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Density-based user clustering in downlink NOMA systems

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Abstract Non-orthogonal multiple access (NOMA) technology, which can effectively improve the bandwidth utilization, is one of the key technologies in the next-generation wireless communication systems. In the downlink multiple antenna NOMA systems, user clustering is one of the problems that must be solved. In this paper, we focus on the user clustering that maximizes the system sum rate. First, a user clustering method based on the density-based spatial clustering of applications with noise (DBSCAN) algorithm is proposed for static user scenarios. Then an improved low-complexity dynamic clustering method is further developed for dynamic user scenarios. Simulation results show that compared with existing clustering methods, the DBSCAN-based method has better clustering performance in complex static user scenarios, and the proposed dynamic clustering method performs close to completely re-executing the DBSCAN-based method but with lower complexity.

Keywords NOMA, user clustering, machine learning, DBSCAN, dynamic clustering

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1 Introduction

Non-orthogonal multiple access (NOMA) technology will be a key technology in the next-generation wireless communications systems [1, 2]. In the NOMA system, since different users can share channel resources, the energy efficiency and sum rate of the system can be improved significantly compared to the orthogonal multiple access (OMA) system [3, 4].

NOMA can be classified into power-domain (PD) [5, 6] NOMA and code-domain (CD) NOMA [7, 8]. In the downlink PD-NOMA system, different users occupy the same channel resource, and multi-user detection technologies, e.g., successive interference cancellation (SIC) is introduced to demodulate different signals [9, 10]. However, in multi-user NOMA scenarios, SIC suffers from device complexity and error propagation. Hence, how to obtain acceptable complexity without significant performance degradation is a key research topic recently.

Hybrid NOMA where users are divided into many clusters, and the resources of each cluster are orthogonal is a solution to the above problem. Ref. [11] proposed two heuristic user clustering algorithms and the approximate optimal solution is obtained to maximize the sum rate. In [12], the authors focused on the user clustering problem for even number of users. In [13], the user clustering problem is jointly optimized with the power allocation problem, and the swap matching theory is introduced to solve them. In [14], some results in [12] are further developed and applied to the IoT-NOMA systems. However, hybrid NOMA schemes need to orthogonally allocate channel resources like in the OMA scheme.

Another promising solution is beamforming at base stations. In this case, multiple channels with strong correlation share the same beam [15]. Compared with the hybrid NOMA scheme, the clustering here takes into account the correlation of the characteristics of different channels. Ref. [16] proposed a solution to the near-far user pairing problem based on the distribution of the distance between the user

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and the base station. In [17], the authors exploited the user channel gain difference and correlation in the MIMO-NOMA system to accomplish the user clustering and beamforming, thereby maximizing the overall cell capacity. Ref. [18] proposed a NOMA user clustering strategy to increase the rate of cell-edge users.

The above studies only use the difference and correlation of channel gain to accomplish user clustering, the information of user distribution is not considered. The base station can obtain the channel state information (CSI) of all users, but it is difficult to recognize the distribution of active users. Therefore, some unsupervised learning clustering algorithms are introduced to utilize the user distribution information more efficiently. In [19], K-Means and its improved version K-Medoids were applied to the user clustering problem in NOMA enabled aerial SWIPT networks. Ref. [20] proposed a dynamic clustering method based on the K-Means algorithm to solve the sum rate maximization problem of the NOMA system. In [21], an expectation maximization (EM) based clustering method was proposed for dynamic user scenarios. The above clustering methods based on distance and user distribution must specify the number of clusters in advance, which is not practical. In addition, those methods have disadvantages such as the inability to recognize non-convex shape clustering and sensitivity to initial values. Therefore, we attempt to apply the density-based clustering algorithms to solve the user clustering problem under more complex user distribution.

In this paper, a typical density-based clustering algorithm, named DBSCAN [22, 23], is employed for the user clustering in the static user scenario. Then an improved dynamic clustering method is proposed to solve the problem in the dynamic user scenario. Simulation results show that compared with the existing methods, the proposed method can perform well in more complex scenarios. And compared with completely re-executing the clustering process, the dynamic clustering method has close performance but with lower computational complexity.

