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Power allocation in NOMA using sum rate-based dwarf mongoose optimization

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ABSTRACT

The increasing number of consumers with diverse data rate needs is leading to increased heterogeneity in traditional cellular networks. Nonorthogonal multiple access (NOMA) has emerged as a promising method to serve a large number of users, but research shows that weak users (WU) and strong users (SU) have different throughputs. Intra-group interference reduces WUs throughput due to the superposition of signals. Improper power distribution impacts NOMA performance and lowers the total system rate. The multi-objective sum rate dwarf mongoose optimization algorithm (M-SRDMOA) is implemented as a solution to the NOMA network power allocation problems. The DMOA approach distributes adequate power to all NOMA users to increase the large sum rate. The effectiveness of the M-SRDMOA approach is supported by existing studies on fair NOMA scheduler (FANS) and multi-objective sum rate-based butterfly optimization algorithm (M-SRBOA). The M-SRDMOA's potential sum rate with an SNR of 9dB and a noise variation=2 is 14.06 bps/Hz, which is high compared to M-SRBOA and FANS.

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1. INTRODUCTION

Nonorthogonal multiple access (NOMA) is a practical option for future wireless networks to serve a large number of customers with various requirements [1]. When evaluating the power domain NOMA technique [2], individuals have the flexibility to cancel identical frequencies in the spectrum domain, match codes in the code domain, and even coincide times in the time domain. However, it's important to note that they are unable to simultaneously share equivalent levels of power within the power domain. The NOMA system for future networks increase spectrum efficiency by allowing numerous users to use the same resource block simultaneously by utilizing power-domain multiplexing technology [3], [4]. The signals of several users are specifically multiplexed in NOMA by making use of the variations in their channel gains and then broadcasting over the same frequency at the risk of some inter-user interference [5], [6]. A key purpose of NOMA is to trade off system throughput for user fairness to remove the disparities between the various user-achievable rates [7]. Spectral efficiency is not fully utilized due to the requirement of orthogonality between subcarriers. It is crucial to explore efficient multiple-access technologies in the framework of limited spectrum resources but NOMA has the potential to improve spectral efficiency. By multiplexing number of users with various power levels on the same frequency resource block, NOMA increases the spectral efficiency of the entire system [8], [9]. When the source has excess power to distribute for two or more users, the power domain of NOMA is well determined. The transmit strengths in underlay cognitive radio are random and constrained by the interference temperature limit (ITL). As a result, NOMA performance in such settings is limited [10]. The basic concept of NOMA is the multi-user sharing of the resource elements such as a spreading code subcarrier or time slot [11], [12]. NOMA multiplexes all active users in the power domain at the transmitter, allowing all of them to utilize the entire available transmission bandwidth at the same time. An interference cancellation decoding approach is used concurrently at the NOMA receiver to recognize and decode the data intended for each user [13]. The weak users next decode their communications and treat the messages of the strong users as interference [14], [15]. NOMA has practical solutions to address these anticipated problems, as well as those related to the development of traffic demand, high spectral efficiency (SE), and increasing the possible sum rate [16]. In contrast to the traditional orthogonal multiple access (OMA), power domain NOMA allows for numerous users to be supplied simultaneously in the same time/frequency resources and multiplexed in power levels [17]. The NOMA network users, in particular, typically employ successive inference cancellation (SIC) to eliminate presumptions from other NOMA users, which effectively increases the signal-to-interference and noise ratio (SINR) and reception reliability [18].

