A Power Allocation Method for Downlink MUSA

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Abstract. Multi-user shared access (MUSA) is a kind of Non-Orthogonal Multiple Access (NOMA), which is suitable for multi-user transmission and has better channel capacity. This paper analyzes the influencing factors of power allocation on the performance of downlink MUSA from the perspective of sum rate of users and bit error ratio (BER) performance. This paper considers a two-user scenario. A power allocation method based on sum rate of users is proposed and a closed-form expression of the sum rate and power allocation coefficients of users is given in the MUSA downlink scenario. In order to analyze and discuss the impact factors of power allocation on MUSA system performance, extensive simulation results are provided to evaluate the performance of the proposed method under different user weight-ratio scenarios. Through these simulation results, the proposed method is proved to be realistic. Based on this result, a power allocation algorithm for a multi-user scenario is presented in this paper.

Keywords: MUSA · Power allocation · BER · Sum rate

1 Introduction

In order to meet the unprecedented massive data demand for wireless services in the future, such as high spectrum utilization, large system throughput and energy efficiency. New wireless access technology is needed. Traditional technology Orthogonal Multiple Access (OMA) is not enough for 5G scenarios. NOMA is proposed to overcome these limitations. Users can share the same time, code and frequency in NOMA [1]. Multi-User Shared Access (MUSA) is a kind of NOMA technology in the code domain. In this technology, the modulation symbols of each user are extended by a complex spreading sequence to realize superimposed transmission of multiple user data. In addition, this technology uses Serial Interference Cancellation (SIC) technology to complete multi-user detection [2]. The principle of SIC is to treat other user data as the interference of user data to be detected. MUSA is very suitable for the Internet of Things (IoT) business due to the diversity of its plural sequence and low cross-correlation [3]. It has been clarified that the channel capacity of MUSA is better thanks to non-zero code spreading, and that the advantages of MUSA are most strongly evidenced in the scenarios of high SNR and multi-user transmission. Thus, MUSA is suitable for 5G massive Machine Type Communications (mMTC). However, because SIC detection has error propagation phenomenon, that is, the accuracy of the user data

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detected earlier will affect the detection of user data later [4]. The power allocation directly affects the SINR of each user, and then affects the detection performance of the MUSA system. Therefore, the impact of power allocation on MUSA system performance needs to be analyzed and discussed.

Current research focuses on the power allocation strategy of NOMA in the power domain. Energy efficient power allocation strategies are studied in [5, 6] and outage based power allocation is investigated in [7, 8]. Although the above research is in the field of NOMA in power domain, there are still some reference values. In [9], it is proved that downlink MUSA can achieve better BER performance than NOMA over Rayleigh fading channel by simulation. Besides, its simulation results show that a reasonable power allocation is the key to improve BER performance of MUSA. However, the simulation results lack of theoretical basis and there is no general rule.

In this paper, we give a closed-form expression of the sum rate and power allocation coefficients of users in downlink MUSA scenario, which is only studied in NOMA of power domain, and combine the simulation results to design a user power allocation method based on channel gain. Besides, we analyze the impact of power allocation on MUSA performance from the perspective of actual Bit Error Rate (BER) detection, which analyzes the actual detection BER of the system and the influence of the power distribution coefficient, and also verifies the correctness of the channel capacity analysis. This paper is based on the analysis two users' case and the multi-user conditions are inferred to reach general conclusions.

2 System Model

We consider a downlink MUSA transmission system that includes a single-antenna base station and K single-antenna users. In this system, the base station allocates the transmission power of K users. These users share the same time and frequency channel resources. The received signals of K users contain the data of all of the users, so each user needs to use MMSE-SIC to detect the data they need. The channel gain from the Base Staion(BS) to the k-th user is h_k, $k \in K$. Users could be assumed to be sorted such that $|h_1| \leq |h_2| \leq \cdots \leq |h_k| \leq \cdots \leq |h_K|$. The transmitted signal of the base station can be expressed as

$$S = \sum_{k=1}^{K} \sqrt{P_k} w_k x_k \tag{1}$$

where $P_k = c_k P$. P is the total transmit power. c_k is the power allocation coefficient of the base station to user k, $\sum_{k=1}^{K} c_k = 1$.w_k is the extended sequence of user k, x_k is the modulated signal of user k. Then, the received signals y_k at the user k from the BS are given by

$$y_k = h_k S + n_k \tag{2}$$

where n_k represents the additive white Gaussian noise (AWGN) at the user k (Fig. 1).

