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Joint user clustering and salp based particle swarm optimization algorithm for power allocation in MIMO-NOMA

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Abstract. Non-Orthogonal Multiple Access (NOMA) provides a positive solution for multiple access issues and meets the criteria of fifth-generation (5 G) networks by improving service quality that includes vast convergence and energy efficiency. The problem is formulated for maximizing the sum rate of MIMO-NOMA by assigning power to multiple layers of users. In order to overcome these problems, two distinct evolutionary algorithms are applied. In particular, the recently implemented Salp Swarm Algorithm (SSA) and the prominent Optimization of Particle Swarm (PSO) are utilized in this process. The MIMO-NOMA model optimizes the power allocation by layered transmission using the proposed Joint User Clustering and Salp Particle Swarm Optimization (PPSO) power allocation algorithm. Also, the closed-form expression is extracted from the current Channel State Information (CSI) on the transmitter side for the achievable sum rate. The efficiency of the proposed optimal power allocation algorithm is evaluated by the spectral efficiency, achievable rate, and energy efficiency of 120.8134 bits/s/Hz, 98 Mbps, and 22.35 bits/Joule/Hz respectively. Numerical results have shown that the proposed PSO algorithm has improved performance than the state of art techniques in optimization. The outcomes on the numeric values indicate that the proposed PSO algorithm is capable of accurately improving the initial random solutions and converging to the optimum.

Keywords: Energy efficiency, MIMO-NOMA, Non-orthogonal multiple access, PSO optimization, power allocation, layered transmission, user clustering

1. Introduction

All communication services aim to provide an efficient, secure, effective, and consistent network, which is the critical need of the hour. Mobile communication has seen a huge development in recent decades. It has transformed from a voice-only service into a complex unified environment with more than one service built on a device that satisfies numerous purposes and offers high-speed access to a large variety of subscribers and machines. The demand for cell information traffic has exponentially grown during the last two years and is predicted to be 500–1000 times larger in terms of traffic volume requirements in 2020 than in 2010 [1]. Researchers from industry and academia are actively exploring the less investigated domains of massive–multiple-input multiple-output (MIMO), small cells, D2D communication, and novel multiple access schemes to support this overwhelming demand for data traffic [2].

MIMO is an effective technique used in the field of wireless communication that achieves full-spectrum efficiency providing broad bandwidth [3]. In the meantime, MIMO exploits spatial multiplexing in

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both ends to have substantial enhancement of the system with minimal increase in power and spectrum [4, 5]. Each antenna in the MIMO system uses the Radio Frequency (RF) chain for digital signal processing. In the downlink channel of the MIMO network, each User Equipment (UE) is used as multiple beams which rely on the transmitting and receiving antennas, to achieve better throughput in the network [6]. NOMA provides a compelling solution for multiple access issues and meets the criteria of 5 G networks by improving service quality that includes significant convergence and spectral performance. The main goal of the NOMA framework is to use the power effectively in the multi-user multiplexing environment and to use the Successive Interference Cancellation (SIC) on the receiver side [7, 8]. Power domain NOMA, which is based on the superposition theorem at the transmitter and successive interference cancellation (SIC) at the receiver has been acknowledged as an assuring technique to carry out communication for multiple devices at the constant time duration, code, and operating frequency. In contrast to the most effective OFDMA, NOMA offers high connectivity, higher spectral efficiency, and a degree of freedom (DoF). Hence in multiuser superposition transmission of 3GPP LTE-A, NOMA is included as it will provide large connectivity in massive machine-type communications and different applications of next-generation communication [43]. The SIC separates the signals by using the power of the channel differences. When NOMA has applied to MIMO, the MIMO-NOMA concept will accumulate more users and there is an enhancement in the performance of the system. Thus, it becomes a trend among academics and industry bodies to research different strategies for resource allocation, signal detection, precoding, cluster formation, and capacity analysis for both downlink and uplink 5 G networks [9].

Accordingly, NOMA enables the user to typically share the frequency and time resources and to operate well with the traditional orthogonal multi-access (OMA) and optimization algorithms [10]. NOMA is included with the MIMO in the design of user clustering, power allocation, beam formation, and volume capacity [11, 12]. MIMO improves channel bandwidth through spatial multiplexing and improves transmission efficiency through antenna diversity [13, 14]. By integrating NOMA, multiple users are managed in a single beam using SIC and intra-beam superposition coding [15, 16].

Due to the reliability of the NOMA system, MIMO-NOMA is used in the 5 G network which provides power multiplexing. MIMO-NOMA significantly increases the connectivity and maximizes the spectral efficiency in the wireless system by using various optimization algorithms [17, 26].

Thus, it becomes a trend among academics and industry bodies to research different strategies for resource allocation, signal detection, precoding, cluster formation, and capacity analysis for both downlink and uplink 5 G networks [18, 19]. In the next generation communication, limitless and ubiquitously accessing and sharing of data will give rise to high consumption of energy and battery which is another health concern of the user due to high power radiation. The limited resources worldwide and the massive increase in equipment usage became the motivation behind this research for Green Communication [20].