The rest of this paper is organized as follows. In Section 2, the system model is presented and the optimization problem is formulated. In Section 3, a density-based clustering method is proposed for static user scenarios. Then, we propose a dynamic clustering method that can update the clustering results quickly in dynamic user scenarios. Simulation results are given in Section 4. Finally, Section 5 concludes this paper.

2 System model and problem formulation

2.1 System model

Consider a downlink multiple antenna NOMA system as shown in Figure 1, where Figure 1(a) is the static user scenario. N users with single antenna are randomly distributed in a service area O, and N will not change over time. The base station (BS) equipped with M antennas is at the center of O. The BS communicates with each cluster simultaneously through multiple three-dimensional beams. N users are divided into K clusters, and C_k denotes the set of users in the k-th cluster.

Considering that in actual scenes, the users involved in communication often change over time. For example, an active user moves out of the BS coverage area or a new user joins the communication as shown in Figure 1(b). When the active users in communication change, the interference within each user will vary accordingly due to the variation of the user distribution, which will eventually affect the sum rate of the whole system. The user clustering results need to be continuously updated. A low-complexity dynamic user clustering method is necessary. In Section 3, we will propose user clustering methods for the static and the dynamic user scenarios respectively.

In the downlink NOMA system, there are both line-of-sight (LoS) and non-line-of-sight (NLoS) paths. A geometric channel model can be used to simulate the real channel between the user-n and BS as follows [24]:

$$\boldsymbol{h}_n = \sqrt{M}\sum_{l=1}^{L}\frac{\alpha_{n,l}\boldsymbol{\alpha}(\theta_{n,l})}{\sqrt{\rho}}, \tag{1}$$

where L denotes the total number of paths between the user and BS, ρ denotes the average path loss, and $\alpha_{n,l}$ is the Gaussian distributed complex gain of the l-th path. $\theta_{n,l}$ is the angle of departure (AoD)

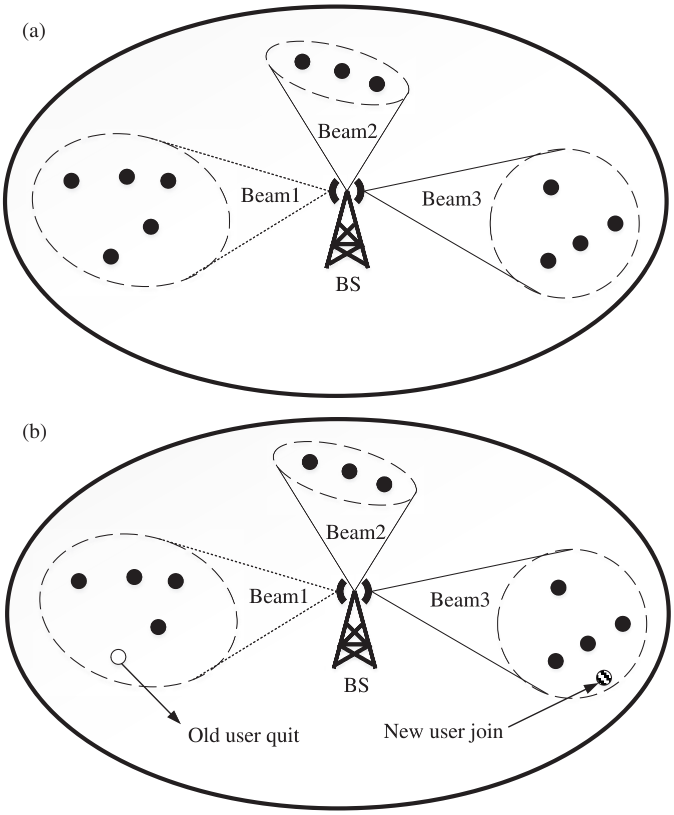

Figure 1 Downlink NOMA system. (a) Static user scenario; (b) dynamic user scenario.

