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Joint QoS Aware Admission Control and Power Allocation in NOMA Downlink Networks

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ABSTRACT In this work, we talk about the problem of joint power allocation and user association based on quality-of-service for non-orthogonal multiple access (NOMA) to downlink networks. The problem is especially difficult due to its non-convex form and the large number of optimization variables, which are solved using two different nature-inspired algorithms with low complexity. We investigate the effect of different network parameters on increasing users. Numerical results show that, for a growing number of users, the problem is becoming increasingly difficult, which indicates the increasing network resources required to solve it. The results of the simulations show that using evolutionary algorithms is a fast and effective way to solve this kind of problem. Moreover, the NOMA advantage over OMA becomes clear as the number of users increases. Evolutionary techniques outperform randomly generated solutions, as expected.

INDEX TERMS 5G, 6G, NGIoT, cellular network, NOMA, QoS, optimization techniques

I. INTRODUCTION

THE introduction of NGIoT next-generation Internet of Things (NG-IoT) creates new research challenges and priorities. The identified priorities encompass multiple components of the IoT stack and thus relate to 6G, Distributed Ledgers, Big Data, Artificial Intelligence, Cybersecurity, and Cloud Computing. The deployment of 5G/B5G paves the way for the NGIoT to become a reality. Due to the increasing popularity of the internet, the number of communication devices is increasing at an exponential rate. Therefore, multiple access technology is being highlighted for the provision of massive access to IoT devices. Moreover, providing a large amount of intelligent IoT devices within a given bandwidth while simultaneously ensuring QoS parameters such as low latency and high throughput can be difficult. Non-orthogonal multiple access (NOMA) is expected to be one of the core technologies in fifth-generation (5G) mobile communication networks and in NGIoT. [1], [2]

In typical orthogonal multiple access (OMA) systems, users with poor channel conditions are allotted network resources, but the spectral efficiency of these systems has deteriorated. But when the power domain NOMA technique is taken into account, this feature does not applIoT a typical NOMA scheme, users can cancel the same frequency in the spectrum domain, the same time in the time domain, and even the same code in the code domain; however,

they cannot share the same level of power in the power domain [3]. The fundamental concept behind this case in a typical NOMA scheme is the utilization of successive interference cancellation (SIC) techniques by users with satisfactory channel conditions in order to mitigate the interference of users with low-quality channel conditions. As a result, SIC techniques lead to a considerable reduction of users' intra-cell and intra-cluster interference [4]. NOMA has been proposed as the main technique by several authors in order to solve the challenge of broadcast and unicast convergence as well as the convergence between broadband and broadcast, [5]–[7].

The user association problem in deployed NOMA networks exhibits various challenges due to its unique features, such as co-channel interference. The authors in [8] utilize a game-theoretic approach to associate the users of a NOMA network example in different resource blocks and group them into orthogonal clusters to address the user association problem. However, several assumptions and certain limitations that are derived from the application of game-theoretic techniques to user association problems in NOMA networks make this approach rather complex and difficult to implement. On the contrary, evolutionary algorithms (EAs) [9] are global optimization techniques that perform satisfactorily under virtually any given optimization problem, each with its own restrictions or peculiarities.

The authors in [10], [11] introduced the utilization of EAs to address both the power allocation and the user association problems of typical NOMA networks having multiple base stations (BSs) as a key parameter in network topology. In [12], the authors study uplink NOMA scenarios with user association having different quality-of-service (QoS) requirements, and propose a solution using game theory techniques. Finally, the authors in [13] consider non-ideal SIC NOMA schemes with QoS constraints to propose a distributed cluster formation and a power-bandwidth allocation approach for downlink heterogeneous networks.

A unified NOMA scheme that encompasses both power and code domains and provides user association along with resource allocation in heterogeneous ultra-dense networks (HUDNs) for 5G mobile communication networks is proposed in [14].

Expanding the work of [8], the authors in [15] introduced a new formulation for the user association problem in NOMA cellular networks. They grouped the users of the given cellular network into orthogonal clusters and associated them with different physical resource blocks by utilizing a game-theoretic technique. In their work, the authors provide all the main parameters of their proposed formulation, including the complexity, convergence, stability, and optimality of their solution.

Moreover, in [16] the authors examine the power consumption minimization problem for a generic multi-cell multiple input and single output non-orthogonal multiple access (MISO-NOMA) system. They use an iterative distributed methodology to solve the optimization problem of the associated joint user grouping, beamforming (BF), and power control problems. Additionally, the joint subcarrier and power allocation problem for the downlink of a multi-carrier nonorthogonal multiple access (MC-NOMA) system is studied in [17]. The problem of joint power and subcarrier allocation for the NOMA system in multi-cell is studied in [18]. The authors in [18] propose a polyblock optimization-based algorithm for obtaining a globally optimal solution.

Moreover, the authors in [19] examine NOMA and cognitive radio (CR) benefits to vehicle-to-everything (V2X) as a spectrum-efficient application. The application of NOMA in IoT networks in combination with mobile edge computing (MEC) is reported in another paper in [20].

In hybrid networks, the different kinds of technologies that are used are one of the important factors in the user association problem. To this end, the authors in [21] investigate a complex, yet practical, indoor scenario, by incorporating visible light communication (VLC) technology and radio frequencyultra-denseology in a hybrid NOMA network. Furthermore, the authors of [22] investigate the effects of a VLC NOMA system on the provided QoS by proposing a QoS-based virtual user association scheme with adaptation.

The authors in [23] propose a deep learning framework to handle user association, as well as subchannel and power allocation problems in NOMA networks. The authors focus on game-theoretic system energy efficiency (EE) under QoS constraints. Additionally, in [24] the authors address the problem of optimizing both power control and user association using a convex optimization framework subject to total transmit power and user-specific quality-of-service constraints.

The user association problem for NOMA-based fog radio access networks (F-RANs) is studied in [25], by analysing its performance characteristics. The authors apply a stochastic geometry tool to provide closed-form analytical results. They presented two different algorithmic approaches based on evolutionary games and reinforcement learning, respectively, to address the user association problem in NOMA-based F-RANs. Moreover, the energy efficiency maximization problem was analysed in [26], by considering a downlink NOMA multicell heterogeneous network under imperfect CSI for specific QoS constraints, such as maximum transmit power, small-cell users, and cross-tier interference.

The authors in [15] proposed a new framework for NOMA cellular networks, namely the FDH-NOMA framework, that combines NOMA schemes and Full-Duplex (FDH) techniques. For the user association problem, they proposed two different modes, the selection criterion mode and the NOMA pairing scheme mode. Moreover, to maximize the sum-rate of the NOMA network system, the authors in [27] employed a coalition game approach that allows cooperation between the small base stations and proposed two distinguished algorithms to address this problem.

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NOMA techniques are combined with mobile edge computing (MEC) in [28]. The authors proposed a new formulation to address a complex optimization problem, by combining the individual problems of user association, resource allocation, and transmitting power control. To address this complex problem, they employed a matching-coalition approach.

Researchers have also used evolutionary algorithms to solve a number of optimization problems that have been written about. There is a vast number of open-source software packages and libraries that can be used for this purpose [29]. Several papers can be found in the literature using swarm intelligence approaches for solving optimization problems in wireless communications [30]–[32]. In [33] an evolutionary approach is employed for joint channel estimation and turbo multiuser detection in the context of orthogonal frequency-division multiplexing multiple-access systems. In the same context, the authors in [34] solve the Unmanned aerial vehicles (UAVs) localization problem using an improved Particle Swarm Optimization (PSO) algorithm. Furthermore, the authors in [35] address the problem of jointly optimizing the computation offloading and resource management of ultradense mobile devices using an approach of both genetic algorithms and PSO. Additionally, the authors in [36] apply both PSO and GWO for cell planning in 4G cellular networks. The problem of predicting the outage probability for mobile IoT networks is addressed by the authors in [37] by applying a combination of an improved GWO algorithm and and Elman neural network The motivation of our work stems from the above-mentioned discussion and from the fact that we want to provide a global solution methodology that does not use relaxation or other approximation techniques. In this work, we look at the problems of power allocation and user association in the downlink connections of a typical NOMA communication network with a single base station and multiple physical resource blocks (PRBs). One of the parameters that increases considerably the complexity of the given problem, which is an optimization one, is the power control. In a common approach, the power of the users in the network is controlled by the power coefficient, i.e., one coefficient for each user, and these are considered constants for the whole network [8]. In our proposed approach, we compute the power coefficient for each user of the NOMA network by utilizing EAs, as a suitable technique to solve this kind of optimization problem [9]. In detail, we utilize the Whale Optimization Algorithm (WOA) [38] and the Grey Wolf Optimizer (GWO) [39], as representative examples of EAs, to address the given optimization problem. The main contributions of this work are summarized as follows:

- Formulation of the QoS aware joint power allocation and user association problems for downlink NOMA cellular networks.
- Problem solution using optimal power coefficients instead of constant ones.

