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Resource Allocation Combining Heuristic Matching and Particle Swarm Optimization Approaches: The Case of Downlink Non-Orthogonal Multiple Access

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Abstract: The ever-increasing requirement of massive connectivity, due to the rapid deployment of internet of things (IoT) devices, in the emerging 5th generation (5G) mobile networks commands for even higher utilization of the available spectrum. Non-orthogonal multiple access (NOMA) is a promising solution that can effectively accommodate a higher number of users, resulting in increased spectrum utilization. In this work, we aim to maximize the total throughput of a NOMA system, while maintaining a good level of fairness among the users. We propose a three-step method where the first step matches the users to the channels using a heuristic matching algorithm, while the second step utilizes the particle swarm optimization algorithm to allocate the power to each channel. In the third step, the power allocated to each channel is further distributed to the multiplexed users based on their respective channel gains. Based on extensive performance simulations, the proposed method offers notable improvement, e.g., 15% in terms of system throughput and 55% in terms of user fairness.

Keywords: 5G; heuristic optimization; non-orthogonal multiple access; resource allocation

1. Introduction

1.1. Preliminaries

Future 5th generation (5G) mobile networks have increased requirements in terms of connectivity, data rates, capacity, and bandwidth. Profound modifications are envisioned in the underlying infrastructure and wireless access technologies ([1–4]) in order to accommodate the exponentially increasing number of mobile devices [5].

The support for a massive number of internet of things (IoT) devices is a substantial requirement for the 5G of mobile networks [6,7]. As a consequence, the dense deployment of a massive number of devices increases the experienced interference. In the widely used orthogonal multiple access (OMA) schemes [8], the interference is mitigated by allocating time, frequency or code resources orthogonally. Nevertheless, the limited available spectrum along with the massive number of deployed devices makes the orthogonal resource allocation inefficient and impractical [9,10].

The non-orthogonal multiple access (NOMA) concept enables devices to share the frequency resources, which leads to improved spectrum efficiency [11,12]. NOMA exploits the power domain, as many users are multiplexed at the same frequency using different power levels. The distinction and separation of the multiplexed messages are achieved by the successive interference cancellation (SIC) process [13,14]. The basic concept of SIC is to detect the strongest user signal from the original received signal, which contains the signals of multiple users transmitting on the same frequency. Once the strongest user signal is detected, its contribution to the original signal is regenerated and subtracted from the received signal. The steps of the SIC process are summarized

1. Detect the strongest user signal from the received signal.
2. Decode the user signal.
3. Regenerate the strongest user signal using its chip sequence.
4. Use the generated signal to cancel the user signal from the received signal.
5. Repeat the process until all the users have decoded their respective signals.

Figure 1 shows a comparison between the NOMA and OMA schemes, where two users are connected to the same base station (BS). User 1 has better channel gain than user 2, as user 1 is located closer to the BS. In the OMA scheme, the BS transmits the signals in different channels, so the interference between them is eliminated. On the other hand, in the NOMA scheme, the two signals are encoded using different power levels and transmitted on the same channel. Upon signal reception, user 1 performs SIC to remove the signal of user 2 and then she/he decodes its respective signal. User 2, having worse channel gain, is not able to perform SIC and considers the signal of user 1 as noise.

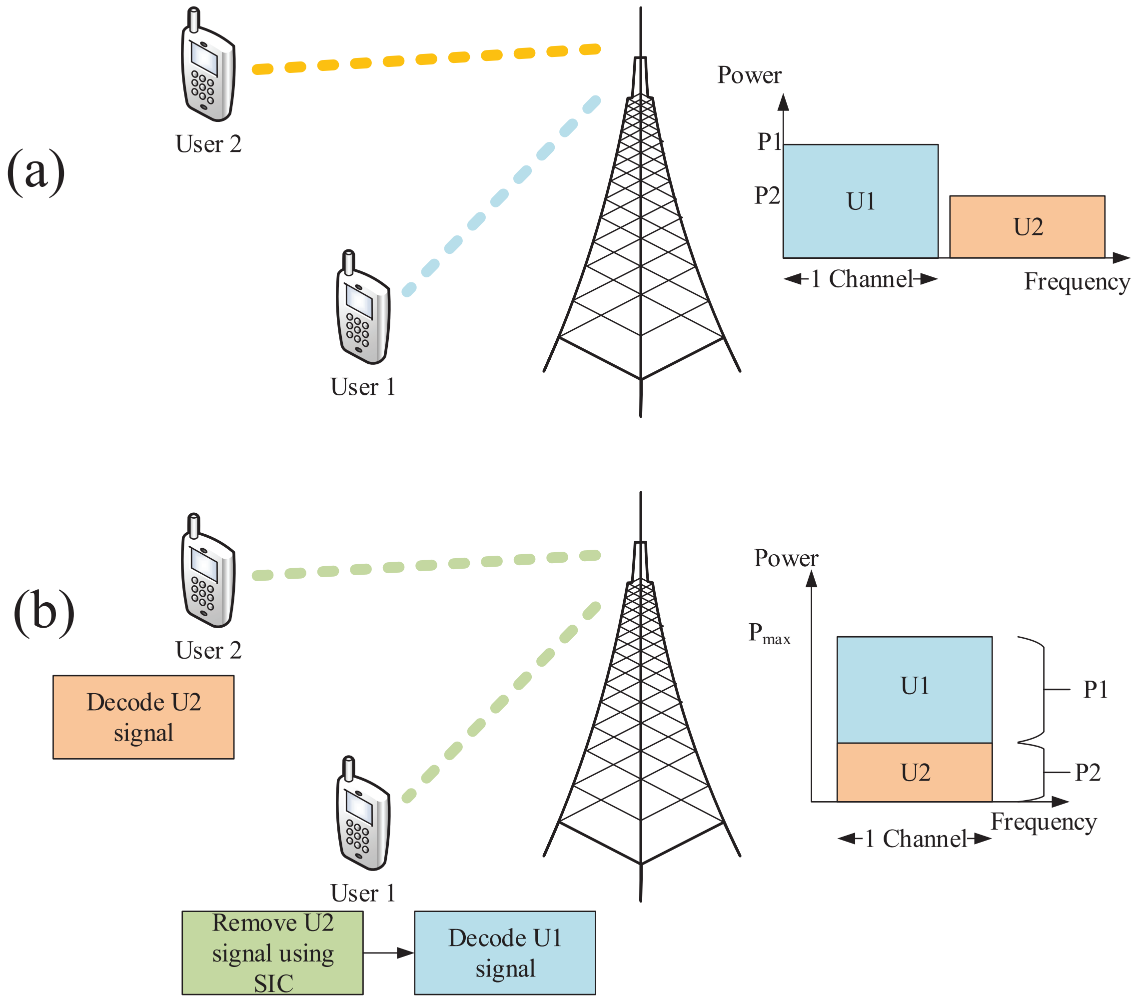

Figure 1. Conceptual comparison between (**a**) orthogonal multiple access (OMA) and (**b**) non-orthogonal multiple access (NOMA).

1.2. Related Work

The aforementioned remarks indicate that the user and channel matching, as well as the power allocation, significantly affect the performance of NOMA systems. A summary of the related works is shown in Table 1. The reference column contains the references of the related works, while the Aim and Proposed method columns contain the problem that the authors aim to solve and their proposed method respectively.

Table 1. Summary of related works.

