Joint User Association and Power Allocation Using Swarm Intelligence Algorithms in Non-Orthogonal Multiple Access Networks

Sotirios K. Goudos
School of Physics
Aristotle University of Thessaloniki
Thessaloniki, Greece
sgoudo@physics.auth.gr

Panagiotis D. Diamantoulakis
School of Electrical and Computer Engineering
Aristotle University of Thessaloniki
Thessaloniki, Greece
padiaman@ieee.org

Achilles D. Boursianis
School of Physics
Aristotle University of Thessaloniki
Thessaloniki, Greece
bachi@physics.auth.gr

Vasilis K. Papanikolaou
School of Electrical and Computer Engineering
Aristotle University of Thessaloniki
Thessaloniki, Greece
vpapanikk@auth.gr

George K. Karagiannidis
School of Electrical and Computer Engineering
Aristotle University of Thessaloniki
Thessaloniki, Greece
geokarag@auth.gr

***Abstract*—In this paper, we address the problem of joint user association and power allocation for non-orthogonal multiple access (NOMA) networks with multiple base stations (BSs). A user grouping procedure into orthogonal clusters, as well as an allocation of different physical resource blocks (PRBs) is considered. The problem of interest is mathematically described using the maximization of the weighted sum rate. We apply two different swarm intelligence algorithms, namely, the recently introduced Grey Wolf Optimizer (GWO), and the popular Particle Swarm Optimization (PSO), in order to solve this problem. Numerical results demonstrate that the above-described problem can be satisfactorily addressed by both algorithms.**

***Index Terms*—Non-Orthogonal Multiple Access (NOMA), user association, power allocation, 5G, evolutionary algorithms**

I. Introduction

Non-Orthogonal Multiple Access (NOMA) techniques will be a key technology of fifth generation (5G) cellular networks [1]. Current orthogonal multiple access (OMA) systems result in low spectrum efficiency, when network resources are assigned to mobile users with poor channel conditions. However, if we consider the power domain, NOMA systems can deliver high spectrum efficiency even with poor channel conditions. In the NOMA scheme, the mobile users may share the same frequency, time, and code, yet they should be differentiated in power levels [2]. To this end, the fundamental concept of NOMA scheme is the use of successive interference cancellation (SIC) technique by the mobile users' receivers with rich channel conditions, to significantly reduce the interference level of mobile users with poor channel conditions. As a result, SIC technique cancels the intra- cell or cluster interference on mobile users' receivers [3]. The user association problem is becoming more challenging in NOMA networks, as some unique features of traditional OMA networks, such as co-channel interferences, require re-design. The authors in [4] formulate the user association problem in NOMA networks by grouping the users into orthogonal clusters and associating them different resource blocks using a game theoretic approach. However, game theoretic approaches which are commonly used in user association problems have limitations and work under certain assumptions. On the other hand, evolutionary algorithms (EAs) are global optimizers that work well regardless of the optimization problem in hand. We describe the problem formulation with the network sum rate utility function.

A parameter that introduces more complexity to the problem is power control. Usually, as in [4] the power coefficients are considered constant for all network. In our case we find the suitable power coefficients for every NOMA user. Evolutionary algorithms inspired by nature are suitable techniques for solving this problem. In this paper, we apply the Grey Wolf Optimizer (GWO) [5], which was recently introduced as a population-based algorithm that mimics grey wolf hunting behavior. Additionally, a comparative study between the GWO obtained results and the legacy particle swarm optimizer (PSO) [6] is performed. The derived results indicate that GWO algorithm outperforms the PSO algorithm in general. Moreover, we conclude that NOMA schemes with power control can be successfully utilized.

II. System Model

We consider, several base stations (BS) and users using NOMA techniques. Additionally, the BSs use physical resource blocks (PRBs) to transmit their data. Therefore, we have a downlink NOMA system that has a set of users $\mathcal{N} = \{1, 2, \cdots, N_u\}$, and $|\mathcal{N}| = N_u$ is the set cardinality or the number of users. Moreover, we consider as $\mathcal{T} = \{1, 2, \dots T_{RB}\}$ with cardinality $|\mathcal{T}| = T_{RB}$, the set of PRBs.

