International Journal of
Communication
and Information Technology

E-ISSN: 2707-6628
P-ISSN: 2707-661X
www.computersciencejournals.com/ijcit
IJCIT 2024; 5(1): 96-104
Received: 05-01-2024
Accepted: 11-02-2024

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NOMA technique based power resource algorithm allocation

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DOI: https://doi.org/10.33545/2707661X.2024.v5.i1b.84

Abstract

The 5G cellular technology has increased demand for high data rates, necessitating the use of greater base station (BS) power and bandwidth. However, these resources' accessibility
are often restricted. Lack of accessible channel restricts user space within the cell, and higher power usage overloads the battery supply (BS) and releases CO2 gas, which is harmful to both human health and the environment. Thus, the creation of a nonorthogonal multiple access (NOMA) system that is energy-efficient is a pressing necessity. Thus, we present in this paper a user fairness-based power allocation strategy along with a channel assignment technique for NOMA cellular networks, where the goal is to maximize overall energy efficiency (EE) while meeting the minimum required data rate within the base station's limited power budget.

Additionally, we explicitly consider the order limits on the user capabilities on each channel, which are frequently disregarded in the literature and demonstrate their substantial influence on SIC in NOMA systems. Additionally, we suggest combining the matching algorithm with the ideal power allocation to provide a low-complexity, effective way to simultaneously optimize channel assignment and power allocation in NOMA systems. Furthermore, we have identified the conditions that need to be satisfied in order for the distributed power optimization approach to be approved as a feasible resolution for the joint power optimization problem. As a result, the outcomes were split into two stages. Step 1 involved taking three network sizes (2*4, 3*6, and 4*8) and determining the best point (Weighted Rate) for each algorithm based on each element (Total Power, Fairing Index, Total Rate, and Energy Efficiency). It was then determined that the algorithms to which the technique was applied are optimization algorithms (GA, GWO, and WOA). Therefore, after applying the technology to multiple algorithms, the algorithm (GWO) was superior to other algorithms based on the reduction in capacity consumption, equal distribution to all users, high productivity, and finally the good efficiency of the technology.

Keywords: 5G, NOMA, SIC technique, algorithms optimization

Introduction

The key to the expansion of 5G and 6G communications systems is the enhancement of data throughput and power allocation. This idea was created through Non-Orthogonal Multiple Access (NOMA) methods. With the advancement of IoT technology, mobile devices (MDs) are extensively employed for data collection and processing. Typically, these devices are designed to be compact, with limited computer resources and power supplies. However, in some applications, calculation tasks are so complex that the mobile device is processing unit may require a considerable amount of time to complete them, raising concerns about the device's excessive energy consumption. [1]. it is shown that the capacity region of the multiuser downlink SISO RIS system can be achieved by NOMA with time-sharing [2]. To this end, NOMA is a promising candidate solution for the beyond-5G (B5G)/sixth generation (6G) wireless networks [3].

The SIC complexity is cubic in the number of multiplexed users. Another issue is error propagation, which increases with the number of multiplexed users. Hence, single carrier NOMA (SC-NOMA), where the signal of all the users is multiplexed, is still impractical for a large number of users. In this line, NOMA is introduced on multi-carrier systems, called multicarrier NOMA (MC-NOMA), [4]. Focus on wide range and minimum rate: This is my first article to present the binary version of the WOA (BWOA) and introduce the penalty method to deal with optimization constraints. Combination of the original WOA with BWOA and penalty method allows us to solve a wide range of optimization problems and obtain a high solution quality, the research focused on expanding and containing the data, but the data was not distributed with Minimum Rate and little Energy Efficiency [5].

There is no limit on the number of users in each cluster, schemes based on the other heuristic algorithms and random user clustering with greedy strategy. Mixed integer nonlinear programming (MINLP) is a non-convex problem. The complexity of finding the optimal solution directly is unacceptable. To solve the problem, a heuristic algorithm based on GA proposed, the systems are using as: downlink NOMA (GA, hill climbing based algorithm (HC) and simulated annealing based algorithm (SA)) [6].

Focus on user fairness to improved objective function to eliminate the tight and redundant constraint of guaranteeing the user fairness in every sub-carrier in the previous joint allocation algorithm and can also make better use of the electrical signal power under the limit of optical signal peak power by reducing the peak-to-average power ratios (PAPRs), These three proposed algorithms address the requirements in fairness-throughput-balanced (FTB), fairness-first (FF), and throughput-first (TF) scenarios, respectively. This research has more than one algorithm for each algorithm that works on a specific part, but in our algorithm, the work is dynamic for all parts of the network and at the same time, it is an integrated work [7]. Power finding globally optimal power allocation algorithms to minimize the BSs power consumption, and maximize SR/EE by using water-filling and Dinkelbach algorithms. The use of the system Multi-carrier Hybrid-NOMA (MC-NOMA) is equivalent to the uses of these systems FDMA-NOMA, but it is better compared to productivity and reduce power [8].

Focus on throughput: the goal of maximizing the overall system through-put while ensuring temporal fairness among the contending users, to propose to dynamically construct reduced cardinality user pair and user triple sets as opposed to using the entire pair and triple sets, out of which a pair or a triple is to be selected, users. The effectiveness of the proposed power allocation method along with the temporal fair scheduling algorithm for downlink NOMA is validated with simulations and the performance impact of the transmit power and the coverage radius of the base station as well as the number of users are thoroughly studied [9]. Apply two different swarm intelligence algorithms, namely, the recently in-troduced Grey Wolf Optimizer (GWO), and the popular Particle Swarm Optimization (PSO), emerging swarm intelligence algorithms with low complexity. Low of quality of service (QoS) constraints to the given problem. To jointly optimize the sub-channel assignment and power allocation to maximize the weighted total sum-rate while taking into account user fairness [10].

