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Antenna Clustering for Bidirectional Dynamic Network With Large-Scale Distributed Antenna Systems

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ABSTRACT To cope with the ongoing trend in data traffic asymmetry of uplink (UL) and downlink (DL) transmissions, bidirectional dynamic networks (BDNs) have been proposed to facilitate simultaneous UL and DL communications. Moreover, the large-scale distributed antenna system (L-DAS) is considered to improve the spectral efficiency (SE). Aiming at maximizing the SE in the BDN with the L-DAS, in this paper, we propose a novel distributed antenna (DA) clustering strategy named flexible antenna clustering (FAC) to allow each user to choose the most effective DAs. This also provides a low-complexity solution to solve the antenna clustering problem in the L-DAS. In FAC, the operation mode (UL or DL transmission) of the DAs can be flexibly changed, which is determined by the baseband processor units. By taking both the homogeneous and heterogeneous interferences into consideration, we propose two novel metrics for the user and DA selection orders. To the best of our knowledge, this is the first time that the user selection order is considered in solving the antenna clustering problem. Compared with the time division duplex system, our FAC strategy used in the BDN is verified to have improved efficiency in achieving better SE performance. Therefore, the BDN with the L-DAS is suitable in practical communication systems thanks to its SE gain. Based on these results, we further provide some specific suggestions for the practical network configuration.

INDEX TERMS Massive multi-input-multiple-output (MIMO), distributed antenna system (DAS), antenna clustering.

I. INTRODUCTION

According to the most recent Ericsson Mobility Report, the mobile data traffic continues to grow, and it is predicted that a 12-fold growth in smartphone traffic between 2015 and 2021 [1]. Besides the surge in data traffic, the massive increase in the use of smartphones and video streaming applications leads to heavily asymmetric data traffic in uplink (UL) and downlink (DL) transmissions [2]. All these call for new communication technologies which can achieve better performance in heavy and asymmetric data traffic.

In the past years, the large-scale multiple-input multiple-output (MIMO) system is regarded as a leading candidate technology that can meet the demand for high data rate [3]. By adopting large antenna arrays at the base stations, the large-scale MIMO can exploit the predicted linearly increasing capacity of MIMO systems [4]. On the other hand, the distributed antenna system (DAS) is proposed recently to improve spectral efficiency (SE) and expand coverage in cellular networks [5]. In DAS, some low-power distributed antenna (DA) ports are geographically placed throughout a cell to reduce the access distance. By bringing the DAs close to users, DAS can improve the signal quality of cell edge users, and the spatial separation property has the potential to fully exploit the spatial degrees of freedom. Hence, it is natural to consider a large-scale DAS (L-DAS) in order to further improve the SE performance. Recent literature have studied the performance of L-DAS, and it becomes a hot topic for the fifth-generation (5G) communication networks [6]–[8].

On the other hand, flexible UL/DL resource allocation across the entire network will compensate for the traffic asymmetry demand [9]. Although frequency division duplex (FDD) systems can handle the traffic asymmetry, it might result in underutilization of the system bandwidth. Meanwhile, time division duplex (TDD) systems provide a solution to the data asymmetry problem by adjusting the time resources. However, it needs strictly synchronous operation and the synchronization signals bring some extra overhead. In addition, the channel reciprocity, known as one of the advantages in TDD systems, suffers from the mismatches of the transceiver radio frequency circuits [10], [11]. In [12], the authors pointed out that the different loads in UL and DL transmissions stimulate a trend towards decoupling the UL and DL in future communication systems. In addition, [12] also suggested a new duplexing approach over the spatial domain to enable UL-DL decoupling: one device receives in DL from the base station, and the other one operates UL transmission to another base station using the same frequency band. A few works [13], [14] have focused on studying this novel communication concept of decoupling UL-DL transmission from the perspective of spatial domain. In our previous work [15], we proposed a Bidirectional Dynamic Network (BDN) supporting the simultaneous and decoupled UL and DL transmissions which can cope with the traffic asymmetry by dynamically adjusting the number of UL and DL base stations. Accordingly, there exists an extra interference between DL and UL communications, whereas, DAS can reduce such kind of interference thanks to its inherent property of physical isolation among the geographically separated DAs.

For BDN in L-DAS with hundreds (or even thousands) of DAs, due to the significant overhead for channel state information (CSI) acquisition and computational cost, it is not practical to perform full cooperation of all DAs. Hence, limited cooperation is more realistic. For example, one can divide a large number of DAs into some user-centric DA clusters. In this paper, our objective is to determine the cooperative DAs for each user by considering the SE of the entire network. Reference [16] suggested each user to choose a few closest DAs by ignoring the effects of wireless channel states. For the users require low-rate communication, [17] indicated randomly selecting a DA is an efficient way to reduce the complexity. However, these DA selection schemes are not the optimal solutions to gain the maximal SE performance. Moreover, [16]–[18] assumed that each user selects the same number of DAs, which is clearly not an optimal assumption for the maximal system performance. In this paper, aiming at maximizing the SE of the entire network, we provide an improved DA selection scheme which allows different numbers of cooperative DAs for each user. On the other hand, the order for users to choose DAs is an essential step when determining the cooperative DAs. However, previous works [19]–[21] do not focus on the user selection order, where random user selection order is usually adopted. To the best of our knowledge, this is the first attempt to design the user selection order and discuss the impact of it on the system performance in terms of the SE.

