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Capacity-Fairness Tradeoff-aware Optimal Power Allocation for Cluster-wise Distributed MU-MIMO System

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Abstract According to the ever-increasing mobile data traffic, ultra-dense distributed antenna system is recommended to support the 5G-advanced system. To mitigate the prohibitively high computational complexity of ultra-dense network, user-clustering is introduced into distributed multiuser multi-input multi-output (MU-MIMO) system and to perform cluster-wise MU-MIMO communication in parallel. However, user-clustering leads to a capacity degradation due to the inter-cluster-interference. Reasonable power allocation strategy can make up this capacity degradation. In our previous study, a sum capacity maximization-based power allocation strategy was proposed while guaranteeing the minimum user capacity under the total transmit power constraint. The user fairness is also a big issue. In this paper, we propose an optimal power allocation (OPA) method which can flexibly tradeoff the sum capacity and the user fairness while guaranteeing the minimum user capacity under the total transmit power constraint. Moreover, we utilize the weighted sum method which integrates two objectives into one. The simulation results show that the proposed power allocation can effectively control a tradeoff between the sum capacity and the user fairness while guaranteeing the minimum user capacity.

Keywords 5G-advanced, ultra-dense network, distributed antenna system, clustering, power allocation

1. Introduction

The mobile radio access network (RAN) is needed to be densified to guarantee the quality of service under the ever-increasing mobile data traffic. Multiuser multi-input multi-output (MU-MIMO) system is the key technology for RAN densification. There are two types of MU-MIMO systems: centralized one applying large-scale antenna array at one location and distributed one applying a large number of spatially separated antennas. Considering that higher frequency band (e.g. millimeter wave band) signals utilized for broader bandwidth may frequently be blocked by obstacles due to their rectilinear propagation nature, distributed MU-MIMO system is preferable since it can effectively avoid blockage problem and accordingly improve the spectral efficiency [1,2].

However, a difficulty of practically implementing large-scale distributed MU-MIMO lies in the prohibitively huge amount of signal processing computation. Accordingly, in our previous work [3], as an efficient way to reduce the signal processing computational complexity, we proposed to introduce user-centric clustering to the large-scale distributed MU-MIMO and to perform the cluster-wise small-scale MU-MIMO in parallel in the base station coverage (called cell in this paper). Unfortunately, forming clusters lead to a new problem, i.e., inter-cluster-interference (ICI) which significantly limits the system capacity when the same radio resource is reused in all clusters.

In order to overcome the ICI problem, the fractional frequency reuse and scheduling which assign orthogonal resource in frequency and time domains can be applied. However, they may bring a segmentation loss. Therefore, in our previous work [4], we considered to reduce the impact of the ICI by an optimal power allocation (OPA) strategy which maximizes the system sum capacity under the total transmit power and minimum user capacity constraints. Meanwhile, we recognized that, besides the sum capacity, user fairness is also an important system indicator in some application scenarios. Thus, in this paper, we propose an OPA method which can flexibly tradeoff the sum capacity and user fairness while guaranteeing the minimum user capacity guarantee under the total transmit power constraint. In general, there exists a tradeoff relationship between the sum capacity and the user fairness. Hence, the multi-objective optimization [5,6] is applied to find the preferable feasible solution with multiple and contradictory objectives in our considered OPA. The proposed OPA method is called the capacity-fairness tradeoff-aware OPA in this paper. The detail of this part will be described in Section 3.

The rest of this paper is organized as follows. In Section 2, we introduce how we construct the user-centric clusters in cell and the transmission model. Then, in Section 3, the proposed capacity-fairness tradeoff-aware OPA problem is formulated by integrating the two objectives, sum capacity and user fairness, by utilizing the weighted sum method [5,6]. In Section 4, computer simulation results are presented to verify the validity of proposed capacity-fairness tradeoff-aware OPA method. Finally, we give some conclusions and implications in Section 5.

