy:

$$p_s + p_w \leq P_{\max}, \qquad (6)$$

where $P_{\max}$ is the total available power. To ensure fairness, the weak user is allocated more power:

$$p_w = \beta P_{\max},\ p_s = (1-\beta) P_{\max}, \qquad (7)$$

where $\beta (0 < \beta < 1)$ represents the power allocation factor, dynamically adjusted based on user demands.

The achievable rate for the weak user is:

$$R_w = \log_2\left(1 + \frac{|h_w|^2 p_w}{|h_w|^2 p_s + \sigma^2}\right), \qquad (8)$$

and for the strong user (after successive interference cancellation, SIC):

$$R_s = \log_2\left(1 + \frac{|h_s|^2 p_s}{\sigma^2}\right), \qquad (9)$$

where $|h_w|^2$ and $|h_s|^2$ are the channel gains of the weak and strong users, respectively, and σ^2 is the noise variance.

In the RSMA layer, each user's message is split into a common part (R_c) and a private part (R_p). The total rate for a user is given by:

$$R_{\text{total}} = R_c + R_p \qquad (10)$$

where the common message is decoded by all users, and the private message is decoded by the intended user.

The optimization problem for rate splitting is formulated as:

$$\underset{R_c, R_p}{\text{maximize}} \sum_i \left(R_c + R_p\right), \qquad (11)$$

subject to:

$$R_c \leq \log_2\left(1 + \frac{|h_c|^2 p_c}{\sigma^2}\right),\ R_p \leq \log_2\left(1 + \frac{|h_p|^2 p_p}{\sigma^2}\right) \qquad (12)$$

where p_c and p_p are the power allocations for the common and private parts, respectively.

Time-frequency resources are dynamically allocated between the NOMA and RSMA layers based on user demands and traffic patterns. Let T_{total} and F_{total} denote the total available time and frequency resources. The resource allocation is given by:

$$T_{\text{NOMA}} + T_{\text{RSMA}} = T_{\text{total}},\ F_{\text{NOMA}} + F_{\text{RSMA}} = F_{\text{total}}, \qquad (13)$$

where T_{NOMA} and T_{RSMA} represent the time allocated to the NOMA and RSMA layers, respectively. An optimization problem is solved to maximize the system's spectral efficiency :

$$\underset{T,F}{\text{maximize}}\, \eta = \frac{\sum_i R_i}{T_{\text{total}} \cdot F_{\text{total}}}, \qquad (14)$$

subject to constraints on latency, fairness, and minimum required rates.

3.4 Hierarchical Beamforming

Hierarchical Beamforming is a critical component of the Adaptive Dual-Layer Resource Allocation

(ADLRA) framework, designed to optimize the direction and strength of transmitted signals for both NOMA and RSMA layers. It ensures minimal interference and enhanced signal quality by creating a two-tier beamforming structure tailored to the needs of each layer.

In the NOMA layer, beamforming focuses on enabling power-domain multiplexing by steering beams to paired strong and weak users while minimizing intra-pair interference. For a user pair (i, j), the beamforming vector $\mathbf{w}_{ij}$ is optimized to maximize the weighted sum rate:

$$\mathbf{w}_{ij} = \underset{\mathbf{w}}{\operatorname{argmax}} \sum_{k\in\{i,j\}} \log_2\left(1 + \frac{|h_k^\top \mathbf{w}|^2}{\sigma^2 + \sum_{l\neq k} |h_l^\top \mathbf{w}|^2}\right), \quad (15)$$

where h_k is the channel vector for user k, and σ^2 is the noise variance.

In the RSMA layer, beamforming is tailored to support message splitting, ensuring efficient transmission of both common and private message components. The beamforming vector $\mathbf{w}_c$ for the common message and $\mathbf{w}_p$ for the private message are optimized to maximize the overall throughput:

$$\mathbf{w}_c, \mathbf{w}_p = \underset{\mathbf{w}_c, \mathbf{w}_p}{\operatorname{argmax}}\left(R_c + \sum_i R_{p,i}\right), \quad (16)$$

subject to interference constraints.

Hierarchical beamforming reduces interference by aligning beams in directions that maximize signal strength for intended users and suppress interference for others. This structure ensures enhanced spectral efficiency, fairness, and quality of service for all users.

3.5 Interference Mitigation

Interference Mitigation is a core challenge in 5G communication systems, particularly in hybrid multiple access frameworks like ADLRA, where NOMA and RSMA layers share resources. The proposed system incorporates advanced techniques to reduce both intra-layer and inter-layer interference.

