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A Novel Approach to Enhance the Energy Efficiency of a NOMA Network

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Abstract: Spectral efficiency is crucial for implementing 5G cellular networks and beyond. Non-orthogonal multiple access (NOMA) is a promising scheme to enhance efficiency. This paper introduces two improvements that will further enhance the channel capacity using the NOMA algorithm. We first introduce a novel algorithm, the User Sub-Channel Fair Matching Algorithm (USFMA), by applying a new sub-channel sorting and compensations scheme and then benefiting from the well-known Hungarian algorithm to allocate users to each sub-channel in a way that guarantees an optimum overall system performance. Then, for per sub-channel power allocation, we convert the non-convex objective function into a convex sub-problem using the concave–convex procedure (CCP) by converting the objective function into convex sub-problems and using the successive convex approximation to solve the convex sub-problems to find effective sub-optimal solutions. We have built a MATLAB simulation cellular environment to evaluate and compare the system performance with other known schemes. The results are promising and showed significant improvements compared to the other capacity and energy efficiency schemes.

Keywords: non-orthogonal multiple access; user allocation algorithm; Hungarian algorithm; user fairness; non-convex problem; DC programming

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1. Introduction

Future 5G cellular mobile communication systems require further ultra-reliability, availability, low latency, and high throughput to fulfil the high projected requirements. Besides its expected enormous connectivity, the Internet of Things (IoT) is intended to support diverse employments for a wide range of devices and applications. Future 5G cellular mobile communication systems are poised to demand even greater levels of ultra-reliability, availability, low latency, and high throughput in order to meet the increasingly ambitious requirements. In addition to its anticipated extensive connectivity, the Internet of Things (IoT) is envisaged to facilitate a broad spectrum of applications catering to diverse needs across a wide array of domains For instance, crucial IoT applications such as digitalis health, smart cities, geological monitoring and control will impose considerable difficulties on spectrum use regarding energy consumption and low latency.

For instance, critical IoT applications such as digital health, smart cities, and geological monitoring and control will present significant challenges in terms of spectrum utilization. In this regard, non-orthogonal multiple access (NOMA) is intended to accomplish the massive expansion of wireless data traffic, resolve the shortage of frequency resources for the next generation of wireless networks [1], and significantly enhance the spectral efficiency of 5G networks [2]. NOMA can be incorporated into various wireless communications techniques like Multiple-Input Multiple-Output (MIMO), beamforming, cooperative communications, and network coding [3,4]. In [5], it was shown that NOMA enhances the IoT structure by utilizing several temporarily unused computational and storage resources by requesting cooperative caching and computing. Unlike Orthogonal Frequency Division

Multiple Access (OFDMA), where each channel can largely be allocated to a single user, NOMA enables multiple user allocations per channel by implementing power-multiplexing and resolves multiple-access interference by applying successive interference cancellation (SIC) at the receivers [6]. However, SIC adds significant complexity to the NOMA structure [6]. In other words, NOMA enhances the spectral efficiency at the expense of a higher complexity compared to OFDMA [7].

On the other hand, MIMO systems employ spatial multiplexing to increase data capacity by establishing multiple paths and effectively using them as additional "channels" to transfer data. By considering the advantages of MIMO, the implementation of NOMA within MIMO systems was considered in [8,9]. As a related technology, it was shown in [10,11] that the implementation of Full Duplex (FD) mode alongside NOMA brings a significant improvement to the performance compared to Half-Duplex (HD) NOMA. The authors of [12] illustrated that the FD-NOMA scheme can achieve tremendous throughput in a multi-cell system concerning user assistance and resource optimization. Based on the above, NOMA and FD systems can coexist cooperatively, and their integration has evolved progressively to enhance spectrum efficiency.

2. Related Works and Motivation

Recently, MIMO-NOMA has attracted the attention of many researchers. The authors of [13] presented an iterative algorithm to minimize the overall transmission power. They investigated optimizing power allocation under fixed beam-forming vectors, achieving ideal beam-forming directions based on definite power allocation. Furthermore, a hybrid relaying scheme proposed in [14] can achieve a significant performance gain over conventional NOMA, HD cooperative NOMA (HD-CNOMA) and FD-CNOMA. In [15], the authors presented a full-duplex device-to-device (DtD)-aided cooperative NOMA scheme and derived the outage probability to show the practicality and effectiveness of their design. The authors of [16] discussed the fundamental notion of MIMO-NOMA to indicate the challenges in this domain. Simultaneous wireless information and power transfer (SWIPT) is the key to increasing energy efficiency. In [17], SWIPT was used in composite precoding based on millimeter wave (mmWave) massive MIMO-NOMA. Compared with LTE systems, MIMO-NOMA networks introduce more enhanced spectral efficiency and network capacity with more practical resource allocation algorithms. The authors of [18,19] investigated resource allocation for NOMA, and their primary emphasis was on sum rate optimization following the total power and proportional rate constraints. The authors of [20] proposed an algorithm to jointly optimize power and channel allocation in NOMA, which significantly optimized throughput and fairness. Regarding ideal channel state information (CSI) at the base station (BS), a near-optimal resolution considering power allocation was proposed in [21]. The authors of [22] presented an effective power allocation design through defective CSI concerning distinct quality-of-service (QoS) conditions. The massive increases in information transfer and wireless end users drive an assured rise in the energy consumption of wireless networks; therefore, energy efficient (EE) schemes for the future generations of wireless systems is of critical concern [23]. Thus, the design of resource allocation schemes with the purpose of enhancing EE has become a vital research topic in NOMA networks. For instance, the authors of [24] analyzed an EE power allocation structure in mmWave massive MIMO with NOMA. Moreover, in [25], the authors investigated an EE transmission design for SISO-NOMA systems. Additionally, the authors of [26] considered a shared power allocation and channel distribution for optimizing the EE of NOMA networks, then later they expanded their work in [27] by introducing a joint subchannel and power optimization structure for a downlink NOMA heterogeneous network that enhances the EE. However, the presented solution concentrated only on increasing the overall EE of networks, driving unbalanced system resource use. The authors of [28] investigated MIMO-NOMA networks for wireless communication networks that aid adaptive multiple access. Three scenarios were used to test and propose innovative adaptive resource allocation mechanisms. An energy efficient strategy for downlinking mmWave-NOMA systems with joint user grouping, scheduling, and optimal power allocation was provided to maximize energy efficiency, proposed by the authors of [29]. This work considers an improved k-means algorithm with NOMA to meet energy efficiency limitations and allocate users to the actual cluster to boost the network sum throughput. The authors of [30] investigated the performance of MC-NOMA technology in an uplink scenario to see how well it can improve system EE by performing energy efficient power and subchannel allocation. They proposed a joint user clustering, subchannel allocation, and power allocation problem to maximize the uplink MC-NOMA scenario's EE (JSPEE). The authors found that the uplink MC-NOMA network's EE performance was significantly improved by utilizing channel gain diversity, even at high minimum data rate parameter values.