2. System model

We consider a 1×1 square-shaped single-cell area, over which A=128 distributed antennas are randomly located so that a minimum antenna spacing of AS=0.0625 is satisfied to keep an even coverage. U=64 users are also randomly distributed over the cell. As we mentioned above, to reduce the computational complexity required for a large-scale distributed MU-MIMO, user-clusters are constructed by modified K-means method based on user location information [3,7]. Then, a disjoint set of antennas is associated with each user-cluster based on the user-antenna distance so as to perform cluster-wise distributed MU-MIMO in parallel, in which zero-forcing (ZF) based precoding/postcoding is utilized to remove the multiuser-interference [8].

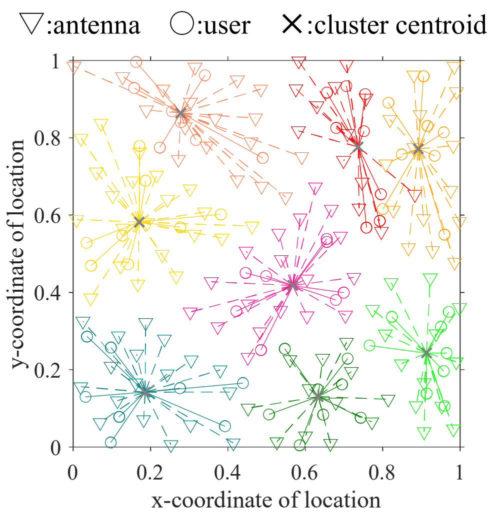


Fig. 1 An example of cluster structure after antenna assignment.
(U=64, A=2×U, AS=0.0625, K=8).

An example of the cluster structure is shown in Fig. 1. It can be seen that K=8 user-clusters are constructed with the same 8 users in each. In fact, the distributed antennas in the cell are connected with the BS through the fronthaul for data interaction. Theoretically, the BS can be located at any position in the cell, and since the BS and fronthaul are not the focus of this paper, they are omitted in Fig. 1. Considering the MIMO channel is characterized by distance-depended path loss, log-normal shadowing and Rayleigh fading, the link capacity of the u_kth user in the kth cluster is computed from

$$C_{u_k}=\begin{cases}\log_2\left(1+\dfrac{\dfrac{P^{\downarrow}_{u_k}}{\left\|\mathbf{W}^{\downarrow}_{k}(:,u_k)\right\|^2}}{\sum\limits_{\substack{m=0,\\ m\neq k}}^{K-1}\sum\limits_{j_m=0}^{U_m-1}\dfrac{P^{\downarrow}_{j_m}\left|\mathbf{h}^{\downarrow}_{u_k,m}\mathbf{W}^{\downarrow}_{m}(:,j_m)\right|^2}{\left\|\mathbf{W}^{\downarrow}_{m}(:,j_m)\right\|^2}+1}\right),\text{downlink}\\ \log_2\left(1+\dfrac{P^{\uparrow}_{u_k}}{\sum\limits_{\substack{m=0,\\ m\neq k}}^{K-1}\sum\limits_{j_m=0}^{U_m-1}P^{\uparrow}_{j_m}\left|\mathbf{W}^{\uparrow}_{k}(u_k,:)\mathbf{h}^{\uparrow}_{j_m,k}\right|^2+\left\|\mathbf{W}^{\uparrow}_{k}(u_k,:)\right\|^2}\right),\text{uplink}\end{cases}, \quad (1)$$

where $\mathbf{h}_{u_k,m}$, $\mathbf{W}_m$, and P_{u_k} denote the channel vector between the u_kth user and antennas in the mth cluster, the ZF precoding/postcoding matrix of the mth cluster, and the transmit power for the u_kth user in the kth cluster, respectively. $\mathbf{A}(x,:)$, $\mathbf{A}(:,x)$, and $\|\mathbf{A}\|$ denote the xth row vector, the xth column vector, and the Frobenius norm of matrix $\mathbf{A}$, respectively. The superscripts of up and down arrows indicate uplink and downlink, respectively.