Reference	Aim	Proposed Method
[15]	Investigation of outage probability in NOMA system with randomly deployed users	Mathematical analysis of the outage probability
[16]	Channel assignment and power allocation optimization	Channel assignment exploiting matching theory and power allocation using water-filling method
[17]	Power allocation optimization	Clustering of deployed users using mixed integer non-linear programming
[18]	Channel assignment and power allocation optimization	Water-filling method in order to maximize the total system throughput
[19]	Interference mitigation in MIMO NOMA systems	Application of beamforming techniques on user clusters
[20]	User scheduling and power allocation optimization	Matching theory and successive convex approximation techniques
[21]	Power allocation optimization in heterogeneous NOMA systems	Iterative distributed power allocation scheme
[22]	Power allocation optimization and interference mitigation in heterogeneous NOMA systems	Interference alignment scheme based on user clustering
[23]	Power allocation optimization in heterogeneous NOMA systems	Exploitation of CoMP schemes in order to apply a low-complexity distributed power optimization method
[24]	Energy efficiency optimization for multi-cluster MIMO NOMA system under QoS constraints	Water-filling-based method in order to maximize the system throughput under a given total power
[25]	Throughput maximization through power control and beamforming	Decomposition of the joint problem into sub-problems and development of a sub-optimal solution
[26]	User scheduling and power allocation optimization	Exploitation of Lyapunov stochastic optimization scheme
[27]	Maximization of spectral efficiency in a NOMA system with mixed-traffic requirements	Developed a group-based power allocation scheme
[28]	Throughput maximization in relay-based NOMA systems	Conversion of the quasi-concave problem into a convex one, and proposal of a dynamic power allocation scheme
[29]	User scheduling and power allocation optimization	Leverage of convex optimization techniques
[30]	Maximization of the minimal achievable user throughput	Development of a two-step joint beamforming and power allocation solution
[31]	Minimization of transmission power under throughput constraints in MIMO NOMA systems	Combination of power allocation, user clustering and beamforming techniques
[32]	Optimization of proportional fairness of the users	Joint user pairing and power allocation method
[33]	Energy efficiency optimization through optimal resource allocation	Formulation as linear programming problem and utilization of CPLEX optimization tool

The outage probability and throughput of a NOMA system are investigated in [15]. Di et al. [16] proposed a method that optimizes the channel assignment and power allocation in order to achieve a balance between the number of scheduled users and system throughput. The authors in [17] proposed a low-complexity sub-optimal clustering scheme, where cluster power allocation is optimized under constraints. Hojeij et al. [18] proposed a water-filling-based power allocation method that is implemented within the proportional fairness scheduler. Ali et al. [19] investigated the application of NOMA with SIC in downlink multiple-input multiple-output (MIMO), where the number of users is greater than the number of antennas in the BS. The users are formed into clusters and a linear beamforming technique is proposed in order to mitigate the intra-cluster interference. The authors in [20] utilized matching theory and successive convex approximation techniques in order to optimize user scheduling and power allocation. Ni et al. [21] solved the resource allocation problem by maximizing the sum-rate of a heterogeneous NOMA network under the constraints of maximum transmit power and Quality of Service requirements. In [22] proposed a method to efficiently calculate the allocated user power in MIMO NOMA systems. Their proposed method involves an interference alignment scheme that organizes users into clusters in order to mitigate the intra-cluster interference. The authors in [23] consider the dynamic power allocation problem in heterogeneous NOMA systems, by exploiting coordinated multi-point (CoMP) schemes. The problem was formulated as a joint power optimization problem among the coordinating BSs and a low-complexity distributed power optimization approach was proposed. Zeng et al. [24] considered the energy efficiency optimization problem for a multi-cluster multi-user MIMO NOMA system under a quality of service (QoS) constraint for each user. The proposed method optimizes energy efficiency by utilizing a water-filling-based method in order to maximize the system throughput under a given total power. Zhu et al. [25] considered the throughput maximization of a 2-user uplink NOMA system through joint power control and beamforming. As the problem is non-convex, they decomposed into two subproblems and proposed a sub-optimal solution. The authors in [26] proposed a joint user scheduling and power allocation scheme based on the Lyapunov stochastic optimization method. Brighente and Tomasin [27] proposed a method to increase the spectral efficiency of a downlink NOMA system with mixed-traffic requirements. They split the power allocation problem into two sub-problems and proposed a group-based power allocation scheme. The power allocation in NOMA systems where the communication among the BS and the users is facilitated through relays is investigated in [28]. The authors converted the original quasi-concave optimization problem into a feasible convex problem and proposed a dynamic power allocation scheme in order to maximize system throughput. The authors in [29] proposed a two-step user scheduling and power optimization scheme based on convex optimization techniques in order to optimize the energy efficiency of a heterogeneous NOMA system. Xing et al. [30] proposed a joint beamforming and power allocation solution, in order to maximize the minimal achievable throughput among multiple users. Jeong et al. [31] proposed a scheme that involves power allocation, user clustering, and beamforming in order to minimize the transmit power under throughput constraints in Multiple Input Single Output NOMA systems. Chen et al. [32] aim to improve the proportional fairness of the users, by proposing a joint user pairing and power allocation approach. An approach to optimize energy efficiency is presented in [33]. The complex resource allocation problem is reformulated as a linear programming problem and solved using the CPLEX optimization tool.

The majority of the works found in the literature aim to increase the performance of NOMA systems in terms of throughput, energy efficiency, and user fairness, through power allocation optimization, user clustering, and beamforming techniques [34]. The resulting optimization problem is non-convex, which means that there are no tractable solutions. Most of the aforementioned works aim to solve the problem by converting it into tractable sub-problems, resulting in a sub-optimal solution. Heuristic and evolutionary algorithms can prove to be promising assets in solving non-convex optimization problems, as they iteratively improve a starting solution until they reach a near-optimal one. Nevertheless, there are limited works that utilize evolutionary algorithms in order to optimize the performance of NOMA systems.

1.3. Novelty of This Work and Structure of the Paper

This paper extends our earlier work, presented in [35], by solving (a) the user-channel matching problem using a heuristic matching algorithm and (b) the power allocation problem using an evolutionary algorithm, namely particle swarm optimization (PSO) [36]. The proposed heuristic matching algorithm, produces a stable matching between two disjoint sets of users and channels, while the PSO algorithm near-optimally distributes the power budget to the channels. Summarizing, the contribution of this work is as follows:

- A heuristic user-channel matching algorithm.
- Optimal power allocation to each channel using the PSO algorithm.
- Intra-channel power allocation to each user based on the channel gain of each user.

The remainder of the paper is organized as follows. Section 2 describes the NOMA downlink system and formulates optimization problem. In Section 3, we describe the proposed method used to solve user-channel matching and power allocation problems. Section 4 presents the system model parameters and the performance indicators, along with the results. Finally, Section 5 concludes the paper.