Proposed a low-complexity user-sub-channel swap matching algorithm in which the users and sub-channels can be matched and form a two-sided ex-change stable matching [11]. Energy efficiency: Simulation results show that the improved algorithm achieves better EE performance than typical schemes, such as convex optimization and the original PSO algorithm for NOMA systems. Because of the NOMA systems is a strictly quasi-concave function, it is difficult to apply the convex optimization directly by adopting the improved particle swarm optimization (PSO) algorithm. Furthermore, in order to avoid the premature convergence, cycle strategy rotation is used in the algorithm [12]. To find the maximum EE point and the respective power distribution among the users for a certain circuitry power consumption, present the fairness index, discuss the solution for the ratio of power optimization problem, possible to optimize the total power for the same rate maximum fairness among all users. We used the techniques of SQP, which presents fast convergence feature [13].

The System method

In addition to the central cell, there are six surrounding cells arranged in a circular arrangement. As indicated in Fig. 1, each cell has one BS. In the middle compartment, BS relays the signal to n user, where n = 1. ..., N. Furthermore, all devices (BS and users) have one antenna. The BS divides the available bandwidth into smaller subchannels S_k, where k = 1, .., K, and the bandwidth of every S_k is expressed by B_k = B/K, and B is the overall system bandwidth. We assume that the BS is aware of the Channel State Information (CSI), the BS assigns power to users in the cell based on their CSI via power allocation algorithms. In NOMA system, multiple users can receive the BS signal across various S_k. Since numerous users are multiplexed on the same S_k, inter and intra interference in the NOMA system is high. As a result, the system cannot reach the optimum performance of NOMA simultaneously for all users.

We believe that the gain of each CSI is constant within each time slot. On S_k, CSI coefficient between the user n and the BS is denoted by $g_{k,n}$. We assume that M are multiplexed users per S_k. The base station's k signal is expressed as follows.

$$u_k = \sum_{n\in N} \sqrt{x_{k,n} \ p_{k,n} \ s_n} \quad (1)$$

where the binary-variable $x_{k,n}$ represents whether S_k is allocated to each user n, and the variable $p_{k,n}$ represents the power allocated to the user n on S_k, s_n is the modulated-symbol, and the expected value of Energy symbol is expressed by $E[|s_n|^2] = 1$. The received signal y at user n and S_k can be written as.

$$y_{k,n} = g_{k,n}\sqrt{x_{k,n} \ p_{k,n} \, s_n} + \sum_{n,\in N, n\neq, n} g_{k,n} \sqrt{x_{k,n} \ p_{k,n} \, s_n}$$

$$+ \sum_{0=1}^{6} \sum_{n^0 \in N} g_{k,n^0} \sqrt{x_{k,n^0} \ p_{k,n^0}} + w_{k,n} \quad (2)$$

Where n′ refer to all the involved users in cell except the intended n, o refer to the other BS, $w_{k,n}(0, \sigma^2)$ is the additive white Gaussian noise (AWGN) with zero average, and σ^2 is the noise variance.

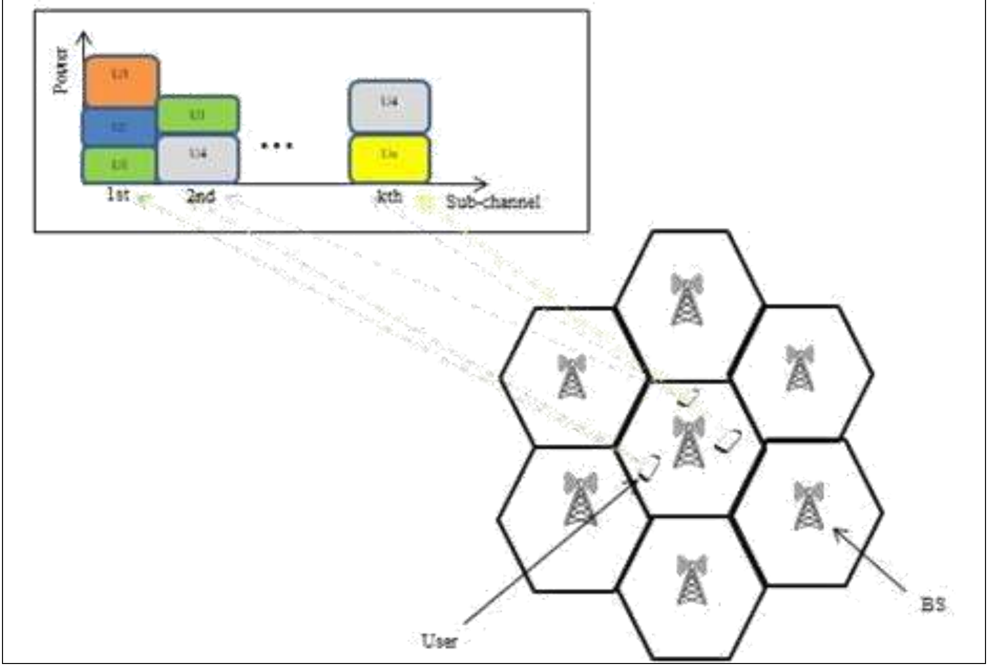


Fig 1: Multi-camera alignment

To demodulate the target message, each user M_j adopts SIC after receiving the superposed signals. In general, the users with higher channel gains are allocated with low power levels, and their signals can be recovered after all users with higher power levels (low channel gain) are recovered in the SIC decoding, while the users with lower channel gains have larger power assignment levels and their signals are recovered by treating the users' signals with lower power levels as the noise in the SIC decoding [8-11]. The decoding order described above guarantees that the upper bound on the capacity region can be reached [14, 15], i.e., the capacity $R_{k,j}$ of user over S_k within one time slot is given by.