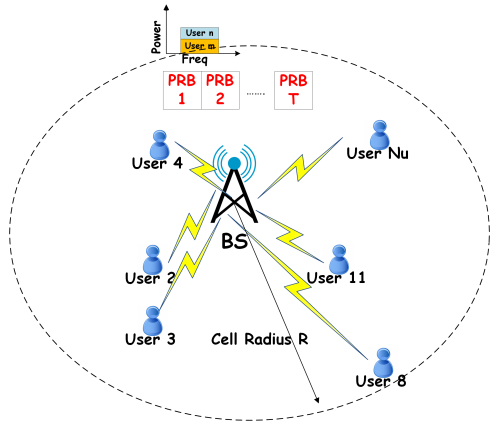

FIGURE 1. Network topology

- Introduce an evolutionary optimization framework for solving the QoS aware joint power allocation and user association problems.
- Develop a specific heuristic algorithm for forming the fitness function.
- Apply two nature inspired algorithms, namely the GWO and the WOA optimizers.
- Study the effect of varying different network parameters to overall QoS.
- Compare the results of two algorithms with randomly generated solutions.

To the best of the author's knowledge, this is the first time that evolutionary algorithms have been applied to address and solve the given problem. The computed results reveal network performance for various cases and demonstrate the benefits of the NOMA approach. Moreover, it seems that WOA clearly outperforms GWO in all cases. An evolutionary approach proves to be more efficient than producing random solutions.

II. SYSTEM MODEL

In general, let's think about a single base station (BS) in a cell network that serves several mobile users using NOMA techniques. Moreover, the BS uses physical resource blocks (PRBs) to transmit its data (Fig 1). Thus, we consider a downlink NOMA network that is being utilized by $\mathcal{U} = \{1, 2, \cdots, N_u\}$ set of users, while $|\mathcal{U}| = N_u$ denotes the set cardinality or the number of users. Additionally, we consider $\mathcal{V} = \{1, 2, \ldots V_{RB}\}$, which denotes the the set of PRBs with cardinality $|\mathcal{V}| = V_{RB}$. Hence, V_{RB} orthogonal clusters exist. If PRB v is associated with a set of users, then this is denoted $\mathcal{O}_v$ with cardinality $|\mathcal{O}_v| = O_v$. One PRB is assigned to one user in OMA systems. However, several users share the same PRB with varying power levels in NOMA networks. In this case, SIC in user receivers is used to eliminate the intra-cluster interference.

We make the assumption that all users in each cluster use the NOMA techniques. Hence user q in any cluster O_v

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receives the signal that is expressed by

$$Y_q^v = \underbrace{h_q^v \sqrt{p_q^v} s_q + n_q}_{\text{desired signal}} + \underbrace{h_q^v \sum_{i=1, i\neq q}^{|O_v|} \sqrt{p_i^v} s_i}_{\text{intra-cluster interference}} \quad (1)$$

where h_q^v denotes the channel coefficient among user q and PRB v that is assigned by the BS, s_q represents the transmitted signal, p_q^v denotes the power allocation coefficient, and n_q denotes the noise.

Furthermore, the channel power gain is expressed as

$$|h_q^v|^2 = |\hat{h}_q^v|^2 G_{\mathrm{PL}}(d_q) \quad (2)$$

where $\hat{h}_q^v \sim \mathcal{CN}(0,1)$ denotes the circular-symmetric complex Gaussian zero-mean noise from PRB v to user q, $G_{\mathrm{PL}}(d_q)$ denotes the propagation path loss. The propagation path loss between user q and the BS is modeled with path gain (loss) $GPL(d)$. In this work, we will use a propagation model from [40]. This is an outdoor macro cell line-of-sight (LOS) model and it is defined by

$$G_{\mathrm{PL}}(d_q) = -128.1 - 37.6 \log_{10}(d_q) \text{ (dB)} \quad (3)$$

where d_q denotes the distance among the user q and the BS expressed in km.

The power allocation coefficients satisfy in any cluster O_v:

$$\sum\nolimits_{j=1}^{|O_v|} p_j^v \leq 1. \quad (4)$$

Moreover, we consider that a maximum number of Q NOMA users can be connected to each PRB. If q-user needs to decode its own signal, then it is necessary to decode and remove intra-cluster interference from the previous user. The SIC technique employed by the u-th user is considered ideal. Therefore, in this case for perfect SIC the necessary condition for $u > v$ is given by

$$Q(O_v) \triangleq |h_{O_v}^v|^2 \geq, ...|h_u^v|^2 \geq |h_q^v|^2 ..., \geq |h_1^v|^2 \quad (5)$$

. We can assume that the $Q-th$ user in each cluster is well-served. The q-th user's receiver in O_v detects the j-th user's signal as noise $(q < j)$ and decodes its own signal based on the signal-to-interference-plus-noise ratio (SINR) given below

$$\gamma_q^v = \frac{|h_q^v|^2 p_q^v}{|h_q^v|^2 \sum\limits_{j=q+1}^{|O_v|} p_i^v + \frac{N_0 W_{PRB}}{P_v}}, \quad (6)$$

where W_{PRB} is the bandwidth of a PRB, P_v denotes the transmit power, and N_0 denotes the noise power spectral density. We specify the transmit signal-to-noise ratio (SNR) as $\rho = \frac{P_v}{N_0 W_{PRB}}$. Additionally, the receiver at the O_v-th user removes intra-cluster interference with SIC and decodes its own signal with SINR:

$$\gamma_{O_v}^v = \rho |h_{O_v}^v|^2 p_{O_v}^v \quad (7)$$

Therefore, in the case of a NOMA scheme, we can express the data rate at the user q assigned to PRB v as

$$R_{q,v}^{NOMA} = \log_2(1 + \gamma_q^v)$$

where W_{PRB} is the bandwidth of a PRB in KHz.

The admission control variable of the i-th user with v-th PRB is denoted with another binary variable, s_{vi} formulated as

$$s_{iv} = \begin{cases} 1, & \text{if user } i \text{ is assigned to PRB } v \\ 0, & \text{otherwise.} \end{cases} \quad (8)$$

We can then, formulate the QoS aware joint admission control and power allocation problem for downlink NOMA scheme as

$$\begin{aligned} \max_{\{\boldsymbol{s},\boldsymbol{a}\}} \quad & \sum_{i\in\mathcal{U}} H(\max(0, R_i - R_{i,\min})) \\ \text{s.t.} \quad & C_1 : s_{uv} \in \{0,1\}, \forall u \in \mathcal{U}, \forall v \in \mathcal{V}, \\ & C_2 : \sum\nolimits_{v=1}^{V_{RB}} s_{uv} = 1, \forall u \in \mathcal{U}, \\ & C_3 : \sum\nolimits_{u=1}^{O_v} s_{uv} \leq Q, \forall v \in \mathcal{V}, \\ & C_4 : \sum\nolimits_{i=1}^{O_v} s_{iv} a_i^v \leq 1 \forall v \in \mathcal{V}, \end{aligned} \quad (9)$$

where $H()$ denotes the Heaviside step function given by

$$H(\rho) = \begin{cases} 0, if \rho < 0, \\ 1, if \rho \geq 1. \end{cases} \quad (10)$$

where $\boldsymbol{a}$ and $\boldsymbol{s}$ are the set of all indicators a and s, respectively. The constraint $C1$ describes whether user u and PRBs v are associated or not. The constraint $C2$ expresses the unique association of one user u with one PRB v. Furthermore, constraint $C3$ indicates that in any PRB, a maximum of Q users can be handled. Constraint $C4$ states that each cluster's total power allocation coefficients should be less than or equal to one. The problem presented above is non-convex and difficult to solve.