NOMA offers advantages over OMA techniques like increased spectrum and energy efficiency, enormous device connectivity, minimal transmission latency, high data rates, improved user fairness, and compatibility with other techniques [19], [20]. Erturk *et al.* [21] implemented a NOMA as a new access radio mechanism for cellular networks in which users of a group use the wireless channel at the same time. NOMA-based schedulers were expected to outperform OMA-based schedulers in terms of performance due to their broader radius and lower transmit power. However, to properly distribute power, NOMA depended on channel conditions. Hence for efficient power allocation, it was necessary to predict and estimate the channel conditions. Wu *et al.* [22] implemented a unique low-complexity power allocation algorithm to decrease the search space of a full search power (FSP) allocation algorithm. By updating the current power allocation coefficients, the implemented approach considerably reduced the computing cost of the FSP allocation process. By enabling users to share frequency and temporal resources, the implemented algorithm increased the efficiency of the spectrum and increased the overall performance. However, to minimize computational overhead and power usage, the power allocation methods needed to be constructed. Rezvani *et al.* [23] implemented a globally optimum power allocation algorithm to maximize system's energy efficiency (EE) and user sum-rate (SR) in the multicarrier non-orthogonal multi-access (MC-NOMA) systems of single-cell downlink. The implemented system was established to provide fairness by providing various power levels to different users and minimizing performance gaps between users on different channels. However, due to discrete modulation and coding schemes in actual systems, the possible rate of users was likewise constrained by a maximum value. Gangadharappa and Ahmed [24] implemented the multi-objective sum rate-based butterfly optimization algorithm (M-SRBOA) to obtain the challenges of NOMA network power allocation. The implemented M-SRBOA was employed to execute an efficient power distribution by selecting suitable power allocation coefficients. The M-SRBOA method allocated an appropriate quantity of power to each NOMA user, resulting in a low outage probability and higher overall rate. However, for large-scale NOMA networks, M-SRBOA was a complicated optimization approach that necessitated a significant amount of computer resources. Agarwal and Jagannatham [25] implemented a two-way relaying communication scheme based on NOMA for maximization of the sum rate that enhanced the performance. The original non-convex problem was converted into a simple difference of convex program for sum-rate maximization of service constraints with customer quality. The implemented method performed significantly better than the fixed and random allocations. However, power allocation was needed to be optimized, to maximize system performance, but identifying the appropriate technique was difficult. The contributions in this paper are listed:
- The multi-objective sum rate dwarf mongoose optimization algorithm (M-SRDMOA) is proposed as a solution to the NOMA network's power allocation problems.
- The NOMA network is designed with numerous users to improve communication,
- Furthermore, an appropriate power allocation for all users is employed in NOMA to reduce the possibility of a power failure.

This research paper is organized as follows: the information regarding the ongoing research of power allocation in NOMA is provided in section 2. Section 3 clearly explains the planned M-SRDMOA-base power allocation for all NOMA users. The results and discussion of the M-SRDMOA approach are presented in section 4, while the conclusion of this paper is given in Section 5.

2. METHOD

In this research, the M-SRDMOA is implemented as a solution to the NOMA network's power allocation problems. Here, the Rayleigh fading coefficients and sum rate in the M-SRDMOA are taken into account to create an optimal power distribution. The main processes of M-SRDMOA are as follows: Modulation of quadrate phase shift keying (QPSK), power allocation, superposition coding, transmission of data symbol across the channel, SCI decoding, and demodulation of QPSK. Figure 1 illustrates the implemented M-SRDMOA method's block diagram.

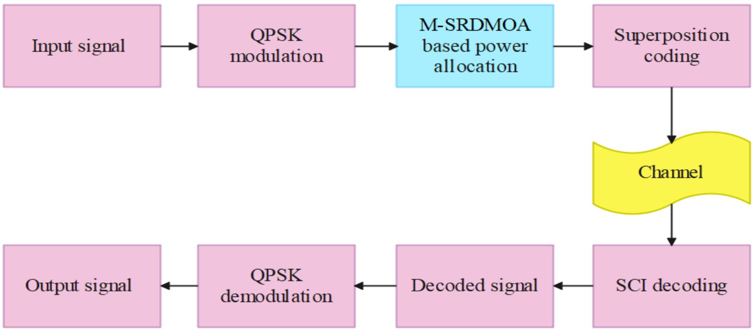


Figure 1. The implemented M-SRDMOA method block diagram

The following are the key steps of the M-SRDMOA method:

- Step 1: three NOMA users are taken into account in the topology of this M-SRDMOA approach for easier communication. A topology where three users are distributed at various distances is considered. The Rayleigh fading model is the channel model taken into account in this NOMA system.
- Step 2: at first, the input signal is modulated using QPSK.
- Step 3: all three NOMA users must receive an ideal power distribution. According to NOMA's guiding principles, the most powerful user receives the least amount of power, while other users receive the most. An M-SRDMOA is employed in this study to distribute the user's electricity most effectively. By taking into account various objective functions, such as the Rayleigh fading coefficient and sum rate, the power allocation is optimized.
- Step 4: on the side of a transmitter in superposition coding carries out NOMA system after the distribution of power to each user. A Rayleigh fading channel model is then used to broadcast the send signal.
- Step 5: on the receiver side, the SCI is completed by decoding each user's send signal, which is then used to prevent interferences. Based on superposition coding and SIC, the NOMA allows several users to share the same spectral resource.
- Step 6: the demodulated signal is used to obtain the signal output after the received signals are decoded.
- Step 7: by comparing the output signal to the input signal, the performance of the implemented approach is evaluated.

2.1. System model

This system includes 1 base station (BS) and M numbers of user's networks are denoted as $\mathrm{U_i}, \mathrm{i} \in \{1,2, \dots, \mathrm{M}\}$, M is equal to 3 are assumed for a downlink NOMA network in M-SRDMOA. Here, the BS used the broadcast channel to transmit M data symbols in total to the x, i to the specific users $\mathrm{U_i}$. The sides of receiver and transmitter of NOMA activated the QPSK, which maintain the NOMA's transmitter and receiver sides. Users and BS both regard the zero mean of Rayleigh fading with N0 representing the variance of additive with gaussian noise (AWGN) as a fast channel. Furthermore, the channel coefficient between BS and $\mathrm{U_i}$ is denoted as zero means and $\mathrm{h_i}$ complex Gaussian random variables represented with a σ_i^2 variance. The NOMA channel gains of $|\mathrm{h_i}|^2$ is discrete variables exponential in random with rates of $\lambda_i \triangleq 1/\sigma_i^2, \forall \mathrm{i} \in \{1,2, \dots, \mathrm{M}\}$. The BS uses superposition coding to transmit all of the NOMA user's data symbols simultaneously. The signal that is received by the user $\mathrm{x_j}$ is expressed in (1),

$$x_j = h_j \sum_{i=1}^{M} \sqrt{a_i P y_i + \eta_j} \tag{1}$$

Here, in BS the total transmit power is written as P, and noise is designed as η_j , and i is the user coefficient of power allocation denoted as a_i that, $\sum_{i=1}^{M} a_i \leq 1$. The channel gains are then arranged in sequence of ascending, as follows $0 < |h_{(1)}|^2 < \cdots < |h_{(M)}|^2$ indicating that $a_{(1)} > \cdots > a_{(M)}$. By using the SIC in the receiver, the data of the user symbol is decoded. In addition, the other users are treated as interference under the optimal channel conditions, meaning that no decodes user of data symbols of further powerful users. The data is detected in, the SINR of the m^{th} user with perfect SIC is used. In (2), the SINR $\gamma_{(m)}$ for the user, m is given as,

$$\gamma_{(m)} = \frac{\rho|h_{(M)}|^2 a_{(m)}}{\rho|h_{(M)}|^2 a_{(m)}+1} \tag{2}$$

Where, $\bar{a}_{(m)} = \sum_{i=m+1}^{M} a_{(i)}$ and $\rho \triangleq P/N_0$ are concerned. When each user decodes their data, in (3) displays the M th order user of the SNR. The DMOA is used to determine the NOMA network's optimal power allocation coefficient a_i.

$$\gamma_{(M)} = \rho|h_{(M)}|^2 a_{(M)} \tag{3}$$

3. RESEARCH METHOD

Here, sum rate-based dwarf mongoose optimization performed for power allocation in NOMA is described briefly. This is divided into two phases including power allocation using M-SRDMOA, and objective function formulation. Power allocation is used for identifying suitable power allocation coefficients in the implemented M-SRDMOA, while in objective function formulation, Rayleigh channel fading and sum rate are the numerous objectives taken into account in M-SRDMOA.