Finally, it was shown that effectively integrating resource allocation and grant-free transmission within NOMA will provide a better EE and throughput than using them separately [31].

This paper deals with resource and user allocation problems for NOMA systems with wireless power transfer to ensure fast rates and energy efficiency. We compare the performance of our proposed USFMA with two other algorithms: The first one being the User Subchannel Matching Algorithm (USMA) [32], which is considered as a many-to-many matching algorithm. The principle of USMA is that each user selects and proposes their preferred sub-channel. Based on the allowed number of users per sub-channel, each sub-channel makes a decision of accepting or rejecting any user offer. When all users have made an offer, a round of proposals is performed, and once all users are assigned to sub-channels, the iteration is ended and user allocation is complete. The criteria and selection algorithm is described in detail in Table I in [32]. The second algorithm is Channel State Sorting–Pairing Algorithm (CSS-PA) [33]. As known, SIC is sensitive to the channel state, and hence the Signal to Interference Plus Noise (SINR) difference between paired users should be large enough to alleviate error propagation. Thus, CSS-PA pairs a user with a good condition with a user with a bad channel condition, which enhances user fairness and increases system capacity

The contributions of this work can be summarized as follows:

- We propose a new user allocation algorithm called User Sub-channel Fair Matching Algorithm (USFMA), benefiting from existing user allocation algorithms and combining their advantages. Unlike USMA, we propose an optimum channel gain compensation, sorting, and selection that can enhance the overall system capacity and performance. This algorithm has a lower computational complexity than the Exhaustive Search Algorithm (ESA) and can ensure user fairness. Moreover, the complexity of the USFMA will not increase sharply when increasing the number of superimposed users.
- Optimization of the energy efficiency of NOMA systems. We propose using the DC programming method to allocate power for end users superimposed on the corresponding sub-channel. The main idea is to utilize DC programming to convert non-convex problems into convex problems.
- Simulations of the proposed algorithm in Matlab. The simulation results confirm that NOMA systems surpass OFDM systems. Additionally, the USFMA is better than the existing USMA and CSS-PA. Therefore, using DC programming to allocate power for end users can improve the system's energy efficiency.

The paper is organized as follows: The system model is described in Section 3. We formulate the problem and propose the objective optimization function in Section 4. The proposed resource allocation scheme is addressed in Section 5. The performance of the proposed method is evaluated in Section 6. We finally conclude our work in Section 7.

3. System Model

We consider that a wireless network consists of many base stations (BSs), where each BS transmits information to U users, where each user is $u \in \{u_1, u_2, \ldots, u_U\}$, through V sub-channels, where each sub-channel is $v \in \{v_1, v_2, \ldots, v_V\}$. Furthermore, each receiver is equipped with SIC and a single antenna. Assuming that the system bandwidth (BW) is B, then the BW of every sub-channel is:

$$B_v = B/V \tag{1}$$

By expressing the total transmitted power of the BS as P_{BS}, and the power of the i_{th} user of the sub-channel v as $P_{i,v}$, then, the signal sent via the BS for n users per sub-channel can be expressed as follows:

$$x_v = \sum_{i=1}^{n} \sqrt{P_{i,v}} s_i \tag{2}$$

where s_i represents the symbol of the ith user. According to the principle of NOMA, each piece of user equipment (UE) receives a superposition of the correct and interfering signals simultaneously. Thus, the received signal for the jth user can be represented as:

$$y_{j,v} = x_v h_{j,v} + w_{j,v} \tag{3}$$

$$= (\sum_{i=1}^{n} \sqrt{P_{i,v}} s_i) h_{j,v} + w_{j,v} \tag{4}$$

$$= \sqrt{P_{j,v}} s_j h_{j,v} + \sum_{i=1, i\neq j}^{n} \sqrt{P_{i,v}} s_i h_{j,v} + w_{j,v} \tag{5}$$

where $h_{j,v}$ is the sub-channel coefficient of the jth user and $w_{j,v}$ is the additive white Gaussian noise (AWGN) with $w_{j,v} \sim \mathcal{N}_{\mathbb{C}}(0, \sigma_v^2)$. Then, SINR (without SIC) received by the jth user can be expressed as:

$$\begin{aligned} \mathrm{SINR}_{j,v} &= \frac{P_{j,v}|h_{j,v}|^2}{\sigma_v^2 + \sum_{i=1, i\neq j}^{n} P_{i,v}|h_{j,v}|^2}, \\ &= \frac{P_{j,v} H_{j,v}}{1 + \sum_{i=1, i\neq j}^{n} P_{i,v} H_{j,v}} \end{aligned} \tag{6}$$

where $H_{j,v} = |h_{j,v}|^2/\sigma_v^2$ represents the channel response normalized by noise for the jth user at sub-channel v. For the SIC optimal decoding order, the channel conditions for user superpositions per sub-channel should be sorted by the channel responses normalized by noise as follows:

$$H_{i,v} \leqslant H_{j,v} \quad , \forall\, (i < j) \in \{1, \ldots, n\} \tag{7}$$

Consequently, the power assigned to users per sub-channel will be according to the following order:

$$|P_{i,v}| \geqslant |P_{j,v}| \quad , \forall\, (i < j) \in \{1, \ldots, n\} \tag{8}$$

Then, after removal of the interference of users with poorer channel conditions, the estimated SINR for the jth user can be expressed as:

$$\widetilde{\mathrm{SINR}}_{j,v} = \frac{P_{j,v} H_{j,v}}{1 + \sum_{i=j+1}^{n} P_{i,v} H_{j,v}} \qquad , j = 1, \ldots,\ n-1. \tag{9}$$

Based on Shannon's capacity formula, the data rate for the jth user is given by:

$$R_{j,v} = B_v\, log_2(1 + \frac{P_{j,v} H_{j,v}}{1 + \sum_{i=j+1}^{n} P_{i,v} H_{j,v}}) \tag{10}$$

The sum rate of the sub-channel v is given by:

$$R_v = \sum_{j=1}^{n} B_v log_2(1 + \frac{P_{j,v} H_{j,v}}{1 + \sum_{i=j+1}^{n} P_{i,v} H_{j,v}}) \tag{11}$$

Accordingly, the total sum rate of the system is:

$$R = \sum_{v=1}^{V} R_v \tag{12}$$

4. Problem Description

Figure 1 depicts the NOMA downlink system for reference. As seen in Figure 1, each sub-channel v serves users that are close and far, with channel and power conditions described in (7) and (8), respectively.

