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# A PSO-Based Approach for User-Pairing Schemes in NOMA Systems: Theory and Applications

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**ABSTRACT** This paper proposes an exhaustive analysis of a particle swarm optimization (PSO)-based configuration applied in non-orthogonal multiple access (NOMA) systems in order to perform user aggregation along different sub-channels. The idea behind this is to highlight the main characteristics of this PSO-based configuration for understanding how this policy enables the transmitter to require the minimum downlink transmitting power while guaranteeing the quality-of-service (QoS) constraint of each user. The analysis is carried out for two representative power-constrained scenarios, i.e., disaster relief network communications and unmanned aerial vehicle (UAV) communications, in which performing low-power transmissions represent an important aspect. Our results find applicability in the definition of explicit channel-state-aware strategies for user multiplexing in NOMA systems, which, at the date, represents a research field that remains to be investigated more in depth. Insightful discussions are provided from our analysis. For instance, depending on the number of available sub-channels and the channel gains experienced by each users along with the whole available bandwidth, it is shown how users must be multiplexed by the transmitter in order to reach the minimum transmitting power.

**INDEX TERMS** NOMA, PSO, sub-band mapping, user-aggregation.

## I. INTRODUCTION

During the last decade, the diffusion of powerful multimedia devices, such as smartphones and tablets, has grown exponentially. In particular, according with the Wireless World Research Forum, in 2020 seven trillions of wireless devices will serve seven billions of people [1]. In addition, the rapid development of the mobile Internet and the Internet of Things (IoT) is drastically accelerating the demand for high data-rate and low-latency applications. As a consequence, there will be a high density of devices sharing the scarce physical radio resources and generating a huge amount of data traffic, i.e., 49 exabytes of monthly global mobile data traffic according to Cisco forecast [2]. This is creating the need for a new wireless communication technology referred to as

5G [3]. More specifically, respect to the actual 4G networks, the 5G wireless communication systems will achieve *i)* from 10 up to 100× higher typical user-data rate, *ii)* 1000× higher mobile data volume per geographical area, *iii)* from 10 up to 100× more connected devices, and *iv)* sub-millisecond level end-to-end latency [4]. Then, in order to meet diverse requirements of 5G, an efficient, scalable and flexible air-interface, which includes different modules of both physical (PHY) layer and medium access control (MAC) layer, is required [5].

In cellular mobile communications, the design of a suitable radio access technology (RAT) represents an important aspect for improving the system capacity in a cost-effective manner. A RAT basically utilizes a channel access technique to provide multiple mobile terminals with a connection to the core network. Nowadays, such multiple access techniques can broadly be categorized into two different classes [6]:

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*i*) orthogonal multiple access (OMA), and *ii*) non-orthogonal multiple access (NOMA).

Frequency division multiple access (FDMA), time division multiple access (TDMA), code division multiple access (CDMA), and orthogonal frequency-division multiple access (OFDMA) are examples of OMA schemes. All these schemes allow each user to entirely separate unwanted signals from the desired signal. For example, in a simple scheme like TDMA, several users share the same frequency and separation is possible since they communicate in rapid succession, each using its own assigned time slot. On the other side, a more sophisticated scheme, like OFDMA, allows multi-user communications through an orthogonal frequency-division multiplexing (OFDM) technique in which subcarrier frequencies are chosen so that the subcarriers are orthogonal to each other.

In contrast to OMA, NOMA allows to allocate one frequency channel to multiple users at the same time within the same cell, offering a number of advantages which permit to label NOMA as a promising multiple access scheme for future radio access technology [7]–[9]. The basic idea of NOMA is to serve multiple users in the same resource (time/frequency/code) block (RB). This is possible through power-domain superposition coding (SC) multiplexing at transmitter and successive interference cancellation (SIC) at receiver [10], [11]. In other words, a Base Station (BS) which serves  $N$  users, within its coverage area, transmits a linear superposition of  $N$  users' data by allocating a fraction  $\beta_i$  of the total available power  $P$  to each user, i.e. the power allocated for the  $i_{th}$  user is  $P_i = \beta_i P$ . Then, each user is able to decode its own data by deleting the interfering users' signals through the SIC principle.

The performance of NOMA-based systems is hence strongly dependent on the adopted power allocation scheme. Indeed, based on users' channel condition, the transmitter needs to carefully choose the proper amount of power which should be assigned to each user in order to satisfy network service requirements, i.e., Quality-of-Service (QoS), user-perceived data, maximum throughput.

Next, for sake of completeness, a brief state of the art related to NOMA power allocation works is provided. However, it is worth to mention that providing an exhaustive state of the art analysis regarding NOMA power allocation scheme is outside the scope of this paper. Then, only a list of some related works, which can be served as a benchmark for new ones, will be provided and discussed.

## A. RELATED WORKS

Since the basic principle of NOMA is to serve multiple users through power-domain SC multiplexing at transmitter and SIC at receiver, as stated earlier, one of the main challenges of this multiple access technique is represented by the power allocation scheme. In other words, the transmitter needs to carefully choose the amount of power which should be assigned to each user during signal transmission. Generally, this choice depends on the channel condition experienced

by each user, i.e., more power should be allocated to users with poor channel gain. Owing to this fact, several studies have been conducted in order to propose power allocation schemes, aiming to optimize some network metrics.

In [12], authors proposed a power allocation scheme to maximize network energy-efficiency (EE), defined as the ratio between the achievable sum rate of the users and the total BS power consumption. It was considered a downlink transmission scenario wherein one single-antenna BS, within a system bandwidth  $B$ , simultaneously serves  $N$  single-antenna users, each with a minimum rate requirement constraint. Based on this system setup, it was formulated and solved a fractional optimization problem in which a closed-form expression for the power coefficients of each user was derived.

A more general study than [12] has been conducted in [13]. Although a similar scenario has been considered, i.e., a single-antenna BS serves  $N$  single-antenna users, in addition it was assumed that the whole bandwidth is divided into  $M = \frac{N}{2}$  sub-channels, performing downlink NOMA transmissions with two users multiplexed in the same sub-channel. Different network optimization problems were analyzed, i.e., EE, sum-rate and fairness maximization, and for each of them a closed-form expression for the optimal power coefficients was provided.

In [14], a dynamic power allocation scheme for downlink multi-carrier NOMA (MC-NOMA) systems has been proposed. It was considered a downlink system where the BS transmits to a pair of users which share  $K$  orthogonal sub-carriers. A low-complexity algorithm was designed for the optimal power allocation which maximizes the weighted sum rate. In particular, through the proposed algorithm it was possible to evaluate the proper amount of power which should be allocated to each user over each sub-channel.

The application of multiple-input multiple-output (MIMO) techniques to NOMA systems represents an important way to further enhance the performance of such multiple access technique. Under this perspective, authors in [15] proposed a joint beamforming and power allocation design in NOMA-MIMO systems. It was considered a downlink transmission scenario where the BS, equipped with  $N_t$  antennas, communicates with two single-antenna users. For that scenario, two beamforming schemes were proposed, each with an optimal power allocation scheme aiming to maximize the sum rate.

A more general and exhaustive study for NOMA-based MIMO system has been presented in [16]. It was analysed a scenario in which a BS is equipped with  $N_t$  antennas and each user is equipped with  $N_r$  antennas. In particular, it was supposed  $N_r > \frac{N_t}{2}$  in order to implement the concept of signal alignment for suppressing co-channel interference [17], [18]. A novel MIMO-NOMA framework for either downlink and uplink transmissions was presented, designing a sophisticated approach for user precoding/detection vector selection and analysing the impact of different power allocation strategies, namely fixed power allocation and cognitive radio inspired power allocation.

Finally, since millimeter-wave (mm-wave) wireless communications represents another important candidate for the development of 5G networks, the possibility for integrating the NOMA technology with mm-wave communications started to be investigated along the last years. Specifically, authors in [19] proposed a game-theory based approach for user clustering and power allocation in mm-wave-NOMA systems. It was considered a downlink mm-wave-NOMA scenario with one BS and  $N$  users, equipped with  $N_t$  and  $N_r$  antennas, respectively. These users are supposed to be organized into  $K$  clusters, each with a cluster-head (CH) node. In addition, it was assumed that only CHs' channel condition are known at the BS for applying hybrid pre-coding techniques. Then, a low complexity game theory-based algorithm for user clustering, and a closed-form solution for power allocation, aiming to maximize the cell sum-rate, were proposed.

