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Genetic Algorithm Based Approach for Optimization of Fair Power Allocation in Pd-NOMA Systems

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Abstract: Power Domain Non-Orthogonal Multiple Access (PD-NOMA) systems provide a viable solution for improving user fairness and spectral efficiency in wireless communication networks. However, to maximize system performance while fulfilling numerous users' high Quality of Service (QoS) needs, innovative fair power allocation algorithms are required. This paper provides a genetic algorithm (GA)-based approach for adaptively optimizing power distribution for three users at varied distances and channel conditions in PD-NOMA systems. The proposed technique dynamically modifies the Power Allocation based on the users' distances from the Base Station (BS), channel fading, and modulation schemes, by offering fair power allocation therefore reducing the Bit Error Rate (*BER*). Unlike traditional approaches such as water-filling and fixed power allocation, GA successfully explores wide solution spaces, reducing the possibility of local optima and guaranteeing equitable power distribution. The simulation results were compared to the conventional approach as uniform, revealing considerable performance gains with *BER* reductions of nearly zero up to 100 dBm for the furthest, mid-range, and nearest users, respectively. GA converges within 4000 iterations and maintains the fitness value at 0.7. These findings show GA's capability to deliver dynamic solutions that adapt to changing network circumstances, as well as its ability to improve fairness and efficiency in PD-NOMA systems.

Keywords: fair power allocation; genetic algorithm; NOMA; non-orthogonal multiple access; power domain

1 INTRODUCTION

A key technology to improve fifth-generation (5G) wireless networks' capabilities is PD-NOMA. PD-NOMA is a technique that uses power allocation to let several users use the same frequency and time resources block by superimposing signals in the power domain and utilizing techniques like Successive Interference Cancellation (SIC) at the receiver, hence improving wireless network capacity, spectral efficiency and throughput. Research on PD-NOMA has shown that it can boost network capacity and enhance connectivity in next wireless systems [1, 2].

More spectral efficiency is provided by PD-NOMA than by conventional orthogonal multiple access methods by multiplexing users in the power domain [3]. Furthermore emphasizing PD-NOMA's flexibility and adaptability in many network situations, it has been suggested as a promising approach for downlink multi-carrier systems with opportunistic bandwidth allocations [4].

The performance and fairness of NOMA systems are directly influenced by the allocation of power, making it a crucial factor. The power allocation approach determines how resources are distributed among multiple NOMA users who share the same time-frequency resource. The distribution of power among users is crucial for maintaining a fair system, as it ensures that each user has enough power to maintain their desired level of service [5].

Considering channel conditions, user data rates and QoS requirements can lead to enhanced user fairness in NOMA systems. The power distribution technique known as Fair-NOMA is designed to improve the performance of NOMA systems by addressing fairness concerns. It achieves this by allocating power in a way that is equitable among users [6, 7].

Allocation of power in NOMA systems can lead to increased system capacity and spectrum efficiency. The NOMA systems aim to improve resource consumption and network efficiency by fairly distributing electricity among users [8]. In order to achieve equitable power distribution, it is important to focus on enhancing the reliability of NOMA systems and reducing interference [1, 2, 9].

In conclusion the importance and motivation for power allocation optimization, NOMA systems is essential to ensure fair distribution of resources, promote user fairness, optimize system performance, and maximize spectrum efficiency. The inclusion of fairness concerns in power allocation strategies enables NOMA systems to effectively meet the diverse requirements of modern wireless communication networks and achieve optimal performance.

Power allocation optimization in PD-NOMA systems is a complex challenge that requires a complete understanding of the interconnections between several elements. One of the key elements to maximize system performance overall is the distribution of power among different consumers. Part of this are well-balanced trade-offs between user fairness, data rates, system capacity and spectrum efficiency [10, 11].

The potential of power allocation optimization in the setting of PD-NOMA systems to enable a more efficient and equitable resource distribution is to radically revolutionize wireless communication. Making sure that every user receives a fair share of the available resources is as important as maximizing the overall performance of the system [2].

Given its ability to handle challenging and non-linear optimisation problems, genetic algorithms offer a workable answer to the complexity of power distribution in PD-NOMA systems. Genetic algorithms may effectively search the space for the optimal power distribution plan while taking into consideration numerous target functions and system constraints by using the concepts of natural evolution [12-14].

In the context of wireless communication, resource allocation, channel assignment, and power regulation have been demonstrated to be good optimisation problems to be solved by genetic algorithms. Considering their history in these fields, evolutionary algorithms constitute a desirable tool for PD-NOMA system power allocation optimization [14-16].

This paper introduces a method for optimizing power allocation using a genetic algorithm. Power allocation strategies in traditional systems are typically determined using fixed parameters and often fail to take into account the varying needs of users and channel conditions. The method we propose utilizes a genetic algorithm to guarantee that power is allocated fairly among all users. The goal is to enhance the performance of users who have weaker channel conditions by giving them more power. The genetic algorithm offers a flexible and adaptable power allocation strategy to optimize users' communication experience.

The significance of this work is that it utilizes a genetic algorithm-based approach to enhance communication performance and increase network efficiency, surpassing traditional power allocation strategies. The goal of the proposed method is to enhance the *BER* performance and increase the overall efficiency of the communication system. This approach provides a dynamic power allocation strategy that can better fulfill the communication requirements of users. Moreover, this method contributes to the existing literature by offering a more comprehensive understanding of how genetic algorithms can enhance the effectiveness and power of communication systems. This paper promotes the use of genetic algorithm-based power allocation optimization in communication systems.