$$R_{k,j} = B_k \log_2\left(1 + \frac{x_{k,n} \cdot p_{k,j}|g_{k,j}|^2}{W_{k,j}+I_{k,j}+I_k^0}\right) \quad (3)$$

Where $I_{k,j}$ is the inter-interference that user M_j receives from other users in S_k and it can be described as follows.

$$I_{k,j} = \sum_{i=1:g_{k,j}<g_{k,j}\forall M}^{M} x_{k,j}\ p_{k,i}\left|g_{k,j}\right|^2 \quad (4)$$

While I_k^o represents the intra-interference that produced from the other neighboring BSs on the central cell users at S_k, which can be expressed as follows:

$$I_k^0 = \sum_{0=1}^{6}\sum_{i^o\in M}\left|g_{k,i^o}\right|^2 p_{k,i^o} \quad (5)$$

Note that SIC performed at the user receiver that may cause considerable complexity O^3 [2]. To have a better understanding of the model, we will discuss NOMA model with power and frequency allocation for total rate, and then power allocation for energy spectral efficiency tradeoff.

A: Power and frequency allocation for total rate

We will assume that the range of M_k is $M_l \leq M_k \leq M\ u$, where M_l and M_u are the lower and upper bounds of the multiplexed-user per S_k. The objective problem is formulated to maximize the total data-rate overall system bandwidth as follows.

$$max_{x_{k,n}\, p_{k,n}} \sum_{k\in K}\sum_{n\in N} B_k \log_2\left(1 + \frac{x_{k,n}\, p_{k,n}|g_{k,n}|^2}{I^0_{k,n} + I_{k,n} + Q^2}\right)$$

$$\text{s.t}:\ \text{C1}: \sum_{n\in M} x_{k,n}\ p_{k,n} \quad \leq p_k\ \forall\in k$$

C2: $\sum_{n\in N}\sum_{k\in K} x_{k,n}\ p_{k,n} \quad \leq p_t$ (6)

C3: $M_1 \leq M_K \leq M_U$

C4: $R_n \ > R_{min}\ \forall n \in N$

C5: $x_{k,n} \in (0,1)\forall k \in K\ \ n \in N$

Where P_k is the maximum S_k transmitted power, P_t is the overall transmitted power of the BS, and R_{min} is the required minimum rate for each user. Due to the power transmitted by the BS and the power allocation for each S_k is limited, the power allocation variable $p_{k,n}$ Must satisfy the constraints C1 and C2, which ensures that S_k transmitted power is less than P_k, and the total transmitted BS power is lower than P_t.

B: Power Allocation for Energy-Spectral Efficiency Tradeoff

The problem of energy efficiency (EE) and spectral efficiency (SE) tradeoff can be formulated by maximizing the global EE (GEE) subject to constraints on minimum rate requirements and transmit power budgets. Accordingly, the following optimization problem is considered for the EE-SE tradeoff [16].

$$max_p\ q = \sum_{n=1}^{N} R_n(p)/\,p_t\ (p)$$

$$\text{s.t. } C1: R_n(p) \geq R_{min}, \forall n = 1, \dots, N, \tag{7}$$

$$C2: 0 \leq p_n \leq p_n^{max}, \forall n = 1, \dots, N$$

Where R_{min} denotes the minimum required rate of the user n and the unit of q is bits/Joule/Hz. The above optimization problem is non-convex and NP-Hard, it is therefore difficult to get the solution in polynomial time.

Rate Residue Elimination Method (RRE)

The major problem of power and frequency allocations lies in system compu-tation complexity. As such, we propose a Rate Residue Elimination (RRE) in two steps. In the first step, the propose method handle the subchannels chal-lenge. The second step finds the optimum power. The third step calculate the frequency allocation based on rate and power of each user-subchannel set.

NOMA Subchannel extension

To remove the constraints C1 in Eq. 7, we utilize the penalty method [16]. How-ever, this method is designed to handle single channel in NOMA system, and limits the performance of NOMA system. Furthermore, this method increases the complexity of SIC decoding. Therefore, we modify the original method to handle more than one subchannel, namely hybrid NOMA, we explain the mathematical formulation as follows.

The target of this step, is to optimize $p_{k,n}$, which can be regarded as a search agent. At the iteration ı, the transmit power p(ı) for each user-subchannel set can be updated by an optimization algorithm. Let us consider the total power consumption P_t from BS to the user-subchannel set includes two main parts: p_k which is the transmit power consumption per S_k, and p^c_k which is the circuit power consumption per S_k, and it can be consider as constant value. We express P_t as follows:

$$p_{t(p)} = \sum_{k=1}^{K} pk + (p_k^c * K) \tag{8}$$

Where pk is calculated as follow:

$$p_k = \sum_{n=1}^{N} x_{k,n}\, p_{k,n} \;\forall k \in K \tag{9}$$

The sum rate of n users per Sk is expressed as follows:

$$R_k(p) = \sum_{n=1}^{N} R_{k,n}(p) \;\forall k \in K \tag{10}$$

In addition, the total rate Rt is expressed as follows:

$$R_t = \sum_{k=1}^{K} R_k(p) \tag{11}$$

The final cost function, which is a minimization problem, which relates to rate, and power subchannels can be described as follows:

$$min_p^q = -\frac{R_t}{p_{t(p)}} + \mu \sum_{n=1}^{N} F_n\left(f_n(p)\right) f_n{}^2(p) \tag{12}$$