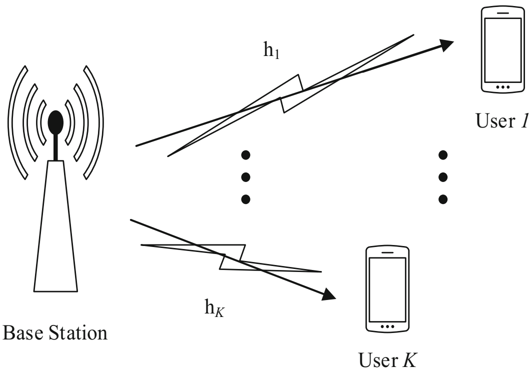

Fig. 1. Downlink MUSA system with K users

According to the detection principle of MMSE-SIC, users with larger SINR are first detected at the receiver, and then the remaining users are detected after reconstruction and elimination. In order to achieve a better sum rate of users, the power distribution coefficient c_k should be allocated reasonably. Assuming ideal power distribution, the SINR of users is

$$\mathrm{SINR}_k = \frac{c_k P|h_k|^2 \|w_k\|^2}{P|h_k|^2 \sum_{i=k+1}^{K} c_i \|w_i\|^2 + N} \tag{3}$$

Since the extended sequence $\|w_k\|^2$ has been normalized by power, Eq. (3) is further simplified as

$$\mathrm{SINR}_k = \frac{c_k P|h_k|^2}{P|h_k|^2 \sum_{i=k+1}^{K} c_i + N} \tag{4}$$

Further, the channel capacity of each user can be obtained, that is, the achievable rate of each user is

$$\mathrm{R}_k = \log_2(1 + \mathrm{SINR}_k) = \log_2\left(1 + \frac{c_k P|h_k|^2}{P|h_k|^2 \sum_{i=k+1}^{K} c_i + N}\right) \tag{5}$$

However, solution to the weighted sum rate maximization problem is not convex and finding a solution is not straight forward [10]. To find the most efficient way of power allocation, we consider the scenario of two users.

3 Channel Capacity Analysis of Power Allocation

In the two-user scenario, c_1 and c_2 are the power distribution coefficients of user *1* and user *2* respectively. In order to draw a general conclusion, we classify and discuss the value of c.

3.1 Classify and Discuss

Case (i): $c_1 < c_2$

In this case, the power allocated to user *1* by the BS is less than the power allocated to user *2*. At this time, according to the detection principle of MMSE-SIC, at user 1, the data of user 2 is first detected, and then the detected data of user *2* is reconstructed and then subtracted from the received signal, then the new received signal is used to detect the data of user *1*; on the user *2* side, the data of user *2* is also detected first, but because user *2* does not need the data of user *1*, there is no need to perform reconstruction and elimination operations, and the detected data of user *2* is directly obtained.

First, on the side of user *1*. The date of user *2* is first detected, the SINR of user *2* is

$$\mathrm{SINR}_2^{(1)} = \frac{c_2 P|h_1|^2}{c_1 P|h_1|^2 + N} \tag{6}$$

After the data of user *2* is detected, the data of user *2* is reconstructed and eliminated, and the new received signal is

$$y_1^{\mathrm{new}} = h_1\sqrt{c_1 P} w_1 x_1 + n \tag{7}$$

Using the new received signal to detect user *1*'s data, the SINR of user *1* can be obtained as

$$\mathrm{SINR}_1^{(1)} = \frac{c_1 P|h_1|^2 \|w_1\|^2}{N} = \frac{c_1 P|h_1|^2}{N} \tag{8}$$

The achievable rate of each user on the side of user *2* is

$$\mathrm{R}_1^{(1)} = \log_2\left(1 + \frac{c_1 P|h_1|^2}{N}\right) \tag{9}$$

$$\mathrm{R}_2^{(1)} = \log_2\left(1 + \frac{c_2 P|h_1|^2}{c_1 P|h_1|^2 + N}\right) \tag{10}$$

