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Provably Energy Efficiency and Lower Power Consumption Based on HOA in 5G MIMO-NOMA Systems

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Abstract— The rapid expansion of 5G communication networks necessitates improved energy efficiency and reduced power consumption. This article explores the integration of Hybrid Optimization Algorithms (HOA) in 5G MIMO-NOMA systems, aiming to enhance energy efficiency and minimize power usage. The proposed methodology leverages MIMO technology and Non-Orthogonal Multiple Access (NOMA). We introduce a new power consumption model based on HOA, recognizing MIMO-NOMA as pivotal in future wireless communication systems. HOA allows simultaneous service for more users, leading to heightened energy efficiency and reduced power consumption compared to conventional MIMO or NOMA systems. A streamlined user admission scheme is presented, admitting users based on ascending power requirements to meet Quality of Service criteria. Numerical results demonstrate the efficacy of HOA and the power allocation strategy in enhancing energy efficiency and user admission. Comparative analysis shows lower power consumption and approximately a 10% increase in energy efficiency compared to traditional methods and other algorithms like GA, PSO, SPPA, and the water-filling algorithm.

Keywords- Energy Efficiency, Power Consumption, Hybrid optimization algorithm, MIMO-NOMA.

I. INTRODUCTION

NOMA offers a means to enhance the energy efficiency of cellular systems [1]. By leveraging the power domain to improve spectral efficiency, particularly in scenarios where users exhibit diverse channel gains. For instance, consider two users—one with a high channel gain and another with a low channel gain. The Base Station (BS) concurrently transmits two signals to users within the same time slot and frequency band. Typically, lower transmission power is allocated to the user with high channel gain, while the user with low channel gain receives higher transmission power. Consequently, the user with a high channel gain can decode the signal intended for the user with a low channel gain. The user with high channel gain first decodes the signal meant for the user with low channel gain subtracts it, then decodes its signal. The decoding at the user with low channel gain is interference-free because the signal from the user with high channel gain is weak. The utilization of successive interference cancellation (SIC) [2] combined with superposition coding (SC) [3]. NOMA allows the increasing of spectral efficiency compared to orthogonal multiple access (OMA). NOMA can be integrated with Multiple Input Multiple Output (MIMO) [4] and is applied in downlink-coordinated two-point systems. Like [5, 6], beamforming is employed for NOMA downlink transmissions when the BS is equipped with multiple antennas. The challenges related to power allocation are discussed in [7], where the capacity of MIMO-NOMA is assessed in the presence of dual users and compared to that of Orthogonal Multiple Access (OMA) employing Time Division Multiple Access (TDMA). The findings indicate that NOMA achieves a higher sum rate than OMA, and the performance gap widens with increasing differences in the channel gains of the two users. Power allocation for dual users is implemented in open-loop MIMO downlink transmissions, where the Base Station (BS) allocates power to both users' signals based on statistical Channel State Information (CSI). Superposition Coding (SC) and Successive Interference Cancellation (SIC) are employed in NOMA to address inter-user interference and are extendable to single-user systems [8, 9]. In MIMO, the article details Layered Transmissions based on SC and SIC, also known as Horizontal Bell Labs Layered Space Time (H-BLAST) schemes [10]. Optimal power allocation for layered transmissions is explained [11], and the advantage of layered transmission lies in reduced complexity in signal decoding at the receiver compared to sequence-by-sequence decoding using SIC. The complexity of MIMO detection experiences an exponential increase with the growing number of transmitting antennas for optimal Performance [12, 13]. However, this requirement is unnecessary as the sequence of each layer can be detected independently. Consequently, decoding complexity in layered transmissions increases linearly with the number of transmitting antennas or layers. It's essential to highlight that intra-user Superposition Coding (SC) and Successive Interference Cancellation (SIC) are employed in MIMO for layered transmissions. At the same time, inter-user SC and SIC are utilized in NOMA. The key advantage of (downlink) MIMO-NOMA with layered transmissions is that the complexity in detection/decoding at the user's end increases linearly with the number of transmit layers or antennas. This becomes crucial due to the limitations in users' devices' energy and computing power [14]. By employing superposition coding at the transmitter and SIC at the receiver, NOMA multiplexes multiple users in the power domain, achieving a similar time-frequency resource. In contrast to the traditional Orthogonal Multiple Access (OMA) scheme, Non-Orthogonal Multiple Access (NOMA) demonstrates the capability to achieve higher energy efficiency (EE) [15]. Simulation results confirm the greater sum rate of NOMA compared to OMA, and the advantageous Performance of NOMA in achievable rate over OMA is elaborated in [16]. Furthermore, it is established that NOMA achieves an elevated ergodic sum rate in cellular downlink scenarios with randomly deployed users when compared to OMA. Energy efficiency is important in fifth-generation (5G) considerations, emphasizing the need to analyze EE for NOMA [17]. The joint analysis of subchannel assignment and power allocation (PA) is conducted in [18] to maximize EE in multicarrier NOMA systems. Most results indicate the effectiveness of NOMA in achieving increased EE and spectral efficiency (SE) compared to OMA [19]. Improving power consumption in MIMO-NOMA systems can increase system capacity, referring to the number of users the System can support [20]. The rationale is that reducing power consumption can liberate more resources for data transmission, thereby enhancing overall system performance. Energy efficiency and power consumption are crucial factors for ensuring fair resource allocation among users in the context of 5G and future generations. Utilizing Hybrid Optimization Algorithms (HOA) with MIMO-NOMA systems enhances energy efficiency. MIMO-NOMA, a technology enabling non-orthogonal sharing of time-frequency resources among multiple users, facilitates higher spectral efficiency and improved system capacity compared to traditional Orthogonal Multiple Access (OMA) schemes. Energy efficiency is paramount in wireless communication systems, directly impacting the battery life of user devices and the sustainability of the overall network. In this context, a key objective of this work is to establish a robust transmit power model for 5G Base Stations, leading to the optimization of energy efficiency and reduction in power consumption. Table .1 below shows some related works and a comparison between them and the proposed algorithm

TABLE I. SHOWS THE RELATED WORKS AND ITS ADVANTAGES AND DISADVANTAGES.

REF	Author &year	Access Domain	Method used	Advantage	Disadvantage
[15]	(A.K. Khandaker et al,2020)	MIMO-NOMA	Hybrid precoding algorithm, user clustering	achieve significant EE improvement	High power consumed
[16]	(Y. Zhang et al.,2021)	Massive MIMO	Joint optimization algorithm for power and energy management	Maximize EE and power management	Not considering user fairness
[17]	(W. Chen et al.,2021)	Massive MIMO	Energy-efficient user pairing algorithm for downlink 5G Massive MIMO system	EE optimization and energy-saving	High power consumed at BS
[18]	(M. S. Hossain et al,2021)	MIMO-NOMA	hybrid beamforming approach to solve power and non-convex problem	Power Control, energy saving	EE did not take into consideration optimization

[19]	(Zhiyao Tang et al.2020)	MIMO	Hybrid user clustering algorithm	optimize two key parameters: transmit power and the number of feedback bits allocated to each user	EE is not optimized; user admitting did not take into consideration the Framework
[20]	(X. Liu et al.,2018)	NOMA	optimal power allocation scheme based on a regularized zero-forcing precoding method	Maximize sum data rate, ensure user fairness, low complexity	High power consumption, EE not optimized
[21]	(Sara Norouzi et al,2022)	MIMO-NOMA	mixed-integer non-linear program (MINLP)	minimize the total transmission power, ensure satisfaction of quality of service	High computational complexity, not consider optimization of EE
[22]	(Sepehr Rezvani et al,2022)	NOMA	employing the rapid water-filling and Dinkelbach algorithms, respectively	EE maximization problems are solved	Quality of service and Fairness are not considered, as high power consumption and high complexity.
[23]	(Lou Salaun et al, 2019)	NOMA	design an optimal and low complexity algorithm (MCPC)	Low complexity and achieves near-optimal sum rate with user fairness	EE, QoS, and User admitting are not considered in this Framework. High power consumption
[24]	(Sara Norouz et al ,2021)	MIMO-SCMA	efficient user clustering algorithm based on the constrained K-means method is proposed	significant improvements in terms of transmit power and spectral efficiency.	Power consumption, Performance, and QoS are not considered, and EE is not optimized

A. Motivation

In light of wireless communication's indispensable role in our modern lives, the unfolding of 5G technology, while promising unprecedented data rates and connectivity, presents significant energy efficiency and sustainability challenges. The pressing need for innovative solutions to enhance the energy efficiency of 5G networks and reduce power consumption has emerged. The global deployment of 5G networks, although ensuring enhanced connectivity for various applications, has raised environmental concerns due to the networks' energy-intensive nature. The substantial operational costs of powering and maintaining 5G infrastructure further highlight the urgency to address power consumption. MIMO-NOMA systems, known for efficiently serving multiple users, hold the potential for optimizing resource utilization, but realizing this potential requires sophisticated optimization techniques. Integrating hybrid optimization algorithms, combining heuristic methods with machine learning, offers a promising approach to revolutionizing energy-efficient resource allocation, beamforming, interference management, and decision-making in 5G MIMO-NOMA systems. This research is motivated by the goal of developing novel strategies that harness the power of Hybrid Optimization Algorithms to enhance energy efficiency and reduce power consumption in 5G MIMO-NOMA systems, contributing to the realization of more sustainable, cost-effective, and environmentally responsible wireless communication networks suited for the digital age.