Where, μ is a constant value, and $f_n(p)$ refer to error function between the minimum required rate and the actual rate at ı, which can be expressed as follows:

$$f_n(p) = R_{min} - R_n(p) \tag{13}$$

Where R_n represent the use rate over all S_k, and it can be describe as follows:

$$R_n(p) = \sum_{k=1}^{K} R_{k,n}(p) \;\forall n \in N \tag{14}$$

And F_n is a switch function to apply the penalty condition as follows:

$$F_n\left(f_n(p)\right) = \begin{cases} 0, & f_n(p) \geq 0 \\ 1, & otherwise \end{cases} \tag{15}$$

Eq. 12, represent the final hybrid NOMA model, which includes K subchan-nels, for each user. The first term of Eq. 12 describes that BS needs power to increase total rate performance (SE), simultaneously, EE is decreases. There-fore, we must optimize the transmitted power p to provide a tradeoff between EE and SE. The second term add a penalty to the cost function in case of $R_n < R_{min}$. As such, we employ GWO to find the optimum p∗ that minimize problem of q. It should be noted that since the model is Hybrid NOMA, we will assume that $x_{k,n} = 1$ [17]. As a result, the efficiency of search algorithm will be improved significantly in term of accuracy and speed.

Subchannel Allocation

When the outcome of the GWO optimization process obtained the final power for each user-subchannel set $p^*_{k,n}$, two issues will rise. Due to the exists of low channel gain in user-subchannel set, there are some users will be assigned with power greater than the allowed threshold p_{Th}. The second issue is raised from user-subchannel set rate where it is less than threshold rate R_{Th}. Therefore, we propose user-subchannel allocation algorithm to handle the above challenges as follows:

$$f_{k,n}^{p_{k,n}{}^*} = \begin{cases} 0, & p_{k,n}{}^* > pTh \\ 1, & otherwise \end{cases} \tag{16}$$

Where $f_{k,n}$ is the user-subchannel allocation set based on power allocation set. By using the above solution, the total consuming power will be reduced, which leads to increase EE.

On the other hand, user-subchannel allocation set based on rate $f_{k,n}$ less than R_{Th} is computed as follows:

$$f_{k,n}^{p_{k,n}^{*}} = \begin{cases} 0, & R_{k,n}^{*} < RTh \\ 1, & otherwise \end{cases} \quad (17)$$

This step will effect SE slightly, consequently will improve the interference and reduces the SIC decoding complexity.

Finally, user-subchannel allocation set $x_{k,n}$ can be obtained by point to point multiplication as describe below:

$$x_{k,n}^{*} = f_{k,n}^{p_{k,n}^{*}} \times f_{k,n}^{R_{k,n}^{*}} \quad (18)$$

After the calculations of p∗ and x∗ of user-subchannel set, we will evaluate model to obtain R_t, EE-SE, $P_t(p)$, p_k, and the value of user rate ζ which is less than R_{min} and can be expressed as follows:

$$\delta = -\sum f_n(p) \;\; \forall f_n(p) < 0 \; f_n(p) \quad (19)$$

Result and Discussion

The important result is to know which algorithm is best for the environment according to the size of the network. The results will be divided into multiple stages. First, each algorithm will be discussed according to the network's required specifications and requirements. Four parameters are relied upon to know whether the algorithm is good or not power allocation, Fairness index, Rate, energy efficiency. The results of this research are divided for the purpose of choosing the best algorithm based on the following parameters (power allocation, Fairness index, Rate and energy efficiency), and the steps are divided into two stages.

Select Weighted Rate

The comparison is based on choosing the best effective point (weighted rate) for each element in each algorithm separately. The comparison is also for three networks (4*2, 6*3 and 8*4) to find the best point for each network for the same algorithm and parameters.

First, we review the results of the (GA) algorithm for all the selected parameters as in the following Fig. 2.

