Tech Science Press

Capacity and Fairness Maximization-Based Resource Allocation for Downlink NOMA Networks

Mohammed Abd-Elnaby[*]

Department of Computer Engineering, College of Computers and Information Technology, Taif University, Taif, 21944, Saudi Arabia
[*]Corresponding Author: Mohammed Abd-Elnaby. Email: maahmed@tu.edu.sa

Abstract: Non-orthogonal multiple access (NOMA) is one of the leading technologies for 5G communication. User pairing (UP) and power allocation (PA) are the key controlling mechanisms for the optimization of the performance of NOMA systems. This paper presents a novel UP and PA (UPPA) technique for capacity and fairness maximization in NOMA called (CFM-UPPA). The impact of the power allocation coefficient and the ratio between the channel gains of the paired users on the sum-rate capacity and the fairness in NOMA is firstly investigated. Then, based on this investigation, the PA and UP algorithms of the CFM-UPPA technique are proposed. The power allocation coefficient of the proposed PA is formulated as an exponentially decaying function of the ratio between the channel gains of the paired users to maximize the capacity and the fairness, and its maximum value is adjusted to guarantee the successive interference cancellation (SIC) constraints. The proposed UP is based on selecting the user that has the highest channel gain per subcarrier as the strong user to maximize the capacity and selecting the user that has the closest lower channel gain to the strong user's channel gain as the weak user to improve the fairness and capacity. The performance evaluation of the proposed CFM-UPPA technique in terms of capacity, fairness, and outage probability demonstrates that its performance significantly outperforms that of the orthogonal multiple access (OMA) system and that of the NOMA system with random UP. Also, the simulation results demonstrate the efficiency of the proposed PA in improving the performance of other UP algorithms, such as the random UP algorithm.

Keywords: 5G; non-orthogonal multiple access; user pairing; power allocation; capacity; fairness

1 Introduction

The rapid development of multimedia applications and the applications of the Internet of Things (IoT), in addition to the huge increase in the number of wireless and mobile devices, paved the way for the emergence of the 5G communication networks. NOMA has emerged as a promising access technology for capacity enhancement in 5G networks by enabling multiple users

to use the same subcarrier at the same time with the aid of successive interference cancellation (SIC) technique implemented at the receiver to detect the user data. The performance optimization of NOMA strictly depends on the efficiency of user pairing (UP) and power allocation (PA) mechanisms. UP and PA mechanisms are responsible for controlling all performance metrics of NOMA, such as system capacity, fairness among users' equipment (UE), and data rate outage probability [1–5].

Existing UP and PA mechanisms try to improve NOMA performance, but most of them succeeded focus on in improving the system capacity at the expense of the other important metrics such as the fairness among users and the outage probability. Also, most of the existing researches require exhaustive searching and high computational complexity to provide a near-optimal solution for the UP and PA problems. So, in this paper, a novel capacity and fairness maximization-based UP and PA (UPPA) technique called (CFM-UPPA) is proposed for downlink NOMA. The main contributions of the proposed CFM-UPPA technique can be summarized as follows:

(1) An extensive investigation of the impact of the power allocation coefficient and the ratio between the channel gains of the paired users (i.e., paired UEs) on the sum-rate capacity and the fairness in NOMA is presented. Also, the investigation results are analyzed to clarify how to adjust the power allocation coefficient using the PA algorithm and select the channel gains of the paired UEs using the UP algorithm to maximize the capacity and fairness.

(2) Then based on the investigation results, the PA algorithm of the CFM-UPPA technique, which is called capacity and fairness maximization-based PA (CFM-PA) is proposed. The power allocation coefficient of CFM-PA is formulated as an exponentially decaying function of the ratio between the channel gains of the paired UEs to maximize the capacity and the fairness, and its maximum value is adjusted to guarantee the SIC constraints.

(3) The UP algorithm of the CFM-UPPA technique, which is called capacity and fairness maximization-based UP (CFM-UP) is based on selecting the user that has the highest channel gain per subcarrier as the strong user to maximize the capacity and selecting the user that has the closest lower channel gain to the strong user's channel gain as the weak user to improve the fairness and capacity.

(4) Both CFM-PA and CFM-UP can be considered as non-exhaustive searching algorithms. Also, unlike the proposed CFM-PA, most of the existing PA algorithms are exhaustive searching algorithms and have no closed-form equation for the power allocation coefficient for the maximization of capacity and fairness.

(5) The performance of the proposed CFM-UPPA technique in terms of capacity, fairness, and outage probability is evaluated, and the simulation results show that its performance significantly outperforms that of the OMA system and that of the NOMA system with random UP. In addition, the proposed CFM-PA is applied to the random UP to demonstrate its efficiency in improving the performance of other UP algorithms.

The paper is organized as follows. Related work is discussed in Section 2. The system model and capacity are outlined in Section 3. The impact of the power allocation coefficient and the ratio between the channel gains of the paired UEs on capacity and fairness in NOMA is presented in Section 4. The proposed CFM-UPPA technique is provided in Section 5. Section 6 presents the results, comparison, and discussion. Finally, Section 7 concludes the paper.

2 Related Work

Resource allocation in terms of UP and PA plays the main role in improving the performance of NOMA especially in terms of the network capacity. However, the traditional UP and PA methods succeeded in improving the capacity of NOMA with different degrees, they fail in improving other important performance metrics such as fairness among UEs and outage probability at the same time. Besides, computational complexity is another important parameter that should be carefully considered in the design of resource allocation mechanisms since it reduces computational efficiency and the speed of allocation decisions [6–9].

A deep neural network (DNN) based resource allocation technique is proposed in [10] to handle the complexity problem of traditional resource allocation methods since DNN can perform the real-time allocation. Generic DNN is trained to approximate the interior point method (IPM) for PA to improve the computational efficiency and increases the capacity of the system. In [11], a joint dynamic PA and UP algorithm is proposed for power-efficient and delay-constrained hybrid OMA/NOMA systems. In this hybrid system, UP determines if the UE will be served by OMA or NOMA. Both queue state information and the channel are observed, and the PA and UP optimization framework is proposed to minimizes the average transmit power while guaranteeing minimum data rates and decreasing the queueing delay.

In [12], multi-objective optimization is used for resource allocation in multi-user downlink NOMA systems to improve spectrum efficiency and energy efficiency. A joint spectrum and energy optimization problem is formulated and solved using dual decomposition while guaranteeing the SIC process by preserving the constraint of the minimum gap among UE transmit powers. In [13], a joint UP and PA algorithm for uplink NOMA systems is proposed to improve the proportional fairness of UEs. A basic scenario in which UEs are distributed in a single base station (BS) and a complex scenario in which the interfering UEs users are randomly distributed outside BS is considered. Tabu search is used to provide a near-optimal solution for the UP problem in the basic scenario and the PA problem in the complex scenario is solved using stochastic programming.

Many research works have investigated the NOMA capacity improvement in heterogeneous networks [14–19]. The selection of the UP method for NOMA according to the network load to make a trade-off between the capacity gain and the complexity of the UP method is presented in [14]. Gale–Shapley, Hungarian, random, and exhaustive methods are considered for UP with dynamic PA, and the results show that for equally loaded cells, the near-optimal UP methods provide the highest network capacity gain (22%–24%). While for unequally loaded cells, simpler UP methods provide higher capacity gains (approximately 29%).