of the l-th path. Assuming uniform linear array, the steering vector $\boldsymbol{\alpha}(\theta_{n,l})$ can be given as

$$\boldsymbol{\alpha}(\theta_{n,l}) = \frac{1}{\sqrt{M}} \left[1, \mathrm{e}^{-\mathrm{j}2\pi\frac{D}{\lambda}\sin(\theta_{n,l})}, \ldots, \mathrm{e}^{-\mathrm{j}2\pi(M-1)\frac{D}{\lambda}\sin(\theta_{n,l})}\right]^{\mathrm{T}}, \tag{2}$$

where D is the BS antenna spacing and λ is the wavelength. Since the path loss of NLoS is much larger than that of LoS [25], this paper applies the single-path model, that is, the impact of NLoS path is not considered under the premise of the existence of LoS path. Therefore, the channel model in (1) can be simplified as

$$\boldsymbol{h}_n = \frac{\sqrt{M}\alpha_{n,l}\boldsymbol{\alpha}(\theta_{n,l})}{\sqrt{\rho}}. \tag{3}$$

In the k-th cluster, the received signal of the n-th user $u_{k,n}$ is

$$y_{k,n} = \boldsymbol{h}_{k,n}^{\mathrm{H}}\boldsymbol{w}_k\sqrt{p_{k,n}}s_{k,n} + \sum_{i\neq n}^{|C_k|}\boldsymbol{h}_{k,n}^{\mathrm{H}}\boldsymbol{w}_k\sqrt{p_{k,i}}s_{k,i} + \sum_{k'\neq k}\sum_{j=1}^{|C_{k'}|}\boldsymbol{h}_{k,n}^{\mathrm{H}}\boldsymbol{w}_{k'}\sqrt{p_{k',j}}s_{k',j} + n_0, \tag{4}$$

where $\boldsymbol{h}_{k,n}^{\mathrm{H}}$ is an $M \times 1$ vector which denotes the channel gain between the BS and $u_{k,n}$, $\boldsymbol{w}_k$ is the beamforming vector of the cluster k, $\boldsymbol{h}_{k,n}^{\mathrm{H}}\boldsymbol{w}_k$ can be regarded as the equivalent channel gain. $p_{k,n}$ and $s_{k,n}$ respectively represent the power and the message sent to $u_{k,n}$. In (4), the first term is the desired signal of $u_{k,n}$, the second term is the intra-cluster interference caused by users in the same cluster, the third term is the inter-cluster interference caused by other clusters. And n_0 is the additive white Gaussian noise. Suppose that the BS can perceive the CSI of all users. SIC is employed in each cluster to reduce the intra-cluster interference. As for the inter-cluster interference, it can be reduced or even completely eliminated in multiple antenna NOMA system.

2.2 Problem formulation

Due to SIC, each user will only receive intra-cluster interference caused by users with channel gain larger than that of itself in one cluster. Without losing generality, assuming the users in the k-th cluster are sorted according to the signal power, that is $p_{k,1} > p_{k,2} > \cdots > p_{k,|C_k|}$, then the received SINR of $u_{k,n}$ can be given as

$$r_{k,n} = \frac{|\boldsymbol{h}_{k,n}^{\mathrm{H}} \boldsymbol{w}_k|^2 p_{k,n}}{|\boldsymbol{h}_{k,n}^{\mathrm{H}} \boldsymbol{w}_k|^2 \sum_{i>n}^{|C_k|} p_{k,i} + \sum_{k' \neq k} |\boldsymbol{h}_{k,n}^{\mathrm{H}} \boldsymbol{w}_{k'}|^2 \sum_{j=1}^{|C_{k'}|} p_{k',j} + \sigma^2}, \tag{5}$$

where the numerator represents the desired signal for $u_{k,n}$, the first term in the denominator is the residual intra-cluster interference after SIC, the second term is the inter-cluster interference that can be reduced in multiple antenna system. Then the sum rate of this system can be calculated by

$$R_{\mathrm{sum}} = B \sum_{k=1}^{K} \sum_{i=1}^{|C_k|} \log_2 (1 + r_{k,i}). \tag{6}$$