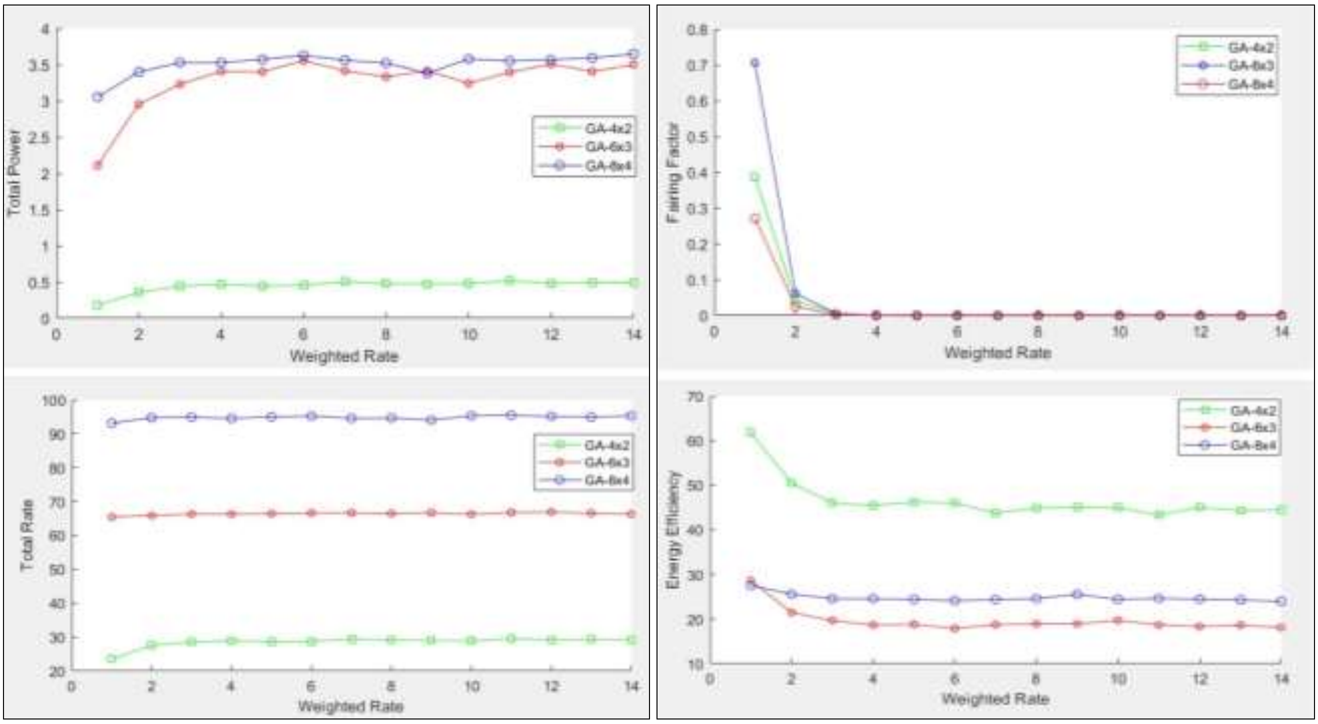
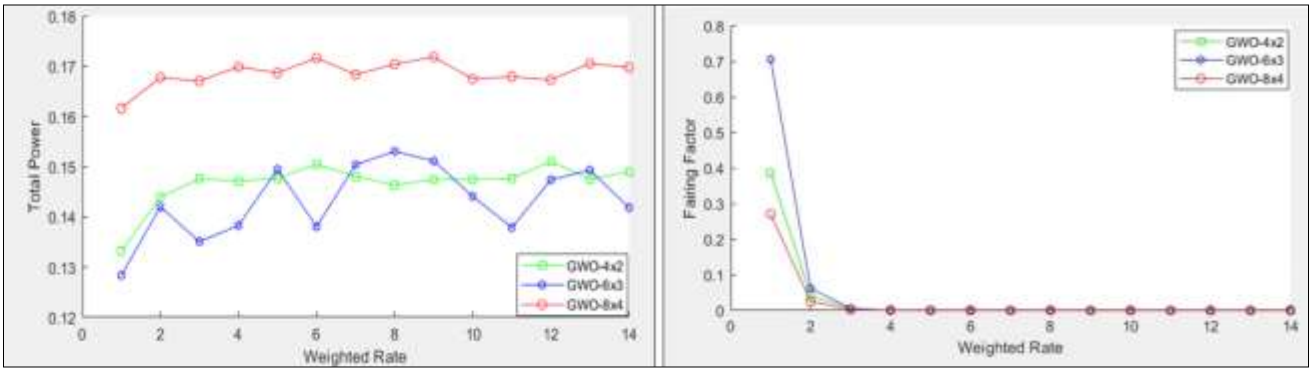


Fig 2: Select Weighted Rate with GA algorithm.

Secondly, we review the results of the (GWO) algorithm for all the selected parameters as in the following Fig. 2.



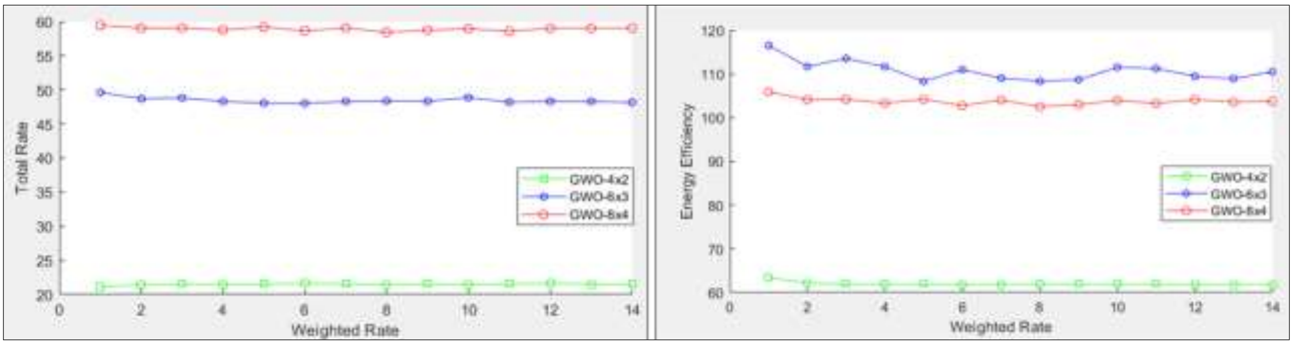


Fig 3: Select Weighted Rate with GWO algorithm

Finally, we review the results of the (WOA) algorithm for all the selected parameters as in the below Fig. 4.