III. OPTIMIZATION ALGORITHMS

In this study, we have applied to the Qos aware joint admission control and power allocation problem two different low-complexity, nature-inspired algorithms. These are the whale optimization algorithm (WOA) [38], and the grey wolf optimizer (GWO) [39]. WOA uses math to model how humpback whales interact with each other, while GWO is based on how grey wolves hunt. There are no control parameters in either algorithm. As a result, they don't require any further settings except the maximum number of iterations or generations and the population size.

A. PROBLEM MODELING ALGORITHM

To tackle the Qos aware joint admission control and power allocation problem using evolutionary algorithms, we need first to model properly the objective function

and the decision vector of the unknown variables. To do this, we make a new heuristic algorithm that computes the value of the objective function and deals with the different constraints. This is presented in Algorithm 1, which returns the fitness value, for a possible solution vector $\mathbf{z}$. The solution vector is defined in the form $\mathbf{z} = (s_{1v}, s_{2v}, .., s_{iv}, .., s_{N_u v}, a_1^v, a_2^v, .., a_i^v, .., a_{N_u}^v)$

Algorithm 1 Calculate objective function value

Input a possible solution vector $\mathbf{z}$
Set $N_{cover} = 0$, the users served by the BS, $fitness = 0$
for i=1 to N_u **do**
  for v=1 to V_{RB} **do**
    if users in $V_{RB} = Q$ **then**
      Continue
    else
      Assign user i to PRB v, $s_{iv} = 1$
      Assign power value a_i^v to user i
    end if
    if user i assignment is feasible according to (9) **then**
      Calculate rate R_i for the i-th user
      if $R_i \geq R_{i,\min}$ **then**
        if the BS can support the user desired rate, QoS is feasible **then**
          $N_{cover} = N_{cover} + 1$,
        end if
      end if
    else
      $fitness = fitness + 10^{20}$
    end if
  end for
end for
$fitness = fitness - (N_{cover}/Nu) * 100$
Return $fitness$ value

B. GREY WOLF OPTIMIZER FOR NOMA USER ASSOCIATION

The GWO method is based on mathematical models of grey wolf hierarchy and hunting behavior in the wild. Its major feature is the preservation of search space information during the iteration process. GWO does not require any additional control settings to be configured. The GWO algorithm classifies the wolf vectors into four groups. The alpha ($alpha$), beta ($beta$), and delta ($delta$) categories are the first three best vectors of association and power values. The omega ($omega$) category contains all unclassified solutions. In a wolf pack, as a social behavior group hunting (optimization process) is oriented by the aforementioned population categories ($alpha$, $beta$, $delta$). The following formulas give a mathematical representation of the encirclement of prey during the hunting process:

$$\vec{V}_{x,G} = |\vec{C}^2 \cdot \vec{P}_{x,G} - \vec{W}_x, G| \tag{11}$$

$$\vec{W}_{x,G+1} = \vec{P}_{x,G} - \vec{C}^1 \cdot \vec{V}_{x,G} \tag{12}$$

where the position vector of the prey is denoted by $\vec{P}_x$, the coefficient vectors are denoted as $\vec{C}^1$ and $\vec{C}^2$, $\vec{W}$ models the position vector of the grey wolf (e.g. the position vector, in this case, corresponds to the size $2 \times N_u$ vector of association and power values), and the current generation is denoted by G. The vectors $\vec{C}^1$ and $\vec{C}^2$ are given by (13) and (14):

$$\vec{C}^1 = 2\vec{u} \cdot \vec{v}_1 - \vec{u} \tag{13}$$

$$\vec{C}^2 = 2 \cdot \vec{v}_2 \tag{14}$$

where $\vec{u} \in [2, 0]$ and $\vec{v}_1, \vec{v}_2 \in [0, 1]$ are randomly obtained vectors from uniform distribution. The GWO algorithm's hunting process, like the social behavior of a grey wolf pack, can be described as the formulation below.

$$\begin{aligned} \vec{V}_\alpha &= |\vec{C}_1^2 \cdot \vec{W}_\alpha - \vec{W}| \\ \vec{V}_\beta &= |\vec{C}_2^2 \cdot \vec{W}_\beta - \vec{W}| \\ \vec{V}_\delta &= |\vec{C}_3^2 \cdot \vec{W}_\delta - \vec{W}| \end{aligned} \tag{15}$$

$$\begin{aligned} \vec{W}_1 &= \vec{W}_\alpha - \vec{C}_1^1 \cdot (\vec{V}_\alpha) \\ \vec{W}_2 &= \vec{W}_\beta - \vec{C}_2^1 \cdot (\vec{V}_\beta) \\ \vec{W}_3 &= \vec{W}_\delta - \vec{C}_3^1 \cdot (\vec{V}_\delta) \end{aligned} \tag{16}$$

$$\vec{W}_{G+1} = \frac{\vec{W}_1 + \vec{W}_2 + \vec{W}_3}{3} \tag{17}$$

The pseudo code of GWO algorithm is outlined in algorithm 2.

C. WHALE OPTIMIZATION ALGORITHM FOR NOMA USER ASSOCIATION

The WOA is a swarm-based nature-inspired algorithm [38]. WOA is based on humpback whales' hunting and social behavior. Whales can detect the location of prey in the wild and make particular maneuvers to encircle them. The prey is represented by WOA as the best solution identified in each iteration. All members of the population (user associations and power vectors) aim to get as near as possible to the optimum solution. Then they update their position vectors appropriately. The following equations can be used to express the whale behavior and in particular the prey encirclement part in WOA:

$$Q_d = \left| U_d \times x_{d,G}^{best} - x_{d,G}^b \right| \tag{18}$$

$$x_{d,G+1}^b = x_{d,G}^{best} - S_d Q_d \tag{19}$$

where $x_{d,G}^b$ denotes the $b-th$ vector of association and power values in the $d-th$ dimension, and $x_{d,G}^{best}$ denotes the best solution found in current iteration G. Moreover, the coefficient vectors in the $d-th$ dimension (the $d-th$ dimension refers to the vector of association and power values containing the unknowns in the optimization problem) are denoted by U_d, S_d, while Q_d corresponds to the distance vector of the current whale position to the prey position. The following equations show how the latter vectors are calculated:

Algorithm 2 GWO algorithm for NOMA User Association

Initialize a population of association variables and power values of size $2N_u \times NP$ $\vec{W}_i (i = 1, 2, \cdots$,NP)
Set up $\vec{u}$, $\vec{C}^1$, and $\vec{C}^2$
for each vector $\vec{W}_i$ of the population **do**
  Calculate the fitness value $F(\vec{W}_i)$ using Algorithm 1 and find the user association vector if $\vec{W}_i$ is feasible
end for
Compute the position vectors for each wolf type: $\vec{W}_\alpha$, $\vec{W}_\beta$, and $\vec{W}_\delta$
while $(t < MaxNumIter)$ **do**
  for each vector of the population **do**
    Calculate new position vector $\vec{W}_i$ of the current member using (17) and update its value
  end for
  Calculate $\vec{u}$, $\vec{C}^1$, and $\vec{C}^2$
  for each vector $\vec{W}_i$ of the population **do**
    Calculate the fitness value $F(\vec{W}_i)$ using Algorithm 1 and find the user association vector $\vec{W}_i$ is feasible
  end for
  Compute the position vectors of all population members
  Renew $\vec{W}_\alpha$, $\vec{W}_\beta$, and $\vec{W}_\delta$
  Increase t by one
end while
Return the best feasible solution vector of association variables and power values

$$S_d = 2s_d r_d - a_d \tag{20}$$

$$U_d = 2r_d \tag{21}$$

where s_d is a variable $\in [2, 0]$, that decreases linearly over iteration, and r_d denotes a random number from a uniform distribution $\in [0, 1]$.