The user clustering problem in multiple antenna NOMA systems can be formulated as

$$\begin{aligned}
&\max_{\{C_k\},\{p_{k,n}\}} \; R_{\mathrm{sum}} \\
&\text{s.t. } \mathrm{C1}: p_{k,n} \geqslant 0, \quad 1 \leqslant k \leqslant K,\ 1 \leqslant n \leqslant |C_k|, \\
&\qquad \mathrm{C2}: \sum_{k=1}^{K} \sum_{i=1}^{|C_k|} p_{k,i} \leqslant P_{\mathrm{total}}, \\
&\qquad \mathrm{C3}: C_k \cap C_{k'} = \phi, \quad 1 \leqslant k,\ k' \leqslant K, \\
&\qquad \mathrm{C4}: r_{k,n} \geqslant r_{k,n}^{\min}, \quad 1 \leqslant k \leqslant K,\ 1 \leqslant n \leqslant |C_k|.
\end{aligned} \tag{7}$$

C1 ensures that the power of each user is nonnegative. C2 shows the total BS power constraint. C3 ensures that each user can and only can belong to one cluster. And in C4 user fairness is guaranteed, $R_{k,n}^{\min}$ is the minimum rate constraint, which can be a fixed value or a dynamic value under different scenarios.

If users in the same cluster have a strong channel correlation through appropriate clustering, then we can utilize the clustering results to effectively reduce or even eliminate the inter-cluster interference. To solve (7), density-based clustering methods are proposed in Section 3.

3 User clustering based on DBSCAN

In this section, the DBSCAN algorithm is employed to solve the user clustering problem. First, we focus on the problem in static user scenarios, then an improved dynamic clustering method is proposed for dynamic user scenarios. Finally, we present the power allocation strategy for each cluster after the user clustering is determined.

3.1 User clustering in static user scenario

In DBSCAN, clusters are defined as areas of closely packed users in the dataset, users in low-density areas are considered to be noise and border users. Compared with distance-based clustering algorithms, such as K-means, DBSCAN does not need to specify the number of clusters in advance. And DBSCAN can identify clusters of arbitrary shapes, which is impossible for other clustering algorithms.

DBSCAN is a non-parameter algorithm. There are two hyperparameters in it, the neighborhood radius ϵ and the minimum number of users required to form a dense region MinPts. Denote the dataset as $\boldsymbol{U} = \{\boldsymbol{u}_1, \boldsymbol{u}_2, \ldots, \boldsymbol{u}_N\}$, where each data point contains the user's location information. For user $\boldsymbol{u}_i$, its density is defined as

$$\rho(\boldsymbol{u}_i) = |N_\epsilon(\boldsymbol{u}_i)|, \tag{8}$$

where $N_\epsilon(\cdot)$ denotes the set of users in its ϵ neighborhood. Obviously, $\rho(\boldsymbol{u}_i)$ is an integer value, which is related to ϵ. If $\rho(\boldsymbol{u}_i) \geqslant \mathrm{MinPts}$, then $\boldsymbol{u}_i$ is called a core user. If $\boldsymbol{u}_i$ does not meet the requirements of the core user, but there are other core users in $N_\epsilon(\boldsymbol{u}_i)$, then $\boldsymbol{u}_i$ is called a border user. In the dataset, users that are neither core users nor border users are noise users. Figure 2 illustrates the user classification process under $\mathrm{MinPts} = 3$.

