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Power Allocation and User Grouping for NOMA Downlink Systems

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Abstract: Non-orthogonal multiple access (NOMA) technology allows multiple users to use the same time-frequency resource to send signals, which can improve spectral efficiency and throughput. We study the problems of user grouping and power allocation in the downlink of a multi-carrier NOMA system. The sum rate is the optimization goal. A step-by-step optimization is adopted. Users are grouped first and then power is allocated. For user grouping, the user grouping method based on the maximum channel gain difference is improved to prevent users with similar channel gains from being grouped together. For power allocation, the deep learning power allocation algorithm is used among subcarriers. Then, the closed-form expressions of power allocation between multiplexed users are derived according to the minimum transmission rate constraint. The simulation results show that compared with the fractional transmit power allocation method and fixed power allocation method, the deep learning power allocation method improves the system sum rate by about 2.2% and 19%, respectively. The power allocation methods we propose improve the system sum rate by about 10% compared to the fractional transmit power allocation method used among subcarriers and between multiplexed users.

Keywords: deep learning; non-orthogonal multiple access; user grouping; power allocation; resource allocation

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1. Introduction

With the rapid developments in wireless communication technology, the research and development of 6G has also started. The interconnection of all things, such as smart cities, intelligent transportation systems, smart homes, and modern agriculture, has raised the requirements for communication. In addition, the spectrum resources used in mobile communication systems are becoming increasingly scarce. In the face of new technical challenges, researchers have proposed various technical solutions to solve spectrum resource shortage. As a critical factor affecting the performance of wireless communication systems, multiple access technology has become one of the hot research topics. In contrast to traditional orthogonal multiple access (OMA), power domain non-orthogonal multiple access (NOMA) supports more users [1,2], has higher spectral efficiency [3], and achieves higher throughput [4,5]. NOMA is expected to become a candidate multiple access technology in the next generation of mobile communication [6]. NOMA systems realize multi-users multiplexed in the power domain [2]. Different users have different transmit powers, and the receiver separates user signals according to the power, so that the data from multiple users can be transmitted on a subchannel. The principle of NOMA is to allocate more power to users with poor channel conditions and less power to users with good channel conditions. In the downlink of a multicarrier NOMA system, the base station (BS) transmits the signals of some users on the same time-frequency resource through superposition coding technology. Successive interference cancellation (SIC) technology at the receivers demodulates and separates the superimposed signal on the same subcarrier. Resource allocation is a critical step affecting the performance of NOMA systems, containing user grouping and power allocation [7].

1.1. Related Work

In the research into user grouping strategies, the best scheme is the exhaustive search method. An algorithm traverses all the user grouping methods and selects the user combination that achieves the best system performance. However, the complexity of this method increases exponentially, so it is not used in practical systems. In [8], a predefined threshold method was proposed which compares the channel gain of users with the threshold value. The users whose channel gain is higher than the threshold are grouped together. The users whose channel gain is lower than the threshold are grouped into another group. One user is selected from each of the two groups to form a NOMA group. However, the performance of this method is affected by the threshold selection, and the threshold selection is not mentioned. In [9], the authors provided a user grouping method based on maximum channel gain difference. Firstly, all users are sorted according to the channel gain. Then, the users with the highest and the lowest channel gain are paired into the first NOMA group. The users with the second highest and second lowest channel gain are paired into the second group. However, as the grouping process progresses, the channel gain difference between users decreases gradually, which aggravates the interference between users, leading to performance degradation. In [10], the authors proposed a method according to matching theory, which considers the process of determining two users on a subcarrier as a two-sided matching problem between users and subchannels. A downlink NOMA system was considered in [11]. In the case of only two users, the optimal power allocation of users under the minimum rate constraint is obtained first. Then, under the obtaining power, the user grouping problem is analyzed in the case of four users to optimize the sum rate. Finally, the closed-form expression of the optimal user pairing in a general case is given. However, this method requires obtaining the power of each user first. Moreover, heuristic algorithms such as the hill climbing pairing algorithm [12], the simulated annealing algorithm [12,13], the Hungarian algorithm [14], the particle swarm optimization algorithm [15] and the artificial neural network approach [16] have also been applied to user pairing problems. However, heuristic algorithms are unstable and need iterative calculations to obtain the optimal solution, which has high complexity. The wireless communication system needs to complete the resource allocation in milliseconds; therefore, user grouping methods require low complexity and ensured system performance.

