Innovative Power Allocation Strategy for NOMA Systems by Employing the Modified ABC Algorithm

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Abstract. *Non-Orthogonal Multiple Access (NOMA) technique is a remarkable component of 5G wireless networks; since NOMA immensely augments the spectral efficiency and serves all users fairly. To accomplish these, efficient power allocation is crucial for improving the NOMA system's performance. Accordingly, in this article, we formulate a power allocation optimization issue, which concentrates on enriching the system sum-throughput, by realizing the transmitted power constraint and also fulfilling the minimum throughput for each user. However, to tackle this mentioned optimization problem, a Modified Artificial Bee Colony (MABC) algorithm is proposed. Besides, the designed MABC algorithm obtains optimal powers among multiplexed users on every sub-channel. Further, simulation results illustrate that the presented power allocation scheme-based NOMA system's sum throughput is higher than the original ABC-based power allocation and other state-of-the-art power allocation schemes. Moreover, the MABC method swiftly converges to optimal solutions compared to the original ABC algorithm under selected control parameters.*

Keywords

NOMA, artificial bee colony, power allocation, sum rate

1. Introduction

The ongoing enormous growth in mobile traffic and ubiquity of smart devices have placed higher demands on the upcoming (5G) wireless systems [1], [2]. In order to meet these emerging cellular industry challenges, the 5G networks need to enhance system capacity further. To this end, Non-Orthogonal Multiple Access (NOMA) has evolved as one of the essential technologies for 5G systems due to its high bandwidth utilization, user fairness, and massive user connectivity [3–6]. Further, contrary to the traditional Orthogonal Multiple Access (OMA) [7–13]; NOMA breaks the orthogonality between users by exploiting the power domain multiplexing, and it serves multiple users simultaneously at different power levels [14].

Moreover, in a downlink NOMA framework, the Base Station (BS) superimposes various users' data for simultaneous transmission over the single radio resource unit [15]. As a result, superimposed data for multiple users can be separated at the receivers (of the corresponding users) by using the Successive Interference Cancellation (SIC) method. However, to ensure successful SIC detection at each user's receiver, users having poor channel gains must be assigned with higher powers than those powers allotted for good channel gain users [16], [17]. Furthermore, the NOMA system can control the user multiplexing and transmission throughput by allocating distinct powers to different users. Therefore, user power allocation becomes a significant issue in addition to user scheduling problems [18], [19].

In recent literature, numerous Power Allocation (PA) techniques for NOMA networks have been investigated to heighten the sum capacity of the system. In [20], [21]; Fixed Power Allocation (FPA) scheme has been exploited for power optimization to enhance system capacity. But, due to fixed power factors between the users, FPA does not provide an optimal solution. In consequence, Fractional Transmit Power Allotment (FTPA) was investigated in [22–25], which is a widely used dynamic power allocation algorithm. Accordingly, FTPA allocates powers to users as per the channel conditions (of users). However, in order to obtain the best performance, FTPA requires prior computer simulations for determining the decay factor of channel gains. Analogously, [26] presents the difference-of-convex programming-based inter and intra-sub-channel power allocation for optimizing the system's sum capacity. In any case, the proposed approach in [26] delivers a sub-optimal solution, even though it outperforms OMA and FTPA techniques.

Additionally, to achieve user fairness, the fair power allocation method was proposed in [27], [28]; that delivers the capacity to every user exceeding the corresponding OMA capacity by ensuring the overall power constraint. Analogously, in [29], authors explored two power allotment methods to optimize the ergodic capacity in two-user NOMA networks with total transmission power and weak user's minimum data throughput constraints. However, in [29], the proposed method did not guarantee the strong user's minimal data throughput. Further, in [30], Karush-Kuhn-Tucker

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optimal conditions have been employed to derive the closed-form results of power allocation factors among multiplexed users on each sub-channel.

However, most of the works discussed above accomplish significant results by either relaxing power allocation constraints or offering a sub-optimal solution. In contrast, Evolutionary Algorithms (EA) can prove to be good assets in handling complex non-linear constrained optimisation problems because they repeatedly renew an initial solution up to the result becomes an optimal solution. Nevertheless, only a very few studies [31–33] have exploited EAs namely: particle swarm optimization, salp swarm optimization, and genetic algorithm to improve the performance of NOMA systems. Hitherto, no study has reported utilizing the Artificial Bee Colony (ABC) algorithm to the issues related to power allocation in the NOMA systems. But, the motivation for adopting ABC (to the NOMA system) is the fact that it requires limited control parameters, and it provides the best solution compared to the other meta-heuristic algorithms [34], [35]. Nonetheless, when dealing with complex problems, ABC algorithm confronts unacceptable exploitation [36]. To overcome this drawback, we developed a Modified ABC (MABC) method and utilized it to enhance the NOMA system performance as given in the below paragraph.

In this article, we propose unique solution search equations by incorporating the best solution in the “employed and onlooker bees phases”, respectively, to enhance exploitation and retain exploration. After that, the MABC approach is operated to address the PA problem, thereby increasing the total throughput of the downlink NOMA system. Ultimately, simulation findings validate that the projected method for NOMA system outperforms the original ABC-based PA, FTPA algorithms, and OMA system. Moreover, MABC shows fast convergence compared to the original ABC method.

The remainder of this article is organized as follows. Section 2 provides the NOMA conceptual framework and formulation of the power allotment problem. Then, the proposed MABC-based power allocation strategy is discussed in Sec. 3. Subsequently, Section 4 validated the proposed MABC with numerical results based on standard test functions and also provides simulations of MABC-based power allocation for NOMA system. Eventually, in Sec. 5, the article is concluded.

2. Downlink System Design and Problem Formulation

To provide explicit elucidation, this section is partitioned into two sub-sections. Section 2.1 gives a brief overview of the downlink NOMA transmission paradigm. Following that, the power allocation optimization problem (to improve the sum-rate) is mathematically developed in Sec. 2.2.

2.1 System Model

Assume a NOMA downlink scenario in which the BS (Base Station) is at the cell’s center, and N users are deployed randomly across the radius (R) of the cell, as shown in Fig. 1. Further, BS as well as User Equipments (UE), are furnished with a single antenna and BS broadcasts information to all the users through M orthogonal sub-channels. Let P_{t} be the overall transmit power of BS. Besides, the available system bandwidth B at the BS is evenly partitioned to all the M sub-channels, with B_{sc} denoting the bandwidth of each sub-channel.

In this work, we adopt the uniform channel gain difference user pairing scheme proposed in [37]. According to this pairing strategy, UEs are arranged as per the descending order of their channel gains. Then, all these arrayed UEs are portioned into two groups (group1 and group2). Subsequently, the highest channel gain users from each group form one NOMA pair (i.e., one user having better channel gain from group1 and the other user having predominant channel gain in group2 represent one user pair). Later, users possessing the second-highest channel gain in each group structure into the second user pair. In this fashion, user pairs are produced, one pair after the other pair. Accordingly, each sub-channel has only two users paired together to simplify receiver SIC (Successive Interference Cancellation). Moreover, for every sub-channel, UE with substantial channel gain is denoted as UE_{s} while weak channel gain UE is represented with UE_{w}.

