Ant-Colony Based User Grouping Modelling for Fast Cellular Networks

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Abstract. The need for efficient allocation of radio bandwidth to the users in the current and future cellular networks is high. As more users are requesting for the network connections, the radio bandwidth must be fairly and efficiently allocated. The bandwidth sharing feature introduced in cellular network technologies like 5G renders a more efficient allocation and utilization of the bandwidth. However, the computational load required to determine and select the users for each of the radio resources tends to increase as the total number of users rises. Therefore, user grouping that requires lower computational complexity such as the heuristic methods are useful to address this problem. An ant-colony optimization has been applied in this paper to perform user grouping in 5G NOMA. The mean throughput and mean square error have been measured when testing the proposed scheme. The result shows that the proposed scheme produces satisfactory throughput results, close to that of the theoretical upper limit. The mean square error is also close to the lower limit and better than the existing scheme.

Keywords: Ant-colony optimization, user grouping, non-orthogonal

1 Introduction

In today's new technology, wireless networking is a growing field. The ubiquity of wireless applications in different fields, such as financial transactions (banking), social networking, environment monitoring, device-to-device communications, etc., creates an open nature of wireless network broadcasting. Recently, there has been a substantial increase in user requirements for higher data rates, performance, better reliability and capacity growth. The key problems of wireless communication networks [1] are the management of these demands. The accessible design of wireless networking networks and the exponential increase in the number of users are causing these problems. The wireless network, for this purpose, needs more effective device scheduling to access the resource blocks. With the advancement of non-orthogonal multiple access (NOMA) wireless networking [2-4], one of the successful schemes to satisfy the rapidly rising user access criteria has been considered.

NOMA is an essential technology for supporting the future cellular networks especially 5G+ networks. Its benefits are greatly illuminated in fulfilling the increasing demands for better throughput, high durability low latency and huge connectivity [6-7]. The value of NOMA lies in a single resource block's capacity to support multiple users. In terms of spectrum, though NOMA is more effective, the network is susceptible to user intrusion from sharing.

More effective scheduling of users to access resource blocks is expected in the urban area, which is increasing rapidly in the number of users who can access the wireless network, causing higher computational complexity. Several mechanisms, such as round robin, are proposed for creating user groups. Since the systems involve a dramatically higher number of computations as more users are present, algorithmically lower approaches for classifying the groups of users have been proposed using heuristic mechanisms. Particle swarm optimization (PSO), dolphin echolocation optimization (DEO), drosophila optimization (DO), firefly optimization (FO), ant-colony optimization (ACO) and genetic optimization are examples of heuristic models formulated and employed in literature. In various fields, such as data analysis, computer vision, transportation and bioengineering, these algorithms constitute as the viable solutions.

ACO is a population-based metaheuristic approach that exploits the nature of the ants' actions in searching for the sources of food. The social interactions and cooperation between the ants contribute in helping the ants to finally find the target food. Rooting from the chemical concept of pheromones, which are deposited by the ants along the path they travel, ACO algorithm is useful for finding the best paths, groups or clusters based on a predefined objective function. It constitutes the big picture of the proposed ACO scheme in this paper before further elaborations are presented in other sections.

1.1 Research Gap

In wireless networking, the rising number of users is a significant and growing issue. By increasing the number of transmitters and receivers the capacity will get higher and as a result the interference and computational complexity will increase. The interference is caused by the contact between antennas and several users positioned next to each other in the base station. To accommodate the demands from the increasingly large number of users, the resource blocks must be allocated and scheduled by selecting groups of users to share the resources. This operation of grouping these users should be carefully developed as the interference and computational complexity for grouping and scheduling will likely increase. The increase in interference in the grouping of a large number of cellular network users is worthy of consideration using the models of heuristic scheduling such as PSO and ACO models. These strategies are developed for wireless and cellular networks to improve spectrum performance, enhance the throughput and decrease interference among users. The gap in this study is notably identified by proposing an integrated framework in mitigating interference mechanisms with ant-colony-based user grouping modelling to maximize mean throughput and minimize complexity.

1.2 Contributions

The contributions of this study are as follows.

- A NOMA system for an increasingly huge number of users for high-speed radio networks.
- An ACO-based user scheduling mechanism for assigning frequency whilst maintaining the optimal average throughput and decreased computational complexity.
- The effect on the mean throughput that caused by increasing the number of users in each resource block.

1.3 Organization

This paper also includes the following section. Section 2 points forth the models of heuristic. Section 3 displays the model of the system. Section 4 shows the effect of rising the number of users in each resource block. Section 5 presents the result and discussion of the paper. Finally, Section 6 present the conclusion of this paper.

2 Heuristic Models

The nature-influenced heuristic models studied here are the strategies that have been used in literature for seeking a solution to optimize pairs or groups of users on a wireless network.