In the research into power allocation, the full space search algorithm can lead to the best performance of NOMA systems. It searches the entire power allocation space according to the minimum search interval and obtains the optimal power allocation scheme by traversing all power allocation situations. However, the complexity of this algorithm is very high, so it is generally not used in practice. In [1], fixed power allocation (FPA) was proposed to allocate power to users according to a fixed factor without considering the channel conditions. The algorithm complexity is very low, but the system performance is also poor. In [4], a suboptimal fractional transmit power allocation (FTPA) algorithm was adopted which allocates power according to the channel conditions. Moreover, the computational complexity is low and a better system performance can be achieved. However, this algorithm is a local optimization algorithm. In [9], by applying the Karush–Kuhn–Tucker (KKT) condition, a closed-form solution was deduced to optimize the system throughput. The optimal global solution is obtained by mathematical theory by establishing an optimization problem with inequality constraints. In [17], the authors optimized the weighted sum rate and a suboptimal solution was obtained by step-by-step optimization. First of all, the total power is equally distributed to each subcarrier. Secondly, FTPA is applied to allocate power to the multiplexed users. However, the first step does not consider the influence of channel conditions on the system sum rate when allocating power among subcarriers, which limits system performance improvement. The sum rate maximization of multi-user NOMA wireless systems with perfect channel state information (CSI) was studied in [18]. FTPA is applied to power allocation among subchannels and the closed form solution of power allocation for multiple users is obtained by establishing the Lagrange function under constraint conditions. However, the FTPA algorithm cannot obtain the global optimal solution. Power allocation requires two steps, which increases complexity. In [13], the authors used the simulated annealing algorithm to optimize user power to maximize the throughput. In [19], the authors studies the power allocation problem of NOMA downlink systems. In order to ensure the quality of service and maximize the energy efficiency of the NOMA system, the authors applied a modified particle swarm optimization algorithm to allocate power. However, heuristic algorithms may stay at the local optimal solution and cannot effectively deal with constraints. Deep learning (DL) and reinforcement learning (RL) in machine learning have also been applied in power allocation of NOMA systems. The work in [20] proposed a DL power allocation scheme. Firstly, the optimal power with maximum energy efficiency under constraint conditions is obtained by the exhaustive search method. Secondly, the results of the power allocation are used as the dataset to train a designed neural network. Finally, the neural network predicts power allocation. In [21], the authors proposed an RL method to perform the dynamic power allocation. An RL framework of the Actor–Critic algorithm is used, and the energy efficiency of the system is defined as a reward function. However, the machine learning methods need huge datasets and a lot of training in the early stage, which is extremely time consuming. The performance of these models depends on the training results of the networks. There has been some research on wireless resource management in NOMA; most of it has focused on the sum rate and energy efficiency of resource allocation. However, future research should make efforts to improve the efficiency of resource allocation and ensure the quality of service.

1.2. Contributions

We propose an improved user grouping method and new power allocation methods to solve the problems in the above research. A mathematical model is established to optimize the sum rate of the system under the constraints of the total power and the minimum transmission rate. We use the idea of step-by-step optimization. We divide a complex non-convex optimization problem into two sub-problems to solve, respectively. Firstly, aiming at the disadvantage that users with a similar channel gain will be divided into one group in the user grouping method based on channel gain difference, when the remaining users are grouped, the grouping method is changed to expand the channel gain difference between users in the same group as much as possible. Secondly, we propose a DL algorithm for the power allocation among subcarriers for the first time. Thirdly, the closed-form solution of power allocation between multiplexed users is derived according to the constraint of the minimum transmission rate.

In this work, we first propose the DL method for power allocation among subcarriers. In contrast to traditional DL methods, the proposed method does not require a large dataset to train the neural network and can optimize the sum rate of the system. The power allocation method we use can handle the constraints well, guarantee the minimum transmission rate of users, and avoid resource waste.

The structure of this article is described as follows. We describe the system model and problem formulation in Section 2. The proposed algorithms are introduced in Section 3. The simulation results and detailed analysis are shown in Section 4. Finally, the work conclusions are drawn in Section 5.

2. System Model

We consider the downlink of a NOMA system [22]. Figure 1 shows the concept of the system. We assume that there is a BS and M users in a cell. The BS is located in the center of the cell, and M users are randomly distributed. The BS and users are equipped with a single antenna. The total bandwidth of the system, B_0, is equally distributed to N subchannels and the bandwidth of each subchannel is $B = B_0/N$. P_T denotes the total transmit power. If the number of users on a subchannel is $M_n(n = 1, 2, \cdots, N)$, $M = \sum_{n=1}^{N} M_n$ and the power of the m-th user on the n-th subchannel is $p_{n,m}(m = 1, 2, \cdots, M_n)$. The BS sends a signal with superposition-coded symbols on the subchannel n as follows:

$$x_n = \sum_{m=1}^{M_n} \sqrt{p_{n,m}} \cdot x_{n,m} \tag{1}$$

where $x_{n,m}$ is the transmitted symbol of the m-th user on the subchannel n.