3.1. Power allocation using M-SRDMOA

By identifying suitable power allocation coefficients, the implemented M-SRDMOA is applied in this study to carry out an efficient power allocation. The foraging and social behaviors of the dwarf mongoose, also known as Helogale, served as the inspiration for the population-based stochastic metaheuristic algorithm known as DMOA. Because food seeking is not a collaborative activity like foraging is, each dwarf mongoose looks for food on their own. The construction of a sleeping mound is adjacent to a plentiful source of food because these animals are seminomadic. In contrast, Rayleigh channel fading and sum rate are the multiple objective functions taken into account in the M-SRDMOA. The next part provides an iterative phase and objective formulation for the M-SRDMOA.

3.1.1. Iterative phase

The distance between each user and BS is used to randomly initialize the power allocation coefficients of each user in the NOMA network. The M-SRDMOA is a swarm intelligence-based approach for solving ideal global challenges that draw inspiration from animal behavior. It imitates the behavioral response of dwarf mongoose. The implemented M-SRDMOA replicates the compensatory behavioral response of the dwarf mongoose, which is modeled as follows:

a. Population initialization

The initialization of the population for mongoose candidate solution (S), as specified in (4) is the first step in the M-SRDMOA. The size of the entire population, and Q is the total number of decision factors of drawn mongoose characteristics is M_p. The number of decision variables Q represents the parameters of the ARX system presented in the parameter vector, as stated in (5), for the parameter estimation issue of the ARX system. Using (6) to generate the population at random. The problem's lower and upper bounds are represented as LB and UB. and three groups of the M-SRDMOA's optimization process are created such as Alpha Group, Scout Group, and Babbysitters and are shown:

$$S = \begin{bmatrix} s_{1,1} & \cdots & s_{1,Q} \\ \vdots & \ddots & \vdots \\ s_{M_p,1} & \cdots & s_{M_p,Q} \end{bmatrix} \tag{4}$$

$$\gamma = [h\ i] \tag{5}$$

$$S_{u,v} = unifrnd\ (LB, UB, Q) \tag{6}$$

b. Alpha group

Following initialization, each solution's population fitness is determined using (7). According to (4), the female alpha is selected based on fitness. The updated mechanism for the solution is determined by using (8) because the quantity of mongoose in the problem is correlated with the quality of babysitter's bb and vocalization of the dominant female. The distributed random number is $\emptyset$. For each repetition, the sleeping mound is computed using (9). Using (10), the average of ε_j is calculated. When the babysitter requirement is satisfied, the algorithm moves on to the next group.

$$\propto = \frac{fit_j}{\sum_{j=1}^{M_p} fit_j} \tag{7}$$

$$S_{j+1} = S_j + \emptyset * \rho \tag{8}$$

$$\varepsilon_j = \frac{fit_{j+1} - fit_j}{max\{|fit_{j+1}, fit_j|\}} \tag{9}$$

$$\sigma = \frac{\sum_{j=1}^{M_p} \varepsilon_j}{M_p} \tag{10}$$

c. Scout group

Scout group is computed using (11) and (12), where, if the family forages far enough during this phase, a new sleeping mound is found. The rand value in this ranged between [0,1]. The mongoose group's collective volitive movement is controlled by the parameter DF, which is derived using (13) and (14).

$$if\ \theta_{j+1} > \theta_j : S_{j+1} = S_j - DF * rand * [S_j - \vec{V}] \tag{11}$$

$$else:\ S_{j+1} = S_j + DF * rand * [S_j - \vec{V}] \tag{12}$$

$$DF = \left(1 - \frac{m}{max\_G}\right)^{\left(2*\frac{m}{max\_G}\right)} \tag{13}$$

$$\vec{V} = \sum_{j=1}^{M_p} \frac{S_j \times \varepsilon_j}{S_j} \tag{14}$$

d. The babysitters

The second group of people that stays with the children are the group of babysitters. The remainder of the team goes on daily hunting expeditions while the alpha female is assisted by the routine recycling of babysitters. The babysitter exchange criterion is changed so that the better-fitted mongoose is produced instead of starting over from scratch as is done in DMO. The counter is then reset to zero after the criterion is satisfied and the babysitters that are exchanged engage with the dwarf mongooses, exchange information about food sources and sleeping mounds.