## B. MOTIVATION

From the previous state of the art analysis, note that most of the contemporary studies on power allocation for NOMA systems can broadly be divided into two main classes: *i*) single-channel analysis and *ii*) multiple-channel analysis. In the first case, optimal power allocation schemes are derived supposing that all  $N$  users are multiplexed into power domain within the same RB [12], [14], [15]. In the second case, the available bandwidth is divided into different *independent* RBs, multiplexing a subset of users on each RB [13], [16], [19]. More particularly, as in [13], [16], the common assumption for multiple-channel analysis are: *i*) the available bandwidth  $B$  is divided into  $N$  sub-bands of dimension  $B/N$ ; *ii*) there are  $2N$  users in the area multiplexed into the power domain in a pair fashion, i.e., two users per sub-band.

Recently, in [20] it has been shown how the user aggregation process and user to sub-band pairing represent another important aspect for the performance of NOMA systems. In particular, it has been illustrated how, respect to the conventional OMA systems, the performances of a fixed power allocation NOMA (F-NOMA) can be further enlarged by multiplexing users carefully, accordingly to their channel condition. However, as we will show in the following sections, the minimum amount of power, required to transmit a linear superposition of  $N$  users' data over the same sub-channel, strongly depends on *i*) the channel gain experienced by each user, and *ii*) the QoS requirements present in the network. Then, users should be aggregated *sharply* in order to require the minimum power at the transmitter, especially in power-constrained scenario like disaster communication and unmanned aerial vehicle (UAV) communication scenarios, where the employment of low-power transmission represents a crucial aspect.

To the best of our knowledge, most of the works published in literature dealt with the aspect optimal user aggregation configuration in each sub-band through matching theory-based algorithm [21], [22], neighbour search

methods, like the hill climbing and simulated annealing [23], or game-theory based approaches [19]. Owing to this fact, an explicit user pairing strategy, which takes into account the characteristics of the channel condition experienced by each user, remains to be investigated yet. In addition, since the optimization problems for user-pairing and user to sub-band pairing in NOMA systems are represented by a mixed integer-linear problem (MILP), using the aforementioned solutions result in a high computational cost depending on the size of the problem, i.e., number of users and sub-channels considered. Then, an interesting solution would be the development of more scalable algorithms which permit the BS to reach concurrently an optimal aggregation and pairing configuration. However, in order to collect as much as possible informations, which permit to define some *rules* (algorithms) for optimal user aggregation and sub-carrier pairing in NOMA systems, the analysis of some optimal configurations arises as a crucial step.

## C. CONTRIBUTIONS

As far as the authors are aware, the technical literature lacks a comprehensive analysis of optimal user aggregation and pairing scheme configurations for NOMA systems, which can provide new insights for the development of scalable and efficient algorithms. Thus, this paper aims to fill partly this gap that exists in the literature. Specifically, in the vision of adding value to the actual state of the art, this paper contains an exhaustive analysis of the optimal user aggregation configuration in two power-constrained scenarios, i.e., disaster relief network communications and UAV communications, obtained through a particle swarm optimization (PSO)-based approach. It is noteworthy that the choice of PSO is because it has shown more promising behaviour when compared to other heuristic approaches [24]. This analysis has been conducted varying the most relevant parameters which influence the optimal user aggregation scheme in each scenario, i.e., number of available sub-channels, QoS constraint of users, cell radius, UAV height and channel gain model. These studies permitted to obtain useful informations like, the optimal number of users along each sub-channel, and how users must be multiplexed into each sub-channel depending on the channel condition experienced by each of them along the whole bandwidth. Then, authors hope that these results can serve as useful tools to scientific community in defining explicit user pairing strategy for NOMA systems.

## D. STRUCTURE OF THE PAPER

The rest of the paper is organized as follows. The system model, which permits to show how the minimum transmitting power depends from user aggregation, as well as the formulation of the minimum-power optimization problem, are presented in Section II. Section III provides the proposed PSO-based aggregation scheme. Section IV carries out the performance analysis of PSO-based approach for user aggregation subject to two scenarios, i.e., disaster communications

and UAV communications. Finally, conclusions and future directions are provided in Section V.

**II. SYSTEM MODEL**

For a sake of having a clear exposition, this section is divided into two subsections. Subsection II-A contains brief introduction of downlink NOMA transmission, illustrating how SC and SIC are implemented. Subsections II-B contains the formulation of the optimization problem for user aggregation.

**A. PRELIMINARIES**

Without loss of generality, we suppose that a single-antenna transmitter serves  $N$  single-antenna users, located within its coverage area and undergoing a channel  $\mathcal{H}$ . Since the characteristics of  $\mathcal{H}$  are specific for each considered scenario, the assumptions on that channel will be discussed in subsections IV-A and IV-B. In addition, it is assumed that users' channel gain are ordered in an ascending manner, i.e.  $0 < |h_1|^2 \leq |h_2|^2 \leq \dots \leq |h_N|^2$ . Then, the signal received by user  $i$  can be expressed as:

$$y_i = h_i \times x + w_i, \tag{1}$$

where  $x = \sum_{i=1}^N \sqrt{P\beta_i}S_i$  is the superimposed transmitted signal, with  $\sum_{i=1}^N \beta_i = 1$ ,  $h_i$  denotes the channel coefficient, and  $w_i$  represents the noise term with spectral density  $\sigma^2$ . The information  $S_i$  is then transmitted with a power level  $P\beta_i$  to user  $i$ . Each user, except the one with worst channel condition, implements the SIC iteratively, decoding signals transmitted to users with weaker channel condition firstly and subtracting them from superimposed received signal. The signal obtained through that subtracting process is used to decoding its own related message. At this step, signals associated to users with better channel condition, are considered as additive noise. Taking that into account and supposing that  $\|S_i\|^2 = 1$ , the downlink achievable rate for user  $i$  can be expressed as:

$$R_{i,DL} = \log_2 \left( 1 + \frac{\beta_i P |h_i|^2}{P |h_i|^2 \sum_{k=i+1}^N \beta_k + \sigma^2} \right). \tag{2}$$

In particular, for a better understanding, considering a two-user case and supposing that the channel gain for user 2 is higher than the one of user 1, indicating with  $P_1$  and  $P_2$  the respective power levels assigned to each user, the downlink achievable rate for each user are expressed as follow:

$$R_{1,DL} = \log_2 \left( 1 + \frac{P_1 |h_1|^2}{P_2 |h_1|^2 + \sigma^2} \right), \tag{3}$$

$$R_{2,DL} = \log_2 \left( 1 + \frac{P_2 |h_2|^2}{\sigma^2} \right). \tag{4}$$

As can be observed from Eqs. (2), (3) and (4), the user with weaker channel gain looks to be penalized. Indeed, in terms of individual rates, the weaker user is not willing to perform NOMA. Its rate is most likely to be lower than OMA case. However, the NOMA power allocation scheme aims to ensure fairness. In particular, considering two users case with asymmetric channel, NOMA technology outperforms OMA technology in terms of sum-rate [8], [11].