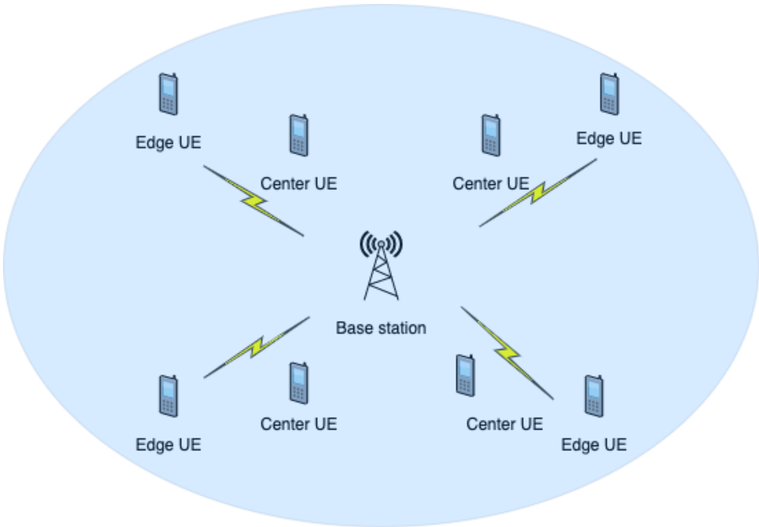

Figure 1. User pairing diagram.

The NOMA energy efficiency is determined as the ratio of the total data transmission rate to the system's total power consumption. The total power consumption includes the base station transmission power and the circuit consumption of the wireless devices [34]. Thus, from (11), the energy efficiency of the sub-channel can be expressed as:

$$E_v = \frac{R_v}{P_{fixed} + P_v} \tag{13}$$

where P_{fixed} is the power of fixed circuit in simulator, and:

$$P_v = \sum_{j=1}^{n} P_{j,v} \tag{14}$$

The energy efficiency of the system is:

$$E = \sum_{v=1}^{V} E_v \tag{15}$$

Hence, we can achieve the goal of energy saving by optimizing the problem via maximizing the data rate that can be transferred per unit of energy. Therefore, to increase the energy efficiency of the system, our objective function is:

$$\max_{P_v>0} \sum_{v=1}^{V} \frac{R_v(\alpha_n)}{P_{fixed}+P_v} \ , 0<\alpha_n<1 \tag{16}$$

subject to

$$C1: R_{j,v} > R_{min}$$

$$C2: \sum_{v=1}^{V} P_v = P_{BS}$$

where α is the coefficient of the power allocation of the worst channel gain. Constraint $C1$ guarantees the user's minimum data rate, where R_{min} is the minimum data rate required by QoS. Constraint $C2$ means that the transmit power at the base station is constant.

The global optimal solution suffers from a high complexity. To obtain sub-optimal solutions, we have divided the objective optimization function into two sub-problems: the user allocation sub-problem and the power allocation sub-problem. These will be discussed in the following section.

5. The Sub-Optimal Solution

In this section, we propose and examine how to maximize the minimum individual EE under transmit power and QoS constraints to ensure fairness among users. As a result of the fractional structure of the EE expression and the binary variable in the channel allocation indicator, the optimization problem at hand is a non-convex problem that is difficult to solve directly. Next, we will introduce the problem optimization solutions; first USFMA will be discussed, then power allocation by DC programming will be detailed.

5.1. User Sub-Channel Fair Matching Algorithm

The proposed USFMA is based on CSS-PA, the USMA, and the Hungarian algorithm [35,36]. Random power allocation (RPA) [37] has a low complexity, but the system performance is poor because the user's channel conditions are not considered. The exhaustive search algorithm (ESA) [38] can maximize the system performance but the computational complexity is too high. Existing user allocation algorithms either have the problem of excessive complexity or sacrifice partial throughput to reduce the complexity. Therefore, we have combined the advantages of several existing user allocation algorithms and proposed a new user allocation algorithm that is not too complex and can ensure user fairness.

According to the CSS-PA, the greater the difference in channel gains of users superimposed on the same sub-channel, the better the system throughput. By exploiting the USMA, we can regard the user allocation problem as a bilateral matching problem between the user and the sub-channel, and then we can use the Hungarian algorithm to find the perfect match with the largest channel gain. Taking into account the complexity of the receiver, we assume that each sub-channel only superimposes two users and hence, the number of users is twice the number of sub-channels, $2V = U$.

We construct a channel gain matrix G of size (UV) from the users and sub-channels, then the gains for every sub-channel are sorted from small to large. After that, G is split in the middle into two square matrices $(G1, G2)$, each with size VV. Then, gain compensation is applied for the users in $G1, G2$, respectively, according to our USFMA. After compensation, we use the Hungarian algorithm for the two matrices to obtain the gain and maximum user allocation.

Let us consider an example of a channel matrix to demonstrate the operation of each algorithm when assigning users to each sub-carrier. We consider in our example a NOMA system with $U = 6$ and $V = 3$. Then, G can be expressed as:

$$G = \begin{bmatrix} 42 & 80 & 1586 \\ 219 & 37 & 183 \\ 309 & 773 & 678 \\ 74 & 91 & 49 \\ 64 & 21 & 23 \\ 2 & 38 & 9 \end{bmatrix} \tag{17}$$

The gain matrices $G1, G2$ after sorting and splitting G are:

$$G1 = \begin{bmatrix} 2 & 21 & 9 \\ 42 & 37 & 23 \\ 64 & 38 & 49 \end{bmatrix} \tag{18}$$

$$G2 = \begin{bmatrix} 74 & 80 & 183 \\ 219 & 91 & 678 \\ 309 & 773 & 1586 \end{bmatrix} \tag{19}$$

We normalize all the elements in $G1$ and $G2$ by their corresponding column sum and compensate them as follows:

$$\bar{\mathcal{G}}_{mn} = \left(\frac{\mathcal{G}_{mn}}{\sum_{m=1}^{U/2} \mathcal{G}_{mn}} \right)^{-\beta}, \mathcal{G} \in \{G1, G2\} \tag{20}$$

where m and n are row and column indices, respectively, and β is the attenuation coefficient. We set $\beta = 0.4$. Therefore, based on (20), the normalized and compensated forms of (18) and (19) are:

$$\bar{G}1 = \begin{bmatrix} 4.9313 & 1.8366 & 2.4082 \\ 1.4590 & 1.4643 & 1.6546 \\ 1.2328 & 1.4488 & 1.2227 \end{bmatrix} \tag{21}$$

$$\bar{G}2 = \begin{bmatrix} 2.3128 & 2.6838 & 2.8215 \\ 1.4985 & 2.5490 & 1.6709 \\ 1.3057 & 1.0832 & 1.1894 \end{bmatrix} \tag{22}$$

