Joint User Grouping and Power Control Using Whale Optimization Algorithm For NOMA Uplink System

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ABSTRACT

Non-orthogonal multiple access (NOMA) scheme is proved to be a potential candidate to enhance spectral potency and massive connectivity for 5G wireless networks. To achieve effective system performance, user grouping, power control, and decoding order are considered to be fundamental factors. In this regard, a joint combinatorial problem consisting of user grouping and power control is considered, to obtain high spectral-efficiency for NOMA uplink system with lower computational complexity. To solve joint problem of power control and user grouping, for Uplink NOMA, up to authors knowledge, we have used for the first time a newly developed meta-heuristic nature-inspired optimization algorithm i.e. Whale Optimization Algorithm (WOA). Further, for comparison a recently initiated Grey Wolf Optimizer (GWO) and the well-known Particle Swarm Optimization (PSO) algorithms are also applied for the same joint issue.To attain optimal and sub-optimal solutions, a NOMA-based model is used to evaluate the potential of the proposed algorithm. Numerical results validate that proposed WOA outperforms GWO, PSO and existing literature reported for NOMA uplink systems in-terms of spectral performance. In addition, WOA attains improved results in terms of joint user grouping and power control with lower system-complexity as compare to GWO and PSO algorithms. The proposed work is novel enhancement for 5G uplink applications of NOMA systems.

INTRODUCTION

Multiple access approaches are increasingly gaining importance in modern mobile communication systems, primarily due to the overwhelming increase in the communication demands at both the user and device level. Over past few years, non-orthogonal multiple access (NOMA) (Ding et al. (2017a, 2014, 2017b); Benjebbovu et al. (2013)) schemes have earned significant attention for supporting the huge connectivity in contemporary wireless communication systems. The NOMA schemes are currently considered as the most promising contender for the 5G and beyond 5G (B5G) wireless communications, which are capable of accessing massive user connections and attaining high spectrum performance. Moreover, a report has been published recently regarding the Third Generation Partnership Project for determining the effectiveness of NOMA schemes for several applications or development scenarios, particularly for Ultra-Reliable Low Latency Communications (URLLC), enhanced Mobile Broadband (eMBB), and massive Machine Type Communications (mMTC) (Benjebbour et al. (2013)). Contrary to the classic orthogonal multiple access (OMA) approaches, the NOMA schemes can offer services to multiple users in the same space/code/frequency/time resource block (RB). The NOMA schemes are also capable of differentiating the users that have distinct channel settings. These schemes are mainly inclined at strengthening connectivity and facilitating users with an efficient broad-spectrum (Islam et al. (2016); Dai et al. (2015)).

Some recent studies (Chen et al. (2018); Wang et al. (2019); Shahini and Ansari (2019)) have discussed the effective use of the NOMA approach in standard frameworks for Internet of Things (IoT) systems and Vehicle-to-Everything (V2X) networks. The successive interference cancellation (SIC) technique, which is pertinent for multi-user detection and decoding is implemented for the NOMA scheme at the receiver end. The SIC technique operates differently for the downlink and uplink scenarios. In the downlink NOMA scenario, SIC is applied at the receiver end, where high energy is consumed during processing when a lot of users are considered in the NOMA group. For that reason, two users are typically considered in a group for optimum grouping/pairing of users in the case of the downlink NOMA system (Al-Abbasi and So (2016); He et al. (2016)). Whereas in the uplink NOMA systems, it is possible to employ SIC at the base station (BS) that has a higher processing capacity. Moreover, in uplink NOMA, multiple users are allowed to transmit in a grant-free approach that leads to a significantly reduced latency rate.

From a practical perspective, the user-pairing/grouping and power control schemes in uplink/downlink NOMA systems are critically required to achieve an appropriate trade-off between the performance of the NOMA system and the computational complexity of the SIC technique. Over the past few years, several studies have discussed different prospects regarding the maximization of sum rate (Zhang et al. (2016a); Ding et al. (2015); Ali et al. (2016)), the transmission power control approaches (Wei et al. (2017)), and fairness (Liu et al. (2015, 2016)) for user pairing/grouping NOMA systems. Regarding the maximization of sum rate, a two-user grouping scheme based on a unique channel gain is demonstrated in (Ding et al. (2015)) whereas another study (Ali et al. (2016)) presented a novel framework for pertinent user-pairing/grouping approaches to assign the same resource block to multiple users.

In reference to the user pairing schemes (Sedaghat and Müller (2018)) used the Hungarian algorithm with a modified cost function to investigate optimum allocation for three distinct cases in the uplink NOMA system. Furthermore, several matching game-based (Liang et al. (2017)) user-pairing/grouping approaches are discussed in (Xu et al. (2017); Di et al. (2016)), wherein the allocation of users and two sets of players are modeled as a game theory problem. Numerous recent studies (Zhai et al. (2019); Zhu et al. (2018); Nguyen and Le (2019)) have also investigated different user-pairing/grouping schemes for NOMA systems. A novel algorithm named Ford Fulkerson (Zhai et al. (2019)) has been introduced for D2D cellular communication to address the user-pairing issue in NOMA systems. In addition to that, optimal user paring is achieved in (Zhu et al. (2018)) by taking two users with appropriate analytical conditions into consideration. A new framework (Song et al. (2014)) is also presented for optimum cooperative communication networks. Besides that, a lookup table (Azam et al. (2019)) is introduced by performing comprehensive calculations to highlight the significance of power allocation and uplink user pairing in obtaining high sum-rate capacity while fulfilling the demands of user data rates. For the uplink case, a cumulative distributive function (CDF)-based resource allocation scheme (Zhanyang et al. (2018)) is presented where for each time slot, the selection of two users is dependent on the highest value of the CDF. Moreover, a few dynamic power allocation and power back-off schemes are also discussed in few studies (Zhang et al. (2016b); Yang et al. (2016)) for scrutinizing the performance of the system to obtain high sum rates and meet the service quality requirements.

In the context of overlapping, a generic user grouping approach (Chen et al. (2020a)) is presented for NOMA, which involves the grouping of many users with a limitation on maximum power. The authors also formulated a problem for generalized user grouping and power control to achieve an optimized user grouping scheme based on the machine learning approach. Furthermore, another study (Chen et al. (2020b)) proposed a framework in which an overlapping coalition formation (OCF) game is used for overlapping user grouping and an OCF-based algorithm is also introduced that facilitated the self-organization of each user in an appropriate overlapping coalition model. Besides that, a joint problem is examined in (Guo et al. (2019)) for user grouping, association, and power allocation in consideration of QoS requirements for enhancing the uplink network capacity. Zhang et.al (Zhang et al. (2019)) also discussed a joint combinatorial problem for obtaining a sub-optimal and universal solution for user-pairing/grouping to boost the overall system performance. Additionally, the authors in (Wang et al. (2018)) considered a user association problem by using an orthogonal approach for grouping users and employing a game-theoretic scheme for the allocation of a resource block to multi-users in a network.

It has been observed that there are certain limitations associated with the game-theoretic schemes that are typically employed in user association techniques. However, the evolutionary algorithms (EAs) are universal optimizers that exhibit exceptional performance irrespective of the optimization problems being studied. The problem formulation is done as a sum rate utility function for the network and a parameter is presented that depicts the intricacy for power control problems. Therefore, the parameters for power control remain constant for all the systems. Moreover, NOMA-based Mobile edge computing (MEC) system (Zheng et al. (2020)) has been investigated to improve the energy efficiency during task offloading process. Further, a matching coalition scheme has been used to address the issue of power control and resource allocation. In addition, a matching theory (Panda (2020)) approach is proposed to enhance the operational system's user patterns and resource management.

Meta-heuristics are high-level processes that combine basic heuristics and procedures in order to provide excellent approximation solutions to computationally complex combinatorial optimization problems in telecommunications(Martins and Ribeiro (2006)) . Furthermore, the key ideas connected with various meta-heuristics and provide templates for simple implementations. In addition, several effective meta-heuristic approaches to optimization problems have been investigated in telecommunications.

Several meta-heuristic algorithms(Sharma and Gupta (2020)) have been proposed to address localization problems in sensor networks. Some of the meta-heuristic algorithms used to solve the localization problems include the bat algorithm, firework algorithm and cuckoo search algorithm. For wireless sensors networks(Wang et al. (2020)), routing algorithm has been developed based on elite hybrid meta-heuristic optimization algorithm.