Because user *2* no longer performs reconstruction and elimination operations, and only needs to obtain the user *2*'s rate as shown in Eq. (11).

$$\mathrm{R}_2^{(2)} = \log_2(1 + \frac{c_2 P|h_2|^2}{c_1 P|h_2|^2 + N}) \tag{11}$$

Hence the sum rate of two users in case(i) is

$$\begin{aligned}\mathrm{R}_{\mathrm{sum}}^{c_1<c_2} &= \mathrm{R}_1^{(1)} + \mathrm{R}_2^{(2)} \\ &= \log_2(\frac{c_1 P|h_1|^2 + N}{N} \bullet \frac{P|h_2|^2 + N}{c_1 P|h_2|^2 + N})\end{aligned} \tag{12}$$

Considering $\frac{P}{N} \to \infty$, that is, the signal power is larger than the noise power, and the noise power can be ignored. At this time, the user sum rate is

$$\mathrm{R}_{\mathrm{sum}}^{c_1<c_2} = \log_2(\frac{P|h_1|^2}{N}) \tag{13}$$

Case (ii): $c_1 > c_2$
In this case, the power allocated to user *1* by the BS is larger than the power allocated to user *2*. At this time, according to the principle of MMSE-SIC detection, on the user *1* side, the data of user *1* is first detected. Because user *1* does not need the data of user *2*, the detection can be stopped after the data of user *1* is obtained. On the user *2* side, the data of user *1* is still first detected. Because user *2* needs the data of user *2*, then the data of user *1* detected will be reconstructed, and then removed from the received signal, and then used. The received signal detects user *2*'s data. Similar to case (i), we get the user sum rate.

$$\begin{aligned}\mathrm{R}_{\mathrm{sum}}^{c_1>c_2} &= \log_2(\frac{P|h_1|^2 + N}{(1-c_1)P|h_1|^2 + N} \bullet \frac{(1-c_1)P|h_2|^2 + N}{N}) \\ &\overset{\frac{P}{N}\to\infty}{=} \log_2(\frac{P|h_2|^2}{N})\end{aligned} \tag{14}$$

Case (iii): $c_1 = c_2$
In this case, the power allocated to user *1* by the BS is equal to the power allocated to user *2*. The receiver can either choose to detect the data of user *1* first, or choose to detect the data of user *2* first.

If we choose to detect the data of user 1 first, the channel capacity is

$$\mathrm{R}_{\mathrm{sum}}^{c_1=c_2} = \mathrm{R}_{\mathrm{sum}}^{c_1>c_2} = \log_2(\frac{P|h_1|^2 + N}{(1-c_1)P|h_1|^2 + N} \bullet \frac{(1-c_1)P|h_2|^2 + N}{N}) \tag{15}$$

On the contrary, if we choose to detect the data of user *2* first, the channel capacity is

$$\mathrm{R}_{\mathrm{sum}}^{c_1=c_2} = \mathrm{R}_{\mathrm{sum}}^{c_1<c_2} = \log_2\left(\frac{c_1 P|h_1|^2 + N}{N} \bullet \frac{P|h_2|^2 + N}{c_1 P|h_2|^2 + N}\right) \tag{16}$$

3.2 Simulation and Analysis

Case(iii) is a special case of case(i) and case(ii). From case(i) and case(ii), we can conclude that sum rate of users is only related to the channel coefficient $|h|^2$ and has nothing to do with the power distribution coefficient c_1 and c_2 when $\frac{P}{N} \to \infty$. Under the condition of $|h_1|^2 < |h_2|^2$, the relationship curve between sum rate and the power allocation coefficient of user *1* under the two detection strategies is obtained. We assume that $|h_1|^2 = 0.15$ and $|h_2|^2 = 0.2$. The simulation result is below (Fig. 2).