B. Contribution

This study is motivated by its contribution to minimizing power consumption and improving energy efficiency. This can be done by allocating different power levels to other users such that the users with better channels can receive signals with lower power levels. This paper proposes an efficient Hybrid Optimization Algorithm (HOA) that combines different optimization techniques to achieve a trade-off between Performance and computational complexity. By leveraging hybrid optimization algorithms, MIMO-NOMA systems can enhance energy efficiency by jointly optimizing power allocation, user clustering, beamforming design, resource allocation, and other system parameters. These algorithms consider the specific characteristics of MIMO-NOMA and aim to strike a balance between energy efficiency and overall system performance to ensure QoS for all network users. The main contributions of this work are as follows:

- In this research study, we introduced an innovative Hybrid Optimization Algorithm (HOA) designed for the MIMO-NOMA system. This algorithm optimizes power by considering channel conditions and interference levels specific to each user group. By applying a hybrid optimization algorithm in the MIMO-NOMA system, the power transmitted can be optimized for both the spatial and non-spatial domains, thus achieving a more efficient power allocation and lower power consumption.

- This research investigates the impact of Energy Efficiency (EE) in multi-cluster and multiuser MIMO-NOMA systems while considering each user's Quality of Service (QoS). The study involves assessing whether all users can be accommodated by comparing the total transmit power to the power needed to meet the QoS requirements of all users. If admission for all users is possible, the goal is to identify the maximum System Energy Efficiency.

- In this study, we assess the effectiveness of the hybrid optimization algorithm in MIMO-NOMA and its impact on enhancing Energy Efficiency (EE) while minimizing power consumption to ensure Fairness among all users. This evaluation is compared to alternative algorithms like the water-filling algorithm (WFA) and Particle Swarm Optimization (PSO).

II. MASSIVE MIMO SYSTEM

The impact is minimal in MIMO systems with an unlimited number of transmitting antennas due to the absence of noise and limited small-scale fading. Using independence among antennas, the authors investigated the scenario based on many transmit antennas at the BSs and showed that higher data throughput was achieved. Massive MIMO networks have a base station with N antennas and user terminals L (UTs) with a single antenna (N >> L >> 1). Equal to the transmission antenna number, or "transmit antennas," is the number of RF chains used. For the UTs 1≤ m ≤ M (≤ L), the received signal $\boldsymbol{\mathcal{Y}km} \in \mathbb{C}^{\boldsymbol{N}}$ For the UT m in the cell, k is given as follows:

$$\mathcal{Y}km = \sqrt{\rho}\, \sum_{j=1}^{J} h_{jkm}^{H} s_j + n_{km} \quad (1)$$

where ρ > 0 is the transmit signal-to-noise ratio (SNR), $h_{jkm} \in \mathbb{C}^{\boldsymbol{N}}$ is the channel vectors, $\boldsymbol{s_j} \in \mathbb{C}^{\boldsymbol{N}}$ Transmit signal vectors and $\boldsymbol{n_{km}}$ is the thermal noise with $\boldsymbol{n_{km}} \backsim \mathcal{CN}\ (0,1)$ We model the channel vectors h_{jkm} as

$$h_{jkm} = R_{jkm} + g_{jkm} \quad (2)$$

where $R_{jkm} \triangleq \tilde{R}_{jkm} \tilde{R}_{jkm}^{H} \in \mathbb{C}^{\boldsymbol{N \times N}}$ Represents the covariance matrix in which the path loss large-scale fading factor is applied, i.e., $\tilde{R}_{jkm} = d_{jkm}^{-\beta/2}\ \mathrm{I}_N$ where d_{jkm} Is the distance between BS j and the m-th UTs in cell k with path loss exponent β, and $g_{jkm} \backsim \mathcal{CN}\ (0, I_N)$ is a channel vector that is related to fast fading. In MIMO systems, the base station creates a precoding matrix to simultaneously broadcast the signal to L UTs, a technique known as multiuser MIMO. The preceding transmits signal vectors. s_J Can be used to indicate signal transmission from a BS to m th purposed UT can be represented as:

$$s_j = \sqrt{\curlywedge_j\, \mathrm{W}_j \mathrm{X}_j} \quad (3)$$

where $W_j = [w_{j1} \cdots w_{jL}] \in \mathbb{C}^{\boldsymbol{N \times L}}$ This represents the precoding matrix and $x_j = [x_{j1} \cdots x_{jL}] \in \mathbb{C}^{\boldsymbol{L}}$ Is the transmit signal vector with $\boldsymbol{x_j} \backsim \mathcal{CN}\ (0,1)$. The power normalization factors $\curlywedge_j$ This can be defined as:

$$\curlywedge_j = \frac{1}{\mathbb{E}\left[\frac{1}{L} \mathrm{tr}\ \mathrm{W_j}\, \mathrm{W_j^H}\right]} \quad (4)$$

III. System Model

The multiuser MIMO systems established at BSs shown in Figure.1 are considered in this work. We assume that there is no cooperation between BSs during downlink communication. Let's suppose a downlink MIMO-NOMA system Similar to that shown in Figure. 1, then let $d1$ and $d2$ denote the distances of $U1$ and $U2$ respective separations from the MIMO transmitter. Here, we presume that d1 > d2. That is, $U1$ is the weak user here, and $U2$ is the strong user. Let x_1 and x_2 denote the information intended for U1 and U2. Following the notation conventions of MIMO, let h_{rt} Denote the Rayleigh fading channel between the t^{th} transmit antenna and r^{th} receiver. MIMO can be used for spatial multiplexing (increased effective rate) or diversity gain (decreasing bit error rate). MIMO is used to achieve diversity gain in this case. As a result, both transmit antennas 1 and 2 send the same data. The channel considers small-scale fading and variable antenna correlations such as path loss (large-scale fading). This paper will depend on generating the data and scenario based on the link-level MATLAB simulator. In 5G, MIMO and NOMA techniques are combined to increase energy efficiency and decrease power consumption using a hybrid optimization algorithm (HOA) [21]. The essential aspect is to spatially separate users using MIMO and non-orthogonally separate users within the same spatial domain using NOMA. During the simulator framework, we will discuss different channel models with varying modulation techniques and see how these parameters can affect the transmit power, EE, and data rate.

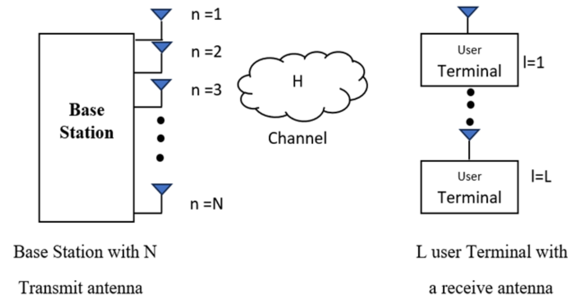

Figure 1. Proposed System Model

IV. Problem Formulation

The overall power consumption consists of two components: the constant circuit power consumption Pc and the adaptable transmit power. $P_t = P_{max} \sum_{m=1}^{M} \sum_{l=1}^{L} \Omega_{m,l}$ [22]. The System's Energy Efficiency (EE) can be defined as:

$$\eta EE = \frac{R^{sum}}{P_c + P_t} \quad (5)$$

Here, $R^{sum} = \sum_{m=1}^{M} \sum_{l=1}^{L} R_{m,l}$ Represents the total achievable sum rate, calculated as the summation of all transmit antennas (m) and users (l). We aim to optimize the System's Energy Efficiency (EE) while ensuring each user achieves a minimum pre-defined rate. The formulation of the problem is as follows:

$$max_{\Omega_{m,l}}\ \eta EE \quad (6)$$

$$R_{m,l} \geq R_{m,l}^{min}, m \in \{1, \dots, M\}, l \in \{1, \dots, L\} \quad (7)$$

$$\sum_{m=1}^{M} \sum_{l=1}^{L} \Omega_{m,l} \leq 1, \quad (8)$$

Equations (7) and (8) depict the minimum rate requirements for users and the constraint on transmit power, respectively.

