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June 24, 2021

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Abstract. The increasing demand for wireless network connections requires efficient network resource allocation. The non-orthogonal multiple access (NOMA) technology offers users sharing the same radio bandwidth to increase the bandwidth efficiency. However, the increase in the number of users demanding for the radio bandwidth and network connections will increase the required computational load for grouping the users to share the radio resources. This paper studies a heuristic method for grouping the users based on the discrete particle swarm optimization. The throughput, the average square error and the fitness function values obtained by the proposed method and the existing schemes are measured and observed. It has been demonstrated that the proposed scheme based on discrete particle swarm optimization has produced the throughput close to the upper limit. The average mean square error is also close to the lower limit. The convergence of the proposed method is mainly less than 10 iterations at different numbers of resource blocks.

Keywords: Particle Swarm, Discrete, User Grouping.

1 Introduction

High speed cellular networks in the future, which include 5G and beyond, are anticipated to offer higher network resources to an increasingly larger number of users. In providing services to more users, 5G networks have been proposed to be implemented with certain methods to ensure that the users are equally or fairly allocated with the available network resources. One of the most notable features in 5G for utilizing and allocating the available network resources such as the bandwidth is the non-orthogonal multiple access system (NOMA) [1–5]. Instead of allocating dedicated bandwidth to the users, as what typically applied in the orthogonal multiple access system (OMA), a NOMA system allows the users to share the bandwidth [6]. Not only does it efficiently utilizes and allocates the bandwidth [7,8], but this mechanism also improves the effective sum capacity which can be achieved by the sharing users.

As the number of users grows bigger, the computational load required to perform the bandwidth allocation in NOMA systems tend to rise. Choosing the best users to be clustered in the same group which is allocated with the same radio bandwidth or frequency carriers requires a number of computations. This number is certainly dependent on the total number of users, which will be likely increasing. Therefore, it is important to devise computationally efficient methods for grouping the users and allocating them with the shared bandwidth. This is certainly timely and essential in improving the NOMA systems, which have been demonstrated to be viable in supporting the Ultra Reliable and Low Latency Communication (URLLC) and Massive Machine Type Communication (mMTC) [9] by permitting more users to share the resource blocks and network connections [10–12].

The computational load incurred in NOMA is also contributed by the implementation of successive interference cancellation (SIC) operation[13–17]. After detecting one of the users who share the same radio bandwidth, the SIC operation will be carried out to remove the signal of the users which has been detected to increase the probability of detecting the next user who shares the same bandwidth. Consequently, the effective sum capacity achievable by both users will be improved. Although the sum capacity improvement is achieved by using the SIC operation, the total required computational complexity will further increase as the number of cellular network users is on the rising trend[18–20]. Therefore, the need for a user grouping and bandwidth allocation mechanism with a relatively lower computational complexity is higher. The users that should be fairly allocated [21] with the same bandwidth should be chosen so as to increase the sum capacity using a computationally lower approach.

Due to complexity, most of the user grouping methods proposed in NOMA only consider user grouping, which allocates the shared bandwidth to a pair of selected users [22]. A user grouping method known as the power fixed fairness allocation (PFFP) is proposed in [22] to reduce the computational complexity and time. When compared with the exhaustive search (ES) scheme, which considers all possible pairs of users before determining the final pairs, this approach performs better in the complexity reduction. However, the PFFP approach has only considered a limited number of cellular network users. When the number of users increases, the computational complexity tends to rise, requiring computationally lower user grouping methods such as the heuristic methods which include particle swarm[23–25], ant-colony and drosophila optimization algorithms [26–30].