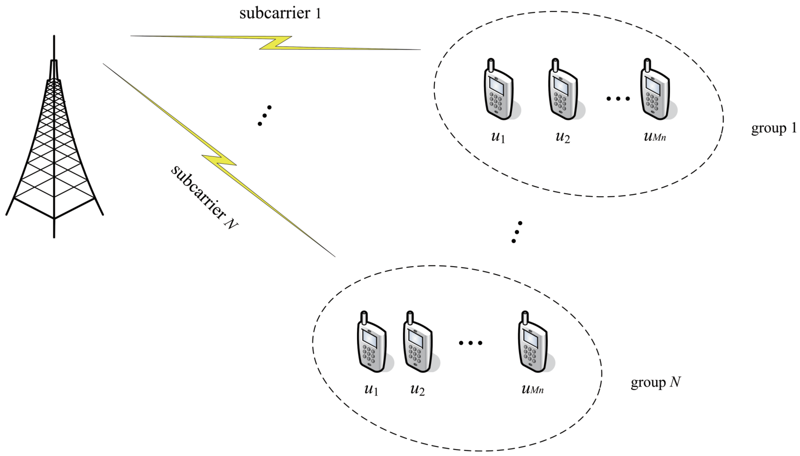

Figure 1. The downlink of a NOMA network.

The received signal at the user m is expressed as follows:

$$y_{n,m} = h_{n,m} \cdot x_n + w_{n,m} = h_{n,m} \sum_{i=1}^{M_n} \sqrt{p_{n,i}} \cdot x_{n,i} + w_{n,m} \tag{2}$$

where $h_{n,m}$ represents the channel coefficient from the BS to the user m, including path loss and Rayleigh fading. $w_{n,m}$ denotes additive white Gaussian noise with mean 0 and variance σ_n^2, where $w_{n,m} \sim CN(0, \sigma_n^2)$. If ee expand Equation (2) further:

$$y_{n,m} = h_{n,m}\sqrt{p_{n,m}} \cdot x_{n,m} + h_{n,m} \sum_{i=1, i\neq m}^{M_n} \sqrt{p_{n,i}} \cdot x_{n,i} + w_{n,m}, \tag{3}$$

we can see that the received signal includes its useful signal and other interference signals. $h_{n,m} \sum_{i=1,i\neq m}^{M_n} \sqrt{p_{n,i}} \cdot x_{n,i}$ is the inter-user interference signal on the subcarrier n.

According to SIC technology, a user signal with a high power will be demodulated first, followed by a user signal with a low power. The order of power allocated to users is $p_1 < p_2 < \cdots < p_{M_n}$. Therefore, the user m can decode and successfully remove the inter-user interference from users $m+1, \cdots, M_n$. However, the signal power from users 1 to $m-1$, who have better channel conditions than the user m, will be considered intra-cell interference. Then, the receiver is processed by SIC and according to the Shannon theorem, the rate of the user m can be expressed as:

$$R_{n,m} = B \log_2\left(1 + \frac{|h_{n,m}|^2 p_{n,m}}{|h_{n,m}|^2 \sum_{i=1}^{m-1} p_{n,i} + \sigma_n^2}\right) \tag{4}$$

Consequently, the sum rate can be expressed as:

$$R_n = \sum_{m=1}^{M_n} R_{n,m} \tag{5}$$

From (4) and (5) we can see that different user combination methods and power allocation results directly impact the total system rate. Therefore, determining the multiplied users and power to reach the system's optimal performance is very important. In this paper, we study how to maximize the sum rate of the NOMA system. The total transmit power and minimum transmission rate are the limiting conditions. The maximum system sum rate is modeled as below:

$$\max_{p_{n,m}} \sum_{n=1}^{N} \sum_{m=1}^{M_n} R_{n,m} \tag{6}$$

$$\text{s.t.} \begin{cases} C1 : \sum_{n=1}^{N} \sum_{m=1}^{M_n} p_{n,m} \leq P_T \\ C2 : p_{n,m} \geq 0 \\ C3 : R_{n,m} \geq R_{\min} \end{cases} \tag{7}$$

where $R_{\min}$ is the minimum data rate. The maximum power P_T limit of the BS is guaranteed according to $C1$. $C2$ indicates that the power allocated to users cannot be less than 0. The user's actual rate cannot be lower than the minimum rate to guarantee the user's quality of service in $C3$.

The above problem is a non-convex optimization problem; therefore, it is difficult to solve the optimal global solution directly. Therefore, we adopt a step-by-step optimization to find a suboptimal solution. Users are grouped first and then power is allocated.

