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Hybrid ABC-JAYA Algorithm for Optimizing Resource Allocation in NOMA-Based Downlink Systems

Karima Ait Bouslam [1], Jamal Amadid [2], Radouane Iqdour [1,3],Abdelouhab Zeroual[1,*]

[1] *I2SP Group, Faculty of Sciences Semlalia, Cadi Ayyad University, Marrakesh, Morocco*
[2] *Higher Institute of Engineering and Business(ISGA)*
[3] *CRMEF, Marrakesh Safi, Morocco*

Abstract Achieving significant spectral efficiency and enabling massive connectivity are paramount for wireless communication systems in the fifth generation (5G) and beyond. Non-Orthogonal Multiple Access is currently an efficient multiple access method to achieve these objectives. NOMA provides a number of advantages, including enhanced sum rates, improved user fairness, and increased spectral efficiency. This is mainly due to allowing several users to share common resources simultaneously, as a result, the conventional orthogonal multiple access method's orthogonality is disrupted. Instead, resource allocation remains the main issue in NOMA due to considering the coupling between power allocation and user pairing. In this article, we propose a methodical approach that involves refining the user pairing strategy and power allocation while adhering to constraints on power allocation and enhancing spectral efficiency. Specifically, our approach utilizes the most considerable user distance for the user grouping strategy. For power allocation, we propose a hybrid algorithm that combines the JAYA and Artificial Bee Colony (ABC) algorithms. Results of simulation indicate that our suggested outperforms conventional approaches, such as fractional, fixed power allocation, NOMA-PSO, NOMA-JAYA and NOMA-ABC by enhancing spectral efficiency by at least $50bits/s/Hz$ and improving the bit-error rate performance. Furthermore, the research explores the impact of different modulation schemes on the proposed strategy.

Keywords NOMA, Spectral efficiency, Power allocation, User pairing, JAYA algorithm, ABC algorithm .

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1. Introduction

With the advent of the 5G technology, several applications have been proposed [1], among them smart devices, e-health, and internet of things smart cities, which fall under the following groups: (i) vast machine type communications, (ii) ultra reliable and low latency communications (U-RLLC) [2], and (iii) enhanced mobile broadband (EMB) [3] [4]. Massive connectivity, lowest latency, massive data rates, and effective spectral efficiency are the requirements of these applications. According to the International Mobile Telecommunications Union (IMTU) and International Telecommunication Union (ITU) [5], 5G networks must be able handle a large user base, and provide a minimum data rate of 10 Gbps, which is 100 times faster than LTE and the Third Generation Partnership Project (3GPP). Additionally, 5G networks should achieve attain 1 ms of latency and a minimum spectral efficiency of 30 bps/Hz [6]. However, existing orthogonal multiple access (OMA) techniques cannot fulfill these requirements or achieve the desired performance. [7].

*Correspondence to: Karima Ait Bouslam (Email: K.aitbouslam.ced@uca.ac.ma). I2SP Group, Faculty of Sciences Semlalia, Cadi Ayyad University, Marrakesh, Morocco.

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Different OMA access has been adopted duringthe fi rst to the fourth generation, where the usage of the orthogonally for different resources, frequencies, times, or codes is common, during the first to the third generation (1G to 3G), the following methods have been used: frequency division multiple access (FDMA), time division multiple access (TDMA), and code division multiple access (CDMA), respectively. Then, the Long-term evolution known as 4G, used the orthogonal frequency division multiple access (OFDMA) [8], where users are spread throughout time and frequency domains and used also for both uplink and downlink for the 5G network [9]. Although OMA techniques offer simple receivers and reduce interference, they inefficiently allocate spectrum by assigning a dedicated bandwidth to each user. Consequently, OMA cannot efficiently serve multiple users while maintaining high spectral efficiency and data rates, which are critical for 5G performance [10], [11]. In response to this challenge, other multiple access techniques must be developed to meet these requirements. Unlike OMA, non-orthogonal multiple access (NOMA), allows multiple users to share the same resources [12], which improves the overall throughput and spectral efficiency of the system [13]. Where, different versions of the NOMA are proposed, depend on the type of resources shared between users (times, frequency or code). Where, the downlink version of the NOMA was introduced by the 3rd Generation Partnership Project (3GPP LTE-A) in the Release 14 [14],known as multiuser superposition transmission (MUST). Then, the studies were restarted Release 15. In this article, we adopt the PD-NOMA, where users are given varying power levels according to their channel conditions, Users who have poor channel conditions are given higher power levels, whereas those who have good channel conditions are given less power levels [15]. At the transmitter the users signals are superposed employing superposition coding (SC) in conjunction with successive interference cancellation (SIC) at the receiver, in which user's signals are decoded successively, where the users with the most significant signal are decoded initially, and then deducted from the signal that was superposed following by decoded the users with weakness signal. This process is iterated until all users signals are decoded.

In PD-NOMA, resource allocation includes power allocation and user grouping is crucial and influenced by channel gain differences between users [16], [17]. Improper power allocation and user grouping strategies can degrade BER(bit-error rate)performance, reduce user fairness, and decrease spectral efficiency. Spectral efficiency is one of the most interesting research topics in the fifth generation, where the optimal resource allocation has been investigated in various research studies for the sum-spectral efficiency subject to the power allocation constraint [18]. In recent studies, several power allocation techniques have been investigated [19], which are categorized as either Dynamics Power Allocation (DPA) or Fixed Power Allocation (FPA). FPA assigns a set ratio of users'power without considering channel conditions [20], while DPA adopts power allocation based on channel state information [21], [22]. Numerous FPA techniques have been investigated, such as Equal Power Allocation (EPA) [23], [24]. Despite its simplicity, FPA cannot provide an optimal power allocation. Consequently, Fractional Transmit Power Allocation (FTPA) for NOMA-based systems was introduced as a dynamic technique based on channel conditions [25]. While power allocation is essential for effective NOMA implementation, user grouping also plays a crucial role. Various user grouping strategies have been proposed based on channel conditions and user distance, such as random pairing [26], the Next Largest User Pairing Algorithm (NLUPA), and the Divided Next Largest User Pairing Algorithm (D-NLUPA) [27]. Overall, resource allocation is the major obstacle in NOMA due to the coupling of power allocation and user grouping. Power allocation optimization is also non-convex problem with various constraints, making it difficult to solve directly. Numerous studies have addressed different performance aspects such as system throughput, fairness, BER, and outage probability. In [28], a hybrid scheme based on the user paring approach and power allocation, was deduced to maximize the entier throughput and fairness, integer linear algorithm has been adopted for the user pairing, the user pairing, whereas power allocation is carried out using particle swarm optimization(PSO). The algorithm's efficiency is very high, but also the complexity is very high. In another study [29], a step-by-step deep learning network (DL) and user pairing strategy optimization was proposed to maximize the sum rate subject to minimum user data rate constraints. Users are first grouped using the maximum gain difference, followed by power allocation. This technique achieves a high sum rate compared to existing methods, with mathematical formulas and simulation results provided. Additionally, a novel approach to power allocation for downlink NOMA-based systems employed an upgraded artificial bee colony algorithm (MABC) to optimize sum rate throughput [30], subject to power allocation constraints and minimum user throughput. The MABC algorithm outperforms standard ABC algorithms and conventional NOMA, with both theoretical and simulation results provided. Furthermore [31], an optimal approach (OPS) for user pairing, suitable for two or three users, was developed based on the Hungarian work assignment problem for fairness index optimization, using a genetic algorithm for power allocation. Simulation results indicate this technique's efficiency compared to conventional NOMA and OMA. Lastly, a hybrid approach to allocating resources that combines user pairing with Walsh-Hadamard Transform for NOMA was proposed [32]. Simulation results confirm this technique's efficiency in terms of high data rates, user fairness, and lower BER.