The whale bubble-net behavior is modeled mathematically in WOA as the exploitation phase of the algorithm. This is achieved by the integration of two distinct movements, the first one is an encircling movement with a reducing radius and the second one is a spiral trajectory updating position. This type of spiral trajectory movement in WOA is modeled by a spiral equation that replicates humpback whales' helix-shaped movements. It is written as:

$$x^b_{d,G+1} = L_d e^{gs} cos(2\pi l) + x^{best}_{d,G} \tag{22}$$

where L_d represents the the distance vector of the $b - th$ vector of association and power values to the best solution (i.e the $d - th$ coordinate of L), g is a fixed value that determines the shape of the logarithmic spiral, and l is a random number $\in [-1, 1]$ from a uniform distribution.

Humpback whales follow a spiral-shaped path in a circle with a decreasing radius while performing two separate mechanism actions at the same time. This type of movement is modeled by the WOA authors using a 50% probability distribution, which is mathematically expressed as:

$$x^b_{d,G+1} = \begin{cases} x^{best}_{d,G} - S_d Q_d, & if \;\; r_b < 0.5 \\ L_d e^{ks} cos(2\pi l) + x^{best}_{d,G}, & otherwise \end{cases} \tag{23}$$

where r_b denotes a random number $\in [0, 1]$.

Additionally, the whales follow a random pattern when looking for prey. The WOA exploration phase is denoted by this type of behavior, and is defined by:

$$Q_d = \left| U_d \times x^r_{d,G} - x^b_{d,G} \right| \tag{24}$$

$$x^b_{d,G+1} = x^r_{d,G} - S_d D_d \tag{25}$$

where r, with $r \neq b$ denotes a randomly selected vector of association and power values that the $b - th$ member will follow.

The pseudo-code is presented in Algorithm 3 to better understand the WOA functionality. The WOA generates a set of random vectors of association variables and power values during initialization. The location vectors and distance vectors to the pey are then calculated at each iteration either in terms of a random search pattern or the best fitness values achieved thus far. The s_d parameter regulates the algorithm's exploitation and exploration phases. Finally, the r_b option toggles between an encircling process with a reducing radius and a spiral trajectory updating position mechanism.

The time complexity of the both GWO and WOA algorithms is comparable to that of other swarm intelligence algorithms, that is at the end of each iteration given by $\mathcal{O}(N_p N_c D + N_p N_c f)$, where D denotes the search space dimension and f denotes the time complexity of the fitness function.

D. CONVERGENCE ANALYSIS OF THE GWO ALGORITHM FOR NOMA ADMISSION CONTROL

The theoretical analysis of the evolutionary algorithms presented in the previous section can be made according to the framework presented in [41]–[43]. The convergence analysis is based on the two conditions reported in [41].

If we define the optimization problem $\langle S, f \rangle$, an objective function f and a feasible solution space S. A new solution x_{n+1} is obtained after an evolutionary algorithm A iterates for n iterations. This solution is found by the previous iteration solution x_n by

$$x_{n+1} = A(x_n, \eta), \tag{26}$$

where algorithm A obtains the solution set η during the iterative process.

The essential infimum of f on S is defined as [41]

$$\beta = \inf\{n : u[x \in S | f(x) < n] > 0\}, \tag{27}$$

where $u[X]$ is the measure ot X. This has the meaning that there exist non-empty subsets in the search space and the objective function value that corresponds to the element in

Algorithm 3 WOA for NOMA User Association

```
Initialize a population of vectors of association variables and power values of size 2N_u × NP
for each vector x⃗^i of the population do
    Calculate the fitness value F(x⃗^i) using Algorithm 1 and find the user association vector if x⃗^i is feasible
end for
Obtain the best user association solution x_j^best
while (G < G_max) do
    for (j = 1 : 2N_u) do
        Compute s_j, r_j, S_j, U_j
        for (i = 1 : NP) do
            if (r_b < 0.5) then
                if (|S_j| ≥ 1) then
                    Calculate the distance vector Q_j using (18)
                    Calculate the position vector x^i_{j,G+1} using (19)
                    Calculate the fitness value F(x⃗^i_{G+1}) using Algorithm 1 and find the user association vector if x⃗^i_{G+1} is feasible
                else
                    Compute distance vector Q_j using (24)
                    Compute position vector x^i_{j,G+1} using (24)
                    Calculate the fitness value F(x⃗^i_{G+1}) using Algorithm 1 and find the user association vector if x⃗^i_{G+1} is feasible
                end if
            else
                Compute position vector x^i_{j,G+1} using (22)
                Calculate the fitness value F(x⃗^i_{G+1}) using Algorithm 1 and find the user association vector if x⃗^i_{G+1} is feasible
            end if
        end for
    end for
    Increase G by one
end while
Return the best feasible solution vector of association variables and power values
```

the non-empty subset can be infinitely close to β. Hence, the neighbourhood or optimality region is defined as

$$R_{\varepsilon,K} = \begin{cases} \{x \in S | f(x) < \beta + \varepsilon\}, & -\infty < \beta < \infty, \\ \{x \in S | f(x) < K\}, & \beta = -\infty, \end{cases} \tag{28}$$

where $\varepsilon > 0$ and $K < 0$. We can assume that if an evolutionary algorithm obtains a point in $R_{\varepsilon,K}$, then the algorithm obtains either the global optimal solution or an approximation of that global optimal solution.

Thus, we may consider two conditions that are needed to ensure that global optimality can be obtained:

Condition 1. *The condition that the sequence $\{f(x^n)\}_{n=0}^{\infty}$ is converging to the infimum of f on S should be satisfied by an optimization algorithm A. This means that if there is $f(A(x,\eta)) \leq f(x)$, and $\eta \in S$ then $f(A(x,\eta)) \leq f(\eta)$*

Condition 2. *For all subsets $\forall D \in S$ subject to $v(D) > 0$, we have*

$$\prod_{n=0}^{\infty}(1 - v_n(D)) = 0, \tag{29}$$

where $v_n(D)$ denotes the probability measure of the n-th iteration best result of the evolutionary algorithm A on D.

The guaranteed global convergence of any evolutionary algorithm or any stochastic optimization method is based on the criteria listed in [41]–[43]

Criterion 1. *Assuming that f is measurable and the feasible solution space S is a measurable subset of R^n, and the evolutionary algorithm A satisfies both Condition 1 and Condition 2. If $\{x_n\}_{n=0}^{\infty}$ denotes a sequence generated by the algorithm A then the following relation should be satisfied*

$$\lim_{n\to\infty} P(x_n \in R_{\varepsilon,K}) = 1, \tag{30}$$

where $P(x_n \in R_{\varepsilon,K})$ denotes the probability that the found after n iterations or generations by algorithm A is in the subset $R_{\varepsilon,K}$.

This means that if the number of iterations is high enough, the evolutionary algorithm will certainly converge, or we may say that the evolutionary algorithm can have almost guaranteed global convergence. So in order to prove that the GWO algorithm converges, we need to prove that GWO may satisfy the above criterion. Without loss of generality, we may express the update equation of GWO of the i-th vector after $n+1$ iterations as

$$\begin{aligned} w_i^{n+1} = \tfrac{1}{3}\left[(w_a^n - r_1^n\,|r_2^n w_a^n - w_i^n|) + \right. \\ + \left(w_\beta^n - r_3^n \left|r_4^n w_\beta^n - w_i^n\right|\right) + \\ \left. + (w_\delta^n - r_5^n\,|r_6^n w_\delta^n - w_i^n|)\right] \end{aligned} \tag{31}$$

where $r_m^n, m = 1, 2, \ldots, 6$ are uniform random numbers from the distribution $U(0,c)$ on $[0,c]$ where c is positive constant.