2.1 PSO Model

One of the useful optimization techniques with relatively lower complexity is PSO or particle swarm optimization. It starts with a random solution to find an effective solution. This algorithm focuses solely on the ability of the groups based on a food process searching concept. PSO mimics swarm behaviors such as bird flocking and fish schooling. Bird can exchange information and find food with others [8]. PSO strategy has been used in a number of applications [9-11]. It is not difficult to execute and it is a combination of restricted parameters. PSO has been introduced for scheduling users via NOMA with its different sub-channels. PSO was often used to delegate power to each band to maximize the total throughput of the network as described in [12]. PSO has been implemented with ACO in [13] to determine whether this improves the efficiency which could be applied to evolutionary schemes. However, these approaches focus more on the power-domain NOMA systems, and not for grouping the users.

2.2 DO Model

DO or drosophila optimization is an ACO-like feature that is simple to use when working with practical problems. This nature-inspired model is suitable for cellular network problems [14]. However, no approach based on this model has been implemented for solving the user grouping issues in NOMA systems.

2.3 Dolphin Echolocation Model

The Dolphin Echolocation (DE) principle is based on the action of dolphin while searching for the target food. It is suitable for detecting the target food's position even if there are several target food locations at varying search areas and spaces [15]. However, the application of this model is more suitable for solving continuous target variable such as power or energy values and not the discrete variable such as the number of users and so on.

2.4 Firefly Optimization Model

This is another bio-inspired model which mimics the actions and movements of the fireflies. It is composed of a perception radius and a value of fluorescence used to quantify a single search and to determine the position output for a single search. Firefly goes to the quest position by monitoring the light that is created by its fellow firefly to mark the position of the target. In literature, this firefly optimization model has been studied and applied generally in telecommunications [16], although not specifically in NOMA scheduling and user grouping problems.

2.5 Ant-Colony Optimization Model

Ant-colony optimization (ACO) imitates rummaging behavior of ants for natural food sources [17]. Interestingly, ants possess the capability of sharing information between each other [18]. To realize this sharing operation, ants deposit and leave pheromones along the paths that they have taken to help other ants finding the better paths to the target food [19],[20]. Various ACO models have been formulated for solving problems in cellular networks [21-23]. Due to the effective implementation of ACO in cellular networks [24],[25], this paper aims to further explore this approach for NOMA scheduling operations in 5G networks.

3 System Model for User Scheduling and Grouping in NOMA

A 5G NOMA system is considered in the downlink direction where signals are transmitted from the base station to the receiver. There are *N* sites considered with three sectors for each site. The network sites are presumed to have a random and uniform number of users present. The mean power obtained per each resource block *r* is formulated as follows:

$$p_{i,j,u,r} = p_u G_{PL}(i,u) c_{i,u} G_A(i,j,u) f_{i,j,u,r} \quad (1)$$

The transmit power, $\boldsymbol{p}_u = \boldsymbol{\alpha}_u \boldsymbol{p}_t$, is evenly allocated per resource block (RB). In order to select the users to be grouped together, the individual signal-to-interference-and-noise ratio (SINR) is calculated for each user where no sharing of bandwidth is made, which is similar to the original Orthogonal Multiple-Access (OMA). The corresponding SINR, $\boldsymbol{\Upsilon}_{u,r}^{1,1}$ for Site 1 and Sector 1 of user $\boldsymbol{u}$ is written as follows:

$$\Upsilon_{u,r}^{1,1} = \frac{p_{1,1,u,r}}{\sum_{i=1}^{N_s} \sum_{j=1}^{3} p_{i,j,u,r} - p_{1,1,u,r}} \quad (2)$$

Once the individual SINR (OMA) values have been determined, the grouping operation is started to choose and group the users. The needed signal for user $\boldsymbol{u}_1$ at the transmitting end is supplied with a transmitted power of $\boldsymbol{\alpha}_{u_1} \boldsymbol{p}_t$ and that of user $\boldsymbol{u}_2$ is $(\mathbf{1} - \boldsymbol{\alpha}_{u_1})\boldsymbol{p}_t$, where $\boldsymbol{p}_t$ is the total allocated power for each group, with $\boldsymbol{\alpha}_{u_1} + \boldsymbol{\alpha}_{u_2} = \mathbf{1}$. After grouping the users, the corresponding SINR $\boldsymbol{\Upsilon}_{u2,r}^{11}(\boldsymbol{u}_1, \boldsymbol{u}_2)$ for user $\boldsymbol{u}_2$ is calculated as:

$$\Upsilon_{u_2,r}^{1,1}(u_1, u_2) = \frac{p_{1,1,u_2,r}}{\sum_{i=1}^{N_s} \sum_{j=1}^{3} p_{i,j,u_2,r} - p_{1,1,u_2,r} + p_{1,1,u_2,r}} \quad (3)$$

where the expression of the **SINR** for user $\boldsymbol{u}_1$ is:

$$\Upsilon_{u_1,r}^{1,1}(u_1, u_2) = \frac{p_{1,1,u_1,r}}{\sum_{i=1}^{N_s} \sum_{j=1}^{3} p_{i,j,u_1,r} - p_{1,1,u_1,r}} \quad (4)$$