Therefore, there are T_{RB} orthogonal clusters. The set of users associated with PRB t is denoted $\mathcal{E}_t$ with cardinality $|\mathcal{E}_t| = E_t$. In OMA systems each PRB is assigned to a single user. This is not the case in NOMA systems, where more users share the same PRB with different power levels. To this end, the users' receivers cancel the intra-cluster interference with SIC. We consider that NOMA techniques are used by all users in individual clusters. The received signal at user m in any cluster E_{tk} is formulated as [4]:

$$Y_{km}^t = \underbrace{g_{km}^t \sqrt{p_{km}^t} s_{km} + n_m}_{\text{desired signal}} + \underbrace{\sum_{i=1, j\neq k}^{K_{BS}} \sum_{j=1}^{|E_{ti}|} g_{im}^t s_{ij}}_{\text{inter-cluster interference}} + \underbrace{g_{km}^t \sum_{i=1, i\neq m}^{|E_{tk}|} \sqrt{p_{ki}^t} s_{ki}}_{\text{intra-cluster interference}} \tag{1}$$

where $|E_{tk}|$ is the size of E_{tk}, g_{km}^t is the channel between user m and PRB t, which is allocated by BS k, s_{km} denotes the transmitted signal, p_{km}^t is the power allocation coefficient, and n_m is the noise.

Additionally, the channel power gain can be expressed as

$$|g_{mk}^t|^2 = |\hat{g}_{mk}^t|^2 G_{\text{PL}}(d_{mk}) \tag{2}$$

where $\hat{g}_{mk}^t \sim \mathcal{CN}(0,1)$ is the circular-symmetric complex Gaussian zero mean noise between BS k and PRB t to user m, $G_{\text{PL}}(d_{mk})$ is the path loss propagation. The path loss propagation among user m and the BS is modeled with path gain (loss) $GPL(d)$. In this study, we use the outdoor macro cell line-of-sight (LOS) model defined in [7]. This is expressed as

$$G_{\text{PL}}(d_{mk}) = -103.4 - 24.2 \log_{10}(d_{mk}) \text{ (dB)} \tag{3}$$

where d_{mk} is the distance between BS k and user m in kilometers.

In any cluster E_{tk}, the power allocation coefficients $\sum_{i=1}^{|E_{tk}|} p_{ki}^t \leq 1$.

We assume that there is an allocation of maximum M NOMA users in each physical resource block, where the power allocation coefficients subject to $p_{k,1}^t \geq p_{k,2}^t \geq, ...p_{km}^t, .. \geq p_{kM}^t$ To this end, we can consider the $M-th$ user as the best-served user within each cluster. The m-th user's receiver in E_{tk} will take into account the i-th user's signal as noise $(m > i)$ and will decode its own signal with signal-to-interference-plus-noise ratio (SINR):

$$c_{km}^t = \frac{|g_{km}^t|^2 p_{km}^t}{|g_{km}^t|^2 \sum\limits_{i=m+1}^{|E_{tk}|} p_{ki}^t + \sum\limits_{i=1, j\neq k}^{K_{BS}} \sum\limits_{j=1}^{|E_{ti}|} |g_{im}^t|^2 p_{ij}^t + \frac{1}{\rho}}, \tag{4}$$

where $\rho = P_t/\sigma^2$ is the transmit signal-to-noise ratio (SNR), P_t denotes the transmit power, and σ^2 is the variance of the Additive White Gaussian noise (AWGN). Additionally, the last M-th user's receiver will apply SIC to cancel the intra-cluster interference, and will decode its own signal with SINR:

$$c_{kM}^t = \frac{|g_{km}^t|^2 p_{kM}^t}{\sum\limits_{i=1, j\neq k}^{K_{BS}} \sum\limits_{j=1}^{|E_{ti}|} |g_{iM}^t|^2 p_{ij}^t + \frac{1}{\rho}}. \tag{5}$$