The states of grey wolves and the state space is expressed as below:

Definition 1. *The grey wolf individual x position, historical best position w_α, historical second best position w_β, and historical third best position w_δ, creates the state or status, which can represented by $\zeta = (x, w_\alpha, w_\beta, w_\delta)$, where $x, w_\alpha, w_\beta, w_\delta \in S$.*

Moreover, it is also $f(w_\alpha) \leq f(w_\beta) \leq f(w_\delta) \leq f(x)$. Thus, we consider that the set of all possible states of all grey wolf vectors create a state space for vectors, which can be expressed as

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$$Z = \Big\{ \zeta = (x, w_\alpha, w_\beta, w_\delta) | x, w_\alpha, w_\beta, w_\delta \in S, \tag{32}$$

$$f(w_\alpha) \leq f(w_\beta) \leq f(w_\delta) \leq f(x) \Big\}. \tag{33}$$

Additionally, we may define the states and state space of the grey wolves population by the following:

Definition 2. *We call the grey wolves group set of all N grey wolves vector. Moreover, The states of this grey wolf group are represented by $\psi = (\zeta_1, \zeta_2, \ldots, \zeta_N)$. We also define the grey wolves group status space as the set of all possible grey wolves group states and this is denoted by*

$$\Psi = \Big\{ \psi = (\zeta_1, \zeta_2, \ldots, \zeta_N), \zeta_i \in Z (1 \leq i \leq N) \Big\}. \tag{34}$$

It is clear from the above that the best solution vector is included in the grey wolves status Ψ. Additionally, we define the state transition for the grey wolves' positions modeling solutions by the following:

For $\forall \zeta_i = (x^i, w^i_\alpha, w^i_\beta, w^i_\delta) \in Z$ and $\forall \zeta_j = (x^j, w^j_\alpha, w^j_\beta, w^j_\delta) \in Z$ during the iterations of the GWO algorithm, we denote the state transition from ζ_i to ζ_j as

$$A_\zeta(\zeta_i) = \zeta_j, \tag{35}$$

where A_ζ denotes the transition function from ζ_i to ζ_j in the state space Z.

Correspondingly, for $\forall \psi_i = (\zeta_{i,1}, \zeta_{i,2}, \ldots, \zeta_{i,N}) \in S$ and $\forall \psi_j = (\zeta_{j,1}, \zeta_{j,2}, \ldots, \zeta_{j,N}) \in S$, the iterative process of the GWO algorithm essentially, the grey wolves' group states are transferred from ψ_i to ψ_j. This is

$$A_\psi(\psi_i) = \psi_j. \tag{36}$$

In the GWO algorithm, the grey wolves' status ζ_i is basically changed to the status ζ_j in a single step, and its transition probability

Lemma 1. *The transition probability of the i-th vector of GWO population from state ζ_n to state $\zeta_n + 1$ is the found by the joint probability*

$$P(A_\zeta(\zeta_{i,n}) = \zeta_{i,n+1}) = P(x^n_i \to x^{n+1}_i) P(w^n_a \to w^{n+1}_a) \tag{37}$$

where $P(x^n_i \to x^{n+1}_i)$ is the probability for the i-th particle changing from the position x^n_i to the spherical region centered at x^{n+1}_i with radius ϵ and $P(w^n_a \to w^{n+1}_a)$ is the transition probability of the best solution of GWO.

Proof. Any individual i of the GWO changes status from from $(x^n_i, w^n_\alpha, w^n_\beta, w^n_\delta)$ to $(x^{n+1}_i, w^{n+1}_\alpha, w^{n+1}_\beta, w^{n+1}_\delta)$. This means that the $x^n_i \to x^{n+1}_i$, and $w^n_a \to w^{n+1}_a$ are performed synchronously. Thus, the joint probability is given by

$$P(A_\zeta(\zeta_{i,n}) = \zeta_{i,n+1}) = P(x^n_i \to x^{n+1}_i) P(w^n_a \to w^{n+1}_a). \tag{38}$$

We consider the single vector model given by (39). Then it obvious that the value of x^{n+1}_i is determined by the six random variables $r^n_m, m = 1, 2, \ldots, 6$. Without loss of generality we may write $r^n_2 = r^n_4 = r^n_6 = 1$. Thus, (39) becomes

$$\begin{aligned} x^{n+1}_i = \tfrac{1}{3} \big[(w^n_a - r^n_1 |w^n_a - x^n_i|) + \\ + \Big(w^n_\beta - r^n_3 \Big| w^n_\beta - x^n_i \Big| \Big) + \\ + (w^n_\delta - r^n_5 |w^n_\delta - x^n_i|) \big] \end{aligned} \tag{39}$$

Then we have similarly with [44]

$$\begin{aligned} P\left(x^n_i \to x^{n+1}_i\right) == & \frac{\int_{x^{n+1}_i - \frac{1}{2}\varepsilon}^{x^{n+1}_i + \frac{1}{2}\varepsilon} d\psi}{\int_{x^n_i}^{x_\iota{}^n + \frac{1}{3}\left(w^n_a + w^n_\beta + w^n_\delta\right)} d\psi} \times \frac{\int_{r^n_1 - \frac{1}{2}\varepsilon}^{r^n_1 + \frac{1}{2}\varepsilon} d\psi}{\int_{x^n_i - r^n_1 |w^n_a - x^n_i|}^{x_\iota{}^n} d\psi} \times \\ \times & \frac{\int_{r^n_3 - \frac{1}{2}\varepsilon}^{r^n_3 + \frac{1}{2}\varepsilon} d\psi}{\int_{x^n_i - r^n_3 |w^n_b - x^n_i|}^{x_\iota{}^n} d\psi} \times \frac{\int_{r^n_5 - \frac{1}{2}\varepsilon}^{r^n_5 + \frac{1}{2}\varepsilon} d\psi}{\int_{x^n_i - r^n_5 |w^n_\delta - x^n_i|}^{x_\iota{}^n} d\psi} = \\ = & \frac{\varepsilon}{\frac{1}{3}\left(w^n_a + w^n_\beta + w^n_\delta\right)} \times \frac{\varepsilon}{c|w^n_a - x^n_i|} \times \frac{\varepsilon}{c|w^n_\beta - x^n_i|} \times \frac{\varepsilon}{c|w^n_\delta - x^n_i|} \end{aligned} \tag{4}$$

Moreover, it is

$$P(w^n_a \to w^{n+1}_a) = \begin{cases} 1, & f(w^{n+1}_a) < f(w^n_a), \\ 0, & f(w^{n+1}_a) \geq f(w^n_a). \end{cases} \tag{41}$$

□

We may now give the proof of the following theorem using these findings:

Theorem 1. *During the iterative procedure of the GWO algorithm, the transition probability of the grey wolves group status changes from ψ_i to ψ_j is given by*

$$P(A_\psi(\psi_i) = \psi_j) = \prod_{n=1}^{N} P(A_\zeta(\zeta_{i,n}) = \zeta_{j,n}), \tag{42}$$

where N denotes the current number of iterations.

Proof. As $A_\psi(\psi_i) = \psi_j)$ shows that each state in the grey wolf group state, ψ_i is concurrently moved to group state ψ_j; this is expressed as

$$A_\zeta(\zeta_{i,1}) = \zeta_{j,1}, A_\zeta(\zeta_{i,2}) = \zeta_{j,2}, \ldots, A_\zeta(\zeta_{i,N}) = \zeta_{j,N}.$$

Then, we can deduct that the transition probability of a group transition of the grey wolf group is actually each iteration step's joint probability. Hence, we may write

$$\begin{aligned} P(A_\psi(\psi_i) = \psi_j) = P(A_\zeta(\zeta_{i,1}) = \zeta_{j,1}) P(A_\zeta(\zeta_{i,2}) = \zeta_{j,2}) \\ \ldots P(A_\zeta(\zeta_{i,N}) = \zeta_{j,N}), = \textstyle\prod_{n=1}^{N} P(A_\zeta(\zeta_{i,n}) = a_{j,n}), \end{aligned} \tag{43}$$

which concludes the proof. □

The state sequence ζ can thus be proven to be a finite, homogeneous Markov chain.

Theorem 2. *The grey wolf group state sequence ζ constitutes a finite homogeneous Markov chain.*

Proof. The the number of iterations or generations and the population size are both finite, thus every evolutionary algorithm's search space for the entire iterative process is

finite. Thus, each of the grey wolf state $\zeta = (x, w_\alpha, w_\beta, w_\delta)$ among the $x, w_\alpha, w_\beta, w_\delta$ are finite. As a result, the state space of the grey wolf is finite.