On the other hand, Swarm intelligence (SI) algorithms, in addition to game theory and convex optimization, has recently emerged as a promising optimization method for wireless-communication. The use of SI algorithms can resolve arising issues in wireless networks such as Power control problem, spectrum allocation and network security problems (Pham et al. (2020b)). Furthermore, two SI algorithms, named Grey Wolf Optimizer (GWO) and particle swarm optimizer (PSO) are also used in literature for solving the joint problem regarding user associations and power control in NOMA downlink systems to attain maximized sum-rate (Goudos et al. (2020)). Additionally, an efficient meta-heuristic approach known as multi-trial vector-based differential evolution (MTDE) (Nadimi-Shahraki et al. (2020)) has been implemented for solving different complex engineering problems by using multi trial vector technique (MTV) which integrates several search algorithms in the form of trial vector producers (TVPs) approach. Recently, an updated version of GWO i.e. Improved- Grey Wolf Optimizer (I-GWO) (Nadimi-Shahraki et al. (2021)) has been investigated for handling global optimization and engineering design challenges. This modification is intended to address the shortage of population variety, the mismatch between exploitation and exploration, and the GWO algorithm's premature convergence. The I-GWO algorithm derives from a novel mobility approach known as dimension learning-based hunting (DLH) search strategy which was derived from the natural hunting behaviour of wolves. DLH takes a unique method to creating a neighbourhood for each wolf in which nearby information may be exchanged among wolves. This dimension learning when employed in the DLH search technique improves the imbalance between local and global search and preserves variation. A parallel variant of the Cuckoo Search method is the Island-based Cuckoo Search (IBCS) (Alawad and Abed-alguni (2021)) using extremely disruptive polynomial mutation (iCSPM). The Discrete iCSPM with opposition-based learning approach (DiCSPM) is a version of iCSPM has been proposed to schedule processes in cloud computing systems focusing on data communication expenses and computations. Moreover, for scheduling dependent tasks to Virtual Machines (VMs), this work offers a discrete variant of the Distributed Grey Wolf Optimizer (DGWO) (Abed-alguni and Alawad (2021)). In DGWO, the scheduling process is considered as a problem of minimization for data communication expenses and computation.

In this paper, a joint combinatorial problem of user pairing/grouping, power control, and decoding order are considered for every uplink NOMA user within the network. To solve this problem, we propose a recently introduced meta-heuristic algorithm known as Whale Optimization Algorithm (WOA) (Mirjalili and Lewis (2016)) that is inspired by the hunting approach of the humpback whale. Furthermore, a Grey Wolf Optimizer (GWO) (Mirjalili et al. (2014b)) and Particle Swarm Optimization (PSO) (Kennedy and Eberhart (1995)) algorithms are also employed in this research study. The results obtained through the algorithms proposed in (Sedaghat and Müller (2018)), WOA, GWO and the popular PSO are exclusively compared in this study. The acquired results indicate that the WOA outperformed the existing algorithm (Sedaghat and Müller (2018)), GWO and PSO in- terms of spectral-efficiency with lower computational complexity.

The rest of the paper is structured as follows. A 'System Model and Problem Formulation' describes the mathematical representation and research problem of NOMA uplink system. The solution is provided in the 'Solution of Proposed Problem' section where an efficient decoding order, power control scheme and user grouping approach are employed for NOMA uplink System. A concise analysis on the simulation is provided in 'Simulation Results' section. The 'Conclusion' section presents the summary of this research work.

SYSTEM MODEL AND PROBLEM FORMULATION

System Model

As illustrated in Figure 1, we consider an uplink NOMA transmission with a single-cell denoted by C. The number of users M served by a single base station (BS) placed at the centre of the cell. To obtain the signal/information requirements of several users, the number of physical resource block (PRB) denoted by N are assigned to multiple-users in a cell.

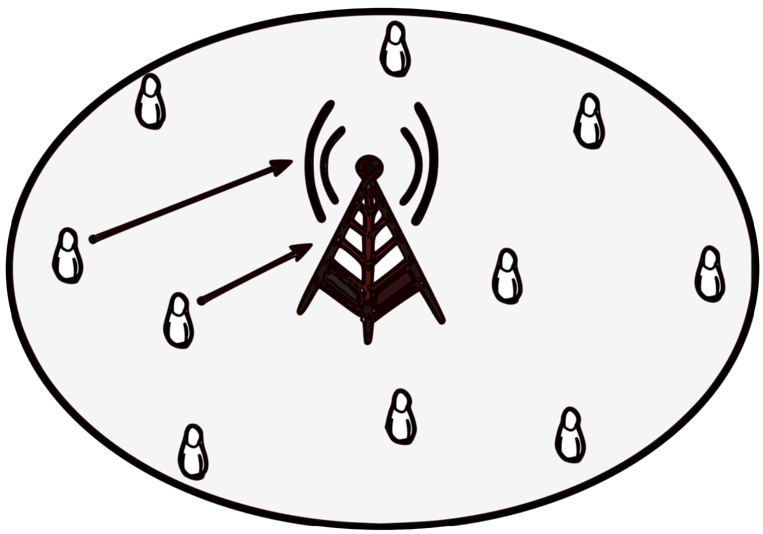

Figure 1. NOMA Uplink Transmission.

For uplink transmission, users in almost in same PRB/group maintaining same PRB execute NOMA operation while users belong to different PRB/group assigned different PRB execute OMA operation. Hence, the received signal z_n at the BS can be represented as:

$$z_n = \sum_{m=1}^{M} \upsilon_{n,m}\, g_m \sqrt{\alpha_m P}\, s_m + \omega_n \tag{1}$$

where $\upsilon_{n,m} \in \{0,1\}$ is the user n indicator assigned to the $n-th$ group. The transmission path between user m and BS is represented by g_m which is Guassian distributed. The power control coefficients is denoted by $\alpha_m (0 \leq \alpha_m \leq 1)$. For each user m, the transmission power and the signal is denoted by P and s_m, where $\mathbb{E}(|s_m|^2 = 1)$. The additive white Gaussian noise (AWGN) power is denoted by ω_n with an average power σ^2. Therefore, the maximum spectral efficiency of user M and the received signal to interference plus noise ratio (SINR) on $n-th$ PRB can be expressed as:

$$S_m = log_2\ (1+\phi_m) \tag{2}$$

$$\phi_m = \frac{|g_m|^2 \alpha_m P}{\sum_{j \neq m}^{M} |g_j|^2 \alpha_j P + \sigma^2} \tag{3}$$

The SIC operation is carried out at the BS for each PRB/group to decode the users signal. The decoding order of a user n is represented by $\delta_{n,m}$ in a cell, where $\delta_{n,m} = a > 0$ assumes that any user m in a group is the $i-th$ one in the $n-th$ PRB is to be decoded. Thus, the maximum spectral efficiency of user n can be represented as:

$$S_m = log_2 \left(1 + \frac{|g_m|^2 \alpha_m \gamma}{\sum_{\substack{j \neq m \\ \delta_{n,j} > \delta_{n,m} > 0}}^{M} |g_j|^2 \alpha_j \gamma + 1} \right) \tag{4}$$

where $\delta_{n,j} > \delta_{n,m}$ represents the decoding order of users in a PRB/group. If users m and j are in the same group, then it implies that user m is decoded first. The transmission power to noise ratio is represented by γ, where $\gamma = P/\sigma^2$. Assuming that, the channel-state-information (CSI) is known by BS of each user within coverage area.

To attain effective user-pairing/grouping and power control for NOMA uplink system, each user M in a cell transmit their power control coefficient α_m along with user indicator $\upsilon_{n,m}$. Hence, the maximum spectral-efficiency in the $n-th$ PRB/group can be expressed as follows:

$$S_t(n) = \sum_{\upsilon_{n,m}=1} S_m \tag{5}$$

$$S_t(n) = \log_2 \left(1 + \sum_{\upsilon_{n,m}=1} |g_m|^2 \alpha_m \gamma \right) \tag{6}$$

The equation (6) clearly shows that the spectral efficiency in each group has not been affected by the order of decoding but has an impact on each user.