1.1. Contributions

Throughout this work, we suggest a hybrid strategy for allocating resources, focusing on both allocating power and using a user pairing approach, for downlink power-domain NOMA-based systems. Our primary goal is to optimize the overall spectral efficiency. We present a detailed mathematical model for the spectral efficiency optimization problem, subject to power allocation constraints. This model addresses the inherent challenges posed by the non-convex nature of power allocation in NOMA-based systems. For tackling the optimization problem's complexity, we decompose it into manageable sub-problems. Initially, users are grouped based on their distance, with a strategy that pairs users with the largest distance differences. This user grouping step is critical in maximizing the channel gain differences among paired users, which is essential for effective NOMA implementation. Then, we introduce ABC-JAYA is a new hybrid optimization algorithm integrates the strengths of JAYA and Artificial Bee Colony (ABC) algorithms. This hybrid approach, addressing the convergence issues typically associated with the conventional ABC algorithm and enhancing the optimization process's overall efficiency. Finally, based on the hybrid optimization algorithm, for power allocation, we derive a closed-form solution that adheres to the defined constraints. This solution ensures optimal power distribution among users, which is crucial for maintaining high spectral efficiency. Our proposed technique significantly improves spectral efficiency and the system's BER. Through optimizing both user pairing and power allocation, the approach ensures a more robust and reliable NOMA-based downlink system.

1.2. Paper organisation

The structure of the article is defined below, Section 2 provides the system model and problem formulation for spectral efficiency optimization. Section 3 offers summary of allocation of resources. Section 4 presents the proposed user pairing technique and power allocation utilizing the ABC-JAYA algorithm. The simulation results of the suggested algorithms are shown in 5. Section 6 provides a summary of the study's findings and outcomes. Lastly, Section 7 presents paper Limitaion.

2. System model

A downlink scenario utilizing a NOMA system is studied, where N users are served by a single Base Station (BS). Both users and the base station use a single antenna (Fig.1 presents a NOMA based multi-users scenario). Considering the use of the SC, signals from various users are superposed on a single subcarrier and given varying power levels. Specifically, users with better channel conditions are assigned lower power levels, while those with poorer channel conditions are assigned higher power levels [33]. The detection of user signals becomes more complex while SC is employed at the transmitter because it raises interference. At the receiver SIC is implemented to overcome this issue. In this process, the signals from various users are successively decoded: after the strongest reception user's signal has been decoded, it is subtracted from the superposed signal. Until the signals of every user are identified, the process is repeated.

Assumed in this study is that users distribute evenly in a circle around the base station, with distances ranging between d_{min} and d_{max}. The BS serves N users, denoted as $n = \{1, \ldots\ldots N\}$. Users are evenly distributed among the p subchannels that make up the system's overall bandwidth, B. There are allowed no more than two users per subchannel. The following is an expression for the superposed signal:

$$X = \sum_{j=1}^{N} \sqrt{p_j} \times data_j \tag{1}$$

The signal of received by the j_{th} user is expressed $data_j$, p_j denoted the power delivered by the BS to the j_{th} user, where The overall power accessible at the transmitter is $P_{total} = \sum_{j=1}^{N} p_j$. The users are allowed with fractional power allocation defined as $p_j = \alpha_j \times P_{total}$ [34]. The superposed signal is transmitted over the Rayleigh channel and expressed as follows:

$$Y_j = X_j h_j + W_j \tag{2}$$

where $h_j = g_j d_j^{\frac{-\zeta}{2}}$ is the wirless channel between the j_{th} user and BS,$g_j \backsim (0, 1)$ is a fading coefficient with the Rayleigh distributions, d_j is the distance separating the j_{th} user and the BS is dependent path loss exponent (i,e.ζ), W_j is the additive white Gaussian noise with zero mean and variance σ_n. Where $p_1 < p_2 < \ldots < p_N$ is the sorted order of the provided power to the users, where the p_1 is assigned to the near user to BS and the P_n to the farthest user. The arrange channel gain of the users in this design is sorted as $g_1 > g_2 > \ldots > g_N$. Then, in each subchannel, the signal of the strong user with the higher power level is demodulated first. Subsequently, the interference is canceled, and the weaker user signal is decoded according to the principles of SIC [35]. Thus, the sum rate of j_{th} user according to Shannon theorem is expressed as follows:

$$R_j = B \times log_2(1 + \frac{\alpha_j P \mid h_j \mid^2}{P \mid h_j \mid^2 \sum_{m=i+1}^{M} \alpha_j + \sigma_n})[bps] \tag{3}$$

Note that the following is the expression for the overall rate of the users nearest to the BS:

$$R_N = B \times log_2(1 + \frac{\alpha_N P \mid h_M \mid^2}{\sigma_m})[bps] \tag{4}$$

The downlink NOMA system's total rate is thus represented as follows:

$$R_c = \sum_{j=1}^{N} R_j \tag{5}$$

Where the spectral efficiency for every subchannel is defined as:

$$SE_c = \frac{R}{B_c} \tag{6}$$

Where SE_c and B_c, are the spectral efficiency and the bandwidth of the subchannel. The downlink NOMA system's total spectral efficiency is thus represented as follows:

$$SE = \sum_{c=1}^{C} SE_c \tag{7}$$

The following is the expression of user fairness:

$$F = \frac{(\sum_{j=1}^{N} R_j)^2}{\sum_{j=1}^{N} R_j^2} \tag{8}$$

Where, R_j is the user data rate.

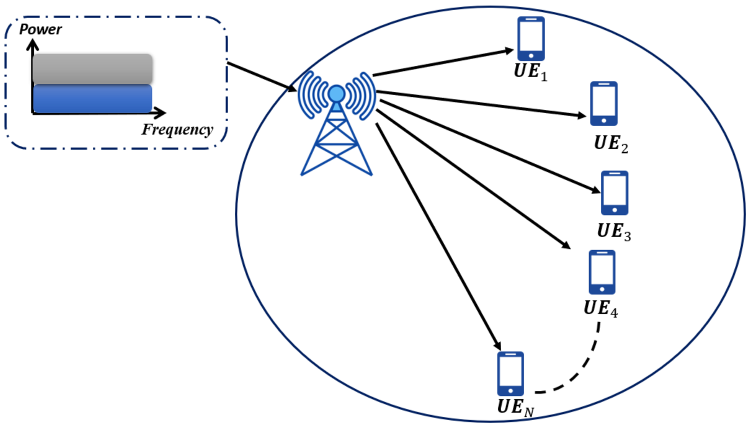

Figure 1. The Basics NOMA System's downlink transmission

2.1. *Problem Optimization*

According to equations (3), (4), (5), and (6), the system's overall spectral efficiency depends on both resource and power allocation. Identifying an effective method for allocating these resources among users is crucial for improving system performance. Therefore, the optimization problem aims to maximize the total sum rate across N users by allocating transmission power appropriately. The optimization framework is driven by several key objectives, including improving the total data throughput. At the same time, compliance with the power budget ensures that the total transmit power does not exceed the base station's power capabilities. Moreover, the bounds on individual power allocation should be enforced to maintain the system's stability and fairness. Achieving these goals involves fundamental trade-offs: maximizing spectral efficiency may lead to disproportionate resource allocation favoring users with superior channel conditions, thereby reducing fairness; conversely, enforcing strict fairness can constrain overall system throughput. Accordingly, the following presents the formulation of the NOMA power allocation problem:

$$SE = max_{p_n} \sum_{n=1}^{N} R_n \tag{9}$$

Subject to:

$$s.t. \begin{cases} C1 : \sum_{n=1}^{N} p_n \leq P_T \\ C2 : p_n \geq 0 \\ C3 : \sum_{n=1}^{N} \alpha_j = 1 \\ C4 : 0 \leq \alpha_j \leq 1 \end{cases}$$

The optimization must account for fairness by imposing appropriate constraints, where $C1$, $C2$, $C3$ and $C4$ represent the constraints on the base station's maximum power limit and the transmit power allocated to each user. These constraints are summarized in Table.1. Furthermore, the optimal power allocation factors, must balance aggressive power utilization with adherence to the regulatory constraints, while also aiming to achieve a globally efficient and equitable outcome.

Table 1. Practical implications of constraints in the power allocation problem

Constraint	Description	Practical Implication
C1	Total transmit power must not exceed P_T.	Ensures that the base station operates within its maximum power capacity, avoiding hardware damage or regulatory issues.
C2	Each user's power allocation p_n must be non-negative.	Ensures physical feasibility, as negative power values are not possible in practice.
C3	The sum of power allocation factors α_j must equal 1.	Ensures the full power budget is fully utilized.
C4	The power allocation factors α_j must lie between 0 and 1.	Enforces fairness and avoids allocating disproportionately high or low power to any individual user.