Although particle swarm optimization (PSO) has been implemented in 5G NOMA, most of the problems addressed are related to power domain NOMA and the corresponding power allocation. None of the proposed PSO methods addresses the issue of grouping the users. Furthermore, the nature of PSO algorithm is not suitable for user grouping problems as PSO is naturally employed for solving continuous desired parameters such as the power allocation. In this paper, an improved PSO is designed for user grouping in NOMA for finding the best pairs of users to be allocated with the available bandwidth in the forms of resource blocks and frequency carriers. This discrete particle swarm optimization (DPSO) approach is designed with the SIC scheme to run a 5G NOMA user grouping model. Comparisons with the existing methods such as the PFFP and the ant-colony optimization approach will also be carried out. This paper is organized as follows:

2 Discrete Particle Swarm Optimization for User Grouping

A cellular network with N_{sites} cells and N_S sectors per cell is studied where NOMA is assumed to be implemented in each cell. There are a total of N_{users} users in a cell and each of these users will be paired using the user grouping schemes that will be further described in this paper. Each of the pairs will be allocated with one resource block from a total of N_{r_b} resource blocks.

In the downlink direction, the total power allocated to a pair of two user signals is P_t and each user u will have an average transmitted power of $P_u = \alpha_u P_t$, with α_u represented as the allocated power ratio to user u from P_t, where $0 < \alpha_u \leq 1$ and $u \in \{1,2\}$. The antenna gain and the fast fading function of user u at cell i and sector j are $G_{antenna}(j,i,u)$ and f_{j,i,u,r_b} respectively, where $j \in \{1,\cdots,N_S\}, i \in \{1,\cdots,N_{sites}\}$ and $r_b \in \{1,\cdots,N_{r_b}\}$. The fading shadow and the path gain of user u at cell i are represented as $c_{u,i}$ and $G_{path}(i,u)$ respectively. Hence, the average received power of a user signal u at cell i and sector j is given as

$$P_{j,i,u,r_b} = P_u G_{antenna}(j,i,u) f_{j,i,u,r_b} c_{u,i} G_{path}(i,u) \tag{2.1}$$

NOMA is implemented by first measuring the signal to interference plus noise ratio (SINR) of all users, assuming that the users are individually and independently allocated with resource blocks. In other words, this is an OMA setting is first and temporarily assumed without any bandwidth sharing as this individual SINR is required to group the users. When choosing the pairs, the first user must possess a higher SINR than the second user so that the first user can first be detected before SIC is performed to detect the second user. At the first cell and the first sector, the individual SINR $\gamma_{u,r_b}^{1,1}$ of user u is written as:

$$\gamma_{u,r_b}^{1,1} = \frac{P_{1,1,u,r_b}}{\sum_{i=1}^{N\_sites} \sum_{j=2}^{3} P_{i,j,u,r_b}}\ , \tag{2.2}$$

where the noise is assumed negligible in this interference-limited scenario.

By comparing between all SINR values, the first and the second user, which are going to be allocated with the same resource blocks, are selected by comparing between the SINR values. Therefore, the first and the second user are selected such that $\gamma_{u_1,r_b}^{1,1} > \gamma_{u_2,r_b}^{1,1}$, where both users are assumed to be allocated with the same transmit power for the purpose of determining the temporary OMA SINR and user selection. As the sharing users are now selected, the NOMA SINR value for the first user u_1 can be determined as follows:

$$\gamma_{u_1,r_b}^{1,1}(u_1) = \frac{P_{1,1,u_1,r_b}}{\sum_{i=1}^{N_{sites}} \sum_{j=2}^{3} P_{i,j,u_1,r_b}}\ . \tag{2.3}$$

The NOMA SINR $\gamma^{1,1}_{u_1,r_b}(u_1)$ for the first user u_1 appears to be very similar to that of OMA SINR calculated before because there is no SIC operation carried out on the first user during the detection process. However, the transmit power allocation for the first user is $P_{u_1} = \alpha_{u_1} P_t$ where $0 < \alpha_{u_1} \leq 1$. In other words, the total transmit power P_t is shared between the first and the second user, whose NOMA SINR $\gamma^{1,1}_{u_1,r_b}(u_2)$ is given as

$$\gamma^{1,1}_{u_1,r_b}(u_2) = \frac{P_{1,1,u_2,r_b}}{\sum_{i=1}^{N\_sites} \sum_{j=2}^{3} P_{i,j,u_2,r_b} - P_{1,1,u_1,r_b}} \,. \tag{2.4}$$