The proposed method suggested system offers Dynamic Power Allocation, Enhanced *BER* Performance, Increased Network Efficiency, Scalability, Adaptive and Robust Solution, Contribution to Literature and Practical Implications. These advantages include:

- Dynamic power allocation strategy that adjusts to the changing communication needs of users, guaranteeing a more effective use of the available power resources.
- The use of a genetic algorithm to optimize power allocation results in a substantial enhancement in the *BER* performance when compared to conventional power allocation techniques.
- This method results in a greater overall network efficiency, allowing for improved usage of communication resources and enhancing the quality of service for all users.
- This study expands the use of genetic algorithms to power allocation in communication systems, showcasing their efficacy in addressing intricate optimization challenges in this field.
- The suggested approach may be expanded to accommodate diverse network sizes and configurations, thereby making it adaptable for varied communication system situations.
- The evolutionary algorithm-based technique offers an adaptable and resilient solution capable of managing the dynamic characteristics of communication settings, guaranteeing constant performance.
- This study enhances the current literature by providing approach to use genetic algorithms for power distribution, hence stimulating more investigation and advancement in this field.
- The results have practical implications for creating and implementing more effective communication systems, which might result in progress in real-life uses.

2 POWER ALLOCATION IN NOMA SYSTEMS USING GENETIC ALGORITHMS

These systems achieve optimal or near-optimal results by going through processes including initial population, fitness value, selection operator, crossover, and mutation. The mathematical foundation of genetic algorithms is built on how each of these phases function and how they perform an effective search in the problem domain. The fundamental components of genetic algorithms, as well as their operational procedures, are theoretically defined this part.

The initial population of the genetic algorithm is created either randomly or according to a predetermined distribution. Every individuals stands is a possible solution. These individuals are typically represented as vectors of real numbers or as binary sequences [17].

$$\wp(0)=\{\varkappa_1, \varkappa_2, \varkappa_3, ..., \varkappa_N\} \tag{1}$$

$\wp(0)$ is denetod by initial population and $\varkappa_i$ is represented by the *i*-th individual.

Each individual's solution quality $f\{\varkappa_i\}$ is evaluated using the fitness function. The fitness function is determined by the optimisation issue and often measures an individual's fitness or performance level.

$$\wp(\varkappa_i)=\frac{f\{\varkappa_i\}}{\sum_{j=1}^{N} f\{\varkappa_j\}} \tag{2}$$

$\wp(\varkappa_i)$ is represented by *i*-th individual's selection probability, $f\{\varkappa_i\}$ by *i*-th individual's fitness value and $\sum_{j=1}^{N} f\{\varkappa_j\}$ represented by sum of fitness values of all individuals in the population [17].

Crossover is the process by which the genetic information of two progenitor individuals is combined to produce new individuals (children). Diversifying the problem space and generating novel solutions are the outcomes of this process. Common crossover methods include uniform crossover, two-point crossover, and single-point crossover [18].

$$\varkappa_{child}=Crossover\left(\varkappa_{parents_1}, \varkappa_{parents_2}\right) \tag{3}$$

The genetic information of individuals is subjected to minor, arbitrary alterations through mutation. This process generates novel solutions and enhances the population's diversity. Mutation probabilities are typically maintained at the lowest possible level [17].

$$\varkappa_{mutant}=Mutant\left(\varkappa_{child}\right) \tag{4}$$

Selection, crossover, and mutation generate new individuals, which constitute the subsequent generation of the population. This procedure is repeated until a specific halting criterion is achieved, such as the utmost number of generations or an acceptable fitness value [17, 18].

$$\wp\left(i+1\right)=\left(y_1, y_2, \ldots, y_N\right)_{NEW} \tag{5}$$

The number of generations or iterations over which the algorithm is executed is denoted by *i* in genetic algorithms. Each generation symbolizes a cycle or evolutionary process within the population. Therefore, the population at the *t*-th iteration of the algorithm is represented by the *t*-th generation.

The selection operator selects parents for the next generation based on the fitness value of the individuals. The probability of an individual being selected is proportional to its fitness value [17].

If we use the genetic algorithm for fair power allocation in NOMA, we can mathematically express it as follows. In this context, each individual represents a power allocation solution and the steps of the genetic algorithm optimize these solutions. In NOMA systems, each individual represents a vector of powers allocated to users.

$$\wp\left(i\right)=\left\{p_1\left(i\right), p_2\left(i\right), \ldots, p_N\left(i\right)\right\} \tag{6}$$

$\wp\left(i\right)$, refers to the population in the *i*-th generation, $p_j(i)$ refers to the *j*-th individual power allocation vector in the *i*-th generation. Each power allocation is in the form of a vector $p_j\left(i\right)=\wp_{j1},\ \wp_{j2}, \ldots,\ \wp_{jk}$, *k* refers to the number of users and $\wp_{J_i}$ power allocated to the *i*-th user.