3.1.2. Objective function formulation

Rayleigh channel fading and Sum rate are the numerous objectives taken into account in M-SRDMOA. To increase sum rate and reduce loss, these targets are employed to acquire a user's suitable coefficient of power allocation. The following is the formulation of the objective function. The following (15) expresses the NOMA network's sum rate.

$$SR\ (M) = log_2\left(1 + \rho\left|h_{(M)}\right|^2 a_{(m)}\right) \tag{15}$$

The distance between users and BS (d) is typically inversely proportional to the Rayleigh channel fading coefficient. The power distribution depends on the strong users, while weak users are determined by the BS and the users are expressed in (16). Where, $\propto$ denotes the path loss exponent, $q_N \sim CN(0,1)$, and CN denotes the complex normal distribution.

$$h_N = q_N \bar{d}_N^{\frac{\propto}{2}} \tag{16}$$

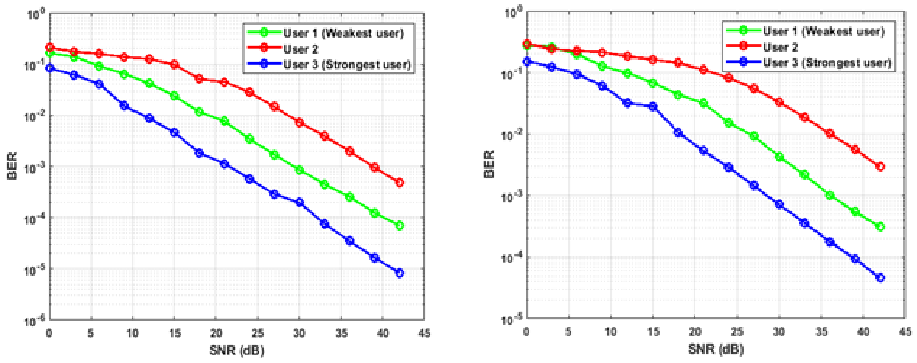
4. RESULTS AND DISCUSSION

4.1. Experiment analysis

The M-SRDMOA is given in the experiment analysis section. The M-SRDMOA method is implemented and simulated using the software MATLAB R2018a, which utilizes an i5 processor and RAM of 6 GB. The M-SRDMOA's main objective is to allocate power effectively to increase the sum rate and decrease outage probability. Communicating over the Rayleigh fading channel represents a NOMA network in this simulation.

4.2. Performance analysis

The bit error rate (BER), attainable outage probability, and sum rate are the performance metrics analyzed in this study. Here, two alternative noise variances σ_i^2 values, namely 2 and 10, are used to analyze the performance. The results of the performance analysis for various noise variances. The performance evaluation of outage probability, BER, and the attainable sum rate is shown in Figures 2-4, respectively. Two noise variances, 2 and 10 are analyzed for the outage probability, BER, and the attainable sum rate. Figure 2 represents the BER analysis' graphical representation. Here, Figures 2(a) and (b) simultaneously present a graph for $\sigma_i^2 = 2$ and $\sigma_i^2 = 10$. Figure 3 illustrates a graphical representation of achievable sum rate.



(a) (b)

Figure 2. Graphical representation of BER analysis (a) for $\sigma_i^2 = 2$ and (b) for $\sigma_i^2 = 10$