3. Capacity-fairness tradeoff-aware OPA method

In this section, we describe the proposed OPA method, which is an extension of our previous work [4]. We want to simultaneously maximize the sum capacity and the fairness of user capacity while sharing the same radio resource in all clusters. The joint maximization of sum capacity defined as Eq. (2a) and the fairness of user capacity defined as Eq. (2b) can be obtained by solving the following multi-objective optimization problem while guaranteeing the total transmit power limitation (see Eq. (2c)) and the minimum user capacity requirement (see Eq.(2d)):

$$\max_{P_{u_k}}\sum_{k=0}^{K-1}\sum_{u_k=0}^{U_k-1}C_{u_k} \quad (2a)$$

$$\max_{P_{u_k}}\sqrt{\frac{\left(\sum\limits_{k=0}^{K-1}\sum\limits_{u_k=0}^{U_k-1}C_{u_k}\right)^2}{U_k\sum\limits_{k=0}^{K-1}\sum\limits_{u_k=0}^{U_k-1}C^2_{u_k}}} \quad (2b)$$

$$s.t.\ \sum_{k=0}^{K-1}\sum_{u_k=0}^{U_k-1}P_{u_k}=U\times P \quad (2c)$$

$$\forall C_{u_k} \geq C_{\min}\ . \tag{2d}$$

Here, the frequently used fairness measure, i.e., Jain's fairness index (JFI) [9] is introduced in Eq. (2b). Then, in Eq. (2c), P is the target transmit power for each user and the total transmit power is defined as P times the number of users. $C_{\min}$ in Eq. (2d) is the minimum required user capacity.

Because the multi-objective optimization problem is difficult to solve, we utilize the commonly used weighted sum method [5,6] to combine the two objectives into one and transform it into a single objective optimization problem. The JFI shown in Eq. (2b) is a unitless number and has a range of (0,1] unlike the sum capacity shown in Eq. (2a). Therefore, straightly combining them by weighted sum method may cause a problem. Therefore, we equivalently convert JFI into the standard deviation of user capacity with the same base unit as the sum capacity. Consequently, the maximization of fairness in Eq. (2b) changes to the minimization of standard deviation of the user capacity. Moreover, in order to effectively adjust the two objectives by weight α, we multiply the number of users in front of the standard deviation to make the ranges of the two objective functions' values close. So, the capacity-fairness tradeoff-aware OPA problem can be modified as

$$\max_{P_{u_k}} \alpha \sum_{k=0}^{K-1}\sum_{u_k=0}^{U_k-1} C_{u_k} - (1-\alpha)U\sqrt{\frac{\sum_{k=0}^{K-1}\sum_{u_k=0}^{U_k-1}\left|C_{u_k}-\overline{C}\right|^2}{U}}\ , \tag{3}$$
$$s.t.\ \text{(2c) and (2d)}$$

where $\alpha \in [0,1]$ is the weight and $\overline{C}$ is the capacity averaged over all users. By changing α, the sum capacity and the user fairness can be flexibly traded off.

Then, since the capacity-fairness tradeoff-aware OPA problem expressed by Eq. (3) is non-convex which is still difficult to solve, we utilize and one of the most effective sequential quadratic programming (SQP) method [6,10,11]. SQP method iteratively solves the quadratic programming subproblems to approximate the solution of the original problem and it is the robust and one of the most effective method for solving non-convex constrained problem.