Also, many researchers investigate resource allocation in MIMO based NOMA systems [20–24]. A greedy-search-based UP and a minimum mean square error (MMSE) based PA is proposed in [20] to maximize the sum-rate of a downlink NOMA network. Also, the transmitted power of all UE pairs and that of each UE in each pair are optimized and an iterative procedure is used to solve the PA problem. Performance improvement of Multi-cell MIMO-NOMA networks is investigated in [25,26]. In [25], to improve system data rate, the resource allocation problem is divided into NOMA mobile user clustering and the base station selection. A new objective function is proposed to integrate mobile user fairness into system data rate optimization. Moreover, a closed-form solution of MIMO-NOMA resource allocation for a single cluster is derived and a new two-side coalitional matching approach to jointly optimize MIMO NOMA clustering and BS selection is proposed. An analytical framework for exploring the benefits of applying MIMO NOMA clustering in dense wireless networks is developed in [26]. With the aid of stochastic

geometry, a new explicit expression for per-cluster average data rates are derived, and the analysis and optimization of area spectral efficiency are considered.

Owing to the important role of cognitive radio as promising solutions to provide high spectral efficiency for future wireless networks, the resource allocation problem in cognitive NOMA Networks is investigated recently in many studies [27–29]. In [27], an uplink IoT device scheduling and power allocation problem based on imperfect spectrum sensing and imperfect channel state information (CSI) is investigated for cognitive heterogeneous NOMA networks. The outage performance of an overlay cognitive NOMA system with imperfect successive interference cancellation (SIC) is investigated in [28]. Closed forms of the outage probability of primary user and secondary user are derived, and an optimal power allocation coefficient is proposed to maximize the system throughput. NOMA-assisted overlay cognitive radio network in which the communication between the pair of primary users is achieved with the aid of the secondary transmitter (ST) is considered in [29]. The authors aim to minimize the outage probability of the secondary system under quality-of-service (QoS) constraints of the primary system by jointly optimizing the decoding order at the receivers and the power allocation factor at ST.

3 System Model and Capacity

A downlink NOMA system is considered, which consists of a base station (BS), multiple subcarriers, and multiple users (i.e., multiple UEs) as shown in Fig. 1. The set of subcarriers donated by $m = \{1,\dots, M\}$, and the set of UEs donated by $k = \{1,\dots, K\}$. The paired UEs transmit over the same subcarriers, and for a subcarrier m it is assumed that UE-1's channel gain is the larger one. Since $|h_{m,1}|^2 > |h_{m,2}|^2$, UE-1's receiver can perform SIC and remove the interference from UE-2's signal. The ratio between the channel gain of UE-2 (weak UE) $h_{m,2}$ to the channel gain of UE-1 (strong UE) $h_{m,1}$ is $\mu = \dfrac{h_{m,2}}{h_{m,1}} < 1$ such that $h_{m,2} = \mu h_{m,1}$. If the power allocation coefficient for UE-1 is $\alpha < 0.5$ then UE-2's signal is allocated $1 - \alpha$ transmit power.

On subcarrier m, the BS transmits a superimposed signal for the paired UEs as

$$x_m = \sqrt{\alpha P_m} s_{m,1} + \sqrt{(1-\alpha) P_m} s_{m,2} \tag{1}$$

where P_m is the power allocated to the subcarrier m and $s_{m,1}$ and $s_{m,2}$ are the message signal transmitted to UE-1 and UE-2 respectively on subcarrier m.

The received signals for both UEs are

$$y_{m,i} = h_{m,i} x_m + n_{m,i} \quad i = 1, 2 \tag{2}$$

where $h_{m,i}$ donates the channel gain between the BS and UE-i, which is assumed to be Rayleigh distributed. and $n_{m,i}$ denotes the additive white Gaussian noise (AWGN) with zero mean and variance σ^2.

By assuming that the transmission bandwidth per subcarrier is normalized to 1 Hz. Then the achievable data rates of the paired UEs are

$$R_{m,1} = \log_2\left(1 + \frac{\alpha P_m |h_{m,1}|^2}{\sigma^2}\right) \tag{3}$$

$$R_{m,2} = \log_2 \left(1 + \frac{(1-\alpha)P_m \left| h_{m,2} \right|^2}{\alpha P_m \left| h_{m,2} \right|^2 + \sigma^2} \right) \tag{4}$$

So, the sum-rate capacity per subcarrier m for NOMA is

$$C_m = R_{m,1} + R_{m,2}. \tag{5}$$

The achievable data rate of the UE-i on subcarrier m in an OMA system is given by

$$R_{m,i}^{OMA} = \frac{1}{2} \log_2 \left(1 + \frac{P_m \left| h_{m,1} \right|^2}{\sigma^2} \right) \quad i = 1, 2. \tag{6}$$

So, the sum-rate capacity per subcarrier m for OMA is $R_{m,1}^{OMA} + R_{m,2}^{OMA}$, where the factor $\frac{1}{2}$ is due to the fact that the OMA system results in a multiplexing loss of $\frac{1}{2}$.
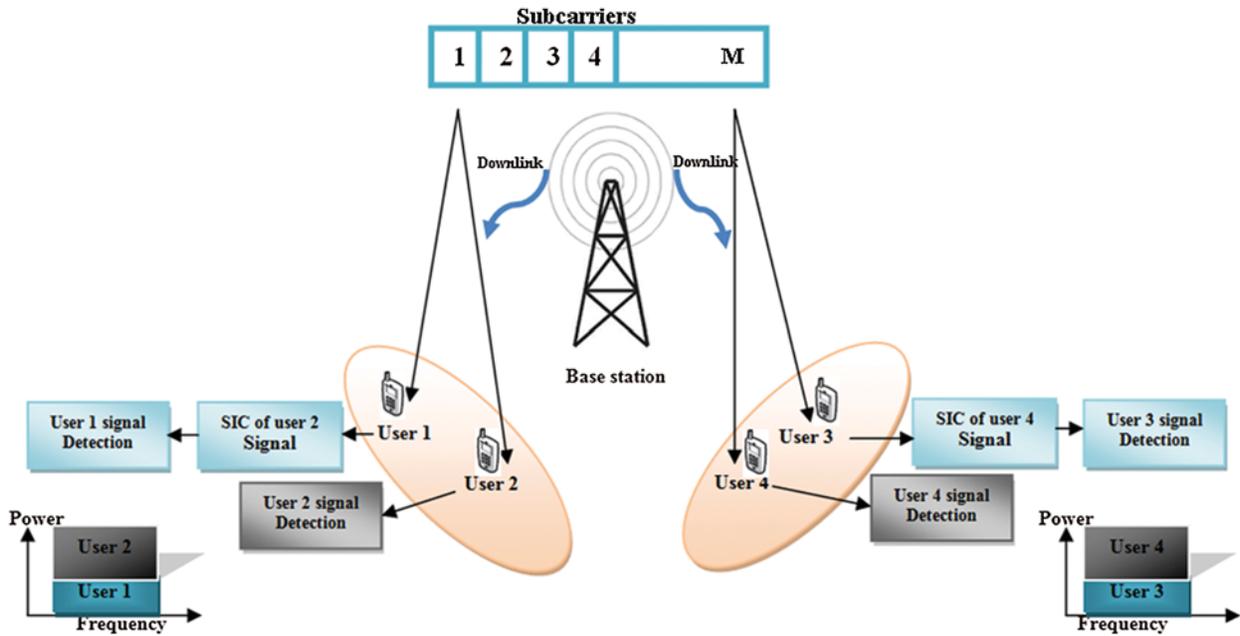
Figure 1: System model of downlink NOMA system

4 The Impact of α and μ on Capacity and Fairness of Paired UEs in NOMA

In this section, the capacity (i.e., sum-rate) and fairness of paired UEs in NOMA will be presented as a function of both the power allocation coefficient (α) and the ratio of UE-2's channel gain of to UE-1's channel gain of (μ). Eq. (3) presents the achieved data rate of strong UE ($R_{m,1}$) while Eqs. (4) and (5) are used after substituting $h_{m,2} = \mu h_{m,1}$ to represent the achieved data rate of weak UE ($R_{m,2}$) and the capacity of the paired UEs (C_m) respectively.