Based on the SINR functions given in (2.3) and (2.4), the total mean throughput achieved by both users who share the same resource block can be written as

$$f(u_1, \cdots, u_{N_{ug}}) = 2W \sum_{n=1}^{N_{ug}} \log_2 \gamma^{s,c}_{u_n,r_b}(u_n) \,, \tag{2.5}$$

2.1 Discrete Particle Swarm Optimization for User Grouping

The proposed algorithm based on discrete particle swarm optimization approach to group the users in 5G NOMA systems. As seen from Algorithm 1, the DPSO algorithm begins by populating S samples required before calculating the distances and velocity variables. Using an initialized set of distances $x_t(i,j)$ for $\forall\, i = 1, \cdots, S$ and $j = 1, \cdots, M$, the algorithm begins the for loop in line 3 to run the iteration up to N times.

At each iteration t, the distance will be recalculated and formulated in discrete form, as given in line 5, Equation (2.7). The current best value will also be updated and the distance which corresponds to the current best value is updated in line 6, Equation (2.8). If the current best value is larger than the global best value, the global best value will be updated accordingly, as shown in line 7 and 8.

From line 10 to 14, the velocity and the distance will be updated based on the general particle swarm optimization formula. The algorithm repeats itself until the maximum iteration has been reached. As explained before, the discretization of the distance happens in line 6. This signifies the main difference proposed in this paper than the other approaches implemented for the general particle swam optimization problems.

The discretization process will sort the values of the currently calculated distances in an ascending order. Once the distances are ordered, the indices of the ordered distances will be read and output as the discrete version of the distances. In literature there have been a number of approaches proposed to produce a discrete particle swarm optimization formula.

Some of the formula proposed in literature apply the exponential operation. Although this approach allows convergence of the learning process, the incurred computational load is relatively high due to the need to perform the exponential operation. For this reason, a more computationally lower approach is proposed in this paper to determine the discrete distance, hence completing the proposed DPSO algorithm.

Algorithm 1: Discrete Particle Swarm Optimization for NOMA User Grouping

Require: Maximum number of iterations, M; acceleration factor, $c_1,\ c_2$;inertia weight, w; population size, S; number of particles, M.

Generate S population samples.
Generate initialized distances $x_t(i,j)$ for $\forall\ i = 1,\cdots,S$ and $j = 1,\cdots,M$
for $t\ =\ 1{:}N$
  for $i\ =\ 1{:}S$
    $x_{d,t}(i,j) = \underset{j}{\text{sortindex}}\, x_t(i,j)$ (2.7)
    $p_b = \underset{x_t(i,j)}{\arg\max} f\left(x_{d,t}(i,j)\right)$ (2.8)
    if $f(p_b) > f(g_b)$ (2.9)
      $g_b = p_b$ (2.10)
    end
    for $j\ =\ 1{:}M$
      $v_t(i,j) = wv_{t-1}(i,j) + c_1r_{1,t}\big(p_b - x_{t-1}(i,j)\big)$
        $+c_2r_{2,t}\big(g_b - x_{t-1}(i,j)\big)$ (2.11)
      $x_t(i,j) = x_{t-1}(i,j) + v_t(i,j)$ (2.12)
    end
  end
end
return fitness function value, $f(g_b)$, user indices in each group

In the next section, the proposed DPSO algorithm will be implemented on a 5G NOMA model to group the users.

3 Results and Discussions

In order to test and validate the proposed scheme, a NOMA model is considered in a 5G cellular network. The total number of cells is 19 and the number sectors per cell is three. The gain and loss parameters and data used in this paper are the established data, as presented in [22,29], which follow the 3GPP standard. The output parameters of the tests and simulations run on the proposed DPSO scheme and the existing methods include the mean throughput, the number of iterations and the average mean square error per user, which has been given and described in the previous section. As for the DPSO parameter settings, the inertia weight, w is chosen between 0.9 and 1.2, the population size, S is varied between 8 and 50, the maximum iteration, N is between 3 to 100 and the acceleration parameters, c_1, c_2 are set to 2 [27].

