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Resource Allocation for Throughput versus Fairness Trade-Offs under User Data Rate Fairness in NOMA Systems in 5G Networks

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Abstract: In this work, we present a resource allocation scheme for managing trade-offs between total throughput maximisation and system fairness in a non-orthogonal multiple access (NOMA) system for 5G networks. Our proposed approach is designed to improve throughput and fairness as performance metrics of NOMA in 5G networks. We apply integer linear programming for user pairing and adopt particle swarm optimisation as the power allocation scheme for reducing resource allocation complexity. To formulate the multi-objective problem, we use scalarisation of multi-objective optimisation, which exhibits flexibility in assigning different weights to a single objective—in the case of this study, either sum rate or fairness. Moreover, the problem is formulated with a penalty function to prevent optimisation violating the constraints of the optimisation function. Simulation results show that the proposed model outperformed the conventional approach by at least 17% in terms of throughput maximisation and fairness rate.

Keywords: 5G communications; wireless communications; integer linear programming (ILP); successive interference cancellation (SIC); multi-objective optimisation (MOO); weighted sum method (WSM); particle swarm optimisation (PSO); Jain's fairness index (*JFI*)

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1. Introduction

1.1. Preliminaries

Non-orthogonal multiple access (NOMA) is a promising access scheme for 5G networks. It multiplexes multiple users on the same radio resources frequency, code, or time with different power levels in the power domain. In contrast with orthogonal multiple access (OMA), the NOMA technique utilises the power domain to multiplex multiple users simultaneously. Thus, NOMA can support 5G requirements, such as massive connectivity, enhanced spectral efficiency, and sum-rate, which can support a balanced data rate in a system. In NOMA, the base station (BS) superimposes the message on the same subchannel for the multiplexed users via superposition coding (SC); then, successive interference cancellation (SIC) is applied to the signal detection receiver [1,2]. The NOMA system can provide balanced throughput for users in the network in accordance with the channel conditions.

One fairness criterion that can be implemented involves using the strong channel condition as a relay to improve the data rate under poor channel conditions; this technique may improve reception reliability for users under poor channel conditions. However, this improvement can come at the cost of additional channel resources, such as dedicated time slots or power balance [3]. Hence, the power allocation scheme and user pairing can be applied to support fairness with less system complexity [4].

1.2. Related Work

The power allocation optimisation problem is formulated as a non-convex optimisation problem that is difficult to solve directly [5–7]. Furthermore, power allocation and user pairing are coupled problems, whilst the trade-off between throughput maximisation and fairness is an additional optimisation challenge. Moreover, the analysed work assumed that fairness can be affected by cell radius, number of users per cell, and path loss channel coefficient [8–10]. The literature review pays particular attention to methods that focus on fairness and throughput maximisation, as detailed in Table 1, and provides details about the objectives of and the algorithms applied in existing approaches in the literature.

Table 1. Summary of the literature review.

Reference	Objective	Proposed Algorithm
[4]	Fairness criteria in downlink NOMA systems with instantaneous channel state information (CSI) and average CSI	Bisection iterative algorithms (BIAs) for power allocation
[8]	Maximum–minimum fairness scheme to maximise the minimum achievable user fairness on the basis of a mm-wave NOMA system	Beamforming and power allocation as a joint problem
[9]	To determine the minimum time window to guarantee and evaluate the specified fairness using Jain's fairness index (*JFI*) for a short-term fairness NOMA system	Simple alternate optimisation (AO) scheme to allocate power with α-fairness under Karush–Kuhn–Tucker conditions
[10]	Achieve equal data rate and maximum energy efficiency for a downlink multiple-input and multiple-output (MIMO) NOMA system	Dinkelbach's method for power allocation and user clustering
[11]	To achieve a better trade-off between throughput and fairness for a downlink NOMA system in 5G networks	Two-stage algorithm that uses proportional fairness with zero-forcing beamforming
[12]	To achieve maximum–minimum fairness and throughput for a downlink NOMA system with two users	Finite blocklength (FBL) to attain an optimal power allocation
[13]	Maximise energy efficiency and throughput fairness for downlink time-NOMA (T-NOMA) systems	Power and time resource allocation optimisation based on time-sharing using an unmanned aerial vehicle (UAV)
[14]	Achieve the minimum required data rate for each user and throughput maximisation	Power discretisation method Global optimal search (GOS) Adaptive proportional fair (APF) and classical waterfalling based on matching theory (MWF)

For example, the authors of [8] formulated a joint beamforming and power allocation problem to achieve a fair user data rate by utilising a maximum–minimum fairness scheme to maximise the minimum achievable user fairness based on a mm-wave NOMA system. The researchers first obtained closed-form optimal power allocation from the problem formulation and then designed the beamforming vector to reduce joint optimisation [8]. In ref. [12], Salehi, Neda, and Majidi developed FBL to attain an optimal power allocation that can also ensure fair throughput for a downlink NOMA system with two users. Their investigation focused on achieving maximum–minimum fairness while enhancing total throughput. The authors of [15] developed hybrid beamforming to improve the rate of fairness and power consumption as multi-objectives. The optimisation scheme deployed an inner approximation algorithm and graph theory and considered power control and quality of service (QoS). In ref. [16], a fair NOMA scheme developed on the basis of a scheduling paradigm assumes that users can always achieve the data rate and compare it if they are using OMA. The authors also derived power allocation coefficient bounds as a channel gain function for two users.