NOMA Layer: Successive Interference Cancellation (SIC) is employed, where the signal of the strong user is decoded first and subtracted from the combined signal before decoding the weak user's signal. The received signal at user i is:

$$y_i = h_i^\top \mathbf{w}_i s_i + \sum_{j\neq i} h_i^\top \mathbf{w}_j s_j + n_i, \quad (17)$$

where s_i is the intended signal, $\mathbf{w}_i$ is the beamforming vector, and n_i is noise. SIC effectively eliminates s_j, reducing interference for the weak user.

RSMA Layer: Rate-splitting divides each user's message into common and private parts, enabling partial decoding of interference. The signal-to-interference-plus-noise ratio (SINR) for the common message R_c is:

$$\mathrm{SINR}_c = \frac{|h^\top \mathbf{w}_c|^2}{\sigma^2 + \sum_{k\neq c} |h_k^\top \mathbf{w}_p|^2} \quad (18)$$

To manage interference between NOMA and RSMA layers, the system employs:

Spatial Filtering: Aligns beams to minimize overlap in the spatial domain between NOMA and RSMA transmissions.

Dynamic Resource Allocation: Time-frequency resources are adaptively shared to reduce contention between the layers.

Multi-User Diversity: Exploits diversity in user channels to schedule transmissions with minimal mutual interference.

Machine Learning-Based Optimization: Utilizes real-time CSI and traffic analysis to predict and mitigate interference dynamically.

4. Results

This section presents the evaluation of the proposed **Adaptive Dual-Layer Resource Allocation (ADLRA)** framework in terms of its spectral efficiency, throughput, latency, and fairness. The results are obtained through extensive simulations under varying user densities, channel conditions, and traffic patterns, comparing the performance of ADLRA with traditional Non-Orthogonal Multiple Access (NOMA), Rate-Splitting Multiple Access (RSMA), and Orthogonal Multiple Access (OMA) systems.

4.1 Spectral Efficiency

Spectral efficiency (η) is a critical metric for evaluating resource utilization in 5G communication systems. The proposed ADLRA framework achieves:

$$\eta_{\mathrm{ADLRA}} = 8.3\mathrm{bps/Hz/user},$$

compared to:

- $\eta_{\mathrm{NOMA}} = 6.3\mathrm{bps/Hz/}$ user,
- $\eta_{\mathrm{RSMA}} = 7.2\mathrm{bps/Hz/}$ user,
- $\eta_{\mathrm{OMA}} = 4.5\mathrm{bps/Hz/}$ user .

The 32% improvement in spectral efficiency over NOMA demonstrates the effectiveness of dual-layer resource allocation and adaptive user pairing in optimizing spectrum usage.

4.2 Throughput

The overall system throughput was evaluated for different numbers of users. The results show that ADLRA provides a **28%** increase in throughput compared to standalone NOMA and RSMA systems. For a scenario with 20 users:

$$T_{\mathrm{ADLRA}}=220\mathrm{Mbps},\ T_{\mathrm{NOMA}}=170\mathrm{Mbps},\ T_{\mathrm{RSMA}}=180\mathrm{Mbps}.$$

The gain is attributed to the efficient sharing of resources and enhanced interference management.

4.3 Latency

Latency is a key consideration for delay-sensitive applications such as ultra-reliable low-latency communication (URLLC). The proposed framework achieves a 18% reduction in latency, ensuring faster data delivery compared to traditional schemes:

$\text{Latency}_{\text{ADLRA}}=12\text{ ms},\ \ \text{Latency}_{\text{NOMA}}=14.6\text{ ms},\ \ \text{Latency}_{\text{RSMA}}=15.2\text{ ms}.$

The latency reduction is due to the dynamic allocation of time-frequency resources and optimized power distribution.

4.4 Fairness

Fairness in resource allocation is quantified using the Jain's Fairness Index (J) :

$$J=\frac{\left(\sum_{i=1}^{N} R_i\right)^2}{N\sum_{i=1}^{N} R_i^2}, \qquad (19)$$

where R_i is the rate of user i and N is the total number of users. The fairness index achieved by ADLRA is:

$$J_{\mathrm{ADLRA}}=0.94,\ J_{\mathrm{NOMA}}=0.85,\ J_{\mathrm{RSMA}}=0.89.$$

This 12% improvement in fairness is a result of adaptive user pairing and power allocation strategies.