In [21], authors have established unique frameworks and algorithmic approaches for the joint optimization of power and channel allocation in NOMA. To maximize the sum rate value, the issues are mathematically analyzed for power allocation of NOMA. The study described in [21] was further enhanced in [22], where the authors have addressed the resource allocation and user scheduling for a downlink non-orthogonal multi-access network. In this process, the Base station assigns the spectrum and power resources to a group of users. While using this technique, the goal is to mutually optimize subchannel assignment and power allocation for the user fairness of the NOMA method with the α-fairness. The authors in [23] modeled the power allocation algorithm in the MIMO-NOMA system. The selection of the antenna is done in the uplink channel to increase the sum rate and number of devices. The Rayleigh fading channel has been used to detect the power region of the NOMA system. User synchronization has not been considered for this work. In order to reduce the transmitting capacity under performance restrictions in multiple input single output NOMA systems, a method involving power allocation, user clustering, and beamforming was proposed in [39]. In [24], the authors have developed linear precoders/beamformers to conduct signal overlays at the base stations of the MIMO-NOMA multicellular networks. It was performed to maximize the overall sum rate based on the quality-of-service criteria of users, which are individually based on the state of the channel of users. In [40], the authors divided the Resource allocation issue into two sub-problems: subcarrier allocation (SA) and power allocation (PA). For the Subcarrier Allocation, a greedy algorithm based on user grouping is implied under the presumption that power is spread equally between all chosen users and for the power allocation, the iterative water-filling algorithm has been used. The authors have established a MIMO-NOMA framework using layered transmissions for power allocation in [25]. The Channel State Information (CSI) was used to assign powers to various levels. The beamforming analysis has not been established and only two users have considered the MIMO-NOMA network. By fractional programming optimization in [26], the authors have calculated the optimum energy-efficient solution when scheduling is done on the transmission side. They have calculated transmission power and achievable data rate etc. In [27], the authors have developed a scheme for sub-channel allocation and optimization of energy efficiency, which is low in complexity and sub-optimal for NOMA downlinking. In [28], the authors have formulated a Joint User Pairing and Dynamic Power Allocation (JUDPA) that achieves the best sum-rate but reduces system efficiency performance. The article proposed the maximization of energy efficiency by optimal power allocation where QOS is taken into consideration but that deals only with one channel in [29]. In [35], the authors have maximized the total throughput of NOMA by implying PSO algorithm and fairness taken into consideration but the paper lacks in multi-antenna and massive user's implementation point of view. In [4], the authors have implemented a linear beamforming method in the MIMO-NOMA system which used a multi-cluster framework for which precoding is performed using the cluster group channel gain. This measures the gain of the cluster channel and eliminates the interference of the cluster. The key disadvantage of this scheme is the allocation of users based on the NOMA concept for each cluster directing the intra-cluster dynamic allocation of power. The authors in [37] have presented the PSO based architecture applied in NOMA for user aggregation along with different sub-channels. But the iteration number is relatively high for achieving optimal value and very a smaller number of users are there in each subchannel. The challenges for power allocation and user association are described for multi-cell downlink Non-orthogonal multiple access in [38]. Two strategies are taken into consideration like maximization of weighted sum rate and maximization of the minimum achievable user rate.

Most of the works contained in the literature seek to improve the performance of NOMA systems through power allocation optimization and beamforming techniques in terms of throughput, spectral efficiency, energy efficiency, and fairness among the users who belong to the cell. The corresponding challenge of optimization is non-convex, which means that almost no tractable solutions exist. In tackling non-convex optimization problems, heuristic and evolutionary algorithms appear to be powerful tools, as they iteratively enhance the solution until they achieve a near-optimal one. The reason for using the proposed Salp-based PSO algorithm is that it is free of parameters and therefore no parameters are needed to be optimized to ensure that the performance of the algorithm is efficient. Yet, there are few works that use optimization algorithms to maximize the efficiency of MIMO-NOMA systems. To the best of our knowledge till now no work has discussed joint User Clustering and Salp based PSO Power allocation in the downlink of MIMO-NOMA.

Various real-world applications are listed here for the viability of the proposed Salp based PSO algorithm. In the most different areas, PSO can be applied to several types of problems in science and technology. In healthcare, for example, PSO was used to diagnose leukemia problems by means of microscopic photography. In a wide range of applications which include telecom, device management, data mining, power systems design, combinatorial optimization, signal processing, network training, and many more, where PSO is applied successfully. In [36], the authors have presented mathematical modeling of PSO algorithm for the heating system planning problem, which will minimize heat system costs as a target in a specific life cycle. In the case of Communication and Networking, the Salp based PSO has been applied for congestion management, wireless sensor network design, Radar networks, Satellite Communication, and for the optimal control and design of phased arrays and routing, etc. It also can resolve numerous issues in the areas of industrial electronics, wireless communications, and electrical systems.

1.1. Novelty and contribution of the work

Compared to the strategies that focus on fixed power allocation, the implementation of the proposed Salp based PSO algorithm helps in increasing the efficiency of the system model. The selection of user clustering is meticulously carried out by analyzing the efficiency of each cluster. Global optimization technique like evolutionary algorithms (EAs), which can be applied to any real-world constrained engineering problem has been taken into consideration.

The major factor for the use of PSO in the proposed system is probably that it the easiest way with improved performance. The proposed user clustering algorithm fabricates a stable and low complex user clustering among the correlated users whereas the proposed Salp-based PSO optimally allocates powers to the users in the MIMO-NOMA using the layered transmission. This strategy enables the SSA's greater versatility in the exploration of the population and guarantees its sustainability and quickly achieves the optimal value. The results of the analysis demonstrate that the suggested approach for the proposed PSO algorithm achieves better results with regard to system throughput, Spectral efficiency, and Energy efficiency.