For instance; let us suppose that UE1, UE2, UE3, and UE4 have the average channel gains of –75.65 dB, –81.94 dB, –90.64 dB & –67.91 dB respectively. Thereafter, users are ordered as: UE4, UE1, UE2 & UE3 as per the sequencing of their channel gains as: –67.91 dB, –75.65 dB, –81.94 dB & –90.64 dB. At present, the group1 contains UE4 and UE1. Correspondingly, group2 includes UE2 and UE3. In both the groups, the highest channel gain users are UE4 & UE2. So, the first user pair is UE4 & UE2. Further, second-highest channel gain users in both the groups are UE1 & UE3. So, the second user pair becomes UE1 & UE3.

The above-given approach of user pairing improves the data rate of weak channel gain users as well.

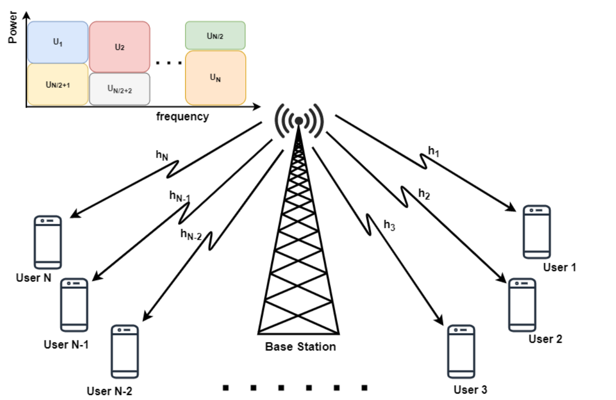


Fig. 1. NOMA system model for multiple users.

Consider that BS has precisely known Channel State Information (CSI). Consequently, according to this identified CSI, BS delivers the multiplexed coded symbols to all users. For each sub-channel; $s_{\mathrm{w},m}$ and $s_{\mathrm{s},m}$ represent the modulation symbols of UE_{w} and UE_{s}, respectively and the multiplexed symbol for the sub-channel m is given as

$$x_m = \sqrt{\alpha_{\mathrm{w},m} P_m}\, s_{\mathrm{w},m} + \sqrt{\alpha_{\mathrm{s},m} P_m}\, s_{\mathrm{s},m} \tag{1}$$

where $\alpha_{\mathrm{w},m}$ & $\alpha_{\mathrm{s},m}$ represent the power allocation factors of UE_{w} and UE_{s} in sub-channel m and $\alpha_{\mathrm{w},m} + \alpha_{\mathrm{s},m} = 1$. Further, P_m is the power for sub-channel m, and is identical over all the sub-channels (i.e., $P_m = \frac{P_{\mathrm{t}}}{M}$). The superposed signal received at arbitrary user n is written as

$$y_{n,m} = h_{n,m} x_m + v_{n,m}. \tag{2}$$

In the above equation, $h_{n,m} = g_{n,m} {d_n}^{-\vartheta}$ gives the complex channel gain in between the BS and n^{th} UE on sub-channel m. Further, Rayleigh fading coefficient is indicated with $g_{n,m}$. Besides, d_n is the distance from BS to UE n. Moreover, ϑ gives path loss slope, and $v_{n,m}$ constitutes Gaussian noise. With no loss of generality, all user's channel qualities are organized as follows: $|h_1|^2 \le |h_2|^2 \le ... \le |h_N|^2$.

Further, the main idea of NOMA is to allocate high power to UE_{w} and less power to UE_{s}. For sub-channel m, if $\left|h_{\mathrm{w},m}\right|^2 \le \left|h_{\mathrm{s},m}\right|^2$ then corresponding power allocation factors are $\alpha_{\mathrm{w},m} > \alpha_{\mathrm{s},m}$. Moreover, weak user signal is directly decodable due to high power allocation. Thus, $s_{\mathrm{w},m}$ is first decoded and removed from superimposed received signal, then UE_{s} decodes $s_{\mathrm{s},m}$. Therefore, UE_{s} extracts its signal without multi user distortion with the assumption of perfect SIC. However, UE_{w} is not able to decode $s_{\mathrm{s},m}$ and remove it from multiplexed signal due to low power assigned to UE_{s}. For this reason, UE_{w} treats $s_{\mathrm{s},m}$ as noise and detects its own signal $s_{\mathrm{w},m}$. In other words, UE_{w} does not perform SIC. Hence, users' data rates in m^{th} sub-channel are represented as

$$R_{\mathrm{w},m} = B_{\mathrm{sc}} \log_2 \left(1 + \frac{\alpha_{\mathrm{w},m} P_m \left|h_{\mathrm{w},m}\right|^2}{N_{\mathrm{o}} + \alpha_{\mathrm{s},m} P_m \left|h_{\mathrm{w},m}\right|^2} \right), \tag{3}$$

$$R_{\mathrm{s},m} = B_{\mathrm{sc}} \log_2 \left(1 + \frac{\alpha_{\mathrm{s},m} P_m \left|h_{\mathrm{s},m}\right|^2}{N_{\mathrm{o}}} \right). \tag{4}$$

In (3) and (4), N_{o} is noise power and it is given by $N_{\mathrm{o}} = kTB_{\mathrm{sc}}$. Here, k, T are Boltzmann's constant, temperature in degree Kelvin respectively. Hence, the achievable sum rate is obtained by summing all the sub-channel's total rate, which is given as

$$R_{\mathrm{sum}} = \sum_{m=1}^{M} \left(R_{\mathrm{s},m} + R_{\mathrm{w},m} \right). \tag{5}$$

2.2 Problem Formulation

The ultimate goal of power assignment problem is to enhance the system's sum throughput while preserving the total transmit power and each user's required rate constraints [38], [39]. Therefore, the sum rate optimization problem is formulated as:

$$\underset{\alpha_{\mathrm{w},m}, \alpha_{\mathrm{s},m}}{\mathrm{Max}} \; R_{\mathrm{sum}}, \tag{6}$$

$$\text{subject to: } \alpha_{\mathrm{s},m} + \alpha_{\mathrm{w},m} = 1, \tag{6a}$$

$$\alpha_{\mathrm{w},m} > \alpha_{\mathrm{s},m}, \tag{6b}$$

$$R_{\mathrm{s},m} \ge R_{\mathrm{s}}^{\min}, \tag{6c}$$

$$R_{\mathrm{w},m} \ge R_{\mathrm{w}}^{\min} \tag{6d}$$

$$\text{and } 0 \le \alpha_{\mathrm{w},m}, \alpha_{\mathrm{s},m} \le 1 \tag{6e}$$

where (6a) represents the sum of the m^{th} sub channel user's powers which is equal to P_m (i.e., $\alpha_{\mathrm{s},m} P_m + \alpha_{\mathrm{w},m} P_m = P_m$). Besides, (6b) indicates the basic NOMA principle that more power is allocated UE_{w} than UE_{s}. Moreover, (6c) and (6d) represents minimum data rate requirement of UE_{s} and UE_{w} respectively. Subsequently, (6e) gives bounds of the power allocation factors of each sub-channel user.

3. Standard ABC Algorithm and its Modified Version for Optimal Power Allocation

3.1 Standard ABC Algorithm

The ABC algorithm is a swarm-pertained optimization scheme that resembles the intelligent foraging demeanor of honey bees and has been used extensively for several practical problems. It was developed by Karaboga as part of the swarm intelligence algorithms family [40]. In the ABC, three kinds of honey bees are involved in the optimization process: employed, onlooker (observer), and scout bees. First, the employed bees search for food near the food source preserved in their memory; in the meantime, they communicate this knowledge about these food sources with the observer bees. Then, observer bees calculate fitness (nectar amount) and choose the best food sources discovered by employed bees. After that, the food source which has not improved the fitness is abandoned by scout bees and replaced that solution with a random food source to enrich the exploration.