Problem Formulation

In this paper, we propose an efficient method for power-control, decoding order and user-pairing/ grouping to increase the spectral-efficiency under their required minimum rate constraint. Therefore, a joint combinatorial problem of power control, decoding order and user pairing/grouping is formulated to maximize the spectral-efficiency. The minimum spectral-requirement of each user in the network is s_m. Therefore, the spectral efficiency maximization problem (Sedaghat and Müller (2018); Zhang et al. (2019)) can be formulated as:

$$\underset{\{\upsilon_{n,m}\},\{\delta_{n,m}\} \in \pi, \{\alpha_m\}}{\text{maximize}} \quad S_t = \sum_{n=1}^{N} S_t(n) \tag{7a}$$

$$\tag{7b}$$

$$\text{subject to} \quad C_1 : 0 \leq \alpha_m \leq 1, \ \forall m, \tag{7c}$$

$$C_2 : S_m \geq s_m, \quad \forall m, \tag{7d}$$

$$C_3 : \upsilon_{n,m} \in \{0,1\}, \forall m, \forall n, \tag{7e}$$

$$C_4 : \sum_{n=1}^{N} \upsilon_{n,m} = 1, \ \forall m \tag{7f}$$

where $\delta_{n,m}$ represents the decoding order and π indicates all possible combinations of users decoding orders in a network. C_1 indicates the upper bound of transmission power. C_2 guarantees the minimum rate of a user. C_3 and C_4 ensures the user indicator and m users assigned to PRB/group.

SOLUTION OF PROPOSED PROBLEM

To achieve the global optimal solution for Problem (7a), the optimization variables $\upsilon_{n,m}$, $\delta_{n,m}$, and α_m are strongly correlated, which makes the problem complex. In connection of the fact that user-pairing variables $\delta_{n,m}$ are combinatorial integer programming variables. Hence, first solve the combinatorial problem of power control and decoding order instead and compute the optimum user-pairing/grouping solution. In case of any fixed scheme of user-grouping, the value of $\upsilon_{n,m}$ are independent among all distinct group regarding both decoding order and power control.

$$\begin{aligned}
&\underset{\{\delta_{n,m}\}\in\pi,\{\alpha_m\}}{\text{maximize}} && S_t(n) && \text{(8a)}\\
&\text{subject to} && S_m \geq s_m, \quad m \in \mathscr{M}_n, && \text{(8b)}\\
& && 0 \leq \alpha_m \leq 1,\, m \in \mathscr{M}_n && \text{(8c)}
\end{aligned}$$

where $\mathscr{M}_n$ indicates set of all possible combination in the $n-th$ PRB.

Optimal Decoding for Optimal User-Pairing/Grouping

In order to apply SIC operation, all users signals/information are decoded by the receiver in the descending order based on channel condition. In uplink NOMA system (Ali et al. (2016)), the users with better channel condition is decode first at the BS while the user with worse channel condition is decode last. As a result the user with better channel condition experiences interference from all the users in the network, while the users with poor channel condition experiences interference free transmission.

To attain an efficient decoding (Zhang et al. (2019)) for NOMA uplink users, the decoding order for M users in a cell concern to same group/PRB, based upon the value of J_n, where different decoding order of each user in a network depend on power control (Zhang et al. (2019)) scheme regarding different feasible region can be represented as:

$$J_m = |g_m|^2(1+\frac{1}{\Psi_m}) \tag{9}$$

where

$$\Psi_m = 2^{s_m} - 1 \tag{10}$$

Based on (9), the user with higher value of J_m in a cell is decoded first . Also applies that the decoding-order does not affect the spectral efficiency of each PRB/group.

Power Control

The nature of the problem in equation (8a) is a mixed integer non-linear programming (MINLP). Hence, we have achieved the optimal solution for decoding order $\delta_{n,m}$. Therefore, it is required to find all the possible group of combination for user pairing/grouping.

For this purpose, k users in a single cell C are considered. Without loss of generality, it is needful to reduce the complexity and simplify the mathematical procedure regarding optimal decoding order $\delta_{n,m}$. The users are listed in a C based on the decreasing order J_m, for example $1,2,3,\ldots,K$. Therefore, equation (8a) can be represented as:

$$\begin{aligned}
&\underset{\{\alpha_k\}}{\text{maximize}} && \sum_{k=1}^{K} |g_k|^2\alpha_k\gamma && \text{(11a)}\\
&\text{subject to} && |g_k|^2\alpha_k\gamma \geq \Psi_k\left(\sum_{j=k+1}^{K}|g_j|^2\alpha_j\gamma+1\right),\, \forall k, && \text{(11b)}\\
& && 0 \leq \alpha_k \leq 1,\, \forall k, && \text{(11c)}
\end{aligned}$$

where $\{\alpha_k\}$ represents power control-variables. Equations (11a) and (11b) show linearity and translated to SNR formulations respectively.

As shown in equation (11a), α_k is increasing. Therefore, the optimal solution for power control will always be upper bound. To determine the lower bound of power control (Zhang et al. (2019)), the following equation can be solved as:

$$\alpha_k^0 = \frac{\Psi_k \gamma_k^{'}}{|g_k|^2 \gamma} \ , \ 1 \leq k \leq K \tag{12}$$

where

$$\gamma_k^{'} = \prod_{u=k+1}^{K} (\Psi_u + 1) \tag{13}$$

Which signifies that the spectral efficiency requirements is equal to the sum of spectral efficiencies of all the users. If $\alpha_k^0 \geq 1$, exceeds the limit of upper bound and hence, no feasible solution for equation (11a). If $0 \leq \alpha_k^0 \leq 1$, equation (11a) has the feasible solution due to bound of α_k variables. Therefore, for all users M in a cell, the optimal solution (Zhang et al. (2019)) of the α_k variables can be illustrated as

$$\alpha_k^* = min\{1, b_k\} \tag{14}$$

where

$$b_k = min\{\frac{|h_u|^2\gamma}{\Psi_u} - \sum_{q=u+1}^{k-1} |h_q|^2\gamma - \sum_{j=k+1}^{K} |h_j|^2 \alpha_j^0 \gamma - 1 (u = 1, 2, 3, \ldots, k-1)\} \tag{15}$$

In reference to equation (14) and equation (15), the optimal power control variables α_k^* mentioned in problem (11a) is achieved. Specifically, if $\alpha_k^* = b_k$, for other users, the optimal power control variables are $\alpha_j^* = \alpha_j^0$ for $j > k$.

User Grouping

An efficient and low computational time algorithm for user-pairing/grouping is one of the key concern for an effective NOMA uplink system. In this regard, three different meta-heuristic algorithms are proposed to solve the issue of complexity. The WOA is investigated for an efficient optimal and sub-optimal solution for user-pairing/grouping problem as a result to enhance the system performance. Further, the user pairing/grouping problem that exploits the channel-gain difference among different users in a network and the objective is to raise system's spectral-efficiency. To determine the optimum user-pairing/grouping, a specific approach of solving user pairing/grouping problem is by using the search approach. For fixed user-pairing/grouping scheme, the optimal solution is obtained (Zhang et al. (2019)). Then, list all the users in the decreasing order of J_m accordingly. The proposed algorithm for user pairing/grouping problem is illustrated in Algorithm 1. Initially, define the feasible solution of user grouping for exhaustive and swarm based algorithm . An exhaustive search explores each data points within the search region and therefore provides the best available match. Furthermore, a huge proportion of computation is needed. Particularly a discrete type problem where no such solution exists to find the effective feasible solution. There may be a need to verify each and every possibility sequentially for the purpose of determining the best feasible solution. The optimal solution using exhaustive search algorithm (Zhang et al. (2019)) is getting obdurate because the number of comparison increases rapidly. Hence, the system complexity of WOA for user grouping scheme is $O(MN)$, where as $O(N^M)$ represent the complexity of the exhaustive search algorithm. Therefore, a WOA approach is employed to reduce the complexity and provide efficient results. In addition, GWO and PSO algorithms are also proposed for the same problem.