2. System Description and Problem Formulation

2.1. Description of the NOMA Scheme with SIC

A summary of all the terms mentioned in this section is summarized in Table 2. We consider a system consisting of a BS and K randomly deployed users connected to the BS. The BS has a total power budget of P_{max}, while the total system bandwidth B is divided into S channels. The BS transmits the multiplexed signals of up to N_s users in the same channel using different power levels. The transmitted signal x_s on channel s is given by:

$$x_s = \sum_{k=1}^{N_s} \sqrt{P_{s,k}} x_{s,k}, \tag{1}$$

where $P_{s,k}$ is the power allocated to the k multiplexed user on channel s, and $x_{s,k}$ the transmitted signal relative to that user. The received signal of user k on channel s is given by $y_{s,k}$.

$$y_{s,k} = h_{s,k} x_s + w_{s,k}, \tag{2}$$

where $h_{s,k}$ denotes the channel gain coefficient of fading channel and $w_{s,k}$ denotes the additive white Gaussian noise (AWGN). The users with better channel gain, denoted by $h_{s,k}$, perform the SIC process ([37,38]) in order to separate their respective signal, considering the other user signals as interference. For example, assuming that $N_s = 2$ and $h_{s,1}^2 > h_{s,2}^2$, the first user performs SIC and removes the second user's signal, while the second user considers the first user's signal as noise. Thus, the achievable throughput of two multiplexed users on channel s is given by:

$$\begin{aligned} R_{s,1} &= \frac{B}{S} \log_2\left(1 + \frac{h_{s,1} P_{s,1}}{\frac{B}{S} N_0}\right) \\ R_{s,2} &= \frac{B}{S} \log_2\left(1 + \frac{h_{s,2} P_{s,2}}{h_{s,2} P_{s,1} + \frac{B}{S} N_0}\right), \end{aligned} \tag{3}$$

where $P_{s,1}$ and $P_{s,2}$ are the BS transmit power to users 1 and 2 respectively, and N_0 is the noise power spectral density of the AWGN, which is assumed to be constant over all channels.

Table 2. Notations and symbols.

Term	Description
B	Total system bandwidth
$h_{s,k}$	Channel gain coefficient
K	Number of users
N_0	Noise spectral density of AWGN
N_s	Number of multiplexed users in the same channel
P_{max}	Total power budget of the Base Station
$P_{s,k}$	Power allocated to user k in channel s
$R_{s,k}$	Achievable throughput of user k in channel s
S	Number of channels
$w_{s,k}$	Additive White Gaussian Noise
x_s	Transmitted signal in channel s
$x_{s,k}$	Transmitted signal of user k in channel s
$y_{s,k}$	Received signal of user k in channel s

2.2. Problem Formulation

The Equation (3) indicates that the selection of the multiplexed users and the amount of power allocated to each user on each channel affects the total achievable throughput of the whole system R_{total}, which is given by:

$$R_{total} = \sum_{s=1}^{S} \sum_{k=1}^{K} R_{s,k} \tag{4}$$

We introduce an $S \times K$ binary matrix Θ, in which each element denotes whether channel s is assigned to user k. For example, consider the following matrix which denotes the assignment of three channels to four users:

$$\Theta = \begin{bmatrix} 0 & 1 & 0 & 1 \\ 1 & 1 & 1 & 0 \\ 1 & 0 & 1 & 0 \end{bmatrix}, \tag{5}$$

The first row, which corresponds to the first channel, indicates that the channel is assigned to the second and fourth users. Similarly, the second channel is assigned to the first, second, and third users. Finally, the third channel is assigned to the first and third users. Therefore, Equation (4) becomes:

$$R_{total} = \frac{B}{S} \sum_{s=1}^{S} \sum_{k=1}^{K} \theta_{s,k} \log_2\left(1 + \frac{h_{s,k} P_{s,k}}{I_{s,k} + \frac{B}{S} N_0}\right), \tag{6}$$

where $I_{s,k}$ denotes the interference the user experiences from other users and $\theta_{s,k}$ is a binary element of the matching matrix Θ. Considering the SIC description from the previous subsection, the interference of user k on channel s is:

$$I_{s,k} = \sum_{i=1, h_{s,k} < h_{s,i}}^{N_s} h_{s,k} P_{s,i}. \tag{7}$$

Consequently, the optimization problem is formulated as follows:

$$\begin{aligned} \max_{\theta_{s,k}, P_{s,k}} \; & \frac{B}{S} \sum_{s=1}^{S} \sum_{k=1}^{K} \theta_{s,k} \log_2\left(1 + \frac{h_{s,k} P_{s,k}}{I_{s,k} + \frac{B}{S} N_0}\right) \\ \text{subject to: } & \sum_{s=1}^{S} \sum_{k=1}^{K} P_{s,k} \leq P_{max} \\ & \theta_{s,k} \in \{0,1\}, \forall s \in S, \forall k \in K \\ & \sum_{k \in \theta_s} \theta_{s,k} \leq N_s, \forall s \in S. \end{aligned} \tag{8}$$

The first constraint ensures that the sum of the allocated power does not exceed the BS total power budget. The second constraint ensures that the elements of matrix Θ are binary. Finally, the third constraint ensures that each channel is not assigned to more than N_s users.

3. Proposed Channel Matching and Power Allocation Methods

The aforementioned optimization problem is a non-convex optimization problem, which is too complex to solve it using conventional methods. Furthermore, there are three substantial requirements, in order to ensure a high QoS: (a) the whole process of channel matching and power allocation should be completed within a few seconds, (b) ensure the connectivity of all the users within the area, and (c) maintain a good level of fairness among the users. Therefore, we decouple the channel–user matching and power allocation problems and we propose a method that solves the optimization problem in three steps. In the first step, we solve the channel assignment problem by utilizing a heuristic matching algorithm, while in the second step we utilize the PSO [39] algorithm to solve the power allocation problem. Finally, the power allocated to each channel is distributed to each user matched to that channel, based on the user's channel gain.

A conceptual example of the proposed approach is shown in Figure 2. In this example, there are six users randomly deployed and five available frequency channels. Using the heuristic user-channel matching algorithm each user is matched with a number of channels. After the matching procedure, the power level of each channel is calculated using the PSO algorithm. Finally, the power level of each channel is distributed proportionally to the corresponding users depending on the channel gain.

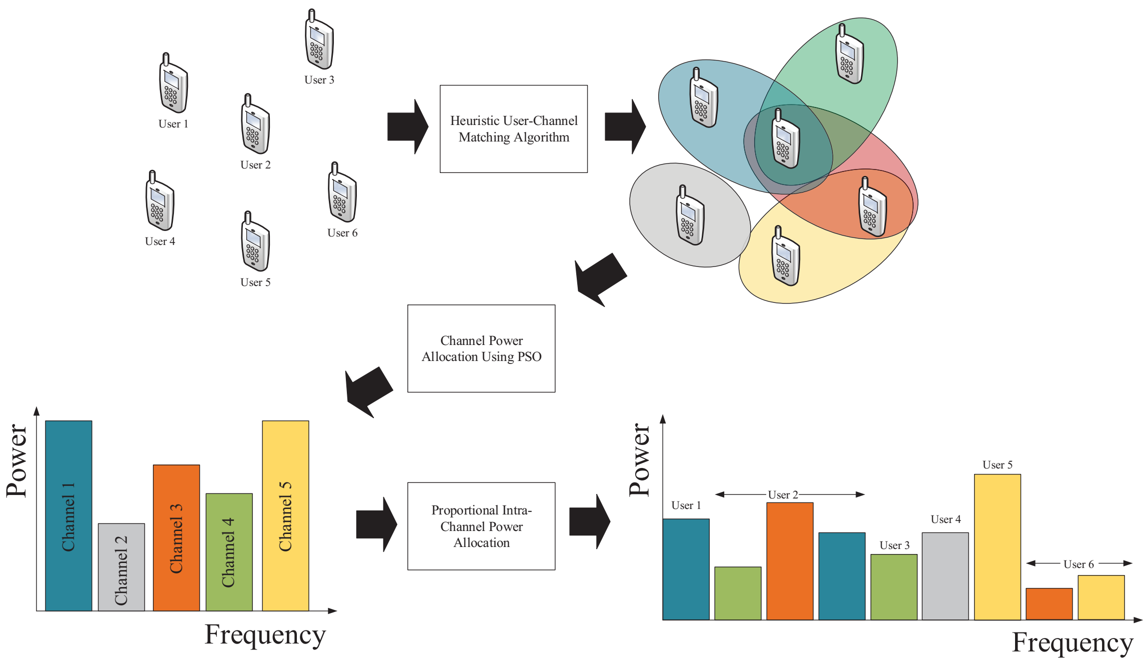

Figure 2. Conceptual example of the proposed approach.