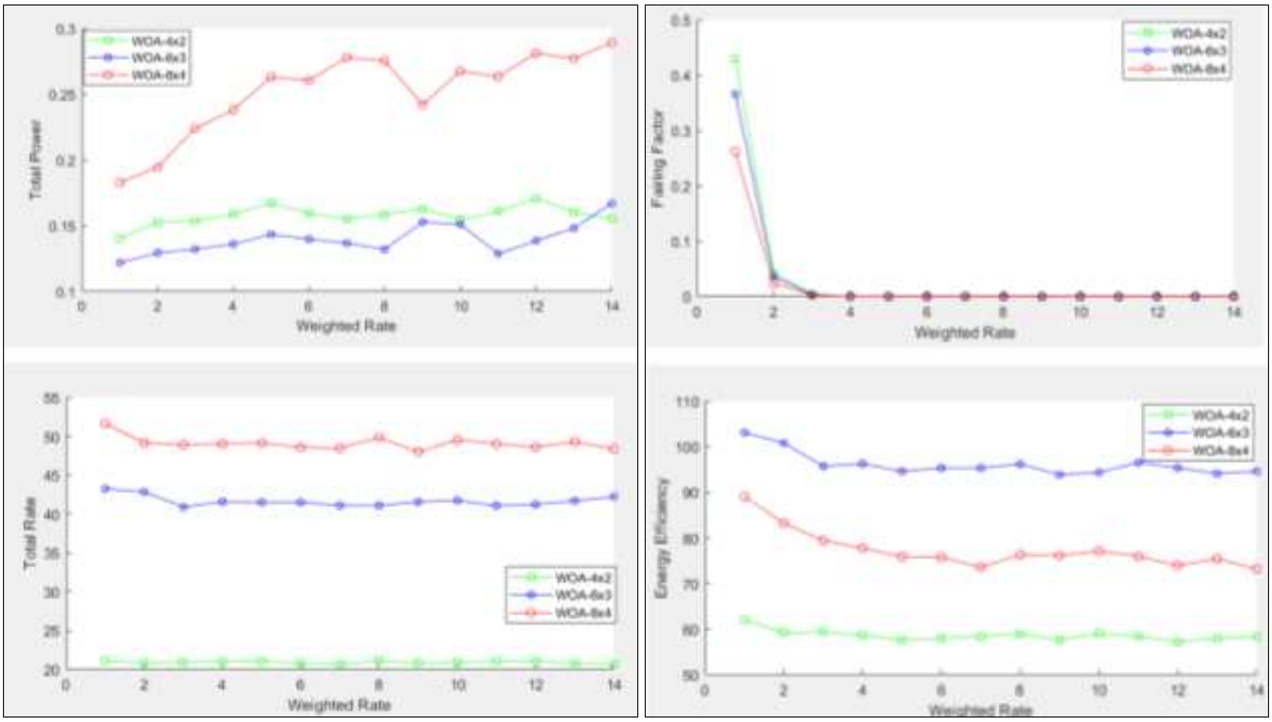


Fig 4: Select Weighted Rate with WOA algorithm

Select Desired Rate

After choosing the best point, all factors for each algorithm are based on the chosen point

In this step, we take the network sizes (2*4, 3*6 and 4*8) to find out which algorithm is best in terms of the factors measured against it.

Desired Rate with total power

The results of all algorithms with the total Power parameter as shown in the following results.

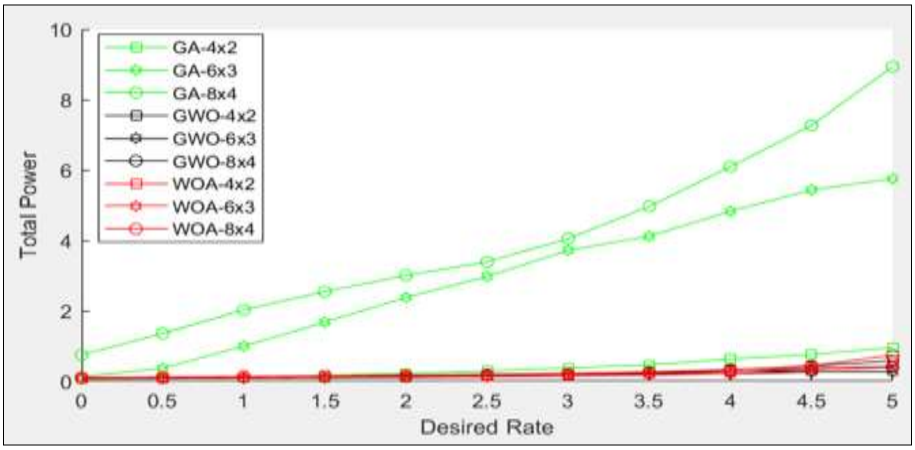


Fig 5: Desired Rate with Total power in GA, GWO and WOA Algorithms.

As we explained previously, the requirements for an ideal network are to have less power and higher productivity. From the fig. 5, it is clear that the GWO algorithm is much better when using a technique using an algorithm that consumes less power compared to the mentioned algorithms.

Desired Rate with Fairing factor

The results of all algorithms with the Fairing factor parameter as shown in the following results.