V. Proposed Solution

Due to the minimum rate requirements outlined in Equation (7), the formulated problem (6) might be infeasible when the transmit power is insufficient. In such instances, prioritizing the maximization of admitted users becomes more meaningful than optimizing Energy Efficiency. Therefore, it is crucial to assess the feasibility of problem (6) by comparing the total transmit power constraint with the minimum power needed to meet the minimum rate requirements for all users. The minimum required power can be mathematically defined as:

$$P_{req} = P_{max} \sum_{m=1}^{M} \sum_{l=1}^{L} \Omega_{m,l} \quad (9)$$

Where $\Omega_{m,l}^{min} = (2^{R_{m,l}^{min}} - 1)(\sum_{k=1}^{l-1} \Omega_{m,l}^{min} + \frac{1}{\rho \left| V_{m,l}^{H} H_{m,l} P_m \right|^2})$) represents the minimum power needed to fulfill the Quality of Service (QoS) requirement for the user (m, l).

$$P_{req} \leq P_{max} \Leftrightarrow \sum_{m=1}^{M} \sum_{l=1}^{L} \Omega_{m,l} \leq 1, \quad (10)$$

Energy efficiency is a crucial aspect of wireless communication systems. Hybrid optimization algorithms

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combine different optimization techniques to achieve a trade-off between Performance and computational complexity [23]. We can find the best solution to the abovementioned problem by applying hybrid optimization and power allocation algorithms. We can investigate whether the merger between these algorithms can give an optimal value for EE and enhance power consumption.

VI. Hybrid MIMO-NOMA Optimization Algorithm

Hybrid (MIMO-NOMA) combines MIMO and NOMA techniques for enhanced Energy Efficiency and reduced power consumption. Using multiple antennas at the transmitter and receiver, HOA employs beamforming and power allocation to distribute resources based on user channel quality. Beamforming focuses transmission power toward intended users, NOMA, on the other hand, non-orthogonally separates the users in the same area. By encoded data non-orthogonally, NOMA enables many users to collaborate on time and frequency resources. Assigning unique power levels based on individual channel quality. Decoding at the receiver involves Successive Interference Cancellation (SIC). Hybrid MIMO-NOMA concurrently serves a larger user population, delivering superior Energy Efficiency and lower power consumption than traditional MIMO or NOMA systems. It is a promising technology for future wireless communication systems, extending beyond 5G.

Algorithm 1: hybrid optimization algorithm for energy efficiency and power consumption

Step 1: User clustering starts by clustering the users with similar channel conditions and considering both spatial and non-spatial domains to cluster users. $N^K = \{ N_1^K, \dots, N_2^K, \dots, N_n^K, \dots N_N^K \}$, $N_n^K = \{ u_{n,1}, u_{n,2}, \dots u_{n,q}, \dots, u_{n,K} \}$, we can define the channel gain matrix $H = [h_{ij}]$is the channel gain between user i and base station j. Then, we can use the k-means algorithm to group the N users into K clusters, assigning each user to the cluster.

Step 2: Beamforming focuses the transmission power in the direction of the intended users. Each cluster of users further separates them and reduces the interference between them in the beamforming matrix. $W_{i\,j}$ For user i in cluster j can be defined as: $W_{ij} = \left(H_j^i H_j\right)^{-1} H_j^H e_{ij}$ where H_j Is the channel gain matrix for the users in cluster j ande_{ij} Is the unit vector that corresponds to the user

Step 3: Successive interference cancellation is used to decode the data of each user by removing interference from other users. We decode the user with the highest channel gain first and then subtract its contribution from the received signal to decode the user with the highest channel gain, and so on. The decoded signal for user i in cluster j can be denoted as x_{ij} and can be computed as $x_{ij} = y_{ij} - sum_{k=i+1}^{|c_j|} W_{kj} S_{kj}$ where S_{kj} is the transmitted signal for user k in cluster j

Step 4:

Generate wireless channel

Initialize parameters

$$P_{max}, R_{m,l}^{min}, \rho \left|\mathrm{V}_{\mathrm{m,l}}^{\mathrm{H}} \mathrm{H}_{\mathrm{m,l}} \mathrm{P}_{\mathrm{m}}\right|^2, l \in \{1, \dots, L\}$$

Calculate:

$$H \leftarrow sort\left(\frac{P_{max} 2^{\sum_{l=1}^{L} R_{m,l}^{min}}}{\rho \left|\mathrm{V}_{m,l}^{\mathrm{H}} \mathrm{H}_{m,l} \mathrm{P}_m\right|^2}\right)$$

$$h_t \leftarrow H(t);$$

$$\lambda^{max} \leftarrow \sum_{t=1}^{M} [\lambda - h_t] = P_{max} - P_{req};$$

$$T \leftarrow \lambda^{max} \in [h_T, h_T + 1];$$

$$\eta_{EE}^{t} \leftarrow max\left\{\eta_{EE}\left(\frac{\partial \eta_{EE}}{\partial \lambda} = 0\right), \eta_{EE}(h_t), \eta_{EE}(h_t + 1)\right\}, t \in \{1, \dots, T-1\}$$

$$\eta_{EE}^{T} \leftarrow max\left\{\eta_{EE}\left(\frac{\partial \eta_{EE}}{\partial \lambda} = 0\right), \eta_{EE}(h_T), \eta_{EE}(\lambda^{max})\right\},$$

$$\eta_{EE}^{max} \leftarrow \max\{\eta_{EE}^{1}, \dots, \eta_{EE}^{T}\}$$

End

If Equation (6) is impractical, a more sensible objective is to admit as many users as feasible rather than prioritizing Energy Efficiency.

$$\eta EE = \frac{\sum_{m=1}^{M} \sum_{l=1}^{L} R_{m,l}^{min} + \sum_{m=1}^{M} [\log_2(\lambda) - \log_2 \frac{P_{max} 2^{\sum_{l=1}^{L} R_{m,l}^{min}}}{\rho \left|V_{m,l}^{H} H_{m,l} P_m\right|^2}]}{P_c + P_{req} + \sum_{m=1}^{M} [\lambda - \frac{P_{max} 2^{\sum_{l=1}^{L} R_{m,l}^{min}}}{\rho \left|V_{m,l}^{H} H_{m,l} P_m\right|^2}]}$$

The problem of admitting users can be expressed as follows:

$$max_{\Omega_{m,l}} \sum_{m=1}^{M} \sum_{l=1}^{L} x_{m,l} \tag{11}$$

$$R_{m,l} \geq R_{m,l}^{min} x_{m,l}\,, \tag{12}$$

$$\sum_{m=1}^{M} \sum_{l=1}^{L} \Omega_{m,l} \leq 1, \tag{13}$$

$$x_{m,l} \in \{0,1\},$$

Here, $x_{m,l}$ Users were admitted one at a time according to the lowest order of their channel gains inside each cluster, according to a recent work [24] that suggested a greedy user admission algorithm with a similar power distribution in each cluster. However, the current approach, in which power is transferred between clusters, requires common user admission. We maintain a similar method of admitting users in each cluster in descending order of their channel gains, prioritizing users with superior channel gains inside each cluster because of Successive Interference Cancellation (SIC). every user admission procedure. Iteratively, the user admission procedure selects the users with the highest channel gain for each iteration, determined by each cluster. In order to account for interference from users who have already been admitted, the necessary power is calculated among these users. The admission process selects the user with the minimum required power for entry. After admission, the user is removed from the candidate pool, and if the remaining power exceeds the necessary amount for admitting this user, the total remaining power is updated. If not, the process concludes, and the iteration repeats until no more users can be admitted [25]. This method enhances the number of admitted users when the users meet the quality-of-service criteria in each cluster.

$$R_{m,k}^{min} \leq R_{m,n}^{min} \forall k \in \{1, \dots, l\}, n \in \{l+1, \dots, L\}, \tag{14}$$

For the proposed scheme, l stands for the overall number of confirmed users for admission in each $m - th$ cluster. as the SINR restrictions of the users in each cluster meets the following conditions, the designed user admission method optimizes the total amount of admitted users:

$R_{m,l}^{min} \leq \cdots \leq R_{m,L}^{min}$. (15)

The recommended user admission method is most effective when considering the sum rate and the maximum number of allowed users, in this case users' QoS requirements are equal. Proof: While (14) is satisfied, as a result, the proposed method improves the number of users admitted [26]. If the users' QoS requirements are equal, it is easy to understand that increasing the number of indicated users can also increase the sum rate.