3.1. Heuristic User-Channel Matching

We consider a set of users, K, and a set of channels, S as two disjoint sets, where each member of each set aims to maximize its performance. The users aim to match with specific channels that provide the best channel gain. On the other hand, the channels aim to match with one or more users, so that the channel has the best performance in terms of throughput. In order to solve this matching problem, we propose a heuristic matching algorithm, which manages to achieve a stable matching between elements of two disjoint sets, while taking into account the preference of each element in the first set.

The proposed method that solves the channel-user matching problem is shown in Algorithm 1. In the initialization phase of the algorithm, a channel preference list is formed for each user and all users and channels are considered unmatched. Additionally, a counter $C(s), \forall s \in S$ holds the number of matched users of each channel. In the main loop, each user proposes itself to its most preferred channel. If the channel has not been matched with a user ($C(s) = 0$), the proposed user is matched with the channel. If the channel has been already assigned to a user, it has to choose among three options, depending on the resulting channel throughput: a) keep the current user, b) drop the current user and match with the new user, and c) keep the current user and multiplex him with the new one. In the case of $C(s) = N_s$, the channel will keep the set of users that result in the maximum throughput. Equation (3) is used for calculating the channel throughput, assuming that $P_{s,1} = P_{s,2} = 1$. Each time a user is matched with a channel or dropped from a match he/she proposes to his/her next preferred channel. The algorithm completes when all users and channels are matched.

Algorithm 1 Heuristic channel–user matching.

Input: S: number of channels, K: number of users, H: channel gain matrix
Output: Θ: user-channel assignment binary matrix

Initialization:
for each user $k = 1$ to K **do**
  initialize the channel preference list *user_pref_list* based on H
end for
for each channel $s = 1$ to S **do**
  set the number of matching users to zero: $C(s) = 0$
end for
Main loop:
while there are unmatched channels and users **do**
  for each *user* in *unassigned_users* **do**
    each user proposed to its most preferred channel
    if $C(s) = 0$ **then**
      the user is matched with the channel
    else if $1 \leq C(s) \leq N_s$ **then**
      the channel matches with the new user if the multiplexing of the users results in better channel throughput
    else if $C(s) > N_s$ **then**
      the channel chooses the set of users that results in the best channel throughput
    end if
    Θ is updated accordingly
  end for
end while
return Θ

3.2. Power Allocation

After all, channels have been matched to their respective users, we utilized the PSO algorithm to calculate the allocated power in each channel. In the case of two users sharing the same channel, for the intra-channel power allocation, the user with better channel gain will be allocated more power.

Therefore, the PSO calculates the power allocated to each channel by considering the user with a better channel gain.

PSO is an optimization technique, which is based on the flocking behavior of birds. A large population (swarm) of candidate solutions (particles) are placed at random initial positions and move in the search-space until the optimal solution is detected.

An implementation of the PSO developed for optimizing the power allocation problem is shown in Algorithm 2. The number of channels, the population size, and the channel gain of each user is used as inputs, while the output vector $\bar{P} = \{P_1, ..., P_s, ..., P_S\}$ contains the final allocated powers to each channel. A penalty function is incorporated to the fitness function [40] in line 10, in order to enforce the constraints of the optimization problem. This means that when a potential solution violates the constraint the corresponding fitness function greatly deteriorates.

Algorithm 2 Channel power allocation using particle swarm optimisation (PSO).

Input: S: number of channels, M: population size, h_s: user gain of each channel
Output: $\bar{P}$: power assigned to each channel

Initialization:
1: **for** each particle $i = 1$ to M **do**
2: initialize the particle's random position x_i
3: set the particle's best known position ($pbest$) to the initial position
4: set the swarm's best known position ($gbest$) to the initial position
5: **end for**

Main loop:
6: **while** termination condition is not met **do**
7: **for** each particle $i = 1$ to M and each channel $s = 1$ to S **do**
8: update the particle's velocity:
$v_{i,s} \leftarrow w * v_{i,s} + c_1 * rand() * (pbest_{i,s} - x_{i,s}) + c_2 * rand() * (gbest_s - x_{i,s})$
9: update the particle's position:
$x_{i,s} \leftarrow x_{i,s} + v_{i,s}$
10: evaluate the fitness function f as:
$f = \sum_{s=1}^{S} \log_2(1 + \frac{h_s^2 P_s}{\frac{B}{S} N_0}) - 100 * max(0, \sum_{s=1}^{S}(P_s - P_{max}))^2$
11: update the particle's best known position $pbest_{i,s}$ and the swarm's best known position $gbest_s$ based on the fitness function
12: **end for**
13: **end while**
14: Output the swarm's best position: $\bar{P} \leftarrow gbest_s$
15: **return** $\bar{P}$

Finally, for determining the intra-channel power allocation, we distribute the allocated channel power to the multiplexed users, proportionally to their channel gains. Hence, the power of each user is calculated as:

$$P_{s,k} = \frac{\bar{P}_s \left(\frac{h_{s,k}^2}{\frac{B}{S} N_0}\right)^{-\gamma}}{\sum_{j \in \theta_s} \left(\frac{h_{s,j}^2}{\frac{B}{S} N_0}\right)^{-\gamma}}, \forall s \in S \text{ and } \forall k \in K, \tag{9}$$

where θ_s is the set of users matched to channel s, and γ is a decay factor ranging from $0 \leq \gamma \leq 1$.

3.3. Numerical Example

In this subsection, an illustrative example of the proposed user-channel matching and power allocation method is presented. We consider four users, namely A–D, aiming to match with six channels.

The channel preference order, which is based on the channel gains, for each user is shown in Table 3. At the beginning of the process, each user proposes to the most preferred channel in order to match. According to Table 3, users A and B will propose to channel 3, while users C and D will propose to channel 5. Each of the channels evaluates its corresponding proposals in terms of achieved throughput. Channel 3 calculates the achieved throughput of all possible options (as described in the previous section) and it determines that the maximum throughput is achieved in the case that both A and B users are multiplexed. Channel 5 determines that it achieves better throughput if it matches only with user C. Therefore, users A and B are matched with channel 3, and user C is matched with channel 5. User D will propose to its next preferred channel (i.e., channel 6). After this first round of matches, channels 1, 2, and 4 remain unmatched. Hence, the channel preference order will be adjusted so it only contains the unmatched channels. Similarly, user A will propose to channel 1, user B will propose to channel 4, user C will propose to channel 2, and user D will propose to channel 4. Channels 1 and 2 have not been previously matched so they will accept the proposals of users A and C respectively. Channel 4 determines that it achieves better throughput if users B and D are multiplexed, so it accepts D's matching proposal. The final matchings are channel 1—user A—channel 2—user C—channel 3—users A and B—channel 4—users B and D—channel 5—user C—and channel 2—user D.