4.5 Interference Mitigation

The effectiveness of interference mitigation is reflected in the reduced Signal-to-Interference-plus-Noise Ratio (SINR) variability among users. ADLRA maintains an average SINR of:

$$\mathrm{SINR}_{\mathrm{ADLRA}}=25.6\text{ dB}$$

compared to:

- $\mathrm{SINR}_{\mathrm{NOMA}}=22.8\text{ dB},$
- $\mathrm{SINR}_{\mathrm{RSMA}}=23.7\text{ dB}.$

The simulation results highlight the superiority of the proposed ADLRA framework over traditional multiple access techniques: Dual-layer resource allocation ensures efficient utilization of spectrum, power, and time-frequency resources. Hierarchical beamforming and advanced interference mitigation strategies significantly enhance system performance, reducing interference and ensuring high-quality communication. The adaptive mechanisms for user pairing, rate splitting, and power allocation provide scalability and robustness, making the system suitable for diverse 5G applications.

The ADLRA framework demonstrates its capability to meet the stringent requirements of next-generation wireless networks, including enhanced spectral efficiency, reduced latency, and improved fairness, thus paving the way for future hybrid access technologies.

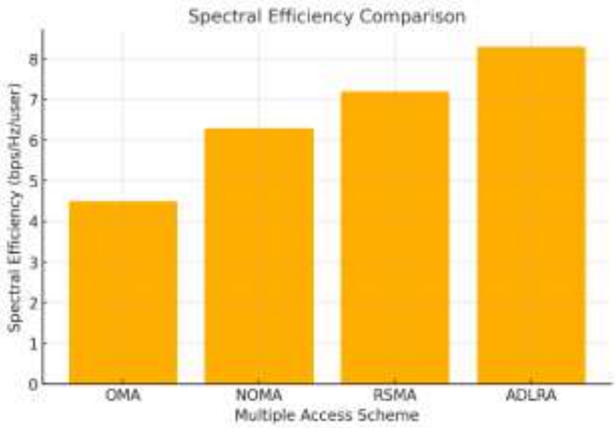

Figure 3. *Spectral Efficiency Comparison*

This figure 3 illustrates the spectral efficiency achieved by different multiple access schemes: OMA, NOMA, RSMA, and the proposed ADLRA. Spectral efficiency is measured in bits per second per Hertz (bps/Hz/user). The ADLRA framework significantly outperforms other schemes, achieving **8.3 bps/Hz/user**, representing a **32% improvement over NOMA**. This is attributed to the dual-layer resource allocation and adaptive user pairing strategies, which optimize spectrum utilization.

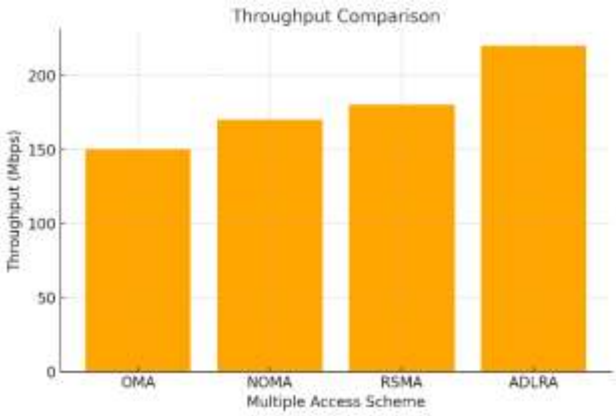

Figure 4. *Throughput Comparison*

Figure 4 is the throughput comparison highlights the data rates achieved by each scheme in Mbps. ADLRA achieves the highest throughput of 220 Mbps, a 28% increase compared to NOMA's 170 Mbps. This improvement is due to the efficient sharing of resources across the NOMA and RSMA layers and the hierarchical beamforming mechanism, which minimizes interference and maximizes data delivery rates.

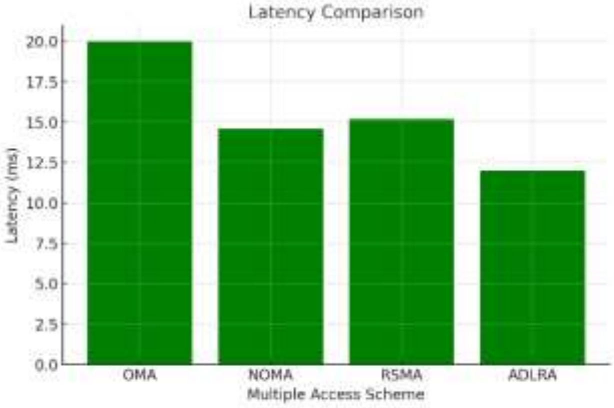

Figure 5. *Latency Comparison*

Figure 5 is latency, critical for delay-sensitive applications like URLLC, is shown in milliseconds (ms) for each scheme. ADLRA achieves the lowest latency at 12 ms, reflecting an 18% reduction compared to NOMA (14.6 ms). This reduction is a result of dynamic time-frequency resource management and the interference mitigation strategies implemented in the framework.