Given these constraints, the problem formulation involves a non-linear function, making optimization issue that is NP-hard and non-convex, making it difficult to solve without significant computational resources. Therefore, in this work, we adopt a methodical optimization approach. First, users are grouped based on their distance, and then power is allocated to users using a combination of the Jaya algorithm and the Artificial Bee Colony algorithm.

3. Resource allocation

3.1. Grouping techniques for users in NOMA

In practical NOMA downlink systems, users are multiplexed on the same subcarrier, causing significant interference between users and a notable decrease in system performance, such as an increased bit error rate. To address this issue, a user grouping strategy should be employed where only two users are grouped on the same subcarriers. This approach helps reduce interference and decreasesthe receiver's computation complexity associated with SIC [36]. Various user grouping strategies based on channel state information have been proposed. One common strategy pairs users with the largest channel gains with users having the lowest channel gains [37]. Another strategy groups users based on channel similarity, where users with similar channel gains are paired in [38]. Also, in [39] a strategy based on medium channel gain quality has also been proposed.

3.2. Power allocation

Considering the PD-NOMA system's performance is dependent on the power allotted to users, power allocation is a crucial task. Inaccurate power allocation can degrade the system's performance, affecting key performance such as the user fairness and BER. Consequently, a variety of techniques for allocating power have been suggested in several research works. These methods divide into two groups: dynamic power allocation and static power allocation. When users are given equal power levels without taking user needs or channel state information (CSI) into account, this is known as fixed power allocation. This approach simplifies implementation and reduces system complexity. However, it is not suitable for all scenarios, particularly with the increases of the number of users or when user requirements vary. Several static power allocation techniques have been presented in previous studies. Among them is Fixed Power Allocation, where users are allocated a fraction of power, defined as follows:

$$\beta_n = \frac{B \times (1 - B)P_t}{N_{users}} \tag{10}$$

Equal power allocation(EPA) is a another static power allocation in which users are assigned with equal power, given as [40],

$$\beta_n = \frac{P_t}{N_{users}} \tag{11}$$

Despite the simplicity of implementation of Static power, FPA is considered as ineffective power allocation because of inconsideration of channel state information. In Dynamic power allocation, the power assigned to users is according to the user's channel state information called Fractional power allocation, where fractional power assigned to users is determined by their channel conditions, the FTPA is given by [41] ,

$$\beta_n = \frac{\mid h_n \mid^{-2*\beta FPTA}}{\sum_{n=1}^{N} \mid h_n \mid^{-2*\beta_{FPTA}}} \tag{12}$$

Where $0 \leq \beta_{FPTA} \leq 1$.

4. Proposed resource allocation technique

4.1. Proposed grouping strategy

Distance-based pairing is one of the most promising and widely used user pairing techniques in the literature. Among these, pairing users with the maximum distance difference, typically the nearest and farthest users, is the most commonly adopted strategy. In [42] , a joint angle and distance-based pairing approach is proposed, where a distance threshold is used to pair users. Simulation results demonstrate that this method outperforms several existing techniques. According to [43], selecting users with a large distance gap (i.e., pairing a far user and a near user with respect to the base station) achieves an accuracy probability of approximately 0.92 under a Poisson Point Process (PPP) model with a path loss exponent of 4. In contrast, random user pairing yields an accuracy probability of around 0.84. This improvement is due to the higher degree of channel distinctness between the farthest and nearest users, which enhances the effectiveness of SIC and reduces inter-user interference, thereby improving overall NOMA performance. Inspired by these insights, we propose a distance-based user grouping strategy, where users are first divided into two groups using a predefined distance threshold. An initial pairing is performed within each group, followed by an intermediate (or middle-user) pairing step to further refine the NOMA clusters. The proposed user grouping strategy consists of three main steps:

Initial Grouping by Distance: The cell is divided into groups based on a specific threshold distance value, where $d_{threshold} = \frac{d_{cellradius}}{2}$. Users with a distance less than the threshold are considered strong users (as shown in Fig.2), while weak users refer to those whose distance is beyond the threshold.

Grouping by Distance Difference: In the second step, pairs of users are formed based on the largest distance difference. Each pair consists of one strong user and one weak user. The user with the shortest distance from the strong group is paired with the user with the greatest distance from the weak group, and this process continues iteratively.

Grouping Middle-Distance Users: Finally, users with middle distances are grouped based on the largest distance difference, ensuring an optimal mix of users within each group.

This strategy ensures that users are grouped in a manner that reduces interference and optimizes resource allocation depending on their distance from the base station.

4.2. Proposed power allocation

4.2.1. Artificial bee colony algorithm based Power allocation

The ABC algorithm, an evolutionary tool according to Karaboga in 2005, is frequently used to address various constrained and unconstrained problems in electrical engineering. This algorithm simulates the behavior of honey bees in their search for high-quality food sources [44],[45]. The ABC algorithm is based on three categories of honey bees (i) employed Bees, (ii) Onlooker Bees (iii) Scout Bees. In conjunction, these bees choose the best feeding locations (flowers) among a range of possible locations (colony). The employed bees look for new food positions, or solutions, and use the amount of nectar to inform the observer bees about the quality of the food source. The observer bees assess the quality of the food sources and select the best one with a higher likelihood

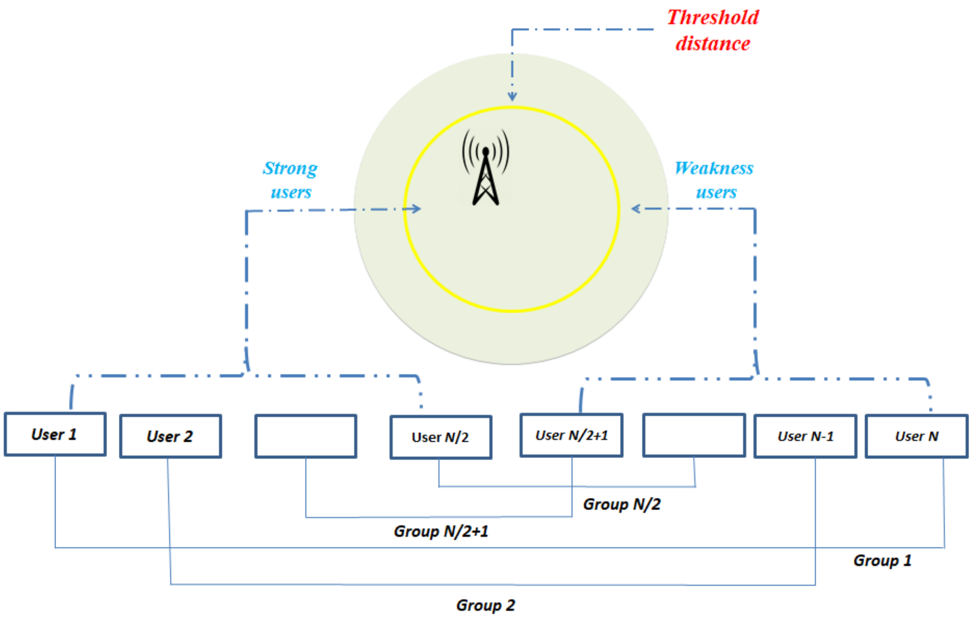

Figure 2. The suggested technique for user grouping

based on the data supplied by the bees that are engaged. Finally, the scout bees choose new food locations randomly if the employed bees are unable to enhance the quality of the food availability.

Every search for a new food source in the ABC algorithm consists of a set of optimization parameters. The quantity of working bees and observer bees is equivalent to the amount of the population (SN). Every solution has a D-dimensional vector representation, with $i = 1, 2, 3 \ldots SN$. The fitness value for each population position represents the amount of nectar or the quality of the food supply. The following is how the ABC algorithm performs:

Employed Bees: In this section is the initialization of the food source, $i = 1, 2, \ldots, SN$, and SN is the number of the initial population, then the fitness function is calculated and evaluated for each population position,

$$X'_{(j,i)} = X_{(j,i)} + \varnothing(X_{(j,i)} - X_{(j,k)}) \tag{13}$$

Where $X_{(j,k)}$ is chosen arbitrary, with k representing the employed Bees' index and $\varnothing$ being a random number between $[-1, 1]$, the fitness value of $X'_{(j,u)}$ is determined using the formula below:

$$fit_i = \begin{cases} \frac{1}{1+fi} & , f_i \geq 0 \\ 1+ \mid f_i \mid & , f_i \geq 0 \end{cases} \tag{14}$$

Where the objectif function is defined as f_i. If $fit(X'_{(j,u)}) > fit(X_{(j,u)})$ employed Bees memorize the best solution.