As it was previously mentioned, the intra-cluster interference decoding and removal signal (due to the previous user) are required, in order to the m-user to be able to decode its own signal. Let us consider that the SIC process, which is executed at the n-th user, is perfect. As a result, we can conclude that the condition, which is required for a perfect SIC process, is stated by the following expression: $R_{k,n\to m}^t \geq R_{k,m\to m}^t$ for $n > m$, i.e. the n-th user for decoding the m-th user's signal is larger than the rate of the m-th user for decoding its own signal. The condition for a perfect SIC process can be transformed to

$$\frac{|g_{kn}^t|^2 p_{km}^t}{|g_{kn}^t|^2 \sum\limits_{i=m+1}^{|E_{tk}|} p_{ki}^t + \sum\limits_{i=1, j\neq k}^{K_{BS}} \sum\limits_{j=1}^{|E_{ti}|} |g_{in}^t|^2 p_{ij}^t + \frac{1}{\rho}} \geq \frac{|g_{km}^t|^2 p_{km}^t}{|g_{km}^t|^2 \sum\limits_{i=m+1}^{|E_{tk}|} p_{ki}^t + \sum\limits_{i=1, j\neq k}^{K_{BS}} \sum\limits_{j=1}^{|E_{ti}|} |g_{im}^t|^2 p_{ij}^t + \frac{1}{\rho}}.$$

Therefore, the n-th user is able to cancel the m-th user's signal by applying the SIC process, if the following condition is true:

$$Q(E_{tk}) \triangleq \frac{|g_{kn}^t|^2}{\sum\limits_{i=1, j\neq k}^{K_{BS}} \sum\limits_{j=1}^{|E_{ti}|} |g_{in}^t|^2 p_{ij}^t + \frac{1}{\rho}} - \tag{6}$$

$$\frac{|g_{km}^t|^2}{\sum\limits_{i=1, j\neq k}^{K_{BS}} \sum\limits_{j=1}^{|E_{ti}|} |g_{im}^t|^2 p_{ij}^t + \frac{1}{\rho}} \geq 0, \tag{7}$$

$$\forall n \in \{2, ..., M\}, \forall m \in \{1, ..., M-1\} \tag{8}$$

As a result, the data rate of any user m, which is connected with BS k, and is allocated within a PRB t is

$$R_{km}^t = \log(1 + c_{km}^t)$$

A. Problem Formulation

We consider the binary variable b_{ki}, which describes the relation between the k-th BS and the i-th user. It can be formulated as

$$b_{ki} = \begin{cases} 1, & \text{if user } i \text{ is related to the BS } k \\ 0, & \text{otherwise.} \end{cases} \tag{9}$$

Moreover, we can define a second binary variable y_{ti}, which describes the relation between the i-th user and t-th PRB as

$$y_{ti} = \begin{cases} 1, & \text{if user } i \text{ is related to the PRB } t \\ 0, & \text{otherwise.} \end{cases} \tag{10}$$

Analogous to [4], we take into account an extra weight factor that is based on the distance between BSs and users. This weight factor can be described as $w_{kn} = (d_{kn}/\sum_{i=1}^{2} d_{ki})^{1/\alpha}$

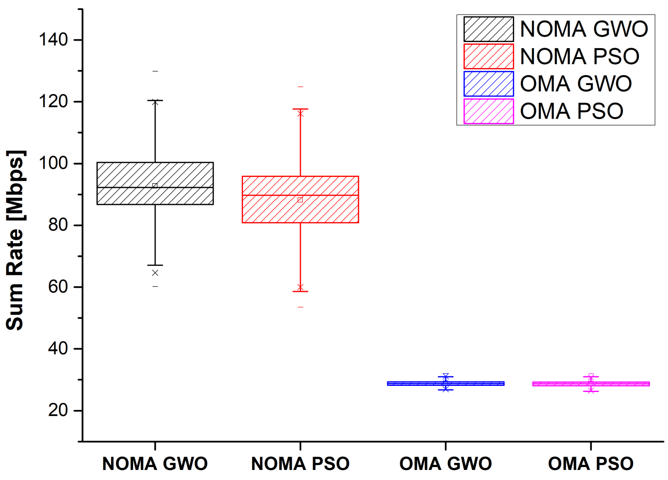

Fig. 1. Box plots of Utility function results K=3 N=15.