**B. USER AGGREGATION AND POWER REQUIREMENTS**

Suppose that the available bandwidth  $B$  is divided into  $M$  sub-bands, each of them used to multiplex an amount of user  $N_j$ , with the constraint  $\sum_{j=1}^M N_j = N$ . From (2), in order to guarantee a minimum QoS to user  $i$  multiplexed into sub-band  $j$ , i.e.,  $R_{i,DL}^j \geq R_{i,min}^j$ , the minimum amount of power  $P_{i,min}^j$  which must be allocated to that user can be formulated as:

$$P_{i,min}^j \geq A_i^j \times \left( \sum_{k=i+1}^{N_j} P_k^j + \frac{\sigma^2}{|h_i^j|^2} \right), \tag{5}$$

in which  $P_i^j = P\beta_i^j$  and  $A_i^j = \left( 2^{R_{i,min}^j} - 1 \right)$ . Considering the user with the best channel condition, and supposing that all the users have the same QoS requirements<sup>1</sup>, i.e.,  $A_{N_j} = A_{N_j-1} = \dots = A_1 = A$ , (5) can be written as:

$$P_{i,min}^j \geq \begin{cases} A \times \frac{\sigma^2}{|h_{N_j}^j|^2} = P_{N_j,min} & i = N_j; \\ A \times \left( \sum_{k=i+1}^{N_j} P_k^j + \frac{\sigma^2}{|h_i^j|^2} \right) & i < N_j; \end{cases} \tag{6}$$

After some mathematical manipulations, the second case can be re-expressed as:

$$P_{i,min}^j \geq A \times P_{N_j,min} + A \times \sum_{k=i+1}^{N_j-1} P_k^j + P_{N_j,min} \times \frac{|h_{N_j}^j|^2}{|h_i^j|^2} \tag{7}$$

Then, the total amount of power required in order to guarantee the QoS of all users into sub-band  $j$  is:

$$P_{tot}^j = \sum_{i=1}^{N_j} P_{i,min}^j \geq \sum_{i=1}^{N_j-1} A \times P_{N_j,min} + A \times \sum_{i=1}^{N_j-1} \sum_{k=i+1}^{N_j-1} P_k^j + P_{N_j,min} \times \sum_{i=1}^{N_j-1} \frac{|h_{N_j}^j|^2}{|h_i^j|^2} + P_N^{min}. \tag{8}$$

Now, grouping by common factors and observing that the first term is independent of index  $i$ , the following expression is attained:

$$P_{tot}^j \geq P_{N_j,min} \times \left( (N_j - 1)A + 1 + \sum_{i=1}^{N_j-1} \frac{|h_{N_j}^j|^2}{|h_i^j|^2} \right) + A \times \sum_{i=1}^{N_j-1} \sum_{k=i+1}^{N_j-1} P_k^j. \tag{9}$$

<sup>1</sup>This is assumed in order to analyze the dependency of the optimal configuration varying QoS constraint of users in the network.

Then, the total power over the whole bandwidth is given by:

$$P_{tot} = \sum_{j=1}^M P_{tot}^j. \quad (10)$$

This represents the minimum amount of power which is necessary to use for guaranteeing the QoS of all users multiplexed into different sub-channels, within the same bandwidth. As can be seen from (9), this amount of energy strongly depends on channel gain and QoS constraint of multiplexed users. Let  $\mathbf{U} \in \{0; 1\}^{N \times M}$  the sparse matrix in which each element  $u_{i,j}$  is equal to 1 if user  $i$  is allocated to sub-carrier  $j$  and 0 otherwise. Then, the optimization problem for minimum power requirement can be formulated as:

$$\min_{\mathbf{U}} P_{tot}; \quad (11a)$$

$$\text{s.t. } R_{i,DL} \geq R_i^{min}, \quad \forall i = 1 \dots N; \quad (11b)$$

$$\sum_{j=1}^M u_{i,j} = 1, \quad \forall i = 1 \dots N; \quad (11c)$$

where the constraint (11b) represents the minimum QoS requirement of each user, while the constraint (11c) ensures that the each user will be multiplexed only into one sub-carrier. Since this type of problem represents a MILP problem, this paper proposes a PSO-based approach to find an optimal solution. It is noteworthy that the choice of PSO is because it has shown more promising behaviour when compared to other heuristic approaches [24].

### III. PSO-BASED APPROACH FOR OPTIMAL USER-PAIRING

In this section, the PSO-based algorithm is presented with the aim to solve the optimization problem in (11). PSO is one of metaheuristic optimization techniques inspired by natural life behaviour like bird flocking and fish schooling [25], [26]. Indeed, in nature these groups of animals cooperate in order to reach a common objective. In particular, each component of the group will adjust its behaviour, i.e., position and velocity, using the group information. Then, a PSO includes a set of a predefined number, say  $N_p$ , of particles. Each particle has a position  $X_i$  and a velocity  $V_i$  in a dimensional space of dimension  $D$  and represents a solution of the optimization problem. As illustrated in Fig. 1, iteratively each particle is evaluated through a fitting function used to evaluate the quality of the solution. The value obtained through the fitting function represents the personal best of the particle, i.e.,  $Pbest_i$ , which is compared with the global best value, i.e.,  $Gbest$ . After this comparison, each particle adjusts its position and velocity along each dimension according to the following equations:

$$\begin{aligned} V_{i,d}(t) = & w \cdot V_{i,d}(t-1) \\ & + c_1 \cdot r_1 \cdot (X_{pbest_{i,d}} - X_{i,d}(t-1)) \\ & + c_2 \cdot r_2 \cdot (X_{gbest_{i,d}} - X_{i,d}(t-1)) \end{aligned} \quad (12)$$

and

$$X_{i,d}(t) = X_{i,d}(t-1) + V_{i,d}(t) \quad (13)$$

where (12) and (13) represent velocity and position along dimension  $d \leq D$  of the particle, respectively,  $w$  is the inertial weight,  $c_1$  and  $c_2$  are two non-negative constants called acceleration factors, and  $r_1$  and  $r_2$  are two different uniformly random distributed numbers in the range [0, 1].

As in [27], in this paper the initial set of particle has been created in a random fashion. In particular, for each user a random number from a uniform distribution in the range [0; 1], say  $CH_i$ , has been extracted. Since all the sub-channels have been numbered from 1 to  $M$ , the choice of channel ID of user  $i$  has been obtained through the ceil function, i.e.,  $CH_{ID,i} = \text{ceil}(CH_i \times M)$ . Regarding the evaluation of  $Pbest_i$  values of each particle, since the goal of the optimization problem is to reduce the minimum power necessary for downlink transmission, the goodness of each particle has been evaluated using (10) as fitting function. During the update of the position through (13), if the result is less than 0, another random number is extracted and assigned. Otherwise, if it is greater than 1, the value 1 has been assigned. In addition, boundary conditions have been set to minimum and maximum velocity, i.e.,  $V_{max}$  and  $V_{min}$ , respectively.

Since PSO is an iterative algorithm, usually it is terminated by setting a stop criterion. In our case, we have observed that no consistent changes to the solution happened after 500 iterations. Then, to ensure consistent results, we have selected the number of 700 iterations as PSO stop criterion. Parameters for PSO implementation are taken the same in [25], [28] and are summarized in Table 1.

TABLE 1. PSO parameters.

Parameter	Value
$N_p$	60
$N_{iterations}$	200
$C_1$	1.4962
$C_2$	1.4962
$w$	0.7968
$V_{max}$	0.5
$V_{min}$	-0.5

### IV. OPTIMAL CONFIGURATION ANALYSIS

In this section, it is investigated the performance analysis of the PSO-based aggregation approach, when applied in two representative power-constrained scenarios, i.e., disaster relief network communications and UAV communications. Under this perspective, this section is organized into three sub-sections. Specifically, Subsection IV-A focused on the analysis in the case of disaster scenario communication, while Subsection IV-B is dedicated to the analysis of UAV communication. Finally, Subsection IV-C compares the results obtained in each scenario, providing some useful insights for the design of aggregation algorithms.

For both investigated scenarios, the adopted performance evaluation index is the policy efficiency (PE). In particular, indicating by  $P_{av,R}$  the average power required through random pairing, and by  $O_{av,i}$  the average power required through

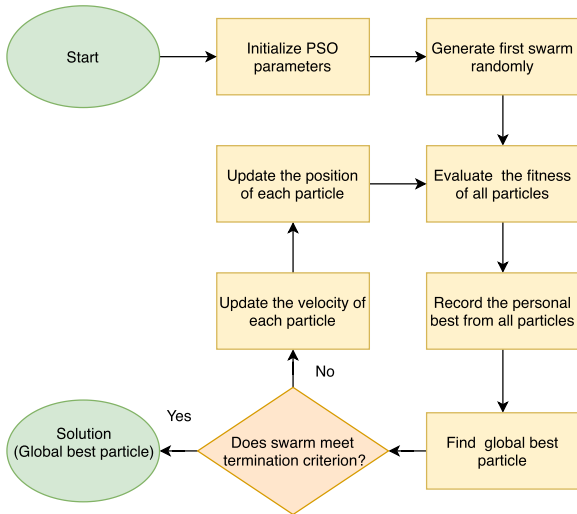


FIGURE 1. Flowchart of PSO algorithm.