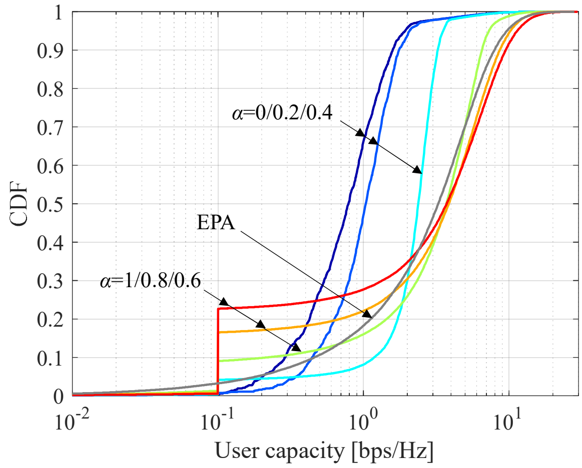
4. Numerical results

In this section, we demonstrate and discuss the adjustability of the proposed weighted sum method based capacity-fairness tradeoff-aware OPA method. We carry out Monte-Carlo simulation to obtain the cumulative distribution function (CDF) of user capacity, sum capacity and user fairness by randomly changing the user location pattern by 1000 times for a fixed antenna location pattern. For each user location pattern, user-clustering and cluster-antenna association are carried out and the link capacity is computed using Eq. (1) by generating the path loss, the log-normal shadowing losses, and the Rayleigh fading gains between each user and distributed antennas, which means that a quasi-static channel condition is considered in this paper. For equal power allocation (EPA) method, users are equally assigned the same transmit power. The transmit power is represented by the normalized transmit signal-to-noise ratio (SNR) which is the received SNR when the transmitter-receiver distance is equal to the side length of the normalized 1×1 square-shaped area. In addition, we set the initial state for the SQP method to the EPA state and use the EPA state if the capacity-fairness tradeoff-aware OPA cannot find a feasible solution. The simulation parameters setting is shown in Table 1.

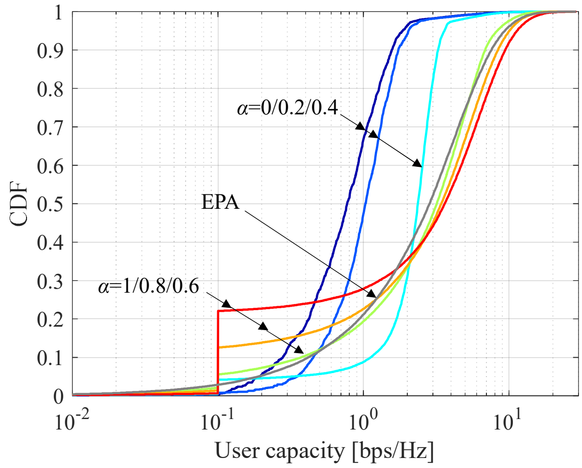
Table 1

Number of distributed antennas	128
Number of users	64
Number of clusters	8
Number of times of user location generations	1000
Path loss exponent	3.5
Log-normal shadowing standard deviation [dB]	8
Fading type	Rayleigh
Transmit SNR per user (P) [dB]	0
Minimum user capacity [bps/Hz]	0.1
Starting point of capacity-fairness tradeoff-aware OPA	EPA state
α	0/0.2/0.4/0.6/0.8/1

We first present the CDF of user capacity for both downlink and uplink cases with α of OPA as a parameter in Fig. 2, where EPA result (the gray line) is also illustrated as a reference. First of all, we can see that adjusting α can effectively bias the transmit power allocation towards the capacity objective or the fairness objective. The CDF curve changes obviously by changing α from 0 to 1, which means that our objective function design based on the weighted sum is very effective. And for each α value, the user capacity is guaranteed above $C_{\min}$. We note that when setting α close to 1 (setting the objective function close to considering the sum capacity maximization only), the probability of user capacity becoming equal to $C_{\min}$ increases above the result of EPA and the achievable maximum user capacity is still higher than that of EPA. This happens because the transmit power of users with a poor channel condition tend to be allocated to the users with a better channel condition to further increase their capacity to maximize the sum capacity. This is the same result as the previous single-objective OPA in [4]. On the other hand, when αreducing, the transmit power allocation is biased towards high user fairness. Specifically, the probability of user capacity becoming equal to $C_{\min}$ can be gradually reduced by reducingα. Moreover, the probability of the capacity exceeding above a certain high capacity and the achievable maximum user capacity can be both reduced. As a consequence, higher user fairness is obtained with smaller α.