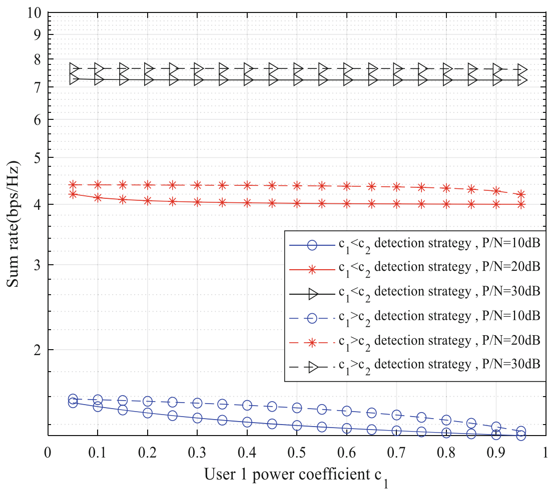

Fig. 2. Sum rate simulation

The above figure compares and analyzes the situation of sum rates under different P/N conditions. According to the curve in the figure, with the increase of P/N, the relationship curve between sum rate and power distribution coefficient of user *1* becomes smoother, that is, the larger the signal power is compared to the noise power, the smaller the relevance between sum rate and power distribution coefficient. At the same time, it is verified that the user and rate are only related to the channel gain, not to the power allocation when the immediate noise power can be ignored compared to the signal power.

It can also be seen that under the condition of $|h_1|^2 < |h_2|^2$, the sum rate of the $c_1 > c_2$ detection strategy are optimal, that is, the strategy of first detecting the data of user *1* and then detecting the data of user *2* can achieve the optimal sum rate. However, considering that in the actual detection, if in the case of $c_1 > c_2$, the data of user *1* is still detected first, the SINR of user *1* is small, which will cause the detection accuracy to be low, and due to the existence of the SIC error propagation phenomenon, the detection accuracy of user *2* will also be low, resulting in poor system detection performance. Aiming at the actual detection situation, this article will conduct a more in-depth analysis from the perspective of detecting BER later.

4 BER Performance

Considering that in the multi-user situation, there are many user power allocation parameters and the simulation parameter setting is more complicated. Therefore, this section mainly simulates and analyzes the situation of two users. The simulation parameter configuration table is shown in Table 1.

Table 1. Simulation parameter configuration

Simulation parameter	Configuration
Coding scheme	Turbo coding with code rate 1/2
Modulation scheme	QPSK
Spreading sequence category	Complex ternary sequence
Spreading sequence length	4
Amount of users	2
Antenna configuration	1Tx,1Rx
Channel	AWGN
Channel estimation	Ideal estimate
Receiver algorithm	MMSE-SIC

Set the channel gain between user 1 and the base station is $|h_1|^2 = 0.15$, and the channel gain between user 2 and the base station is $|h_2|^2 = 0.2$. Figure 3 is the simulation curve.

It can be seen from the simulation results that under the conditions of $|h_1|^2 < |h_2|^2$, the detection BER of the MUSA system in the case of $c_1 > c_2$ is lower and the detection performance is better, which is consistent with the previous sum rate analysis results.

According to the simulation results, the BER of user *1* first decreases and then increases within the range of $c_1 < 0.5$, and the BER continues to decrease within the range of $c_1 \geq 0.5$, while the BER of user *2* continues to increase within the range of $c_1 < 0.5$, and first decreases and then increases within the range of $c_1 \geq 0.5$; the average BER of user *1* and user *2* first decreases and then increases in the range of $c_1 < 0.5$, and also decreases first and then increases in the range of $c_1 \geq 0.5$, and the average BER is obtained the minimum value in $c_1 = 0.65$. The reasons for this trend are analyzed as follows.

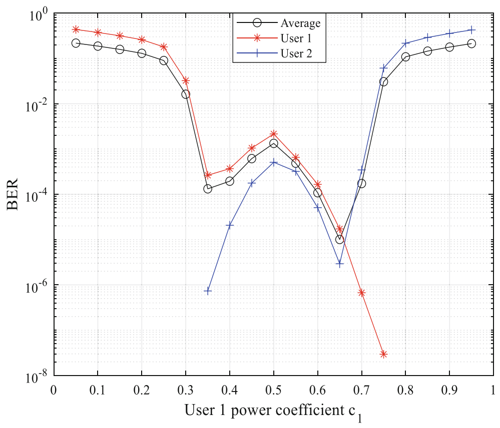

Fig. 3. BER simulation ($|h_1|^2 = 0.15$, $|h_2|^2 = 0.2$)