After that, we apply the Hadamard product between each matrix and its corresponding normalized counterpart as follows:

$$\hat{G}1 = G1 \circ \bar{G}1 = \begin{bmatrix} 10 & 39 & 22 \\ 61 & 54 & 38 \\ 79 & 55 & 60 \end{bmatrix} \tag{23}$$

$$\hat{G}2 = G2 \circ \bar{G}2 = \begin{bmatrix} 171 & 215 & 516 \\ 328 & 232 & 1133 \\ 403 & 837 & 1886 \end{bmatrix} \tag{24}$$

Then, we use the Hungarian algorithm to perform perfect matching on the $\hat{G}1$ matrix and the $\hat{G}2$ matrix, respectively. The channel gain and the largest user allocation are found under perfect matching. After using the Hungarian algorithm, the user's allocation result is:

$$\hat{G}1 = \begin{bmatrix} 10 & \mathbf{[39]} & 22 \\ \mathbf{[61]} & 54 & 38 \\ 79 & 55 & \mathbf{[60]} \end{bmatrix} \tag{25}$$

$$\hat{G}2 = \begin{bmatrix} 171 & \mathbf{[215]} & 516 \\ \mathbf{[328]} & 232 & 1133 \\ 403 & 837 & \mathbf{[1886]} \end{bmatrix} \tag{26}$$

As seen in (25) and (26), we can obtain the first user allocated to each sub-channel from $\hat{G}1$ and the second user allocated to each sub-channel from $\hat{G}2$, as indicated in Table 1. After this, the user assignment is complete.

Table 1. The matching result of the user allocation.

Matching Results	v_1	v_2	v_3
u_1	10	**[39]**	22
u_2	**[61]**	54	38
u_3	79	55	**[60]**
u_4	171	**[215]**	516
u_5	**[328]**	232	1133
u_6	403	837	**[1886]**

Table 1 shows the matching results. This result indicates that users u_2 and u_5 are superimposed on the first sub-channel v_1, while u_1 and u_4 are superimposed on v_2 and u_3 and u_6 are superimposed on v_3. From the allocation result, we can see that the gains of the two users superimposed on the same sub-channel are quite different, so the system will have better throughput. Based on the premise of perfect matching [39], user fairness can be guaranteed. The specific process of Algorithm 1 is as follows:

Algorithm 1: User Sub-Channel Fair Matching Algorithm (USFMA)

1. Calculate the channel gain matrix of users $u \in \{u_1, u_2, \ldots, u_U\}$ and sub-channels $v \in \{v_1, v_2, \ldots, v_V\}$
2. Sort the gain matrix in column-wise ascending order starting from first row to get a new gain matrix G of size UV.
3. Generate a gain compensation matrix as shown in (20), where β is the the attenuation coefficient. We set $\beta = 0.4$ in this paper.
4. Let the sorted gain matrix G be multiplied, element wise, by the compensation matrix $\bar{G}$ as in (23) to get compensated, the new compensated gain matrix is $\hat{G}$.
5. Split $\hat{G}$ into two matrices $\hat{G}1, \hat{G}2$, each of size $\frac{U}{2}V$
6. Using the Hungarian algorithm for $\hat{G}1$, the first matching user on each sub-channel is obtained. Using the Hungarian algorithm for $\hat{G}2$, the second user matched on each sub-channel is obtained.
7. End.

If the number of super-positions is increased to three, then the user channel gain matrix is divided into three groups, and the other steps are the same as Algorithm 1.

Complexity Analysis

If there are V sub-channels and $U = 2V$ users, the time complexity of the ESA with the best performance in user allocation is $O(\frac{(2V)!}{2^V})$, and the time complexity of the

USFMA considered in this paper is $O(2V^3)$. Furthermore, the complexity of the CSS-PA is $O(Vlog(V))$, while the complexity of the USMA is $O(UV^2)$. Accordingly, we can notice that when the number of users is large, the complexity of the user allocation algorithm proposed in this paper is much lower than that of the ESA. The CSS-PA shows the lowest complexity; however, the USFMA still shows comparable complexity with other schemes.

In summary, the algorithm is suitable for superimposing multiple users on the same sub-channel, and the complexity will not increase sharply.

5.2. Power Allocation by DC Programming

In this section, corresponding to the USFMA, to maximize the system's energy efficiency, we use the difference of convex (DC) programming method to solve the power allocation problem of users on the sub-channel. The DC programming approach is widely used in solving non-convex optimization problems. Moreover, DC programming can be applied if the objective function can be written as a minimization of the difference of two convex functions.

Suppose the objective function of a non-convex optimization problem can be formulated as a difference minimization between two convex functions. In that case, the non-convex optimization problem can be solved by DC programming, which is given by:

$$\min_{\alpha \in \chi} L(\alpha) = f(\alpha) - g(\alpha) \quad , \; \chi = [\alpha_1, \alpha_2, \ldots, \alpha_n]^T \tag{27}$$

where χ is a convex set and $f(\alpha)$ and $g(\alpha)$ are continuous, convex, or quasi-convex [40].

The solution methods of DC programming can be divided into two methods: The first is to obtain the global optimal solution, for example, as done in the branch-and-bound technique [41] and the cutting plane method. The other approximation methods are based on combinatorial optimization ideas; although these types of methods can obtain the global optimal solution, the computational complexity is relatively high. Different types can obtain local optimal solutions and global sub-optimal solutions, for instance, the concave–convex procedure (CCP) algorithm [42]. Although this type of method can only obtain a locally optimal solution, its computational complexity is relatively low [43–45].

The CCP algorithm converts the objective function into convex sub-problems by linearizing the non-convex part of the objective function and using the successive convex approximation to solve the convex sub-problems to find effective sub-optimal solutions. In our work, we use the CCP algorithm to find the sub-optimal solutions.