The fitness function is used to measure fair power allocation. It is usually defined to minimize the *BER* of users or maximize the throughput. For example, a fitness function that minimizes the total bit error rate could be

$$f\left(p_j\right)=\sum\nolimits_{i=1}^{k} BER\left(p_{J_i}\right) \tag{7}$$

$$\wp\left(p_j\right)=\frac{f\left(p_j\right)}{\sum\nolimits_{i=1}^{k} f\left(p_i\right)} \tag{8}$$

Crossover creates new individuals from the selected parents. The two parents p_i p_j exchange power allocation vectors by setting a breakpoint:

$$\begin{aligned}
&Parents_1\text{:}\ \left[\wp_{i_1},\ \wp_{i_2}, \ldots,\ \wp_{i_k}, \wp_{i_{(k+1)}}, \ldots,\ \wp_{i_k}\right]\\
&Parents_2\text{:}\ \left[\wp_{j_1},\ \wp_{j_2}, \ldots,\ \wp_{j_k}, \wp_{j_{(k+1)}}, \ldots,\ \wp_{j_k}\right]\\
&Child_1\text{:}\ y_1\ \left[\wp_{j_1},\ \wp_{j_2}, \ldots,\ \wp_{j_k}, \wp_{j_{(k+1)}}, \ldots,\ \wp_{j_k}\right]\\
&Child_2\text{:}\ y_2\ \left[\wp_{j_1},\ \wp_{j_2}, \ldots,\ \wp_{j_k}, \wp_{j_{(k+1)}}, \ldots,\ \wp_{j_k}\right]
\end{aligned} \tag{9}$$

Mutation makes minor changes to an individual's power allocation vector with a given probability. A given power of an individual mutates with a minor change.

$$\wp'_{j_i}=\wp_{j_i}+\delta \tag{10}$$

$\wp'_{j_i}$ represents new power, δ represents a random little value.

2.1 Power Allocation Strategy

Power allocation in Power Domain NOMA Access systems is a technique used to distribute transmission power among users who are being serviced at the same time and on the same frequency band. The goal is to enhance system performance by taking into account limitations such as available power and QoS for every user. Optimal power allocation plays a critical role in the design of PD-NOMA systems as it has a direct impact on the system's capacity, user fairness, and spectral efficiency. Various network scenarios, power limits, and advanced user pairing strategies are taken into account to achieve the best possible performance in PD-NOMA systems [19, 20].

There are some important points regarding the power allocation strategy for PD-NOMA. This include User Priority, Non-Orthogonality, Successive Interference Cancellation, Optimization, Algorithms and Quality of Service [21, 22].

PD-NOMA prioritizes allocating more power to users who have poorer channel conditions, such as being far away or having obstacles that affect signal quality. On the other hand, it allocates less power to users who have better channel conditions. It thus allows the receiver differentiate signals even when they connect in frequency and time [22].

Non-Orthogonality is when using a non-orthogonal approach, several users sharing the same spectral resources, PD-NOMA can greatly improve the spectral efficiency of the system over conventional orthogonal access techniques [1, 23].

SIC is a technique used by receivers to decode signals that are superimposed on each other. The user with the highest power is prioritized for decoding, while the remaining users are considered as irrelevant background noise. Next, the contribution of the user is deducted, and this procedure is repeated for the remaining users [15, 22].

Optimization is that power allocation is typically treated as an issue, in which an algorithm seeks to identify the most efficient method of distributing power among consumers. The goal is to optimize variables such as throughput, taking into account limitations such as the overall power allocation and the minimal QoS requirements [24].

Power allocation problem can be tackled using several techniques, including genetic algorithms. Genetic algorithms excel in their ability to address complex, non-linear problems and effectively uncover nearly optimal solutions by simulating natural selection [25, 26].

It is essential to prioritize QoS criteria in order to provide a satisfactory level of service. It is possible to incorporate minimum data rate guarantees or latency limits [24, 27].

2.2 Genetic Algorithm for Power Allocation Optimization

Genetic Algorithm (GA) is a strong optimization method that has been used to solve problems with NOMA systems' power allocation optimization. GA is very useful because it can quickly look through a big solution space and find almost perfect answers to difficult optimization problems [28]. In the case of NOMA, GA can be used to find the best way to divide up power among users by gradually changing a group of possible solutions using genetic operators like mutation, crossing, and selection [16].

Studies have demonstrated that GA-based power allocation algorithms in NOMA systems have the capacity to effectively cope with the multimodal character of the optimization issue. These techniques seek for optimal power allocation solutions while considering account variables such as user grouping and channel conditions [29]. Scholars have become able to develop power allocation strategies that improve system performance, decrease computing complexity, and encourage fairness among users [16]. These approaches have been developed via the application of GA.

As a further matter of interest, GA-based power allocation algorithms in NOMA systems have been particularly intended to optimize power allocation variables, maximize energy efficiency, and improve throughput while taking into consideration limitations such as channel status information and user pairing [28]. These algorithms make use of the inherent parallelism and adaptability of GA in order to efficiently explore the solution space and settle on solutions that achieve a balance in power distribution among users, which ultimately results in increased system performance [28].

It may be concluded that the Genetic Algorithm has become an extremely useful instrument for optimizing the distribution of power in NOMA systems. Researchers have created power allocation algorithms that increase system performance, reduce complexity, and promote fairness among users in NOMA networks. These algorithms were developed by exploiting the capabilities of GA to search across solution spaces in an efficient manner and identify solutions that are near optimal [16, 28, 29].