The authors of [17] developed a scheme for a fairness system based on a nonuniform power distribution to measure the rate difference between users to achieve data fairness. A user's data rate is measured with a fraction of the total power allocated to the user whilst continuously checking the fairness index, where a value of '1' is attained at fair rates.

In ref. [14], Long, Wang, Wei, and Chen investigated spectrum resource and power allocation to achieve the minimum required data rate for each user and throughput maximisation as a trade-off scheme for a NOMA system. Their work formulated the problem as a double-objective optimisation problem; the power discretisation method was then used to convert the problem into a single-objective optimisation problem. Moreover, matching the user-subchannel problem and power allocation is achieved by conducting GOS to determine the upper bound of user throughput due to high complexity. The power allocation scheme considers APF for throughput fairness and applied power allocation using MWF.

Alternatively, the authors of [13] proposed power and time resource allocation optimisation based on time-sharing to maximise energy efficiency and throughput fairness for downlink T-NOMA systems using UAV. The joint optimisation scheme was proposed to utilise the advantages of UAVs in communication systems for the maximisation of throughput fairness and energy efficiency.

In ref. [6], a standalone simulated annealing algorithm was proposed for resource allocation to maximise throughput for a NOMA system. As observed in this work, the approach can maximise the total throughput but at the cost of a less fair throughput distribution. Hence, investigating throughput maximisation while ensuring a fair data rate in a 5G network is important.

In this work, we propose a hybrid scheme (ILPSO) for user pairing and power allocation based on integer linear programming (ILP) and particle swarm optimisation (PSO), respectively, to achieve trade-offs between throughput maximisation and fairness. The optimisation problem is formulated by converting multi-objective functions into a single function using the scalarisation of multi-objective optimisation problems (SMOO). ILP is the method proposed to perform the user pairing scheme to reduce the complexity of the resource allocation problem [18]. The optimisation techniques used in PSO are inspired by the behaviours of natural organisms, such as birds flocking and fish schooling [18,19]. Cooperation amongst individual animals assists the groups to which they belong in achieving common objectives, such as sourcing food within an efficient time.

The rest of the paper is organised as follows. In Section 2, the NOMA system model is described, and the problem formulation for the objective function is proposed. In Section 3, the user pairing scheme is suggested, and the PSO algorithm used for power allocation is presented. Section 4 describes the simulations for the proposed algorithms. Finally, Section 5 summarises the results.

2. NOMA System Model

We consider a single-cell NOMA network equipped with a single-input, single-output (SISO) design in which the BS is located at the centre of the cell. The numbers of users and subchannels are defined as U and N, respectively. Users U are uniformly distributed within the cell. The BS transmits the superimposed signal for multiple users over N subchannels, where a subchannel is indexed as $n \in \{1, 2, \ldots.., N\}$. The total bandwidth B_{Total} is divided by the number of subchannels, and the subchannel bandwidth B_{sc} is divided equally for each subchannel. Moreover, multiple users share the same subchannel in accordance with NOMA concepts, where U_n is the set of users sharing the same subchannel n. The total transmit power distributed over the subchannels is P_{Max}, where $P_{u,n}$ is the user power, and system power allocation is limited as $\sum_n^N \sum_u^{U_n} P_{u,n} \le P_{Max}$. The BS transmits signal x_n on subchannel n, and the transmitted signal is given by:

$$x_n = \sum_{u=1}^{U_n} \sqrt{P_{u,n}}\, \widetilde{x}_{u,n}\ , \tag{1}$$

where $P_{u,n}$ is the power allocated to user u multiplexed on subchannel n, and the modelled symbol is denoted as $\widetilde{x}_{u,n}$. The signal received by user u over subchannel n is described as follows:

$$\begin{aligned} y_{u,n} &= g_{u,n} x_{u,n} + \mathbb{Z}_{u,n} , \\ y_{u,n} &= g_{u,n} \sqrt{P_{u,n}}\, \widetilde{x}_{u,n} + g_{u,n} \sum_{i=u+1}^{U_n} \sqrt{P_{i,n}}\, \widetilde{x}_{i,n} + \mathbb{Z}_{i,n} , \end{aligned} \tag{2}$$

where the channel gain coefficient between the uth user and the BS is represented as $g_{u,n} = d_{u,n}^{-1} h_{u,n}$, where $d_{u,n}^{-1}$ represents the path loss coefficient. The Rayleigh fading channel gain is $h_{u,n}$. $d_{u,n}$ is the distance between the uth user for each channel and the BS. $\mathbb{Z}_{i,n}$ is the additive white Gaussian noise (AWGN) with a zero-mean complex random variable and σ_n^2 variance is $\mathbb{Z}_{i,n} \sim \mathcal{CN}(0,\ \sigma_n^2)$. The design assumes that the number of users is two times the number of channels $(U = 2N)$. The data rate on a given subchannel for the uth user is described as follows:

$$R_{u,\ n} = B_{sc} \log_2(1 + SINR_{u,n}), \tag{3}$$

where the signal-to-interference-plus-noise ratio ($SINR$) is given as:

$$SINR_{u,n} = \frac{p_{u,n} |g_{u,n}|^2}{\sigma_n^2 + \sum_{i=1}^{l-1} p_{u,n} |g_{u,n}|^2}, \tag{4}$$