Onlooker Bees: The onlooker bees probabilistically select their new food sources, taking into account the food source acquired from the employed bees by employing the following formula:

$$p_i = \frac{fit_i}{\sum_{q=1}^{SN} fit_q} \tag{15}$$

The new food source is calculated using the greedy selection and the improved solution with maximum fitness value is memorized.

Scout Bees: If the solution can't be improved within this limit value L, then the scout bees search randomly new solution by the following formula ,

$$X'_{(i,u)} = min(X_{(i,u)}) + \varnothing(max(X_{(i,u))} - min(X_{(i,u))}) \tag{16}$$

4.2.2. *JAYA algorithm*

In 2016, Rao introduced the JAYA algorithm, which is an evolutionary tool, this optimization method used for constrained as well as unconstrained optimization task. With the exception of two regulating parameters, the JAYA algorithm does not require any specific controlling parameters, the population size (i,e., the candidate solutions) and the number de generations (i,e. the number of iteration) [46]. The optimization process of the JAYA algorithm is based on a single phase, where the idea of optimizing a solution involves transitioning from the worst possible solution to the best possible solution. The following is a description of the JAYA algorithm:

Step 1: The solution $k = 1, 2, 3....SN$ is initialized in this phase, where SN is the population size. For every k_{th} solution, the fitness function will be evaluated to determine which is the best $X_{l,best,i}$, and the worst solution $X_{l,worst,i}$ during l_{th} iteration.

step 2: for each i_{th} solution during l_{th} iteration, the worst and best solutions are used to calculate the candidate solution:

$$X'_{l,i} = X_{l,i} + r_{1,i}(X_{l,best,i} - |X_{l,i}|) + r_{2,i}(X_{l,worst,i} - |X_{l,i}|) \tag{17}$$

$r_{2,i}$ and $r_{1,i}$ are randomly selected in the range of $[0, 1]$. Where, $(X_{l,best,i} - |X_{l,i}|)$ is the tendency to approach to the optimal solution and $(X_{l,worst,i} - |X_{l,i}|)$ is the tendency to avoid the worst candidate. The fitness value is evaluated for each new solution, after the greedy selection is applied, the process is iterated until the convergence to the limit iteration.

4.2.3. *Proposed Modified JAYA-ABC Algorithm for power allocation*

Despite the ABC algorithm is widely used in several research works, but it suffers from a slow convergence to the optimum solution in the constrained problems [47]. To enhance the improper finding capability and overcome the weakness of the ABC algorithm, the onlooker and scout bees steps are modified using the JAYA algorithm phase. Consequently, the following equation is the updated solution search equation for the employed and onlooker bees phases:

$$\gamma = X_{l,i} + r_{1,i}(X_{l,best,i} - |X_{l,i}|) + r_{2,i}(X_{l,worst,i} - |X_{l,i}|) \tag{18}$$

The total rate and the power allocation represent the food source and objective function, respectively. After all users are paired using the proposed user pairing technique. The proposed technique for power allocation is explained as follows,

Step 1: This is the initialization parameters of the proposed algorithm, such as user grouped, the total power P_t , channel gains g_j and g_M, data length N, limits value L, number of iteration Max_{iter}, population size (SN) with D dimension .

Step 2: The power allocation factors is generated randomly using the following equation:

$$\beta_{i,u} = L\beta_{i,u} + rand(0, 1)(U\beta_{i,u} - L\beta_{i,u}), u \in SN andi \in D \tag{19}$$

Where $L\beta$ and $U\beta$ represent both the higher and lower limits of the power allocation population.

Step 3: To evaluate the objective function, the equation ((5)) is used, if any solution $\beta_{i,u}$ unable to meet the constraints conditions the penalty is integrated to the objective function and the best solution is Memorized. Each solution is updates using the modified search equation ((15)), after the greedy selection is applied and the optimal solution is memorized.

Step 4: Based on the probability calculated using this equation $p_i = \frac{fit_i}{\sum_{q=1}^{SN} fit_q}$, the onlooker bees select the power allocation position and produces new solution using equation ((15)).

Step 5: If any solution does not updated within the limit value L, then the scout bees generate randomly new solution using the following equation,

$$\beta'_{(l,i)} = min(\beta_{l,i)}) + \varnothing(max(\beta_{(l,i))} - min(\beta_{(l,i))}) \quad (20)$$

Step 6: This process (Step: **2** through **5**) is repeated for the number of iterations and best solutions are memorized. The suggested power allocation approach is depicted in Fig.3 and the psudo code is represnts in **Algorithm 1**.

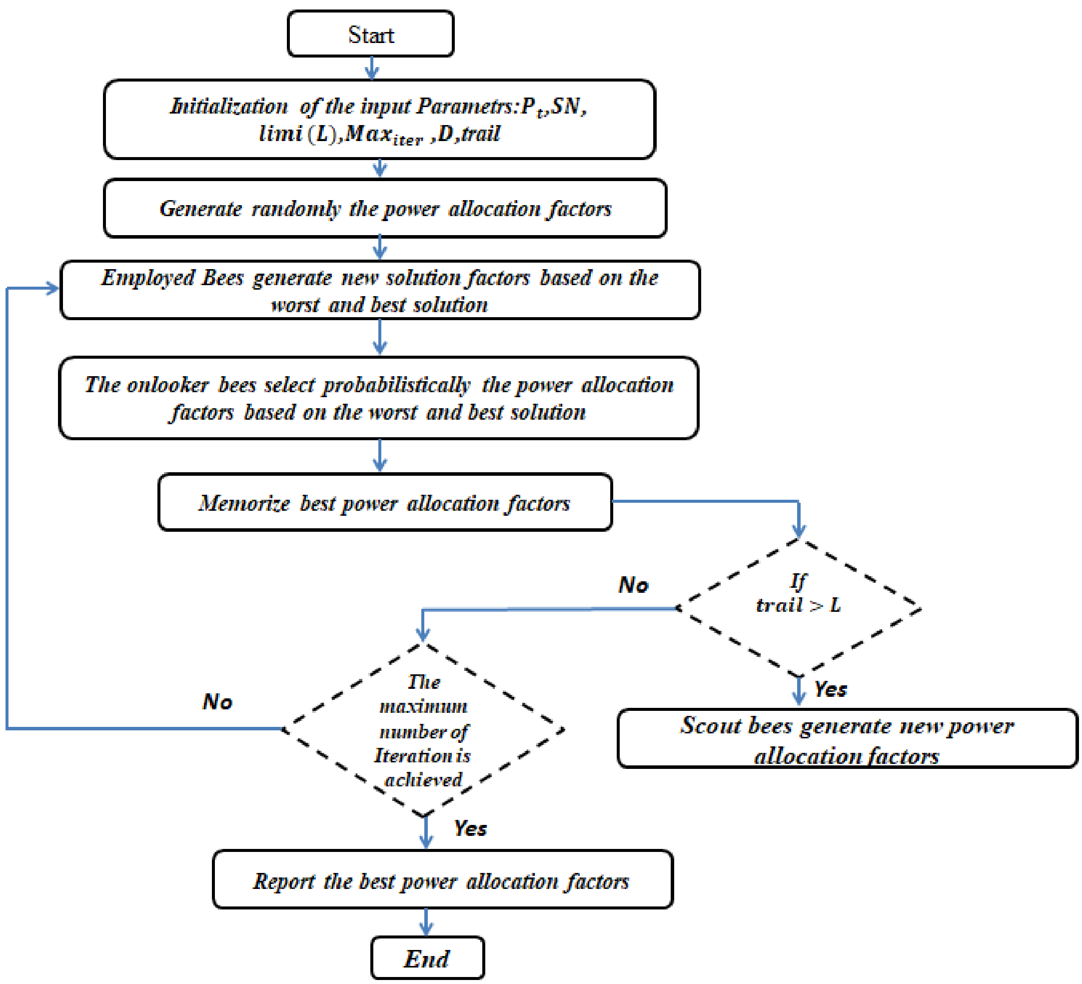

Figure 3. The flow diagram for the suggested power allocation method

Algorithm 1: Modified ABC with JAYA Phase for Power Allocation

REQUIRE: User groups, total power P_t, channel gains g_j, g_M, data length N, limit L, max iterations Maxiter, population size SN, dimension D, lower bounds L_β, upper bounds U_β