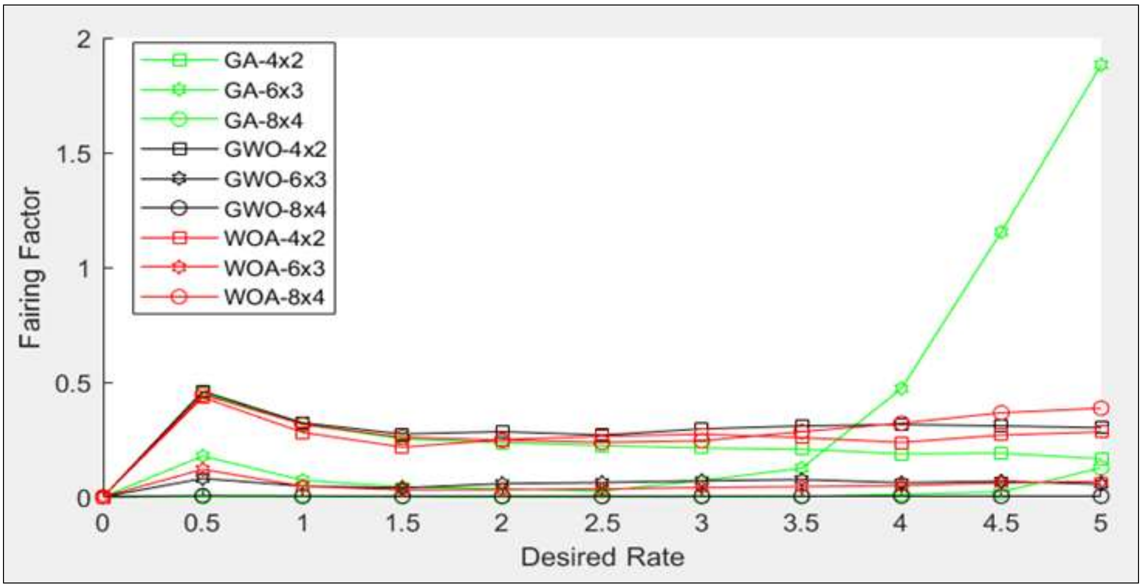


Fig 6: Desired Rate with Fairing factor in GA, GWO and WOA Algorithms

As we explained previously, the closer this factor is to zero, the better the network will be with equal distribution among users. The fig. 6, shows the closeness of the fairness of the distribution of values between the algorithm (GWO) and (WOA), and this indicates the quality of the chosen algorithms and their productivity at work.

Desired Rate with Total Rate

The results of all algorithms with the Total Rate parameter as shown in the following results.

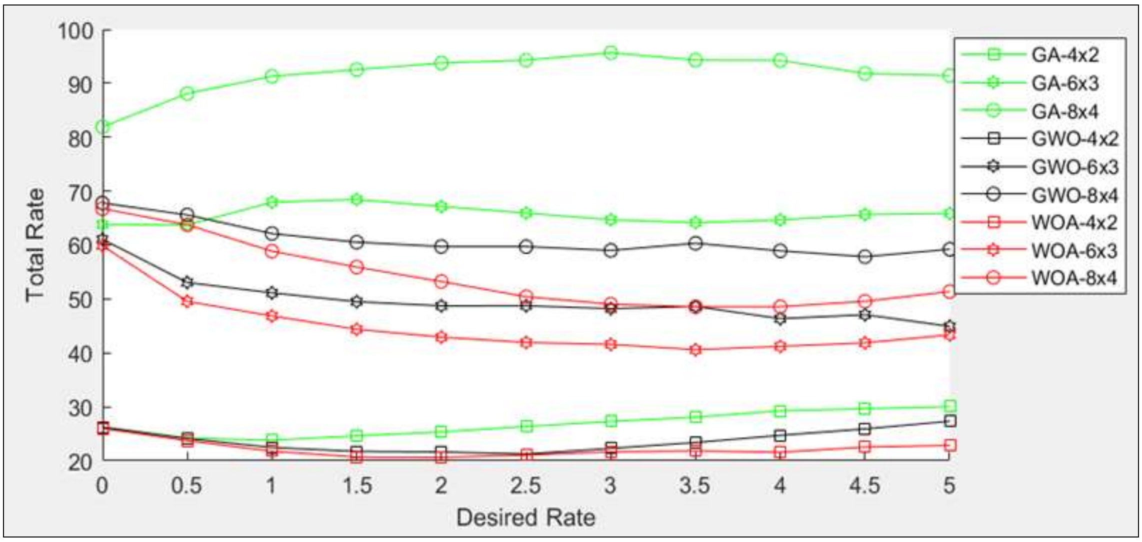


Fig 7: Desired Rate with Total Rate in GA, GWO and WOA Algorithms

From the fig. 7, it is clear that the algorithms that had high power, this factor results in a higher productivity for the algorithm itself (GA), and therefore this has a negative effect because it consumes high power. Therefore, the best rate of productivity must be taken compared to good power. So the comparison between the algorithms (GWO and WOA) is based on the network sizes and it is the superior GWO algorithm.

Desired Rate with Energy efficiency: The results of all algorithms with the Energy efficiency parameter as shown in the following results. This factor is considered the most important in this research because it measures the efficiency of the algorithm.

The evidence is clear, according to the fig. 5 below, showing that competition continues between algorithms to prove efficiency at the best point at which algorithmic techniques work. Therefore, the (GWO) algorithm outperforms the other algorithms for all network sizes.