$$= \frac{\frac{p_{u,n}|g_{u,n}|^2}{\sigma_n^2}}{1 + \sum_{i=1}^{l-1} \frac{p_{u,n}|g_{u,n}|^2}{\sigma_n^2}}, \tag{5}$$

$$= \frac{p_{u,n} G_{u,n}}{1 + \sum_{i=1}^{u-1} p_{u,n} G_{u,n}} , \tag{6}$$

where $p_{u,n}$ is the power allocated to the uth user on the nth subchannel. $g_{u,n}$ is the channel response coefficient on the downlink for the uth user on the nth subchannel. $G_{l,n}$ is the channel response normalised by noise (CRNN) for the corresponding user. System design is strictly multiplex, with only two users on each channel. For example, the subchannel n multiplexes the two users $U_{1,n}$ and $U_{2,n}$ with $|G_{1,n}|^2 \geq |G_{2,n}|^2$, where the power allocation scheme is $P_{1,n} \leq P_{2,n}$ in accordance with the power domain multiplexing protocol in NOMA [20–22].

In our design, we assume that subchannels are sorted such that $|G_{1,n}| \geq |G_{2,n}| \geq \cdots \geq |G_{U_n,n}|$. SIC is applied to each channel, where the intended signal can be detected by each user. The high channel gain user firstly decodes the signal of the low channel gain user, cancels the interference power, and then decodes the intended signal. By contrast, the low channel gain user regards the interference power on the same subchannel as noise. This assumption is common in NOMA based on SIC. Thus, the total throughput is:

$$R = \sum_{n=1}^{N} \sum_{i=1}^{N_{sc}} B_{sc} \log_2(1 + SINR_{u,\ n}). \tag{7}$$

2.1. Problem Formulation

The resource allocation problem involves user pairing, channel power allocation, and power ratio allocation to maximise throughput for a NOMA system in 5G networks. The first objective is to maximise the throughput with respect to power allocation and user pairing. The throughput function is described as follows:

$$f(\delta, P) = B_{sc} \sum_{n=1}^{N_{sc}} \log_2(1 + \delta_n P_n G_{1,n}) + B_{sc} \sum_{n=1}^{N_{sc}} \log_2\left(1 + \frac{(1-\delta_n) P_n G_{2,n}}{1 + \delta_n P_n G_{2,n}}\right). \tag{8}$$

where $\delta = [\delta_1, \delta_2, \ldots \delta_{N_{sc}}]^T$ and $P = [P_1, P_2, \ldots P_{N_{sc}}]^T$ are the power ratio and channel power, respectively. Furthermore, the power ratio for the multiplexed users is denoted as δ_n on a subchannel n, and P_n is the subchannel n power.

The system is designed to achieve trade-offs between throughput maximisation and system fairness to obtain the optimal solution. The problem design is formulated on the basis of the SMOO approach to convert it into a single objective (SO) function [23]. The primary objective function is formulated by adding each objective and pre-multiplying each with a supplied weight scale [23]. The weight scale is set in proportion to the relative importance of the objective. The problem is formulated as follows:

$$\text{Maximise} \qquad f(\delta, P) \tag{9}$$

$$\text{Subject to} \qquad C_1 \;:\; 1^T P \leq P_{max}, \tag{10}$$

$$C_2 : P \geq 0, \tag{11}$$

$$C_3 : F \geq F_{des}, \tag{12}$$

$$C_4 : R_i \geq R_{min}, \tag{13}$$

$$C_5 :\; 0 \leq \delta \leq 1, \tag{14}$$

where C_1 is the total transmit power constraint and C_2 is the channel power constraint. The fairness constraint is denoted as C_3 ; the minimum data rate constraint is represented as C_4. The power ratio allocation varies between 0 and 1, as denoted in C_5. Moreover, C_5 prevents the power ratio from reaching 1, previous work showing that the highest value of the power ratio is sufficient to provide the maximum objective function [6]. These constraints are applied to the objective function to protect the function from violating the constraint. The fairness value is added as a constant that balances objective function maximisation. For the implementation, the problem is converted into a minimisation problem, and, thus, the throughput function is negated. The design of SMOO problems uses the weighted sum method (WSM) [23]. Hence, the throughput objective function is normalised and scaled by the number of users, such that the calculation can be generalised for any number of users. The normalised objective function is written as follows:

$$q = -\frac{f(\delta, P)}{U}, \tag{15}$$

where q is the normalised value of the fitness function. The cost function must include the other constraints because PSO only allows upper and lower bound constraints. Any violation in the sum of power, fairness and minimum user data rate constraints is added to the cost function. More violations result in a higher cost function; thus, if no violation occurs, then $q^* = 0$. The penalty functions are presented as follows:

$$q_p = max\left(0, 1^T P - P_{max}\right), \tag{16}$$

$$q_F = max\,(0, F_{des} - F), \tag{17}$$

$$q_R = max\,(0, R_{min} - R_i). \tag{18}$$

The constraint can make the optimisation problem considerably more difficult where it is an essential step in making the optimisation more flexible and less complex. Consequently, the constrained problems are converted into unconstrained problems by means of an artificial penalty for violating the constraint as a new penalty function. The minimisation problem is presented below, where p^* denotes the corresponding penalties for violations. Furthermore, the objective function is developed as follows:

$$minimise \;\; q + p_p q_p + p_F q_F + p_R q_R, \tag{19}$$

$$\text{Subject to } C_1 : P \geq 0, \tag{20}$$

$$C_2 \,:\, 0 \leq \delta \leq 1, \tag{21}$$

where F_{des} is the fairness weight constant that can be predefined in the system. The minimum user data rate is denoted as R_{min}, where p_R, p_F, and p_p are the penalty for user's data rate, fairness, and power violation, respectively.