If we consider the position, global optimal values, second global optimal value, and third optimal value to be grouped in one state Ψ, then it is obvious that state $\Psi(n+1)$ will not depend on previous states but just on state $\Psi(n)$. Thus, the sequence Ψ has the proper Markov chain features.

It is clear that the system state $\Psi(n-1)$ and its transition at time n to the new state $\Psi(n)$ is totally predetermined by its state at time n. Moreover, the random numbers $r_m^n, m = 1, 2, \ldots, 6$ and the iteration n are independent of the system state prior to n.

From $\Psi(n-1)$ to $\Psi(n)$ of grey wolf group state sequence $\{\Psi(n); n \geq o\}$, The transition probability $P(A_\Psi(\Psi(n-1)) = \Psi(n))$ of the two states is given by the transition probability of all individuals in the grey wolf group. This transition probability is given by (1). This probability is only related to the state $\zeta_{i,n-1}, 1 \leq i \leq N$ of all grey wolves at iteration $n-1$. Thus, the Markov chains are finite. Moreover, we deduct from Theorem 1, that $P(A_\zeta(\zeta(n-1)) = \zeta(n))$ is independent of time (iteration) $n-1$. In similar way, we notice that $P(A_\Psi(\Psi(n-1)) = \Psi(n))$ is also independent of $n-1$. Thus, we have proven that the finite Markov chains are homogeneous. □

Next, we can define the optimal state set of the grey wolf algorithm for the global optimum solution g_α, the second best global optimum solution, g_β, and the third global optimum solution g_δ as

Definition 3.

$$E = \Big\{\zeta = (x, w_\alpha, w_\beta, w_\delta), f(w_\alpha) = f(g_\alpha), f(w_\beta) = f(g_\beta), f(w_\delta) = f(g_\delta),\ \zeta \in Z\Big\}.$$

Clearly, the E is a subset of Z, it is $E \subseteq Z$ Moreover, we can define the optimal grey wolf state group as

Definition 4.

$$\Phi = \Big\{\psi = (\zeta_1, \zeta_2, \ldots, \zeta_N) \Big| \exists \zeta_m \in E(1 \leq m \leq N)\Big\}. \quad (45)$$

The above definition implies that the optimal grey wolf state set Φ is defined as the set of all grey wolf groups such that at least one vector grey wolf individual of the population with its state belong to E.

Theorem 3. *When $\Phi \subset E$, there is no closed set J other than E such that $J \bigcap \Phi = \emptyset$.*

Proof. Reductio ad absurdum. If we assume there is a closed set J so that $J \bigcap \Phi = \emptyset$ and that $f(w_{a,j}) > f(w_{a,b})$ for $\psi_i = (w_{a,b}, w_{a,b}, ..., w_{a,b}) \in \Phi$ and $\forall \psi_j = (\zeta_{j1}, \zeta_{j2}, ..., \zeta_{jn}) \in J$, this implies that

$$P(A_\psi(\psi_j) = \psi_i) = \prod_{n=1}^{N} P(A_\zeta(\zeta_{j,n}) = \zeta_{i,n}), \quad (46)$$

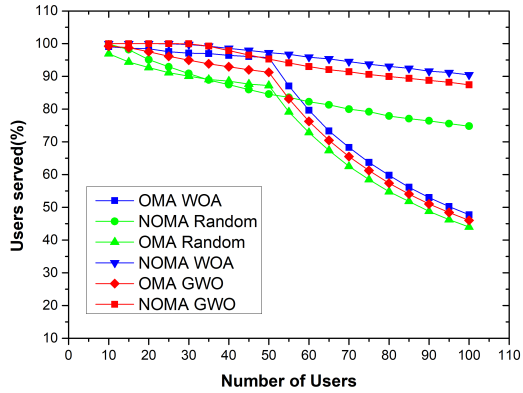

FIGURE 2. Number of users versus percentage of users served for $M = 2, T = 50$ for different association algorithms

For each $P(A_\zeta(\zeta_j) = \zeta_i)$, it holds that $P(A_\zeta(\zeta_j) = \zeta_i) == P(x_i \to x_i)P(w_{a,i} \to w_{a,j})$. It is $P(w_{a,i} \to w_{a,j}) = 1$ then $P(A_\zeta(\zeta_j) = \zeta_i) \neq 0$, implying that J is not closed, which contradicts the assumption. Thus, there is no non-empty closed set outside Φ in Ψ. □

The following theorem has been proven in [45], [46].

Theorem 4. *If we assume that a Markov chain has a non-empty set U and there is not any closed set G satisfying $U \bigcap G = \emptyset$, then the following relation is valid*

$$\lim_{n\to\infty} P(x_n = i) \begin{cases} = \sigma_i, \text{only if } i \in U \\ = 0, \text{only if } i \notin U \end{cases} \quad (47)$$

Moreover, the following theorem can be derived from the above theorems:
(44)

Theorem 5. *When the number of iterations reaches infinity or is sufficiently large, then the grey wolf group state sequence will converge to the optimal state (solution) set Φ.*

Additionally, from the above four theorems, it is straightforward to prove the following global convergence theorem:

Theorem 6. *The GWO algorithm with the Markov chain model as defined previously has guaranteed global convergence.*

Proof. We need to prove that GWO satisfies both Condition 1 and Condition 2 defined earlier in this subsection. If this is valid, then GWO will converge to global optimality. The iterative process of GWO, where the global best value w_α of the population is kept or is updated after every iteration, ensures that the first convergence condition is met. Moreover, we may deduct from the previous theorem, that after a sufficient number of iterations, the GWO group state sequence will converge toward the optimal set. or when the number of iterations tends to infinity. Thus, we may conclude that in this case, the probability of not

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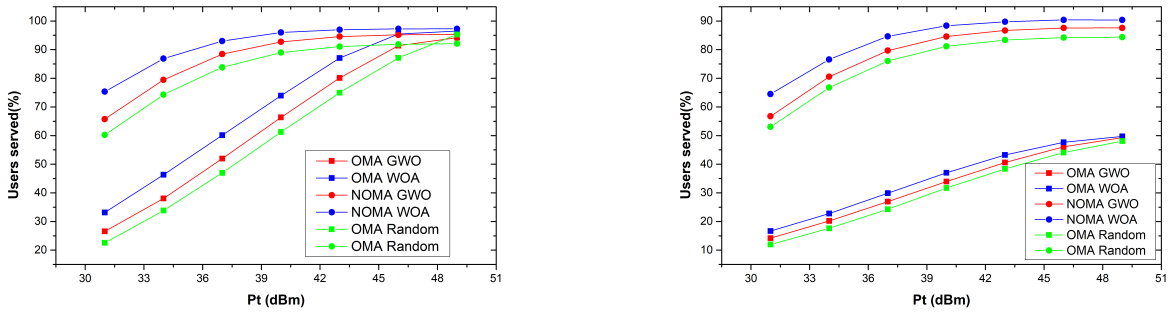
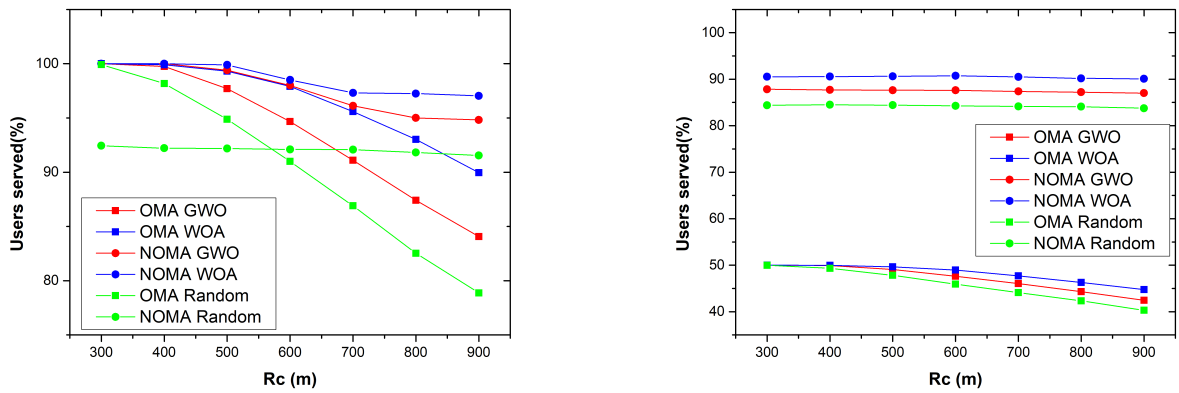