ENSURE: Best power allocation vector β_{best}

1. Initialize population β randomly for each solution $u = 1$ to SN and dimension $i = 1$ to D :
   $\beta[i, u] \leftarrow L_\beta[i] + \text{rand}(0, 1) \times (U_\beta[i] - L_\beta[i])$
2. Evaluate fitness of each $\beta[u]$ based on the objective function using Eq.14
3. Memorize best solution β_{best}
4. Initialize trail counters trail$[u] \leftarrow 0$ for all u
5. **for** $iter = 1$ to Maxiter **do**
   %%%%% **Employed Bees Phase**
6. **for** $u = 1$ to SN **do**
7. Identify best solution X_{best} and worst solution X_{worst} in the population
8. Generate new candidate γ using:
   $\gamma \leftarrow \beta[u] + r_1 \times (X_{\text{best}} - |\beta[u]|) + r_2 \times (X_{\text{worst}} - |\beta[u]|)$
9. Evaluate fitness of γ
10. **if** γ better than $\beta[u]$
11. $\beta[u] \leftarrow \gamma$
12. trail$[u] \leftarrow 0$
13. **else**
14. trail$[u] \leftarrow$ trail$[u] + 1$
15. **end if**
16. Calculate probability $p[u]$ for each solution proportional to fitness
17. **end for**
   %%%%% **Onlooker Bees Phase**
18. Select solution $\beta[u]$ based on probability $p[u]$
19. **for** $u = 1$ to SN **do**
20. Generate new candidate γ using the JAYA update:
   $\gamma \leftarrow \beta[u] + r_1 \times (X_{\text{best}} - |\beta[u]|) + r_2 \times (X_{\text{worst}} - |\beta[u]|)$
21. Evaluate fitness of γ
22. **if** γ better than $\beta[u]$
23. $\beta[u] \leftarrow \gamma$
24. trail$[u] \leftarrow 0$
25. **else**
26. trail$[u] \leftarrow$ trail$[u] + 1$
27. **end if**
28. **end for**
   %%%%% **Scout Bees Phase**
29. **for** any solution $\beta[u]$ with trail$[u] > L$ **do**
30. Generate new random solution:
   $\beta[u] \leftarrow \min(\beta) + \phi \times (\max(\beta) - \min(\beta))$
31. Reset trail$[u] \leftarrow 0$
32. Update β_{best} if a better solution is found
33. **end for**
34. **end for**
35. **return** β_{best}

4.2.4. The computational complexity analysis

Since the suggested approach is a hybrid, the computational complexity of both the ABC and JAYA algorithms must be considered. The computational complexity of the ABC and JAYA algorithms is the same, and there are no extra loops in either. Typically, the complexity of the initialization step is $O(SN \times D)$, where D represents the problem's size, which is the number of users N over each iteration. The fitness function operates over (N) dimensions per iteration for each solution, and equations (18) and (19) are used to modify the candidate solution during the JAYA-ABC phase. Consequently, in a worst-case scenario, the complexity of the computation of the suggested algorithm during Max_{iter} can be written as O($Max_{iter} \times SN \times N_{users}$). For the PSO-based power allocation in the NOMA system, the computational complexity is defined as $O(t_{PSO} \times \xi_{PSO} \times log(t_{PSO} \times \xi_{PSO}))$ [48], where ξ_{PSO} is the population size and t_{PSO} is the maximum number of iterations. A fair comparison of the computational and temporal complexity of previous methods, NOMA-ABC-JAYA, NOMA-ABC, NOMA-JAYA, and NOMA-PSO, is shown in the Table. 2. NOMA-JAYA, NOMA-ABC, and ABC-JAYA-NOMA approaches have the same computational complexity except for NOMA-PSO, but they execute slightly differently. For 1 iteration, NOMA-ABC-JAYA takes about 0.03 seconds to complete, which is a little faster than NOMA-ABC, which takes 0.05 seconds. In instances where cutting down on computing time is beneficial, this discrepancy implies that NOMA-ABC-JAYA would be a more effective choice.

Table 2. Algorithm complexity and computation time.

Algorithm	Complexity	1 Iteration	10 Iterations	100 Iterations
NOMA-JAYA	$\mathcal{O}(Max_{ier} \times SN \times N_{users})$	0.023sec	0.057sec	0.341 sec
Proposed(i,e.,NOMA-ABC-JAYA)	$\mathcal{O}(Max_{ier} \times SN \times N_{users}))$	0.03 sec	0.09 sec	0.70 sec
NOMA-ABC	$\mathcal{O}(Max_{ier} \times SN \times N_{users})$	0.05 sec	0.2sec	2.4sec
NOMA-PSO	$\mathcal{O}(t_{PSO} \times \xi_{PSO} \times log(t_{PSO})$	0.049 sec	0.24 sec	1.71 sec

5. Simulation Results and Discussion

The downlink NOMA scenario is implemented with 20 users uniformly distributed within a $500-meter$ radius cell, ranging from 50 meters to 500 meters from the BS. The users and the BS each have a single antenna, the channel gains between the BS and users are modeled using the Rayleigh fading channel, The Matlab 2016 is used for simulation steup . We employe 16- quadrature amplitude modulation $(16-QAM)$ with a noise power density of $-174dBm/Hz$ and a path loss exponent of 4. The overall bandwidth is set to $80MHz$. The simulation parameters utilized are summarized in Table.3. Additional simulation parameters are detailed in the figure captions. Optimizing the control parameters (i.e., limit value and population size SN and termination criteria) of

Table 3. Simulation parameters

Bandwidth, B	80 MHz [49]
Number of users, N_{users}	20
Path loss exponent,α	4 [49]
Modulation used	$16-QAM$
Cell radius (R)	500 m
Size of the population (SN)	50
Noise power, N_o	$-174dBm/Hz$ [29]
Transmission power P_t	0to30dBm [49]
Termination criteria (T)	100
Distance threshold	250m
Population size	50

evolutionary algorithms like ABC and JAYA is important for achieving the best performance. These parameters significantly influence the convergence speed, solution quality, and overall stability of the algorithms. To select the population size SN we examine the spectral efficiency of our suggested assignment of resources in Table.4

for population sizes ($SN = 5, 10, 30, 50$), the results demonstrate that the gain in spectral efficiency reaches approximately 10% when increasing the population size from $SN = 5 to 50$. This improvement is due to the fact that larger initial population increases the probability of finding a highly effective solution. As the population size grows, the search space becomes more diverse, allowing the algorithms to explore a wider range of possibilities and potentially converge on an optimal solution with higher spectral efficiency. In this study, the maximum number of iterations was empirically set to 100 [50], as preliminary evaluations indicated that further increases in this parameter did not yield any appreciable improvement in performance metrics. This setting ensures computational efficiency while maintaining solution quality. For the proposed hybrid ABC-JAYA algorithm, the limit value is a key control parameter that governs the abandonment of stagnating food sources, thereby influencing the balance between exploration and exploitation. The limit value was determined using the standard formulation:

$$\text{limit} = SN \times D[50] \tag{21}$$

where SN denotes the population size, representing the number of food sources (i.e., candidate solutions), and D refers to the problem dimensionality, which, in this context, corresponds to the number of users in the system. This formulation allows the algorithm to adapt the abandonment threshold relative to the complexity of the problem, promoting a more effective and scalable search process.

Table 4. Effect of population size on spectral efficiency (bits/s/Hz) under different transmit total power

pop \ $P_t(dBm)$	0	5	10	15	20	25	30
5	4.7	7.4	9.459	12.3	17.48	23	32.18
10	5	8.3	10.84	14.01	19.48	25.01	34.22
30	6	9.01	11.2	14.15	20.35	25.9	35.74
50	7.8	13.4	18.31	24	32.05	39.3	50

On the other hand, Fig.4 illustrates the user distribution within the cellular network. The base station, represented by a red dot, is located in the middle of a 500-meter-radius circular cell. Each blue dot represents a user who distributed throughout the cell and at least 50 meters away from the base station.