2.2. Jain's Fairness Index

JFI is a well-known metric applied to wireless communications to evaluate a system's fairness. The efficient resource allocation scheme can provide a flexible system to achieve fair data distribution in NOMA systems [24]. Therefore, the second objective is to generate a balanced data rate as Jain's fairness objective. *JFI* is defined as follows:

$$JFI = \frac{\sum_{i=1}^{U} R_i}{U \sum_{i=1}^{U} R_i^2}, \tag{22}$$

where R_i is the user data rate and U is the total number of users. This indicator varies in accordance with the number of users and the achieved throughput. Given that two users are multiplexed on the same channel as high and low channel gains, the minimum user data rate for the user with low channel gain is ensured. Thus, fairness is an indicator of the QoS in NOMA systems.

3. Resource Allocation Problem

The resource allocation problem is a joint optimisation based on user pairing and the power allocation problem. The optimisation scheme can be decoupled to reduce system design complexity. User pairing and the power allocation problem are addressed separately to reduce system complexity. Consequently, we firstly formulate the user pairing scheme by using ILP. Then, we apply PSO for power allocation optimisation. The system design is developed in three scenarios for system performance. The first scenario is applied without a constraint on minimum data rate and fairness. The second scenario is applied with only a minimum data rate constraint. The third scenario is applied with minimum data rate and fairness constraints.

3.1. User Pairing Using ILP

ILP is proposed to perform the user pairing scheme because user pairing is addressed as a discrete problem [18,23]. The ILP method is a decision-making scheme that can improve decision quality.

The user pairing problem formulation is described as follows. The first user is firstly selected on each channel as a high channel gain user. The second user is then matched to the same channel as a low channel gain user. In this problem, user pairing begins by selecting the high channel gain user and then choosing a second user with low channel gain in each channel. Let us denote the $(U \times N_{sc})$ gain matrix M. Let Z be a $(U \times N_{sc})$ binary selection matrix.

$$Z_{ij} = \begin{cases} 1 \; if \; user \; i \; in \; channel \; j \; is \; selected \\ 0 \qquad\qquad\qquad\qquad Otherwise \end{cases} \tag{23}$$

The first objective is to select one user from each channel such that the sum of the gains is maximised. That is, a matrix Z is found such that the sum of the elements of MZ is maximised. This optimisation problem can be expressed as follows:

$$Maximize \sum_{i=1}^{U} \sum_{j=1}^{N_{sc}} M_{ij} Z_{ij}, \tag{24}$$

$$\text{Subject to } 1^T Z = 1, \tag{24a}$$

$$Z^1 \leq 1, \tag{24b}$$

$$Z_{ij} = \{0,1\},\ i = 1, ..., U,\ j = 1, \ldots, N_{sc}, \tag{24c}$$

The newly updated matrix is denoted as the optimal solution Z^H. Once the high gain users are selected, the channels are updated with the first user selection. The second objective is to select one user from each channel to minimise the sum of the gains. Similarly, this optimisation problem can be expressed as follows:

$$Minimize \sum_{i=1}^{U} \sum_{j=1}^{N_{sc}} M_{ij} Z_{ij}, \tag{25}$$

$$\text{Subject to } \ 1^T Z = 1, \tag{25a}$$

$$Z^1 \leq 1, \tag{25b}$$

$$Z_{ij} = 0,\ if\ Z^H{}_{ij} = 1, \tag{25c}$$

$$Z_{ij} = \{0,1\},\ i = 1, ..., U\ ,\ j = 1, \ldots, N_{sc}, \tag{25d}$$

The solution to this problem is denoted as Z^L. The final selection matrix is $Z^* = Z^H + Z^L$, which has a pair of users on each channel. This process is encapsulated by a function $S : \mathbb{Z} \rightarrow \mathbb{R}^{2\times N_{sc}}$. This function performs a mapping from a permutation number z to the vectors of the sorted gain values in all the channels, concatenated vertically.

$$S(z) = \begin{bmatrix} G_{1,1} & G_{1,2} & \ldots & G_{1,N_{sc}} \\ G_{2,1} & G_{2,2} & \ldots & G_{2,N_{sc}} \end{bmatrix} \tag{26}$$

A value z is given. To obtain the gain value of a particular user i with either high or low channel gain on a channel j, i.e., Gi, we assess the $(i\text{th}, \ j\text{th})$ element of $S(z)$, denoted $Z_{ij}(z)$.

3.2. PSO for Power Allocation

PSO is an algorithm based on natural organisms that are seeking habitats with sufficient food, such as birds and fish. PSO is known as an agent-based algorithm because it uses multiple agents or particles [18,19]. The implementation of PSO is considerably simpler than those of the genetic algorithm (GA) and the ant colony algorithm (ACO), which share some similarities with PSO's optimisation techniques. PSO works on the basis of the real-number randomness and global communication between swarm particles rather than the mutations, crossover operators or pheromones used in GA and ACO. In the current work, the PSO algorithm is proposed to obtain the optimal power solution in a NOMA system based on the objective function (8).