in E_{tk} cluster. As a result, the users with poor channel conditions and interference are less affected, whereas the users with good channel conditions are more affected and therefore, their data rate is reduced. Taking into account all the above remarks, the joint user association and power allocation can be expressed as

$$
\begin{aligned}
U^* = \max_{\{\boldsymbol{b},\boldsymbol{y},\boldsymbol{p}\}} \quad & \sum_{i\in\mathcal{N}} U_{kt}(R_i) \\
\text{s.t.} \quad & C_1 : Q(E_{tk}) \geq 0 \\
& C_2 : b_{kn} \in \{0,1\}, \forall n \in \mathcal{N}, \forall k \in \mathcal{K}, \\
& C_3 : y_{tn} \in \{0,1\}, \forall n \in \mathcal{N}, \forall t \in \mathcal{T}, \\
& C_4 : \sum\nolimits_{i=1}^{K_{BS}} b_{in} = 1, \forall n \in \mathcal{N}, \\
& C_5 : \sum\nolimits_{i=1}^{T_{RB}} y_{in} = 1, \forall n \in \mathcal{N}, \\
& C_6 : \sum\nolimits_{n=1}^{N} y_{tn} \leq M, \forall t \in \mathcal{T}, \\
& C_7 : \sum\nolimits_{i=1}^{|E_{tk}|} p_{ki}^t \leq 1 \forall t \in \mathcal{T}, \forall k \in \mathcal{K},
\end{aligned}
$$

where $U_{kt}(R_i) = w_{ki} b_{ki} y_{ti} R_{ki}^t$ defines the utility function, and $\boldsymbol{b}$ and $\boldsymbol{y}$ are the set of all indicators b and y, accordingly. The condition of SIC is given by the constraint C_1 that classifies the users in each cluster. Whether a relation between user n and BS k will take place, it is denoted with constraint C_2. In a similar way, whether a relation between user n and PRBs t will take place, it is described by the constraint C_3. Constraints C_4 and C_5 denote the unique relation among a single user n, a BS k, and a physical resource block t at the same time. Moreover, constraint C_6 indicates the fact that the most M users may be served in any PRB. The total power allocation coefficients in each cluster should be less or equal to one and this described by constraint C_7.

III. Numerical Results

A set of simulations is performed to evaluate the algorithms' performance and to find a solution to the user association problem. In this context, we generate users and the BSs randomly uniform distributed within an area of radius of 550 m. In our case, we consider a scenario of 15 randomly deployed users, which are served by 3 BSs, each having 5 PRBs. Moreover, each physical resource block supports $M = 2$ NOMA users at the most. The shadowing is assumed to be a lognormal distribution with a standard deviation of 8 dB. We set the PRB bandwidth equal to 180 kHz, which is the value used in 4G/LTE.

A comparative study between the results of the two algorithms GWO and PSO is outlined. We select the population size to be equal to 200, and the maximum number of iterations to be equal to 24. The derived set results in 500 different simulations. In each simulation, a random topology is created, and each of the two algorithms is performed to find a solution. Apparently, simulation results from 500 different random