- We concisely review the current state of the art of principle of downlink MIMO-NOMA using Layered Transmission in 5 G and describe the system model in which all users in MIMO shares NOMA resources in the Rayleigh fading environment.
- An optimal and low complexity Joint user clustering and Salp based PSO power allocation (PPSO) method is proposed for downlink MIMO-NOMA in 5 G. Here, the users are grouped into clusters based on their gain of the channels and correlation amongst the users to maximize the total sum rate.
- For the allotted clusters of MIMO-NOMA using layered transmission, Salp based PSO optimal power allocation is proposed which increases the evaluation parameters in the cluster and in the same way optimize the power allocation among the users in the cell.
- The efficacy of the proposed Salp PSO (PPSO) is demonstrated by conducting extensive analysis and simulating numerically. Simulation results portray that the PPSO method exhibits better and improved system efficiency compared to other existing methods and proven the impact of MIMO-NOMA for various scenarios of 5 G communication.

The paper is shaped accordingly: section 2 confers about the system model for downlink MIMO-NOMA using layered Transmission and problem formulation. The User Clustering and proposed Salp PSO based power allocation are detailed in section 3. The authentication through simulation results of this novel power allocation strategy is described in section 4 whereas the conclusion drawn is reported in section 5.

2. System model and power model

2.1. System model

A downlink MIMO-NOMA system with multiple antennas in both base stations and user terminals (UTs), where a base station is situated at the center and the users are randomly deployed. The base station (BS) is having M number of antennas and every user in the BS is connected to the N number of antennas. The chancel matrix is indicated as M_k, which is calculated from the base station to users. The signal vector for the user k with the size $[N \times 1]$ is represented by a_k. The signal vector a_k is designed to use for the coded sequence.

The signal vector received by the user k is represented as

$$b_k = M_k (a_1 + a_2) + c_k \tag{1}$$

Where c_k is the vector for background noise for user k. Due to the higher scale fading, the magnitude of the M_1 elements greater than the magnitude of M_2. Hence, the power assigned to the user 1 is less than the power assigned to the user 2.

Let us assume,

$$E [a_i] = 0 \tag{2}$$

To enhance the spectral efficiency, the power difference and the power level is used in the NOMA transmission. The term a_2 is decoded at user 1 as it has the maximum transmission power. The desired signal after receiving a_2 through SIC is expressed as,

$$\bar{b}_1 = M_k a_1 + c_k \tag{3}$$

The power of a_1 is less than the power of a_2, so a_2 is decoded at user 1. Generally, the BS has more number of antennas than the user, $M > N$. In such a case, the BS is precoded using the precoding matrix with the size of $[M \times N]$.

The users are partitioned into different groups using the channel gain difference of the users and the channel correlation. Every user carries the sequence by sequence decoding through SIC in the layered transmission approach. Hence, the decoding complexity of the user is lower in the layered transmission approach. Assume the Base station would be to send coded signals to each individual concurrently, as in H-BLAST [44]. Each user will perform sequential decoding with SIC for temporal multiplexing using the layered transmission technique.

The n^{th} element of a_k is denoted as a_k, n. The symbol sequence is independently decoded at each layer. The QR factorization is expressed as,

$$M_k = a_k T_k \tag{4}$$

Where a_k denotes the orthogonal matrix of $[N \times N]$, and T_k represents the upper triangular matrix.

The transmission power at the receiver is given by

$$\begin{aligned} p_k &= a_k b_k \\ p_k &= T_k(a_1 + a_2) + \bar{b}_k \end{aligned} \tag{5}$$

where, $\bar{b}_k = a_k c_k$

Hence, at layer n, the power of the n^{th} element in the k^{th} vector is represented as,

$$p_{k,n} = \sum\nolimits_{g=k}^{A} e_{k,g,n}(a_{k,1} + a_{k,2}) + c_{k,n} \tag{6}$$

Where, e_k, g, n denote (k, g) th element of T_k, and c_k, n indicate the n^{th} element. The standard equation for the element at the layer is given in Equation (6) such that the standard equation is modified using the power allocation coefficient as in Equation (7). By adding the power allocation coefficient of every layer, the resulted element is expressed as,

$$p_{k,n} = \sum\nolimits_{g=k}^{A} \alpha_k[e_{k,g,n}(a_{k,1} + a_{k,2}) + c_{k,n}] \tag{7}$$

Where α_k denotes the power allocation coefficient.

The power allocation in the MIMO-NOMA system is performed with the layered transmission approach [25]. User 1 is to execute SIC within that layered transmission scheme with reference to the messages of user 2 as well as its signals in the other layers.

Let us assume,

$$\omega_k = \left|e_{k,g,1}\right|^2 \tag{8}$$

$$\mu_k = \left|e_{k,g,2}\right|^2 \tag{9}$$

The signal powers are indicated as

$$G_k = E\left[\left|a_{k,1}\right|^2\right] \tag{10}$$

$$H_k = E\left[\left|a_{k,2}\right|^2\right] \tag{11}$$

Hence, the sum rate is represented as,

$$R_k = \sum_{k=1}^{A} log2\left(1 + \frac{f_k a_k}{f_k G_k + 1}\right) + \log_2(1 + \omega_k G_k) \tag{12}$$

Hence, the proposed achievable sum-rate is expressed as,

$$R_k = \sum\nolimits_{k=1}^{A} log_2\left(1 + \frac{f_k a_k}{f_k G_k + 1}\right) + \log_2(1 + \omega_k G_k) + \alpha \sum\nolimits_{g=1}^{k} \omega_{k_m ax} \tag{13}$$

Where, the power allocation coefficient is expressed as,

$$\alpha_k = \alpha \sum\nolimits_{g=1}^{k} \omega_{k_m ax} \tag{14}$$

The maximum power allocation of every layer is indicated as, [max R], where ai is the coded sequence of the user in every layer

The Spectral Efficiency is given by

$$Spectral\_Efficiency = \frac{\text{Achievable\_sum\_rate}}{\text{Bandwidth}} \tag{15}$$

The parameter for energy efficiency is a multi-objective scheme, where it must deal with two conflicting metrics total sum rate and transmission power. Again, this EE metric must exploit the total power while maintaining a trade-off between the sum rate and total power consumption by the system. Energy efficiency is a quantifiable metric characterizing the performance of wireless networks, which refers to the data bits transmitted per unit energy.

$$\mathrm{EE} = \frac{\mathrm{R_k}}{\mathrm{p_c + p_t}} \tag{16}$$

Where p_t is the transmission power and p_c is the circuit power.