Whale Optimization Algorithm (WOA)

To enhance the spectral-throughput and reduce the system complexity, an innovative existence meta-heuristic optimization technique named whale optimization algorithm (WOA) (Mirjalili and Lewis (2016)) is proposed in this paper. The algorithm WOA is resembles to the behaviour of the humpback whales, which is based on the bubble-net searching approach. Three distinct approaches are used to model the WOA is described as

Encircling Prey

In this approach, the humpback-whales can locate the prey-location of the prey and en-circle that region. Considering that, the location of the optimal design in the search region is not known in the beginning. Hence, the algorithm WOA provides the best solution that is nearer to the optimal value. First determine the best solution regarding location and then change the position according to the current condition of the other search agents concerning to determine the best solution. Such an approach is described mathematically and can be expressed as:

$$\overrightarrow{E} = |A.\overrightarrow{X^*}(t) - X(t)| \tag{16}$$

$$\overrightarrow{Y}(t) = \overrightarrow{X}(t+1) \tag{17}$$

$$\overrightarrow{Y}(t) = \overrightarrow{X^*}(t) - \overrightarrow{B}.\overrightarrow{E} \tag{18}$$

where, $\overrightarrow{B}$ and $\overrightarrow{A}$ represents the coefficients-vectors, t defines the initial iteration and X^* and $\overrightarrow{X}$ both describes the position- vector where X^* includes the best solution so far acquired. $|\ |$ and . defines the absolute and multiplication. Noted that the position vector X^* is updated for each iteration until to find the best solution. The coefficients vector vectors $\overrightarrow{B}$ and $\overrightarrow{A}$ can be determined as:

$$\overrightarrow{B} = 2\overrightarrow{b}.\overrightarrow{r} - \overrightarrow{b} \tag{19}$$

$$\overrightarrow{A} = 2.\overrightarrow{r} \tag{20}$$

where $\overrightarrow{r}$ indicates random vector $0 \leq r \leq 1$ and $\overrightarrow{b}$ represent a vector with a value between 2 and 0, which is decreasing linearly during the iteration.

Spiral bubble-net feeding maneuver

Two techniques are proposed to predict accurately the bubble-net activity of humpback-whales.

1. Shrinking en-circling

This type of techniques is achieved by decreasing the value of $\overrightarrow{b}$ using equation(19) . It is to be noted that the variation range of $\overrightarrow{B}$ is also reduced by the value $\overrightarrow{b}$. Therefore, $\overrightarrow{B}$ is a random value from $[-b,b]$, where the value of b is decreasing from 2 to 0 during the iterations.

2. Spiral updating position

In spiral method, a relationship between the location of prey and whale to impersonate the helix-shaped operations is represented in the form of mathematical equation of humpback-whales in the following manner:

$$\overrightarrow{Y}(t) = \overrightarrow{E}'.e^{pq}.\cos(2\pi q) + \overrightarrow{X}^* \tag{21}$$

where $\overrightarrow{E}' = |\overrightarrow{X}^*(t) - \overrightarrow{X}(t)|$, which represents the distance between prey and the $i-th$ whale. l denotes the random number$(-1 \leq l \leq 1)$. b represents logarithmic spiral, which is a constant number and . indicates the multiplication operation. It's worth noting that humpback-whales swim in a shrinking-circle around their prey while still following a spiral-shaped direction. To predict this concurrent action, an equation is derived to represent the model can be expressed as:

$$\overrightarrow{Y}(t) = \begin{cases} \overrightarrow{X}^*(t) - \overrightarrow{E}.\overrightarrow{B}, & \text{if } d < 0.5 \\ \overrightarrow{E}'.e^{pq}.\cos(2\pi q) + \overrightarrow{X}^*, & \text{if } d \geq 0.5 \end{cases} \tag{22}$$

where d represents a random number $(0 \leq d \leq 1)$. Further, the searching behaviour of humpback-whales for prey is randomly in the bubble-net approach. The following is the representation of mathematical model for bubble net approach.

Prey Searching Technique

To locate prey, same strategy based on the modification of the $\overrightarrow{B}$ vector can be utilized (exploration). In reality, humpback-whales search at random based on their location. As a result, we select $\overrightarrow{B}$ randomly with values $\overrightarrow{B} > 1$ or $\overrightarrow{B} < -1$ to compel the search-agent to step away from a target value. Comparison with exploitation, modify the location of every search- agent in the sample space, based on randomly selected process until to obtained a better solution. This operation and $|\overrightarrow{B}| > 1$ place an emphasis on the exploration phase and enable WOA to perform global-searching. This can be represented below:

$$\overrightarrow{E} = |\overrightarrow{A}.\overrightarrow{X_{rand}} - \overrightarrow{X}| \tag{23}$$

$$\overrightarrow{Y}(t) = \overrightarrow{X_{rand}} - \overrightarrow{B}.\overrightarrow{E} \tag{24}$$

where $\overrightarrow{X_{rand}}$ indicates a position-vector that is randomly selected from the existing space.

The algorithm WOA comprised of a selection of random samples. For every iteration, the search agents change their locations in relation to either a randomly selected search agent or the best solution acquired so far in this. For both cases exploitation phase and exploration the value of b is decreasing in the range from 2 to 0 accordingly. As the value of $|\overrightarrow{B}| > 1$, a randomly searching solution is selected, while the optimal solution is obtained when $|\overrightarrow{B}| < 1$ for updating the search- location of the agents. Based on the parameter d, the WOA is used as a circular or spiral behaviour. Ultimately, the WOA is ended by the successful termination condition is met. Theoretically, it provides exploration and exploitation capability. Therefore, WOA can still be considered as a successful global optimizer. The WOA is described in Algorithm 1.

Grey Wolf Optimizer (GWO)

A popular meta-heuristic algorithm, which is influenced by the behaviour of grey-wolves (Mirjalili et al. (2014b)).This algorithm is based on the hunting approach of grey wolves and their governing- hierarchy. Grey wolves represent predatory animals, which means these are heading up in the hierarchy. Grey wolves tended to stay in groups. The wolves in a group is varying between 5 to 12. The governing-hierarchy of GWO is shown in Figure 2, where several kinds of grey wolves have been used particularly α, β, δ, and ω.

Both wolves (male and female) are the founders known as αs. The α is mainly in favour of producing decision making regarding hunting, sleeping and waking time, sleeping place etc. The group is governed by the αs actions. Even so, some egalitarian behaviour has been observed, such as an alpha wolf following other wolves in the group. The whole group respects the α by keeping their tails towards ground at gatherings. The α wolf is also regarded as superior since the group must obey his/her orders. The group's α wolves are the only ones that can mate. Usually, the α is not always the biggest member of the group,

Data: Set the input control variables
$M, N, \gamma_m, \{g_m\}, \{s_n\}$
Population initialization $X_1, X_2, \ldots\ldots\ldots X_n$
Result: X^* (Best search agent for user- pairing/grouping).
List all the users with decreasing order of J_m.
while $t < (total\ iterations)$
  for *every search user*
  Initialize b,B,A,q and d
   if1$(d < 0.5)$
    if2$(|B| < 1)$
    Existing search user position is updated using equation (16)
    else if2$(|B| \geq 1)$
    Randomly selected a search user (X_{rand})
    Existing position of search user is updated using equation (23)
    end if2
   else if1$(d \geq 0.5)$
   Exiting position of search user is updated using equation (21)
   end if1
  end for
  Examine the position of every search user in the search region if above the search region then modify it.
  Determine the Position of every search user
  If a best solution becomes available, Update X*
  t=t+1
end while
return X^*

Algorithm 1: WOA

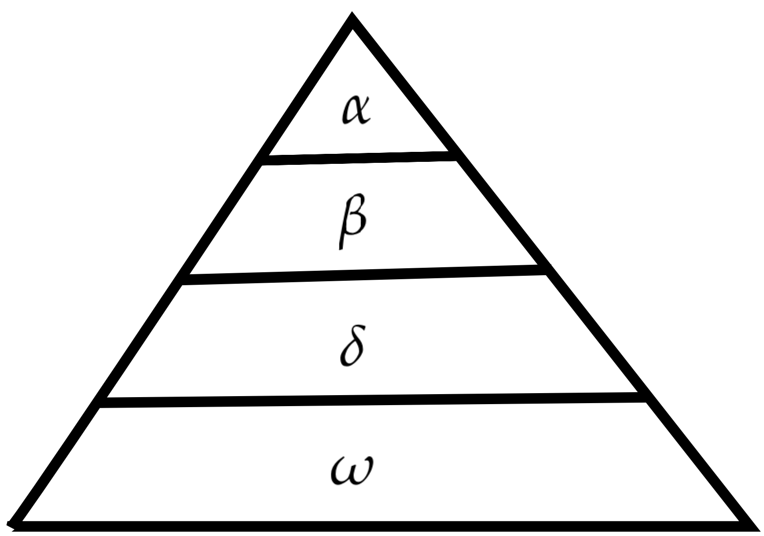

Figure 2. Grey wolf hierarchy (Mirjalili et al. (2014b)).