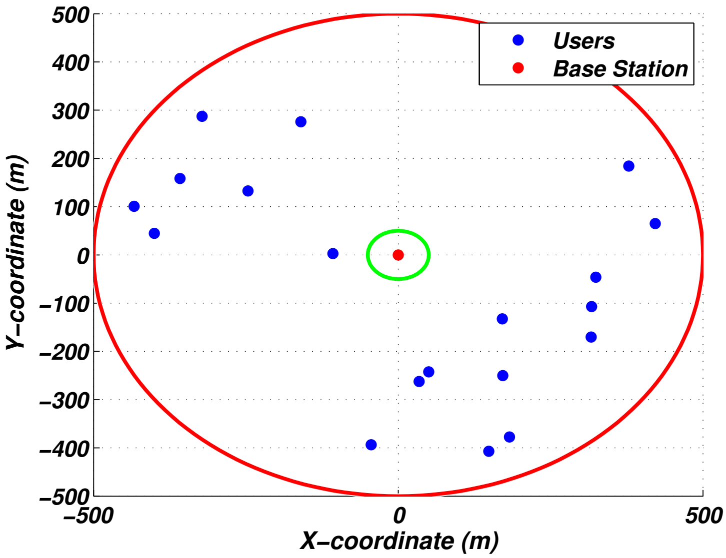

Figure 4. Distribution of users around Base Station

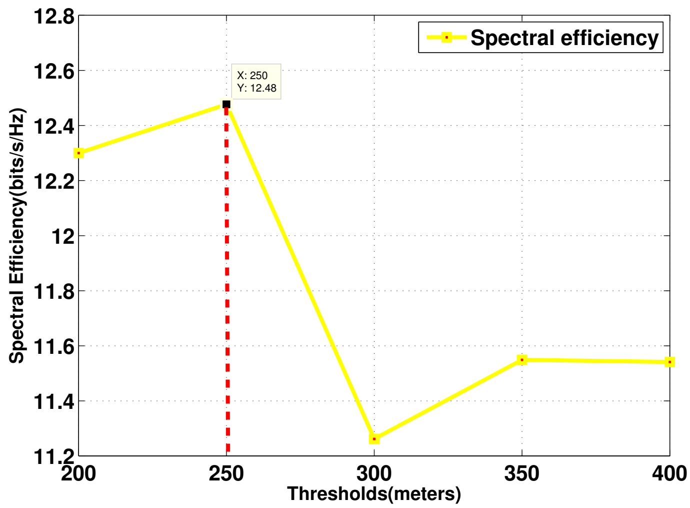

Figure 5. Spectral Efficiency(bits/s/Hz) of the paired user versus the distance threshold

5.1. Threshold distance Selection

The choice of the threshold distance is crucial, as it directly impacts the performance of the system. To examine this effect, we evaluate how varying the threshold value influences the spectral efficiency of the paired user, as shown in Figure.5. The analysis is conducted using the proposed allocation technique, which combines distance-based user pairing and power allocation based on the ABC-JAYA algorithm, with a transmit power of $P_t = 10$ dBm. As illustrated in Figure.5, increasing the distance threshold leads to a decrease in spectral efficiency. Notably, when the threshold distance is set to $d_{\text{threshold}} = 250$ m, the spectral efficiency reaches $SE = 12.48$ bits/s/Hz. This result validates the selection of $250m$ as an appropriate threshold value.

5.2. Study of the Convergence of the proposed technique

We set the termination criterion at $Tmax = 50$ iterations and transmit the power at $Pt = 25dBm$ to assess the convergence of the suggested repetitive hybrid technique. The optimal spectral efficiency values for every iteration are shown in Table.5. While the conventional ABC NOMA starts with a lower value of $23.1bits/s/Hz$ and reaches $30.88bits/s/Hz$ by the stiteration 50 , the proposed JAYA-ABC algorithm begins at $28.11bits/s/Hz$ at 10 iterations and reaches $34.96bits/s/Hz$ by 50 iterations. The results indicate that the suggested technique exhibits faster convergence with better spectral efficiency than the conventional ABC-NOMA.

Table 5. Optimal Value (spectral efficiency($bit/s/sHz$)) over 50 iterations

$Iteration$ / System	10	20	30	40	50
NOMA-ABC-JAYA	28.11	34.19	34.41	34.905	34.96
NOMA-ABC	23.1	28.68	29.46	30.15	30.88

To assess the convergence of the proposed technique the fitness function is plotted versus the number of terations (i,e. the number of iterations is 30) for both NOMA-ABC-JAYA and NOMA-ABC in Fig.6. As shown in this figure the proposed algorithm converge for 9 iterations, while the NOMA-ABC does not converge even for 30 iterations, which proves the efficiency of the proposed hybrid ABC-JAYA. Although, the ABC algorithm has a good searsh exploration to the gloobal optima however the converegence is main limitation [51], instead the JAYA algorithm

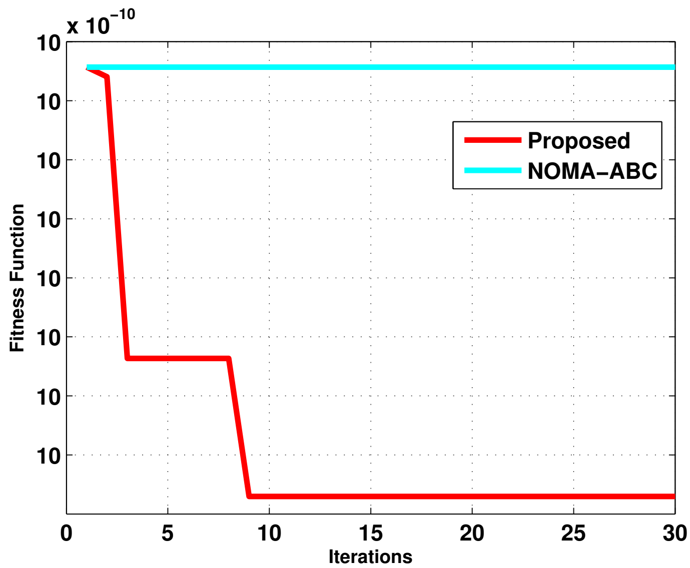

Figure 6. The convergence of the fitness function over 30 iterations

has a good convergence and suffer from search exploration. Therfore, the combination of the JAYA algorithm with ABC algorithm enhance the convergence of JAYA algorithm and strenght the search ability of NOMA-ABC-JAYA.

5.3. Spectral efficiency

The spectral efficiency (bits/s/Hz) of the various approaches (EPA, FPA, FTPA, and OMA) covered in this study is plotted against the total transmitted power produced by the BS, which ranges from 0 to $30dBm$, in Fig.7. 20 users are assumed to be paired across 10 subcarriers. According to [24], for FPA and FTPA, the power partial ratios $\beta = 0.6$ and $\beta = 0.2$, respectively. The results indicate that increasing the transmission power enhances the spectral efficiency of the 5 techniques. However, because of the orthogonality restriction, which limits the spectral efficiency by allocating unique resources to each user without interference, OMA achieves the lowest spectral efficiency. Even while FTPA and FPA techniques increase spectral efficiency, they are still not the most effective. In contrast to the NOMA principle, which asserts the user has the most robust channel gain should to be allowed less power, where the user exhibiting lowest channel gain should be given more, the FPA achieves the lowest spectral efficiency because it overlooks the user channel gain. The suggested technique, on the other hand, exceeds all other approaches and achieves the best network performance since it looks into the users' channel gain. After pairing users based on the suggested grouping strategy, the power is allocated to users following with the NOMA principle, meaning that the user with the lowest channel requirement receives more power, as well as the user who received the greatest channel gain receives less. At a transmitted power of $30dBm$, for instance, this method shows its advantage; the suggested method produces a spectral efficiency of roughly $49bits/s/Hz$.