VII. Signal Model for Both Transmitter and Receiver

A. *Transmit Signals*

The signal emanating from both the transmitting antennas is expressed as:

$$x = \sqrt{P}(\sqrt{\alpha_1 x_1} + \sqrt{\alpha_2 x_2}) \quad (16)$$

Where α_1 and α_2 are the NOMA power allocation coefficients. Since $U1$ is the weak user, we have $\alpha_1 > \alpha_2$

B. *Received Signals*

x is transmitted simultaneously by the transmit antennas. Therefore, the received signal at $U1$ is,

$$y_1 = xh_{11} + xh_{12} + n_1 = x(h_{11} + h_{12}) + n_1 \quad (17)$$

Similarly, the signal received by $U2$ is given by

$$y_2 = xh_{21} + xh_{22} + n_2 = x(h_{21} + h_{22}) + n_2 \quad (18)$$

Here, n_1 and n_2 are AWGN noise samples with mean zero and variance σ^2

C. *Method of decoding at User 1*

$U1$ now needs to decode x_1 from y_1 . Since U1 is a weak user, more power is given to the user signal x_1 That is $\alpha 1 > \alpha 2$. This result can interrupt the x_2 the term as interference and immediately decode x_1, from y_1 [27].

Substituting for x in (6), we get,

$$y_1 = \sqrt{P}(\sqrt{\alpha_1 x_1} + \sqrt{\alpha_2 x_2})\,(h_{11} + h_{12}) + n_1 \quad (19)$$

$$y_1 = \sqrt{P}(\sqrt{\alpha_1 x_1}(h_{11} + h_{12}) + \sqrt{P}\sqrt{\alpha_2 x_2})\,(h_{11} + h_{12}) + n_1 \quad (20)$$

Now, we can formulate the SINR equation for $U1$ in decoding x_1 in the following manner,

$$\gamma_1 = \frac{P\alpha_1 |h_{11}+h_{12}|^2}{P\alpha_2 |h_{11}+h_{12}|^2+\sigma^2} \quad (21)$$

Hence, the attainable rate at $U1$ can be expressed as:

$$R_1 = \log_2 1 + \gamma_1 \quad (22)$$

D. *Method of decoding at User 2*

The second user, which U2 denotes, should be decoded x_2 which come from y_2. Even before, U2 was the strongest user. The signal, x_2 allocated less power. consequently, in y_2 , the x_1 term's power will be overwhelming. To acquire x_1, U2 will first execute direct decoding on y_2 . Then successive interference cancellation (SIC) is utilized to get rid of x_1 before x_2 is decoded [28].

Substituting for x in (18) and expanding**,** we get,

$$y_2 = \sqrt{P}(\sqrt{\alpha_1 x_1}(h_{21} + h_{22}) + \sqrt{P}\sqrt{\alpha_2 x_2})\,(h_{21} + h_{22}) + n_2 \quad (23)$$

The SINR expression for U1 when directly decoding x_1 is:

$$\gamma_1 = \frac{\boldsymbol{P\alpha_1 |h_{21}+h_{22}|^2}}{\boldsymbol{P\alpha_2 |h_{21}+h_{22}|^2+\sigma^2}} \quad (24)$$

The initial component of Equation (23) is eliminated through Successive Interference Cancellation (SIC), leaving the residual signal as:

$$y_2 = (\sqrt{P}\sqrt{\alpha_2 x_2})\,(h_{21} + h_{22}) + n_2 \quad (25)$$

To decode the U2 signal, SNR can be expressed as:

$$\gamma_2 = \frac{P\alpha_1 |h_{21}+h_{22}|^2}{\sigma^2} \quad (26)$$

In conclusion, the attainable rates at U2 for decoding x_1 and x_2 are provided by:

$$R_{12} = \log_2(1 + \gamma_{12}) \quad (27)$$

$$R_2 = \log_2(1 + \gamma_2) \quad (28)$$

To assess our MIMO-NOMA network's Performance, we'll contrast it with a MIMO-OMA network [29]. The time slots for MIMO-OMA transmission will be divided into two equal parts. Both antennas will transmit to U1 during the initial time slot, and in the subsequent slot, both antennas will transmit to U2. The transmitted signal to U1 from both antennas in time slot one is denoted as Px_1 . The received signal at U1 is as follows,

$$y_{1,oma} = (\sqrt{P}x_1)\,(h_{11} + h_{12}) + n_1$$

Similar to this, the signal sent by both antennas in time slot 2 to U2 is Px_2 while the signal received at U2 is,

$$y_{2,oma} = (\sqrt{P}x_2)\,(h_{21} + h_{22}) + n_1$$

The SNRs at U1 and U2 are, $\gamma_{1,oma} = \frac{P||h_{11}+h_{12}|^2|}{\sigma^2}$ and $\gamma_{2,oma} = \frac{P||h_{21}+h_{22}|^2|}{\sigma^2}$

Hence, for U1 and U2, the MIMO-OMA rates that can be achieved are,

$$R_{1,oma} = \frac{1}{2}\log_2(1 + \gamma_{1,oma}) \quad (29)$$

$$R_{2,oma} = \frac{1}{2}\log_2(1 + \gamma_{2,oma}) \quad (30)$$

The factor $\frac{1}{2}$ In both equations (29) and (30), it is because of the realization that only half of each user's time slot is devoted to communication. (In contrast, MIMO-NOMA utilizes the entire time slot for data transmissions to both users) [30]. Table 2 presents the simulation parameters: d1=500m, d2=200m, path loss exponent η=4, α1=0.75, α2=0.25, and bandwidth = 10 MHz the sum rate for MIMO-feasible NOMA is denoted as $R_1 + R_2$, while that for MIMO-OMA is denoted as, $R_{1,oma} + R_{2,oma}$.

VIII. Numerical Analysis for Energy Efficiency and MIMO-NOMA Systems

In this section, we examine the energy efficiency of a specific cellular system model by incorporating MIMO at base stations and comparing the results across various cell configurations. The simulation parameters outlined in Table 3 correspond to the configurations of the cellular systems described in [31], [32], and [33], featuring massive MIMO systems at base stations. The energy efficiency at a base station is illustrated in Figure. 7, considering the number of transmit antennas. Additional factors

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influencing the results include the size of the cells, encompassing Pico, micro, and macro cells, and the transmit signal-to-noise ratio (SNR). Pico-, micro- and macro-cell networks transmit SNRs of -5 dB, 0dB, 5dB, and 10dB, respectively [34].

TABLE II. TABLE TYPE STYLES

Simulation Program	MATLAB
Scenario	MIMO-NOMA
Number of Transmit antenna	0 – 100
Number of users served	50 -100
No. of Tx power (Users, BS)	(30,30)
B, η	3.9, 0.38
Pdac, pmix, pfilt, psyn(mW)	15.6,34.3,20 ,30
Distance (d1, d2)	(500, 200) m
Channel Bandwidth	10 MHz
Power allocation coefficient	α1=0.75, α2=0.25
Pathloss exponent	η=4
Noise Model	Gaussian Noise
Channel Model	Rayleigh, Rician

The requirement for an increasing number of transmit antennas to attain optimal energy efficiency persists despite a decline in the maximum energy efficiency as the transmit SNR rises. This phenomenon arises because the linear increase in power consumption outweighs the logarithmic decrease, resulting in an ongoing need for more transmit antennas.

TABLE III. TABLE TYPE STYLES

	Single cellular System	Multiple cellular System
$\rho = -5dB$	9	15
$\rho = 0dB$	15	30
$\rho = 5dB$	35	78
$\rho = 10dB$	72	210

The EE curves for 5G networks are more pronounced, it should be noted. In a small-scale cellular 5G network, more transmit antennas are necessary to enhance energy efficiency. Moreover, at a certain number of antennas, the EE becomes linear in the case of high transmit SNR. Although more antennas are used to provide faster data rates, the increased total power consumption reduces energy efficiency. The utilization of massive MIMO systems contributes to effective power management, enhancing energy efficiency by transmitting data efficiently with minimal power consumption [35]. The energy efficiency of various massive MIMO cellular systems at base stations is depicted in Figure. 7. In a multi-cellular system structure, intercell interference caused by signals from base stations in neighboring cells can impact users. This interference negatively affects the absolute value of energy efficiency compared to a single-cell system. Despite this, adopting more transmit antennas, as outlined in Table 3, helps mitigate intercell interference and improves overall energy efficiency [36].