The standard ABC algorithm solves any optimization problem in four phases:

1. *Initialization*
2. *Employed Bees*
3. *Onlooker Bees*
4. *Scout Bees*

The steps required for all the phases are outlined below:

1. *Initialization*:

   In this phase, ABC produces a random number of *NP* food sources (solutions). Here, *NP* indicates size of bees, which is same for both employed and onlooker bees. Let's take i^{th} food source as $\alpha_i = \{\alpha_{i1}, \alpha_{i2}, \ldots, \alpha_{iD}\}$, where D is the optimization variables' dimension. Each solution is obtained with in the range of j^{th} index by

$$\alpha_{i,j} = \alpha_j{}^{\min} + \psi(\alpha_j{}^{\max} - \alpha_j{}^{\max}). \quad (7)$$

   Here, $\alpha_j{}^{\min}$ and $\alpha_j{}^{\max}$ denotes minimum and maximum limits for index j, respectively. Besides, ψ represents randomly generated value which lies in the range $[0, 1]$, $i = \{1, 2, \ldots, NP\}$, and $j = \{1, 2, 3, \ldots, D\}$. Then every solution is evaluated by

$$fit_i = \begin{cases} \dfrac{1}{1 + f_i}, f_i \geqslant 0 \\ 1 + |f_i|, f_i < 0 \end{cases} \quad (8)$$

   where fit_i, f_i indicates the fitness and objective functions of food source i respectively. The cost function can be utilized directly as a fitness function for maximizing problems.

2. *Employed Bees*:

   Employed bees produce the neighborhood solution for every initial solution. The position of new solution can be computed as

$$\beta_{i,j} = \alpha_{i,j} + \lambda_{i,j}(\alpha_{i,j} - \alpha_{k,j}). \quad (9)$$

   In (9), j is a random integer and $j \in \{1, 2, 3, \ldots, D\}$; k is selected partner solution & $k \in \{1, 2, \ldots, NP\}$, $k \neq i$. $\lambda_{i,j}$ represents randomly generated parameter, which is lies between -1 and 1. Note that β_i is different from α_i only at the j^{th} component. Then, fitness value of the updated solution is evaluated, and compares with the previous solution α_i. If the updated fitness is greater as compared with old solution fitness, α_i is replaced with the β_i. Otherwise, the previous solution would be carried on.

3. *Onlooker Bees*:

   After employed bees have completed their quests, they communicate knowledge about fitness and food source locations with onlooker bees. Then, each onlooker bee chooses a solution according to the probability P_i and it is determined by

$$P_i = \frac{fit_i}{\sum\limits_{i=1}^{NP} fit_i}. \quad (10)$$

   Once the onlookers select the food source position, it produces a new solution and corresponding fitness by utilizing (9) and (8) respectively. Subsequently, the greedy mechanism is performed between new and old food sources similar to the employed bees.

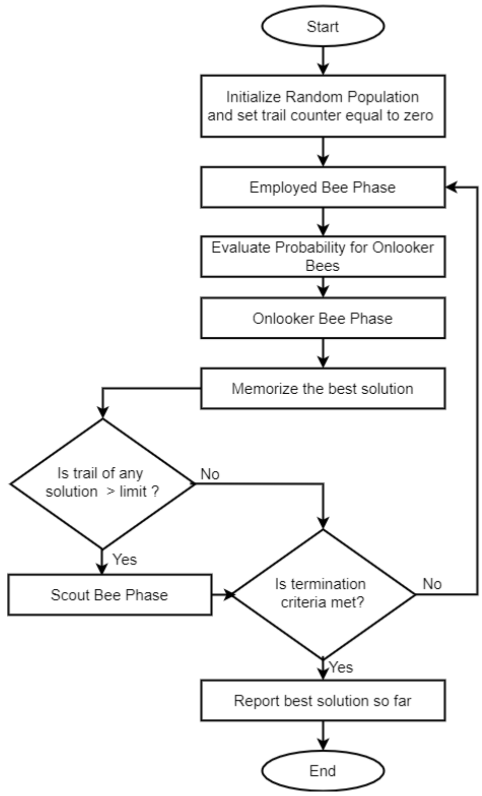


Fig. 2. Flow chart of ABC Algorithm.

4. *Scout Bees*:

   If a solution has not been updated within a given number of trials, it is exited, and the related bee evolves into a scout bee. Then, it generates a random solution by using (7). Finally, evaluate the better solution α_{best} and objective function f_{best} and repeat the phases: (2)–(4) until the total number of iterations. For easier comprehension, the ABC flow diagram is depicted in Fig. 2.

3.2 Proposed Modified ABC Algorithm

As previously stated, the ABC algorithm faces some difficulties in balancing exploration and exploitation and also the slow convergence when solving complex constrained optimization problems. To overcome the slow convergence rate and improve the performance, the current position of "employed and onlooker bees" is updated by incorporating the best solution position in the modified ABC algorithm. Hence, MABC produces the new solution nearer to the best solution in both bee phases (employed and onlooker) for every iteration. Therefore, the modified solution search equation for the "employed and onlooker bees phase" is represented as

$$\beta_{i,j} = \alpha_{\text{best},j} + \lambda_{i,j}(\alpha_{i,j} - \alpha_{k,j}). \quad (11)$$

In (11), α_{best} is the best solution before finding the new solution of each phase (both employed and onlookers bees). Moreover, food sources and the objective function of the algorithm represent the power allocation factors and sum throughput, respectively.

After all the users are paired to each sub-channel according to user pairing scheme. The propounded MABC-based Power Allocation (MABC-PA) assigns optimized powers to each paired user of the sub-channel to maximize sum throughput. The steps required for MABC-PA method for downlink NOMA system are detailed below.

Step 1: Set the initial parameters of the MABC-PA scheme such as paired users channel gain values of m^{th} sub-channel, BS total power (P_t), number of users (N), system bandwidth (B), population size (NP), dimension of NP (D), number iterations (T) and limit.

Step 2: Randomly generate the population matrix with in the bounds (i.e power allocation factors matrix) using $\alpha_{i,j} = \alpha_j{}^{\min} + \psi(\alpha_j{}^{\max} - \alpha_j{}^{\max})$, $i \in NP$ and $j \in D$.

Step 3: Evaluate the objective function of each solution by using $R_{m,i} = (R_{\mathrm{s},i} + R_{\mathrm{w},i})$. If any solution do not satisfy the constraints (mentioned in (6a)–(6d)) then the penalty is added to the corresponding objective function [41].

Step 4: Memorize the best objective function and best solution.

Step 5: 'Employed Bees' update the every solution by using modified solution search equation $\beta_{i,j} = \alpha_{\mathrm{best},j} + \lambda_{i,j}(\alpha_{i,j} - \alpha_{k,j})$.

Step 6: Find the objective function for the updated solution and and compare with the older solution. If the updated solution sum rate (objective function) is better than older solution. Then replace older solution with updated solution and memorize the best objective function and solution.