but rather the best at handling the batch. Which illustrates that a group's structure and discipline are often more critical than its capacity. β is the second phase of the grey wolf hierarchy. The β's are the sub-ordinate wolves who assist the α in taking decision. The β wolf (male or female), is most likely the better choice to be the α wolf in the event that one of the α wolves dies or gets very old. Therefore, β wolf would honour the α while still commanding all other lower-level wolves. It serves as an adviser to the α and a group disciplinarian. Throughout the group, the β confirms the αs orders and provides guidance to the α. The grey wolf with the lowest rating is ω. The ω serves as a scapegoat. ω wolves must still respond towards other dominant wolves in a group. They are the last wolves permitted to feed. While it might seem that the ω is not a vital member of the group, it has been found that when the ω is lost, the entire group experiences internal combat and problems. This would be attributed to the ω venting his anger and resentment on both wolves (s). This tends to please the whole group while still preserving the dominance system. In certain circumstances, the ω is also the group's babysitter. Whenever a wolf should not be an α, β, or ω, he or she is referred to as a subordinate also called δ. where δ wolves must yield to αs and βs, however they rule the ω. This group contains scouts, sentinels, elders, hunters, and caregivers. Scouts are in charge of patrolling the area and alerting the group if there is any threat. Sentinels defend and ensure the group's safety. Furthermore, the mathematical model of GWO is described as:

Social hierarchy

For mathematical representation of GWO, we assume that α is fittest alternative solution used to mimic the social hierarchy. As a result, the second and third best solutions are designated as β and δ, respectively. The remaining member approaches are now considered to be ω. For algorithm, the hunting (optimization) is led by α, β and δ. These three wolves are accompanied by the ω.

Encircling prey

Grey wolves encircle prey during the hunting. The following equations are presented to mathematical model the encircling actions.

$$\overrightarrow{A} = |\overrightarrow{D}.\overrightarrow{X_s}(t) - \overrightarrow{X(t)}| \tag{25}$$

$$\overrightarrow{Y}(t) = \overrightarrow{X}(t+1) \tag{26}$$

$$\overrightarrow{Y}(t) = \overrightarrow{X_s}(t) - \overrightarrow{B}.\overrightarrow{A} \tag{27}$$

where $\overrightarrow{B}$ and $\overrightarrow{D}$ represents coefficient vectors, t is the exiting iteration, $\overrightarrow{X}$ and $\overrightarrow{X_s}$ defines the position vector of a grey wolf and prey.

The vectors and are computed in the following manner:

$$\overrightarrow{B} = 2.\overrightarrow{b}.\overrightarrow{d_1} - \overrightarrow{b} \tag{28}$$

$$\overrightarrow{D} = 2.\overrightarrow{d_2} \tag{29}$$

where $0 \leq d_1 \leq 1$ and $0 \leq d_2 \leq 1$ indicates random vector and $\overrightarrow{b}$ component decreasing linearly over the entire iteration from 2 to 0.

Hunting

Grey wolves do have capability to detect and encircle prey. The α normally leads the chase. The β and δ can also engage in hunting. However, in an arbitrary search space, we have no idea that where is the optimal(prey) location. Hence, first acquired the three best solutions so far and then search other agents (containing ω's) in accordance with the best search agent's location. In this respect, the following equations are provided.

$$\overrightarrow{A_\alpha} = |\overrightarrow{D_1}.\overrightarrow{X_\alpha} - \overrightarrow{X}| \tag{30}$$

$$\overrightarrow{A_\beta} = |\overrightarrow{D_2}.\overrightarrow{X_\beta} - \overrightarrow{X}| \tag{31}$$

$$\overrightarrow{A_\delta} = |\overrightarrow{D_3}.\overrightarrow{X_\delta} - \overrightarrow{X}| \tag{32}$$

$$\overrightarrow{X_a} = \overrightarrow{X_\alpha} - \overrightarrow{\beta_1}.(\overrightarrow{A_\alpha}) \tag{33}$$

$$\overrightarrow{X_b} = \overrightarrow{X_\beta} - \overrightarrow{\beta_2}.(\overrightarrow{A_\beta}) \tag{34}$$

$$\overrightarrow{X_c} = \overrightarrow{X_\delta} - \overrightarrow{\beta_3}.(\overrightarrow{A_\delta}) \tag{35}$$

$$\overrightarrow{Y}(t) = \frac{\overrightarrow{X_a} + \overrightarrow{X_b} + \overrightarrow{X_c}}{3} \tag{36}$$

Attacking prey

The wolves complete the chase by hitting the target once it cease running. The mathematical model of attacking prey approach can be achieve by decreasing the value of $\overrightarrow{b}$. It's worth mentioning that the variance range of $\overrightarrow{B}$ is also limited by $\overrightarrow{b}$.

That is $\overrightarrow{B}$ in the range of $[-b,b]$, which is a random value and decreasing over the entire iteration from 2 to 0. If any random values ranges between $[-1,1]$, then new location of a search-agent lies between exiting and prey location.

Search for prey

Grey wolves primarily hunt depending on the locations of the α, β, and δ. At the starting they diverge from other wolves to hunt and then combine to hit prey. The mathematical model of divergence can be achieved by utilizing the value of $\overrightarrow{B}$. For divergence, random values of $\overrightarrow{B} < 1$ or $\overrightarrow{B} > 1$ is used by the search agent. This process enables the GW algorithm to search globally. In nature, the D vector can even be assumed as the impact of barriers to pursuing prey. In general, natural barriers arise in wolves' hunting paths and discourage them from approaching prey effectively and easily. This is precisely depend on the vector D. It will arbitrarily give the prey a weight to find it tougher and farther to catch for wolves, depending on location of the wolf, or likewise.

The suggested social hierarchy supports GWO in sustaining the best solutions achieved so far through iteration. By using hunting approach, it enables agents to search the likely location of prey. The GWO is described in Algorithm 2.

Particle Swarm Optimization (PSO)

Kennedy and Eberhart (Kennedy and Eberhart (1995)) introduced PSO as an evolutionary computation method. It was influenced by the social behaviour of birds, which involves a large number of individuals (particles) moving through the search space to try to find a solution. Over the entire iterations, the particles map the best solution (best location) in their tracks. In essence, particles are guided by their own best positions, which is the best solution same as achieved by the swarm. This behaviour can modelled mathematically by using velocity vector (u), dimension (S), which represents the number of parameters and position vector (x). In the entire iterations, the position and velocity of the particles changing by the following equation:

$$u_i^{t+1} = vu_i^t + e_1 \times rand \times (pbest_i - x_i^t) + e_2 \times rand \times (gbest - x_i^t) \tag{37}$$

Data: Set the input control variables
$M, N, \gamma_m, \{g_m\}, \{s_n\}$
Population initialization $X_1, X_2, ...X_n$
Initialization of B,b and D

Result: X_α (Best search agent for user- pairing/grouping).

List all the users with decreasing order of J_m.
Determine fitness of every search agent
X_α,X_β and X_δ.
while $t < (total\ iterations)$
  for *every search user*
    Update the existing location of search agent by using equation (36)
    Update B, b and D
    Determine fitness of search agent
    $Update X_\alpha$, X_β and X_δ
    t=t+1
  end for
end while
return X_α

Algorithm 2: GWO

Data: Set the input control variables
$M, N, \gamma_m, \{g_m\}, \{s_n\}$
Population initialization $X_1, X_2, ...X_n$

Result: *pbest and gbest* (Best search agent for user- pairing/grouping).

List all the users with decreasing order of J_m.
  for *each generation* **do**
    for *each particle* **do**
    Update the position and vector by using equation (37) and equation (38)
    Estimate the fitness of the particle
    Update both *pbest* and *gbest*
    t=t+1
    end for
  end for
return $pbest,\ gbest$

Algorithm 3: PSO

$$x_i^{t+1} = u_i^{t+1} + x_i^t \tag{38}$$

where $v(0.4 \le v \le 0.9)$ represents the inertial weight, which control stability of the PSO algorithm. cognitive coefficient $e_1(0 < e_1 \le 2)$, which limits the impact of the individual memory for best solution. Social factor $e_2(0 < e_2 \le 2)$, which limits the motion of particles to find best solution by the entire swarm, *rand* indicates a random number in the range between 0 and 1, attempt to provide additional randomized search capability to the PSO algorithm and two variables *pbest* and *gbest*, used to accumulate best solutions achieved by each particle and the entire swarm accordingly. The PSO is described in Algorithm 3.

SIMULATION RESULTS

This section evaluates the performance of the proposed meta-heuristic algorithms, namely, WOA, GWO and PSO of the user groping, power control and decoding order for NOMA uplink systems.