3. Resource Allocation

3.1. User Grouping

In NOMA, multiple users use the same time-frequency resource to transmit signals and different users on the same subcarrier will inevitably lead to a great difference in system performance. Although the exhaustive search method can optimize this, the algorithm complexity is too high to be used in practical scenarios. To ensure the accuracy of the SIC at the receiver and reduce the signal separation delay, we decided to superpose only the signals of two users on each subcarrier, $M_n = 2$. The greater the channel gain difference between the multiplexed users, the greater the throughput improvement of the NOMA systems compared with the OMA systems [23,24]. On the contrary, when the channel gain difference is small, the throughput cannot be significantly improved. In [9], users with medium channel quality may obtain a relatively small channel gain difference between the multiplexed users when they are grouped, which will increase the interference between users. We changed the grouping method to increase the channel gain difference when remaining users with medium channel quality are grouped.

Based on user instantaneous CSI obtained by the BS, the channel gains of all users are sorted in ascending order. The number of users M is even. User grouping consists of two steps, as shown in Figure 2. First, the two users with the largest difference in channel gain are divided into a group; that is, the user with the largest channel gain is paired with the user with the smallest channel gain, and the user with the second largest channel gain is grouped with the user with the second smallest channel gain, and so on. In the second step, another matching method is used when the middle six users are grouped. The first user is paired with the fourth user. The second user is paired with the fifth user. The third user and the sixth user are paired.

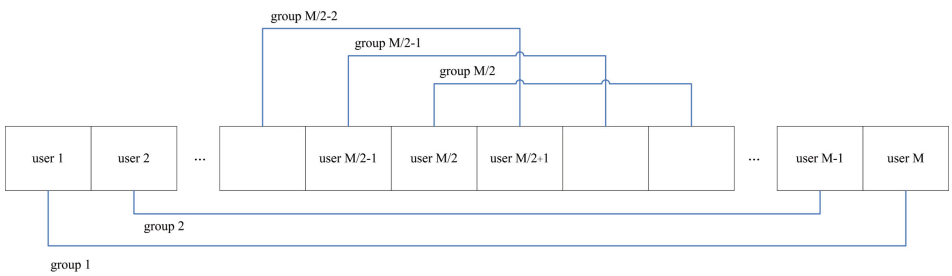

Figure 2. Proposed user grouping method.

3.2. Power Allocation

Power allocation is next performed for all users. Firstly, we apply the DL algorithm to allocate the power among subchannels, and then the power of the multiplexed users is given according to constraints. The specific power allocation process is as follows.

3.2.1. Power Allocation among the Subcarriers

At present, more and more studies are using the DL algorithm for resource allocation and have achieved good results. The deep neural network (DNN) is one of the most basic and widely used networks in DL [25]. Therefore, in this paper, the DNN is used for power allocation among the subcarriers. Ideally, multi-carrier NOMA systems are orthogonal frequency division multiplexing (OFDM) combined with NOMA. Therefore, the subcarriers are orthogonal and there is no mutual interference, only noise interference. According to the user grouping result in the previous section, the channel gains, $|h_{n,1}|^2$ and $|h_{n,2}|^2$, of two users on the subcarrier n are compared, and the largest is selected as the equivalent channel gain, $|h_n|^2$. For power allocation among the subcarriers, the optimization problem can be expressed as follows:

$$\max\text{: } B\sum_{n=1}^{N}\log_2\left(1+\frac{|h_n|^2 P_n}{\sigma_n^2}\right) \tag{8}$$

$$\text{subject to: } \sum_{n=1}^{N} P_n = P_T \tag{9}$$

where (8) represents the maximum sum rate of the system. P_n represents the power of the subcarrier n. (9) indicates that the sum of the subcarrier power is the total transmit power.

The N equivalent channel gain, $|h_n|^2$, of N subcarriers, which we denote as the vector $\boldsymbol{H}$, is the input of the DNN. After the neural network is trained, the output of the DNN is normalized transmit power, which we denote as the vector $\boldsymbol{\beta}_n$. The power can be determined as $\boldsymbol{P}_n = \boldsymbol{\beta}_n P_T$, where $\boldsymbol{P}_n$ is the vector of $P_n (n = 1, 2, \ldots, N)$.

As shown in Figure 3, we design a network with two hidden layers: one input layer, and one output layer. Since the number of subcarriers is N, the input layer size is N. The output is power in the subcarriers. Therefore, the output layer size is N. The first hidden layer contains 15 neurons, and the second hidden layer consists of 10 neurons. Furthermore, we use sigmoid as the activation function: $y = \frac{1}{1+e^{-x}}$ (x is the input of the activation function and y is the output of the activation function). A softmax layer needs to be connected after the output layer to obtain the normalized power. The formula of the softmax activation function is expressed as:

$$\mathrm{softmax}(y)_n = \beta_n = \frac{e^{y_n}}{\sum_{i=1}^{N} e^{y_i}} \tag{10}$$

where y_n denotes the power value of the n-th subcarrier and $\sum_{n=1}^{N}\beta_n = 1$. In the experiment, we adopt the adaptive moment estimation (Adam) optimizer to update the weight and bias of the network and 0.01 is the learning rate. The back propagation algorithm is used to minimize the loss function, but the optimization goal is to maximize the sum rate. Therefore, the loss function is defined as the inverse of the sum rate, as shown in the following formula:

$$\mathrm{loss} = \frac{1}{B\sum_{n=1}^{N}\log_2\left(1+\frac{|h_n|^2 P_n}{\sigma_n^2}\right)} \tag{11}$$

Compared with traditional DNN usage, our usage does not need large datasets to train the neural network. The channel gain vector is the input of the DNN. When the neural network is trained to minimize the loss function, the output is the power of the subcarriers.