3. Dynamic user clustering and salp PSO power allocation

In this proposed power allocation method, two stages are involved. In the first stage, the users are grouped into clusters, and in the second stage, the power has been allocated in both intracluster and inter-cluster by the Salp Particle swarm optimization technique.

3.1. Dynamic user clustering

User clustering is proven to be very advantageous in multiuser MIMO-NOMA. In SISO-NOMA, the users are operated orthogonally whereas, in MIMO-NOMA the users in the clusters share the resources by exploiting the MIMO concept [30]. So, there will be high complexity in user clustering when high numbers of antennas are associated with practical deployment. We have intended to offer an optimal user clustering/grouping strategy for the multiuser single-cell downlink MIMO-NOMA system. The proposed approach utilizes the differences between user's channel gain and aims to maximize the amount of throughput of the MIMO-NOMA model. In this paper clustering and grouping, words are used interchangeably for better understanding.

Two and three user clusterings are considered out of many users for making NOMA more practicable where some are cell-centered and others lie in cell edge. The users having maximum channel strength are known as strong users whereas users with the least channel strength are referred to as weak users. Inspired by [31], a two-user scenario has been taken into consideration as their user grouping approach is sub-optimal due to the presence of the pairing of users with a marginal difference in channel gain. The data meant for users in each cluster are consecutively deciphered as below. First, the data for the weak user is interpreted by the strong user. Then the data for the strong user is successively decoded by the strong user after canceling the interference from the weaker user. To improve the efficiency of users with low channel quality, grouping them with users with high channel gains is beneficial. The purpose is that by using low power levels, high channel gain users will reach a higher output while keeping a substantial percentage of power available to weak users. Figure 1(a) depicts the two-user's grouping whereas Fig. 1(b) shows the three-user's clustering scenario.

The main aim of the proposed PSO algorithm is to perform the power allocation optimally through the maximization of the achievable rate at every layer. However, it allocates the power to the users with maximal efficiency in the layered transmission scheme.

Algorithm 1 User Pairing Algorithm:

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1. Input: Users in the system model
2. Sort users in ascending order of channel gain i.e., $h_{1,n} > h_{2,n} > h_{3,n} ... > h_{k,N}$.
3. Define h_t =threshold value of channel gain between h_1 and h_N.
4. Initialize user set $A = \{1, 2, 3, ..., t\}$ and $B = \{t+1, t+2, ..., N\}$.
5. While $h_{k-1,N-1} > h_{t,n}$
6. Allocate h_{t+1} user randomly for pairing with h_1 user.
7. If $h_{k,N} < h_{t,n}$, then
8. Do an exhaustive search among the rest.
9. End if
10. End while
11. Output: The corresponding user pairing.

Algorithm 2: 3- User Clustering Algorithm.

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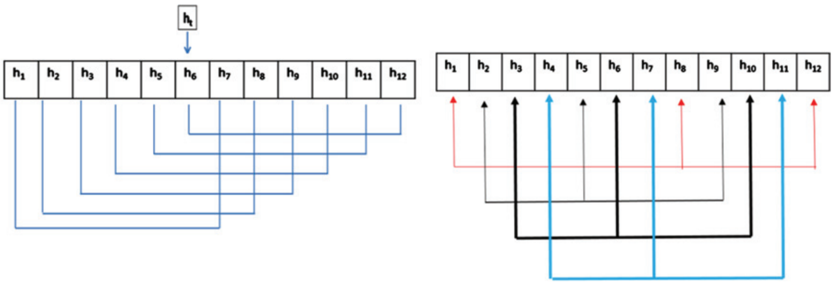
1. Input: Users in the system.
2. Sort users in ascending order of channel gain i.e. $h_{1,n} > h_{2,n} > h_{t,n} .., h_{m,n} > h_{k,N}$.
3. Define the set of users whose channel gain value between h_1 and h_N where $h_t > h_m > h_N$.
4. Initialize user set high channel gain (HGC)=$\{h_1, h_2, h_3 ... h_t\}$, Medium channel gain (MGC) = $\{h_{t+1}, h_{t+2} ..., h_m\}$ and Low channel gain (LGC) = $\{h_{m+1}, h_{m+2} \ldots h_N\}$ and $S \in \{HGC, MGC, LGC\}$.
5. While $h_1 > h_N$
6. Allocate MGC and LGC users for clustering with HPC users with large channel gain difference.
7. If $h_1 < h_N$, then
8. Do an exhaustive search among the rest.
9. End if
10. End while
11. Repeat steps 1 to 6 whenever users locations changed (channel gain value) to revise the user sets.
12. Output: The corresponding user grouping.

The closed-form expression is derived using the CSI present at the transmitter side. The CSI allows the users to efficiently allocate the powers to different layers in the layered transmission approach.



(a) (b)

Fig. 1. User clustering (a) Two user (b) Three user.

3.2. Proposed salp based PSO power allocation

After the users are being clustered into their respective clusters, the Salp based PSO algorithm is used to calculate the allocated power in each cluster. For the intra channel power allocation, the user with lower channel gain will be given more power as per the NOMA principle. For both Spectral Efficiency and Energy Efficiency, the fitness function is approximated by using the Achievable sum rate. The optimal fitness benefit relies on the effective distribution of powers to various levels. The CSI on the transmitter side is used to extract a closed-form expression. The PPSO algorithm is developed with the layered transmission approach to increase the sum rate to solve the problem of allocating the powers in the MIMO-NOMA system.