Interference caused by user $\boldsymbol{u_2}$ is then removed using a SIC operation before detecting user $\boldsymbol{u_1}$, which has a better SINR without $\boldsymbol{u_2}$. Therefore, the objective of the grouping algorithm based on ACO is to optimize the throughput for all groups of users, which can be expressed as:

$$R_{t,u,g} = \sum_{i=1}^{N_{\text{ug}}} \Upsilon_{u_i,r}^{c,s}(u_1, \dots, u_{N_{\text{ug}}}) \tag{5}$$

4 ACO-based User Scheduling and Grouping Algorithm

The suggested user grouping approach which is based on ACO is designed by segregating users into groups or pairs which are allocated with the available radio resources. In order to apply the ACO, $\boldsymbol{N_{ant}}$ ants are generated to find the best groups for each user, with $\boldsymbol{N_{user}}$ users are present and $\boldsymbol{N_{\text{u}}}$ users in a group, the number of groups is determined as:

$$N_{ug} = \frac{N_{user}}{N_u} \tag{6}$$

The ants which act as the agents finding the best routes, or essentially groups will leave behind the pheromone along the routes that have been gone through. The more the pheromone value is, which depends on the number of ants as well as the evaporation rate, the more likely that the routes, or the groups, will be chosen as the groups for the target users, based on the objective function value $R_{t,u,g}$. The two methods of ACO optimization algorithms, ACO and ACS, as presented in [24], have been applied and tested for grouping. Table 1 tabulates the computational complexity for the two ACO-based algorithms along with another grouping method, SHS, which is based on binary-swapping concept. It shows that the ACO method performs better with lower complexity than the rest.

Table 1: Computational complexity comparison

Schemes	Computational Complexity	
ACO	$N_{ant}\left(\sum_{k=1}^{N_{user}} k\right)$	(7)

ACA	$N_{ant}\left(\sum_{k=1}^{N_G-1}\binom{N_u+kN_u}{N_u}\right)$	(8)
SHS	$N_{iter}\left(\frac{N_{user}^2}{N_u^2}+N_{user}\left(\sum_{k=1}^{N_G-1}\binom{kN_u}{N_u-1}\right)\right)$	(9)

5 Results and Discussions

The proposed ACO user grouping method is tested to determine the achievable throughput in a 5G NOMA system. For a comparison purpose, two other existing schemes have been run and tested, which are the ES and PFFP scheme [25]. The comparison is implemented to measure the performance of user grouping by grouping the users with one resource block allocated to each pair or group. Fig. 1 the first result on the achievable throughput by the three schemes including the proposed ACO method is shown where the number of resource blocks N_{RB} is varied between 1 and 15.

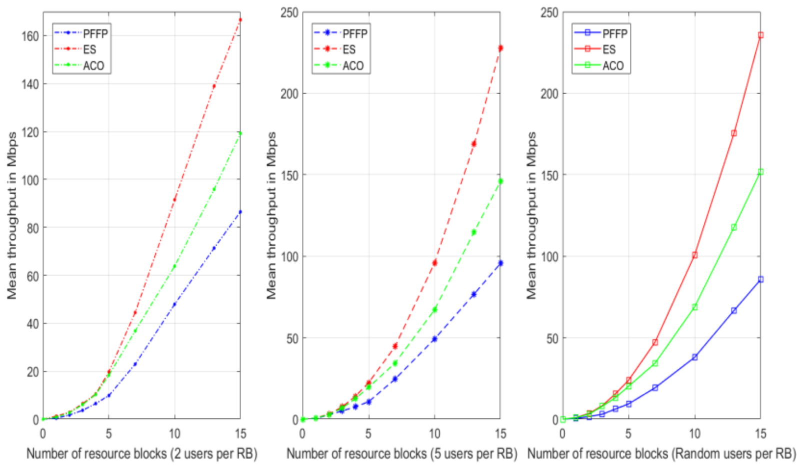

Fig. 1. The mean throughput Mbps of the Large antenna system.

As can be seen the throughput performance recorded in Fig. 1, the main performance rises steadily when the resource blocks are between 1 and 5. When the N_{RB} is set ranging from 5 to 15, the throughput improvement can be further observed. From Fig. 1, it can be observed that the performance of PFFP is lower as compared with ACO, especially when the number of resource blocks increases. The achievable performance of ACO throughput is very close to ES, which stands as the upper bound.

Moreover, the impact of increasing the users per resource block is investigated on the mean throughput. Table 4 illustrates the mean throughput achieved by applying the ACO technique at 15 RB with a different number of users.

Table 2. the mean throughput achieved by applying the ACO technique at 15 RB.

Number of users per RB	Throughput [Mbps]
2	119.2164
5	145.872164
Random (more than 5)	151.872164

Based on Table 1 and Fig. 1, we observe that by increasing the number of users per resource block the performance of the ant-colony optimization further improves. This observation is very significant as the number of resource blocks increases in inevitable due to the increasing demand from the users.

6 Conclusion

The ant-colony optimization scheme has been developed and implemented for grouping the users in 5G NOMA networks. The results show that the performance of the proposed scheme is close the theoretical exhaustive search, which considers all options to find the highest possible throughput. This is essential as the total number of users tend to increase and without a computationally efficient approach like this ant-colony optimization scheme, the required and incurred computational load may significantly increase and affect the whole performance of the network.

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