Step 7: 'Onlooker Bees' select solution based on the probability (P_i), which can be obtained by using formula $P_i = \frac{R_{m,i}}{\sum_{i=1}^{NP} R_{m,i}}$.

Step 8: Once the onlooker bee identifies the solution position, it produces the new solution similar to the 'Employed Bees'. Then, find the objective function ($R_{m,i}$). Subsequently, perform greedy selection procedure and then replace the older solution with the better solution.

Step 9: If any solution not updated in Employed and Onlooker Bees Phases for a particular limit. Then, Scout Bees replace that solution with random solution which can be computed by using $\alpha_{i,j} = \alpha_j{}^{\min} + \psi(\alpha_j{}^{\max} - \alpha_j{}^{\max})$.

Step 10: Finally, compute the better objective function and corresponding solution. This process (steps: 5 to 9) repeated for given number of iterations.

Step 11: Furthermore, entire process is repeated for all the M sub channels. Then, system's total throughput is obtained by combining the sum rate of all the sub-channels (i.e., $R_{\mathrm{sum}} = \sum_{m=1}^{M} R_m$).

The summary of the presented power allocation algorithm is described in Algorithm 1 is in accordance with the presented sum-throughput maximization problem.

Algorithm 1. Proposed MABC-based Power Allocation Algorithm

Require: *Control Parameters*: Population size (NP), Number of iterations (T), *limit*.
System Parameters: $N, M, B_{\mathrm{sc}}, N_{\mathrm{o}}, P_m, g_{\mathrm{s},m}$, and $g_{\mathrm{w},m}$.
Ensure: Optimal power allocation factors and Sum rate.

for $i = 1 : NP$ **do**
Generate random solution by using (7);
Evaluate the objective function by (6);
end for
$iteration = 1$;
while ($iteration \leq T$) **do**
  //Employed Bee Phase:
  for $i = 1 : NP$ **do**
  Produce new solution β_i of the solution α_i for employed bees using (11);
  Compute objective function (sum rate) and fitness function fit_i;
  Perform greedy selection procedure among β_i and α_i, then retain with best solution;
  If solution is not updated $trail_i \leftarrow trail_i + 1$,
  else $trail_i \leftarrow 0$;
  end for
  Memorize the best solution;
  Evaluate probability P_i by (10) for fitness functions of employed bee solutions;
  //Onlooker Bee Phase:
  $\eta = 0$; $i = 1$;
  while ($\eta < NP$) **do**
    if $rand < P_i$ **then**
      Generate new β_i by (11) for onlooker bee;
      Perform greedy selection approach between β_i and α_i and then select best solution;
      If solution is not updated $trail_i \leftarrow trail_i + 1$,
      else $trail_i \leftarrow 0$;
      $\eta \leftarrow \eta + 1$;
    end if
  end while
  //Scout Bee Phase:
  if $\max(trail_i) > limit$ **then**
    Update the α_i with new solution obtained solution by (7);
  end if
  Store better solution obtained so far;
end while

Besides, Theorem 1 shows that optimal powers are provided by the MABC algorithm.

Theorem 1 *Proposed MABC algorithm induces optimal powers for each sub channel's users to maximize the system sum throughput.*

Proof. To solve the sum-rate maximization problem given in (6); MABC is employed in this work. However, in order to optimize the system's sum throughput, MABC finds the optimal powers for all users in the following way:

- The users are paired to every sub-channel (for receiver simplicity, two users are paired in each sub-channel). For the given control and system parameters, Algorithm 1 produces the appropriate power factors $\alpha_{s,m}$, $\alpha_{w,m}$ for the sub-channel m by satisfying all the constraints.
- Algorithm 1 renews the power factors in every iteration and stores the better result. Hence, it provides optimal power to every user on each sub-channel at the end of the T iterations.

Hence, it is proved.

4. Numerical Results and Discussion

4.1 Experimental Validation of Proposed MABC Algorithm

In order to corroborate the MABC algorithm's performance, we took the eight distinct benchmark test functions consisting of four Uni-Modal (UM) and four Multi-Modal (MM) functions as displayed in Tab. 1. The uni-modal functions are mainly used to analyze the convergence performance rate of any algorithm. On the other hand, multi-modal functions play a vital role in testing whether the proposed algorithm is escaping from the local optimum solution efficiently. Besides, in Tab. 1, the parameter D denotes the dimensionality of solution search space.

The significance of the proposed MABC method is determined by comparing its results to the classic ABC [40]. In order to make an accurate comparison with the original ABC, both algorithms were studied utilizing the identical control parameters: the size of population $NP = 30$, $limit = NP \times D$, number of iterations $T = 1000$.

To ensure that the experimental results are consistent, we performed each algorithm 30 times and averaged the results. We evaluated the five statistical parameters such as Best, Average, Median, Standard Deviation (SD), and Worst solutions for comparing the performance of ABC and MABC algorithms. Table 2 and Table 3, respectively, illustrate the experimental results produced by each algorithm for $D = 10$ and $D = 30$ dimensions. As a result of the numerical findings, the MABC performs admirably on almost all of the benchmark functions except f_2. Since, the second part $100\left(x_{i+1} - x_i^2\right)^2$ in f_2 (Rosenbroack function) significantly impacts the value of the function.

Furthermore, the solution accuracy of MABC and the ABC algorithm are identical for functions f_5 (Rastrigen) and f_6 (Schwefel) with $D = 10$. When the dimension is smaller, the multi-modal functions f_5 and f_6 easily obtain the optimal solutions. The complexity of achieving the optimal solution gradually increases as the dimension grows larger. However, even with larger dimensions ($D = 30$), MABC provides better solution accuracy for the functions f_5, f_6. In addition, Figure 3 demonstrates how the average of the Best Fitness Value of both the schemes (i.e., MABC and ABC) varies

Function Name	Mathematical Expression	Type	Search Range	$f_{\min}$
Sphere	$f_1(\vec{x}) = \sum_{i=1}^{D} x_i^2$	UM	$[-100, 100]_D$	0
Rosenbrock	$f_2(\vec{x}) = \sum_{i=1}^{D-1} \left[(x_i - 1)^2 + 100\left(x_{i+1} - x_i^2\right)^2 \right]$	UM	$[-30, 30]_D$	0
Sum Squares	$f_3(\vec{x}) = \sum_{i=1}^{D} i x_i^2$	UM	$[-10, 10]_D$	0
Step	$f_4(\vec{x}) = \sum_{i=1}^{D} (x_i + 0.5)^2$	UM	$[-100, 100]_D$	0
Rastrigin	$f_5(\vec{x}) = 100 + \sum_{i=1}^{D} \left(x_i^2 - 10\cos(2\pi x_i)\right)$	MM	$[-5.12, 5.12]_D$	0
Schwefel	$f_6(\vec{x}) = -\sum_{i=1}^{D} \left(x_i \sin\left(\sqrt{\lvert x_i \rvert}\right) - 418.9829 \times D\right)$	MM	$[-500, 500]_D$	0
Ackley	$f_7(\vec{x}) = \mathrm{e} + 20 - 20\exp\left(-0.2\sqrt{\frac{1}{D}\sum_{i=1}^{D} x_i^2}\right) - \exp\left(\frac{1}{D}\sum_{i=1}^{D}\cos(2\pi x_i)\right)$	MM	$[-32, 32]_D$	0
Griewank	$f_8(\vec{x}) = \frac{1}{4000}\sum_{i=1}^{D} x_i^2 - \prod_{i=1}^{D}\cos\left(\frac{x_i}{\sqrt{i}}\right) + 1$	MM	$[-600, 600]_D$	0