In summary, deploying massive MIMO systems at base stations can enhance energy efficiency, especially in addressing intercell interference challenges in multiple cellular downlink communication systems. This results from the need for more transmit antennas to eliminate inter-cell interference [37]. Numerical results are provided for different system configurations, such as when all users experience the same channel fading characteristics when a multiplicative white Gaussian noise process distorts the received signal of each user, and when the users do not experience any fading at all [38]. The impact of augmenting the count of active users on the overall system power consumption is examined. It is demonstrated that while an elevation in power consumption might occur with an increase in active users, this upsurge can be counterbalanced by boosting system throughput, achievable with a more significant number of active users. However, it is crucial to ascertain the optimal number of active users to effectively maximize system throughput and minimize power consumption, aligning with specific requirements [39]. This investigation is centered on optimizing energy efficiency in the Massive MIMO-NOMA system. A representation of the precoding matrix matching W_k It is described as follows:

$$W_k \triangleq \widehat{H}_{kk} \qquad (31)$$

Where $\widehat{H}_{kk} = [\hat{h}_{kk1} \dots . \hat{h}_{kkM}] \in \mathbb{C}^{N \times M}$

We introduce an energy efficiency formula for cellular systems incorporating massive MIMO systems at base stations (BSs), aligning with the updated power consumption model outlined in the preceding section. This formula is constructed using the newly introduced power consumption model from the previous section. The methodology for deriving the achievable total rate for energy efficiency is based on the lower boundary techniques outlined in [40]. To initiate this process, we break down the incoming signal. y_{km} For the user terminal m in the cell k as below:

$$y_{km} = \sqrt{\rho} \leftthreetimes_k \mathbb{E}[h_{kkm}^H W_{km}] x_{km} + \sqrt{\rho} \leftthreetimes_k h_{kkm}^H W_{km} x_{km} - \sqrt{\rho} \leftthreetimes_k \mathbb{E}[h_{kkm}^H W_{km}] x_{km} + \sum \sqrt{\rho} \leftthreetimes_j h_{jkm}^H w_{jl} x_{jl} + n_{km}$$
(32)

$where\ (j, l) \neq (k, m)$

We emphasize the inter-cell interference for received signals since we assume that UT can effectively learn the average effective channels. $\sum_{(j,l)\neq(k,m)} \sqrt{\rho} \leftthreetimes_j h_{jkm}^H w_{jl} x_{jl}$ That must be considered when operating in multiple cellular systems. The signal to interference plus noise ratio (SINR) γkm can be computed by considering intra- and inter-cell interference. The definition of γkm is as follows:

$$\gamma km = \frac{\leftthreetimes_j \left| \mathbb{E}[h_{kkm}^H W_{km}] \right|^2}{\frac{1}{\rho} + \leftthreetimes_k Var[h_{kkm}^H W_{km}] + \sum_{(j,l)\neq(k,m)} \leftthreetimes_k \left| \mathbb{E}\left[h_{jkm}^H W_{jl}\right] \right|^2} \qquad (33)$$

The calculation of SINR γkm and the resulting achievable rate $R_{\ km}$ This can be demonstrated for the user terminal m in cell k as well as the achievable sum rate. R_k This can be illustrated as follows:

$$R_{km} = \log_2(1 + \gamma_{km}) \qquad (34)$$

$$R_k = \sum_{m=1}^{M} R_{km\,.} \qquad (35)$$

The energy efficiency EE_k This can be expressed as follows by using the development of a viable sum rate and the suggested power consumption model:

$$EE_k = \frac{R_k}{P_{k,total}} \qquad (36)$$

The balance between the maximum achievable data transmission and the associated power consumption poses a challenge in massive MIMO systems [41]. While the increase in the number of antennas contributes to higher power usage, the convex shape of the energy efficiency curve reflects the overall improvement in energy efficiency with antenna expansion [42]. This research aims to identify the optimal number of transmit antennas for energy efficiency. We specifically seek to determine the total number of antennas employed for transmission, denoted as $N_{k,max}$ To optimal energy efficiency. The issue is stated as follows:

$$N_{k,max} = arg_{1 \le n \le N} max \ EE_k(n) \quad (37)$$

IX. Simulation Results

Through this section, we will analyse the model of the System mentioned in Figure. 1, and based on the parameters of Table 2 and Table 3, this research will use MATLAB simulation code. To analyse the results based on the theoretical view of EE and the Power consumption model before applying the optimization algorithm and compare this result after using the optimization algorithm (HOA). The second stage of the simulation results show the proposed method of the HOA -power allocation algorithm. The developed Power Allocation (PA) method and user admission technique have been validated through simulations. Table 2 shows the particular values of the parameters for the simulation that were used. All results were obtained, with one notable exception: when the total power transmitted is excessive to satisfy the QoS demands of all users, the Energy Efficiency during these scenarios is set to zero, because the objective is not EE maximization. MIMO-NOMA reaches an improved sum rate, then MIMO-OMA when both users share similar frequency resource simultaneously, as shown in Figure. 2. More information is available. Further insights can be gained from the individual feasible rates graph:

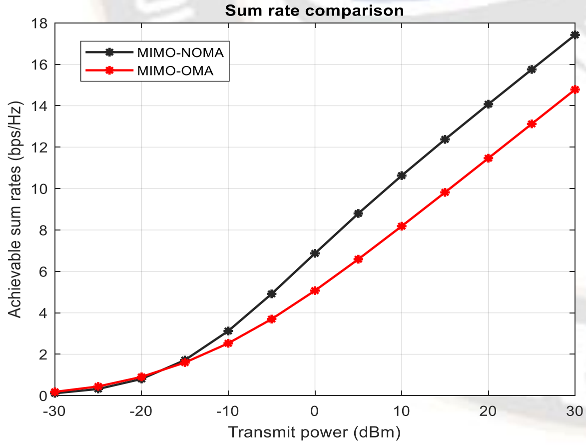

Figure 2. Shows a comparison between MIMO-OMA and MIMO-NOMA according to achievable sum rate.

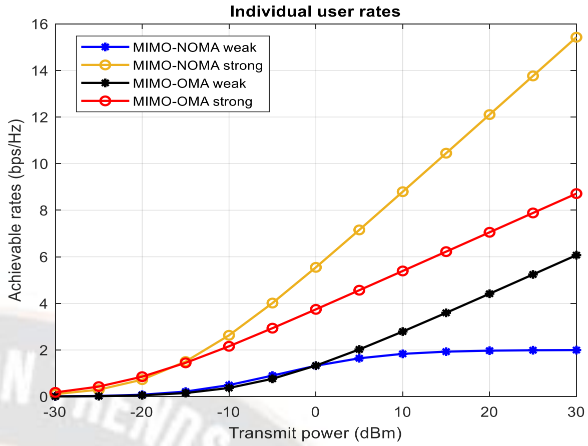

Figure 3. Achievable rates for individual user rates between MIMO-OMA and MIMO-NOMA

We can notice Figure.3 shows that the weak user's achievable rate reaches saturation after a transmission power of 10 dBm [43]. This pattern is frequently observed in various NOMA systems. The interference recognized by the less efficient user causes the achievable rate to be saturated. Saturation of the achieved rate is not considered as issue if the minimum data rate needed for the less efficient user is less than the saturation curve [44]. This problem cannot be observed in OMA because the ineffective user is not vulnerable to interference from concurrent transmissions.

A. *Outage Probabilities*

Next, generate user outage plots for both MIMO-NOMA and MIMO-OMA approaches. Since we are utilizing fixed power allocation, choosing the target rates and power allocation parameters is crucial. Let's determine the target rate for the weak user (U1) [45].

$R_1^* = 1bps/Hz$

and that of the strong user (U2) to be

$R_2^* = 3\ bps/Hz$

B. *MIMO-NOMA*

If the weak user's (U1) achievable rate, R_1 is lower than his desired rate, R_1^* . The user is experiencing an outage. Mathematically, this can be represented as,

$P_{noma}^1 = Pr\ (R_1 < \ R_1^*)$

The powerful user must successfully decode both his message and U1's message. In other words, the strong user must achieve the desired rates for U1 and U2. U2 will experience an outage if the target rate for U1 is not achieved OR if the target rate for U1 is achieved but not that of U2. Mathematically,

$P_{noma}^2 = P\,r(R_{12} < R_1^*) + Pr\ (R_{12} < R_1^*, R_2 < R_2^*)$

C. *MIMO-OMA*

The outage equations for MIMO-OMA can be expressed in a straightforward

$P_{oma}^1 = pr(R_{1,oma} < R_1^*)$

$P_{oma}^2 = pr(R_{2,oma} < R_2^*)$

The outage graph looks like this:

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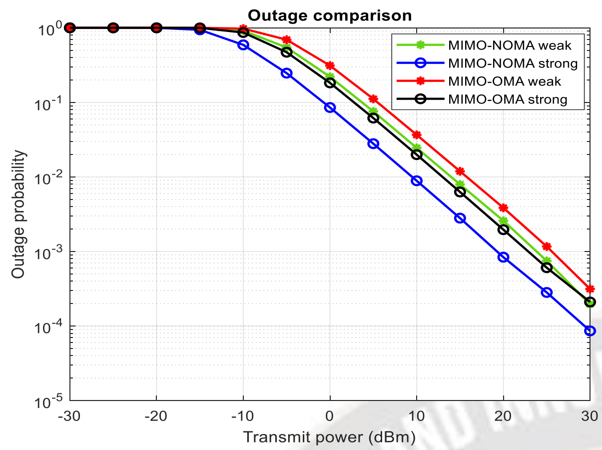

Figure 4. Illustrates a comparison of outage probability graphs between MIMO-OMA and MIMO-NOMA.