Table 1 presents the simulation parameter values attained from the literature (Sedaghat and Müller (2018); Zhang et al. (2019); Mirjalili and Lewis (2016); Mirjalili et al. (2014b); Kennedy and Eberhart

(1995)) for WOA, GWO and PSO algorithms that participated in the simulation. Further, the Wilcoxon test and Friedman test (?) are performed for experiments and the statistical analysis of GWO and PSO is also provided in Table 2. Based on the results of tests, the proposed WOA outperforms the other algorithms in comparison.

Table 1. Parameters for Proposed Uplink NOMA

Parameter	Value
C	1
M	6
N	3
s_m	1.1 $bits/s/Hz$
γ	30 dB

Table 2. Statistical analysis of GWO and PSO

Wilcoxon	GWO	PSO
$p-value$	$1.8E-169$	$4.7E-181$
Friedman	**GWO**	**PSO**
$p-value$	$4.5E-161$	$1.2E-164$

Both channel of the users and location are allocated randomly in the simulation. Therefore, the range between the user and BS are uniformly distributed and considered that the channel response is Gaussian distribution (Zhang et al. (2019)).

Figure 3 indicates the comparison of convergence of WOA (Mirjalili and Lewis (2016)) , GWO (Mirjalili et al. (2014b)) and PSO (Kennedy and Eberhart (1995)) algorithms proposed for NOMA uplink system. We may conclude that WOA, GWO and PSO algorithms converge at a comparable rate, hence WOA converges after a greater number of iterations than GWO and PSO. The proposed WOA attains significant performance in-terms of spectral efficiency as compare to GWO and PSO algorithms. Also the proposed WOA (Mirjalili and Lewis (2016)) provides stability and attains the minimum rate requirement without such a noticeable drop in the results.

Figure 4 compares the spectral-efficiency of NOMA and OMA approaches with varying γ, respectively. It has been proved that the spectral-efficiency of NOMA scheme is considerably higher than those of scheme. Moreover, the spectral-efficiency of the proposed sub-optimal approach is nearer to the optimal value. The proposed WOA algorithm attains near optimal performance with minimal computational complexity. In addition, as the number of users increases the computational cost of the exhaustive-search algorithm increases as compared to WOA.

For NOMA uplink systems, the power control approach in (Sedaghat and Müller (2018)) is provided as a benchmark scheme, where the spectral efficiency are near to the optimal value. Noted that the approach used in (Sedaghat and Müller (2018)) is valid only for two user-pairing. Hence, the proposed scheme performs admirably in-terms of having efficient user grouping for multiple users.

Figure 5 and 6 evaluates the performance of GWO and PSO algorithms in-terms of spectral-efficiency. For uplink NOMA system, the spectral-efficiency of NOMA scheme outperform OMA scheme with

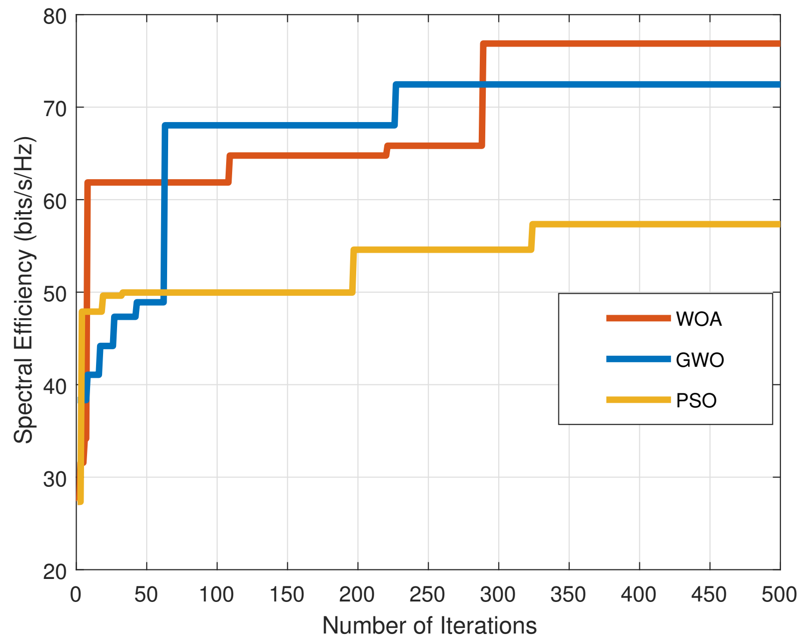

Figure 3. Illustration of convergence of WOA, GWO and PSO.

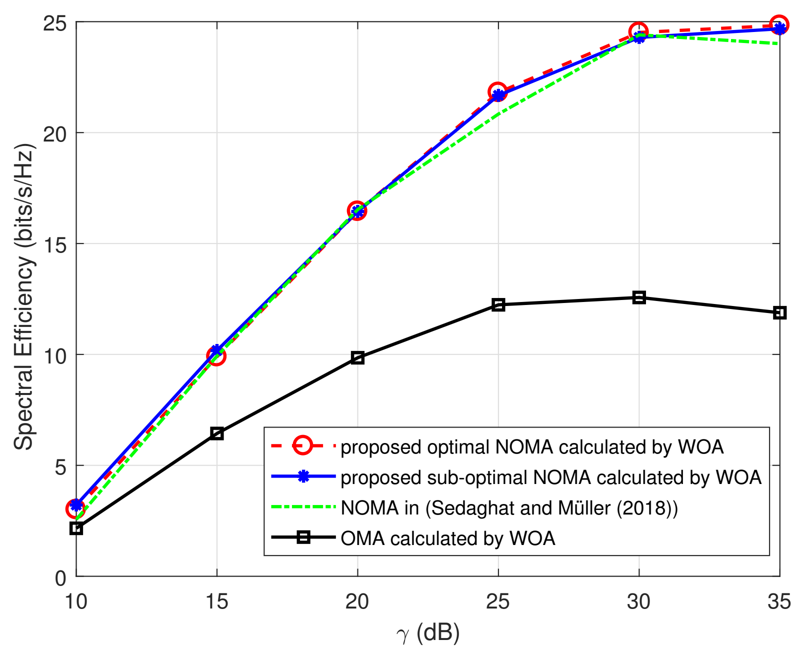

Figure 4. Illustration of spectral efficiency of WOA with increasing γ.

varying γ. Moreover, the spectral-efficiency of optimal and sub-optimal solutions are nearer to each other. The power control scheme for NOMA uplink system in (Sedaghat and Müller (2018)) is used as a benchmark. It has been observed that the spectral-efficiency of both GWO and PSO algorithms shows better results than power control (Sedaghat and Müller (2018)) and OMA scheme.

Moreover, a comparison of proposed optimal WOA, GWO and PSO has shown in Figure 7. The

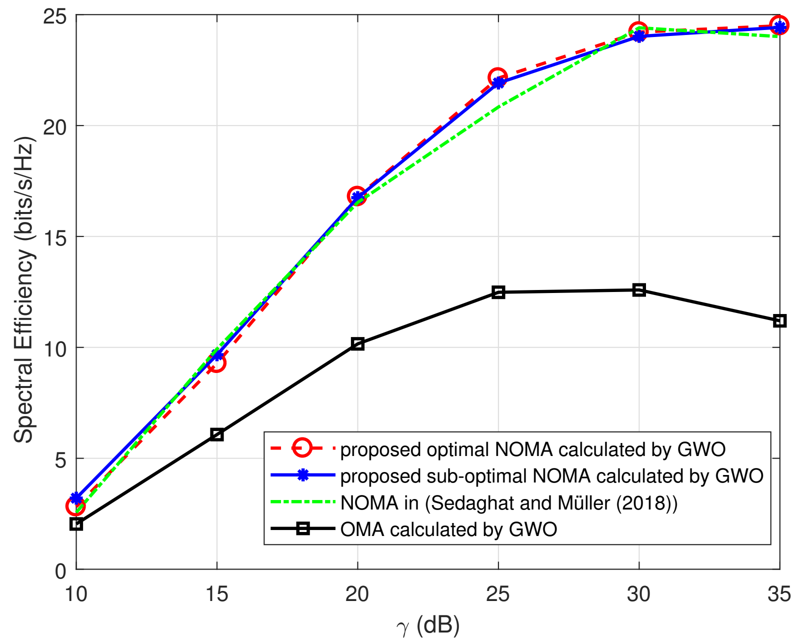

Figure 5. Illustration of spectral efficiency of GWO with increasing γ.