We consider two users superimposed on the same sub-channel, where we assume u_1 is an edge user who is far away from the base station with poor channel conditions. u_2 is near the base station with good channel conditions, illustrated in Figure 2. Consider that the symbol sent by the base station over a sub-channel is:

$$x_v = \sqrt{\alpha P_v} s_1 + \sqrt{(1-\alpha) P_v} s_2 \quad , \; 0 < \alpha < 1 \tag{28}$$

where α is the power allocation coefficient. Then, the received symbols of u_2 and u_2 are:

$$\begin{aligned} y_{1,v} &= \sqrt{\alpha P_v} s_1 h_{1,v} + \sqrt{(1-\alpha) P_v} s_2 h_{1,v} + w_{1,v} \\ y_{2,v} &= \sqrt{\alpha P_v} s_1 h_{2,v} + \sqrt{(1-\alpha) P_v} s_2 h_{2,v} + w_{2,v} \end{aligned} \tag{29}$$

Based on the SIC decoding sequences, u_2 is able to cancel the interfering power term of u_1. Then, the acceptance symbol for two users can be rewritten as:

$$\begin{aligned} y_{1,v} &= \sqrt{\alpha P_v} s_1 h_{1,v} + \sqrt{(1-\alpha) P_v} s_2 h_{1,v} + w_{1,v} \\ y_{2,v} &= \sqrt{(1-\alpha) P_v} s_2 h_{2,v} + w_{2,v} \end{aligned} \tag{30}$$

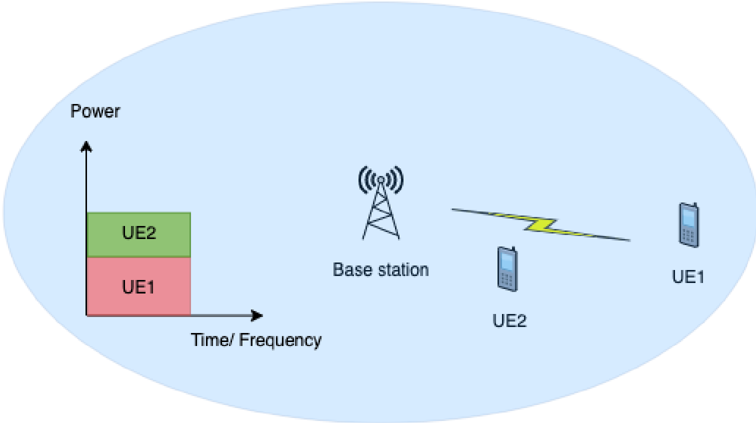

Figure 2. Two users transmitting on the same channel.

Based on Shannon's capacity formula, the data rate for each user is given by:

$$\begin{aligned} R_{u_1}, v &= B_v log_2(1 + \frac{\alpha P_v H_{1,v}}{1 + (1-\alpha) P_v H_{1,v}}) \\ R_{u_2}, v &= B_v log_2(1 + (1-\alpha) P_v H_{2,v}) \end{aligned} \tag{31}$$

where H as defined in (6). Then, the rate sum for the sub-channel v is:

$$R_v = B_v log_2(1 + \frac{\alpha P_v H_{1,v}}{1 + (1-\alpha) P_v H_{1,v}}) + B_v log_2(1 + (1-\alpha) P_v H_{2,v}) \tag{32}$$

Therefore, as in (16), the maximum energy efficiency for the sub-channel problem can be expressed as:

$$\begin{aligned} E_v^{max} &= \max_{\alpha \in (0,1)} \frac{B_v log_2(1 + \frac{\alpha P_v H_{1,v}}{1+(1-\alpha) P_v H_{1,v}}) + B_v log_2(1 + (1-\alpha) P_v H_{2,v})}{P_{fixed} + P_v} \\ &= \max_{\alpha \in (0,1)} \left\{ \frac{B_v log_2(1 + \frac{\alpha P_v H_{1,v}}{1+(1-\alpha) P_v H_{1,v}})}{P_{fixed} + P_v} + \frac{B_v log_2(1 + (1-\alpha) P_v H_{2,v})}{P_{fixed} + P_v} \right\} \end{aligned} \tag{33}$$

We transform the maximization problem into the minimization problem via deploying the DC programming approach as follows:

$$\min_{\alpha \in (0,1)} -\frac{B_v log_2(1 + \frac{\alpha P_v H_{1,v}}{1+(1-\alpha) P_v H_{1,v}})}{P_{fixed} + P_v} - \frac{B_v log_2(1 + (1-\alpha) P_v H_{2,v})}{P_{fixed} + P_v} \tag{34}$$

This can be rewritten as:

$$\min_{\alpha \in (0,1)} (f(\alpha) - g(\alpha)) \tag{35}$$

where $f(\alpha) = -\frac{B_v log(1+\frac{\alpha P_v H_{1,v}}{1+(1-\alpha) P_v H_{1,v}})}{P_{fixed}+P_v}$ and $g(\alpha) = \frac{B_v log(1+(1-\alpha) P_v H_{2,v})}{P_{fixed}+P_v}$.

Since the second derivatives of function $f(\alpha)$ and function $g(\alpha)$ are both greater than zero, that is, $\nabla^2 f(\alpha) > 0$ and $\nabla^2 g(\alpha) > 0$, these two functions are convex functions of α that satisfy the conditions to apply the DC programming method. Accordingly, we can use the DC programming approach to allocate power to different sub-channel users. The principle in deploying Algorithm 2 is to convert a non-convex problem into convex sub-problems by using successive convex approximations. The specific algorithm is demonstrated as follows:

Algorithm 2: Power Allocation by DC Programming [46]

1. Initialize $\alpha^{(0)}$, set iteration number $i = 0$, set differential tolerance value ξ
2. **while** $|L(\alpha^{(i+1)}) - L(\alpha^{(i)})| > \xi$ **do**
3. Define convex approximation of $L^{(i)}(\alpha)$ as

$$\hat{L^{(i)}}(\alpha) = f(\alpha) - (g(\alpha^{(i)}) + \nabla g^T(\alpha^{(i)})(\alpha - \alpha^{(i)})) \tag{36}$$

4. Solve the convex problem

$$\alpha^{(i+1)} = \arg\min_{\alpha \in \chi} \hat{L}^{(i)}(\alpha) \tag{37}$$

5. $i \leftarrow i + 1$
6. **end while**.

In the algorithm, ξ is the difference tolerance and α presents the allocated powers of the sub-channels. The $g(\alpha)$ objective function in (27) is substituted by the $g(\alpha^{(i)}) + \nabla g^T(\alpha^{(i)})(\alpha - \alpha^{(i)})$ function in (36), where $\nabla g^T(\alpha^{(i)})$ is the partial derivative of $g(\alpha^{(i)})$ for $\alpha^{(i)}$. Therefore, the convex problem in (37) can be determined utilizing the standard algorithm of convex optimization theory [44], such as the interior point and sequential quadratic programming methods. In the simulation part of this article, we use sequential quadratic programming.