The Jain fairness index (FI) presented in Eq. (7), which measures of the fairness among the achieved users data rate R_k is used to evaluate fairness performance.

$$F = \frac{(\sum_{k=1}^{K} R_k)^2}{K \sum_{k=1}^{K} (R_k)^2}$$ (7)

The performance is investigated at SNR per subcarrier $\left(\frac{P_m}{\sigma^2}\right) = 10$ dB. The investigation results when the channel gain of the strong UE is normalized to 1 ($h_{m,1} = 1$) are presented in Figs. 2–5 while the investigation results at $h_{m,1} = 2$ are presented in Figs. 6–9 to show the impact of increasing $h_{m,1}$. The capacity of paired UEs presented in Fig. 2 shows that as μ decreases (i.e., as the channel gains of the paired UE diverge), the capacity decreases especially at small values of α. On the other hand, the increase of α has a significant impact on increasing the capacity, especially as μ decreases. So. we can conclude that α should be increased as μ decreases to increase the capacity and vice versa.
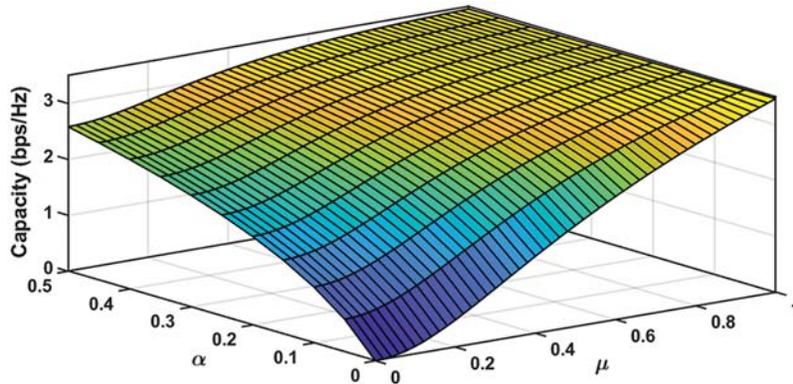
Figure 2: NOMA capacity of paired UE at $h_{m,1} = 1$
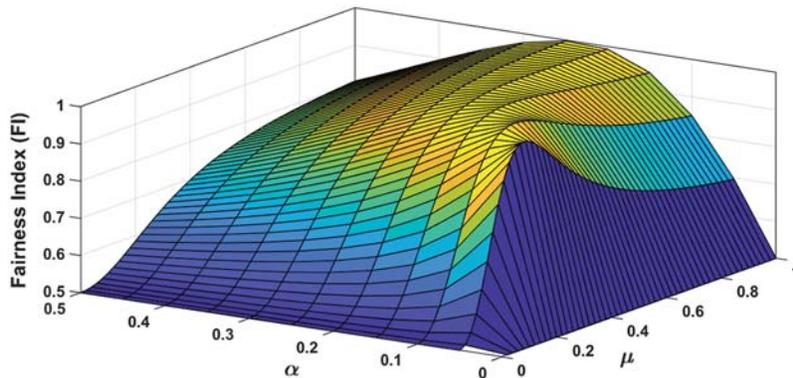
Figure 3: Fairness index at $h_{m,1} = 1$

Fig. 3 shows that the fairness performance significantly deteriorates as μ becomes lower than 0.5 and as α increases. On the other hand, the fairness performance significantly improves as μ increases (i.e., the channel gains of the paired UEs converge) and with the use of small values of α. The obtained results in Fig. 3 can be more clarified by looking to Figs. 4 and 5, which present the achieved data rate of weak UE and the achieved data rate of strong UE. For weak UE, the achieved data rate sharply increases as μ increases, and α decreases, as shown in Fig. 4. On the other hand, the achieved data rate of strong UE independents on μ and increases as α increases as shown in Fig. 4.
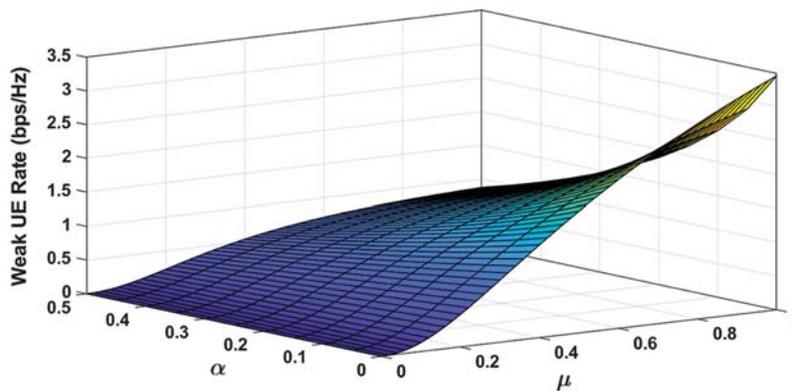
Figure 4: Data rate of weak UE $(R_{m,2})$ at $h_{m,1} = 1$
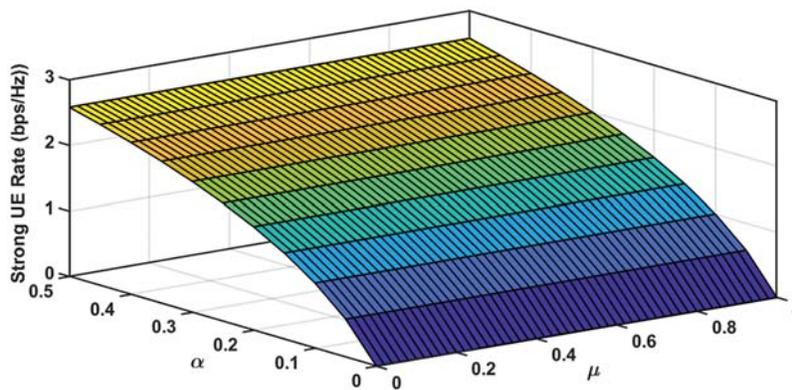
Figure 5: Data rate of strong UE $(R_{m,1})$ at $h_{m,1} = 1$