PSO policy, the PE can be defined as:

$$PE_i = \frac{P_{av,R} - O_{av,i}}{P_{av,R}} \quad (14)$$

Note that (14) represents the reduction in power requirements obtained by using the configuration from PSO output instead of random policy assignment. It is worthwhile to mention that the scope of this paper is not the validation of PSO-based approach efficiency, respect to other approaches for user aggregation present in contemporary literature, but to highlight the importance of an optimal configuration in reducing power requirements and providing some useful features obtained through the analysis of such optimal configurations. Then, the random policy aggregation, even if simple, represents a good benchmark to compare the policy obtained through the PSO approach.

### A. DISASTER SCENARIO COMMUNICATION

As illustrated in Fig. 2, we consider a disaster scenario in which a BS has been fully damaged and then victims are not able to communicate their status or request help. As in [29], [30], we suppose that users are organized into clusters, and for each cluster there is a cluster head (CH) which performs radio resource management functionalities (RMM) among their users. In addition, such CHs are able to reach a functional BS organizing themselves into a relay network. Then, each cluster can be considered as a pico-cell.

In such scenario, the employment of NOMA technology can be beneficial since users of different clusters can be multiplexed into different sub-bands, reducing hence the inter-cluster interference and then the outage probability of each user which sends aid requests. However, CHs are usually power-constrained devices and the employment of a proper aggregation scheme is definitely beneficial.

A pico-cell scenario is considered in which an available bandwidth  $B$  is divided equally into  $M$  sub-bands. This band

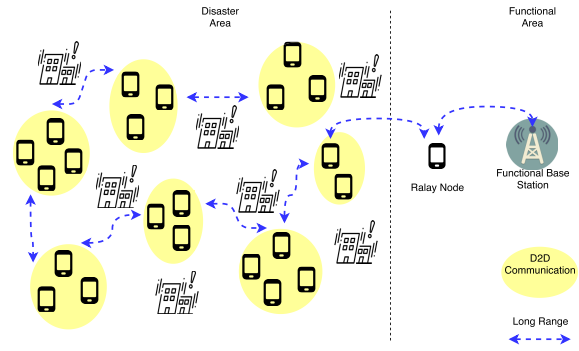


FIGURE 2. Typical disaster scenario considered.

TABLE 2. Simulation parameters for disaster scenario.

Parameter	Value
Cell Radius (m)	200
$M$ (average number of nodes)	100
Bandwidth (MHz)	40
Pathloss exponent $\alpha$	4
$N$ number of sub-channels	[25:50]
QoS Threshold [bps/Hz]	[1:5]
$\sigma$ Rayleigh	1

will be used to multiplex  $N$  users through a NOMA transmission approach. These users are distributed into a circular area of radius  $R$  according to a Poisson Point Process (PPP) and the transmitter is located at the center of this area. It is assumed that the channel statistics of all users in the bandwidth are known. The channel coefficient of Eq. (1) has been formulated as  $h = d^{-\alpha/2} \times g$ , where  $g$  follows a Rayleigh distribution,  $d$  represents the distance between transmitter and receiver, and  $\alpha$  is the path-loss exponent. The noise power at the receivers in the whole bandwidth is  $N_0 = 290 \cdot k \cdot B \cdot NF$ , where  $k$  and  $NF$  are Boltzmann constants and noise figure at 9 dB, respectively. Then, the noise power in each sub-channel is  $N_0/M$ . The most relevant simulation parameters are summarized in Table 2 and all results represent the average of 10 different simulation runs.

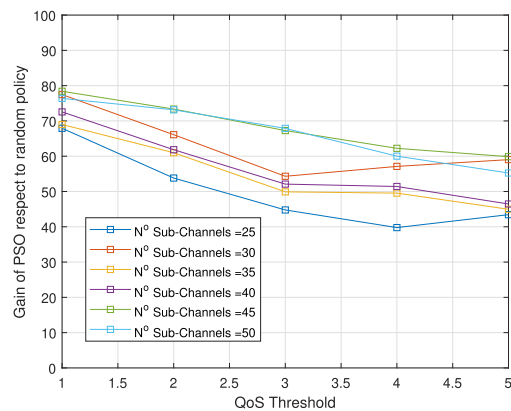


FIGURE 3. Policy efficiency gain over different QoS thresholds.

In Fig. 3 and Fig. 4, it is analysed the variation of PE gain, expressed in percentage, by varying the QoS thresholds and

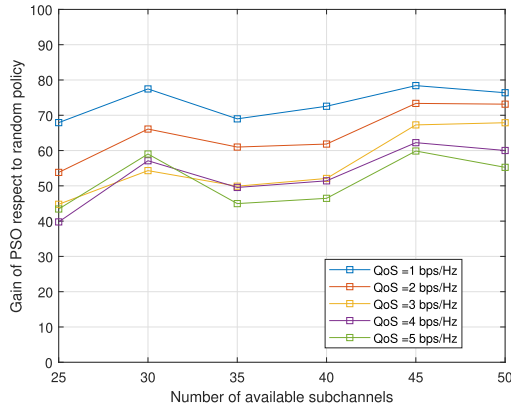


FIGURE 4. Policy efficiency gain over different number of sub-channels thresholds.

the number of sub-channels, respectively. Firstly, from these figures, one can observe how the PE range from a minimum of 45% to a maximum of 80%. This shows that for each scenario the PSO is able to find the optimal solution to proper multiplex users, requiring the minimum transmission power and guaranteeing the QoS constraints for each user. In addition, one can observe how the efficiency increases by increasing the number of available sub-channels and decreases by increasing the QoS constraint. These results are in line with Eq. (9). Indeed, an increase of the QoS constraint results in an exponentially increase of the minimum required power for all the users. Moreover, reducing the number of sub-channels implies that more users are multiplexed in each sub-band and, according to Eq. (7), the minimum required power for each of them increases as well. As a consequence the total required power increases. This further confirms the efficiency of the PSO in finding the optimal configuration that for each scenario permits to require the minimum power in order to satisfy the QoS requirements of each user.

For each pico-cell configuration, which can be obtained varying either  $M$  or the QoS constraint of each user, it is also analysed the relation between channel gain of users allocated to the same sub-channel. In particular, according to Eq. (6), for each sub-channel, we turn our attention on the quantity  $\frac{|h_i^j|^2}{|h_{N_j}^j|^2}$ , where  $|h_{N_j}^j|^2$  represents the highest channel gain allocated to sub-channel  $j$ . In other words, we analyse how, in the PSO configuration, channel gains are chosen with respect to the highest.

Since the number of users in the area is  $N = 100$  and the number of available sub-channels  $M$  varies in the range [25; 50], firstly one can note that the number of users, allocated per sub-channels through the PSO configuration, varies from a minimum of two to a maximum of four users per sub-channel, following the trend illustrated in Table 3. From these results, which have been obtained on each simulation run, one can conclude that, in addition to reach the minimum required power, the optimal configuration also tries to increase the spectrum utilization allocating all the users along all the

available sub-channels. Furthermore, one can also note that by increasing  $M$  the PSO try to allocated less user to each sub-channel.

In Fig. 5, we illustrate the channel gain ratio by varying  $M$ . In particular, these ratio values are plotted in a descending order from highest to lowest value, i.e., ID = 1 is the highest, ID = 2 is the second-highest and so on. Although these figures are labelled with the value of  $M$ , each point represents an average along the QoS dimension and has been plotted with its 95% confidence interval.

TABLE 3. Number of users spread per sub-channel.

N	With 4 UE	With 3 UE	With 2 UE
25	25	-	-
30	10	20	-
35	-	30	5
40	-	20	20
45	-	10	35
45	-	-	40

With respect to results reported in Table 3, four users per sub-channel are only allocated only when  $N = 25$  and  $N = 30$ . For this reason, Fig. 5a includes two cases and Figs. 5b-5c include four cases. It is interesting to note that most of the confidence intervals show a variation range less than 5%. This means that the QoS constraint does not strongly affect the channel ratio distribution. Regarding the points with a confidence interval higher than 5%, they are motivated by the fact that a not sufficient number of points to collect reliable statistics is present. Indeed, for each case it is observed a decrease of confidence interval as the number of cases increases, i.e., 25 for the case with 4 users per sub-channel, 30 for the case with 3 users per sub-channel and 50 for the case with 2 users per sub-channel. However, the most important result is the fact that, regardless of the number of sub-channels, channel gain ratios are maintained for each configuration, i.e., the second, third and the fourth channel gain are almost the 40%, 20% and 10% of the highest respectively.