In the layered transmission method, the proposed Salp based PSO algorithm assigns the powers to multiple user layers. The proposed Salp based PSO algorithm is the combination of the Salp Swarm Algorithm (SSA) [32] and the Particle swarm optimization (PSO) algorithm [33]. Both algorithms are combined to achieve more flexibility of SSA in PSO for improving exploitation, diversity in the solutions, and optimum result in the power allocation.

Salp's main activity is swarming the behavior, which is efficiently used in MIMO-NOMA's power allocation framework. The salp builds a chain in deep seas, called the salp chain. In MIMO-NOMA the power allocation utilizes the salp's swarming activity with layered transmission to achieve a better sum rate. Mathematically the salp chain is modeled by splitting the population into two groups namely the leaders and the followers. The salp leader is available in the salp chain at the front situation, and the remaining salps accessible in the salp chains are named followers. The head salp directs the swarm, while another swarm follows the follower salp. The position of the salp is specified using the r dimension search space, where r represents the maximum variety of solutions shown in the problem of optimization. Therefore, all of the salp locations are preserved using the two-dimensional matrix, defined as, L. In the search space, the food source of the salp is indicated as, F,

$$F_s = \begin{cases} L_s + o_1\left((M_s - N_s)\, o_2 + N_s\right) o_3 \geq 0.5 \\ L_s - o_1\left((M_s - N_s)\, o_2 + N_s\right) o_3 < 0.5 \end{cases} \tag{17}$$

Where Fs shows the scale of the leader salp (first salp). Ls represents the location of the source of salp food in the s^{th} dimension. Ns depicts the salp's lower portion in the s^{th} dimension and Ms depicts the salp's upper portion at the same dimension. The random numbers are o_1, o_2, and o_3. The leader can reconsider their position only depending on the source of the food. Hence, the term o_1 is expressed as,

$$o_1 = 2e^{-\left(\frac{4q}{T}\right)^2} \tag{18}$$

Where the total iterations are included to be used to change their location and q is the initial iteration. The words o_1 and o_2 are the coefficients that use the random numbers that are developed uniformly between 0.5 and 1. In particular, the salp identifies the next place in the sth dimension either as positive or negative infinity.

The location of the follower salp is updated using the below equation,

$$F_s^j = \frac{1}{2}\frac{s_{final}}{s_0}t^2 + s_0 t \tag{19}$$

Where Fs denotes the location of the j^{th} follower salp swam in s^{th} dimension and t represent the time. The time specified in the optimization is the iteration. Hence, the discrepancy among the iteration is equivalent to 1.

Let us assume $v_0 = 0$ and the modified equation is

$$F_s^j = \frac{1}{2}\left(F_s^j + F_s^{j-1}\right) \tag{20}$$

where, $j > 3$, and F_s^j represents the location of the followers' salp swam at the dimension.

Algorithm 3: Proposed Salp based PSO algorithm.

1. Specify population size N, and n is the number of iterations.
2. Randomly generate a population of size N Salps, uniformly distributed.
3. Evaluate fitness function values for all Salps of the population.
4. Revise the best Salp in the solutions.
5. Calculate o_1 using Equation (18).
6. For i = 1 to N,
7. if i = = 1 then,
8. Update the position of Salp using Equation (17).
9. else
10. Update the position of the Salp using (19).
11. End if.
12. End for.
13. Update Salp vector for a better outcome.
14. Until stop criterion
15. Return the best optimal solution.

So, the salp swarm's salp chain is modeled with the Equation (17). To determine the optimal global solution, the salp swarm utilizes the single target optimizer. The follower salp swarm in the swarm model obeys the actions of lead salp in the salp chain. The leading salp runs swiftly toward the food source. If the food source is updated to the optimal regional, then the salp chain travels directly to the food source. The best solution measured using the salp swarm is defined as the optimum global, and thus the salp chain chases the food source. The fitness is determined for each salp and the salp swarm is defined with the optimum fitness.

The location of the leading salp swarm is modified using Equation (17) for each dimension.

Moreover, the location of the follower salps is modified using Equation (20).

Besides, the interpretation of particle motions is defined with the velocity parameter P. For convenience, the above Equation (20) is written as,

$$L_{ki}^{h+1} = 0.5 \left(L_{ki}^{h} + L_{k-1,i}^{h} \right) \tag{21}$$

To determine the best optimal solution, the moving velocity parameter P is combined with the leader salp in the salp chain. Also, the power allocation in the layered transmitted MIMO-NOMA has used these variables to obtain a greater sum rate, spectral efficiency, and energy efficiency. The PSO algorithm's fractional behavior equation is updated using the leader salp position.

The time complexity of algorithms is a function that defines the running time of the algorithm. The time complexity of the proposed Salp based PSO algorithm is defined as O (n(v*s + ftf*s), where n is the number of iterations, s is the number of solutions, v is the number of variables and ftf is the fitness function.

4. Results and discussion

This section outlines the findings and discussions in the MIMO-NOMA framework about the proposed power allocation model. In the MATLAB method, the proposed model of power allocation is implemented. The channel coefficient exhibits i.i.d. Gaussian distribution. The noise in each user is assumed to be AWGN with zero mean and unit variance. The proposed power allocation is evaluated with the layered transmission model using the performance metrics that include Achievable Rate, Spectral Efficiency, and Energy efficiency. The performance of the proposed Salp PSO algorithm (PPSO) is evaluated and a comparative analysis is made using the existing methods, namely Gain Ratio power allocation (GRPA) [34], Channel gain difference power allocation (CGDPA) [4], Heuristic matching combining PSO power allocation (MCPSO) [35], respectively.