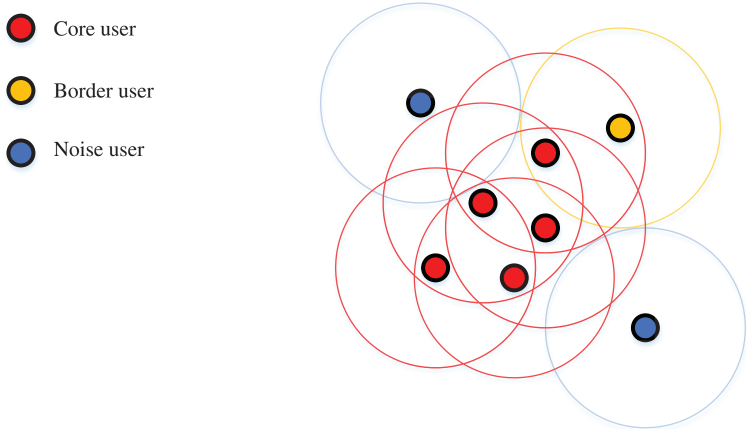

Figure 2 (Color online) User classification under MinPts = 3.

The clustering process of DBSCAN starts from a core user, it continuously expands to other core users in its ϵ neighborhood until it obtains a maximized area containing core users and border users, thereby completing one cluster. The clustering of the core users is clear, so the beamforming vector $\boldsymbol{w}_k$ can be designed according to the clustering results of these core users. For k-th cluster, the beamforming vector $\boldsymbol{w}_k$ can be given by

$$\boldsymbol{w}_k = \frac{1}{\sqrt{M}} \left[1, \mathrm{e}^{-\mathrm{j}2\pi\frac{D}{\lambda}\sin(\bar{\theta}_k)}, \ldots, \mathrm{e}^{-\mathrm{j}2\pi(M-1)\frac{D}{\lambda}\sin(\bar{\theta}_k)}\right]^{\mathrm{T}}, \tag{9}$$

where $\bar{\theta}_k$ is the average AoD of all core points in this cluster. The detailed algorithm is shown in Algorithm 1, a real number set $\{x\}$ is introduced to represent the clustering results as follows:

$$x_i = \begin{cases} j, & \text{if } \boldsymbol{u}_i \text{ belongs to } j\text{-th cluster;} \\ -1, & \text{if } \boldsymbol{u}_i \text{ is a noise point.} \end{cases} \tag{10}$$

First, the density of all users is calculated, then the clustering process starts from an arbitrary core user until all users are traversed. Finally, each non-core user is assigned to the cluster where its closest core user is located. $\{\boldsymbol{w}_k\}$ is designed only with the data of core users, and then the entire cluster uses it including nearby noise users.

Algorithm 1 User clustering based on DBSCAN

Set $k = 1, \boldsymbol{h} = \phi, x_i = 0, 1 \leqslant i \leqslant N$;
Calculate $\rho(\boldsymbol{u}_i)$ of all users using (8);
while $\boldsymbol{U} \neq \phi$ **do**
  Take an arbitrary user $\boldsymbol{u}_i$ from $\boldsymbol{U}$;
  if $x_i = 0$ **then**
    if $\rho(\boldsymbol{u}_i) < \text{MinPts}$ **then**
      $x_i = -1$;
    else
      $x_i = k$, add users in $N_\epsilon(\boldsymbol{u})$ to $\boldsymbol{h}$;
      while $\boldsymbol{h} \neq \phi$ **do**
        Take an arbitrary user $\boldsymbol{u}_j$ from $\boldsymbol{h}$;
        if $x_j = 0$ or -1 **then**
          $x_j = k$;
        end if
        if $\rho(\boldsymbol{u}_j) \geqslant \text{MinPts}$ **then**
          Add users in $N_\epsilon(\boldsymbol{u}_j)$ into $\boldsymbol{h}$;
        end if
      end while
      $k = k + 1$;
    end if
  end if
end while
Calculate $\{\boldsymbol{w}\}$ using Eq. (9).