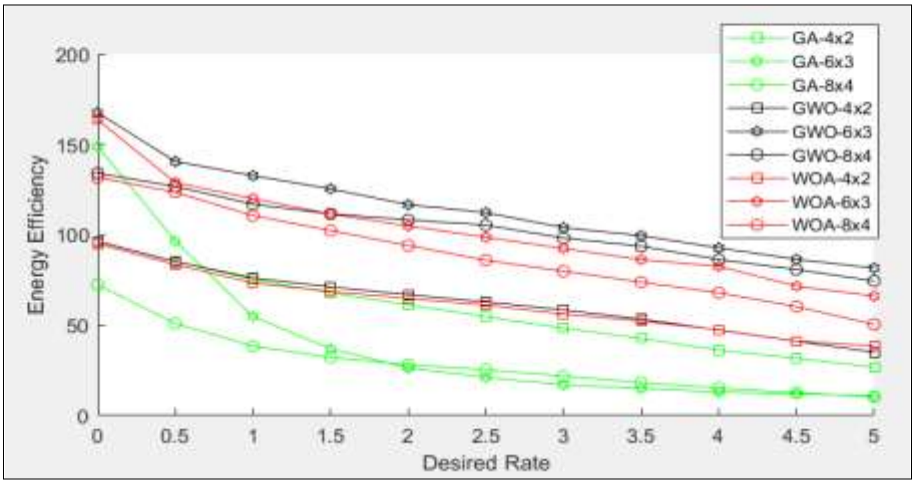


Fig 8: Desired Rate with Energy efficiency in GA, GWO and WOA Algorithms

Conclusion

We have modeled and examined the dynamic power allocation for Hybrid NOMA issue in this article. For every coordinating BS, a low-cost distributed power optimization technique has been suggested due to the high computational complexity of the suggested joint power optimization methodology. The ideal distribution of power under the distributed method, the solutions at each coordinating BS are separate from those at the other coordinating BSs. Additionally, we have determined the prerequisites that must be met for the distributed power optimization solution to be accepted as a workable solution for the joint power optimization issue. Therefore, the results were divided into two steps. Step 1, the best point (Weighted Rate) for each algorithm was determined according to each element (Total Power, Fairing Index, Total Rate and Energy Efficiency), and three network sizes(2*4, 3*6 and 4*8) were taken, knowing the algorithms to which the technique was applied are (GA, GWO and WOA) optimization algorithms. Step2, After choosing the best point, all factors for each algorithm are based on the chosen point, in this step, we take the network sizes (2*4, 3*6 and 4*8) to find out which algorithm is best in terms of the factors measured against it. So the comparison between the algorithms (GA, GWO and WOA) depends on the network sizes and the surrounding environment.

Therefore, to apply an ideal network for 5G hybrid MOMA must be apply a technique to the GWO algorithm because it contains fair distribution (J) between users, less power consumption (P), and higher productivity (R), so it contains high energy efficiency (E) when used.

References

1. Ding Z, Liu Y, Choi J, Sun Q, Elkashlan M, Chih-Lin I, *et al*. Application of non-orthogonal multiple access in LTE and 5G networks. IEEE Communications Magazine. 2017;55(2):185-191.
2. Mu X, Liu Y, Guo L, Lin J, Al-Dhahir N. Capacity and optimal resource allocation for IRS-assisted multi-user communication systems. IEEE Transactions on Communications. 2021;69(6):3771-3786.
3. Maraqa O, Rajasekaran AS, Al-Ahmadi S, Yanikomeroglu H, Sait SM. A survey of rate-optimal power domain NOMA with enabling technologies of future wireless networks. IEEE Communications Surveys & Tutorials. 2020;22(4):2192-2235.
4. Dai L, Wang B, Yuan Y, Han S, Chih-Lin I, Wang Z, *et al*. Non-orthogonal multiple access for 5G: Solutions, challenges, opportunities, and future research trends. IEEE Communications Magazine. 2015;53(9):74-81.
5. Pham QV, Mirjalili S, Kumar N, Alazab M, Hwang WJ. Whale optimization algorithm with applications to resource allocation in wireless networks. IEEE Transactions on Vehicular Technology. 2020;69(4):4285-4297.
6. You H, Pan Z, Liu N, You X. User clustering scheme for downlink hybrid NOMA systems based on genetic algorithm. IEEE Access. 2020;8:129461-129468.
7. Wang G, Shao Y, Chen LK, Zhao J. Improved joint subcarrier and power allocation to enhance the throughputs and user fairness in indoor OFDM-NOMA VLC systems. Optics Express. 2021;29(18):29242-29256.
8. Rezvani S, Jorswieck EA, Joda R, Yanikomeroglu H. Optimal power allocation in downlink multicarrier NOMA systems: Theory and fast algorithms. IEEE Journal on Selected Areas in Communications. 2022;40(4):1162-1189.
9. Erturk E, Yildiz O, Shahsavari S, Akar N. Power allocation and temporal fair user group scheduling for downlink NOMA. Telecommunication Systems. 2021;77(4):753-766.
10. Goudos SK, Diamantoulakis PD, Boursianis AD, Papanikolaou VK, Karagiannidis GK. Joint user association and power allocation using swarm intelligence algorithms in non-orthogonal multiple access networks. In: 2020 9th International Conference on Modern Circuits and Systems Technologies (MOCAST). IEEE; c2020. p. 1-4.
11. Di B, Song L, Li Y. Sub-channel assignment, power allocation, and user scheduling for non-orthogonal multiple access networks. IEEE Transactions on Wireless Communications. 2016;15(11):7686-7698.
12. Xiao H, Wang Y, Cheng Q, Wang Y. An improved PSO-based power allocation algorithm for the optimal EE and SE tradeoff in downlink NOMA systems. In: 2018 IEEE 29th Annual International Symposium on Personal, Indoor and Mobile Radio Communications (PIMRC). IEEE; c2018. p. 1-5.
13. Ren Z, Zhao A. Dual-band MIMO antenna with compact self-decoupled antenna pairs for 5G mobile applications. IEEE Access. 2019;7:82288-82296.

14. Jacob JL, Abrao T. NOMA systems optimization to ensure maximum fairness to users. arXiv preprint arXiv:2001.03827; c2020.
15. Zhu J, Wang J, Huang Y, He S, You X, Yang L, *et al*. On optimal power allocation for downlink non-orthogonal multiple access systems. IEEE Journal on Selected Areas in Communications. 2017;35(12):2744-2757.
16. Khan WU, Jameel F, Ristaniemi T, Khan S, Sidhu GAS, Liu J, *et al*. Joint spectral and energy efficiency optimization for downlink NOMA networks. IEEE Transactions on Cognitive Communications and Networking. 2019;6(2):645-656.
17. Pang L, Wu W, Zhang Y, Yuan Y, Chen Y, Wang A, *et al*. Joint power allocation and hybrid beamforming for downlink mmwave-NOMA systems. IEEE Transactions on Vehicular Technology. 2021;70(10):10173-10184.