3 METHODOLOGY

This section shows how to employ a genetic algorithm (GA) to enhance power allocation in NOMA, Optimizing power allocation in NOMA systems is critical for improving performance metrics such as *BER* and throughput.

It provides a step-by-step guide on how to establish an objective function, initiate the genetic algorithm, evaluate fitness, carry out selection, crossover, and mutation operations, and determine convergence criteria for NOMA fair allocation.

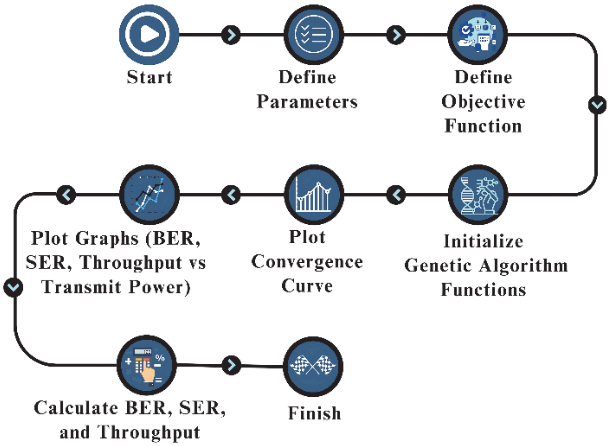

Figure 1 Flowcart of fair allocation PD-NOMA

This section on methodology provides a well-organized summary of the approach utilized to determine the optimal power distribution in NOMA systems through the application of a genetic algorithm. It emphasizes the critical steps and considerations to keep in mind throughout the process. The flowchart of the method used in this context is shown in Fig. 1.

In additionally, this study pseudocode is in Algorithm 1 written to show how genetic algorithms are implemented and how the best solution for optimal power allocation is obtained.