The results presented in Figs. 6–9 show that increasing the channel gain of the strong UE to 2 $(h_{m,1} = 2)$ significantly increases the capacity of paired UE as shown in Fig. 6. This is because the achieved data rate of both weak UE and strong UE is considerably increased as shown in Figs. 8 and 9, respectively. Also, it is shown that the capacity decreases as μ considerably decreases especially at small values of α. So. α should be increased as μ decreases to increase the capacity. On the other hand, increasing $h_{m,1}$ makes the fairness performance deterioration more sensitive to the increase of the value of α, and the FI considerably decreases as α increases especially at low values of μ as shown in Fig. 7.
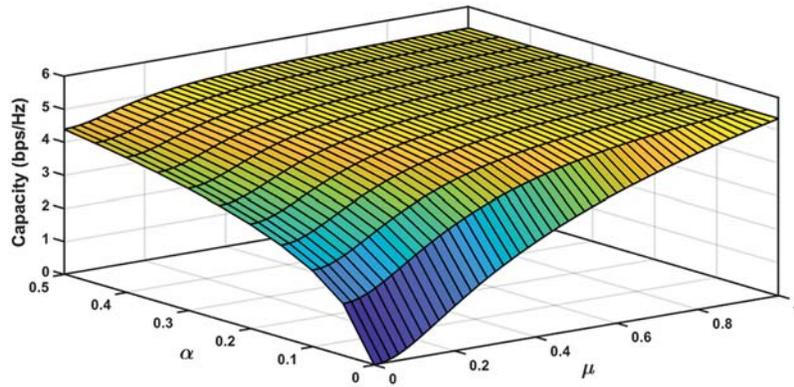
Figure 6: NOMA capacity of paired UE at $h_{m,1} = 2$
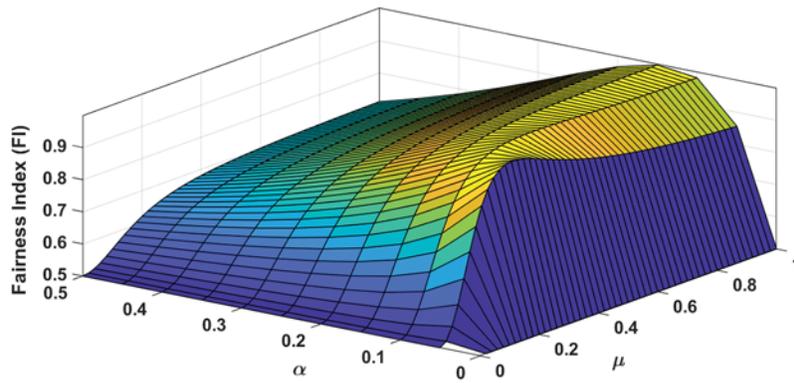
Figure 7: Fairness index at $h_{m,1} = 2$
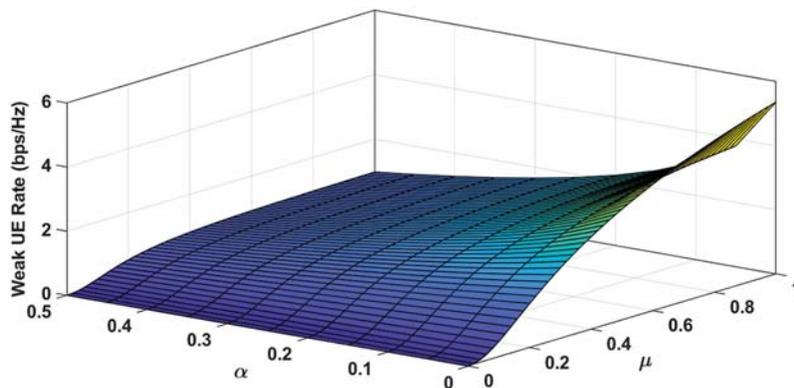
Figure 8: Data rate of weak UE ($R_{m,2}$) at $h_{m,1} = 2$

From the analysis of the investigation results, we can conclude the following concepts:

- To increase the capacity, α should be increased as μ decreases and vice versa. Since the capacity decreases as μ decreases especially at small values of α.

- The fairness performance significantly improves as μ increases (i.e., the channel gains of the paired UEs converge) and with the use of small values of α.
- The capacity significantly increases as the channel gain of the strong UE ($h_{m,1}$) increases.

It should be noted that the selection of the value of α is the responsibility of the power allocation (PA) algorithm, while the selection of the values of μ and $h_{m,1}$ is the responsibility of the user pairing (UP) algorithm.
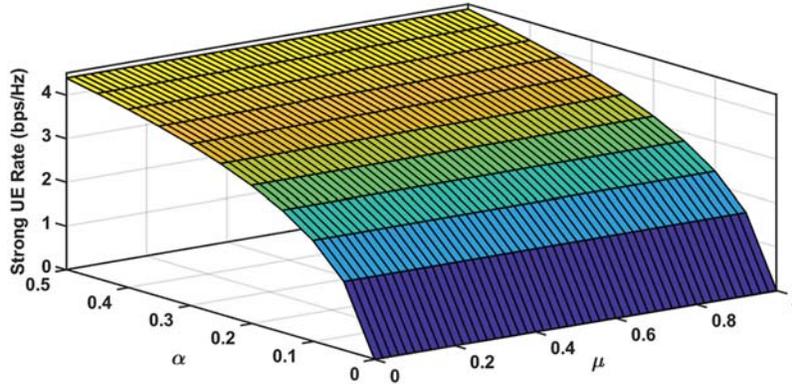
Figure 9: Data rate of strong UE ($R_{m,1}$) at $h_{m,1} = 2$

5 The Proposed CFM-UPPA Technique

The proposed CFM-UPPA technique consists of capacity and fairness maximization-based PA (CFM-PA) algorithm and capacity and fairness maximization-based UP (CFM-UP) algorithm. Both CFM-PA and CFM-UP algorithms based on the concepts concluded from the investigation results of the impact of α and μ on capacity and fairness in NOMA which is presented in the previous section. A detailed description of each algorithm is given in the next sections.

5.1 The Proposed CFM-PA Algorithm

With respect to the selection of the value of α, which is the responsibility of the PA algorithm, the investigation results presented in Section 4 demonstrate the following:

- To increase the capacity, α should be increased as μ decreases.
- The fairness performance significantly improves with the use of small values of α. In other words, the fairness performance deteriorates as α increases, especially at small values of μ.

So, the objectives of CFM-PA are as follows:

(1) Increase α as μ decreases to maximize capacity, and this will be at the expense of some degradation in fairness performance at small values of μ.
(2) Considerably decrease α as μ increase to maximize both capacity and fairness.
(3) Adjust the maximum value of α (α_{max}) to guarantee the SIC constraints.

To achieve these objectives, the proposed relation between α and μ is formulated as follows:

$$\alpha = \alpha_{max} e^{-3\mu} \tag{8}$$

where

$$\alpha_{max} = 0.5 \left(1 - \frac{\theta}{P_m \left| h_{m,1} \right|^2} \right) \tag{9}$$

Eq. (9) for α_{max} is derived from the required gap between the received powers of paired users for successful SIC [12].

$$[(1-\alpha) P_m - \alpha P_m] \left| h_{m,1} \right|^2 \geq \theta \tag{10}$$

where θ is the minimum required gap.

5.2 The Proposed CFM-UP Algorithm

With respect to the selection of the values of μ and $h_{m,1}$ which is the responsibility of the user pairing (UP) algorithm, the investigation results presented in Section 4 demonstrate the following:

- To increase the capacity, μ should be increased. Since the capacity decreases as μ decrease especially at small values of α
- The fairness performance significantly improves as μ increases.
- The capacity significantly increases as $h_{m,1}$ increases.