In particular, the velocity and position of each particle are adjusted in accordance with the group information. In PSO, the number of particles (Q_P) is predefined. X_i is the position and V_i is the velocity of each particle. The dimension D_S is the search space for potential solutions to the optimisation problem. The quality of the solution is evaluated iteratively for each particle through an objective function. The personal best of a particle is $P_{best\ i}$ for the obtained objective function value, which is compared with the global best value as G_{best}.

Consequently, the position and velocity of each particle are modified along each dimension. The position and velocity are coupled dynamics of a PSO particle. The velocity dynamics are influenced by inertia and cognitive and social components, and these, in turn, influence the position dynamic of PSO. Position and velocity dynamics are mathematically described as follows:

$$V^i(t) = w(t)V^i(t-1) + r_1 c_1(t)\left(X^i_{pbest}(t) - X^i(t-1)\right) + r_2 c_2(t)\left(X_{gbest}(t) - X^i(t-1)\right), \tag{27}$$

$$X^i(t) = X^i(t-1) + V^i(t), \tag{28}$$

where $V^i(t)$ is the velocity and $X^i(t)$ is the position of the particle along dimension $d \leq D$. w is the inertia weight, c_1 and c_2 are two acceleration factors as non-negative constants, and r_1 and r_2 are two different uniformly and randomly distributed numbers within the range [0, 1]. Inertia and acceleration vary in each iteration to improve PSO performance with the following parameters:

$$w(t) = W_{max} - \frac{t \times (W_{max} - W_{min})}{t_{max}}, \tag{29}$$

where w_{max} and w_{min} are the maximum and minimum inertia weights, respectively. The acceleration factor is determined as follows:

$$c_1(t) = c_{1,0} + \frac{t \times \left(c_{1,f} - c_{1,0}\right)}{t_{max}}, \tag{30}$$

$$c_2(t) = c_{2,0} + \frac{t \times \left(c_{2,f} - c_{2,0}\right)}{t_{max}}, \tag{31}$$

where $c_{1,f}$ and $c_{1,0}$ represent the initial values and $c_{2,f}$ and $c_{2,0}$ are the iterative final values of c_1 and c_2, respectively. The parameters, constants, and values of PSO are listed in Table 2.

Table 2. Design Parameters of PSO.

Parameters	Values
Size of particle swarm (Q_P)	50
Maximum inertia weight (W_{max})	0.9
Minimum inertia weight (W_{min})	0.4
Acceleration constants (c_1,c_2)	1.4962
Maximum number of iterations (t_{max})	500
Maximum velocity (V_{max})	0.5
Minimum velocity (V_{min})	−0.5

PSO is used to address the power optimisation problem, as illustrated in Figure 1.

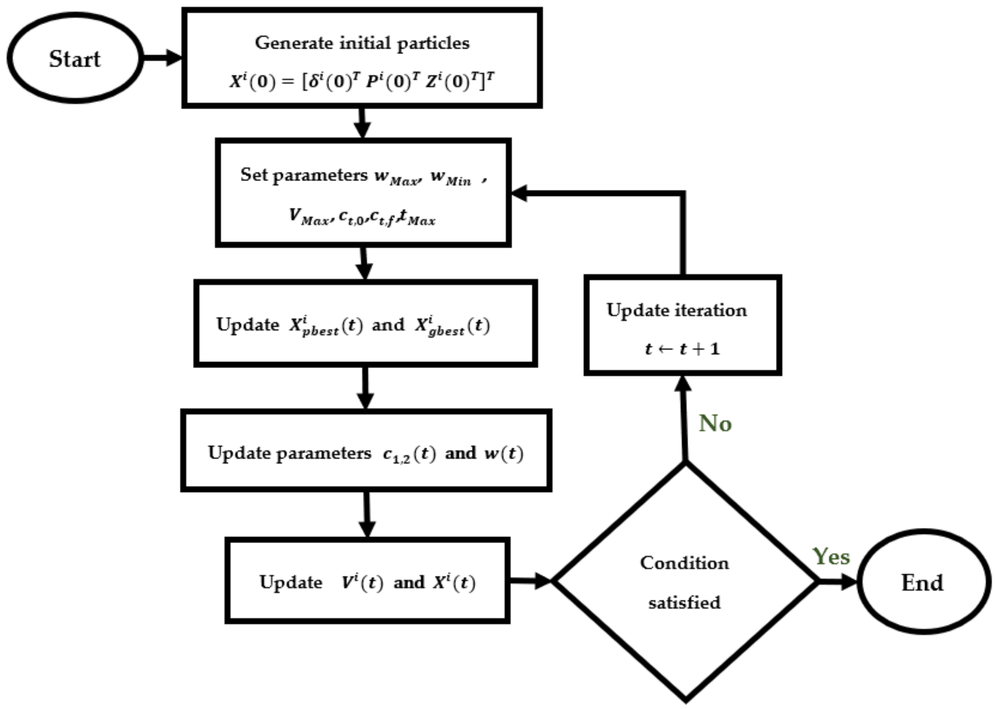

Figure 1. PSO flowchart.