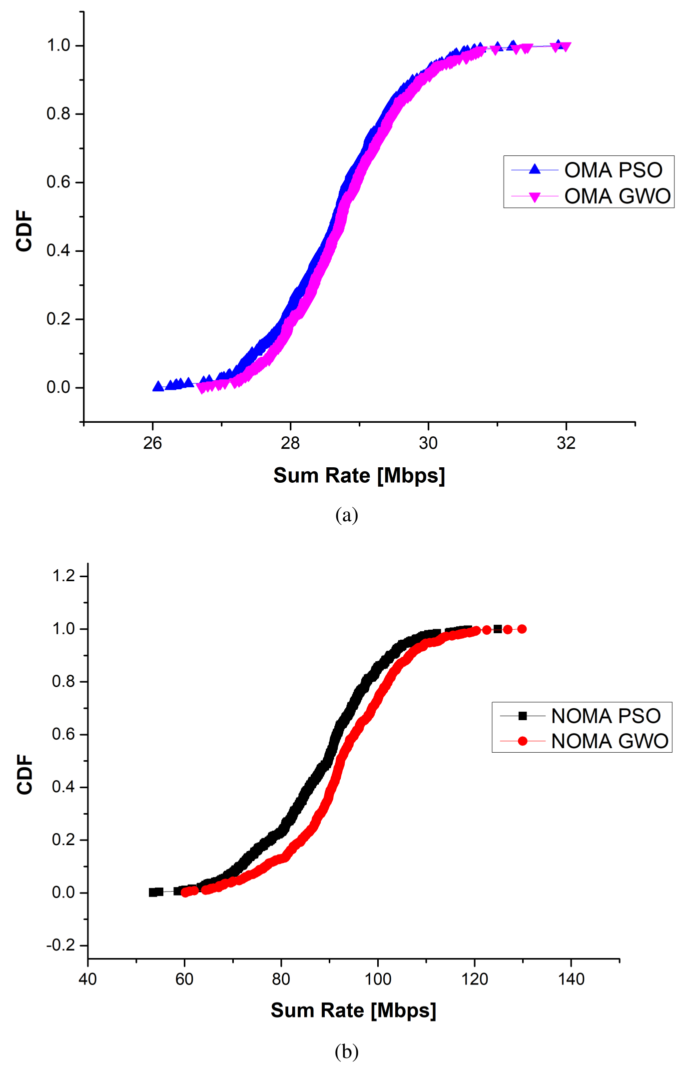

Fig. 2. CDF of Utility function results for a) OMA b) NOMA

topologies are obtained.

Fig. 1 illustrates the obtained results (in box plots) of each NOMA and OMA scheme combined with GWO and PSO. We can easily conclude that the 50% percentiles (median value) of sum rate for the NOMA schemes (for both algorithms) is greater than the corresponding values of OMA ones. Moreover, we observe that GWO algorithm produces better results, in terms of median values, compared to PSO algorithm.

Fig. 2 portrays the Cumulative Distribution Function (CDF) for both OMA and NOMA schemes. From the presented graphs, it is clear that the GWO algorithm outperforms the PSO algorithm in the NOMA scheme, whereas the two algorithms have a similar performance in the OMA scheme.

One of the performance metrics in EAs is the convergence speed. Fig. 3 shows the obtained average convergence rate after 500 trials. We can deduce that both algorithms converge at a similar speed, however GWO converges at a larger value of iterations than PSO.

Next, we study the effect of increasing the number of users. To this end, we set the number of users to be varied from 12 to 24 by a step of 3. In each users case, 500 simulations are performed for both algorithms. Fig. 4 depicts the average sum rate results versus the increasing number of users. We can notice that, for the NOMA scheme, GWO algorithm produces better results than PSO. It is also noticeable that both algorithms perform in a similar way for the OMA scheme. Moreover, the sum rate values for the NOMA scheme decrease, when the number of users increases. Therefore, we can conclude that more network resources are required, as the number of users increases, thus becoming more difficult to solve the problem.