Algorithm 1 Pseudecode for fair allocation NOMA using genetic algorithm

```
1. INITIALIZE PARAMETERS:
Bandwidth = 2 MHz
User distances: d1 = 400 m, d2 = 150 m, d3 = 50 m
Power fading exponent: n = 4
Transmit power range: P_dbm = [0, 20, ..., 200] dBm
Alpha range: alpha_min = [0.01, 0.01, 0.01], alpha_max = [0.99, 0.99, 0.99]
Mutation probability: mutation_prob = 0.01
Crossover probability: crossover_prob = 0.001
Number of generations: num_generations = 5000
Population size: population_size = 2000
Number of parameters: num_params = 3

2. DEFINE OBJECTIVE FUNCTION:
f(alpha) = alpha[0]^2 * (1 + (d1 / d3)^n) + alpha[1]^2 * (1 + (d2 / d3)^n) + alpha[2]^2

3. GENETIC ALGORITHM:
Initialize population:
    population = random values within alpha_min and alpha_max
Evaluate fitness of the population:
    fitness_values = calculate fitness for each individual in population
Main loop for num_generations:
    For generation = 1 to num_generations do:
        Select the best individual and save it
     Create a new population:
            Select two parents based on fitness values
            Create two children by combining parents' genes (crossover)
            Randomly mutate genes of the children (mutation)
            Add children to new population
        Update population with new_population

4. CALCULATE BER, SER, AND THROUGHPUT FOR BEST SOLUTION:
Generate random channel gains for each user: h1, h2, h3
For each transmit power level P in P_dbm:
    Convert P_dbm to Watt
Compute SNR for each user
Calculate BER, SER, and Throughput using SNR

5. PLOT RESULTS:
Plot BER vs Transmit Power for each user
Plot SER vs Transmit Power for each user
Plot Throughput vs Transmit Power for each user
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In the step of determining the parameter values, various theorems and literature were utilized and the values to obtain optimum results were selected. In the studies conducted in this context, first of all, while selecting the bandwidth value, determining the amount of data that the communication channel can carry according to the Shannon-Hartley theorem, the capacity of a channel is:

$$C = B\log_2\left(1+SNR\right) \tag{11}$$

It is expressed in the Eq. (11) C (bps) characterizes the capacity of the channel, while B (Hz) is the bandwidth and Signal-to-Noise Ratio (*SNR*) [30].

Bandwidth select 2 MHz. Bandwidth is a typical value used in many mobile and wireless communication systems. This determines the data transmission rate of the system and affects the channel capacity. By choosing a medium bandwidth, the aim is both to simulate practical applications and to evaluate the performance of the system under medium bandwidth conditions.

User distances selects d_1 = 400 m, d_2 = 150 m, d_3 = 50 m [25]. Since the distance of users from the base station is inversely proportional to the share of users with channel state information, it is based on the principle of fair power allocation by allocating the highest power to the user with weak channel state information, i.e. the user farthest from the base station. In this context, different distances are chosen to observe that they have a direct impact on signal strength and hence *SNR*, and that they are inversely proportional to channel state information. Users with different distances are chosen to evaluate how the system performs under different channel conditions. This is especially important in NOMA systems to optimize fair power allocation between users.

The power loss exponent is determined by selecting the Free Space Path Loss Model or the Log-Distance Path Loss Model. The free-space path loss model shows how the signal attenuates in a free environment, i.e. without obstacles, where the attenuation is inversely proportional to the square of the distance, i.e. n = 2. In real-world environments, signal propagation is more complex than the free-space model. Therefore, the log-distance path loss model is used. This model shows that the signal attenuates at an exponential rate with distance. In communication channels, the signal strength decreases exponentially with distance. This exponential decrease usually has a value between 2 and 4. The value of 4 was chosen as it represents more challenging and weaker signal conditions and allows for a more realistic assessment of the robustness and performance of the system [31, 32].

$$PL(d) = PL(d_0) + 10\log_{10}\left(\frac{d}{d_0}\right) \tag{12}$$

In Eq. (12), $PL(d)$ refers to Path loss (d_B) at d distance, $PL(d_0)$ refers to Path loss at reference distance and d_0 = 1 m, d(meters) refers to distance between transmitter and receiver and n refers to power loss exponent. Free space n = 2, urban open space n = 2.7 - 3.5, indoor n = 3.5 - 4 is generally accepted [31, 32].

A value of n = 4 simulates extreme environmental conditions and shows that the signal attenuates faster with distance in Eq. (13) and Eq. (14) [31-33].

$$P_r(d) \propto \frac{1}{d^n} \tag{13}$$

For the path loss exponent n = 4 chosen in this study,

$$P_r(d) \propto \frac{1}{d^4} \tag{14}$$

Transmit Power Range: P_{dBm} = [0, 20, ..., 200] dBm is selected. Transmit power determines the minimum and maximum points of the allocated power in increments by increasing the start and end range of the signal that users send to the base station. This power has a direct impact on *SNR* and hence on *BER*. By selecting a wide power range, this range is used to test the performance of the system under both low and high power conditions and to determine the optimum transmit power [34].

Alpha Range: $alpha_{\min}$ = [0.01], $alpha_{\max}$ =[0.99] are selected. Alpha parameters represent the power distribution ratios between users. Minimum and maximum power values are determined with total power being 1. It is critical for fair power allocation between users in NOMA systems. Setting a wider alpha range and allocating power in steps of 0.01 to 0.01 allows the genetic algorithm to optimize the fair power allocation between users [33].