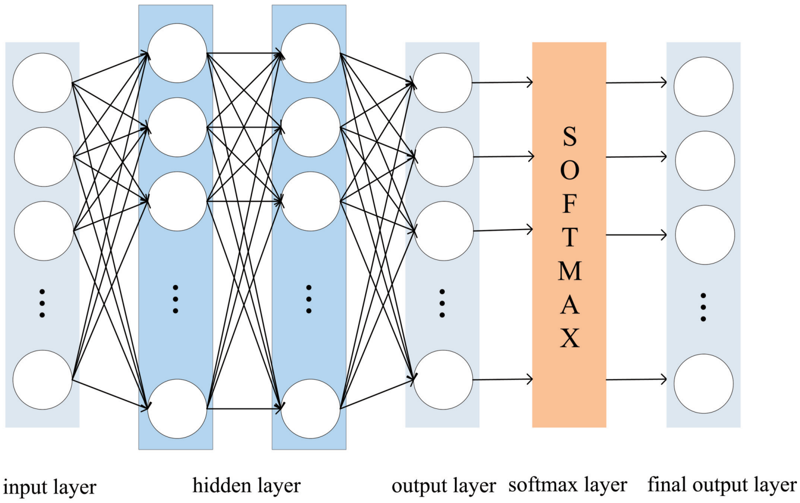

Figure 3. The DNN structure used in this work.

3.2.2. Power Allocation between the Users

Power is now allocated between paired users within each subcarrier. We assume that the channel condition of user 1 on the subcarrier n is better than that of user 2; that is, $|h_{n,1}|^2 \geq |h_{n,2}|^2$. According to the SIC detection order, the signal of user 2 is directly demodulated and the signal of user 1 is treated as interference noise. User 1 needs to perform SIC. First, the receiver demodulates the signal of user 2, then subtracts it from the received signal, and finally demodulates the signal of user 1. The achievable rate of users can be calculated by the formulas [26]. Therefore, the rate of user 1 can be expressed as:

$$R_{n,1} = B\log_2\left(1 + \frac{p_{n,1}|h_{n,1}|^2}{\sigma_n^2}\right) \tag{12}$$

The rate of user 2 can be expressed as follows:

$$R_{n,2} = B\log_2\left(1 + \frac{p_{n,2}|h_{n,2}|^2}{p_{n,1}|h_{n,2}|^2 + \sigma_n^2}\right) \tag{13}$$

We have obtained the power, P_n, allocated to each subcarrier. Assuming that the power allocation coefficient of user 1 is α, then $p_{n,1} = \alpha P_n$ and $p_{n,2} = (1-\alpha)P_n$. According to the power allocation principle of NOMA systems, users with good channel conditions are allocated less power, while users with poor channel conditions are allocated more power. Hence, we obtain $0 < \alpha < \frac{1}{2}$. The total transmission rate of the subcarrier n is:

$$\begin{aligned} R_n(\alpha) &= R_{n,1} + R_{n,2} \\ &= B\log_2\left(1 + \frac{\alpha P_n|h_{n,1}|^2}{\sigma_n^2}\right) + B\log_2\left(1 + \frac{(1-\alpha)P_n|h_{n,2}|^2}{\alpha P_n|h_{n,2}|^2 + \sigma_n^2}\right) \\ &= B\log_2\left(\frac{\alpha P_n|h_{n,1}|^2 + \sigma_n^2}{\alpha P_n|h_{n,2}|^2 + \sigma_n^2}\right) + B\log_2\left(\frac{P_n|h_{n,2}|^2 + \sigma_n^2}{\sigma_n^2}\right). \end{aligned} \tag{14}$$

The latter part of (14) is a constant. We set $f(\alpha) = \frac{\alpha P_n|h_{n,1}|^2 + \sigma_n^2}{\alpha P_n|h_{n,2}|^2 + \sigma_n^2}$. By solving the first derivative, we obtain

$$f'(\alpha) = \frac{P_n|h_{n,1}|^2\left(\alpha P_n|h_{n,2}|^2 + \sigma_n^2\right) - P_n|h_{n,2}|^2\left(\alpha P_n|h_{n,1}|^2 + \sigma_n^2\right)}{\left(\alpha P_n|h_{n,2}|^2 + \sigma_n^2\right)^2}. \tag{15}$$