The first test is run to measure the fitness function values achieved at each iteration for a range of N_{rb} values, from 1 to 5. The resource block number N_{rb} determines the number of users which can be paired. Therefore, 5 resource blocks can be allocated up to 10 users since each resource block will be shared by two users. Figure 1 shows the resulted fitness function values when the proposed DPSO method is run at iteration for different N_{rb} values ranging from 1 to 5. It general, the quickest convergence is achieved when $N_{rb} = 1$ and the slowest convergence occurs when $N_{rb} = 5$. The maximum fitness value is achieved at a value more than 0.9 when $N_{rb} = 5$ and the minimum fitness value is achieved at a value of about 0.2 when $N_{rb} = 1$. It can be also further observed that the maximum number of iterations before the graph curve is converged is 8, which is for the case of $N_{rb} = 5$, and the minimum number of iterations achieved before the graph is converged is 3, which is for the case of $N_{rb} = 1$.

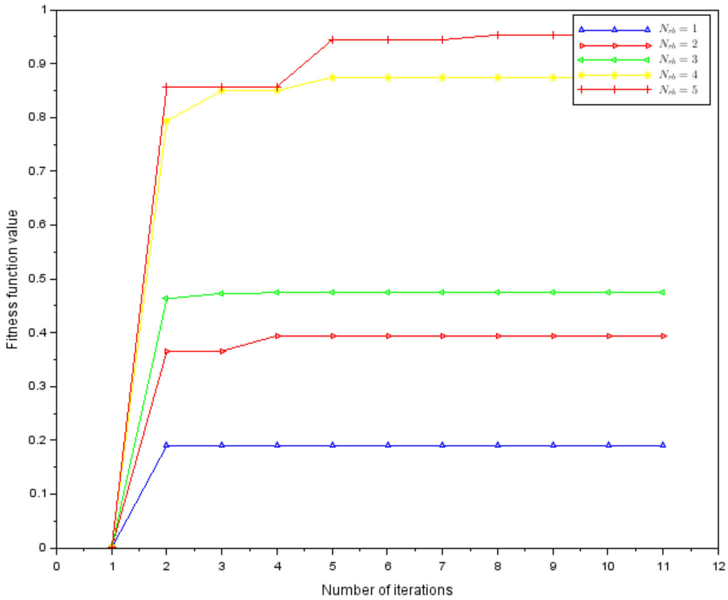

Figure 1: Measurement of fitness function values at different N_{rb} values.

The results obtained and shown in Figure 1 shows that the convergence of the proposed DPSO is considerably quick. This is due to the discrete nature of the proposed DPSO algorithm used to group the users, leading to a faster convergence.

Apart from measuring the fitness function values, the mean throughput achieved is also measured. The proposed DPSO scheme has been run along with PFFP and ES schemes to record the mean throughput achieved in Mbps. As can be seen in Figure 2, the proposed DPSO scheme has achieved the mean throughput close to the theoretical upper limit set by the ES scheme, which considers all options to perform the pairing of the users for allocating the resource blocks. The lowest mean throughput is recorded for PFFP method, although it has a relatively low computational complexity. It can be also observed that the proposed DPSO scheme has gained more than 4 Mbps as opposed to the PFFP scheme when $N_{rb} = 5$. This results further demonstrates the better performance of DPSO against the existing scheme, PFFP.