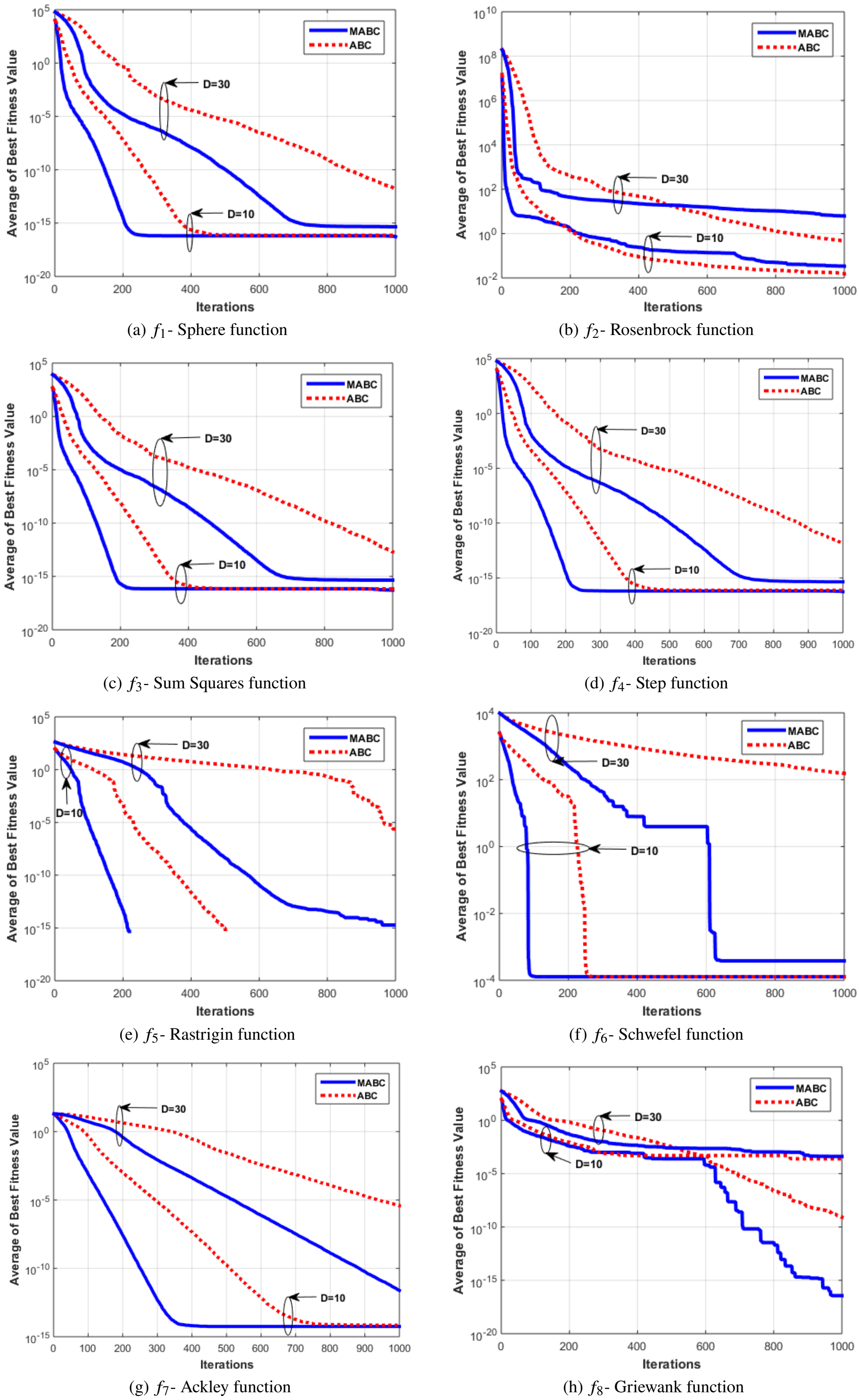
Tab. 1. Standard optimization test functions [42], [43].

Benchmark Functions	Algorithm	Best	Average	Median	Standard Deviation	Worst
f_1	ABC	2.4937×10^{-17}	7.2440×10^{-17}	7.3362×10^{-17}	1.8895×10^{-17}	1.0211×10^{-16}
	MABC	1.9596×10^{-17}	5.3625×10^{-17}	5.2804×10^{-17}	1.6420×10^{-17}	8.0280×10^{-17}
f_2	ABC	2.7867×10^{-4}	1.5300×10^{-2}	9.6000×10^{-3}	1.7100×10^{-2}	6.4100×10^{-2}
	MABC	1.2757×10^{-4}	3.4100×10^{-2}	1.3700×10^{-2}	5.1000×10^{-2}	2.3430×10^{-1}
f_3	ABC	1.2757×10^{-4}	3.4100×10^{-2}	1.3700×10^{-2}	5.1000×10^{-2}	2.3430×10^{-1}
	MABC	2.5746×10^{-17}	5.3061×10^{-17}	5.3406×10^{-17}	1.1987×10^{-17}	7.7252×10^{-17}
f_4	ABC	5.1404×10^{-17}	9.6161×10^{-17}	9.1912×10^{-17}	3.2381×10^{-17}	1.8299×10^{-16}
	MABC	2.3582×10^{-17}	6.5347×10^{-17}	6.7802×10^{-17}	1.9038×10^{-17}	1.0276×10^{-16}
f_5	ABC	0.0000×10^{0}	0.0000×10^{0}	0.0000×10^{0}	0.0000×10^{0}	0.0000×10^{0}
	MABC	0.0000×10^{0}	0.0000×10^{0}	0.0000×10^{0}	0.0000×10^{0}	0.0000×10^{0}
f_6	ABC	1.2830×10^{-4}	1.2830×10^{-4}	1.2830×10^{-4}	0.0000×10^{0}	1.2830×10^{-4}
	MABC	1.2830×10^{-4}	1.2830×10^{-4}	1.2830×10^{-4}	0.0000×10^{0}	1.2830×10^{-4}
f_7	ABC	4.3899×10^{-15}	6.8094×10^{-15}	7.8894×10^{-15}	1.7034×10^{-15}	7.8894×10^{-15}
	MABC	4.4389×10^{-15}	5.6251×10^{-15}	4.4409×10^{-15}	1.7034×10^{-15}	7.9936×10^{-15}
f_8	ABC	0.0000×10^{0}	2.4654×10^{-4}	0.0000×10^{0}	1.4000×10^{-3}	0.0074×10^{0}
	MABC	0.0000×10^{0}	3.7007×10^{-17}	0.0000×10^{0}	8.9073×10^{-17}	4.4409×10^{-16}

Tab. 2. The best, average, median, SD, and worst values obtained by ABC and MABC on benchmark test functions at $D = 10$.