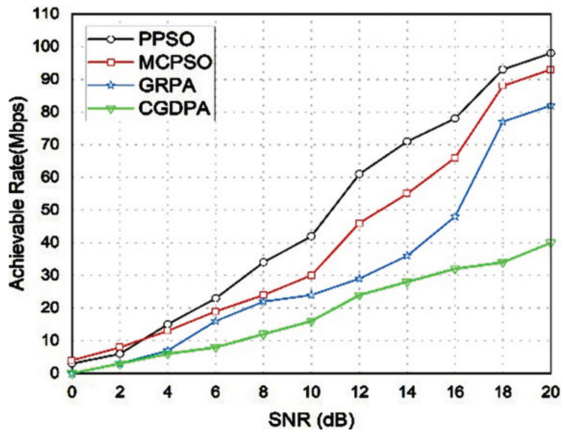
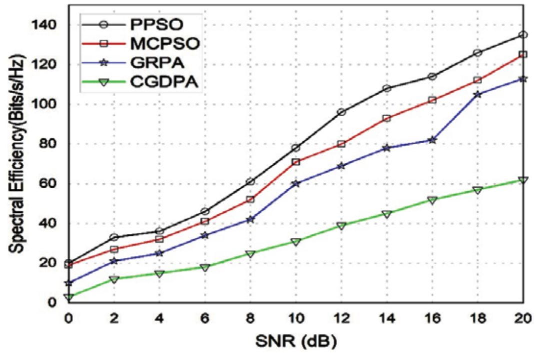


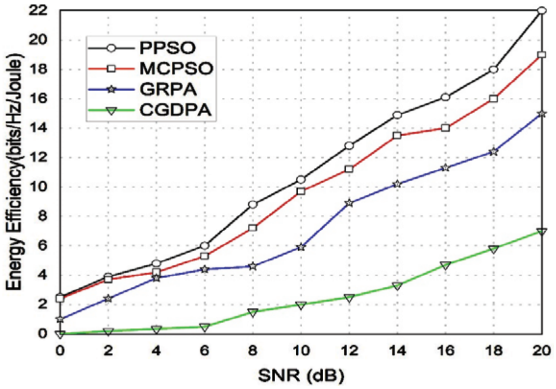
Fig. 2. Achievable sum-rate vs SNR.

Figure 2 shows the analysis of the achievable rate concerning the SNR. When the value of SNR is 10 db, the achievable rate obtained by the proposed PSO is 41.24 Mbps, while the percentage of improvement reported by the proposed PSO to the existing methods, like HMPSO, GRPA, and CGDPA is 40%, 75%, and 86% respectively. From the above figure, it is shown that the achievable rate for the proposed PSO is better than other existing systems.

Performance in respect of spectrum and energy is one of the main obstacles the MIMO-NOMA scheme will encounter. They tend to face varying channel conditions and communication specifications due to the vast number of signal transmissions that happen simultaneously. Figure 3(a) describes Spectral efficiency with respect to SNR. When the SNR is 10 dB, the spectral efficiency of the Proposed PSO is 78.65 bits/s/Hz. As seen in the figure, the MIMO-NOMA scheme for proposed PSO outperforms Matching combining PSO. Furthermore, PPSO outperformed GRPA and CGDPA too. This is because the proposed salp based PSO resource allocation uses the advantages of both SSA and PSO to achieve the optimal power allocation for maximizing spectral efficiency, while the other discussed NOMA method leads to a suboptimal power allocation. This implies that the proposed power allocation method is essential to the performance of the MIMO- NOMA system.



(a)



(b)

Fig. 3. Analysis of parameters based on SNR of the system (a) Spectral Efficiency (b) Energy Efficiency.

Figure 3(b) shows the energy efficiency for SNR of the proposed PSO system for MIMO-NOMA. The EE of the PPSO at SNR 10 dB is 11.56 bits/Hz/Joule, which is way higher than other referred systems. The percentage of improvement by the proposed PSO for other systems is 13%, 31%, and 68% for MCPSO, GRPA, and CGDPA respectively.

In Fig. 4, there is an analysis of the achievable sum-rate with the number of users in the system. As shown in the figure, the achievable rate is increasing with the increasing number of users. When the number of users increases, it becomes more challenging for the system to distribute power to implement all users at high rates since traffic levels often rise. The Proposed Salp PSO system is having a better sum rate than that of other existing systems depicted in this work. When the number of users is 30, the achievable sum-rate is 62.75 Mbps whereas 58.72 Mbps, 43.25 Mbps, and 26 Mbps for MCPSO, GRPA, and CGDPA respectively.

Figure 5(a) depicts the analysis of spectral efficiency with respect to the increasing number of users.