3.2 User clustering in dynamic user scenario

The above method is proposed for the static user downlink NOMA system. However, in dynamic user scenarios, user clustering results are not static, and BS needs to constantly update the dataset and the clustering results. Compared with completely re-executing the DBSCAN-based user clustering method, a reliable low-complexity dynamic clustering method is necessary.

We can see that the results obtained by Algorithm 1 are independent of each other, that is, the increase or decrease of users will only affect the related clusters, and the results of other clusters remain unchanged. Hence, we can only update the affected clustering results to accomplish the clustering process.

Take the scenario where a new user joins as an example. Considering a system where a new user $\boldsymbol{u}_{N+1}$ joins the communication, $\boldsymbol{u}_{N+1}$ will only affect the clustering results related to users in $N_\epsilon(\boldsymbol{u}_{N+1})$, so it only needs to start from $\boldsymbol{u}_{N+1}$ and execute the clustering algorithm for all reachable users of $\boldsymbol{u}_{N+1}$. The approach when an active user quits is similar. Details are shown in Algorithm 2. First, the density of all reachable users of the changed users is updated, then the dynamic clustering process starts from an arbitrary core user until all reachable users are traversed. Finally, $\{\boldsymbol{w}_k\}$ is updated in the same way as Algorithm 1.

As for computational complexity, on one hand, Algorithm 1 needs to cluster all users participating in the NOMA system, while Algorithm 2 only needs to focus on the clustering results related to the changed users. On the other hand, except for users who are directly in the ϵ neighborhood of changing users, the $N_\epsilon(\boldsymbol{u}_{N+1})$ of all users does not need to be recalculated in the proposed dynamic clustering method. Therefore, the computational complexity of Algorithm 2 is significantly lower than that of Algorithm 1.

Algorithm 2 Dynamic user clustering based on DBSCAN

Add all reachable users of $\boldsymbol{u}_{N+1}$ to the set $\boldsymbol{U}_{\text{change}}$;
Set $k=1, \boldsymbol{h}=\phi, x_i=0, 1 \leqslant i \leqslant |\boldsymbol{U}_{\text{change}}|$;
Update $\rho(\boldsymbol{u}_i)$ of all users in $\boldsymbol{U}_{\text{change}}$;
while $\boldsymbol{U}_{\text{change}} \neq \phi$ **do**
  Take an arbitrary user $\boldsymbol{u}_i$ from $\boldsymbol{U}_{\text{change}}$;
  if $x_i = 0$ **then**
    if $\rho(\boldsymbol{u}_i) <$ MinPts **then**
      $x_i = -1$;
    else
      $x_i = k$, add users in $N_\epsilon(\boldsymbol{u}_i)$ to $\boldsymbol{h}$;
      while $\boldsymbol{h} \neq \phi$ **do**
        Take an arbitrary user $\boldsymbol{u}_j$ from $\boldsymbol{h}$;
        if $x_j = 0$ or -1 **then**
          $x_j = k$;
        end if
        if $\rho(\boldsymbol{u}_j) \geqslant$ MinPts **then**
          Add users in $N_\epsilon(\boldsymbol{u}_j)$ into $\boldsymbol{h}$;
        end if
      end while
      $k = k+1$;
    end if
  end if
end while
Update $\boldsymbol{w}_i$ related to the new clustering results using Eq. (9).

3.3 Power allocation strategy

In this subsection, a power allocation strategy is proposed to ensure fairness relatively. The power allocation problem can be given as follows:

$$\begin{aligned} &\max_{\{p_{k,n}\}} R_{\text{sum}} \\ &\text{s.t. C1}: p_{k,n} \geqslant 0, \quad 1 \leqslant k \leqslant K,\ 1 \leqslant n \leqslant |C_k|, \\ &\qquad \text{C2}: \sum_{k=1}^{K} \sum_{i=1}^{|C_k|} p_{k,i} \leqslant P_{\text{total}}, \\ &\qquad \text{C3}: r_{k,n} \geqslant r_{k,n}^{\min}, \quad 1 \leqslant k \leqslant K,\ 1 \leqslant n \leqslant |C_k|. \end{aligned} \tag{11}$$