Table 3. Channel Preference Order of Each User

User	Channel Preference Order
A	3, 1, 2, 6, 5, 4
B	3, 4, 5, 2, 1, 6
C	5, 2, 6, 3, 4, 1
D	5, 6, 4, 1, 2, 3

The PSO algorithm was used to calculate the power allocated to each channel, so the total system throughput is maximized. As stated in the previous section, in the case of two users sharing the same channel, the user with the better channel gain was considered for the calculation of the allocated channel power. In this example, we utilized four particles for the PSO algorithm.

Three representative snapshots of the initial, intermediate, and final phases of the PSO algorithm are shown in Table 4. Each particle consists of six values, which correspond to the power levels of each channel. The throughput column shows the sum throughput of all channels.

In the initialization phase, each particle's value was set to a random number ranging from 0 to P_{max}. In this phase, the third particle achieves the best performance. In the intermediate phase, the values of the particles start to converge, while the 1st particle achieves the best performance. In the final phase, all particles have converged to the same values, along with the sum-throughput of the channels.

Upon the completion of the PSO algorithm, the intra-channel power allocation is calculated for the channels that are shared between two users, using Equation (9).

Table 4. PSO Phases

	Channels	1	2	3	4	5	6	Channel Throughput
Initialization	1st Particle	1.399	4.636	3.282	0.489	1.463	5.427	79.269
	2nd Particle	2.438	5.058	4.756	0.390	1.663	5.024	80.480
	3rd Particle	3.971	4.386	5.258	3.001	2.370	5.861	**84.798**
	4th Particle	5.036	2.699	4.879	0.132	2.608	4.496	79.584
Intermediate	1st Particle	6.690	6.217	7.386	5.243	3.706	8.447	**88.520**
	2nd Particle	6.082	6.181	7.651	4.680	3.644	8.637	88.269
	3rd Particle	5.676	6.231	7.435	4.269	3.373	8.318	87.842
	4th Particle	5.331	7.295	7.647	4.379	3.403	8.477	88.096
Final	1st Particle	6.869	6.694	8.020	5.399	3.961	9.058	**89.023**
	2nd Particle	6.869	6.694	8.020	5.399	3.961	9.058	**89.023**
	3rd Particle	6.869	6.694	8.020	5.399	3.961	9.058	**89.023**
	4th Particle	6.869	6.694	8.020	5.399	3.961	9.058	**89.023**

4. Performance Evaluation

4.1. System Model Parameters

In order to evaluate the proposed method, we utilize a realistic scenario similar to the one depicted in Figure 2. In this scenario, we utilize the heuristic user-channel matching algorithm to match the available frequency channels to the users, which are randomly deployed in the cell area. Afterward, we calculate the power allocated to each channel using the PSO algorithm. Finally, the power of each user in each channel is calculated proportionally to the channel gain of that user.

A simulation environment in Matlab was developed, where the aforementioned scenario was designed to evaluate the proposed method against the methods proposed in [16,35], as well as the conventional OMA scheme. The final results were derived by taking the average values from running 10^4 simulations. The parameters of the system are based on the LTE/LTE-advanced specifications [41] and they are summarized in Table 5. A BS is placed at the center of a 500m radios cell, with a maximum power budget of 46 dBm, while the users are randomly deployed. The number of users ranges from 6 to 20, while the QoS threshold ranges from 1 to 15 Mbps. The system bandwidth is 10 MHz, divided into 8, 16, 32, 64, or 128 channels, with a carrier frequency of 2 GHz. The distance-dependent path loss model is considered with a decay factor of 3.76, while the noise power spectral density is -174 dBm/Hz. The maximum number of multiplexed users is $N_s = 2$, while perfect channel estimation is assumed.

For the PSO algorithm, we utilize a population size of $M = 100$ particles. The inertia weight w decreases in each iteration from $w_{max} = 0.9$ to $w_{min} = 0.4$, while the acceleration factors are set to $c_1 = c_2 = 0.25$ [42]. The *main loop* of the PSO algorithm terminates if the algorithm reaches 1000 iterations or if the *gbest* value is not optimized further than a tolerance factor of 10^{-12}. Finally, the decay factor for intra-channel power allocation is set to $\gamma = 0.7$.

Table 5. Simulation parameters.

Parameter	Value
Carrier Frequency	2 GHz
Cell Radius	500 m
Maximum Transmission Power	46 dBm
Number of channels	8, 16, 32, 64, 128
System Bandwidth	10 MHz
QoS Threshold	1–15 Mbps

Table 5. *Cont.*

Parameter	Value
Distance Dependent Path Loss	128.1 + 37.6log10(d), d in km
Noise Power Spectral Density	−174 dBm/Hz
Number of deployed users	6–20
Maximum number of multiplexed users	2
PSO Population Size	100
PSO Inertia Weight	0.9–0.4
PSO Accelaration Factors	0.25
PSO Maximum Iterations	1000
PSO Best Value Gain Tolerance	10^{-12}
Intra-channel Power Allocation Factor	0.7

4.2. Numerical Results

For the evaluation of the results, we adopted three performance metrics, namely the total achieved system throughput, the user fairness and the average number of unconnected users. The user fairness is calculated using the Gini fairness index [43], which is defined as:

$$G = \frac{1}{2K^2\bar{r}} \sum_{x=1}^{K} \sum_{y=1}^{K} |r_x - r_y|, \text{ where}$$
$$\bar{r} = \frac{1}{K} \sum_{k=1}^{K} r_k \text{ and } r_k = \sum_{s=1}^{S} R_{s,k}. \tag{10}$$

The Gini index ranges from 0, corresponding to the maximum fairness level, to 1, corresponding to the minimum level of fairness among users. We evaluate the proposed user–channel matching PSO (UCM-PSO) method, by comparing it with the User-subchannel matching algorithm (USMA) proposed in [16], our previously proposed extensive tabu search PSO (ETS-PSO) method [35], as well as with the conventional OMA scheme.

Figure 3 depicts the achieved system throughput as a function of the number of channels, assuming that the number of deployed users is $K = 10$. In the USMA case, the total system throughput was about 185 Mbps, while in the UCM-PSO, ETS-PSO, and OMA, the throughput was 155 Mbps, 147 Mbps, and 145 Mbps, respectively. The USMA had the best performance of all compared methods as the users close to the BS are matched with more channels because. The UCM-PSO method has better performance compared to the ETS-PSO as the channel preference of each user is considered instead of enforcing a tabu search scheme which may result in a user not having a chance to match with a more preferred channel. The OMA scheme had the worst performance as each user was matched with a single channel, so the available bandwidth was not utilized effectively.

Figure 4 depicts the achieved system throughput as a function of the number of users, assuming that the number of channels is $S = 128$. In all cases the total system throughput is increasing as the number of users increases. Specifically, the USMA's throughput increases from 172 Mbps to 197 Mbps. The UCM-PSO ranges from 150 Mbps to 158 Mbps, while the ETS-PSO ranges from 145 Mbps to 150 Mbps. The OMA scheme ranges from 143 to 148 Mbps. The results indicate that the USMA has the best performance as the number of channels is considerably higher than the number of users, so the users closest to the BS have wider allocated bandwidth. The UCM-PSO and ETS-PSO methods present an increase in the achieved system throughput as the number of users increases. This is expected as more users are multiplexed over the channels, thus increasing the bandwidth utilization. The UCM-PSO has better performance than the ETS-PSO as each user has a better chance to match with his/her preferred channels. The OMA scheme has the worst performance due to the lower efficiency of bandwidth utilization.