### B. UAV COMMUNICATION

In the previous subsection, it was analysed the performance of an optimal configuration of user pairing and sub-band mapping in NOMA systems, reached through the PSO algorithm in a typical pico-cell scenario. In literature, this scenario is used to model power-constrained communications like Wireless Sensor Networks (WSN) and disaster scenario communication [29]–[33]. In addition to this scenario, we investigate now the case when the same PSO algorithm is applied to UAV communication scenario. Although, as stated earlier, this represents another power-constrained scenario, some relevant differences can be identified. For example, one key feature of a UAV is the possibility to establish a line-of-sight (LoS) towards the users in its communication range. On the one hand, the presence of a LoS communication provides the possibility to increase network coverage as well

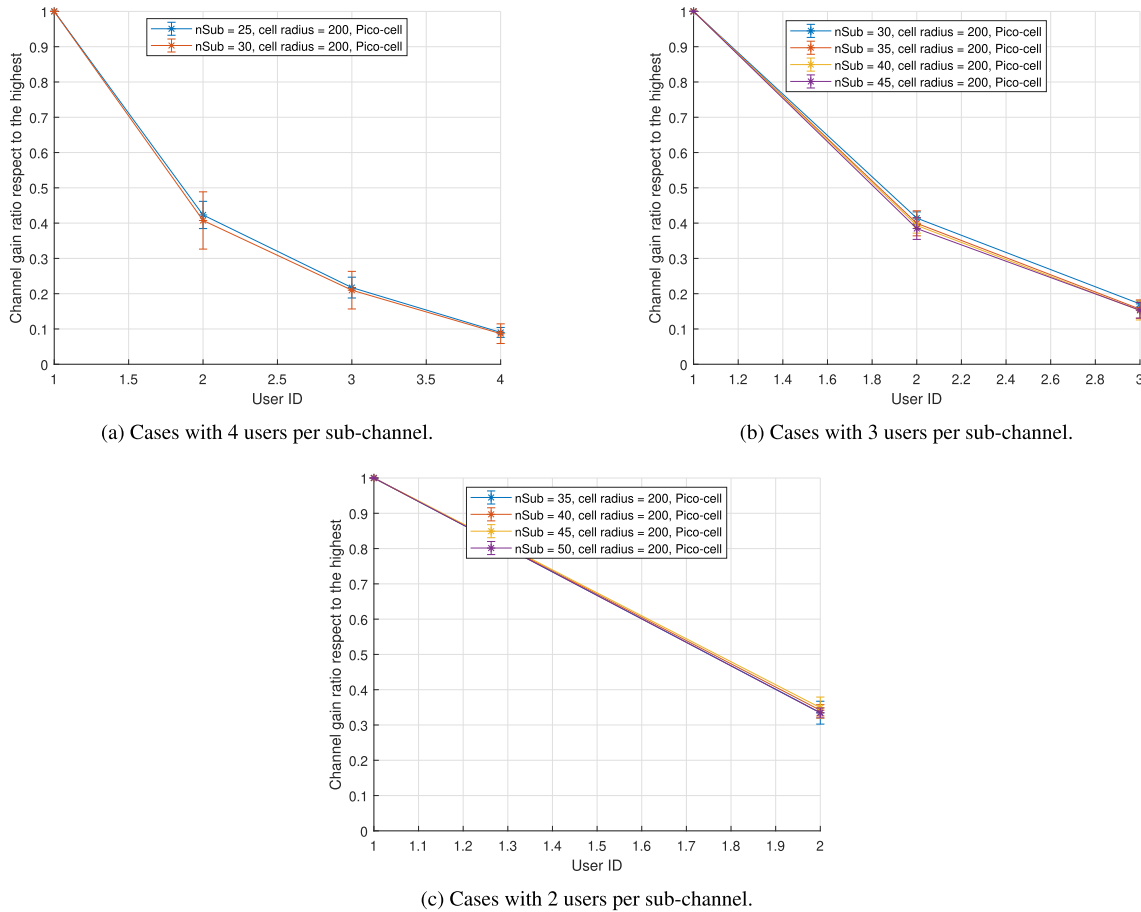


FIGURE 5. Channel gain ratio per each sub-channel in a pico-cell scenario.

as downlink/uplink throughput and QoS of users. On the other hand, this opens new challenges in the area of UAV network design and modelling [34]–[42]. Although most of the above cited works focus in maximizing a network metric, like throughput [37], energy efficiency [38], [40], [41] and spectrum efficiency [42], as function of either power control or optimal UAV trajectory/deployment, another important aspect which must be considered is the UAV propagation channel model. Indeed, due to the agility and mobility of UAV devices, several critical aspects like *i*) the highly dynamic communication channels due to UAV velocity, *ii*) the excessive spatial and temporal variations induced due to the mobility of both the aerial base station and the ground operators, and *iii*) airframe shadowing caused by the structural design and rotation of the UAV, create the need of more accurate propagation channel model than the one used for modelling the traditional channel for terrestrial communication. Exhaustive surveys about the UAV channel modelling can be found in [43], [44].

As for the pico-cell scenario, herein it is also considered a scenario in which an available bandwidth  $B$  is divided equally into  $M$  sub-bands. This band will be used to multiplex  $N$  users through a NOMA transmission approach. These users are distributed into a circular area of radius  $R$  according to a

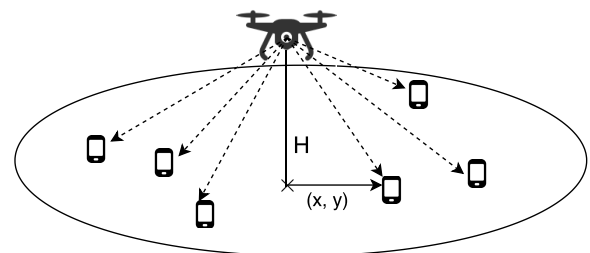


FIGURE 6. Typical UAV scenario considered.

PPP process. As illustrated in Fig. 6, the UAV is supposed to be stationary at the centre of this circular area within a predefined height  $H$ . In addition to the analysis of PE as function of  $M$  and QoS constraint, it is also investigated the performances of the PSO algorithm by varying the UAV’s height and the radius of the circular area where users are distributed. In order to perform this investigation, it is exploited the air-to-ground (ATG) channel model for D2D UAV-assisted communication provided in [45], [46]. In particular, referring to Eq. (1), the channel gain  $h_i$  from the UAV to the  $i$ -th user located at