Mutation Probability: $mutation_{prob}$ = 0.01 is selected. Mutation is used in the genetic algorithm to explore the solution space. The mutation probability allows the population to diversify and the algorithm to avoid local minima. Based on the simulation results and the optimum values obtained, a mutation probability of 1% was chosen to ensure sufficient diversity while maintaining the stability of the algorithm [35].

Crossover Probability ($crossover_{prob}$ = 0.01) was chosen. While crossover is used in the genetic algorithm to combine genes and generate new solutions, the crossover probability increases diversity in the population [35]. According to the simulation studies and the optimum values obtained, a low crossover probability was decided to be 0.001 as it was observed that it promotes a more stable evolutionary process and prevents solutions from degrading too fast.

Number of Generations ($num_{generations}$ = 5000) selected. Genetic algorithms tend to converge when a sufficient number of generations is reached. Since the number of generations determines the capacity of the algorithm to find the optimal solution, according to the simulation studies and the optimum values obtained [36], the 5000 th generation was chosen because it was observed that it provides sufficient time for the solution to converge and increases the probability of finding optimal solutions.

Population Size ($population_{size}$ = 2000) selected. The population size determines the number of individuals that the genetic algorithm evaluates in each generation. Large populations ensure diversity and a comprehensive exploration of the solution space [35]. In the simulation studies, 2000 individuals were chosen as it was observed that it provides sufficient diversity and a comprehensive exploration of the solution space.

The noise power ($Noise_{Power}$) is set to 0.1, 0.1, and 1 watt per square metre. The signal-to-noise ratio (*SNR*) and, ultimately, the *BER* are affected by the background noise level in the communication system, which is indicated by this number. Realistic audio power level is necessary for a correct performance assessment.

4 SIMULATION

4.1 Parameter Settings

This section will be dedicated to discussing the parameters that were used in our simulation. The operational conditions and limitations of our communication system are largely determined by these features, which are of the utmost importance. These parameters are Bandwidth (B), Distances (d_1, d_2, d_3), Power Fading Exponent (n), Transmit Power (P_{dbm}), Power Allocation Bounds ($alpha_{\min}$, $alpha_{\max}$), Mutation Probability ($mutation_{prob}$), Crossover Probability ($crossover_{prob}$), Number of Generations ($num_{generations}$), Population Size ($population_{size}$), Number of Parameters (num_{params}), Noise Power ($Noise_{Power}$).

The bandwidth of a signal is the range of frequencies across which it may be conveyed. 2 MHz bandwidth is used by most communication networks to balance data speed with noise immunity. A broader bandwidth makes it possible to send more data in a shorter period of time. However it additionally renders noise and interference more probable to affect the system. In contrast, even though lowering data speeds, a narrower bandwidth provides better noise shielding. Thus, the choice of 2 MHz is a compromise that ensures acceptable data rates at acceptable levels of interference and noise [37].

Distances are chosen to model a typical cellular network scenario where users are located at different distances from the BS, affecting received signal strength and QoS. In this context, channel state information is assumed to be inversely proportional to their distance from the BS. It is an important parameter for realizing optimal fair power allocation. In this context, the distances of users 1, 2, 3 to the BS are represented by d_1, d_2 and d_3 respectively. The designed system is as shown in Fig. 2. The distance between the BS and the farthest user is denoted by d1 and given by $d_1 = 400$ meters. This indicates the user who is close to the edge of the cell and has the largest path loss. The distance between the BS and the intermediate user is denoted by d_2 and given by $d_2 = 150$ meters. It shows a user who is not too far from the BS but has intermediate path loss. The BS and the adjacent user are separated by $d_3 = 50$ meters. It stands for the user with the lowest path loss who is nearest to the BS.

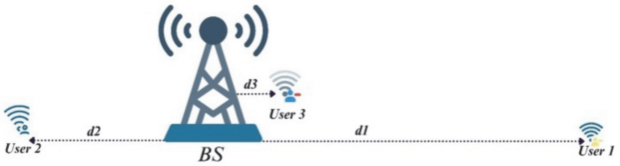

Figure 2 Fair allocated NOMA system with three users at varying distances from the base station

Power fading exponent. This parameter simulates the route loss exponent in cities, when major signal attenuation is brought on by trees and buildings. In this kind of settings, a value of 4 is normal, meaning that the signal strength drops down quickly with distance as like $1/d^4$.

The transmit power (P_{dBm}) is another parameter that allows system performance can be investigated at very low to very high transmission powers. For this reason, it can be used between 0 and 200 dBm. The corresponding power in watts is calculated using the formula:

$$P = \frac{10^{(P_{dBm}/10)}}{1000} \tag{15}$$

Assuming that the total allocated power is $\alpha = 1$, we can use the following constraint for the minimum and maximum power allocation limit.

$\alpha_{\min} = 0.01$, numbers provided indicate the minimum power allocation factors for each user, guaranteeing that each user gets a minimum of 1% of the total transmit power. This limitation ensures that no user is entirely deprived of power, hence ensuring a minimum degree of connection for all users. $\alpha_{\max} = 0.99$, these numbers indicate the maximum power allocation factors for each user, guaranteeing that no user may control more than 99% of the total transmit power. This limitation is intended to foster equity in the distribution of power, preventing any user from dominating the accessible power and so guaranteeing a more equal and fair allocation of resources among all users.

$$p = \alpha_1 + \alpha_2 + \alpha_3 = 1 \tag{16}$$

For this parameters will be using superposition we obtained transmitted signal for BS.

$$x = \sqrt{p}\left(\sqrt{\alpha_1}x_1 + \sqrt{\alpha_2}x_2 + \sqrt{\alpha_3}x_3\right) \tag{17}$$