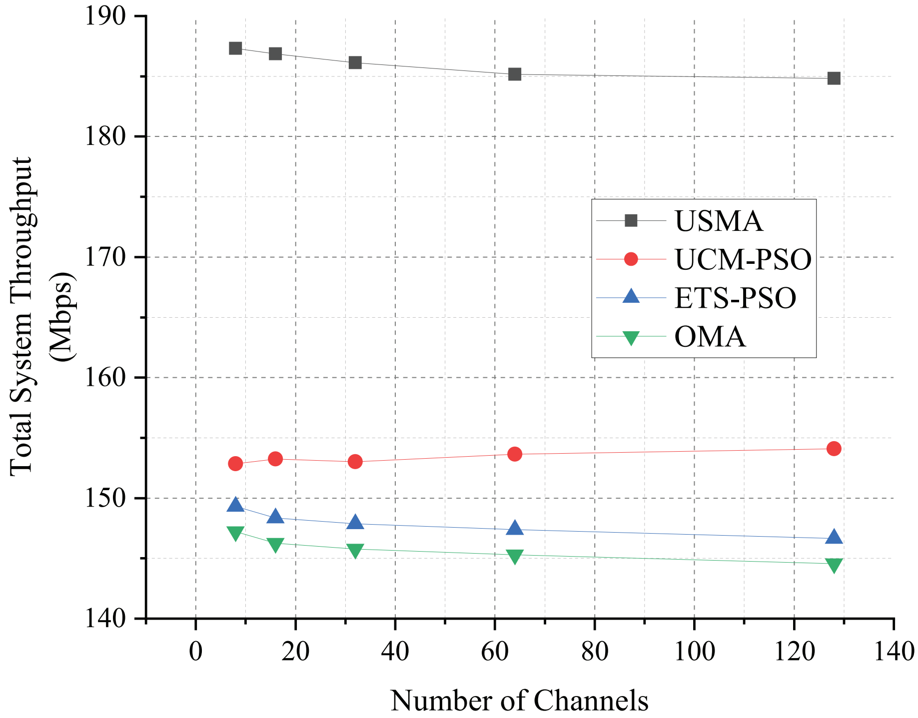

Figure 3. Achieved system throughput for $K = 10$ users, when the number of channel ranges from 8 to 128.

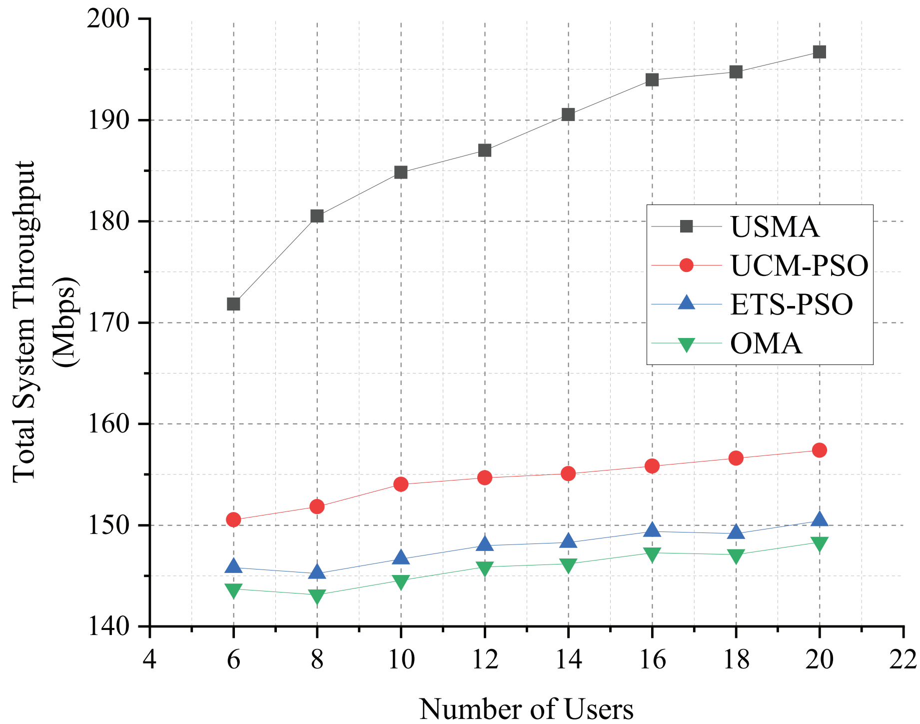

Figure 4. Achieved system throughput for $S = 128$ channels, when the number of users ranges from 6 to 20.

Figure 5 depicts the Gini fairness index as a function of the number of channels, assuming that the number of deployed users is $K = 10$. The USMA had an index value of about 0.80, while OMA's value was around 0.55. The index values of ETS-PSO and UCM-PSO decreased as the number of channels increase. Specifically, ETS-PSO ranges from 0.50 to 0.25, and UCM-PSO ranges from 0.38 to 0.12. The USMA had the worst performance in terms of fairness as the users closest to the BS will be matched to more channels, while the users farthest from the BS were matched to less or no channels. Similarly, in the OMA scheme, the users closest to the BS were matched to more channels. The ETS-PSO had better performance as the employed tabu search scheme enforces that all channels uniformly matched to all users. The proposed UCM-PSO achieved performance increases as the number of channel increases as the users have a higher number of preferred channels to match to, meaning that the available bandwidth is more effectively utilized.

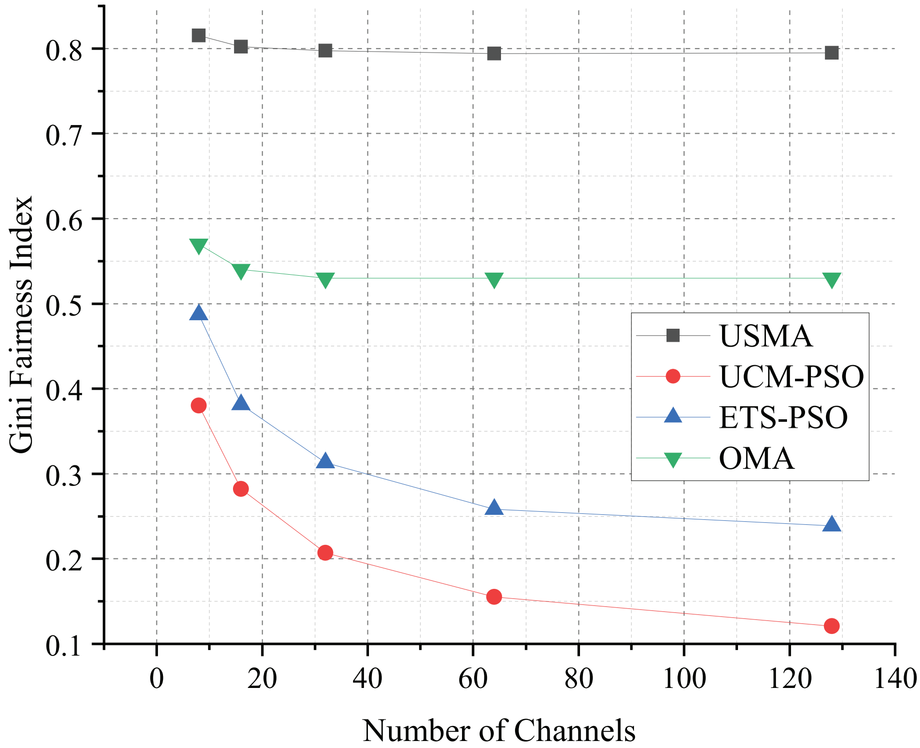

Figure 5. Gini fairness index for $K = 10$ users, when the number of channel ranges from 8 to 128.