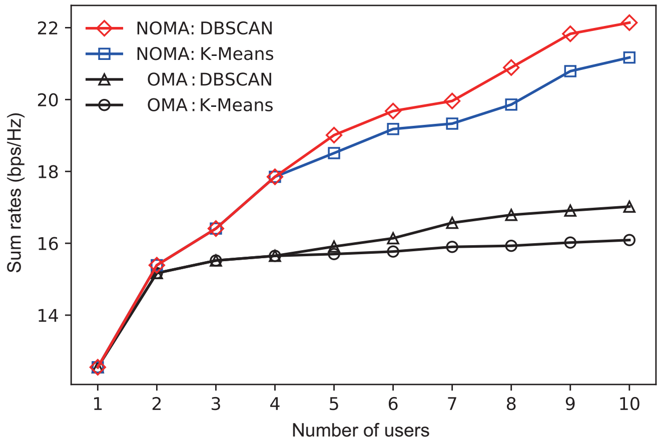

Figure 3 (Color online) Sum rates versus user number under non-convex shape cluster scenarios.

The power allocation among different clusters is independent, we can only consider it in one cluster. C3 is the key to solve this problem, which can be rewritten as

$$\log_2\left(1+\frac{|\boldsymbol{h}_{k,n}^{\mathrm{H}}\boldsymbol{w}_k|^2 p_{k,n}}{|\boldsymbol{h}_{k,n}^{\mathrm{H}}\boldsymbol{w}_k|^2\sum_{i>n}^{|C_k|}p_{k,i}+\sum_{k'\neq k}|\boldsymbol{h}_{k,n}^{\mathrm{H}}\boldsymbol{w}_{k'}|^2\sum_{j=1}^{|C_{k'}|}p_{k',j}+\sigma^2}\right)\geqslant r_{k,n}^{\min}. \tag{12}$$

Then the lower limit of $p_{k,n}$ can be presented as

$$p_{k,n}\geqslant(2^{r_{k,n}^{\min}}-1)\left(\sum_{i>n}^{|C_k|}p_{k,i}+\sum_{k'\neq k}\frac{|\boldsymbol{h}_{k,n}^{\mathrm{H}}\boldsymbol{w}_{k'}|^2}{|\boldsymbol{h}_{k,n}^{\mathrm{H}}\boldsymbol{w}_k|^2}\sum_{j=1}^{|C_{k'}|}p_{k',j}+\frac{\sigma^2}{|\boldsymbol{h}_{k,n}^{\mathrm{H}}\boldsymbol{w}_k|^2}\right), \tag{13}$$

where $\sum_{i>n}^{|C_k|}p_{k,i}$ represents the sum power of users with better channel conditions in cluster-k. The remaining items in (13) are all determined. Then we can easily find the solution of problem (11) via linear programming methods.

4 Simulation results

In this section, we present numerical results for the performance of the proposed density-based clustering methods in downlink multiple antenna NOMA scenarios. The carrier frequency $f_c = 28$ GHz is used with a millimeter wave bandwidth (BW) of 2 GHz. The path-loss exponent is assumed to be 1.75 with a noise figure $N_f = 1.82$ dB and noise power $\sigma^2 = -174$ dBm/Hz. We assume the users are physically clustered around the BS. Unless otherwise mentioned, the total number of users, $N = 10$.

First, we consider the static scenario containing a non-convex shape user distribution. In Figure 3, we compare the performance of the proposed DBSCAN-based user clustering with that of K-Means based method under the same power allocation strategy, as well as those of OMA systems. The sum rates of all schemes increase with the user number. It can be seen that the performance of the proposed DBSCAN-based method is better than the K-means based method, and the gain is due to the ability of the DBSCAN-based method to recognize arbitrary shape clusters. In addition, the DBSCAN-based method does not require specifying the number of clusters, which is another advantage compared with other methods.