So, the objectives of CFM-UP are as follows:

(1) Increasing the values of μ which results in maximization of both the capacity and fairness. So, CFM-UP aims to pair the weak UE that has the closest lower channel gain to the strong UE's channel gain.
(2) Selecting the UE that has the highest channel gain over the subcarrier as the strong UE (UE-1) to maximize the capacity of the NOMA system.

The steps of CFM-UP are as follows:

(1) For each subcarrier, the channel gains of UEs are sorted in descending order, and the highest UE' channel gain is detected.
(2) Sorting the subcarriers in descending order according to its highest UE's channel gain and follows this order during the UP process in the following steps.
(3) CFM-UP starts the selection process by selecting the strong UE for each sorted subcarrier (i.e., the subcarrier with highest UE's channel gain first). The UE that has the highest channel gain over the subcarrier is selected as the strong UE, and each selected UE is discarded from subsequent selection during the UP process since each UE can be paired on a single subcarrier.
(4) After completing the selection process of the strong UE for each subcarrier in step 3, CFM-UP starts the selection process of the weak UE for each sorted subcarrier. The UE that has the closest lower channel gain to strong UE's channel gain over the subcarrier is selected as the weak UE, and each selected UE is discarded from subsequent selection during the UP process.

The pseudo-code of the proposed CFM-UP is shown in Algorithm 1.

Algorithm 1: Proposed CFM-UP Algorithm

1: *Initialization*: Construct channel gain matrix $H = \left|h_{m,k}\right|^2$ ∀ *m ∈ M subcarriers & k ∈ K users.*
2: for m = 1 to M do
3:      detect the highest UE's channel gain for each m subcarrier: $h_m^{Highest} = \max \left|h_{m,k}\right|^2 \forall m$.
4:      Sort the M subcarriers in descending order according to $h_m^{Highest}$.
5: end for
6: Start the selection process of the strong UE for each subcarrier.
7:      for the sorted M subcarrier do
8:           Select the UE that has the highest channel gain ($h_m^{Highest}$) for each sorted m
                subcarrier as the strong UE.
9:           discard the selected UE from any subsequent selection for any subcarrier.
10:      end for
11: Start the selection process of the weak UE for each subcarrier.
12   for the sorted M subcarrier do
13:           Select the UE that has the closest lower channel gain to strong UE's channel gain
                for each sorted m subcarrier as the weak UE.
14:           discard the selected UE from any subsequent selection for any subcarrier.
15:      end for
16: *End of the Algorithm.*

---

6 Results, Comparison, and Discussion

In the simulation, we consider the NOMA system, which is characterized by the frequency selective fading channel with six independent multipath. The fading parameter in the channel model is a random variable and follows the Rayleigh distribution. It is assumed that the transmission bandwidth per subcarrier is normalized to 1 Hz. The results presented below refer to ensemble averages across 5000 channel realizations.

In this section, the performance of the proposed CFM-UPPA scheme is evaluated and compared with the performance of the OMA system, as well as that of NOMA utilizing random UP. Random UP is considered as the lowest complexity UP algorithm, which provides suboptimal capacity performance since it is based on the random selection of the paired UEs on each subcarrier without considering the users' channel conditions [30]. Both the proposed CFM-PA and Fractional Transmit Power Allocation (FTPA) [31,32] are used for power allocation for random UP to demonstrate the efficiency of the proposed CFM-PA in improving the performance of other UP algorithms. During the simulation, the decay power allocation factor of FTPA is set to be 0.2, and the value of minimum power gap θ for CFM-PA is set to be 1W.

Firstly, the performance is evaluated as a function of SNR at $M = 32$ subcarriers (i.e., $K = 64$ UEs). Fig. 10 shows that the proposed CFM-UPPA technique achieves considerably higher capacity than that of random UP and that of OMA. It is clear that the capacity of CFM-UPPA is higher by more than 2 bps/Hz than the capacity of OMA and higher by slightly less than 2 bps/Hz than the capacity of random UP for all SNR values.
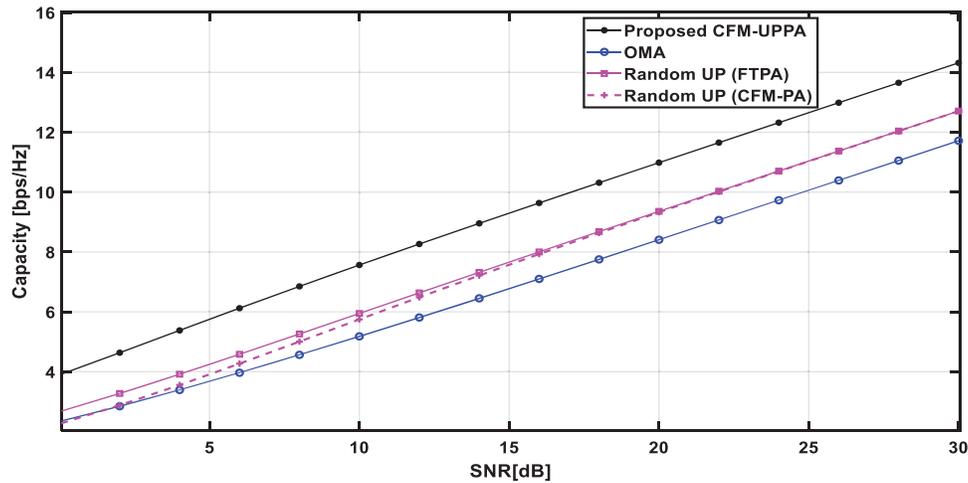
Figure 10: The system capacity *vs*. SNR at 32 subcarriers (64 UEs)

Despite the good fairness performance is the main feature of NOMA random UP due to its random allocation nature, Fig. 11 demonstrates the efficiency of CFM-UPPA in providing a significantly high degree of fairness among UEs compared to NOMA random UP. In addition, Fig. 11 demonstrates the significant efficiency of CFM-PA in improving the fairness of random UP compared to the FTPA algorithm. On the other hand, the high FI obtained by OMA is a result of the nonexistence of interference among UEs in OMA and the uniform power allocation.
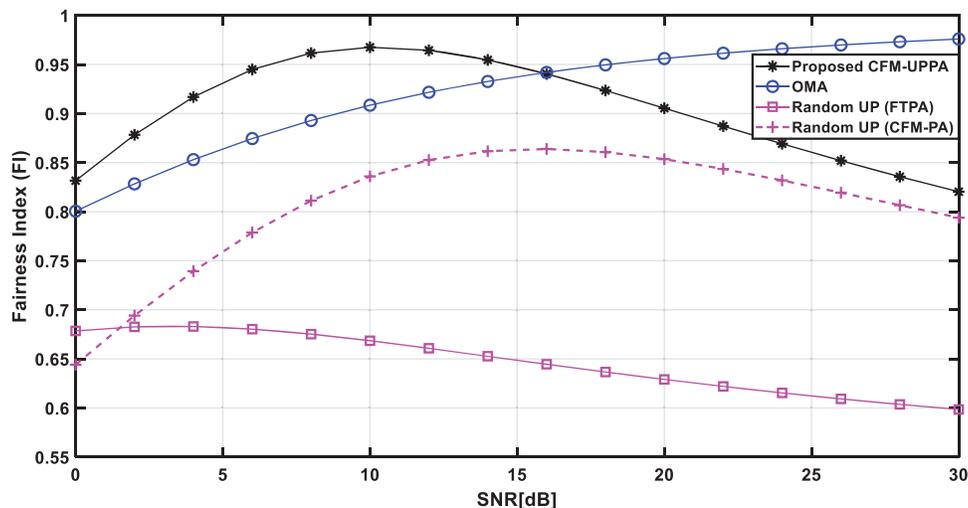
Figure 11: Fairness index (FI) *vs*. SNR at 32 subcarriers (64 UEs)