The optimisation problem is non-convex with respect to variables δ and P for the NOMA system. Therefore, PSO is utilised to obtain the optimal solution as a global optimisation scheme. Let $X^i(t)$ be the position vector of a PSO particle i in iteration t, where $X^i(t)$ contains the optimisation variables, as shown below.

$$X^i(t) = \begin{bmatrix} \delta^i(t) \\ P^i(t) \end{bmatrix}. \tag{32}$$

The algorithm generates initial variable particles $X^i(0) = \left[\delta^i(0)^T \; P^i(0)^T\right]^T$, where the subchannel power is P and δ is the power ratio. The PSO parameters are set as follows: w_{max}, w_{min}, V_{max}, $c_{t,0}$, $c_{t,f}$, and t_{max}. Then, the objective function is evaluated for each particle as $f\left(X^i(t)\right)$, $where\ i = 1, \ldots, N_{Particle}$. The possible solution is represented as the position of each particle. Each particle updates the best position $X^i_{pbest}(t)$ and then updates the best position amongst all particles $X_{gbest}(t)$. Subsequently, the inertia weight $w(t)$ and the two acceleration factors c_1 and c_2 are updated. Consequently, the velocity and position of a particle are updated until the maximum iterations or the global best $X^i_{gbest}(t)$ is returned. This iterative algorithm continues until the optimal power allocation solution is found.

4. Result and Performance Analysis

The NOMA system design was investigated using MATLAB. The simulation parameters are summarised in Table 3.

Table 3. Parameters of the system design.

Parameters	Values
Bandwidth (BW)	5 MHz
Cell radius	200 m
Maximum transmit power (Bs)	30 dbm (1 W)
Noise power spectral density $(N_\circ)$	−174 dBm/Hz
User minimum data rate	500 b/s
Number of transmission antennas	1
Noise figure	9 dBm
Shadow standard deviation	8 dB
Throughput calculation	Shannon's capacity

Figure 2 shows the trade-offs between throughput maximisation and system fairness with 4 to 24 users. The proposed algorithm, i.e., ILPSO, outperformed GOS by 17%, MWF by 21.9%, and orthogonal frequency-division multiple access (OFDMA) by 33% [14]. As observed in Figure 2, ILPSO Scenarios 1 and 2 outperformed Scenario 3, along with GOS, MWF, and OFDMA. These two scenarios achieved higher throughput because no minimum data rate constraint was imposed during the optimisation process. However, ILPSO Scenario 3 still achieved a higher data rate than the other schemes whilst also considering fairness and data rate constraint. Considering that system design in ILPSO Scenario 3 assigned higher priority to fairness, it also exhibited higher throughput than GOS, MWF, or OFDMA. The system design applied a penalty during power optimisation, restricting the power ratio, user data rate, and fairness to prevent constraint violation. ILPSO Scenario 3 is the preferred scenario because of the penalty and fairness weight applied to the function.

The objective function was evaluated for the three ILPSO scenarios that achieved better performance than the existing approaches. ILP was performed earlier as a pairing scheme to relax the optimisation process. Hence, PSO was applied to two variables restricted by optimisation penalty to prevent the power constraint from reaching the upper and lower power bounds. The penalty function and scaled weight were used in the objective function to assist the algorithm in achieving the highest throughput during the optimisation.

Moreover, the PSO algorithm achieved a good solution in earlier iterations and escaped the local optimal search space. Considering that reasonable solutions were found after a few iterations, an exploration can identify all possible solutions, enhancing the search for a better solution. Therefore, PSO provides acceptable solutions for power allocation that maximise throughput.

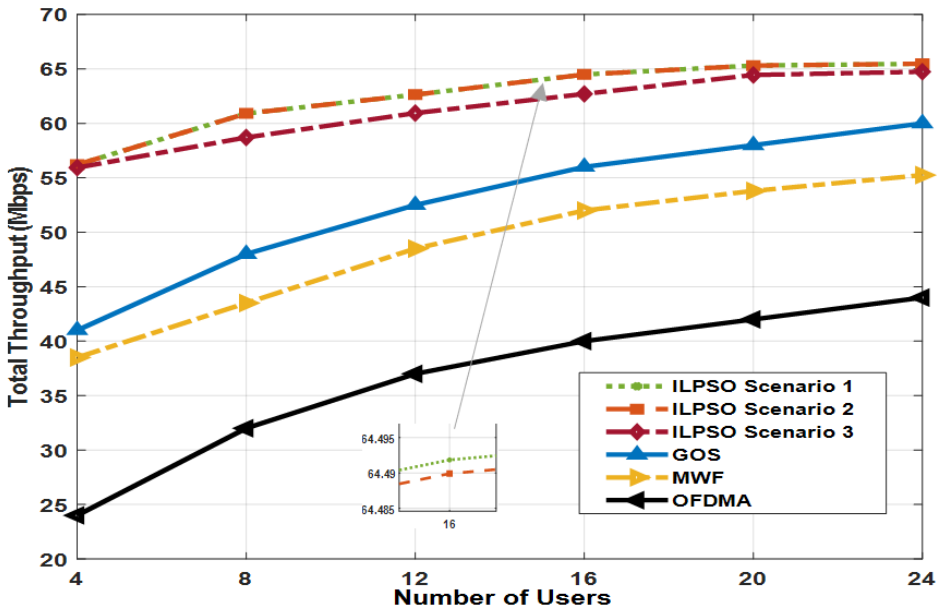

Figure 2. System throughput vs. the number of users.