Received signal for order by 1, 2 and 3 users.

$$y_1 = h_1 \cdot x + n_1 \tag{18}$$

$$y_2 = h_2 \cdot x + n_2 \tag{19}$$

$$y_3 = h_3 \cdot x + n_3 \tag{20}$$

n_1, n_2, n_3 represents order by 1, 2 and 3 users additive white gaussian noise. The SIC is used to extract the message signals, and then the *BER* is computed. The fading through the channel and signal power both affect the *BER*.

Tab. 1 shows the parameters used. These parameter choices form the cornerstone of our simulation and direct the optimisation process. This reduces *BER* and maximizes throughput, therefore guaranteeing a reliable and effective communication system.

Table 1 Parameters of genetic algorithms

Total Users Value	Base Station	User Distances From Base Station	Bandwidth	Number Of Generations	Population Size	Crossover Probability	Mutation Probability	Alpha Range	Power Fading Exponent
3	1	$d_1 = 400$ m $d_2 = 150$ m $d_3 = 50$ m	2 MHz	5000	2000	0.001	0.01	0.01 - 0.99	4

4.2 *BER* Calculation

BER is a crucial measure for assessing the effectiveness of communication networks, especially in the context of NOMA systems. *BER* is a measure of the rate at which mistakes happen while transmitting bits via a communication channel [38].

BER is calculated by dividing the total number of bit errors by the total amount of bits transferred during a certain time period. Mathematically, it may be represented or described using mathematical notation.

$$BER = \frac{N_e}{N_t} \tag{21}$$

where N_e is the number of erroneous bits, and N_t is the total number of transmitted bits [38].

4.3 Throughput Analysis

Throughput is a key measure used to assess the efficiency of communication networks, especially in NOMA systems. Throughput is the measure of the quantity of data that is effectively sent across a communication channel during a certain time period. It quantifies the speed at which data is effectively sent from a source to a recipient across a communication link. Throughput, measured in bits per second (bps), is affected by many variables including channel conditions, *SNR*, and power allocation schemes. [39].

NOMA systems attempt to maximize the total amount of data sent by enabling different users to use the same frequency resources. This is accomplished by power domain multiplexing, where users with varying channel gains are assigned distinct power levels. The main concept is to allow users with better channel circumstances to decode and eliminate the signals of users with worse channel conditions (SIC), thereby enhancing the overall spectral efficiency [2].

The throughput for each user in a NOMA system may be determined using the following calculation:

$$T_i = B\log_2\left(1+\frac{p\alpha_i^2 h_i^2}{BN_0 + I_i}\right) \tag{22}$$

P is the total transmit power, α_i power allocation coefficient for user i, h_i channel gain for user i, N_0 noise power spectral density, I_i interference experience by user i [40].

The study analyzes our NOMA system consisting of three users located at different distances from the BS. Traditional methods usually determine power allocation using closed-form solutions or simple optimization techniques. For example, methods such as the water-filling algorithm or Lagrange multipliers can be used. These methods operate under certain assumptions and constraints and usually do not guarantee global optimization. GA aims to reach a global optimum by avoiding local minima in optimization problems. While this is not guaranteed in traditional methods, GA's random mutation and crossover operations increase the probability of finding better solutions in a large search space. The channel gains for users are represented by the best channel conditions, while user 1 has the worst conditions. The optimized power allocation coefficients derived from the genetic algorithm can be used to calculate the throughput for each user:

$$Throughput_1 = B\log_2\left(1+\frac{p\alpha_1^2 h_1^2}{BN_0 + I_1}\right) \tag{23}$$

$$Throughput_2 = B\log_2\left(1+\frac{p\alpha_2^2 h_2^2}{BN_0 + I_2}\right) \tag{24}$$

$$Throughput_3 = B\log_2\left(1+\frac{p\alpha_3^2 h_3^2}{BN_0 + I_3}\right) \tag{25}$$

Interference experienced by users 1, 2, and 3, respectively, is denoted by I_1, I_2, I_3.

The interference in NOMA systems is managed through SIC, in which the strongest user (user 3) experiences the least interference, and the weakest user (user 1) experiences the most.

5 RESULTS AND DISCUSSION

The evaluation of the efficacy and effectiveness of GAs is significantly influenced by convergence analysis. It involves the examination of the accelerated and precise manner in which a GA approaches the optimal solution over the course of multiple generations. This analysis is indispensable for guaranteeing that the algorithm not only identifies the optimal solution but also executes it efficiently.

Convergence analysis has a substantial impact on the assessment of the efficacy and effectiveness of GAs. It entails the analysis of the accelerated and precise manner in which a GA approaches the optimal solution over the course of multiple generations. This analysis is essential for ensuring that the algorithm not only identifies the optimal solution but also executes it efficiently.

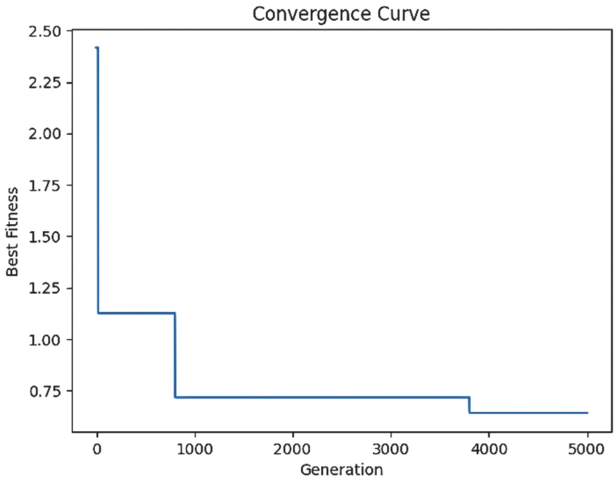

Figure 3 Convergence curve

Fig. 3 assesses the effectiveness of fair power allocation optimization in NOMA systems. The best fitness value is around 2.5 at first, but it quickly reduces to 1.25 after a few generations. This demonstrates that the method initially improves the unequal power allocation scheme quickly. The fitness value then gradually drops to around 0.75 starting with the 1000 th generation. At this point, the algorithm fine-tunes the power allocation among users to make it more equitable. Finally, after the 4000 th generation, the fitness value drops to 0.7 and stabilizes. This means that the algorithm has identified an optimal or near-optimal solution and cannot make any further improvements.