We also examine how the number of users affects the suggested strategy's spectral efficiency, since serving numerous users in a single cell effectively is among the primary considerations and crucial needs of 5G systems. We analyze the spectral efficiency of alternative resource allocation techniques under varied transmit powers for two situations with distinct user counts ($N_{users} = 24$ and $N_{users} = 28$) in Fig.8. This chart illustrates how our suggested method outperforms EPA, FPA, and FTPA in terms of spectral efficiency. As an example, the performance difference surpasses 30% and reaches 67% in comparison to OMA at a transmit power of $P = 25dBm$ with $N_{users} = 28$. Likewise, with $N_{user} = 24$ and the same transmit power, the spectral efficiency performance difference ranges from 23% to 67%. Furthermore, the spectral efficiency is observed to increase as the number of users increases, with our suggested technique achieving an improvement of up to 20% at a transmit

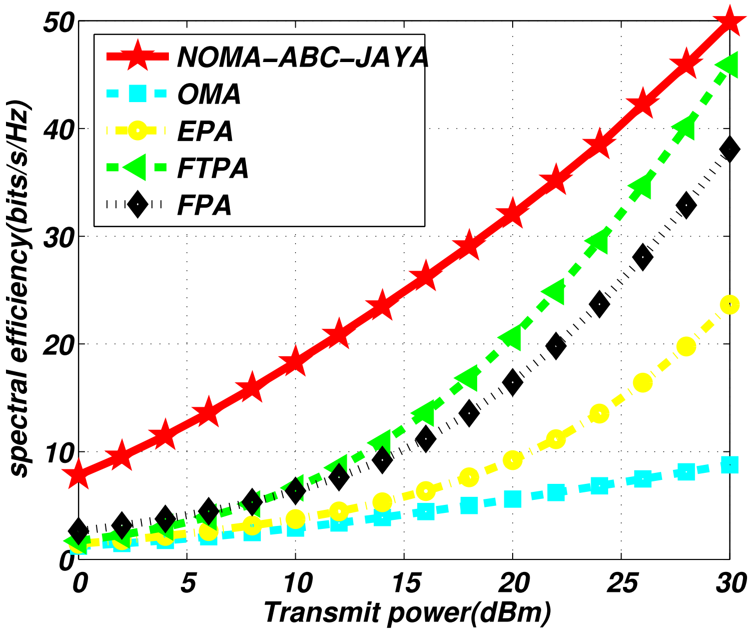

Figure 7. Spectral efficiency(bits/s/Hz) comparison under diffrent transmit total power

power of $30dBm$.

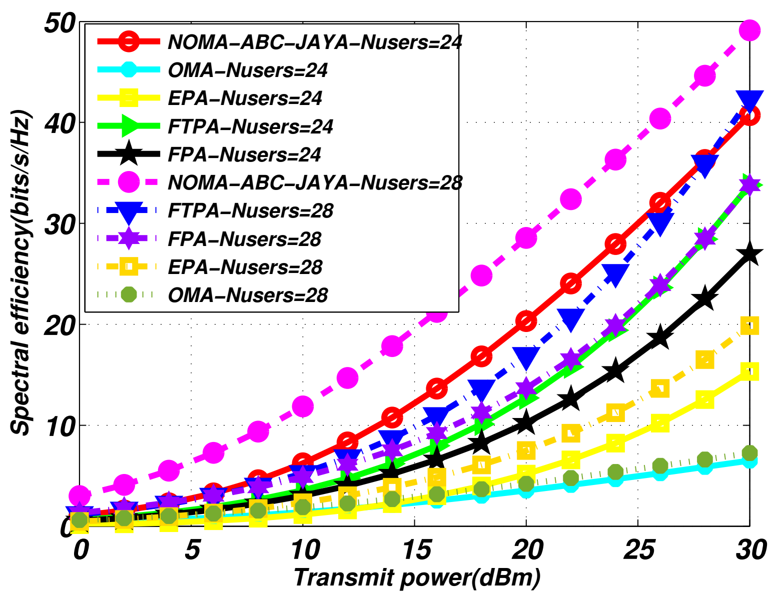

Figure 8. Spectral efficiency(bits/s/Hz) comparison under different numbers of users

The proposed technique based ABC-JAYA algorithm yields better spectral efficiency than other techniques (i,e. FTPA, OMA, FPA, EPA), which makes it suitable for 5G networks, as the proposed technique can provide a high spectral efficiency downlink communication superior to $30bits/s/Hz$ to meet the IMT-2020 criteria for the 5G according to ITU, in the other hand, the proposed technique provides a higher spectral efficiency within a larger number of users, this indicates the efficiency of the suggested resource allocation in serving multiple users, which is one of the biggest challanges of the 5G network [5].

To highlight the performance of the proposed power allocation technique, the spectral efficiency is plotted versus the transmit power, for four benchmarks algorithms the NOMA-PSO, NOMA-JAYA and the proposed NOMA-ABC-JAYA, as shown in Figure.9. For the fair comparison the same data and the proposed grouping strategy are used, as observed, the proposed technique outperforms the others across the transmit power range. For example at transmit power $P_t = 25dBm$ the proposed technique achieves $SE = 26bits/s/Hz$, whereas NOMA-PSO and NOMA-JAYA achieve around $SE = 20bits/s/Hz$ and the N0MA-JAYA lags behind $SE = 18bits/s/Hz$. This improvement is due to the superior exploration balance achieving by combining the strengths of both and JAYA algorithms. Although, JAYA exhibits lower time complexity and faster convergence, its suffers from limited search capability [52]. By integrating it with ABC algorithm, the proposed hybrid algorithm overcomes this limitation and achieves enhanced performance in terms of both convergence and spectral efficiency [51].

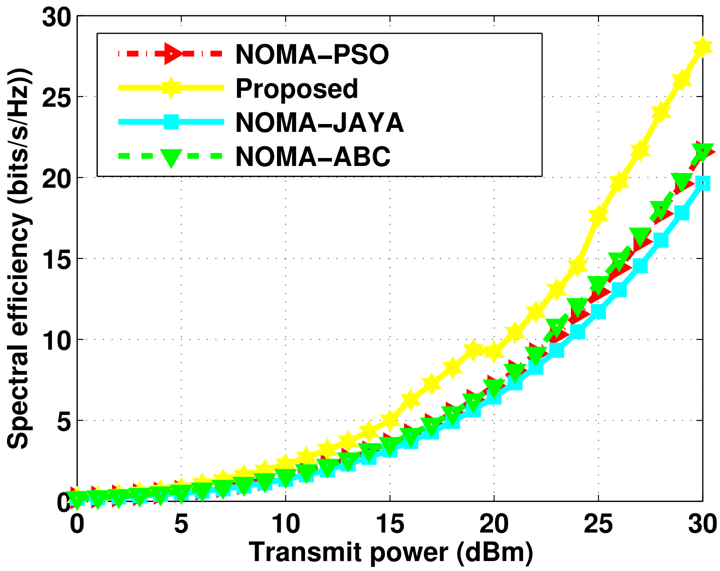

Figure 9. Spectral Efficiency(bits/s/Hz) Comparison Under Different Benchmark Algorithms

5.4. User fairness

The primary metric for assessing the quality of 5G systems is user fairness, which measures how equally users share data rates [53]. The user fairness attained by the various resource allocation techniques previously discussed (FTPA, FPA-OMA, EPA, and ABC-JAYA) is contrasted in Fig.10. As this figure illustrates, the proposed technique exhibits lower use fairness than the FTPA at lower transmit power values (i.e., from $0dBm$ to $30dBm$). This is because the FTPA uses fixed ratios to allocate power to users, which is deterministic allocation targeting that assures critical users (i.e., the weakest user channel) receive their minimum required power directly. Additionally, the FTPA doesn't waste time allocating power to users; instead, it is direct and deterministic. The suggested ABC-JAYA-NOMA, on the other hand, is based on a metaheuristic algorithm that iterates and seeks to achieve an acceptable equilibrium between the fairness and spectral efficiency. The search space is constrained at lower transmit power, which hinders the algorithm's capacity to identify better trade-offs. Notably, the proposed outperforms the FTPA due to its search space, achieving great user fairness at the highest transmit power. Consequently, at higher transmit power values, the suggested approach performs better than the existing methods.