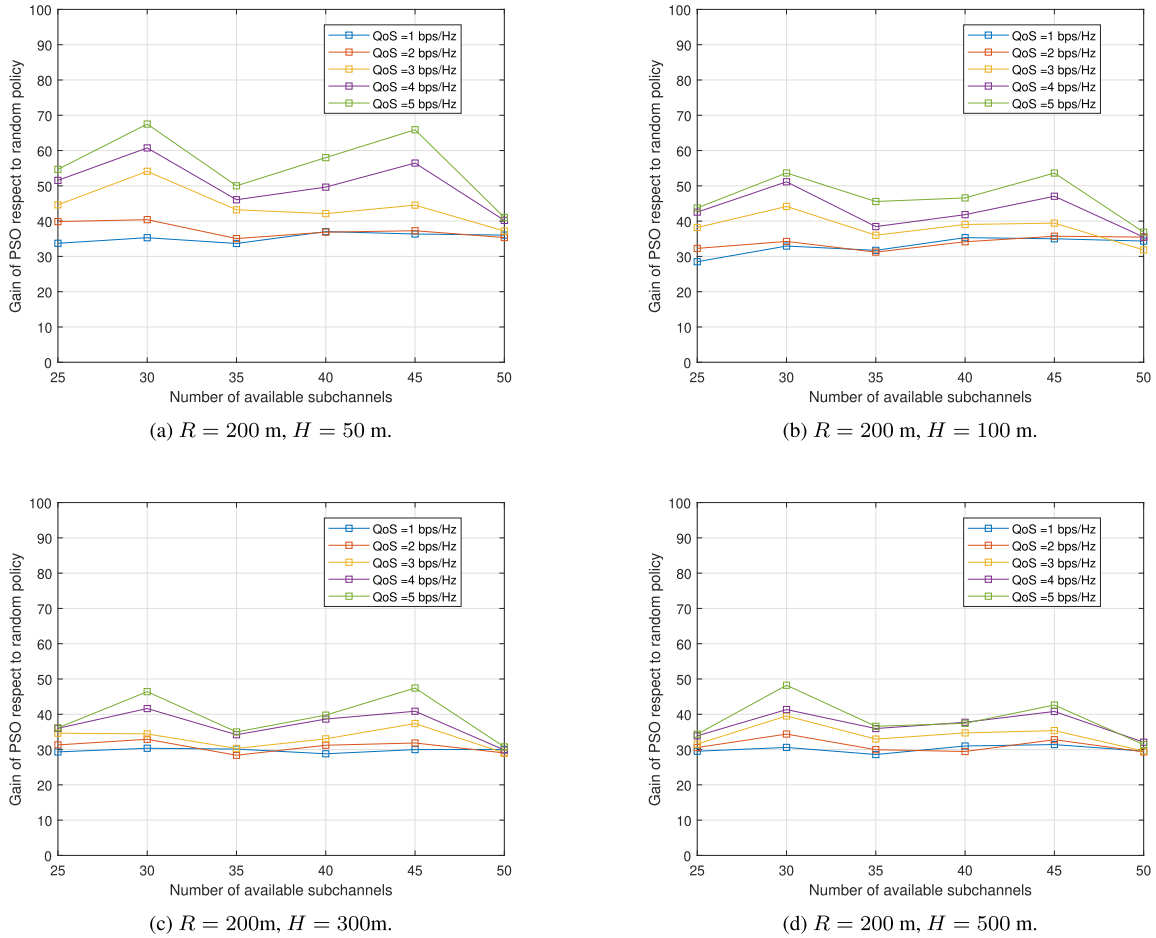


FIGURE 7. PSO algorithm efficiency by varying the number of sub-channels, QoS constraint and UAV height.

(x, y) position can be written as:

$$h_i = P_{rLOS} \times \left(\sqrt{x^2 + y^2 + H^2}\right)^{-\alpha} + P_{rNLOS} \times \gamma \left(\sqrt{x^2 + y^2 + H^2}\right)^{-\alpha} \quad (15)$$

where  $\alpha$  represents the path-loss exponent and  $\gamma$  is the excessive attenuation factor in case of the non-LoS (NLoS). Finally,  $P_{rLOS}$  and  $P_{rNLOS} = 1 - P_{rLOS}$  represent the LoS and the NLoS probability, respectively. These last two quantities are obtained from the following formula [45]:

$$P_{rLOS} = \frac{1}{1 + a \times \exp(-b[\phi - a])}, \quad (16)$$

where,  $a$  and  $b$  are constant values depending on the environment, and  $\phi$  is the elevation angle between the UAV and the user expressed in degree as follow:

$$\phi = \frac{180}{\pi} \times \arcsin\left(\frac{H}{\sqrt{x^2 + y^2 + H^2}}\right). \quad (17)$$

In order to obtain a more realistic system-level model for mobile communication, as in [47], we consider random

components  $\zeta_{LOS}$  and  $\zeta_{NLOS}$  extracted from a log-normal distribution with a zero mean and  $\sigma_{LOS}$  and  $\sigma_{NLOS}$  respectively. Then, (15) can be expressed as:

$$h_i = P_{rLOS} \times \zeta_{LOS} \left(\sqrt{x^2 + y^2 + H^2}\right)^{-\alpha} + P_{rNLOS} \times \zeta_{NLOS} \times \gamma \left(\sqrt{x^2 + y^2 + H^2}\right)^{-\alpha} \quad (18)$$

The simulation parameters used to investigate this scenario are summarized in Table 4. Simulations were conducted through MATLAB and results provided next represent, for a fixed set of parameters, the average over 10 different simulation runs.

As for the pico-cell scenario, in Fig. 7 it is illustrated the PE when the cell radius is fixed, varying the number of available sub-channels, QoS constraint of users and UAV height. From these figures, one can note that, as for the pico-cell scenario performances illustrated in Fig. 4, for a fixed QoS constraint, PE presents the highest values at  $N = 30; 45$  and respect to the last point, the same value is maintained or decreases at  $N = 50$ . Despite these similarities, one can note that, in UAV scenario, the PE increases with increasing the QoS constraint

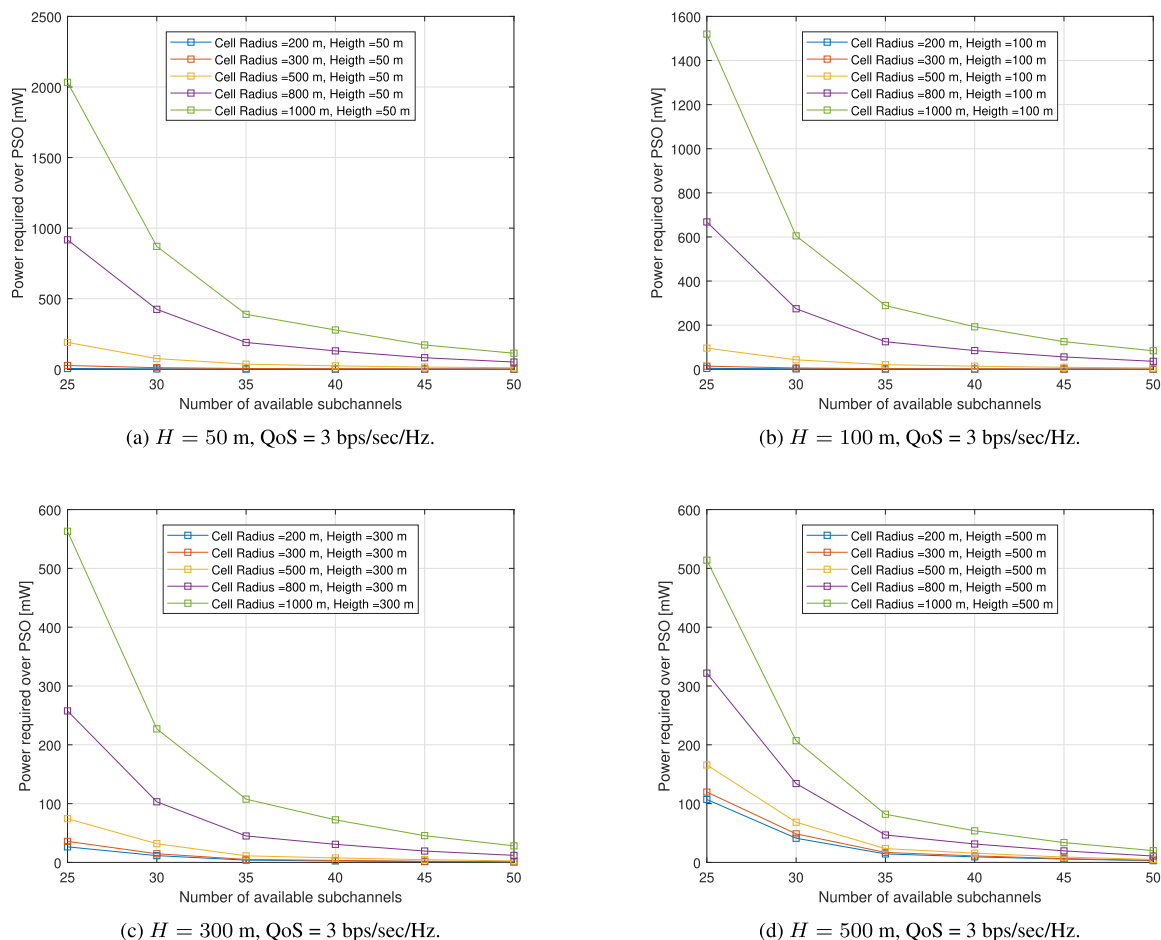


FIGURE 8. PSO maximum transmission power required by varying number of sub-channels, UAV height and cell radius.

TABLE 4. Simulation parameters for UAV scenario.