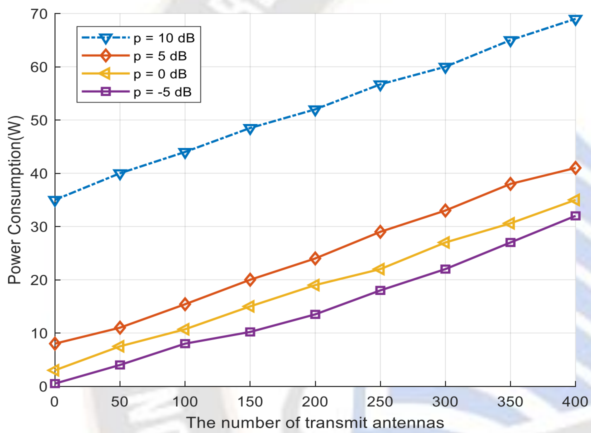

Figure 5. Depicts the Transmit power consumed and the count of transmit antennas corresponding to each ρ value.

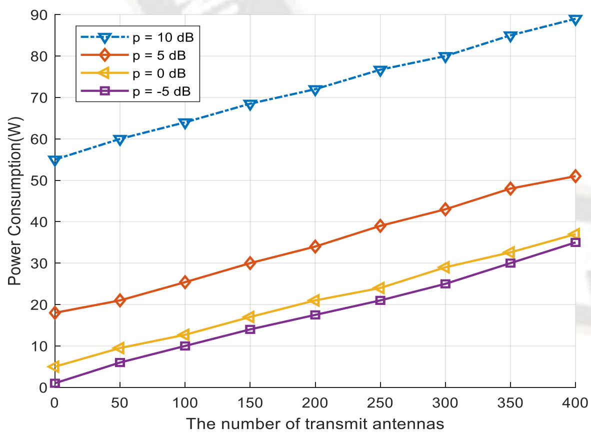

Figure 6. Shows the Transmit power consumption and the quantity of transmit antennas for each ρ value.

Figure 5 shows the power consumed and its relationship with the number of transmit antenna. For Figure 5, we found that the power consumption increases for each value of ρ, and it's could be reaching 88 W, which not good if the System requires enhanced EE. Based on the proposed algorithm, we can find that the power consumed decreased more than once, which is better than the traditional method. We can see that in Figure 6, which will be affected by the value of EE due to the lower power consumed compared to Figure 5.

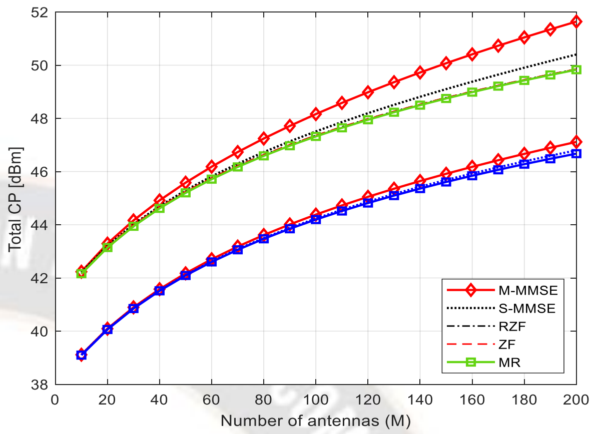

Figure 7. Illustrates the strategies and associated value sets, with the conditional probability (CP) showing improvement with the M (number of antennas) increase in the M-MMSE.

In Figure 7, we set K to 15 and vary M from 15 to 200. The Conditional Probability (CP) improves with the increase in M for both schemes and value sets. M-MMSE exhibits the highest CP, followed by S-MMSE. Notably, S-MMSE, which lacks inter-cell channel estimations for Value Set 1, experiences an overall CP reduction ranging from 0.5% to 25%.

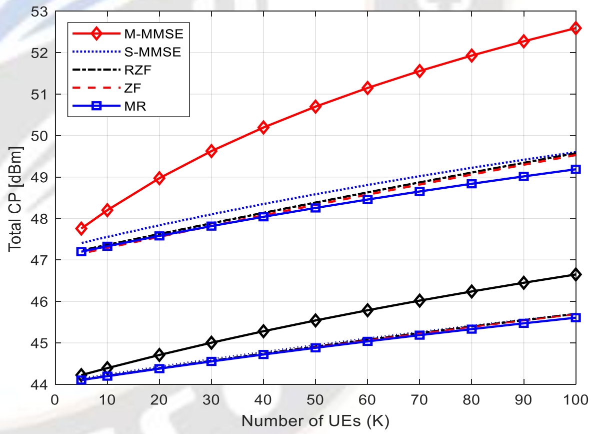

Figure 8. Shows the Circuit Power rises when Users increase

In Figure 8, we fix M at 100 and vary K from 10 to 100. The Circuit Power shows an increase with the rising number of users, yet the rate of increase is less pronounced compared to variations in M. The general trends for both values remain consistent, with M-MMSE requiring the highest CP and MR the lowest. For Value Set 1, M-MMSE demands 8%–100% higher CP than S-MMSE, a reduction to 5%–25% for CP.

Figure 9 and Figure 10 illustrate the variation in Energy Efficiency (EE) with transmit power. The curves in the first figure represent 'Max EE,' while those in the second figure depict 'Max SE.' At minimal power transmit, 'Max SE' corresponds to 'Max EE,' and the two metrics increase as transmit power increases. However, once the transmit power reaches a certain level, further increases do not result in higher EE. Consequently, 'Max EE' stabilizes while 'Max SE' declines. This underscores the importance of implementing energy-efficient Power Allocation, particularly in scenarios with high transmit power.

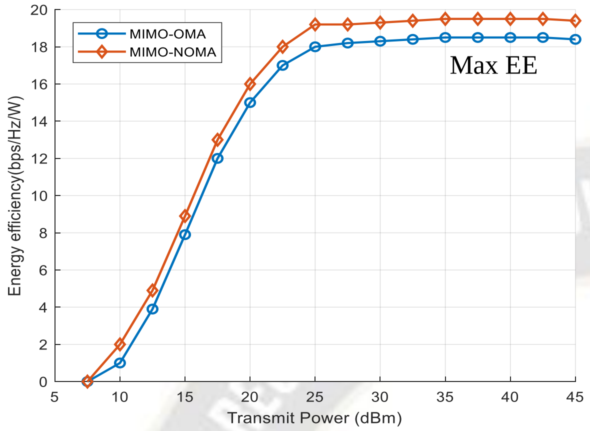

Figure 9. It illustrates the maximum energy efficiency plotted against the total power available at the base station for MIMO-OMA compared to MIMO-NOMA.

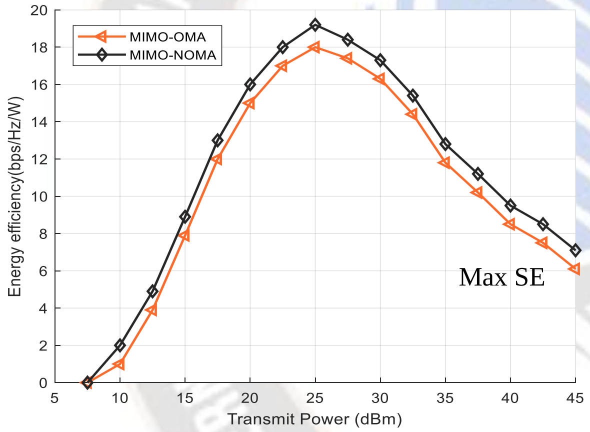

Figure 10. Shows the maximum spectral efficiency (SE) plotted against the total power available at the base station for MIMO-OMA compared to MIMO-NOMA.

NOMA demonstrates superior Energy Efficiency (EE) at lower transmit power levels. However, contrasting results are observed under higher transmit power conditions. This can be rationalized by the increased difficulty in meeting Quality of Service (QoS) for numerous users at low power levels. Conversely, at higher power levels, more users contribute to greater diversity, elevating EE. Yet, as the distance disparity between users grows, the energy cost of admitting an additional user escalates. Consequently, even at higher transmit power, the advantageous diversity effect is insufficient to offset the energy is essential to admit additional users. The relationship that exists between allowing extra users to be admitting and attaining higher EE is depending on transmit power levels and user distance disparity.

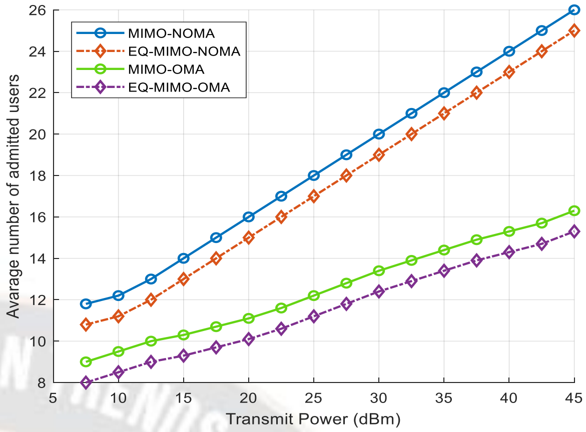

Figure 11. Shows the Average number of admitted users versus transmit power where the number of requesting users per cluster is 18 for MIMO-NOMA and MIMO-OMA.