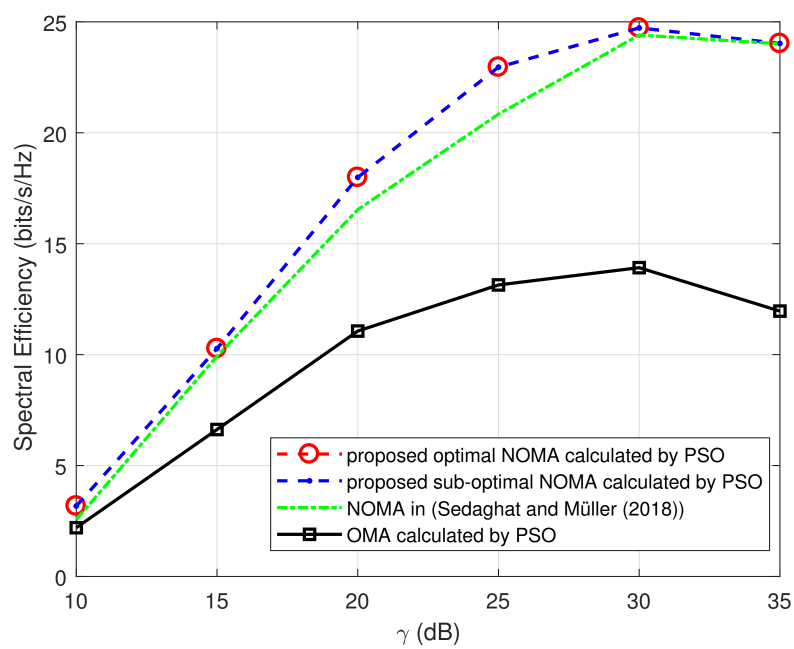

Figure 6. Illustration of spectral efficiency of PSO with increasing γ.

performance of proposed optimal WOA, GWO and PSO are almost nearer to one another. Moreover, as the value of γ above 30 dB, the optimal WOA performs better in-terms of spectral-efficiency as compare to GWO and PSO.

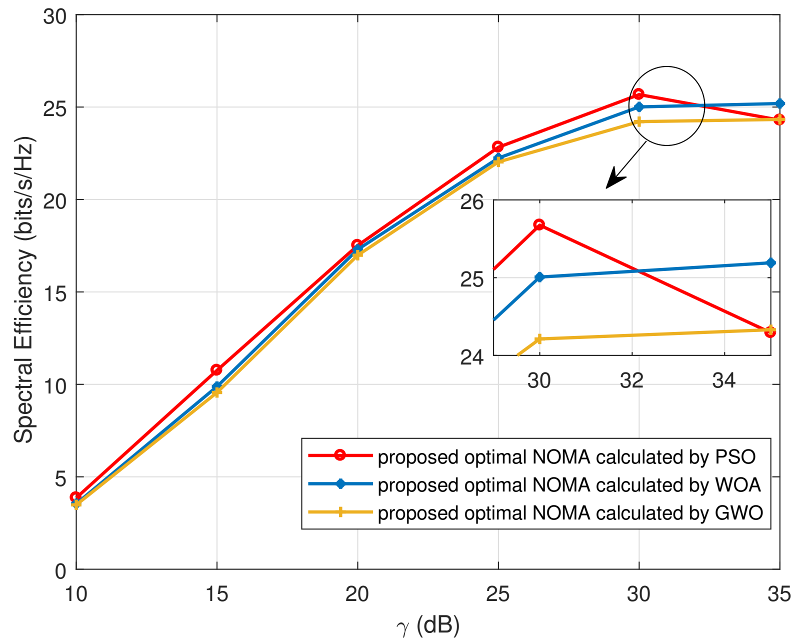

Figure 7. Comparison of optimal solution of WOA, GWO and PSO.

CONCLUSION

NOMA systems have garnered a lot of interest in recent years for 5G cellular communication networks. The efficient user grouping and power control scheme play an essential role to enhance the performance of communication network. In this paper, we have examined for the first time up to authors knowledge, a joint issue of user-grouping and power control for NOMA uplink systems. we have solved this problem by proposing WOA with low complexity. Further, for comparison GWO and PSO are adopted to solve the same problem. Simulations results show that the WOA proposed for this combine issue in uplink allows better performance than the conventional OMA in-terms of spectral-efficiency. Further, proposed WOA provides better result as compared to GWO, PSO and existing algorithm in literature with lower system complexity by considering same constraint regarding uplink NOMA systems.The acquired results also suggest that the combinatorial joint problem gets more difficult to solve as the number of users grows and needs additional network resources. In the future, the study might be expanded to include more performance parameters to the mentioned problem and implementation of multiple antennas combinations which leads to massive MIMO (Mulitiple-Input and Multiple-Output) scenario in order to further enhance the performance of the network.

ACKNOWLEDGMENTS

REFERENCES

Abed-alguni, B. H. and Alawad, N. A. (2021). Distributed grey wolf optimizer for scheduling of workflow applications in cloud environments. *Applied Soft Computing*, 102:107113.

Al-Abbasi, Z. Q. and So, D. K. (2016). User-pairing based non-orthogonal multiple access (noma) system. In *2016 IEEE 83rd vehicular technology conference (VTC Spring)*, pages 1–5. IEEE.

Alawad, N. A. and Abed-alguni, B. H. (2021). Discrete island-based cuckoo search with highly disruptive polynomial mutation and opposition-based learning strategy for scheduling of workflow applications in cloud environments. *Arabian Journal for Science and Engineering*, 46(4):3213–3233.

Ali, M. S., Tabassum, H., and Hossain, E. (2016). Dynamic user clustering and power allocation for uplink and downlink non-orthogonal multiple access (noma) systems. *IEEE access*, 4:6325–6343.

Azam, I., Shahab, M. B., and Shin, S. Y. (2019). User pairing and power allocation for capacity maximization in uplink noma. In *2019 42nd International Conference on Telecommunications and Signal Processing (TSP)*, pages 690–694. IEEE.

Benjebbour, A., Saito, Y., Kishiyama, Y., Li, A., Harada, A., and Nakamura, T. (2013). Concept and practical considerations of non-orthogonal multiple access (noma) for future radio access. In *2013 International Symposium on Intelligent Signal Processing and Communication Systems*, pages 770–774. IEEE.

Benjebbovu, A., Li, A., Saito, Y., Kishiyama, Y., Harada, A., and Nakamura, T. (2013). System-level performance of downlink noma for future lte enhancements. In *2013 IEEE Globecom Workshops (GC Wkshps)*, pages 66–70. IEEE.

Chen, C., Wang, B., and Zhang, R. (2018). Interference hypergraph-based resource allocation (ihg-ra) for noma-integrated v2x networks. *IEEE Internet of Things Journal*, 6(1):161–170.

Chen, W., Zhao, S., Zhang, R., Chen, H., and Yang, L. (2020a). Generalized user grouping in noma: An overlapping perspective. *IEEE Transactions on Wireless Communications*.

Chen, W., Zhao, S., Zhang, R., and Yang, L. (2020b). Generalized user grouping in noma based on overlapping coalition formation game. *IEEE Journal on Selected Areas in Communications*.

Dai, L., Wang, B., Yuan, Y., Han, S., Chih-Lin, I., and Wang, Z. (2015). Non-orthogonal multiple access for 5g: solutions, challenges, opportunities, and future research trends. *IEEE Communications Magazine*, 53(9):74–81.

Di, B., Song, L., and Li, Y. (2016). Sub-channel assignment, power allocation, and user scheduling for non-orthogonal multiple access networks. *IEEE Transactions on Wireless Communications*, 15(11):7686–7698.

Ding, Z., Fan, P., and Poor, H. V. (2015). Impact of user pairing on 5g nonorthogonal multiple-access downlink transmissions. *IEEE Transactions on Vehicular Technology*, 65(8):6010–6023.

Ding, Z., Lei, X., Karagiannidis, G. K., Schober, R., Yuan, J., and Bhargava, V. K. (2017a). A survey on non-orthogonal multiple access for 5g networks: Research challenges and future trends. *IEEE Journal on Selected Areas in Communications*, 35(10):2181–2195.

Ding, Z., Liu, Y., Choi, J., Sun, Q., Elkashlan, M., Chih-Lin, I., and Poor, H. V. (2017b). Application of non-orthogonal multiple access in lte and 5g networks. *IEEE Communications Magazine*, 55(2):185–191.