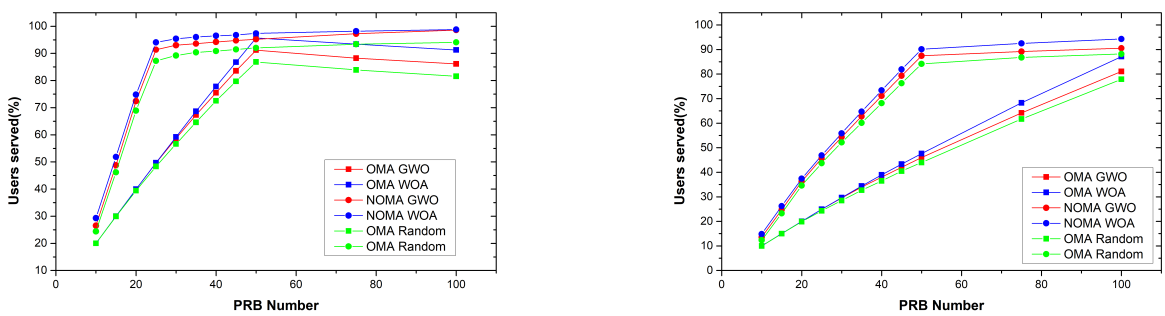
(a) N=50 (b) N=100

FIGURE 3. Number of users versus percentage of users served for $T = 50$ and different P_t values



(a) N=50 (b) N=100

FIGURE 4. Number of users versus percentage of users served for $T = 50$ and different R_c values



(a) N=50 (b) N=100

FIGURE 5. Number of users versus percentage of users served for different T values

obtaining the globally optimal solution is 0. Hence, the second convergence condition is satisfied. As an outcome, the global convergence of GWO to global optimality is assured. □

The above proof uses a Markov chain framework, similar to the literature [45], [46]. This means that the convergence concept is in a probabilistic sense. It shows that the GWO can certainly converge. However, the above theorem provides no information about the convergence rate or how the population size and the number of iterations may have an impact on the GWO convergence behaviour. The global

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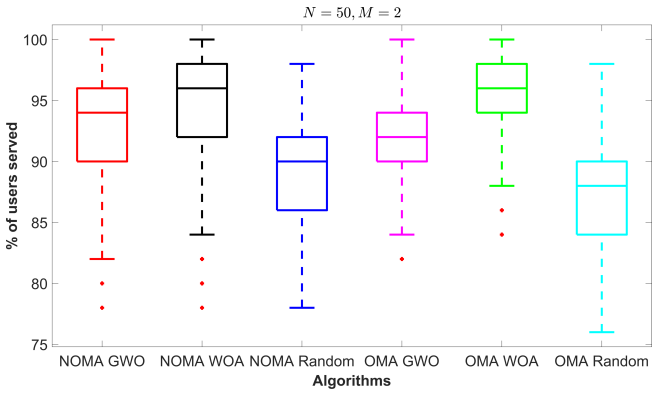
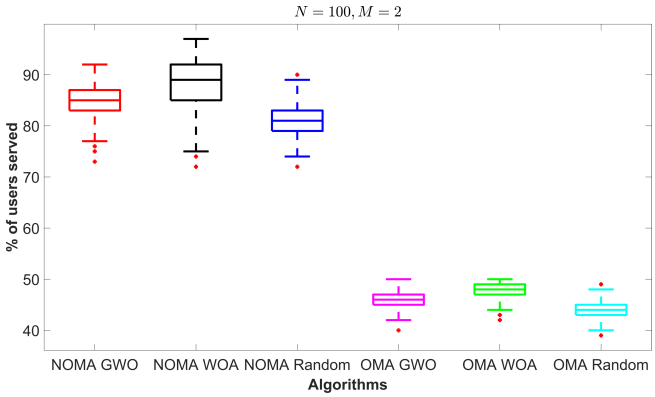
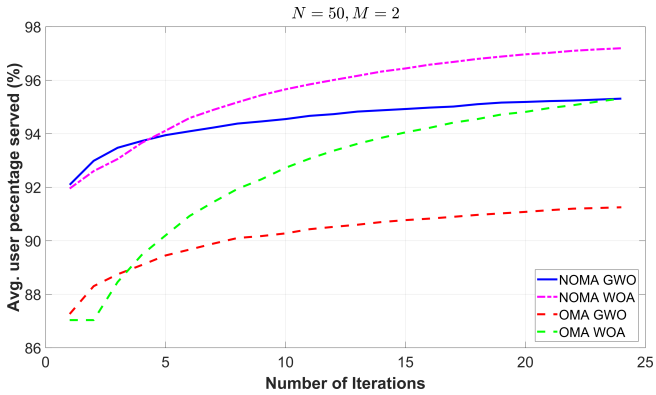


(a) N=50

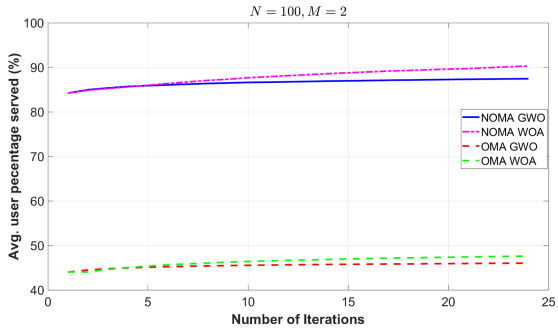


(b) N=100

FIGURE 6. Boxplot results of all algorithms for 1000 runs for a) N=50 users, b)N=100 users



(a) N=50



(b) N=100

FIGURE 7. Convergence rate graph for 1000 runs for a) N=50 users, b)N=100 users

convergence of WOA may be proven similar to the above.

IV. NUMERICAL RESULTS

A. BENCHMARK FUNCTIONS

In this subsection, we evaluate the performance of GWO and WOA in high-dimensional problems using different types of test functions, both unimodal and multimodal. We compare GWO and WOA on a set of nine numerical benchmark functions. Additionally, we also compare the above-mentioned algorithms with other popular evolutionary algorithms. These are namely the Artificial Bee Colony (ABC) [47], the Differential Evolution (DE) [48], the Harmony Search (HS) [49], the Invasive Weed Optimization (IWO) [50], and the Particle Swarm Optimization (PSO) [51]. The numerical benchmark functions and their properties are listed in Table 1. In order to evaluate the algorithm's performance in high-dimensional problems, we run two different sets of tests, one for problem dimension $D = 100$, and one for $D = 200$. All benchmark problems run for 100 independent trials. The maximum number of iterations is set to 1000, while the population size is set to 100 for all algorithms. The unknown variables limits are set to $[-10, 10]$ for all problems. Table 2 holds the algorithm's comparative results for $D = 100$. We notice that WOA and GWO obtained the best results in most of the cases. The corresponding results for $D = 200$ are presented in Table 3. Again the results are similar as previously, WOA and GWO perform better or the same with the other algorithms in most of the cases. The latter is shown directly using the Friedman ranking, a non parametric statistical test [52], [53]. Table 4 holds the algorithm rankings according to the Friedman test. It is clear that the WOA and the GWO emerge as the first and the second algorithm in ranking.

B. NOMA SIMULATIONS

The numerical results of the simulations and the optimization problem solutions are presented in this section. We have used both GWO and WOA algorithms to solve the QoS aware admission control problem by performing several simulations. Table 5 lists the values for all simulations.

We consider the following scenario where the total number of users ranges from 10 to 100 with step 5. The BS deploys and serves the users at random. We assume that the BS operates having 50 PRBs. Moreover, each PRB supports at the maximum $M = 2$ NOMA users.