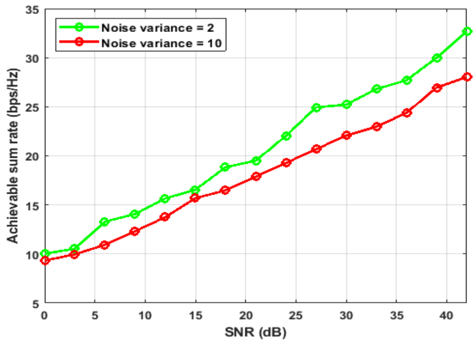


Figure 3. Graphical representation of achievable sum rate

Table 1 compares the bit error rate, whereas Table 2 compares the outage probability and attainable sum rate for various values of σ_i^2. It is called from analysis BER, where the 3rd User (the strongest user) has a lower bit error rate than the other users. In comparison to the M-SRDMOA with variance of the noise $\sigma_i^2 = 10$, the M-SRDMOA with variance of noise $\sigma_i^2 = 2$ obtains lower outage probability and greater sum rate. The M-SRDMOA's sum rate varies between 10.03 to 32.68 bps/Hz when the noise variance $\sigma_i^2 = 2$, while the M-SRDMOA's sum rate varies between 9.31 to 28.02 bps/Hz when the noise variance $\sigma_i^2 = 10$. Additionally, for $\sigma_i^2 = 2$ the outage probability ranges from 0.0491 to 3.2000×10^{-6}, but for $\sigma_i^2 = 10$, the outage probability ranges from 0.2635 to 8.7173×10^{-6}. Figure 4 denotes graphical representation of outage probability analysis.

Table 1. M-SRDMOA method's bit error rate

SNR (dB)	Noise variance=2			Noise variance=10		
	1st user	2nd user	3rd user	1st user	2nd user	3rd user
0	0.6151	0.2101	0.0827	0.2783	0.2924	0.1525
3	0.1384	0.1748	0.0614	0.2584	0.2419	0.1229
6	0.0917	0.1591	0.0411	0.1975	0.2254	0.0941
9	0.0644	0.1372	0.0152	0.1264	0.2132	0.0605
12	0.0418	0.1247	0.0086	0.0984	0.1824	0.0315
15	0.0237	0.0977	0.0046	0.0678	0.1621	0.0281
18	0.0116	0.0512	0.0018	0.0440	0.1427	0.0105
21	0.0076	0.0448	0.0011	0.0318	0.1105	0.0053
24	0.0034	0.0281	0.0005	0.0153	0.0822	0.0028
27	0.0017	0.0146	0.0002	0.0091	0.0546	0.0014
30	0.0008	0.0073	0.0001	0.0043	0.0330	0.0007
33	0.0004	0.0039	7.6666×10^{-5}	0.0021	0.1878	0.0003
36	0.0002	0.0020	3.5000×10^{-5}	0.0010	0.0101	0.0001
39	0.0001	0.0009	1.6666×10^{-5}	0.0005	0.0056	9.3442×10^{-5}
42	7.0000×10^{-5}	0.0004	8.3333×10^{-6}	0.0003	0.0029	4.5901×10^{-5}

Table 2. M-SRDMOA method's achievable sum rate and outage probability

SNR (dB)	Achievable sum rate (bps/Hz)		Outage probability	
	Noise variance=2	Noise variance=10	Noise variance=2	Noise variance=10
0	10.0326	9.3108	0.0491	0.2635
3	0.5260	9.9602	0.0272	0.1706
6	13.2909	10.9295	0.0196	0.0808
9	14.0686	12.3100	0.0061	0.0393
12	15.6536	13.7469	0.0032	0.0163
15	16.5409	15.6815	0.0015	0.0073
18	18.8346	16.4802	0.0007	0.0051
21	19.4935	17.8741	0.0003	0.0020
24	22.0212	19.2686	0.0001	0.0010
27	24.9353	20.6634	0.0001	0.0005
30	25.2096	22.0584	4.4800×10^{-5}	0.0002
33	26.8040	22.9545	2.5600×10^{-5}	0.0001
36	27.6944	24.3786	9.6000×10^{-6}	7.4115×10^{-5}
39	29.9929	26.9438	6.4000×10^{-6}	3.6363×10^{-5}
42	32.6814	28.0290	3.2000×10^{-6}	8.7173×10^{-6}