Ding, Z., Yang, Z., Fan, P., and Poor, H. V. (2014). On the performance of non-orthogonal multiple access in 5g systems with randomly deployed users. *IEEE signal processing letters*, 21(12):1501–1505.

Gou, P., He, B., and Yu, Z. (2021). A node location algorithm based on improved whale optimization in wireless sensor networks. *Wireless Communications and Mobile Computing*, 2021.

Goudos, S., Diamantoulakis, P., Boursianis, A., Papanikolaou, V., and Karagiannidis, G. (2020). Joint user association and power allocation using swarm intelligence algorithms in non-orthogonal multiple access networks. In *9th International Conference on Modern Circuits and Systems Technologies (MOCAST)*, pages 1–4. IEEE.

Guo, F., Lu, H., Zhu, D., and Gu, Z. (2019). Joint user association, grouping and power allocation in uplink noma systems with qos constraints. In *ICC 2019-2019 IEEE International Conference on Communications (ICC)*, pages 1–6. IEEE.

He, J., Tang, Z., and Che, Z. (2016). Fast and efficient user pairing and power allocation algorithm for non-orthogonal multiple access in cellular networks. *Electronics letters*, 52(25):2065–2067.

Husnain, G. and Anwar, S. (2021). An intelligent cluster optimization algorithm based on whale optimization algorithm for vanets (woacnet). *Plos one*, 16(4):e0250271.

Islam, S. R., Avazov, N., Dobre, O. A., and Kwak, K.-S. (2016). Power-domain non-orthogonal multiple access (noma) in 5g systems: Potentials and challenges. *IEEE Communications Surveys & Tutorials*, 19(2):721–742.

Kennedy, J. and Eberhart, R. (1995). Particle swarm optimization. In *ICNN'95-international conference on neural networks 1995*, pages 1942–1948. IEEE.

Liang, W., Ding, Z., Li, Y., and Song, L. (2017). User pairing for downlink non-orthogonal multiple access networks using matching algorithm. *IEEE Transactions on communications*, 65(12):5319–5332.

Liu, F., Mähönen, P., and Petrova, M. (2015). Proportional fairness-based user pairing and power allocation for non-orthogonal multiple access. In *2015 IEEE 26th annual international symposium on personal, indoor, and mobile radio communications (PIMRC)*, pages 1127–1131. IEEE.

Liu, Y., Elkashlan, M., Ding, Z., and Karagiannidis, G. K. (2016). Fairness of user clustering in mimo

non-orthogonal multiple access systems. *IEEE Communications Letters*, 20(7):1465–1468.
Martins, S. L. and Ribeiro, C. C. (2006). Metaheuristics and applications to optimization problems in telecommunications. In *Handbook of optimization in telecommunications*, pages 103–128. Springer.
Mirjalili, S. and Lewis, A. (2016). The whale optimization algorithm. *Advances in engineering software*, pages 51–67.
Mirjalili, S., Lewis, A., and Sadiq, A. S. (2014a). Autonomous particles groups for particle swarm optimization. *Arabian Journal for Science and Engineering*, 39(6):4683–4697.
Mirjalili, S., Mirjalili, S., and Lewis, A. (2014b). Grey wolf optimizer. *Advances in engineering software*, pages 46–61.
Nadimi-Shahraki, M. H., Taghian, S., and Mirjalili, S. (2021). An improved grey wolf optimizer for solving engineering problems. *Expert Systems with Applications*, 166:113917.
Nadimi-Shahraki, M. H., Taghian, S., Mirjalili, S., and Faris, H. (2020). Mtde: An effective multi-trial vector-based differential evolution algorithm and its applications for engineering design problems. *Applied Soft Computing*, 97:106761.
Nguyen, M. T. and Le, L. B. (2019). Noma user pairing and uav placement in uav-based wireless networks. In *ICC 2019-2019 IEEE International Conference on Communications (ICC)*, pages 1–6. IEEE.
Panda, S. (2020). Joint user patterning and power control optimization of mimo–noma systems. *Wireless Personal Communications*, pages 1–17.
Pham, Q.-V., Mirjalili, S., Kumar, N., Alazab, M., and Hwang, W.-J. (2020a). Whale optimization algorithm with applications to resource allocation in wireless networks. *IEEE Transactions on Vehicular Technology*, 69(4):4285–4297.
Pham, Q.-V., Nguyen, D. C., Mirjalili, S., Hoang, D. T., Nguyen, D. N., Pathirana, P. N., and Hwang, W.-J. (2020b). Swarm intelligence for next-generation wireless networks: Recent advances and applications. *arXiv preprint arXiv:2007.15221*.
Sedaghat, M. A. and Müller, R. R. (2018). On user pairing in uplink noma. *IEEE Transactions on Wireless Communications*, 17(5):3474–3486.
Shahini, A. and Ansari, N. (2019). Noma aided narrowband iot for machine type communications with user clustering. *IEEE Internet of Things Journal*, 6(4):7183–7191.
Sharma, N. and Gupta, V. (2020). Meta-heuristic based optimization of wsns localisation problem-a survey. *Procedia Computer Science*, 173:36–45.
Song, L., Niyato, D., Han, Z., and Hossain, E. (2014). Game-theoretic resource allocation methods for device-to-device communication. *IEEE Wireless Communications*, 21(3):136–144.
Wang, B., Zhang, R., Chen, C., Cheng, X., Yang, L., and Jin, Y. (2019). Interference hypergraph-based 3d matching resource allocation protocol for noma-v2x networks. *IEEE Access*, 7:90789–90800.
Wang, H., Li, K., and Pedrycz, W. (2020). An elite hybrid metaheuristic optimization algorithm for maximizing wireless sensor networks lifetime with a sink node. *IEEE Sensors Journal*, 20(10):5634–5649.
Wang, K., Liu, Y., Ding, Z., and Nallanathan, A. (2018). User association in non-orthogonal multiple access networks. In *2018 IEEE International Conference on Communications (ICC)*, pages 1–6. IEEE.
Wei, Z., Ng, D. W. K., Yuan, J., and Wang, H.-M. (2017). Optimal resource allocation for power-efficient mc-noma with imperfect channel state information. *IEEE Transactions on Communications*, 65(9):3944–3961.
Xu, W., Li, X., Lee, C.-H., Pan, M., and Feng, Z. (2017). Joint sensing duration adaptation, user matching, and power allocation for cognitive ofdm-noma systems. *IEEE Transactions on Wireless Communications*, 17(2):1269–1282.
Yang, Z., Ding, Z., Fan, P., and Al-Dhahir, N. (2016). A general power allocation scheme to guarantee quality of service in downlink and uplink noma systems. *IEEE transactions on wireless communications*, 15(11):7244–7257.
Zhai, D., Zhang, R., Wang, Y., Sun, H., Cai, L., and Ding, Z. (2019). Joint user pairing, mode selection, and power control for d2d-capable cellular networks enhanced by nonorthogonal multiple access. *IEEE Internet of Things Journal*, 6(5):8919–8932.
Zhang, H., Zhang, D.-K., Meng, W.-X., and Li, C. (2016a). User pairing algorithm with sic in non-orthogonal multiple access system. In *2016 IEEE International Conference on Communications (ICC)*, pages 1–6. IEEE.
Zhang, J., Zhu, L., Xiao, Z., Cao, X., Wu, D. O., and Xia, X.-G. (2019). Optimal and sub-optimal uplink

noma: Joint user grouping, decoding order, and power control. *IEEE Wireless Communications Letters*, 9(2):254–257.
Zhang, N., Wang, J., Kang, G., and Liu, Y. (2016b). Uplink nonorthogonal multiple access in 5g systems. *IEEE Communications Letters*, 20(3):458–461.
Zhanyang, G., Toor, W. T., and Jin, H. (2018). Cdf-based scheduling for uplink non-orthogonal multiple access. In *2018 IEEE 87th Vehicular Technology Conference (VTC Spring)*, pages 1–5. IEEE.
Zheng, G., Xu, C., and Tang, L. (2020). Joint user association and resource allocation for noma-based mec: A matching-coalition approach. In *2020 IEEE Wireless Communications and Networking Conference (WCNC)*, pages 1–6. IEEE.
Zhu, L., Zhang, J., Xiao, Z., Cao, X., and Wu, D. O. (2018). Optimal user pairing for downlink non-orthogonal multiple access (noma). *IEEE Wireless Communications Letters*, 8(2):328–331.