IV. Conclusion

In this paper, we have introduced the formulation of the joint user association and power control problem for downlink NOMA networks. We have addressed this problem by using

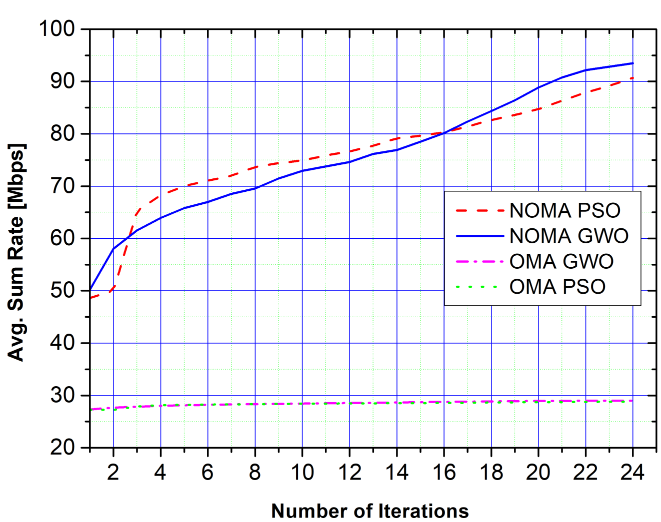

Fig. 3. Average convergence rate graph.

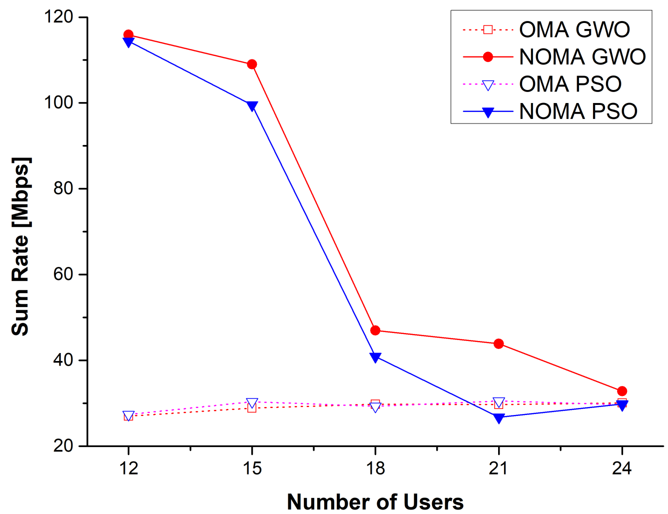

Fig. 4. Sum rate with increasing number of users.

emerging swarm intelligence algorithms with low complexity.Numerical results demonstrate a better overall performance of GWO algorithm, compared to PSO, for the same network topologies. In terms of convergence speed, GWO produces better of equal results, when compared to PSO algorithm. The derived results also imply that the problem becomes more difficult to solve and requires more network resources, when the number of users increases. Future work includes the addition of of quality of service (QoS) constraints to the guven problem.

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References

[1] Z. Ding, Y. Liu, J. Choi, Q. Sun, M. Elkashlan, I. Chih-Lin, and H. Poor, "Application of non-orthogonal multiple access in LTE and 5g networks," *IEEE Communications Magazine*, vol. 55, no. 2, pp. 185–191, 2017, cited By 312.

[2] Z. Ding, Z. Yang, P. Fan, and H. Poor, "On the performance of non-orthogonal multiple access in 5g systems with randomly deployed users," *IEEE Signal Processing Letters*, vol. 21, no. 12, pp. 1501–1505, 2014, cited By 583.

[3] Y. Saito, Y. Kishiyama, A. Benjebbour, T. Nakamura, A. Li, and K. Higuchi, "Non-orthogonal multiple access (noma) for cellular future radio access," 2013, cited By 632.

[4] K. Wang, Y. Liu, Z. Ding, and A. Nallanathan, "User association in non-orthogonal multiple access networks," in *2018 IEEE International Conference on Communications (ICC)*, May 2018, pp. 1–6.

[5] S. Mirjalili, S. M. Mirjalili, and A. Lewis, "Grey wolf optimizer," *Advances in Engineering Software*, vol. 69, pp. 46–61, 2014.

[6] J. Kennedy and R. Eberhart, "Particle swarm optimization," vol. 4, 1995, pp. 1942–1948, cited By 29622.

[7] 3GPP, "Tr 36.814, further advancements for e-utra physical layer aspects, v9.0.0, mar), year = 2010," Tech. Rep.