Figure 6 depicts the Gini fairness index as a function of the number of users, assuming that the number of channels is $S = 128$. As the number of users increased, the USMA's index value increased from 0.65 to 0.90, while OMA's value increased from 0.50 to 0.60. The ETS-PSO's index maintained a steady value of 0.25, while UCM-PSO's value slightly increases from 0.10 to 0.16. The OMA scheme matched each channel to a single user, meaning that the users close to the BS will have greater throughput compared to the others, which justifies the poor performance. Similarly, in the USMA, the users close to the BS were matched with more channels. In ETS-PSO a tabu search scheme is employed, so all users have an equal number of matched channels. The proposed UCM-PSO method has the best performance as it manages to maintain a balance between the channel preference of each user and the number of channels matched to each user.

Figure 7 shows the average number of unconnected users as a function of the number of channels, assuming that the number of deployed users is $K = 10$. As the OMA scheme matches one user to each channel, the number of unconnected users was zero when the number of channels was greater than the number of users. The USMA leaves some users unconnected as the users close to the BS were matched to more channels, while users far from the BS were not matched to any channel at all. The ETS-PSO method equally distributes the channels to all users, while the proposed UCM-PSO method enforces that all users were matched to the available channels.

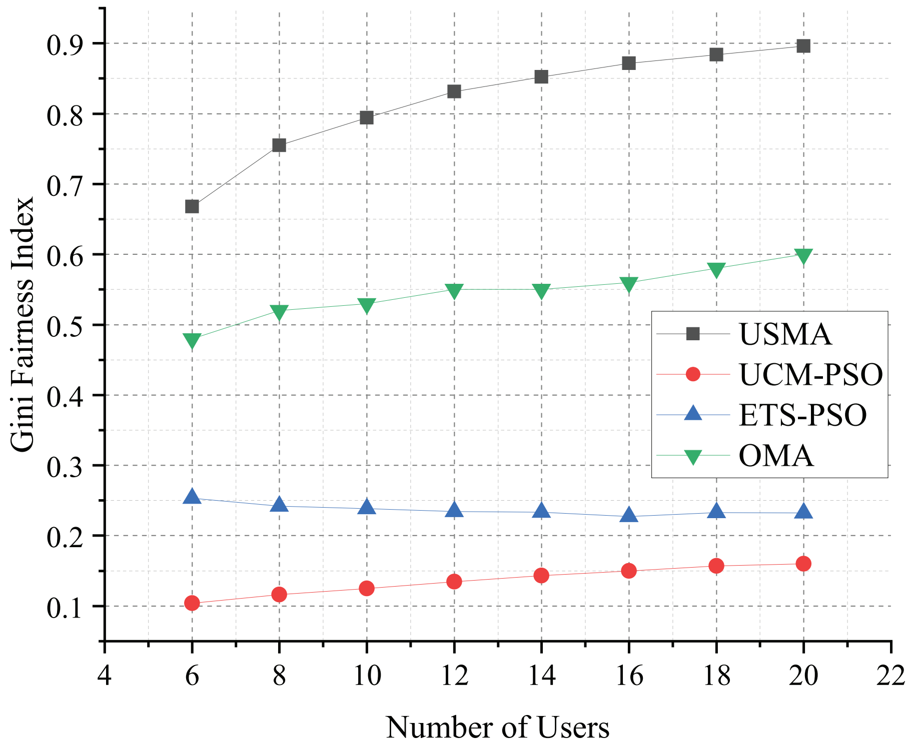

Figure 6. Gini fairness index for $S = 128$ channels, when the number of users ranges from 6 to 20.

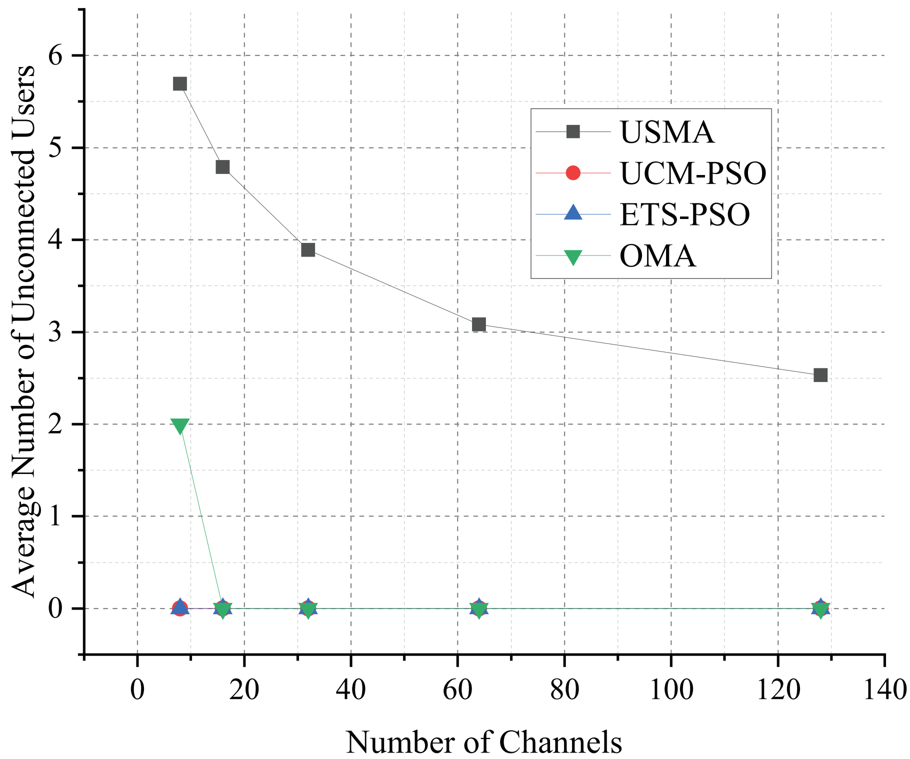

Figure 7. Average number of unconnected users for $K = 10$ users, when the number of channel ranges from 8 to 128.

Figure 8 shows the average number of unconnected users as a function of the number of users, assuming that the number of channels is $S = 128$. The OMA scheme, the ETS-PSO, and the UCM-PSO present similar performance as there is not a single unconnected user. In the USMA the average number of unconnected users linearly increases with the number of deployed users.