We simplify (15) to get

$$f'(\alpha) = \frac{\left(|h_{n,1}|^2 - |h_{n,2}|^2\right) P_n \sigma_n^2}{\left(\alpha P_n |h_{n,2}|^2 + \sigma_n^2\right)^2} \tag{16}$$

As a result of $|h_{n,1}|^2 \geq |h_{n,2}|^2$, we can obtain that $f'(\alpha) > 0$. $f(\alpha)$ is a monotone increasing function in the domain, so $R_n(\alpha)$ is also a monotone increasing function in the domain. According to the minimum transmission rate, $R_{\min}$; that is, $R_{n,1} \geq R_{\min}$ and $R_{n,2} \geq R_{\min}$, we obtain

$$\frac{\left(2^{\frac{R_{\min}}{B}} - 1\right)\sigma_n^2}{P_n |h_{n,1}|^2} \leq \alpha \leq \frac{1 - \frac{\left(2^{\frac{R_{\min}}{B}} - 1\right)\sigma_n^2}{P_n |h_{n,2}|^2}}{2^{\frac{R_{\min}}{B}}}. \tag{17}$$

From the above analysis, the sum rate is at a maximum when

$$\alpha = \frac{1 - \frac{\left(2^{\frac{R_{\min}}{B}} - 1\right)\sigma_n^2}{P_n |h_{n,2}|^2}}{2^{\frac{R_{\min}}{B}}}. \tag{18}$$

Hence, we obtain the power of multiplexed users, $p_{n,1} = \alpha P_n$, $p_{n,2} = (1-\alpha)P_n$. Above, we have obtained the closed-form expressions (CFE) method that maximizes the sum rate under the constraints. All power allocation steps have been completed.

3.3. Research Limitation

In this paper, we assume that under ideal conditions there is no SIC detection error, and the multi-carrier NOMA system is a combination of OFDM and NOMA, without considering the inter-carrier interference. The DL algorithm proposed in this paper needs iterative training, so its complexity is slightly higher than that of FTPA and FPA. Our main goal is to maximize the sum rate of the system, so complexity is not covered.

4. Numerical Results

In this section, we evaluate the performance of the proposed resource allocation algorithms through simulation. We use MATLAB (R2017a) to simulate the performance of FTPA and FPA. Furthermore, the simulation environment of the DL algorithm is as follows: Python 3.5 with TensorFlow 1.15.0 an a NVIDIA GeForce GTX 960M. In the simulations, we consider a situation in which the users are uniformly distributed in a circle range with a radius of 500 m. We set the minimum distance from the users to the BS as 50 m. It is supposed that the instantaneous CSI of each user can be obtained. The methods introduced in this paper have been simulated in this section. Table 1 shows the system parameters [1,13,18].

Figure 4 shows the sum rate for two user grouping schemes. When the total power changes from 50 mW to 55 mW, we compare our method with the maximum channel gain difference method [9]. We assume that 12 users are randomly and evenly distributed in a cell. We want to reduce the complexity of the power allocation algorithm; thus, equal power allocation is adopted among subcarriers. In other words, the total transmit power is equally distributed to each subcarrier. The users within the subcarriers adopt the FTPA algorithm. We can see that the sum rate of the system increases with the increase in transmit power. Compared with the method in [9], the improved user grouping method in this paper avoids users with similar channel gain in a group and slightly improves the sum rate.

Table 1. System Parameters

Parameters	Values
Cell Radius/m	500
Minimum Distance from User to BS/m	50
Overall System Bandwidth/MHz	10
Noise Power Spectral Density/(dBm/Hz)	−174
Path Loss/dB	128.1 + 37.6log(d)
Fading Model	Rayleigh Fading
Minimum Rate/Mbps	1
FTPA Factor	0.7
FPA Factor	0.5

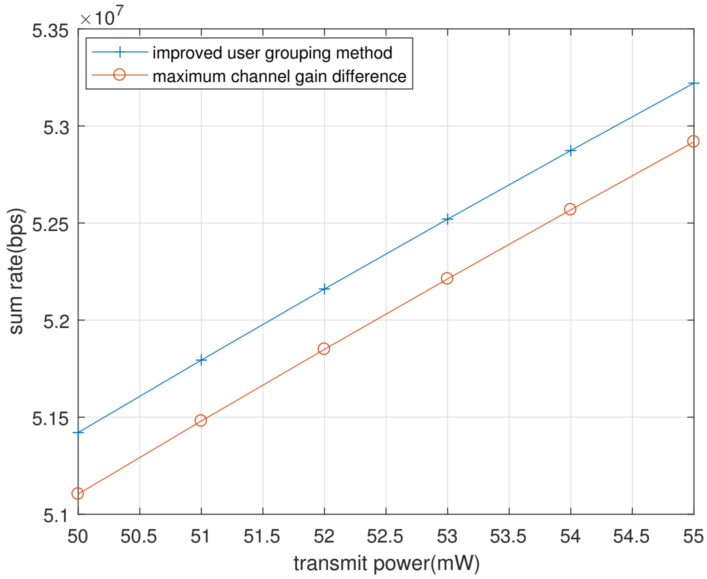

Figure 4. System sum rate comparison of two user grouping methods.