Parameter	Value
$a$	11.95
$b$	0.136
$H$ [m]	[50,100,300,500]
Cell Radius [m]	[200,300,500,800,1000]
Excessive attenuation factor $\gamma$ [dB]	20
Pathloss exponent $\alpha$	3
$\sigma_{LOS}$ [dB]	4
$\sigma_{NLOS}$ [dB]	10

and decreases with increasing of UAV height, maintaining a minimum between 30% and 35% (see cases for QoS= 1) and the maximum between 50% and 70% (see cases for QoS= 5). Since all these trends are only scaled when the UAV height varies, in order to better understand the characteristics of PSO configuration, in Fig. 9 and Fig. 8 we illustrate the PE efficiency and the maximum required power, respectively, varying the UAV height and cell radius. Without loss of generality, it is plotted the case when QoS= 3 bps/Hz.

On one side, from Fig. 8a to Fig. 8d one can note that the minimum amount power, required by the PSO configuration in order to maintain a QoS for all users, decreases

with increasing the number of available sub-channels. From Eq. (9), this means that, as also highlighted in the pico-cell scenario, the PSO configuration tries to multiplex the minimum amount of users per sub-channel in order to require less power. In particular, also in this case we observed the configurations reported in Table 3. In addition, note that, fixing the UAV height the required power increases with increasing the cell radius, and fixing the cell radius the required power decreases with increasing the UAV height till 300 m. After that point, in Fig 8d we can note that the required power slightly increases or remains the same.

On the other side, from Fig. 9a to Fig. 9d one can see that, fixing the UAV height the PE does not show considerable variations varying the cell radius. For example in Fig. 9a and Fig. 9d the values of each graph are very close to each other. Only in Fig. 9c one can note a case where the PE varies from 35% to 50% increasing the cell radius, i.e.,  $N = 30$ . However in all other cases these variations remain under the 10%. Therefore, a most considerable variation can be observed within the UAV height. Indeed, in all graphs of Fig. 9 one can note how the efficiency decreases with increasing the UAV elevation.

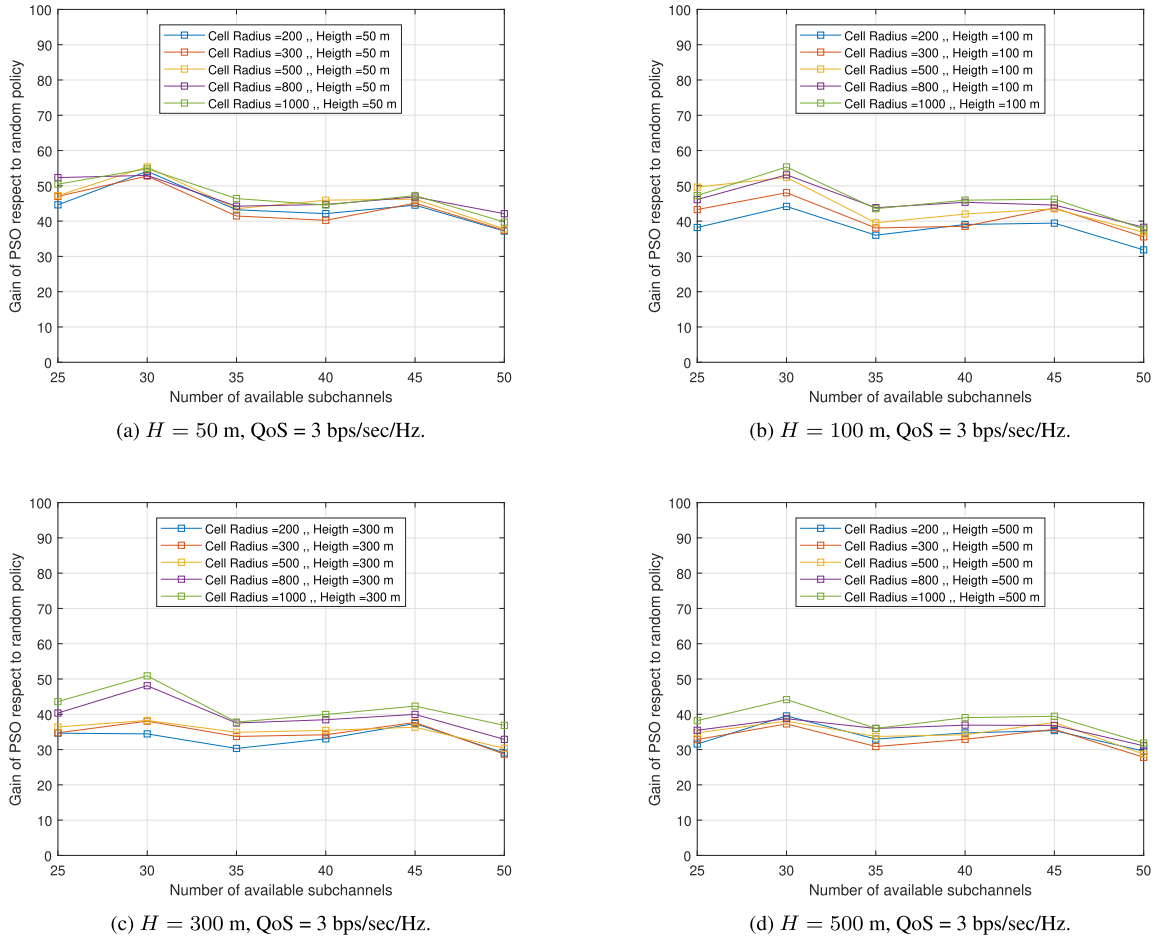


FIGURE 9. PSO algorithm efficiency by varying number of sub-channels, UAV height and cell radius.

In summary, analysing Fig. (7), Fig. (9) and Fig. (8) one can note that:

- i) for a fixed QoS constraint, the PE slightly increases with increasing the cell radius and decreases increasing UAV elevation height;
- ii) for a fixed QoS constraint, the required power increases with increasing the cell radius and/or decreasing the UAV height;
- iii) the PE increases with increasing the QoS constraint;

All these characteristics can be deduced analysing the properties of UAV channel model present in Eq. (16) and Eq. (17).

For a fixed height and cell radius, the UAV establishes a LoS communication with a subset of users distributed within its coverage area. Then, in average, the channel condition for each user results better than the pico-cell scenario where, due to the Rayleigh channel model, NLoS is supposed. This means that, during UAV communications, high QoS constraint can be reached more easily and more efficiently than the pico-cell scenario. This explain the results observed in Fig. 7 where, the efficiency of the PSO-based policy increases with increasing the QoS constraint.

These results, in conjunction with results obtained in the pico-cell scenario, can be considered as a proof that the PSO finds the optimal user multiplexing scheme related to the context in which it operates, i.e., pico-cell or UAV scenario.

As regards the trends of PE and power requirements as function of UAV height and cell radius, one can note that, an increase of  $H$ , as well as a decrease of  $R$ , corresponds to an increase of the elevation angle expressed in (17) and then, a further increase of  $P_{rLOS}$ . Increasing  $P_{rLOS}$ , due to a LoS connection, more users experience *similar* channel gain. Conversely, a decrease of  $H$  or an increase of  $R$ , results to an increase of  $P_{rNLOS}$ , reducing the number of users which experience a LoS connection. Taking that into account, we can say that on the one hand, when  $H$  is low and  $R$  is high, due to bad channel condition among users, the PSO policy spends more effort in finding the optimal solution since there are consistent differences between channel gains experienced by users. On the other hand, when  $H$  increases and  $R$  decreases, the PSO spends less effort since users experiments a *similar* channel condition. Then, a decrease of PE does not mean that the PSO *start to fail*, but simply that the PE is very sensitive to channel condition. In other words, according to Eq. (14), a small difference between the random policy and