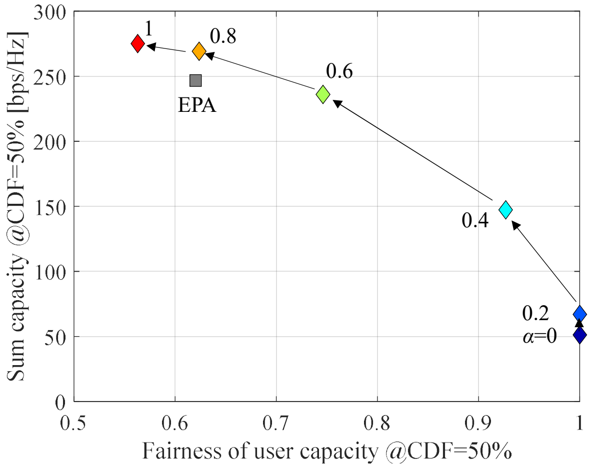
(a) Downlink



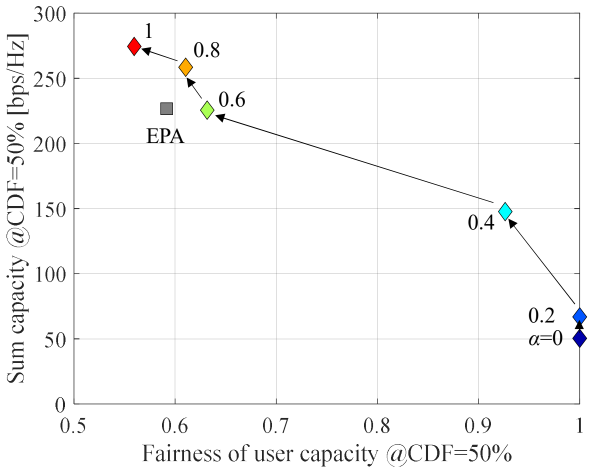
(b) Uplink

Fig. 2 CDF comparison of user capacity with α of capacity-fairness tradeoff-aware OPA as a parameter.

Next, we compare the impact of α on two indicators in the objective function: sum capacity and user fairness. Here, we plot the relationship between the sum capacity at CDF=50% and the user fairness at CDF=50% in Fig. 3. Similar to Fig. 2, we also plot the result of EPA as a reference. From Fig. 3, we can clearly see that adjusting α can effectively bias the transmit power allocation towards the capacity objective or the fairness objective. When α is equal to 0, capacity-fairness tradeoff-aware OPA considers the user fairness maximization only and the sum capacity becomes lowest. On the other hand, by increasing α, the user fairness decreases gradually and the sum capacity increases gradually. In addition, we can also see from Fig. 3 that when α is equal to 0.8, both the sum capacity and the user fairness improve compared to the EPA case.



(a) Downlink



(b) Uplink

Fig. 3 Relationship between sum capacity and user fairness with α of capacity-fairness tradeoff-aware OPA as a parameter.

It can be summarized from Figs. 2 and 3 that the proposed capacity-fairness tradeoff-aware OPA method based on weighted sum method can flexibly tradeoff the sum capacity maximization and the user fairness maximization by changing the value of α while guaranteeing the minimum user capacity, which indicates that the proposed capacity-fairness tradeoff-aware OPA can be applied to many practical application scenarios with a variety of quality of services.

5. Conclusion

In this paper, we proposed a capacity-fairness tradeoff-aware OPA method for the cluster-wise MU-MIMO system to meet the needs of different application scenarios in the 5G-advanced systems. We have realized the proposed capacity-fairness tradeoff-aware OPA by transforming the multi-objective problem to single-objective problem based on weighted sum method and by utilizing SQP method to solve the non-convex optimization with minimum user capacity guarantee and limited total transmit power constraint.

From Monte Carlo simulation, we demonstrated that the sum capacity and the user fairness can be flexibly traded off while guaranteeing the minimum user capacity by adjusting the weight α in the objective function of OPA.

In fact, ensuring the minimum capacity requirement of users is often a key indicator. However, meeting the minimum capacity requirement is closely related to user distribution, clustering results and channel status. In a real environment, guaranteeing the minimum capacity may not be possible. How to effectively avoid such a situation is left as our future work.

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