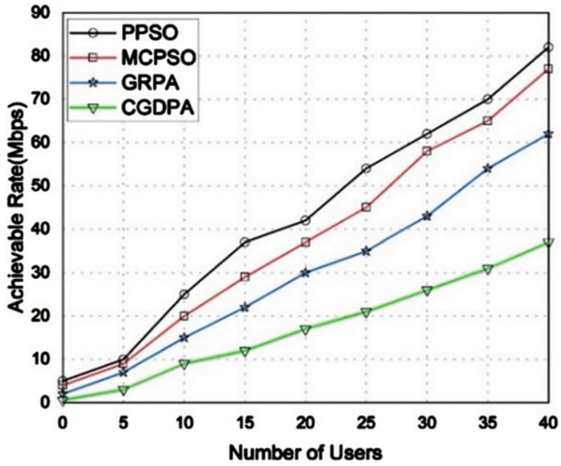
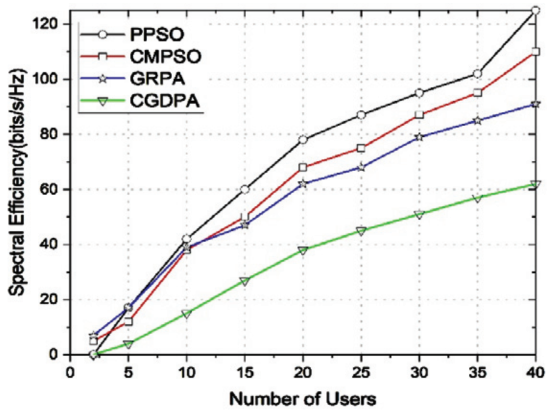


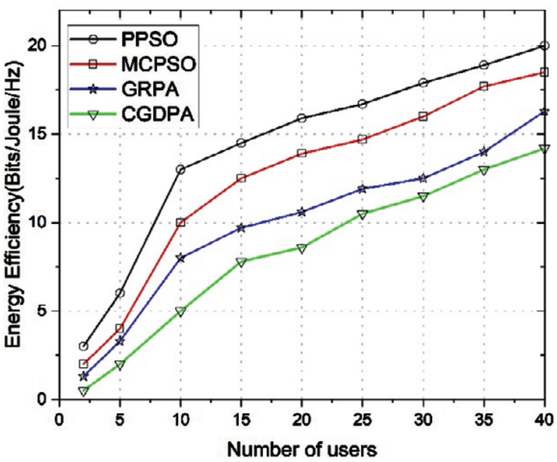
Fig. 4. Achievable sum Rate vs Number of Users.

The transmission power has been kept constant at the base station throughout the transmission. An increase in spectral efficiency following an increase in the number of users is observed. As the number of users increases, there is a higher chance that a user with better channel conditions can be picked for user pairing and power allocation. To achieve high throughput, low channel gain users need more spectrum resources in OFDMA. However, in the case of NOMA, it can be achieved by allocating more power to low channel gain users. So, the proposed Salp-based PSO algorithm performs better than other optimization techniques regardless of the number of users.

Figure 5(b) shows the analysis of Energy efficiency based on the number of users. As we can see from the figure that there is an increase in energy efficiency as the number of users increases in the system. When the number of users is 25, the energy efficiency of the proposed PSO is 17.89 bits/Joule/Hz. So, the percentage of improvement stated by the proposed PSO with respect to the existing methods, like MCPSO, GRPA, and CGDPA is 62%, 45%, 24%, 16%, and 10%, respectively. The transmission power is kept constant at the base station throughout the transmission. The sum-rate becomes more when the number of users increases in the cell, therefore the energy efficiency also increases. If a large number of users are in the system, then the resources are used efficiently due to user diversity. The justification is that a static search is adopted by the convex optimization algorithm whereas Global search power is required for our proposed PSO algorithm. The improved algorithm incorporates deep search and wide search resulting in a better optimal global location. It is proved that



(a)



(b)

Fig. 5. An analysis based on the number of users present in the MIMO-NOMA system (a) Spectral Efficiency (b) Energy Efficiency:

the optimal power allocation coefficient is attained by our proposed Salp based PSO algorithm.

Figure 6 gives the comparison of spectral efficiency when 2, 3, and 4 users are grouped in the cluster respectively in the proposed PSO based Power allocation for layered transmission in MIMO-NOMA. It is clearly shown that the 2-user cluster outperforms the 3- user and 4-user clusters in the proposed PSO. When the transmission power of the base station is 15 dBm, then the spectral efficiency for 2 user cluster MIMO-NOMA system is 11.25 kbps/s/Hz, while there is an improvement of the spectral efficiency for other clusterings, for instance, the improvement for 3- user and 4-user is 37% and 64% respectively. These findings show that the proposed Salp based PSO does have a strong balance between the processes of exploration

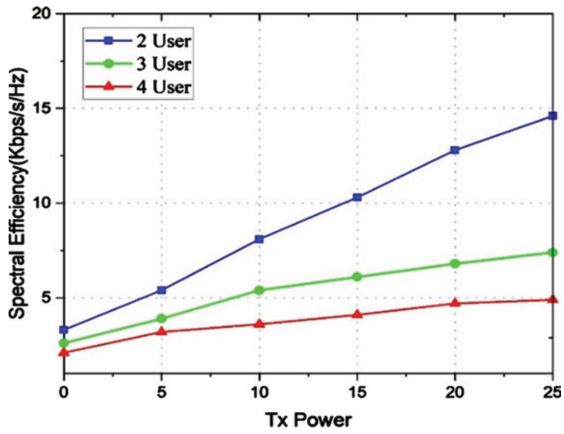


Fig. 6. Comparison of Energy efficiency for a different number of users in the cluster.

and exploitation, and the recombination between the SSA and the PSO increases the efficiency of the basic PSO in solving the fitness functions.

The speed of convergence is a challenge when resolving problems of optimization. In seeking an accurate estimate of the global optimum, converging speed is necessary.

Figure 7 shows the convergence ability of the proposed salp-based PSO in comparison with other optimization techniques described in related works. The PPSO has a greater capacity to explore, which can make the solutions move from the optimum local point when compared to the existing optimization techniques. The proposed PSO is increasingly converging, which enables the proposed algorithms ideal for realistic applications. The proposed approach has a higher rate of growth and a better outcome.