Figure 5 shows the sum rate comparison of different power allocation methods among subcarriers. They are the deep learning power allocation (DLPA) method proposed in this paper, water-filling power allocation (WFPA) [27], FTPA, and FPA. We assume that there are 20 users and 10 subcarriers. The total power ranges from 5 W to 10 W. With the increase in transmit power, the sum rate obtained by the three methods is improved. We can see that the WFPA method is better than the other methods in the sum rate. However, WFPA may allocate the power of subcarriers with particularly poor channel conditions as zero. The sum rate of DLPA is about 2.2% higher than that of FTPA and about 19% higher than that of FPA. The reason is that DLPA maximizes the sum rate according to the channel gain. Although FTPA considers the channel gain, it only allocates more power to users with lower channel gain and less power to users with higher channel gain. The FPA algorithm does not take into account the influence of channel conditions and allocates power according to a fixed allocation factor, so this method has the worst performance. Figure 6 illustrates the sum rate obtained by the four methods with different numbers of users. The total power is 10 W and the number of users ranges from 20 to 40. As we can see, the DLPA algorithm is still better than FTPA and FPA.

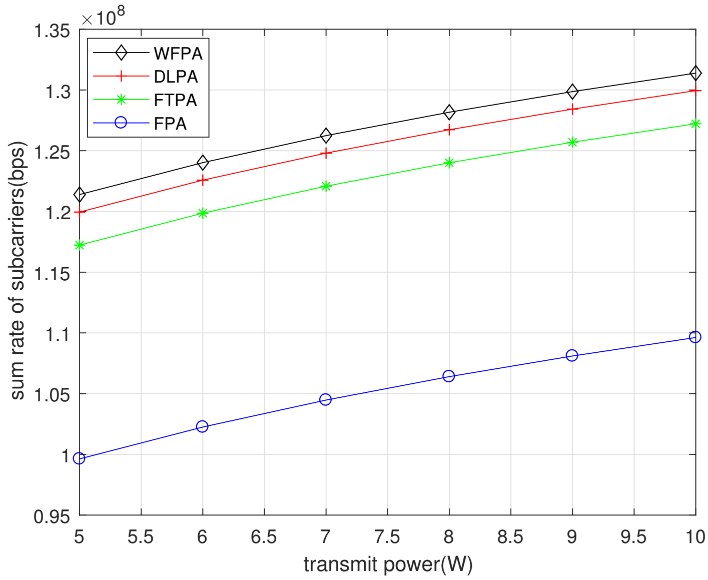

Figure 5. Sum rate comparison under different transmit powers.

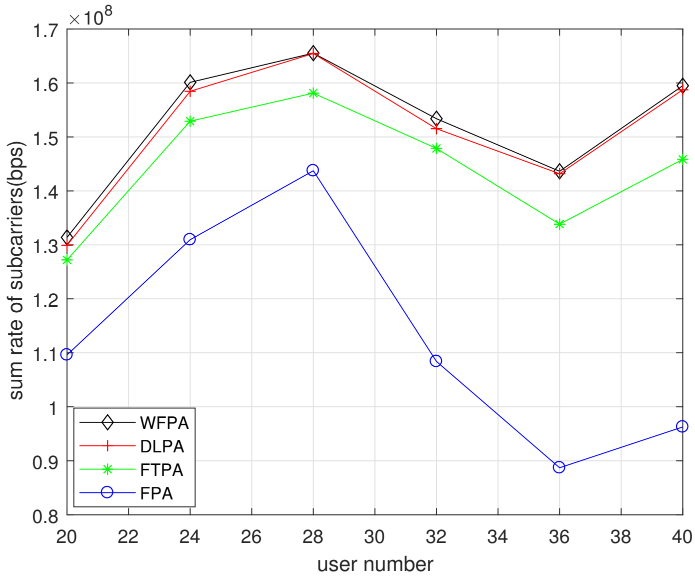

Figure 6. Sum rate comparison under different numbers of users.

The DLPA algorithm is used among subcarriers and CFE of power allocation is used between multiplexed users. We call this power allocation method DLPA–CFE. Similarly, DLPA is used among subcarriers and FTPA is used between multiplexed users. We call it DLPA–FTPA. FTPA–CFE is the power allocation method that uses FTPA among subcarriers and CFE between multiplexed users. FTPA is used among subcarriers and multiplexed users, which we call FTPA–FTPA.