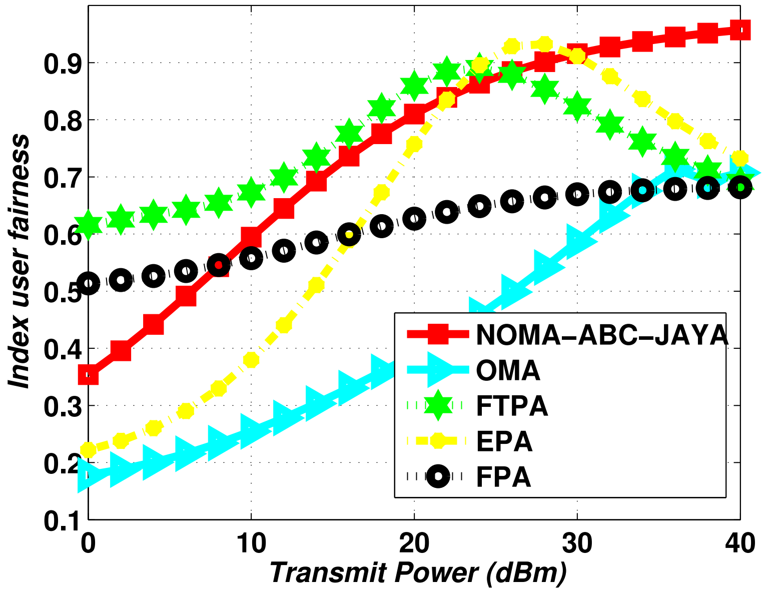

Figure 10. The index user fairness comparison under different Transmit total power

5.5. BER performance

Considering the above benefits of NOMA's spectral efficiency and the support enormous users, interference remains the major limitation of NOMA access, caused by sharing the same bandwidth between users. To address this, we examine the BER efficiency of our Suggested Resource allocation approach (NOMA-ABC-JAYA) under Rayleigh fading channels. For the analysis, we take into account SIC and SC at the transmitter. In Fig.11, we plot the BER performance versus the overall transmission power for the proposed technique and the OMA, FPA, and FTPA. The farthest user from the BS is taken into consideration, and the 16-QAM modulation. It is obvious from this figure that OMA performs the minimum BER among these five techniques (OMA, FPA, FTPA, and NOMA-ABC-JAYA), while the proposed technique achieves BER performance slightly better than FTPA and FPA. The superiority of the OMA arises because the transmission process is based on the orthogonality between the users, which reduces the interferences between the users [54]. Through incorporating the suggested method, which prioritizes the user with the poorest channel conditions (i.e., granting the weakest user more power and the strongest user less), along with the use of SC, which allows multiple users to share the same resource, NOMA subsequently achieves high spectral efficiency. Nevertheless, inter-user interference increases due to the use of SC at the transmitter and imperfect SIC at the receiver, leading to a deterioration in BER performance. Despite this, the high spectral efficiency offered by NOMA remains a critical advantage for 5G systems, even though its BER may be lower than that of OMA. To address this issue, several advanced modulation schemes and precoding techniques have been proposed. Among them, Index Modulation (IM)-aided NOMA is considered one of the most promising approaches for 5G and beyond. IM enables better user separation by encoding part of the data into indices (e.g., antenna indices, subcarrier positions), thereby reducing inter-user interference and lowering the complexity of SIC [55]. This improves user separability and ultimately enhances BER performance. Another competitive technique for improving NOMA performance is the use of precoding [32]. In particular, Walsh Hadamard Transform (WHT)-based NOMA has been proposed, where the orthogonality of WHT sequences enables efficient user separation. As a result, this approach improves signal detection, minimizes inter-user interference, and enhances BER performance.

In Fig.12, we evaluate several modulation techniques' BER performance. The figure plots BER against transmit power for modulation order $Mod = 16$, using both $QPSK$ (Quadrature Phase-Shift Keying) and QAM modulation schemes. The results show that the proposed technique achieves a lower BER compared to FTPA , EPA, and FPA

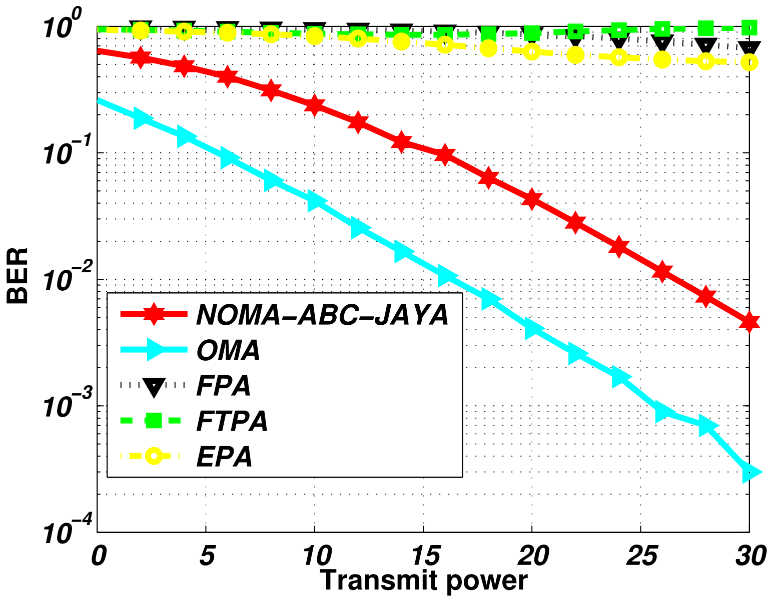

Figure 11. BER performance comparison under Rayleigh channel.

[56]. However, OMA still exhibits the lowest BER among all the techniques discussed above. Additionally, the proposed technique with QPSK modulation demonstrates a lower BER compared to when using QAM modulation.

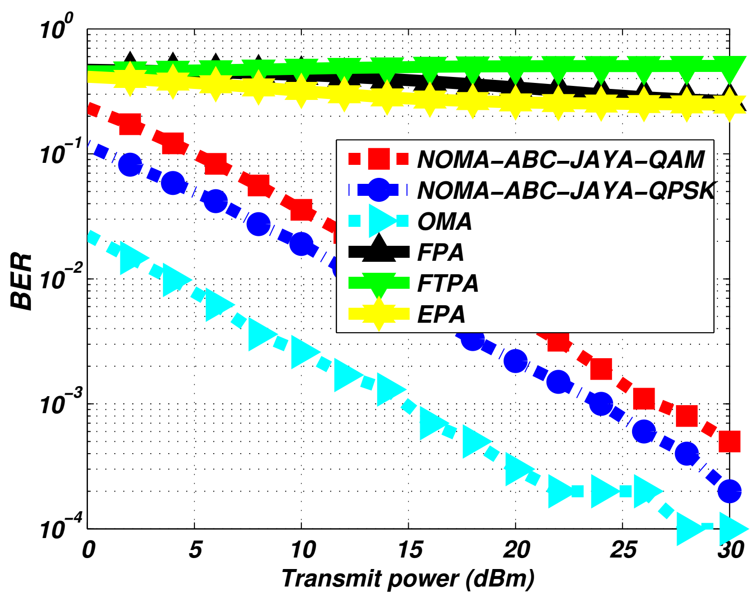

Figure 12. BER performance comparison under QPSK and QAM modulations.

6. Conclusion

In this study, we suggested a hybrid strategy centered around user pairing strategy and the ABC-JAYA algorithm to optimize resource allocation and achieve high spectral efficiency. Moreover, the proposed approach achieves acceptable user fairness and low BER for a 5G network in a downlink NOMA system. The suggested resource allocation is based first on pairing users with the largest distance difference. Then, the hybrid JAYA-ABC algorithm is applied for power allocation, taking into account the power allocation constraint. Besides, we have evaluated the suggested method in terms of BER, user fairness, and spectrum efficiency. Where it shows high spectral efficiency by at least $50 bits/s/Hz$, acceptable user fairness and a lower BER than the existing schemes. These performance advantages enable it to meet the IMT-2020 requirements for 5G as defined by the ITU.

7. Limitation

While this study provides a valuable resource allocation for the NOMA-based system, several limitations should be addressed. One key restriction arises in high-mobility users, where rapid changes in user channels can degrade the performance of the proposed technique. To address these limitations, future work can explore dynamic user re-pairing mechanisms that adapt to changing mobility patterns in real-time. Incorporating mobility prediction algorithms and channel tracking techniques may enhance robustness in dynamic environments.

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