6. Performance Analysis

In this section, we analyze our proposed resource allocation algorithms through extensive MATLAB simulations. Through the simulations, we assume one base station is placed in the centre and the users are classified randomly in a circular area. In the NOMA system, we assume that only two users are superpositioned on each sub-channel. In the OFDMA system, every user can be allocated to one sub-channel only. During the simulation, we compared the performances of NOMA and OFDMA systems using the same resource allocation algorithm. Table 2 illustrates the values of the simulation parameters.

Table 2. The list of simulation parameters.

Simulation Parameters	Parameter Value
Cell radius	500 m
Minimum distance between BS and UEs	50 m
Minimum distance between two users	40 m
System bandwidth	5 MHz
Maximum number of UTs	60
Fixed circuit power [47]	1 W
Noise power spectral density	−174 dBm/Hz
Difference tolerance in Algorithm 2	0.01
Compensation matrix attenuation coefficient	0.4
Base station peak power P_{BS}	41 dBm

Simulation Results

The network capacity curve as the number of users in a cell increases from 10 to 60 is shown in Figure 3. It can be seen that as the number of users grows, the cell system's capacity grows as well. We can see from Figure 3 that the proposed USFMA offers the highest system capacity for the NOMA system. When there are 40 users, the USFMA outperforms the USMA by 13.11% and the CSS-PA by 40.27%. Furthermore, the USFMA outperforms the OFDMA by 77.72%; this can be justified by the capability of the OFDMA, which can only use one user per sub-channel. As a result, the BS is unable to utilize the spectrum resources to their fullest potential.

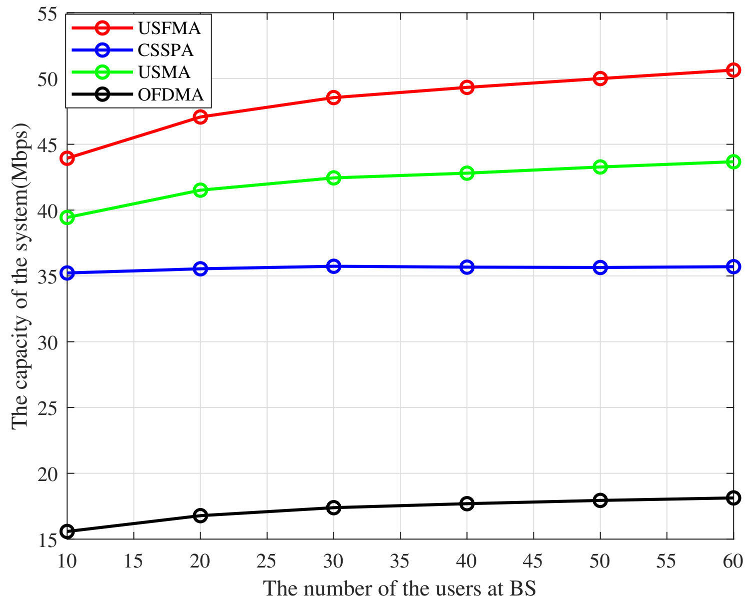

Figure 3. Capacity of the system versus different number of users.

Figure 4 depicts the network energy efficiency as a function of P_{BS}. As predicted, The figure shows that when the power of the BS is increased, the system's capacity also grows, with the USFMA giving the best performance. The energy efficiency equation shows that this curve trend is identical to the sum rate curve trend. We can see from Figure 5 that all NOMA system schemes outperform the OFDMA scheme. Furthermore, the energy efficiency of the USFMA is the best through our proposed sub-channel and power allocation using DC programming. When there are 40 users, the USFMA outperforms the USMA by 12.47%, the CSS-PA by 32.43%, and the OFDMA by 75.19%.

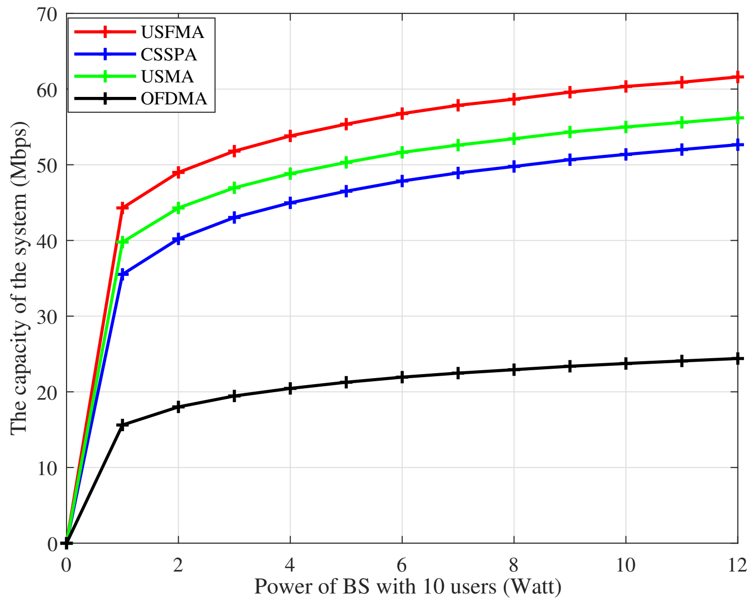

Figure 4. Capacity of the system vs. BS power.

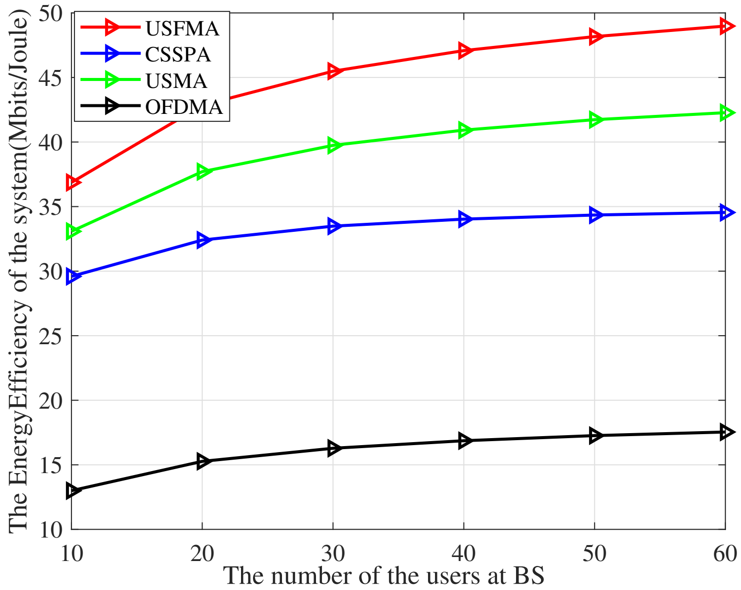

Figure 5. Energy efficiency of the system versus the number of users.