In Figure 3, *JFI* is evaluated for 4 to 24 users. The ILPSO scenarios are compared with GOS [17], MWF [14], and OFDMA. ILPSO Scenario 3 assigns higher priority to system fairness, as indicated by its highest fairness value, because more weight is assigned to making system fairness a priority in the objective function. ILPSO Scenarios 1 and 2 exhibit lower fairness (below 0.5 for 12 users) due to constraint considerations, i.e., fairness weight is not considered. The ILPSO scenarios achieve better fairness for a higher number of users compared with GOS and OFDMA. ILPSO Scenario 3 is applied to ensure that system will have a minimum user data rate and fairness. It demonstrates greater fairness due to the fixed penalty used in the problem formulation. ILPSO Scenarios 1 and 2 present lower fairness values due to violation of the constraints. However, ILPSO Scenario 2 shows better fairness than ILPSO Scenario 2 because of the minimum data rate constraint applied to the objective function.

In Figure 4, user throughput for the number of channels is estimated with the number of users on the basis of the high and low channel gains. The primary concern is to ensure that a low channel gain user is still achieving a sufficient data rate whilst a high channel gain user is always achieving a better data rate. In ILPSO Scenario 3, a higher user data rate is observed for a low channel gain user than in ILPSO Scenarios 1 and 2. By contrast, ILPSO Scenario 3 exhibits a lower user data rate for a high channel gain user than ILPSO Scenarios 1 and 2 to ensure that ILPSO Scenario 3 can guarantee a higher data rate for low channel gain users. In ILPSO Scenarios 1 and 2, the user data rate gap between the high and low channel gain users is considerable due to violation of the constraints. ILPSO Scenario 2 reduces the gap between high and low channel gain users more than ILPSO Scenario 1, which has no user data rate constraint. Therefore, ILPSO Scenario 3 achieves a better balance between the high and low channel gain users whilst the low channel gain users still receive a sufficient data rate.

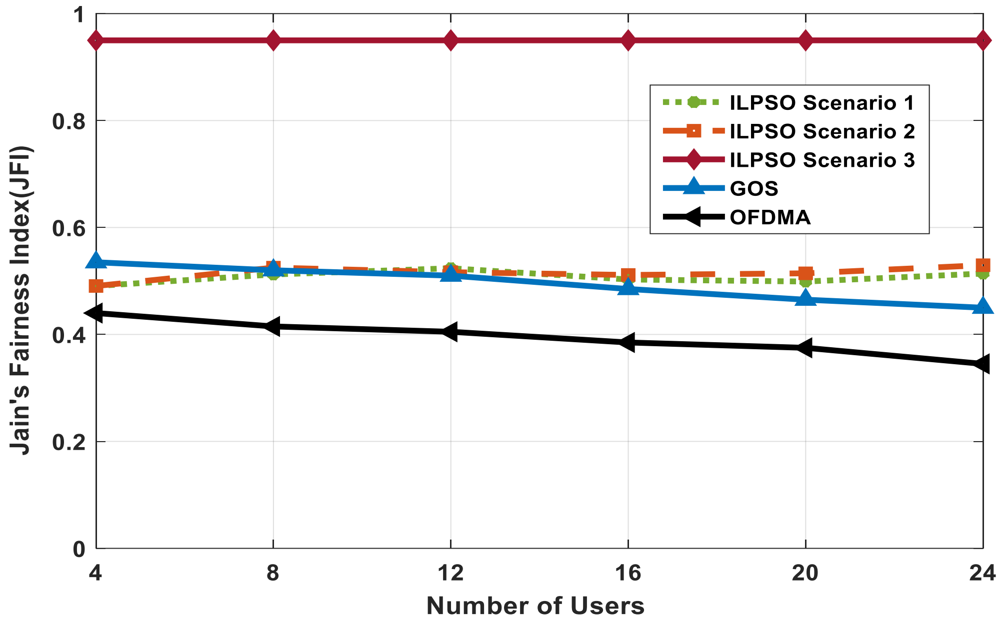

Figure 3. Achieved Jain's fairness vs. the number of users.