In the case of $c_1 < c_2$, user *2* directly detects its data. As user *1*'s power allocation coefficient increases, user *2*'s SINR gradually decreases. When the data of user *2* is detected, the MAI of user *1* increases, sot the detection performance deteriorates, and the detection BER gradually increases. On the user *1* side, the data of user *2* is detected first, and then the data of user *2* is reconstructed and eliminated, and then the data of user *1* is detected. Considering the influence of error propagation, the detection accuracy of user *2* data will affect the data of user *1* detection. In the case of $c_1 < 0.35$, User *2* data detection is affected by user *1*'s MAI smaller, and the detection accuracy of user *2* data was higher. Therefore, the detection accuracy of user *1* data gradually improved with the increase of c_1, and the detection BER of user *1* gradually decreased; In the case of $0.35 < c_1 < 0.5$, User *2* data detection is subject to user *1*'s MAI. As c_1 increases, the detection accuracy of user *2* gradually deteriorates. Due to the effect of error propagation, the detection accuracy of user *1* also gradually deteriorates. The BER of user *1* gradually increases. Therefore, in the case of $c_1 < c_2$, the average BER of user *1* and user *2* also shows a trend of first decreasing and then increasing.

In the case of $c_1 \geq c_2$, user *1* directly detects the data of user *1*, so as the power allocation coefficient of user *1* increases, the detection performance of user *1* gradually becomes better, and the detection BER of user *1* gradually decreases. On the other hand, user *2* first detects user *1*'s data, then reconstructs and eliminates user *1*'s data, and then detects user *2*'s data. However, considering the error propagation phenomenon, the accuracy of user *2* data detection is affected by user *1* data detection. In the case of $0.5 \leq c_1 \leq 0.65$, with the increase of c_1, the detection accuracy of user *1* gradually improved, so the detection accuracy of user *2* gradually improved, and the detection BER of user *2* gradually became smaller; In the case of $c_1 > 0.65$, with the increase of c_1, the detection accuracy of user *1* is still gradually getting better, but c_1 becomes very large at this time, and therefore c_2 becomes very small. User *2* cannot obtain good detection performance when detecting the user *2* data, so as the increase of c_1, the detection performance of user *2* gradually deteriorates, and the detection BER gradually increases. Therefore, in the case of $c_1 \geq c_2$, the average BER of user *1* and user *2* also shows a trend of first decreasing and then increasing.

To get a general conclusion, we also set the channel gain between user 1 and the base station is $|h_1|^2 = 0.05$, the channel gain between user 2 and the base station is $|h_2|^2 = 0.2$. The trends of the three curves in the Fig. 4 are basically the same as the simulation curves in Fig. 3.

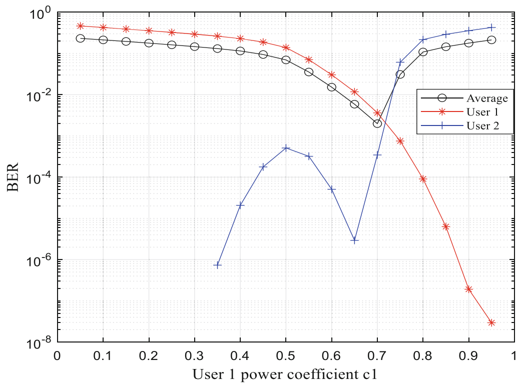

Fig. 4. BER simulation ($|h_1|^2 = 0.05$, $|h_2|^2 = 0.2$)

In summary, through the analysis of channel capacity and detection of BER, it can be concluded that the user's power allocation will affect the detection performance of MUSA.

5 Conclusion

This paper analyzes the impact of power allocation on the performance of the MUSA system from the perspective of channel capacity and detection BER, and gives a closed-form expression of the sum rate of users and user power allocation coefficient in the MUSA downlink scenario, and combines the simulation results to design user power allocation method based on the channel gain. That is, in the case of $|h_1|^2 \leq |h_2|^2 \leq \cdots \leq |h_k|^2 \leq \cdots \leq |h_K|^2$, when the power allocation coefficient satisfies $c_1 \geq c_2 \geq \cdots \geq c_k \geq \cdots \geq c_K$, that is, users with lower channel gains are allocated more transmit power, which enables the MUSA system to effectively improve the BER performance on the premise of ensuring high user sum rate.

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