Benchmark Functions	Algorithm	Best	Average	Median	Standard Deviation	Worst
f_1	ABC	1.1409×10^{-13}	1.4039×10^{-12}	1.1574×10^{-12}	1.0900×10^{-12}	5.5826×10^{-12}
	MABC	3.1151×10^{-16}	4.4983×10^{-16}	4.6959×10^{-16}	7.0653×10^{-17}	5.3091×10^{-16}
f_2	ABC	1.8400×10^{-2}	4.5720×10^{-1}	2.7740×10^{-1}	4.8610×10^{-1}	2.3057×10^{0}
	MABC	6.7875×10^{-4}	6.1876×10^{0}	5.2060×10^{-1}	1.4642×10^{1}	7.3902×10^{1}
f_3	ABC	3.1631×10^{-14}	2.0529×10^{-13}	1.5573×10^{-13}	1.4625×10^{-13}	6.8523×10^{-13}
	MABC	2.9023×10^{-16}	4.4656×10^{-16}	4.7004×10^{-16}	7.0883×10^{-17}	5.3520×10^{-16}
f_4	ABC	4.9412×10^{-13}	8.8238×10^{-12}	3.8833×10^{-12}	9.4115×10^{-12}	3.5768×10^{-11}
	MABC	5.0766×10^{-16}	6.4164×10^{-16}	6.6189×10^{-16}	9.4713×10^{-17}	8.7348×10^{-16}
f_5	ABC	2.3010×10^{-10}	2.3740×10^{-6}	1.4206×10^{-9}	1.2891×10^{-5}	7.0630×10^{-5}
	MABC	0.0000×10^{0}	0.0000×10^{0}	0.0000×10^{0}	0.0000×10^{0}	0.0000×10^{0}
f_6	ABC	3.8185×10^{-4}	1.5394×10^{2}	1.1846×10^{2}	8.3483×10^{1}	3.5536×10^{2}
	MABC	3.8183×10^{-4}	3.8183×10^{-4}	3.8183×10^{-4}	3.3210×10^{-13}	3.8183×10^{-4}
f_7	ABC	9.3781×10^{-7}	3.8397×10^{-6}	4.0328×10^{-6}	3.4970×10^{-6}	9.1354×10^{-6}
	MABC	1.2195×10^{-12}	2.4306×10^{-12}	2.3705×10^{-12}	8.0011×10^{-13}	4.2251×10^{-12}
f_8	ABC	1.3687×10^{-11}	8.2836×10^{-10}	2.9129×10^{-10}	1.3363×10^{-9}	5.8847×10^{-9}
	MABC	0.0000×10^{0}	4.1117×10^{-4}	1.1102×10^{-16}	2.2000×10^{-3}	1.2300×10^{-2}

Tab. 3. The best, average, median, SD, and worst values obtained by ABC and MABC on benchmark test functions at $D = 30$.



(a) f_1- Sphere function

(b) f_2- Rosenbrock function

(c) f_3- Sum Squares function

(d) f_4- Step function

(e) f_5- Rastrigin function

(f) f_6- Schwefel function

(g) f_7- Ackley function

(h) f_8- Griewank function

Fig. 3. Convergence performance (best solution in each iteration) comparison between MABC and ABC algorithms for eight benchmark test functions (f_1 to f_8) at different dimensions.

with the total iterations for $D = 10$ and $D = 30$ dimensions. Here, the "Average of the Best Fitness Value" is obtained by computing the mean of the best fitness values of all the runs (i.e each algorithm repeated for 30 independent runs) in each iteration. The lines in Fig. 3(a)–(h), which do not reach the end of the iterations indicate that the next computation has acquired a zero value. As exhibited in the Fig. 3, except for function f_2 with $D = 10, 30$ and function f_8 with $D = 30$, MABC has a swifter convergence speed than the ABC algorithm.

4.2 Performance Evaluation of MABC-based Power Allocation

The MATLAB simulations are shown in this part to assess the effectiveness of the presented MABC-PA algorithm. A single cell with $N = 20$ randomly distributed users is considered in the simulations. Moreover, each sub-channel is paired with the two users based on the adopted pairing scheme. The Rayleigh fading wireless channel model is presumed between BS and users. Further, the BS total transmission power ($P_t = 30$ dBm) is partitioned to all the sub-channels equally. Finally, the proposed MABC-PA is employed to allocate power to paired users of each sub-channel optimally by satisfying all the constraints. We consider the average results based on 10^4 channel accomplishments. Besides, the parameter values taken for simulation are detailed in Tab. 4. The parameters of the algorithm have been determined after thorough simulations and performance evaluations. We compared the proposed power allocation strategy with ABC-PA, FTPA [25] methods, and OMA scheme.

Figure 4 displays the comparison between the sum throughput and transmit power at the BS for $N = 20$ users. Accordingly, it is clear from Fig. 4 that the sum throughput rises as the transmission power varies. Moreover, at the low transmit powers, the sum rate of MABC-PA is much greater than the FTPA. On the other hand, MABC-PA, ABC-PA, and FTPA methods' performance are nearer at the higher transmit powers because the power allocation factor for a strong user is saturated for higher values of P_t. In other words, the channel gain will become a less significant aspect when the BS transmitted power is more. Further, it can be heeded that due to the modified solution search equation, the proposed MABC-PA exceeds the ABC-PA in terms of achievable sum rate. Besides, we set the minimum capacity for strong and weak users to be 200 kbps and 20 kbps, respectively.

Figure 5 shows the influence of the various users on the total throughput of the system. Here, the transmission power is fixed to 30 dBm. Further, it demonstrates that the system's total throughput augments as the number of user equipments per BS increases, which signifies that multi-user diversity gain. We can also see that the sum throughput of all NOMA schemes is superior to the OMA due to multiplexing gain when NOMA is used. As a result, Figures 4 and 5 revealed that the propounded MABC-PA is outperformed the ABC-PA, FTPA algorithms, and traditional OMA.

Figure 6 depicts the convergence plot of the MABC-PA and ABC-PA algorithms for NOMA system. From Fig. 6, it is clearly explicit that MABC-PA delivers better performance than the ABC-PA algorithm. Here, the sum rate is averaged over 30 independent runs at $P_t = 30$ dBm for $N = 20$ users. Furthermore, MABC-PA is rapidly converged to an optimal solution compared to the ABC-PA scheme.

Parameters	Values
Cell radius (R)	500 m
Transmission power (P_t)	30 dBm
Overall bandwidth (B)	5 MHz
Noise density (N_o)	−174 dBm/Hz
Number of users (N)	20
Number of sub-channels (M)	10
Path loss exponent (ϑ)	4
Min. data rate for UE_s (R_s^{min})	200 kbps
Min. data rate for UE_w (R_w^{min})	20 kbps
Size of the population (NP)	50
Limit	$NP \times D$
Termination criteria (T)	100

Tab. 4. Parameters chosen for simulations.

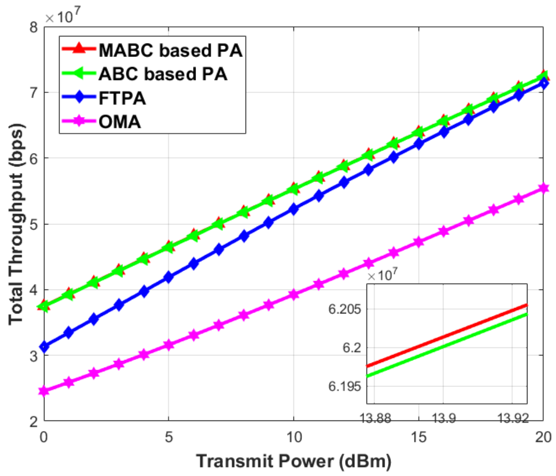


Fig. 4. Comparison of total throughput against transmit power for $N = 20$ users.