Additionally, we generate users randomly from a uniform distribution and they are placed in a circle of 700 m radius. We consider shadowing lognormal that a value with a standard deviation equal to 8 dB. The PRB bandwidth W_{PRB} is selected to be equal to 180 kHz as the bandwidth in 4G/LTE. We compare the results between the two algorithms WOA, and GWO. In order to evaluate if using EAs is worth, we

TABLE 1. Numerical Benchmark functions

A/A	Name	Type	x^*	$F(x^*)$
f_1	Ackley	Multimodal,non-convex	$(0,..,0)$	0
f_2	Drop-wave	Multimodal, high complexity	$(0,..,0)$	0
f_3	Levy	Multimodal	$(1,..,1)$	0
f_4	Rastrigin	Highly Multimodal, non-convex	$(0,..,0)$	0
f_5	Sphere	Unimodal, convex	$(0,..,0)$	0
f_6	Sum of different powers	Unimodal, nonseparable	$(0,..,0)$	0
f_7	Sum squares	Unimodal, nonseparable	$(0,..,0)$	0
f_8	Zakharov	Unimodal, continuous	$(0,..,0)$	0
f_9	Rosenbrock	Narrow valley, non-convex	$(0,..,0)$	0

TABLE 2. Numerical Benchmark functions results for D=100

Function	WOA	GWO	ABC	DE	HS	IWO	PSO
f_1	**8.88E-16**	3.29E-14	1.35E+01	3.13E-01	4.91E+00	2.69E-02	5.55E-06
f_2	**-1.00E+00**	**-1.00E+00**	**-1.00E+00**	**-1.00E+00**	-1.00E+00	-1.00E+00	**-1.00E+00**
f_3	**4.76E-02**	4.82E+00	6.65E+02	4.58E+00	2.42E+01	1.09E+02	4.18E+00
f_4	**0.00E+00**	**0.00E+00**	2.91E+03	6.64E+02	3.08E+02	3.10E+02	2.06E+02
f_5	**6.19E-206**	1.63E-44	1.98E+03	2.36E-01	9.50E+01	3.20E-03	1.38E-11
f_6	**0.00E+00**	2.01E-245	1.12E+68	7.05E+11	5.82E+23	5.83E-06	5.12E-15
f_7	**1.67E-209**	1.02E-42	7.76E+04	7.91E+00	3.40E+03	2.47E+00	2.67E-09
f_8	2.75E+03	**5.14E-09**	3.13E+03	2.61E+03	1.38E+03	8.47E+02	6.54E+01
f_9	9.58E+01	9.50E+01	1.14E+07	2.54E+03	9.70E+04	9.30E+01	**7.83E+01**

TABLE 3. Numerical Benchmark functions results for D=200

Function	WOA	GWO	ABC	DE	HS	IWO	PSO
f_1	**8.88E-16**	1.29E-13	1.45E+01	5.70E+00	7.15E+00	1.78E+00	1.52E+00
f_2	**-1.00E+00**	**-1.00E+00**	**-1.00E+00**	**-1.00E+00**	-1.00E+00	-1.00E+00	**-1.00E+00**
f_3	**1.39E-01**	1.26E+01	1.86E+03	3.91E+02	1.83E+02	2.56E+02	1.88E+01
f_4	**0.00E+00**	**0.00E+00**	7.24E+03	2.11E+03	1.57E+03	1.22E+03	5.03E+02
f_5	**6.33E-203**	3.38E-30	5.14E+03	2.28E+02	6.14E+02	3.19E-01	2.19E-02
f_6	**0.00E+00**	2.21E-218	########	1.65E+86	8.82E+91	7.39E+33	1.18E+17
f_7	**1.78E-201**	2.88E-28	5.17E+05	1.41E+04	5.53E+04	3.66E+02	1.85E+00
f_8	5.79E+03	**2.29E+00**	7.10E+03	5.94E+03	4.48E+03	4.22E+03	5.94E+02
f_9	1.95E+02	**1.95E+02**	2.74E+07	1.18E+06	1.57E+06	4.37E+02	**5.51E+02**

TABLE 4. Average Ranking achieved by the Friedman test

Algorithm	Average Ranking	Normalized Ranking
WOA	2.08	1.00
GWO	2.19	1.05
ABC	6.67	3.20
DE	5.00	2.40
HS	5.22	2.51
IWO	3.94	1.89
PSO	2.89	1.39

TABLE 5. Simulation parameters

Frequency F (GHz)	2
Transmission power Pt (dBm)	46
Noise power (dBm/Hz)	-174
Pathloss model	3GPP TR36814 LOS

additionally generate random solutions and compare them with the EA-approach. Moreover, we apply all algorithms to both NOMA and OMA cases. We choose a population of parametric vectors and 100 is the maximum number of iterations. The algorithms run for 1000 different simulations. We generate a random topology in each simulation run that each algorithm tries to solve. Therefore, we obtain results that are from 1000 different random topologies We run the simulations with QoS constraints and without any additional constraint. The desired user data ranges from 100 to 500 kbps, which QoS-aware selected for each user. The problem dimensions are $2N_u$, thus for the maximum number of 100 users the total number of unknowns is 200. In all cases, a user can be served or not only if the required data rate can be achieved. All values presented in the figures that follow are mean values and each point corresponds to the mean result of 1000 random topologies. Fig. 2 illustrates the number of users versus the percentage of users served for $M = 2, T = 50$ for all cases. We notice that NOMA schemes become better when the total number of users is larger than the available PRBs. It is also clear that both algorithms achieve better performance than the random case. The difference between the random and the EAs becomes more significant for the NOMA case. Additionally, WOA performs, in general, better than GWO.

Moreover, Figs. 3a-3b show the total number of users versus the percentage of users served for increasing BS transmission power for $N_u = 50$, and $N_u = 100$. By increasing the BS transmission power for $N_u = 50$ equal

to the number of PRBs almost all users can be served. This is quite similar to both OMA and NOMA cases. However, the NOMA advantage is clearly shown in $N_u = 100$, where clearly with NOMA about 90% of the users can be served.

Figs. 4a-4b depict the total number of users versus the percentage of users served for increasing cell radius. In all OMA cases, the results become worse as the cell radius increases. However, in the NOMA case, there is only a small drop in the user percentage served and the lines are almost straight. This means that NOMA schemes perform better regardless of the cell radius.

Additionally, we study the effect of increasing PRBs. Figs. 5a-5b present the total number of users versus the percentage of users served for increasing PRBs. It is clear that by increasing the PRB number the problem becomes easier to solve since more slots are available for the users. It is evident that WOA performs better than GWO. In all cases, the evolutionary algorithms are better than the random case.

The details of the algorithm's performance are further presented in the boxplots of Figs. 6a-6b. We notice that for $N_u = 50$ the distribution of values seem similar in all cases, while the EAs clearly outperform the random case. The difference between the OMA and the NOMA case can be seen more clearly in Fig. 6b. Moreover, WOA outperforms the GWO in terms of median values. However, GWO obtained results with a smaller dispersion of values.

Finally, the average convergence speed of the algorithms over 1000 runs for two user cases is shown in Figs. 7a-7b. We notice that in both figures the algorithms converge at a similar speed. However, it is apparent that WOA converges at better objective function values.

V. CONCLUSION

In this paper, we provide the formulation for the QoS aware admission control and power allocation optimization problem in NOMA downlink networks. We have solved this problem using emerging swarm intelligence algorithms inspired by nature with low complexity. The results indicate that when the number of users that are trying to connect to the network increases, the problem becomes harder to solve. NOMA schemes outperform the OMA ones especially as the number of users grows higher. Evolutionary algorithms in general perform better than randomly generated solutions. We have provided proof that the GWO algorithm has the potential to converge to a global optimum using Markov chain modeling. We have applied two different algorithms, the GWO and WOA. The results show that for this type of problem, WOA performs better or is similar to other algorithms. However, both algorithms can be applied to obtain feasible solutions quickly. In our future work, we will expand this framework to other network types where NOMA techniques may play an important role e.g. visual light communications (VLC) networks.

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