The genetic algorithm-based power allocation method was compared with the classical uniform power allocation method to evaluate its effects on system performance at different transmission power levels, as shown in Fig. 4. This comparison was conducted to analyze the effectiveness of the genetic algorithm in reducing bit error rates and increasing data transmission rates due to its sensitivity to channel conditions and optimization capability. This graph shows the effects of both methods on *BER*, *SER*, and throughput for three users.

When examining the *BER* and *SER* graphs, it is shown that GA-based power allocation provides lower error rates for users. Especially at transmission power levels exceeding 100 dBm, it is observed that GA significantly reduces error rates.

Table 2 Comparison of genetic algorithm-based NOMA power allocation strategies in similar studies

Study	Method	Objective	Results
[14]	Genetic Algorithm	Allocating radio resources to multiple users in NOMA systems	Determines user groups and optimizes transmission power, ensuring overall system efficiency and balance among users.
[26]	Genetic Algorithm	Provide power allocation to maximize the total transmission rate	Offers a higher total transmission rate and lower computational complexity than the fixed power allocation algorithm.
[41]	Q-learning, Genetic Algorithm	Optimizing power allocation in the NOMA system	Higher minimum bit rate compared to existing theoretical methods. Q-learning exhibits exponential complexity, while GA shows linear complexity.
[42]	Multi Objective Genetic Algorithm (MOGA)	Making power allocation considering QoS, SIC, and transmission power	MOGA performs well in NOMA IoT networks.

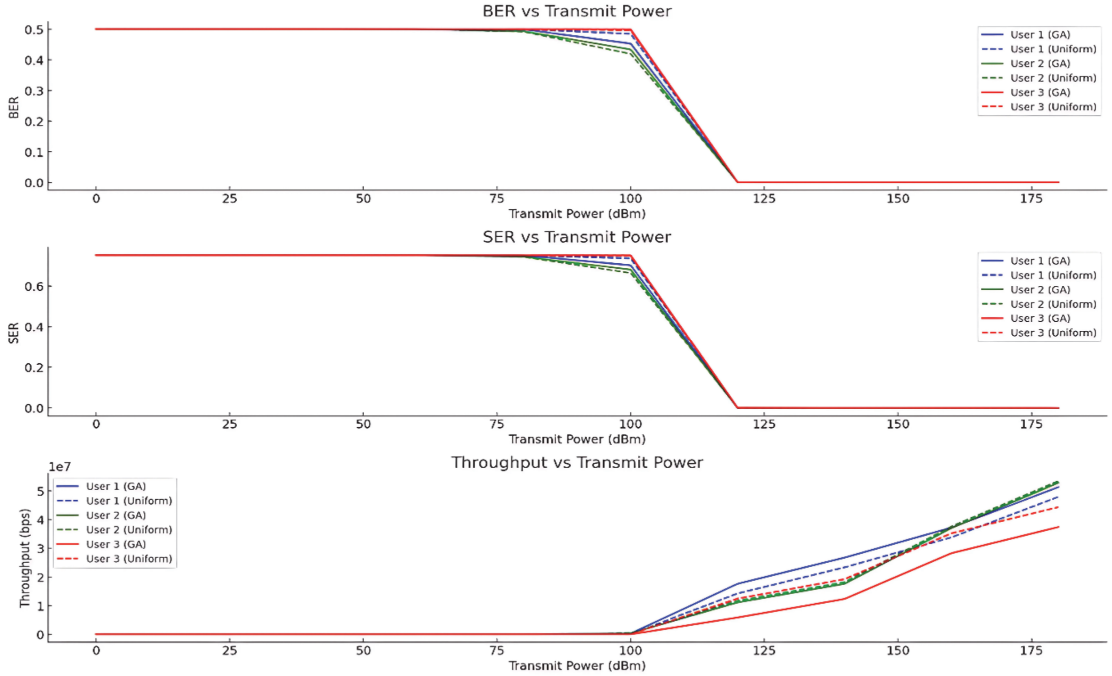

Figure 4 *BER*, *SER*, throughput vs transmit power graph

Uniform power allocation negatively affects users with poor channel conditions because power is distributed equally, resulting in higher *BER* and *SER* values. On the other hand, GA offers a more balanced performance by optimizing channel conditions.

The throughput graph clearly shows that GA provides a higher data transmission rate for each user. Especially at high transmission power levels, it is observed that GA more effectively optimizes the throughput balance among users. In the uniform power allocation method, however, throughput remains lower, especially for weak users.

In this study, comparisons with previous works related to the genetic algorithm used for NOMA-based power and resource allocation are presented in Tab. 2. Tab. 2 presents the effectiveness and advantages of the proposed methods through comparisons with similar studies.

GA-based power allocation enhances system performance by optimizing fair power distribution among users in a channel condition-sensitive manner. This method provides significant advantages over the uniform power allocation method, especially at high transmission power levels, by offering lower error rates and higher data transmission rates. The results reveal the potential of genetic algorithms with channel-adaptive optimization strategies to enhance efficiency and user satisfaction in NOMA systems.

These findings suggest that power allocation based on genetic algorithms can be used more effectively in NOMA systems and that this method could play an important role in future communication systems.

6 CONCLUSION

This study explores the optimisation of fair power distribution in NOMA systems, as well as its impact on system performance based on user distance and transmission power. The data and analyses shown in the graphics lead to the following major conclusions:

Initially, the fair power allocation optimization algorithm significantly improves inequitable power allocation in NOMA systems, as seen in the first few generations. The algorithm makes significant initial benefits by more evenly distributing power across users. The advancements then slow down as they reach a stable solution. The graphs show that after 4000 generations, the algorithm discovers an essentially optimal or near-optimal solution and is unable to improve further.

On the other hand, the graphs depicting the link between transmission power and *BER* indicate how *BER* values and transmission power requirements vary based on the customers' distance from the BS. To achieve minimum *BER*, remote users demand larger transmission powers. Users who are closer together, on the other hand, can obtain low *BER* values even at modest transmission powers. The same graphs demonstrate how consumers' data throughput grows as transmission power increases. This demonstrates that NOMA systems can increase data transmission efficiency and ensure consistent performance throughout the system by optimising power allocation based on user distances.

Finally, our study demonstrated the relevance and effectiveness of fair power allocation optimization in NOMA systems. The method may immediately address unjust power distribution by making significant initial improvements and provides long-term stability. This technique presents a valuable paradigm for enhancing fair power distribution and efficiency in wireless communication networks, and it can serve as a foundation for future study.

Potential areas of investigation for future research in power allocation for NOMA systems, using genetic algorithms, include several intriguing avenues. Integrating more sophisticated and accurate channel models, which include factors like movement and changing environmental circumstances, would improve the practical usefulness of these algorithms. Furthermore, the use of machine learning methodologies with genetic algorithms has the potential to enhance the flexibility and effectiveness of power allocation systems. Researchers might also examine the influence of various modulation schemes and error-correction coding on the efficiency of NOMA systems.

Furthermore, extending the research to multi-cell situations and considering inter-cell interference will provide a more comprehensive understanding of the system's capabilities. Finally, we believe that real-world implementation and testing under different network conditions is crucial to validate the theoretical results and optimize the algorithms for real deployment, which can inspire future work.

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