The probability that UE's data rate is lower than a minimum data rate R_0 is called the outage probability and it is represented in Fig. 12 for $R_0 = 1$ bps/Hz and in Fig. 13 for $R_0 = 2$ bps/Hz. It is shown that CFM-UPPA technique provides the lowest outage probability especially at small SNR values and its values are approximately lower by a factor 0.1 than the values of random

UP and OMA for most of the SNR values. Also, it is shown that CFM-PA efficiently reduces the outage probability of random UP compared to the FTPA algorithm especially at $R_0 = 2$ bps/Hz.
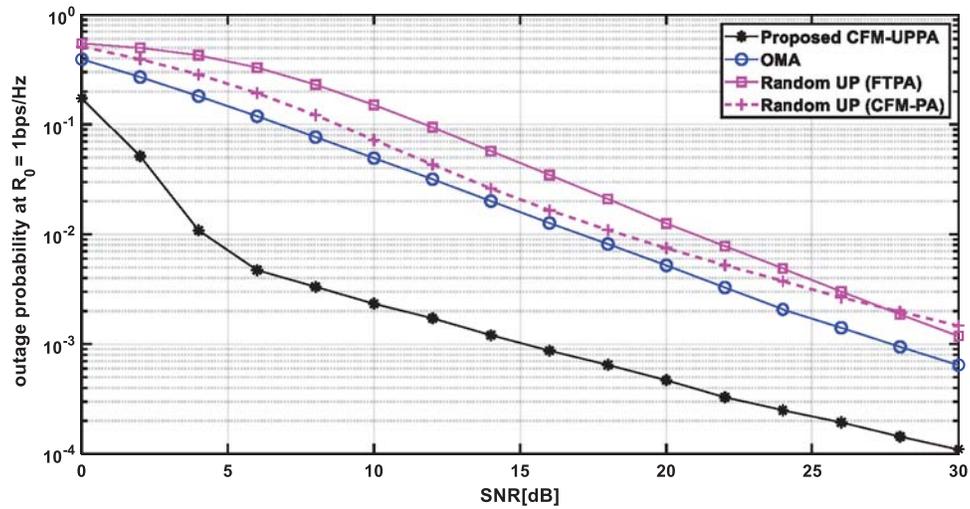
Figure 12: Outage probability at $R_0 = 1$ bps/Hz *vs.* SNR at 32 subcarriers (64 UEs)
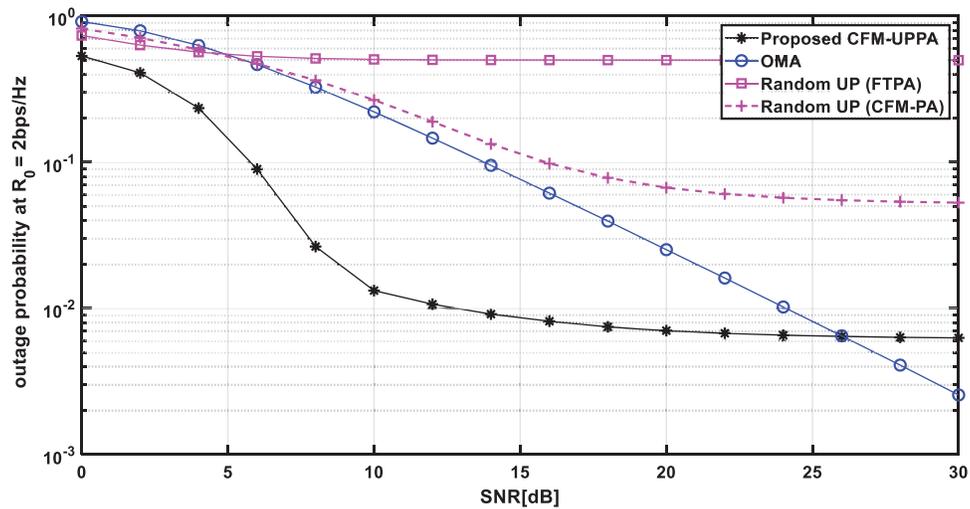
Figure 13: Outage probability at $R_0 = 2$ bps/Hz *vs.* SNR at 32 subcarriers (64 UEs)

Secondly, the performance is evaluated as a function of the number of UEs at SNR = 20 dB where the number of UEs is double the number of subcarriers. Fig. 14 shows that the capacity of the proposed CFM-UPPA outperforms that of OMA by approximately 30% and that of NOMA random UP by approximately 17%. Also, it is shown that the capacity of the CFM-UPPA improves as the number of UEs increases, while the capacity of the other algorithms tends to reach its maximum value as the number of UEs becomes greater than 16 UEs. With respect to the fairness performance, Fig. 15 shows that CFM-UPPA achieves significantly high FI equals 0.9 compared to 0.63 obtained by random UP with FTPA, and the proposed CFM-PA can improve