Figure 7 shows the sum rate comparison of different power allocation algorithms. We used the method proposed in Section 3.1 to implement user grouping. We assume that there are 20 randomly distributed users in a cell, the number of subcarriers is 10, and the transmit power of the BS is between 5W and 10W. We can see that DLPA–CFE achieves the largest system sum rate compared with the other three methods, and the improvement is about 10% compared to the FTPA–FTPA method. This is because DLPA performs better than FTPA in power allocation among subcarriers. When power is allocated to users within subcarriers, the user power calculated by CFE can maximize the sum rate under the condition of a minimum transmission rate. FTPA only allocates more power to users with poor channel conditions. Although FTPA ensures certain fairness, it cannot achieve the optimal global solution. Figure 8 verifies that the DLPA–CFE power allocation scheme is the scheme that achieves the maximum system sum rate. The transmit power of the BS is 10 W and the number of users ranges from 20 to 40.

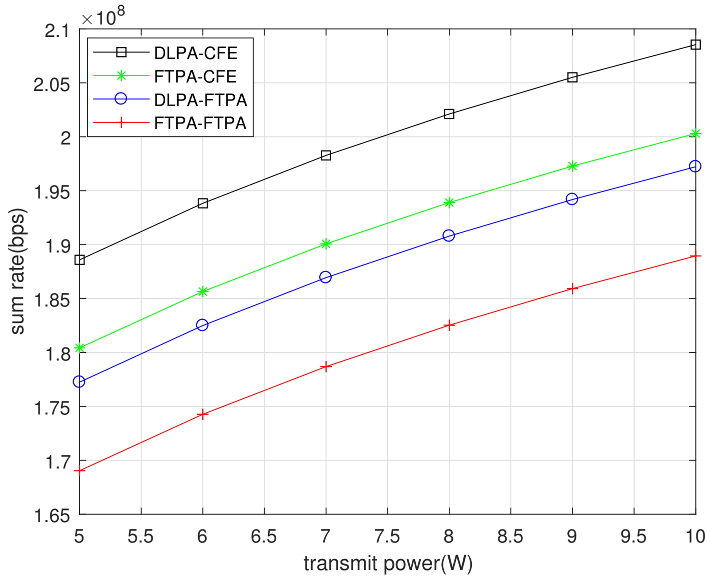

Figure 7. System sum rate comparison under different transmit powers.

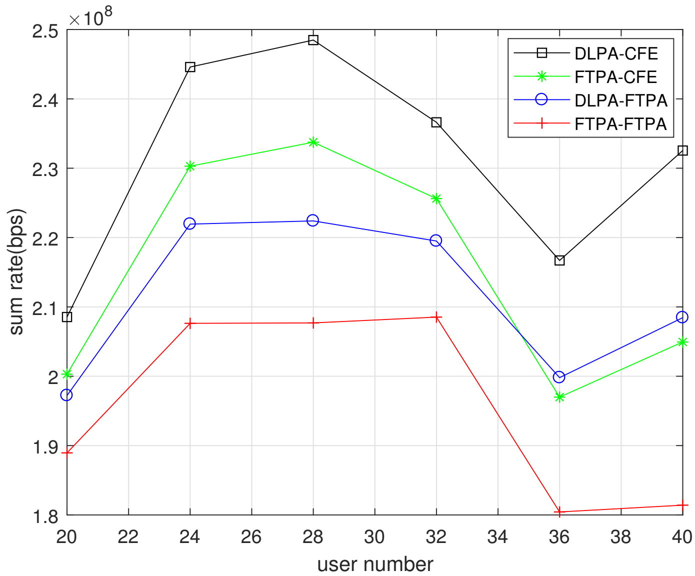

Figure 8. System sum rate comparison under different numbers of users.

5. Conclusions

In this article, we analyze the problem of user grouping and power allocation in the downlink of a multi-carrier NOMA system. We establish a mathematical model that optimizes the system sum rate. The complexity of directly solving the optimal solution is higher; therefore, we adopt a step-by-step optimization approach. Users are grouped first and then power is allocated.

(1) Aiming to fix the shortcomings of the user grouping based on the maximum channel gain difference, we propose a new user grouping method to avoid users with similar channel gains being divided into one group. The proposed method improves the system sum rate.

(2) In terms of power allocation, the DNN in DL is proposed for the first time to obtain the power for each subcarrier. The simulation results illustrate DLPA improves the sum rate by about 2.2% and 19% compared with FTPA and FPA, respectively.
(3) After determining the power of the subcarriers, we derive the power allocation CFE of superimposed users according to the minimum transmission rate constraint. The simulation results illustrate that when the DLPA method is used among subcarriers and the CFE method is used between users, the rate increases by about 10% compared with the FTPA method.

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