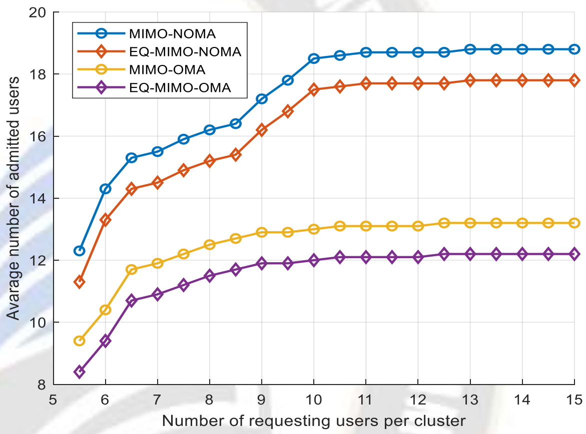

Figure 12. Illustrates the mean number of accepted users with the count of requesting users per cluster, with a fixed transmit power of 20 dBm.

In Figures 11 and 12, We evaluate the effectiveness of the proposed NOMA user admission scheme. For comparative analysis, we introduce a baseline algorithm labeled 'EQ-NOMA,' derived from the NOMA method in [42] distributes equal power across each cluster. In contrast to traditional OMA, provided two scenarios: OMA with power distribution throughout clusters ('OMA') and OMA with equal power distribution across clusters ('EQ-OMA'). The figures show that NOMA outperforms OMA in terms of the total number of admitted users, considering parameters such as transmit power, minimum rate needed, and the number of requesting users. Additionally, enabling power transfer among clusters for NOMA and OMA results in more admitted users. Moreover, the average number of admitted users shows an increasing trend with transmit power. This is explained by the increased likelihood of users with superior channel gains seeking service when there is a higher demand, leading to lower power requirements to fulfill their minimum rate criteria and allowing the admission of more users within the fixed total power constraint.

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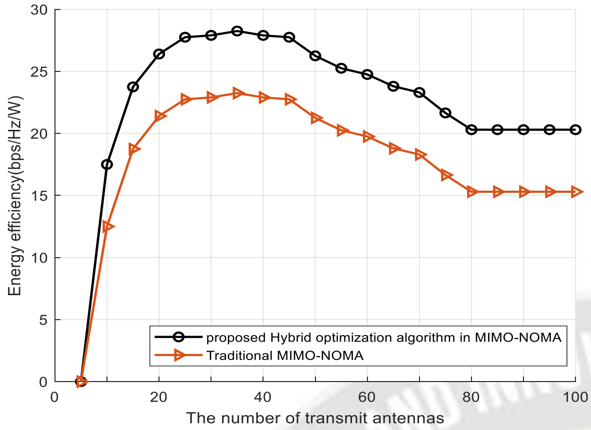

Figure 13. Ilsturate a comparison between the energy efficiency of the proposed method and the typical MIMO-NOMA multiple cellular systems for $\rho = -5$ *and* $\rho = 0$.

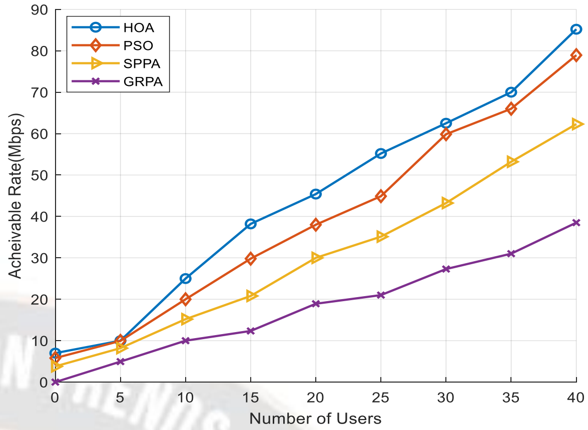

Figure 15. Shows a comparison between the Achievable rate against the number of uses for different optimization algorithms HOA vs. PSO vs. SPPA vs. GRPA

Figure.13. shows how the proposed optimization algorithm (HOA) can give better energy efficiency compared to the traditional way of solving the formulation problem of the MIMO-NOMA system, which can provide a better performance of transmitting data, especially since this algorithm can provide lower power consumption. We can see that clearly in Figure 5. And figure.6

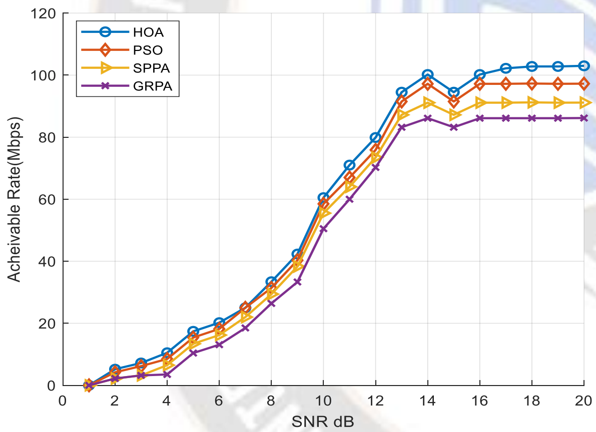

Figure 14. Shows a comparison between the Achievable rate against SNR for different optimization algorithms HOA vs. PSO vs. SPPA vs. GRPA

Figure.14. shows how the Proposed optimization algorithm (HOA) can achieve a high Achievable rate compared to the PSO [44], SPPA [45], and GRPA [46] because HOA combines different optimization techniques and strategies, leveraging the strengths of multiple methods. This hybridization allows it to adapt to a wide range of optimization problems. We can see from Figure.15 that the hybrid algorithm outperforms the most-used algorithms because HOA can dynamically adjust its search strategy and parameters based on the issue and its progress. This adaptability allows it to fine-tune the optimization process.

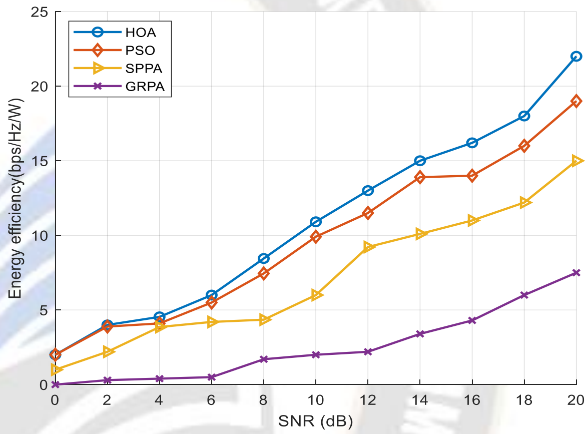

Figure 16. Shows a comparison between Energy Efficiency against SNR for different optimization algorithms HOA vs. PSO vs. SPPA vs. GRPA

In terms of optimization technique, we can see from Figure.16. that HOA can increase EE by more than (10 – 20) % compared to other algorithms such as PSO, SPPA, and GPRA. And that's because HOA often incorporates parallelism in its evaluation of solutions. This parallel processing can accelerate the optimization process, helping to find energy-efficient solutions more quickly. From Figure.17. it's easy to notice that the HOA overtakes these algorithms. HOA's ability to adapt to individual user requirements, multi-objective optimization capabilities, and resource allocation strategies allow it to achieve high energy efficiency for each user within a MIMO-NOMA network. However, the specific Performance of HOA in achieving energy efficiency depends on the problem, parameters, and the quality of its implementation in the given context.