the fairness performance of random UP by 35% (FI = 0.85) compared to the FTPA algorithm. In terms of outage probability, the lowest outage probability for $R_0 = 1$ bps/Hz and $R_0 = 2$ bps/Hz is achieved by CFM-UPPA and it slightly improves as the number of UEs increases. on the other hand, the worst outage probability is achieved by random UP with FTPA as shown in Figs. 16 and 17. Also, it is shown that CFM-PA considerably reduces the outage probability of the random UP compared to the FTPA algorithm.
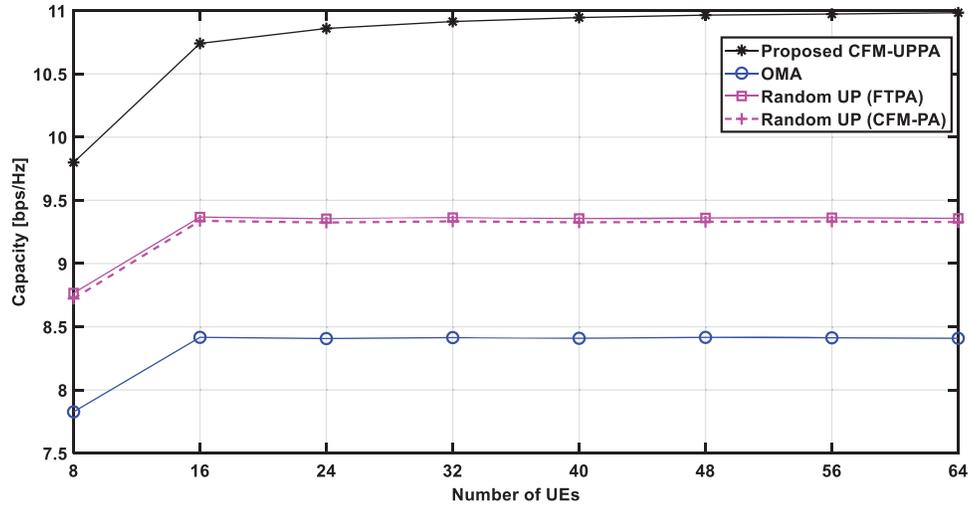
Figure 14: The system capacity *vs*. the number of UEs at SNR = 20 dB
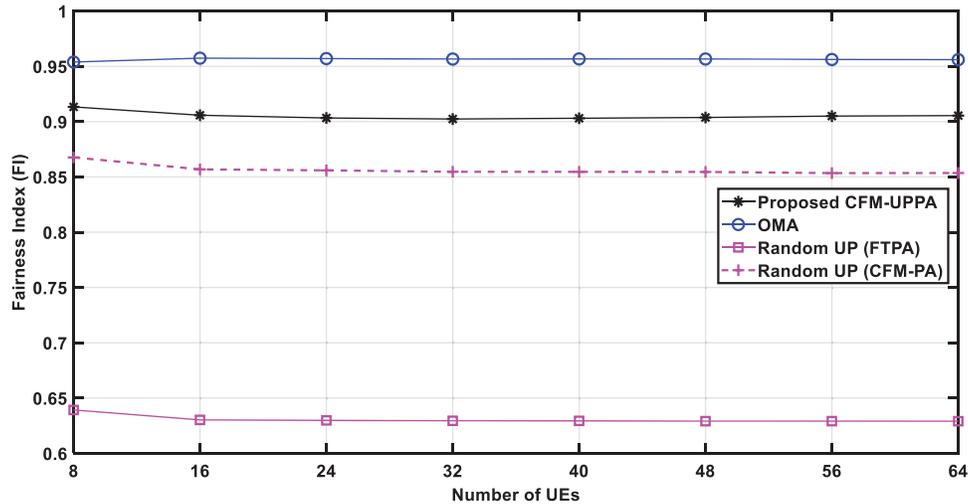
Figure 15: Fairness index (FI) *vs*. the number of UEs at SNR = 20 dB
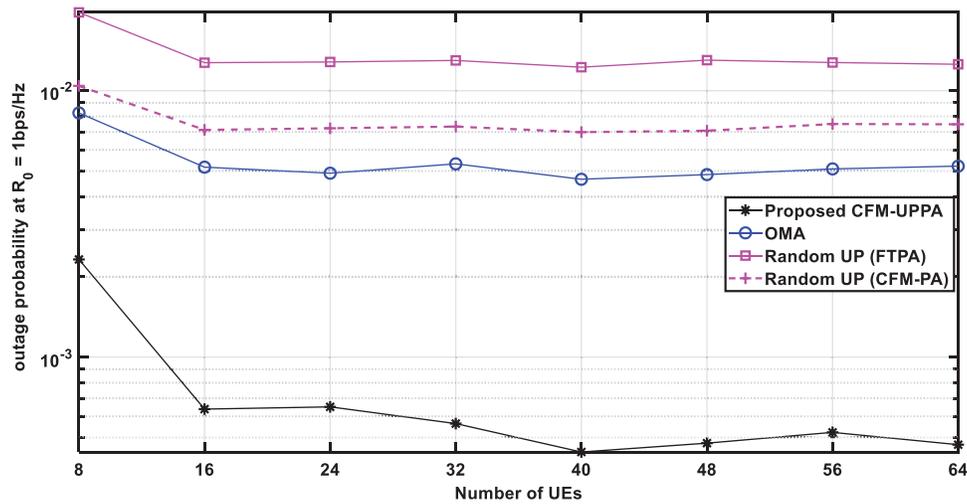
Figure 16: Outage probability at $R_0 = 1$ bps/Hz *vs.* the number of UEs at SNR = 20 dB
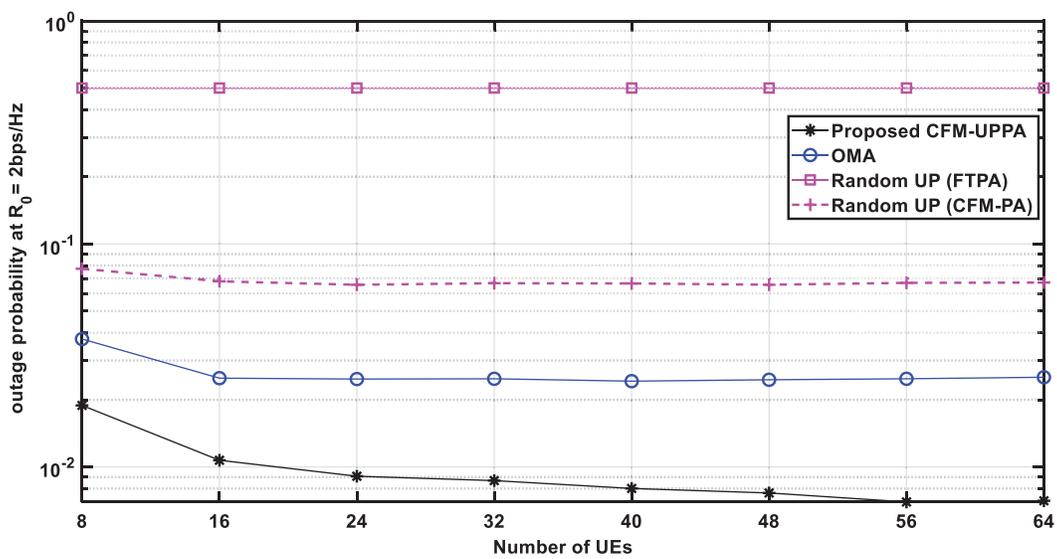
Figure 17: Outage probability at $R_0 = 2$ bps/Hz *vs.* the number of UEs at SNR = 20 dB

7 Conclusion

Since the performance of the NOMA system is controlled by UP and PA. So, this paper presents a novel UP and PA (UPPA) technique for capacity and fairness maximization called (CFM-UPPA). Firstly, the paper investigates the effect of the power allocation coefficient and the ratio between the channel gains of the paired users on the capacity and the fairness of the NOMA systems. Then, capacity and fairness maximization-based PA (CFM-PA) is proposed in which the power allocation coefficient is formulated as a function of the ratio between the channel gains of the paired users, and its maximum value guarantees the SIC constraints. After that, capacity and fairness maximization-based UP (CFM-UP) is proposed to pair the strong user that has the highest channel gain per subcarrier with the weak user that has the closest lower channel gain

to the strong user's channel gain to maximize the capacity and fairness. Simulation results show that the performance of the proposed CFM-UPPA technique significantly outperforms that of the OMA system and that of the NOMA system with random UP. Also, applying the proposed CFM-PA to the random UP significantly improves its performance.

Conflicts of Interest: The author declares that he has no conflicts of interest to report regarding the present study.

References

[1] M. Vaezi, G. A. Aruma Baduge, Y. Liu, A. Arafa, F. Fang *et al.,* "Interplay between NOMA and other emerging technologies: A survey," *IEEE Transactions on Cognitive Communications and Networking*, vol. 5, no. 4, pp. 900–919, 2019.

[2] P. Wang, J. Xiao and L. Ping, "Comparison of orthogonal and non-orthogonal approaches to future wireless cellular systems," *IEEE Vehicular Technology Magazine*, vol. 1, no. 3, pp. 4–11, 2006.

[3] J. Schaepperle and A. Ruegg, "Enhancement of throughput fairness in 4G wireless access systems by non-orthogonal signaling," *Bell Labs Tecnical Journal*, vol. 13, no. 4, pp. 59–77, 2009.