The energy efficiency of the system affected by base station power growth with a fixed number of users ($U = 10$) is shown in Figure 6. We set the power to between one and twelve watts. We can observe in Figure 6 that there is almost a linear relation between system energy efficiency and BS power, and the energy deficiency is inversely proportional to BS power also. All NOMA methods outperform the OFDM system, with the USFMA showing the best performance using DC for sub-channel power allocation.

The impact of a fixed circuit to base station power ratio ($\frac{P_{fixed}}{P_{BS}}$) on the system energy efficiency is shown in Figure 7. From the figure, we can notice that the relationship is inversely proportional, i.e., as the power ratio increases, the system energy efficiency decreases. The system is less energy efficient when P_{fixed} increases and BS power is fixed at 12 watts. However, the NOMA systems, particularly the USFMA, still outperform the OFDMA system when using the recommended resource allocation algorithms.

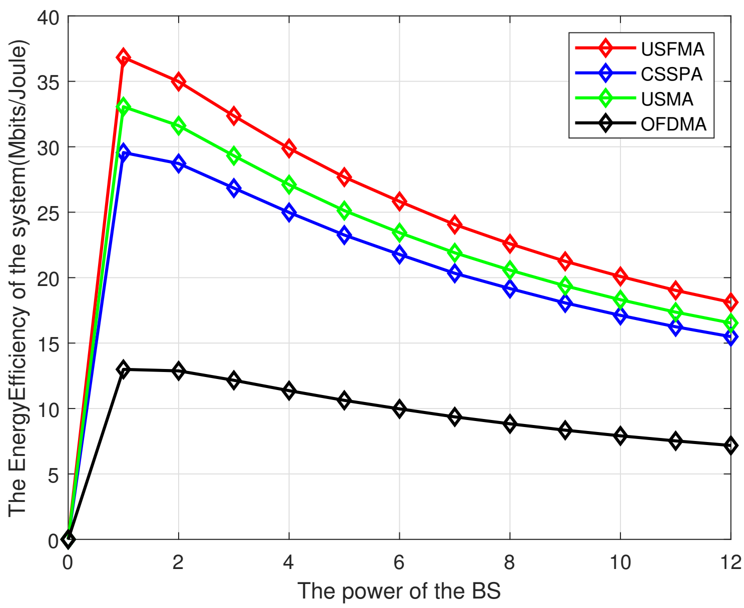

Figure 6. Energy efficiency of the system versus BS power.

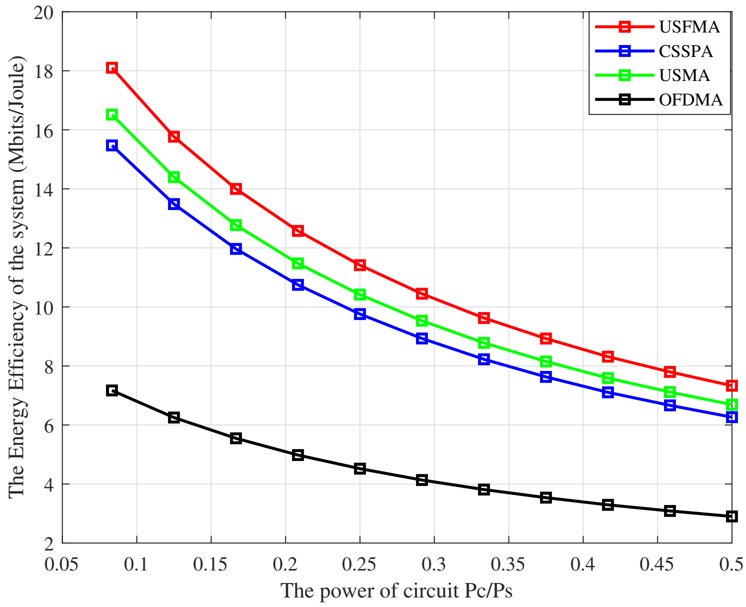

Figure 7. Energy efficiency of the system versus $\frac{P_{fixed}}{P_{BS}}$.

The effect of implementing DC programming alongside the USFMA was studied in both Figures 8 and 9, and the results were compared with USFMA implementing fixed power allocation (FPA). In Figure 8, it can be seen that sum rate for both USFMA-DC and USFMA-FPA is better than OFDMA, with the former showing the best results. Furthermore, when comparing the system's energy efficiency vs. the number of users, it can be seen, as shown in Figure 9, that USFMA-DC provides the best results. For example, if there are 30 users, DC programming has a 1.8% higher energy efficiency than FPA. These results show that DC programming will provide further improvements to the optimized USFMA as discussed above.

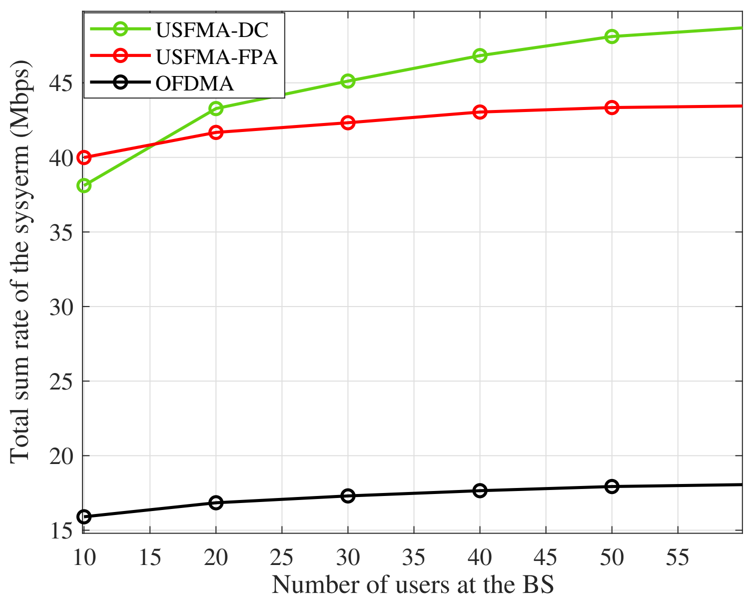

Figure 8. Sum rate of the system versus BS power.