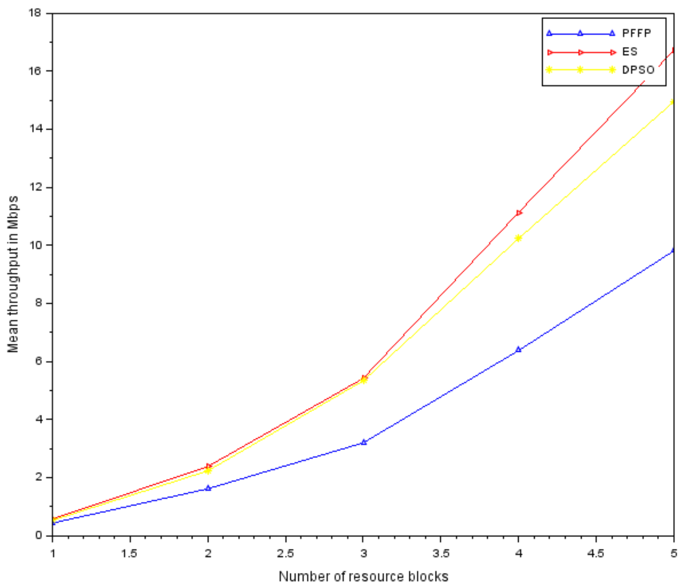

Figure 2: Measurement of the mean throughput achieved by the proposed DPSO, PFFP and ES.

In Figure 3, the average mean square error (MSE) per user is measured as $MSE = 1/(1 + SINR)$ from all schemes under consideration when the number of resource blocks is between $N_{rb} = 1$ and when $N_{rb} = 5$. The mean square error is a good measurement of the performance of the SIC operation. As generally seen from the figure, the highest and the worst error is produced by the PFFP and the lowest error is achieved by the ES scheme. The proposed DPSO scheme follows closely the ES scheme in the error performance. This result further signifies the improved performance of the proposed DPSO as opposed to the existing PFFP scheme.

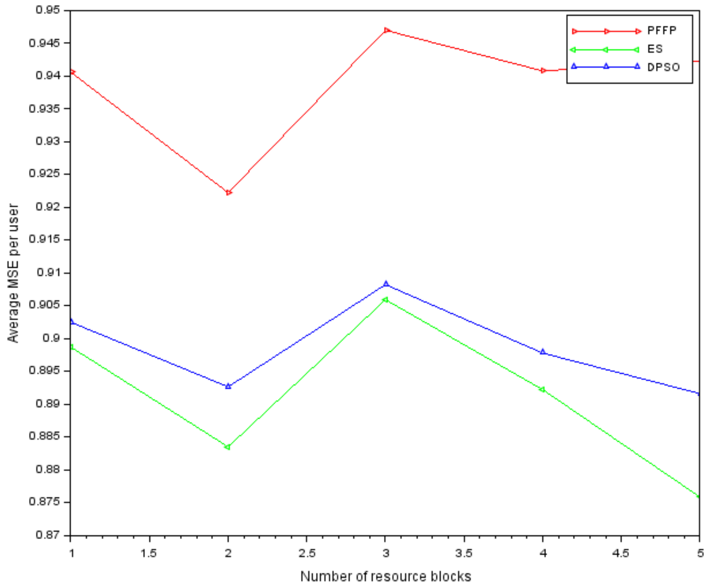

Figure 3: Measurement of the average MSE per user.

4 Conclusion and Future Work

In supporting the increasing number of users demanding the network connections from 5G networks and beyond, the proposed DPSO has been demonstrated to perform well in increasing the achievable mean throughput whiles reducing the average MSE per user. It has also been demonstrated that the required computational complexity by the proposed DPSO at each iteration is also low, hence potentially suitable to be implemented with more users. In the future, the proposed DPSO can be further enhanced and integrated with power domain NOMA systems which requires power allocation. A larger number of users can also be considered and compared against other heuristic approaches such as the ant-colony optimization method.

5 Acknowledgement

This paper is prepared in accomplishment of a project at University Malaysia Kelantan (UMK) under a research fund, UMK-Fund Grant (R/FUND/A0100/01860A/001/2020/0082). The authors are hugely grateful to UMK and all parties who have helped to complete this paper.

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