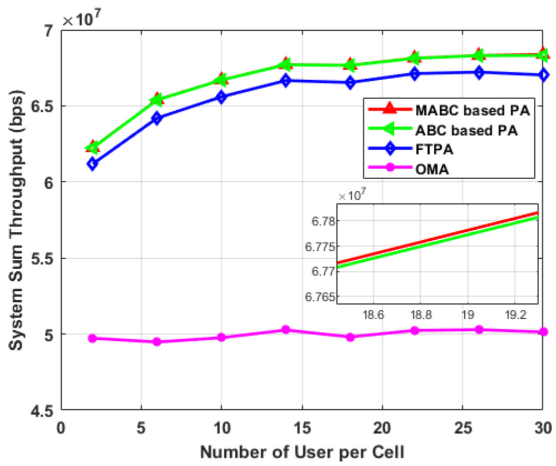


Fig. 5. Overall throughput of the system vs. different number of users per cell at $P_t = 30$ dBm.

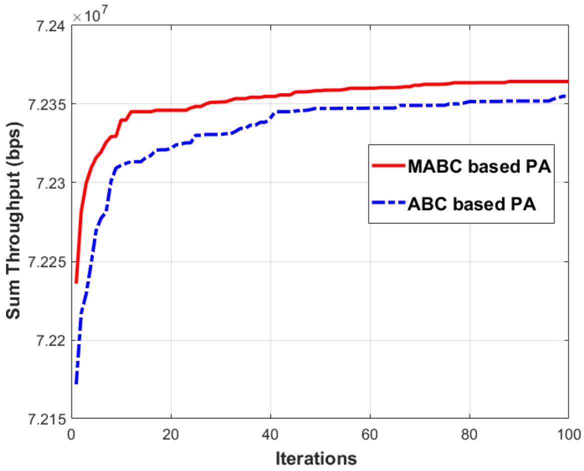


Fig. 6. Total throughput improvement at particular transmission power (P_t) comparison with number of iterations.

5. Conclusion

This article studied the unprecedented power allocation approach to enhance the sum throughput for downlink NOMA system, considering BS transmit power and the user's minimum rate constraints. First, we proposed the Modified ABC approach by improving the solution search equation of "employed and onlooker bees", thereby enhancing the exploitation in the ABC algorithm. Then, we evaluated every sub-channel user's optimal powers by employing the proposed MABC optimization method to improve the system's total throughput. Further, presented MABC-PA algorithm validated with standard benchmark test functions. Moreover, the simulation findings revealed that the MABC-based PA is superior concerning the system's sum rate to ABC-PA, FTPA, and traditional OMA. In addition, the proposed MABC algorithm has converged faster than the standard ABC algorithm.

In the future, we plan to implement the multi-user downlink NOMA system with the proposed MABC-based power allocation strategy utilizing the software-defined radio platform. Moreover, this work could be expanded to include additional performance metrics for the problem mentioned above, as well as the implementation of the MIMO-NOMA scenario in order to improve the system's performance further.

References

[1] ANDREWS, J. G., BUZZI, S., CHOI, W., et al. What will 5G be? *IEEE Journal of Selected Areas in Communications*, 2014, vol. 32, no. 6, p. 1065–1082. DOI: 10.1109/JSAC.2014.2328098

[2] ISLAM, S. M. R., AVAZOV, N., DOBRE, O. A., et al. Power-domain non-orthogonal multiple access (NOMA) in 5G systems: Potentials and challenges. *IEEE Communications Surveys & Tutorials*, 2017, vol. 19, no. 2, p. 721–742. DOI: 10.1109/COMST.2016.2621116

[3] GUPTA, A., JHA, R. K. A survey of 5G network: Architecture and emerging technologies. *IEEE Access*, 2015 vol. 3, p. 1206–1232. DOI: 10.1109/ACCESS.2015.2461602

[4] LIU, Y., QIU, Z., ELKASHLAN, M., et al. Non-orthogonal multiple access for 5G and beyond. *Proceedings of IEEE*, 2017, vol. 105, no. 12, p. 2347–2381. DOI: 10.1109/JPROC.2017.2768666

[5] DAVIS, K., BERNDT, H. 6G vision and requirements: is there any need for beyond 5G?. *IEEE Vehicular Technology Magazine*, 2018, vol. 13, no. 3, p. 72–80. DOI: 10.1109/MVT.2018.2848498

[6] ISLAM, S. M. R., ZENG, M., DOBRE, O. A., et al. Resource allocation for downlink NOMA systems: Key techniques and open issues. *IEEE Wireless Communications*, 2018, vol. 25, no. 2, p. 40–47. DOI: 10.1109/MWC.2018.1700099

[7] KALPANA, N., ALI KHAN, M. Z. Fast computation of generalized water-filling problems. *IEEE Signal Processing Letters*, 2015, vol. 22, no. 11, p. 1884–1887. DOI: 10.1109/LSP.2015.2440653

[8] KALPANA, N., ALI KHAN, M. Z. An efficient direct solution of cave-filling problems. *IEEE Transactions on Communications*, 2016, vol. 64, no. 7, p. 3064–3077. DOI: 10.1109/TCOMM.2016.2560813

[9] KALPANA, N., RAMESH, B. Quick resource allocation in heterogeneous networks. *Wireless Networks*, 2018, vol. 24, no. 8, p. 3171–3188. DOI: 10.5555/3287990.3288049

[10] KALPANA, N., RAMESH, B. Swift resource allocation in wireless networks. *IEEE Transactions on Vehicular Technology*, 2018, vol. 67, no. 7, p. 5965–5979. DOI: 10.1109/TVT.2018.2805938

[11] RAJESWARI, K., THIRUVENGADAM, S., J. Optimal power allocation for channel estimation in MIMO-OFDM system with per-subcarrier transmit antenna selection. *Radioengineering*, 2015, vol. 24, no. 1, p. 105–114. DOI: 10.13164/re.2015.0105

[12] KALPANA, N., PARCHURI, A. Efficient allotment of resources in heterogeneous communication. *Wireless Networks*, 2021, vol. 27, p. 3761–3783. DOI: 10.1007/s11276-021-02599-x

[13] KALPANA, N., SREENU, S. Remote health monitoring system using heterogeneous networks. *Healthcare Technology Letters*, 2021, vol. 9, no. 1–2, p. 1–9. DOI: 10.1049/htl2.12020

[14] BENJEBBOVU, A., LI, A., SAITO, Y., et al. System-level performance of downlink NOMA for future LTE enhancements. In *IEEE Globecom Work Shops (GC Wkshps)*. Atlanta (USA), 2013, p. 66–70. DOI: 10.1109/GLOCOMW.2013.6824963

[15] LEI, L., YUAN, D., HO, C. K., et al. Power and channel allocation for non-orthogonal multiple access in 5G systems: Tractability and computation. *IEEE Transactions on Wireless Communications*, 2016, vol. 15, no. 12, p. 8580–8594. DOI: 10.1109/TWC.2016.2616310.