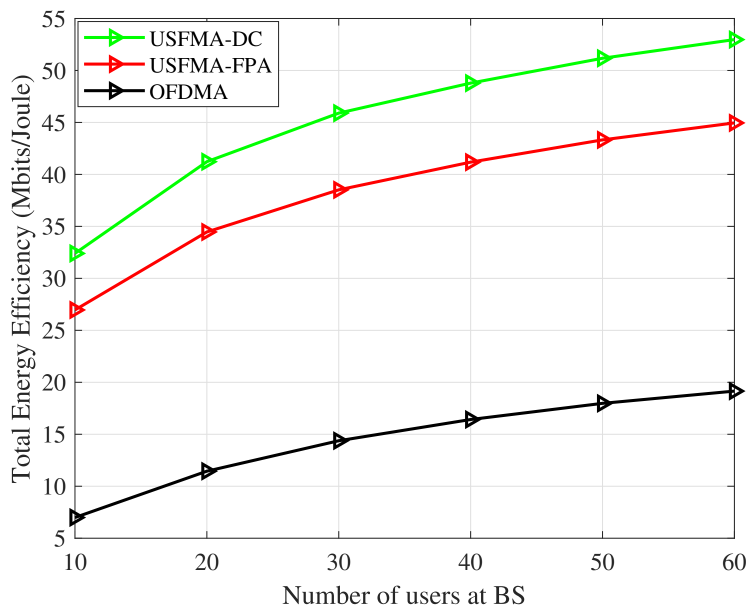

Figure 9. Energy efficiency versus the different number of users.

On the other hand, we studied the impact of USFMA on user capacity fairness. After running Monte Carlo simulations considering $P_{BS} = 10$ dB, $u = 20$, and $v = 10$, the results are shown in Figure 10. It can be seen that, with the power equally distrusted among sub-channels, the capacity is almost equal between all sub-channels. The system fairness was also evaluated based on Jain's fairness index (JFI), which can be expressed as [48]:

$$\mathrm{JFI} = \frac{(\sum_{u=1}^{U} R_u)^2}{U \sum_{u=1}^{U} R_u^2} \tag{38}$$

The JFI comparison, as shown in [49], is depicted in Figure 11. The results are obtained by setting $P_{BS} = 45$ dBm. It can be seen that USFMA and USMA are fairly close to each other, with our algorithm being slightly better.

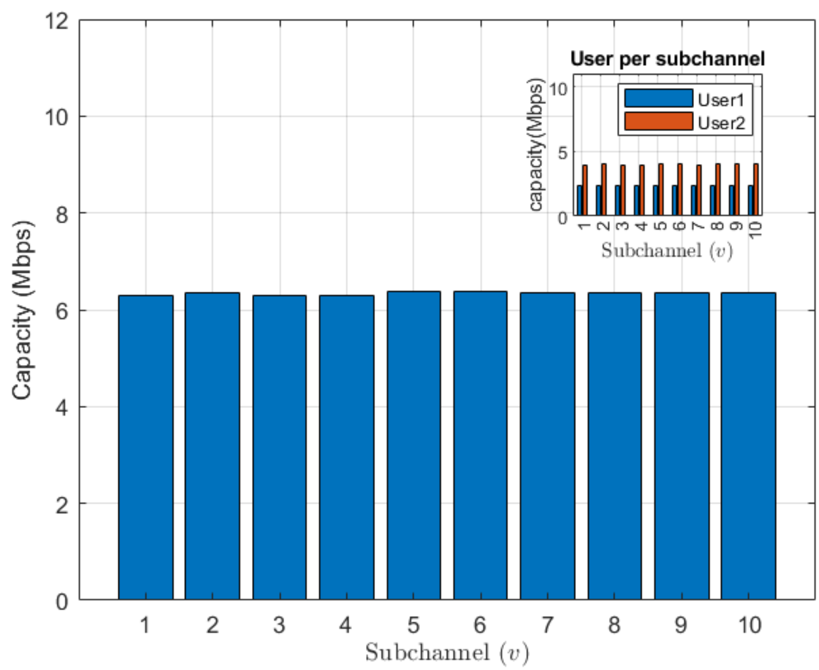

Figure 10. USFMA capacity distribution per sub-channel (v).

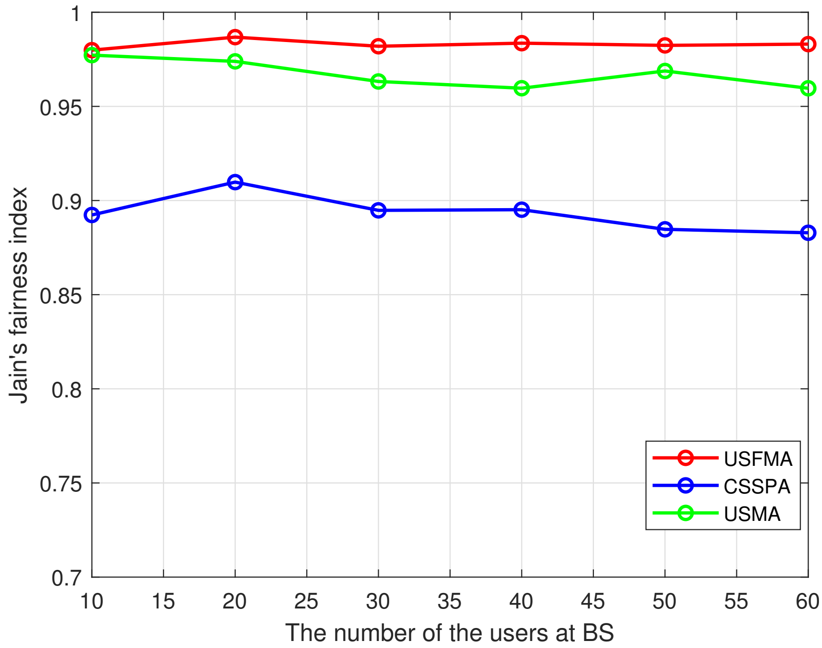

Figure 11. Jain's fairness index comparison.

7. Conclusions

NOMA is one of the most promising techniques to enable massive connectivity in 5G systems and enhance data rates in future mobile communication systems. This work offers a novel user allocation algorithm (USFMA) that builds on the advantages of other existing user allocation algorithms. We also proposed implementing a DC programming approach to assign power to superimposed users on the same sub-channel to maximize the system's energy efficiency. The fundamental concept is to use the DC programming method to convert non-convex problems into convex problems. We also used Matlab to simulate the proposed novel technique. The results of the simulation show that the NOMA system outperforms the OFDM system, and the proposed USFMA outperforms the existing USMA and CSS-PA. For future exploration, we suggest the integration of USMA with emerging technologies like massive MIMO, millimeter wave communications, and device-to-device communications for enhanced performance and capabilities.

Author Contributions: H.R. as the principal investigator takes the primary responsibility for this research and analyzed the results. B.R. and T.C. conceived the study and participated in its design and coordination and helped to draft the manuscript. All authors have read and agreed to the published version of the manuscript.

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