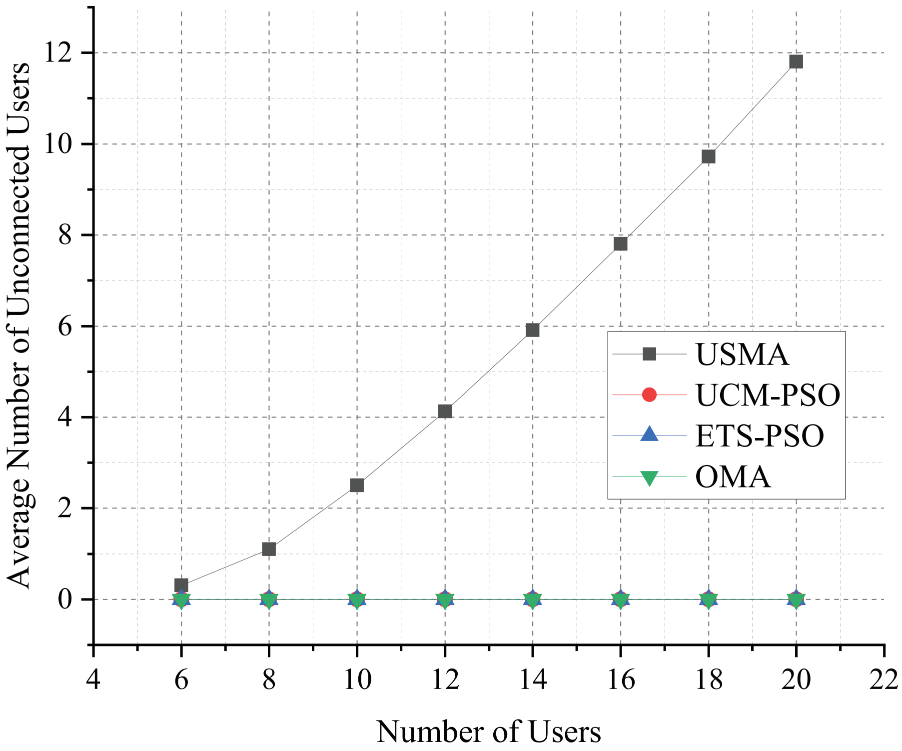

Figure 8. Average number of unconnected users for $S = 128$ channels, when the number of users ranges from 6 to 20.

Figure 9 shows the average user throughput as a function of the number of users, assuming that the number of channels is $S = 128$. The OMA and the ETS-PSO schemes achieved similar performance. The UCM-PSO achieved slightly better performance, while USMA achieves the best performance in terms of the average user throughput.

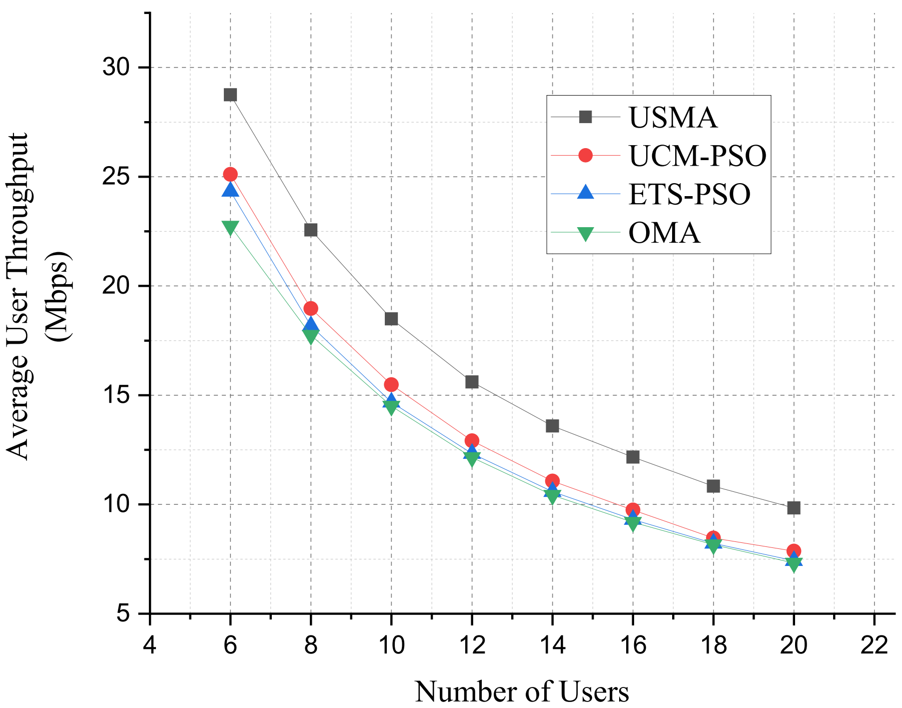

Figure 9. Average user throughput for $S = 128$ channels, when the number of users ranges from 6 to 20.

Figure 10 shows the percentage of users that achieve lower performance than the QoS threshold, assuming that the number of channels is $S = 64$ and the number of users is $N = 10$. The QoS threshold ranges from 1 to 15 Mbps. The UCM-PSO algorithm achieves the best performance, as the percentage of users bellow the QoS threshold is low, compared to the others. The ETS-PSO achieves similar performance, while the percentage is very high in the OMA and USMA schemes.

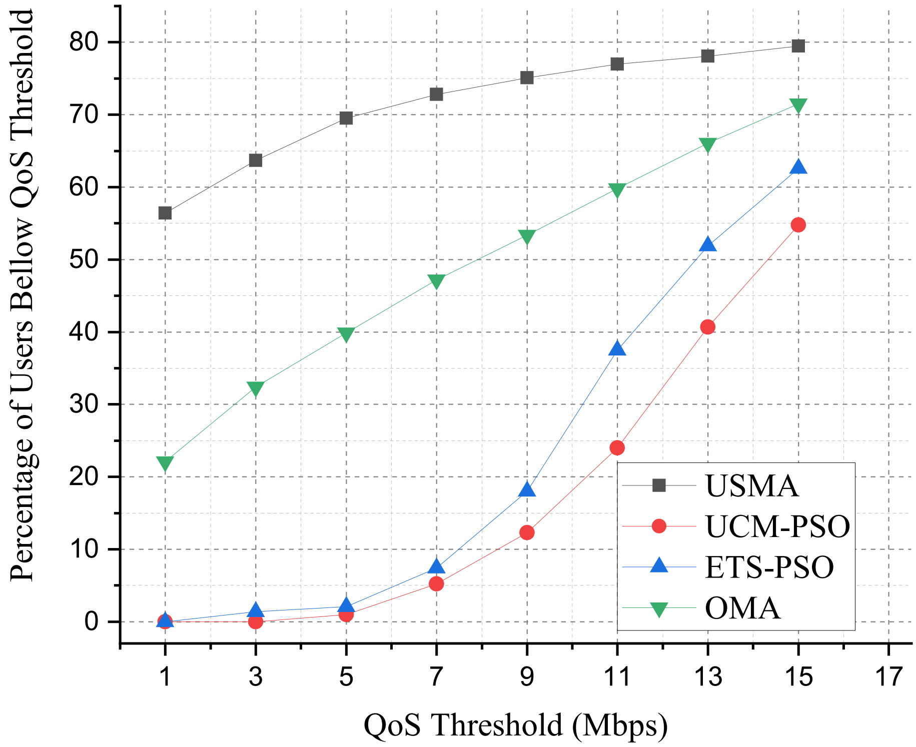

Figure 10. Percentage of users that achieve lower performance than the quality of service (QoS) threshold, for $S = 64$ and $N = 10$.

5. Conclusions

Driven by the limited spectrum availability and the exponential proliferation of IoT devices, we proposed a method that improves the 5G mobile network performance. In particular, we proposed a three-step method that solves the user-channel matching and power allocation problems. In order to evaluate the performance of the proposed method, we performed extensive simulations and compared the results with the USMA proposed in [16], our previous method presented in [35] and the conventional OMA scheme. The results indicate that our proposed method outperforms all the compared ones in terms of system fairness and average number of unconnected users.

In the future, we aim to extend this method to a more complicated system involving Multiple Input Multiple Output antenna configurations. Additionally, the mitigation of inter-cell interference among the users who are deployed on the cell edge will be investigated [44,45]. Finally, data offloading are promising techniques in order to provide high quality of service and experience [46,47] in dense heterogeneous 5G network deployments. Hence, we plan to extend the work by investigating interference mitigation techniques among different wireless communication technologies.

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