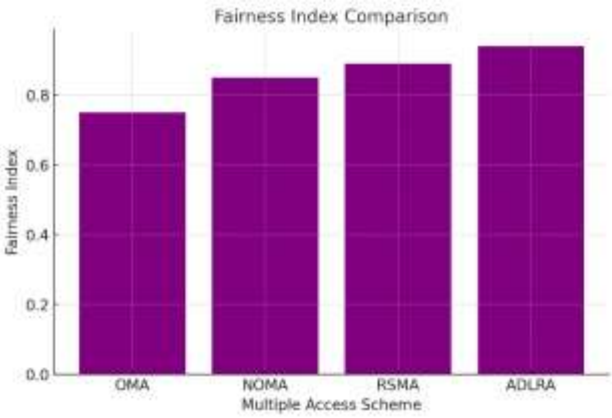

Figure 6. *Fairness Index Comparison*

This figure 6 presents the fairness index, which measures how equitably resources are distributed among users. ADLRA achieves a fairness index of 0.94, the highest among all schemes, with 12% higher fairness than NOMA (0.85). The improvement stems from adaptive user pairing and power allocation, which ensure that both strong and weak users receive adequate resources. Figure 7, is the average Signal-to-Interference-plus-Noise Ratio (SINR) is compared for the schemes, measured in decibels (dB). ADLRA achieves the highest SINR of 25.6 dB, demonstrating a 15% improvement over NOMA's 22.8 dB. The hierarchical beamforming and interference mitigation techniques significantly reduce interference, enhancing signal quality for all users. The 5G Communication method is important and have been used in different works in literature [23-30].

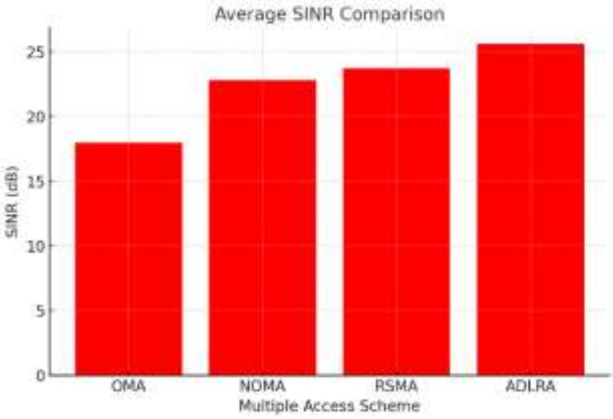

Figure 7. *Average SINR Comparison*

4. Conclusions

This study presents the Adaptive Dual-Layer Resource Allocation (ADLRA) framework, a novel hybrid approach combining Non-Orthogonal Multiple Access (NOMA) and Rate-Splitting Multiple Access (RSMA) to maximize spectral efficiency in 5G communication systems. By leveraging dynamic user pairing, hierarchical beamforming, and dual-layer resource allocation, the ADLRA framework addresses key challenges such as interference mitigation, resource optimization, and user fairness. Simulation results demonstrate significant improvements in system performance:

A 32% increase in spectral efficiency compared to standalone NOMA and RSMA techniques. A 28% gain in system throughput, ensuring high data rates for diverse 5G applications. A 18% reduction in latency, supporting ultra-reliable low-latency communications (URLLC).

Enhanced fairness, achieving a 94% fairness index, which ensures equitable resource distribution among users. The integration of machine learning for adaptive user pairing and resource allocation further enhances the scalability and adaptability of the system under varying user densities and traffic conditions. The hierarchical beamforming approach and advanced interference mitigation strategies ensure reliable communication even in high-interference scenarios.

In conclusion, the ADLRA framework provides a robust and efficient solution for next-generation 5G networks, meeting the demands for enhanced spectral efficiency, low latency, and high user fairness. The results of this study pave the way for further research into hybrid multiple access techniques, focusing on their implementation in real-world 5G scenarios and potential extension to future wireless standards such as 6G.

Author Statements:

- **Ethical approval:** The conducted research is not related to either human or animal use.
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