Next, we consider the performance of the proposed dynamic user clustering method. In Figure 4, we compare the sum rate of completely re-executing the DBSCAN-based method and the proposed dynamic clustering method under dynamic user scenarios. The dynamic scene is simulated by adding a user randomly to the NOMA system. The sum rates of all schemes increase with the total power. It can be seen that the dynamic clustering method can get performance close to that of completely re-executing the DBSCAN-based method. But as mentioned in Section 3, the complexity of the dynamic clustering method is much smaller, which has certain practical value in real systems.

In Figure 5, we further compare the performance of completely re-executing the DBSCAN-based method and dynamic clustering method with different numbers of changed users. We set the initial

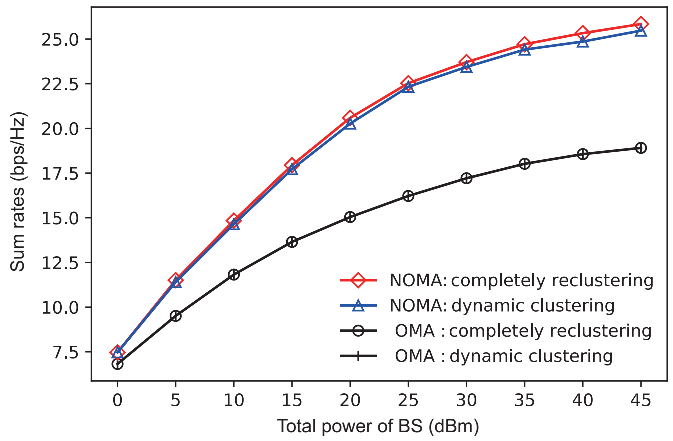

Figure 4 (Color online) Sum rates versus total power of BS under different systems.

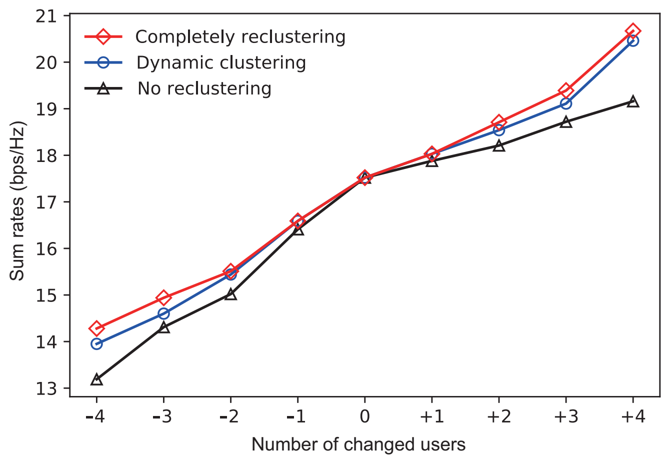

Figure 5 (Color online) Sum rates versus number of changed users between different reclustering methods.

users in the NOMA system to 5 and added the no-reclustering method, that is, assigning the changed user to its nearest cluster as a performance comparison. We can see that the dynamic clustering method can get performance close to the completely reclustering method in general, especially when the number of changed users is small. The performance of the dynamic clustering method decreases slightly when the number of changed users is large. This is because when designing the beamforming vector, each non-core user is assigned to the cluster where its closest core user is. The clustering results of these non-core users will not be updated in the dynamic clustering method, which causes a slight performance difference between the proposed dynamic clustering method and the completely reclustering method.

5 Conclusion

In this paper, the user clustering problem in downlink multiple antenna NOMA systems is investigated to maximize the system sum rates. We consider this problem in the static user scenario and dynamic user scenario, respectively. First, a density-based user clustering method is proposed for static user scenarios. Then considering the variation of active users, a dynamic clustering method is developed for dynamic user scenarios. Simulation results show that the DBSCAN-based method proposed in this paper can get better performance in complexly static user scenarios, and the dynamic clustering method can perform close to the completely reclustering method but with lower complexity.

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