As the real-time issues also have a large set of variables, the scalability of the proposed SSA algorithm is assessed in this segment. Figure 8 shows that when raising the number of variables, the output of the proposed PSO reduces because already several solutions were set throughout this experiment. We can observe that the proposed algorithm doesn't deteriorate significantly when a large number of parameters are incorporated for real-world application scenarios.

Here as a pairwise data analysis function, the Wilcoxon signed-rank test is used. The test begins by identifying the variations from every test function between the results of the different techniques. The outcomes of each method that runs 30 times on each test function are considered as individual variables and split into four categories for statistical analysis. For every test pair, the proposed PSO is taken as the

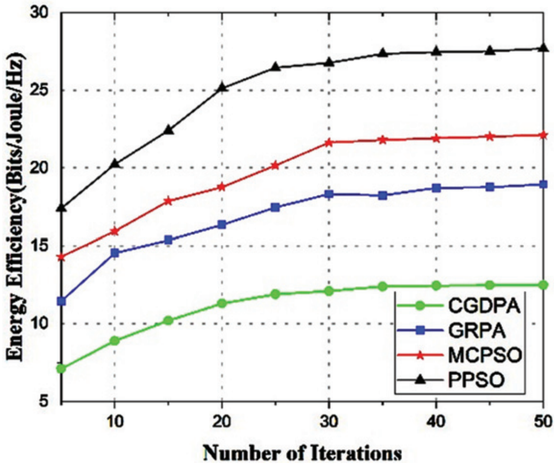


Fig. 7. Convergence analysis of Salp based PSO algorithm.

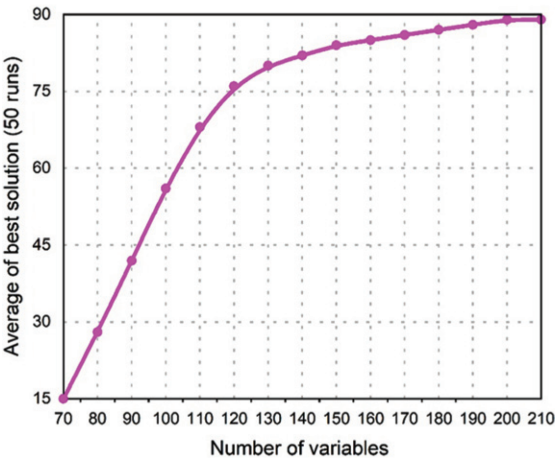


Fig. 8. Scalability analysis for Salp based PSO algorithm.

Table 1
Simulation setup

Parameters	Value
Cell radius	1000 m
Carrier frequency	2 GHz
System bandwidth	10 MHz
Transmission power	46 dBm
Noise spectral density	–174 dBm/Hz
Path loss	128.1 + 37.6 log10(d), d in km
Number of users	30
Users in cluster	2,3,4
Antenna gain at BS and receiver	0 dBi
Number of BS antenna	5
Number of user antenna	3
Channel model	Rayleigh fading
PSO population size	1000
Inertia weight	0.9–0.4
Acceleration factors	0.30
Best value gain tolerance	10–15
Maximum iterations	1000

Table 2
Wilcoxon test

PPSO vs	R+	R-	p-value
MCPSO	71	9	0.028
GRPA	64	10	0.016
CGDPA	56	5	0.009

first algorithm whereas other techniques are considered as the second algorithm. The test mainly focused on the capability of the techniques for maximizing the fitness function. A significance level of 0.055 is selected in the Wilcoxon signed-rank test.

By observing Table 2, one can conclude that the proposed salp-based PSO outperforms other optimization techniques with a significance level of 0.055. Taking into consideration, individual pairwise comparisons, the PPSO algorithm surpasses these algorithms since the p-values are less than alpha = 0.055. The findings of the p-values obtained from the Wilcoxon test in Table 2 indicate that supremacy of the proposed salp based PSO algorithm is highly significant. R+ is the number of ranks for the cases, where the second was outperformed by the first algorithm, and R-is the sum of ranks for the counter.

The findings and analysis show that the proposed PSO algorithm with undefined search spaces is practically necessary to solve real-world issues. The position of the global optimum is uncertain in a realistic solution space. The equilibrium between exploration and exploitation, thus, significantly increases the probability of deciding the global optimum. This explanation, which was derived from the evolutionary system, was primarily the result of the proposed salp based PSO algorithm. It can infer that the proposed PSO algorithm is capable of discovering the most promising searching space areas, improving the average performance of all salps, and finding better solutions during optimization.

5. Conclusion

The proposed PSO algorithm is developed to efficiently allocate the powers in the layered transmission MIMO-NOMA system, where joint users are clustered in groups followed by the optimal power allocation. In the search for solutions, the proposed algorithm uses the features of the PSO strategy to boost the SSA's efficiency. Hence the convergence rate is then boosted. The trial of the proposed algorithm is carried out using the evaluation metrics, namely Achievable Sum rate, Spectral efficiency, and energy efficiency with respect to SNR, Transmission Power, and users present in the 5 G network. The proposed joint user clustering and PSO power allocation algorithm for MIMO-NOMA is compared with the existing systems, which capably produce higher energy efficiency of 22.35 bit/Joule/Hz and enhanced spectral efficiency, and achievable rate of 120.8134 bits/s/Hz, 98 Mbps, respectively. This shows the efficiency of the proposed algorithm in allocating the powers optimally to different layers. In the future, the power allocation will be done for optimization of both spectral efficiency and energy efficiency when the users are virtually clustered in heterogeneous networks under both instantaneous and statistical CSI. Besides, further simulations will be carried out and other algorithms will be verified, including the Gray Wolf Optimizer [41] and the ant colony [42] algorithm.

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