[16] DING, Z., YANG, Z., FAN, P., et al. On the performance of non-orthogonal multiple access in 5G systems with randomly deployed users. *IEEE Signal Processing Letters*, 2014, vol. 21, no. 12, p. 1501–1505. DOI: 10.1109/LSP.2014.2343971

[17] HUSSAIN, Q., SARMAD, S. Full duplex relaying in non-orthogonal multiple access system with advanced successive interference cancellation. *Radioengineering*, 2020, vol. 29, no. 4, p. 654–662. DOI: 10.13164/re.2020.0654

[18] SREENU, S., KALPANA, N. Novel user association scheme deployed for the downlink NOMA systems. In *International Conference on Communication and Intelligent Systems*. New Delhi (India), 2021.

[19] CHEN, W., ZHAO, S., ZHANG, R., et al. Generalized user grouping in NOMA based on overlapping coalition formation game. *IEEE Journal on Selected Areas in Communications*, 2021, vol. 39, no. 4, p. 969–981. DOI: 10.1109/JSAC.2020.3018832

[20] BENJEBBOUR, A., SAITO, Y., KISHIYAMA, Y., et al. Concept and practical considerations of non-orthogonal multiple access (NOMA) for future radio access. In *International Symposium on Intelligent Signal Processing and Communication Systems*. Naha (Japan), 2013, p. 770–774. DOI: 10.1109/ISPACS.2013.6704653

[21] HE, J., TANG, Z. Low-complexity user pairing and power allocation algorithm for 5G cellular network non-orthogonal multiple access. *Electronics Letters*, 2017, vol. 53, no. 9, p. 626–627. DOI: 10.1049/el.2016.4190

[22] BENJEBBOUR, A., LI, A., KISHIYAMA, Y., et al. System-level performance of downlink NOMA combined with SU-MIMO for future LTE enhancements. In *IEEE Globecom Workshops (GC Wkshps)*. Austin (USA), 2014, p. 706–710. DOI: 10.1109/GLOCOMW.2014.7063515

[23] HOJEIJ, M., FARAH, J., NOUR, C. A., et al. Resource allocation in downlink non-orthogonal multiple access (NOMA) for future radio access. In *IEEE 81st Vehicular Technology Conference (VTC Spring)*. Glasgow (UK), 2015, p. 1–6. DOI: 10.1109/VTCSpring.2015.7146056

[24] SARAEREH, O. A., ALSARAIRA, A., KHAN, I., et al. An efficient resource allocation algorithm for OFDM-based NOMA in 5G systems. *Electronics Journal*, 2019, vol. 8, no. 12, p. 1–13. DOI: 10.3390/electronics8121399

[25] SAITO, Y., KISHIYAMA, Y., BENJEBBOUR, A., et al. Non-orthogonal multiple access (NOMA) for cellular future radio access. In *IEEE 77th Vehicular Technology Conference (VTC Spring)*. Dresden (Germany), 2013, p. 1–5. DOI: 10.1109/VTCSpring.2013.6692652

[26] PARIDA, P., DAS, S. S. Power allocation in OFDM based NOMA systems: A DC programming approach. In *IEEE Globecom Workshops (GC Wkshps)*. Austin (USA), 2014, p. 1026–1031. DOI: 10.1109/GLOCOMW.2014.7063568

[27] OVIEDO, J. A., SADJADPOUR, H. R., A fair power allocation approach to NOMA in multiuser SISO systems. *IEEE Transactions on Vehicular Technology*, 2017, vol. 66, no. 9, p. 7974–7985. DOI: 10.1109/TVT.2017.2689000

[28] TANG, T., MAO, Y., HU, G. Fair power allocation approach to OFDM-based NOMA with consideration of clipping. *Electronics Journal*, 2020, vol. 9, no. 10, p. 1–12. DOI: 10.3390/electronics9101743

[29] SUN, Q., HAN, S., LI, C., et al. On the ergodic capacity of MIMO NOMA systems. *IEEE Wireless Communication Letters*, 2015, vol. 4, no. 4, p. 405–408. DOI: 10.1109/LWC.2015.2426709

[30] ALI, Z. J., NOORDIN, N. K., SALI, A., et al. Novel resource allocation techniques for downlink non-orthogonal multiple access systems. *Applied Sciences*, 2020, vol. 10, no. 17, p. 1–19. DOI: 10.3390/app10175892

[31] MA, X., WU, J., ZHANG, Z., et al. Power allocation for downlink of non-orthogonal multiple access system via genetic algorithm. In *International Conference on 5G for Future Wireless Networks*. Beijing (China), 2017, p. 459–470. DOI: 10.1007/978-3-319-72823-0

[32] GUO, Y. X., HUI, L. A power allocation method based on particle swarm algorithm for NOMA downlink networks. *Journal of Physics: Conference Series*, 2018, vol 1087, no. 2, p. 1–7. DOI: 10.1088/1742-6596/1087/2/022033

[33] GOUDOS, S. Joint power allocation and user association in non-orthogonal multiple access networks: An evolutionary approach. *Physical Communication*, 2019, vol. 37, p. 1–7. DOI: 10.1016/j.phycom.2019.100841

[34] KARABOGA, D., AKAY, B. A comparative study of artificial Bee colony algorithm. *Applied Mathematics and Computation*, 2009, vol. 214, no. 1, p. 108–132. DOI: 10.1016/j.amc.2009.03.090

[35] KARABOGA, D., AKAY, B. A survey: Algorithms simulating bee swarm intelligence. *Artificial Intelligence Review*, 2009, vol. 31, no. 14, p. 61–85. DOI: 10.1007/s10462-009-9127-4

[36] CAO, Y., LU, Y., PAN, X., et al. An improved global best guided artificial bee colony algorithm for continuous optimization problems. *Cluster Computing*, 2019, vol. 22, no. 2, p. 3011–3019. DOI: 10.1007/s10586-018-1817-8

[37] SHAHAB, M. B., IRFAN, M., KADER, M. D., et al. User pairing schemes for capacity maximization in non-orthogonal multiple access systems. *Wireless Communications and Mobile Computing*, 2016, vol. 16, p. 2884–2894. DOI: 10.1002/wcm.2736

[38] FU, Y., HONG, Y., CHEN, L., et al. Enhanced power allocation for sum rate maximization in OFDM-NOMA VLC systems. *IEEE Photonics Technology Letters*, 2018, vol. 30, no. 13, p. 1218–1221. DOI: 10.1109/LPT.2018.2839094

[39] CETINKAYA, C., ARSLAN, H. Energy and spectral efficiency trade-off in NOMA: Multi-objective evolutionary approaches. In *IEEE International Conference on Communications Workshops (ICC Workshops)*. Dublin (Ireland), 2020, p. 1–6. DOI: 10.1109/ICCWorkshops49005.2020.9145261

[40] KARABOGA, D. *An Idea Based on Honey Bee Swarm for Numerical Optimization*. Technical Report - TR06, Erciyes University, Computer Engineering Department, Turkey, 2005.

[41] YENIAY, O. Penalty function methods for constrained optimization with genetic algorithms. *Mathematical and Computational Applications*, 2005, vol. 10, no. 1, p. 45–56. DOI: 10.3390/mca10010045

[42] GAO, W.-F., LIU S.-Y. A modified artificial bee colony algorithm. *Computers and Operations Research*, 2012, vol. 39, no. 3, p. 687–697. DOI: 10.1016/j.cor.2011.06.007

[43] PANG, B., SONG, Y., ZHANG, C., et al. A modified artificial bee colony algorithm based on the self-learning mechanism. *Algorithms*, 2018, vol. 11, no. 6, p. 1–21. DOI: 10.3390/a11060078

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