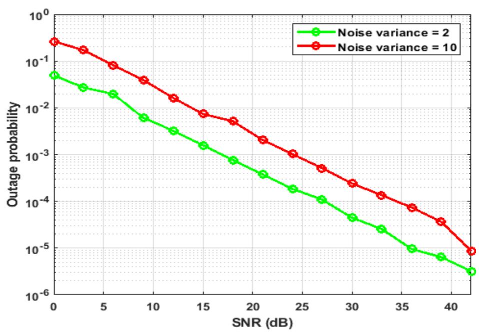


Figure 4. Graphical representation of outage probability analysis

4.3. Comparative analysis

This section displays an analysis of the M-SRDMOA's achievable sum rate in comparison to other models. The comparison performance of the M-SRDMOA achievable sum rate with FANS [21] and M-SRBOA [24] is shown in Table 3. Considering Table 2, the M-SRDMOA approach outperforms the FANS [21] and M-SRBOA [24] with respect to the achievable sum rate. The sum rate of M-SRDMOA, for example, 27.69 bps/Hz for 36 dB of SNR with noise variance= 2, which is superior in comparison to the FANS [21] and M-SRBOA [24]. To distribute an ideal amount of power to NOMA users which leads to a better achievable sum rate, the M-SRDMOA with an applicable objective function is applied. The method is modeled after the cooperative behavior of dwarf mongooses, in which individuals collaborate to attain a common objective. Mongoose agents in DMOA improve outage probability and sum rate through communication and information sharing about the ideal NOMA network. The algorithm's cooperative character improves its capacity to escape local optima and produce globally optimal solutions. Rayleigh channel fading coefficient and sum rate are two different objectives considered by M-SRDMOA. The objectives are employed to achieve an appropriate power distribution coefficient for customers in order to enhance sum rate and reduce loss.

Table 3. The M-SRDMOA comparative analysis

SNR (dB)	Achievable sum rate (bps/Hz)					
	$\sigma_i^2 = 2$			$\sigma_i^2 = 10$		
	FANS [21]	M-SRBOA [24]	M-SRDMOA	FANS [21]	M-SRBOA [24]	M-SRDMOA
9	10.0002	11.1049	14.0686	7.8625	8.7928	12.3100
12	11.1021	12.1000	15.6536	8.2010	9.7835	13.7469
15	12.0031	13.0957	16.5409	9.5321	10.7768	15.6815
18	13.0134	14.0919	18.8346	10.7682	11.7716	16.4802
21	14.0579	15.0882	19.4935	11.6574	12.7672	17.8741
24	15.0191	16.0847	22.0212	12.2571	13.7632	19.2686
27	16.0487	17.0812	24.9353	13.6734	14.7595	20.6634
30	17.0228	18.0778	25.2096	14.5879	15.7560	22.0584
33	18.0437	19.0743	26.8040	15.8732	16.7525	22.9545
36	19.0990	20.0709	27.6944	16.3464	17.7490	24.3786

4.4. Discussion

The advantages of the implemented method and the limitations of the existing methods are discussed in this section. A unique low-complexity power allocation algorithm [22] to minimize computational overhead and power usage, the power allocation methods need to be constructed. Globally optimum power allocation algorithm [23] had coding schemes and discrete modulation in actual systems, the possible rate of users is likewise constrained by a maximum value. M-SRBOA [24] was a complicated optimization approach in large-scale NOMA networks that necessitated a significant amount of computer resources. Two-way relaying communication [25] power allocation needs to be optimized so as to maximize the system performance, but identifying the appropriate technique was difficult. To overcome these abovementioned challenges, implemented M-SRDMOA considers multiple objective functions such as Rayleigh fading coefficients and sum rate to efficiently allocate power to users. The sum rate of M-SRDMOA, for example, 27.69 bps/Hz for 36 dB of SNR with noise variance=2, which is superior when compared to other existing methods. By utilizing this implemented method, an appropriate power allocation for all users is employed in NOMA to reduce the possibility of a power failure.

5. CONCLUSION

The M-SRDMOA method for distributing power to all NOMA network users is developed in this paper. The M-SRDMOA considers multiple objective functions such as Rayleigh fading coefficients and sum rate to efficiently allocate power to users. The implementation of power allocation based on M-SRDMOA enhances both the attainable outage probability and total data transmission rate for all NOMA users. Additionally, the NOMA network utilizes superposition coding in combination with SCI decoding to reduce user interference. The M-SRDMOA method outperforms more effectively than the FANS and M-SRBOA based on the result of the performance analysis. The M-SRDMOA's potential sum rate with an SNR of 9dB and a noise variation=2 is 14.06 bps/Hz, thereby being more robust in contrast to the M-SRBOA and FANS. In the future, an efficient power allocation over the NOMA network can be achieved using a novel optimization technique.

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