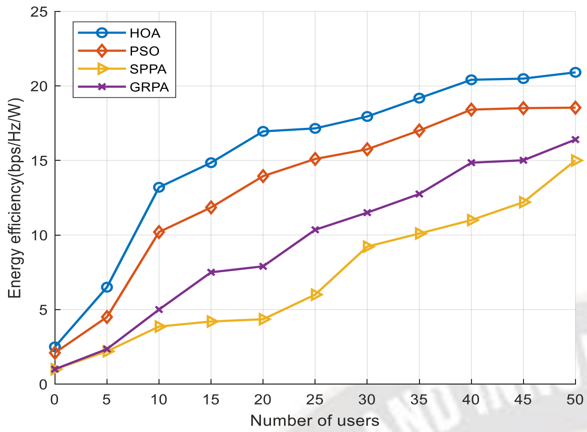

Figure 17. Shows a comparison between Energy efficiency against the number of uses for different optimization algorithms HOA vs. PSO vs. SPPA vs. GRPA

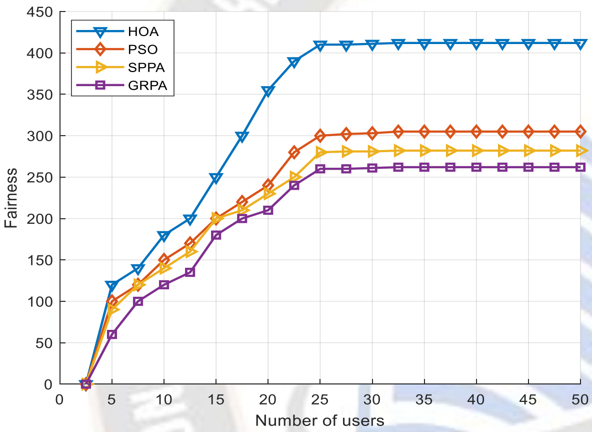

Figure 18. Shows a comparison of Fairness against the number of uses for different optimization algorithms HOA vs. PSO vs. SPPA vs. GRPA

In the context of user fairness, the user-centric approach of HOA is evident in Figure. 18, where it prioritizes individual user needs and characteristics. This approach ensures that resource allocation decisions are tailored to each user's specific channel conditions, traffic demands, and Quality of Service constraints. HOA can integrate fairness metrics and constraints into its optimization objectives, promoting equitable resource distribution among users while maintaining accuracy. Regarding accuracy, as depicted in Figure. 19, HOA demonstrates superior Performance with minimum mean square error compared to PSO, SPPA, GA, and GRPA. To summarize, HOA's adaptability, multi-objective optimization capabilities, user-centric approach, and dynamic resource allocation position it as a suitable choice for achieving high levels of user fairness and accuracy in resource allocation and optimization tasks.

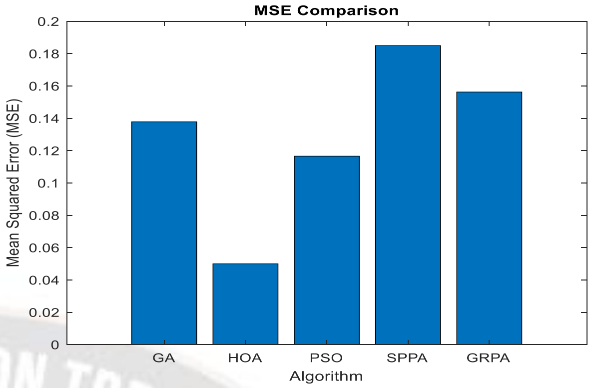

Figure 19. Shows a comparison of MSE for different optimization algorithms HOA vs. PSO vs. SPPA vs. GRPA

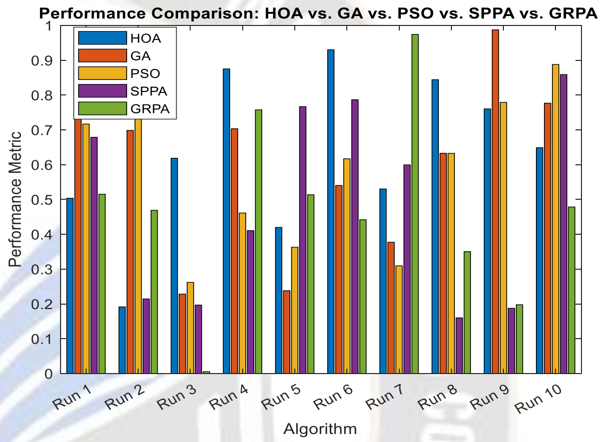

Figure 20. Shows a Performance comparison for the first running scenario for different optimization algorithms HOA vs. GRPA vs. PSO vs. SPPA vs.GA

In terms of Performance, we compare HOA with different algorithms. We notice from scenario one (first running scenario), as in Figure.20. that some algorithms can reach better Performance than HOA, as in Run 1, Run 2, Run 5, Run 7, Run 9, and 10 for the first running scenario. But let's refer to Figure.21. After improvement, we start with a second running scenario. In this case, we can notice that HOA overtakes all other algorithms, such as GA, PSO, SPPA, and GRPA.

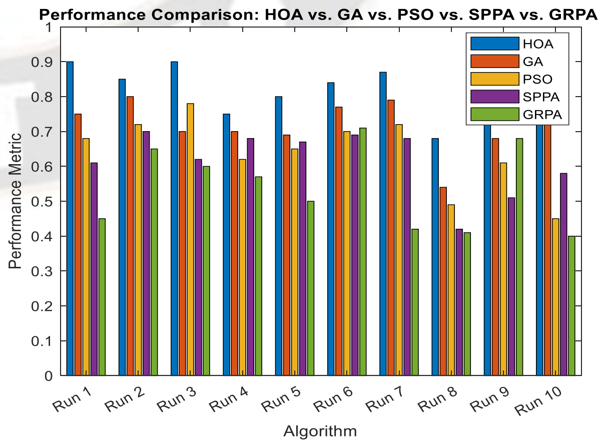

Figure 21. Shows a Performance comparison for the third running scenario for different optimization algorithms HOA vs. GRPA vs. PSO vs. SPPA vs.GA

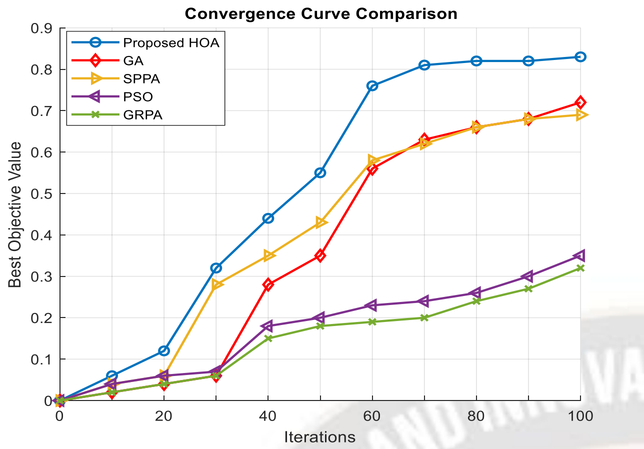

Figure 22. Shows a convergence comparison for best objective value against iteration for different optimization algorithms HOA vs. GRPA vs. PSO vs. SPPA vs.GA

The proposed HOA algorithm, as depicted in Figure. 22, excels in achieving the best objective value based on the application. HOA provides the flexibility to create tailored objective functions that explicitly prioritize user fairness and accuracy. This effectiveness stems from several factors. Firstly, HOA dynamically adapts its optimization strategy and parameters to the characteristics of the specific problem at hand, allowing it to fine-tune its approach for optimal results. Secondly, HOA often conducts parallel evaluations of solutions, leading to faster convergence and better solution space exploration, particularly in high-dimensional problems. The adaptability of HOA extends to parameter tuning, enabling the fine-tuning of algorithmic parameters to optimize Performance for different scenarios. For applications where energy efficiency is paramount, HOA can be customized to prioritize energy-saving objectives and power allocation strategies, considering the next generation as a waste of energy. However, it's essential to recognize that the Performance of an optimization algorithm can vary based on the nature of the optimization problem. While HOA may excel in specific scenarios, it may not always be optimal for every situation. The selection of an algorithm should be guided by the particular requirements and characteristics of the problem at hand, and empirical assessments are crucial for identifying the most appropriate algorithm for a given task.

X. Conclusion

This study introduced a sustainable power consumption model incorporating transmit power considerations. We examined the evolution of Energy Efficiency (EE) in multiple cellular systems, mainly focusing on 5G Base Stations (BSs) equipped with MIMO and NOMA systems. The deployment of MIMO systems at BSs in cellular networks emphasizes the need for more energy-efficient communication. Our research facilitates identifying the optimal number of transmit antennas at BSs for peak energy efficiency, drawing insights from multi-cell systems. Comparative analysis with other algorithms highlights the superior Performance of the Hybrid Optimization Algorithm and Power Allocation strategies, outperforming PSO, WTF, SPPA, and GA in optimizing Energy Efficiency (EE), power consumption, and the number of users who have been admitted. the energy efficiency of the system is dependent on the first user's channel condition, emphasizing the importance of energy-efficient PA methods, especially for high transmitted power levels. The effect of increasing number of users on energy efficiency is determined by the transmit power level and the diversity of users' channel gains. Future research may leverage Artificial Intelligence for learning-based models maximizing Spectral Efficiency (SE) and EE metrics for environmentally sustainable wireless communication. While progress has been made in intelligent machine-learning solutions, this research area is developing and requires additional attention and resources. Exploring innovative ML architectures prioritizing computational efficiency and minimal energy consumption during training and application, coupled with advanced power control methods, holds promise. In intricate scenarios like Coordinated Multi-Point (CoMP) massive MIMO setups, including joint Access Point (AP) selection and user assignment, developing novel power control algorithms is crucial for superior outcomes in complex configurations.

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