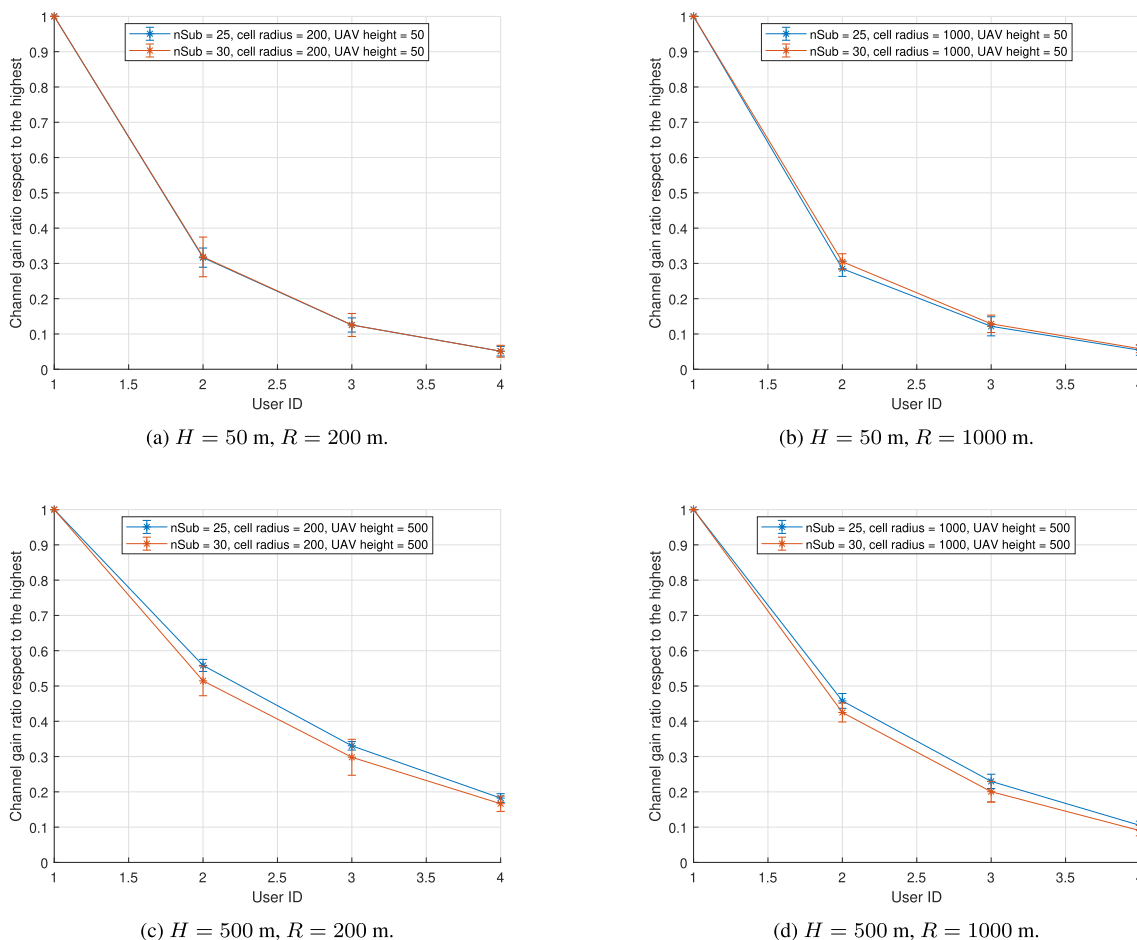


FIGURE 10. Channel gain ratio per each sub-channel in UAV scenario.

the PSO policy in user aggregation, results in a high PE in case of bad channel condition, i.e., low UAV elevation and high radius, than to the case with better channel condition, i.e., high elevation and low radius. This feature motivates also the decrease of the required power since, increasing the UAV elevation contributes in better channel condition and then less energy, for reaching the target QoS, is required. However, in Fig. 8d one can note that the required power start to increase again after a certain UAV Height. In that case, the channel condition of users starts to get worse due to distance attenuation and then, although comparing Fig. 9d with Fig. 9c the PE is maintained, more power is required.

As regards the analysis of channel gain ratio distribution, for a fixed cell radius and UAV height, one can notice some similarities with the pico-cell scenario, i.e., user distribution along the sub-channels reported in Table 3, a soft dependence from QoS constraint, i.e., small confidence intervals, and maintenance of channel gain ratio trend in each configuration, i.e., channel gains proportions do not depend from the number of users allocated in each sub-channel. Then, for a sake of concision, Fig. 10 illustrates the cases when four users per sub-channel are multiplexed. Comparing Fig. 10a with

Fig. 10b one can note that the channel gain distribution looks to be independent from cell radius. Conversely, comparing Fig. 10a with Fig. 10c is possible to note that the channel gain distribution strongly depends from UAV height, resulting in a channel gain ratio rise of 20% at least. Finally, comparing Fig. 10c with Fig. 10d we can observe that, in contrast with the cases when  $H = 50$ , in this case there is a dependence from the cell radius, resulting in channel gain ratio decrease of 10% at most. However, this dependence results to be less than the one from UAV height.

Once again, all these results can be explained considering UAV channel model properties, i.e., LoS probability and the elevation angle presented in (16) and (17), respectively. Indeed, for the cases when  $H = 50$ , varying the cell radius does not cause consistent change in elevation angle and therefore neither on LoS probability. This means that channel gain among users and then channel gain ratios remain *stable* varying the cell radius. This can explain the result obtained comparing Fig. 10a with Fig. 10b.

On the other side, an increase of the UAV height corresponds to an increase of the elevation angle. Then all users start to experience even more better channel gain obtaining

the results observed comparing Fig. 10a with 10c. Finally, when  $H$  assumes high values, a variation of cell radius more affect the elevation angle than the case when  $H$  is low. Then, the number of users which experience best channel condition start to decrease, obtaining even more low channel gain ratios among users allocated to the same sub-channel. This explain the result obtained comparing Fig. 10c with Fig. 10d.

### C. DISCUSSIONS

Our results and findings highlight the importance of an optimal user aggregation configuration for reducing power requirements in NOMA-based transmission systems. Indeed, through the performance analysis of the optimal configuration, obtained with a PSO-based approach, it is shown how the power requirement strongly depends on the QoS constraint of users and the number of available sub-channels in which users can be multiplexed into power domain.

According to Eq. (9), the power required on each sub-channel depends also from the channel gain of each user. Then the choice on which users should be multiplexed into the same sub-channel represents another issue to address. Under this perspective, we also analysed the relations between the channel gains of users multiplexed in each sub-channel.

Although we conducted these analysis on different communication scenarios, similarities on either user distribution among available sub-channels, and channel gain ratio distributions over each sub-channel, have been observed. In particular, in both cases:

- Users are distributed along available sub-channels as reported Table 3.
- While the channel gain ratio between the first two highest channel gains, i.e.,  $ID = 2$ , varies between 55% and 30%, depending on the considered scenario, an almost fixed relation can be observed between the second and the others, i.e., the third and the fourth are almost always the 50% and the 25% of the second, respectively (see Figs. 5 and 10).

Then, this permits to define a *smart rule* which, knowing the channel gain and the QoS constraint of each user, enables the transmitter to explicitly implement an optimal or sub-optimal user aggregation configuration, requiring the minimum transmitting power and maintaining the QoS of its users.

### V. CONCLUSIONS AND FUTURE DIRECTIONS

In this paper, we highlighted how in NOMA systems the minimum amount of power, required to transmit a linear superposition of  $N$  users' data over a sub-channel, strongly depends on the number of available sub-channels, the QoS requirements of each user and by the channel gain experienced by each of them. Then, adopting an optimal user aggregation scheme can be beneficial to reduce power requirements, especially for transmissions performed in power-constrained scenarios. At the time of writing, most of the works published in literature face the user aggregation aspect through matching theory-based algorithms, neighbour search methods, or game-theory based approaches, which, depending on the

size of the problem, i.e., number of users and number of available sub-channels, can result in high computational cost procedures. Then, an interesting solution would be the development of more scalable algorithms which, knowing the channel statistics and the QoS constraint of each user, permit the BS to reach an optimal user-aggregation. Under this perspective, we analysed an optimal user pairing configuration, obtained through a PSO-based approach, applied into two different power-constrained communication scenarios, i.e., disaster scenario communications and UAV communications. Despite the differences between these scenarios, consistent similarities on either user distribution among available sub-channels, and channel gain ratio distributions over each sub-channel, have been noted. These results and remarks can be exploited for the definition of explicit user-aggregation strategies for NOMA transmissions which, at the time of writing, represents a research field that still remains to be investigated more in depth. Under this perspective, future directions, which can contribute in filling partly this area, can be identified as: *i*) further investigations of other optimal user-aggregation configurations in order to find additional useful informations; *ii*) use the results obtained from these analysis for the design of new efficient and scalable channel-state-aware user aggregation policy for NOMA systems.

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