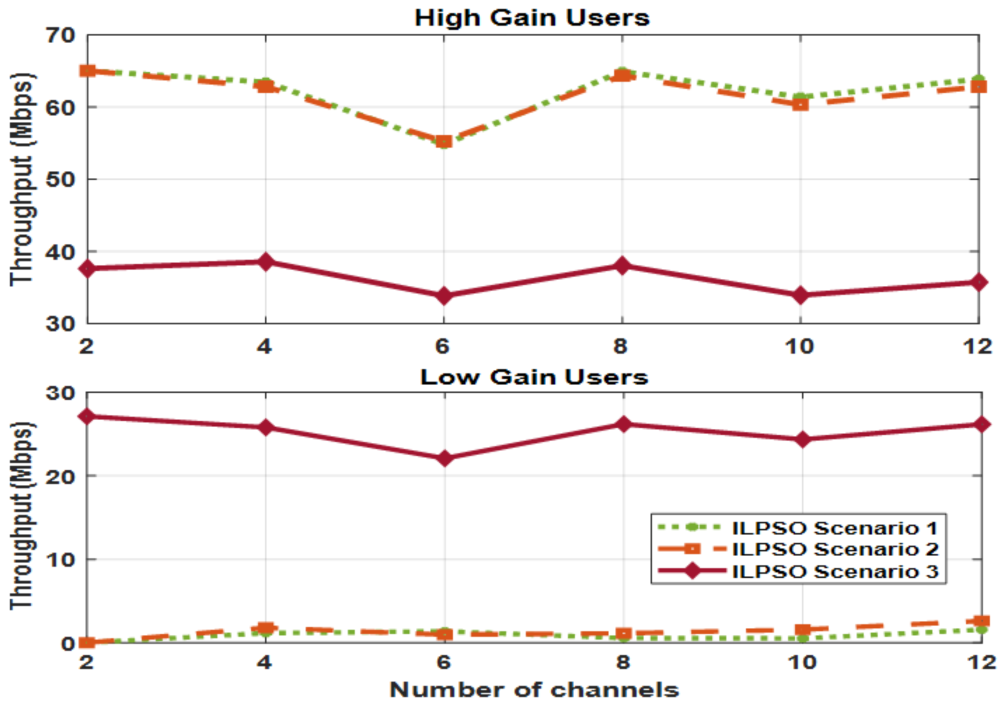

Figure 4. Achieved user throughput for high and low channel gain users.

Figure 5 illustrates the convergence of the proposed algorithm for the three scenarios. ILPSO Scenario 3 violates the constraints in the first 100 iterations. This scenario converges after 200 iterations and at lower throughput than ILPSO Scenarios 1 and 2. Moreover, ILPSO Scenarios 1 and 2 start with higher throughput and converge after 50 iterations with higher achieved throughput. The ILPSO algorithm stops once convergence is achieved, and higher throughput is reached during the last iteration. Hence, the algorithm stops moving through the maximum number of iterations because no changes occur in the convergence. ILPSO converges after at least 200 iterations for Scenario 3 and 50 iterations for Scenarios 1 and 2. ILPSO ends the process when the change per iteration is less than the tolerance $1e^{-6}$ for the scenario that finishes with a lower number of iterations. ILPSO runs the risk of producing a sparse solution during earlier iterations. The set of constraints is important such that increasing the swarm size is unnecessary when capturing the global optimum.

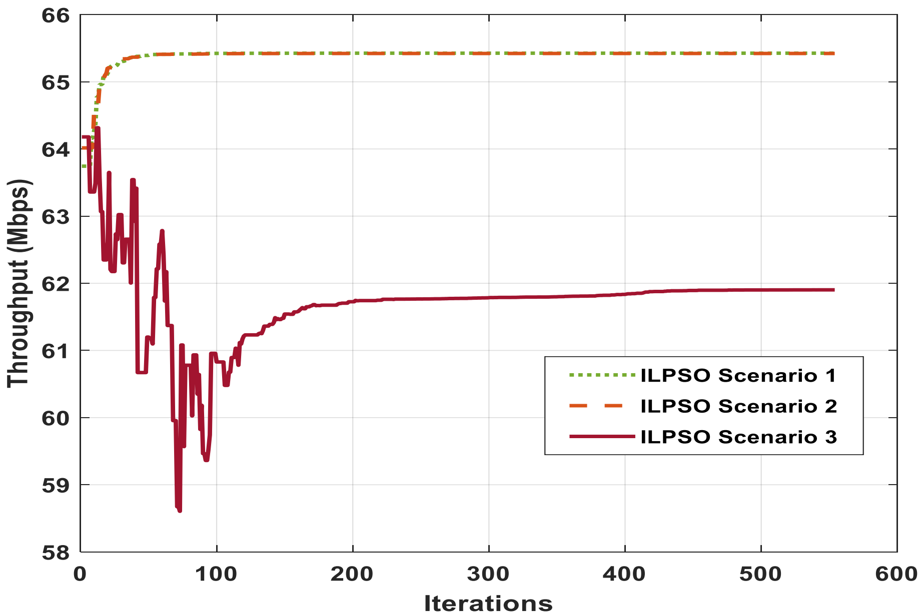

Figure 5. Algorithm convergence vs. achieved throughput.

5. Conclusions

In this study, we proposed a hybrid resource allocation scheme (i.e., ILPSO) to optimise the resource allocation and achieve a trade-off between throughput maximisation and system fairness in a downlink NOMA system-based 5G network. Resource allocation complexity can be reduced by separating the user paring and power allocation schemes. The PSO algorithm was applied to two variables of power allocation with the assistance of a penalty function to prevent the power constraint from reaching the upper and lower power bounds. Therefore, PSO achieved acceptable solutions with simple control parameters and a minimum number of iterations. The design of SMOO problems that used WSM was applied to the optimisation problem to convert it into a SO function. Three ILPSO scenarios were investigated to evaluate system fairness for the cost of total throughput maximisation. The proposed method outperformed other approaches. In Scenario 3, it outperformed GOS by 17%, MWF by 21.9%, and OFDMA by 33%. Moreover, the system exhibited greater fairness than existing schemes, with Scenario 3 outperforming Scenarios 1 and 2. Finally, the proposed scheme can satisfy throughput maximisation and fairness for future NOMA system-based 5G networks.

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