[4] T. Takeda and K. Higuchi, "Enhanced user fairness using non-orthogonal access with SIC in cellular uplink," in *Proc. IEEE Vehicular Technology Conf.*, San Francisco, CA, USA, pp. 1–5, 2011.

[5] S. Tomida and K. Higuchi, "Non-orthogonal access with SIC in cellular downlink for user fairness enhancement," in *Proc. Int. Symp. on Intelligent Signal Processing and Communications Systems*, Chiang Mai, Thailand, pp. 1–6, 2011.

[6] W. U. Khan, Z. Yu, S. Yu, G. A. S. Sidhu and J. Liu, "Efficient power allocation in downlink multi-cell multi-user NOMA networks," *IET Communications*, vol. 13, no. 4, pp. 396–402, 2019.

[7] N. Gunantara, "A review of multi-objective optimization: Methods and its applications," *Cogent Engineering*, vol. 5, no. 1, pp. 1502242, 2018.

[8] M. Naeem, A. S. Khwaja, A. Anpalagan and M. Jaseemuddin, "Green cooperative cognitive radio: A multiobjective optimization paradigm," *IEEE Systems Journal*, vol. 10, no. 1, pp. 240–250, 2014.

[9] J. Cui, Y. Liu, Z. Ding, P. Fan and A. Nallanathan, "QoE-based resource allocation for multi-cell NOMA networks," *IEEE Transactions on Wireless Communications*, vol. 17, no. 9, pp. 6160–6176, 2018.

[10] N. Yang, H. Zhang, K. Long, H.-Y. Hsieh and J. Liu, "Deep neural network for resource management in NOMA networks," *IEEE Transactions on Vehicular Technology*, vol. 69, no. 1, pp. 876–886, 2020.

[11] M. Choi, J. Kim and J. Moon, "Dynamic power allocation and user scheduling for power-efficient and delay-constrained multiple access networks," *IEEE Transactions on Wireless Communications*, vol. 18, no. 10, pp. 4846–4858, 2019.

[12] W. U. Khan, F. Jameel, T. Ristaniemi, S. Khan, G. A. S. Sidhu *et al.,* "Joint spectral and energy efficiency optimization for downlink NOMA networks," *IEEE Transactions on Cognitive Communications and Networking*, vol. 6, no. 2, pp. 645–656, 2020.

[13] L. Chen, L. Ma and Y. Xu, "Proportional fairness-based user pairing and power allocation algorithm for non-orthogonal multiple access system," *IEEE Access*, vol. 7, pp. 19602–19615, 2019.

[14] A. S. Marcano and H. L. Christiansen, "Impact of NOMA on network capacity dimensioning for 5G HetNets," *IEEE Access*, vol. 6, pp. 13587–13603, 2018.

[15] Y. Xu, H. Sun, R. Q. Hu and Y. Qian, "Cooperative non-orthogonal multiple access in heterogeneous networks," in *Proc. IEEE Global Communications Conf.*, San Diego, CA, USA, pp. 1–6, 2015.

[16] Z. Song, Q. Ni and X. Sun, "Distributed power allocation for nonorthogonal multiple access hetero-geneous networks," *IEEE Communications Letters*, vol. 22, no. 3, pp. 622–625, 2018.

[17] J. Zhao, Y. Liu, K. K. Chai, A. Nallanathan, Y. Chen *et al.,* "Spectrum allocation and power control for non-orthogonal multiple access in HetNets," *IEEE Transactions on Wireless Communications*, vol. 16, no. 9, pp. 5825–5837, 2017.

[18] D. Ni, L. Hao, Q. T. Tran and X. Qian, "Power allocation for downlink NOMA heterogeneous networks," *IEEE Access*, vol. 6, pp. 26742–26752, 2018.

[19] W. Xu, R. Qiu and X.-Q. Jiang, "Resource allocation in heterogeneous cognitive radio network with non-orthogonal multiple access," *IEEE Access*, vol. 7, pp. 57488–57499, 2019.

[20] L. Shi, B. Li and H. Chen, "Pairing and power allocation for downlink nonorthogonal multiple access systems," *IEEE Transactions on Vehicular Technology*, vol. 66, no. 11, pp. 10084–10091, 2017.

[21] X. Sun, N. Yang, S. Yan, Z. Ding, D. W. K. Ng *et al.,* "Joint beamforming and power allocation in downlink NOMA multiuser MIMO networks," *IEEE Transactions on Wireless Communications*, vol. 17, no. 8, pp. 5367–5381, 2018.

[22] N. Nonaka, Y. Kishiyama and K. Higuchi, "Non-orthogonal multiple access using intra-beam super-position coding and SIC in base station cooperative MIMO cellular downlink," in *Proc. IEEE 80th Veh. Technol. Conf.*, Vancouver, BC, Canada, pp. 1–5, 2014.

[23] B. Kimy, S. Lim, H. Kim, S. Suh, J. Kwun *et al.*, "Non-orthogonal multiple access in a downlink multiuser beamforming system," in *Proc. 2013 IEEE Military Communications Conf.*, San Diego, CA, USA, pp. 1278–1283, 2013.

[24] S. Liu, C. Zhang and G. Lyu, "User selection and power schedule for downlink non-orthogonal multiple access (NOMA) system," in *Proc. IEEE Int. Conf. Commun. Workshop*, London, UK, pp. 2561–2565, 2015.

[25] J. Ding and J. Cai, "Two-side coalitional matching approach for joint MIMO-NOMA clustering and BS selection in multi-cell MIMO-NOMA systems," *IEEE Transactions on Wireless Communications*, vol. 19, no. 3, pp. 2006–2021, 2020.

[26] G. Chen, L. Qiu and C. Ren, "On the performance of cluster-based MIMO-NOMA in multi-cell dense networks," *IEEE Transactions on Communications*, vol. 68, no. 8, pp. 4773–4787, 2020.

[27] L. Xu, W. Yin, X. Zhang and Y. Yang, "Fairness-aware throughput maximization over cognitive heterogeneous NOMA networks for industrial cognitive IoT," *IEEE Transactions on Communications*, vol. 68, no. 8, pp. 4723–4733, 2020.

[28] L. Luo, Q. Li and J. Cheng, "Performance analysis of overlay cognitive NOMA systems with imperfect successive interference cancellation," *IEEE Transactions on Communications*, vol. 68, no. 8, pp. 4709–4722, 2020.

[29] G. Li, D. Mishra and H. Jiang, "Channel-aware power allocation and decoding order in overlay cognitive NOMA networks," *IEEE Transactions on Vehicular Technology*, vol. 69, no. 6, pp. 6511–6524, 2020.

[30] Z. Ding, P. Fan and H. V. Poor, "User pairing in non-orthogonal multiple access downlink transmis-sions," in *2015 IEEE Global Communications Conf.*, San Diego, CA, pp. 1–5, 2015.

[31] S. M. R. Islam, M. Zeng, O. A. Dobre and K. Kwak, "Resource allocation for downlink NOMA systems: Key techniques and open issues," *IEEE Wireless Communications*, vol. 25, no. 2, pp. 40–47, 2018.

[32] A. Benjebbovu, A. Li, Y. Saito, Y. Kishiyama, A. Harada *et al.,* "System-level performance of downlink NOMA for future LTE enhancements," in *2013 IEEE Globecom Workshops*, Atlanta, GA, pp. 66–70, 2013.