The main contributions are summarized in the following.

1) Taking both homogeneous and heterogeneous interferences in BDN into consideration, we propose an effective and efficient DA clustering strategy, namely the flexible antenna clustering (FAC) strategy since the working status (UL or DL transmission) of the DAs can be flexibly changed to handle the DA clustering problem. Specifically, FAC consists of three phases.
   Phase 1: Determination of the initial DA candidate sets
   In Phase 1, the DA set is divided into some subsets for all users with two thresholds of the UL and DL transmissions. By doing this, the computational complexity can be reduced dramatically.
   Phase 2: User Ordering
   Different from most previous works which do not mention the user selection order or just use random order, we are the first to design a brand new and efficient metric for the user selection order, leading to an effective user ordering.
   Phase 3: DA selection
   We also propose a novel metric for the antenna selection order, which not only further reduces the computational complexity by terminating the selection in an efficient manner but also has the ability to mitigate the optimality loss.
2) To the best of our knowledge, we are the first to investigate the effects of different user selection orders on the network SE performance. The designed user selection ordering includes the ascending order which gives the highest selection priority to the user with the fewest surrounded users, and the descending order which gives the highest selection priority to the user with the most neighboring users. Some interesting conclusions are obtained, that is, when in a sparse network or the numbers of UL and DL users are significantly different, ascending order is usually a better option in terms of network SE, whereas when in a dense network or the numbers of UL and DL users are not significantly different, descending order will always achieve better network SE performance. This conclusion can be utilized as a system configuration guideline in practical applications.
3) We prove that the BDN in L-DAS with FAC strategy significantly outperforms typical TDD systems in terms of the SE for the entire network. This further motivates BDN to be applied in practical L-DAS scenarios.

The remainder of this paper is organized as follows. In Section II, we introduce the system model and formulate the DA clustering problem. Section III presents the FAC strategy, in which we decompose the main problem into three parts. Numerical results are shown in Section IV. Section V concludes the paper.

The notation adopted in this paper conforms to the following convention. Vectors are column vectors, denoted in bold lower case letters, e.g., $\boldsymbol{x}$. Matrices are bold upper case letters, e.g., $\boldsymbol{A}$. $\boldsymbol{I}_M$ denotes the identity matrix with size $M \times M$. $(\cdot)^{\mathrm{T}}$ and $(\cdot)^{\mathrm{H}}$ represent transpose and Hermitian transpose, respectively. $\mathcal{CN}(\mathbf{0}, \boldsymbol{\Sigma})$ stands for the complex Gaussian distribution with mean $\mathbf{0}$ and covariance matrix $\boldsymbol{\Sigma}$. $|\mathcal{M}|$ denotes the cardinality of set $\mathcal{M}$.

II. SYSTEM MODEL AND PROBLEM FORMULATION

We consider an L-DAS consisting of M DAs in a certain area, denoted by the set $\mathcal{M}$. Each DA port consists of a transceiver, and it can perform in either UL or DL manner according to the current traffic requirement. There are K randomly distributed users denoted by $\mathcal{K}$, including K_{UL} and K_{DL} UL and DL users, denoted by $\mathcal{K}_{\mathrm{UL}}$ and $\mathcal{K}_{\mathrm{DL}}$, respectively. In addition, the UL and DL users simultaneously work to form a BDN system. Assume that each user is equipped with a single antenna, and the L-DAS uses a very large number of DAs compared with the number of users, i.e. $M \gg K$. Our goal is to determine the working status of DAs and optimal serving DA sets for each UL and DL user to maximize the SE of the entire network.

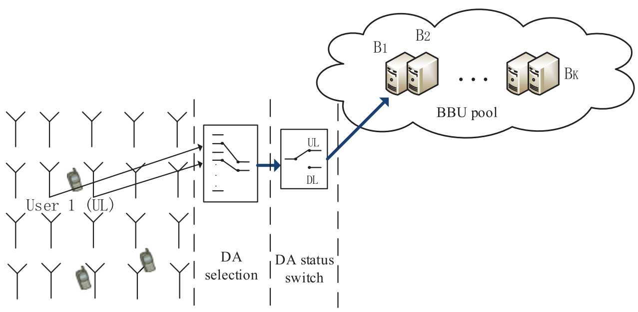

FIGURE 1. The considered C-RAN model in BDN.

In this paper, a cloud radio access network (C-RAN) is considered, where each DA is connected to a centralized baseband processor unit (BBU) cloud via highspeed fronthaul. An improved C-RAN is presented as depicted in Fig. 1. One BBU processes the signal for a single user, e.g., B1 takes charge of user 1, where B1 stands for the first BBU. Two selection switches are designed, where one is used to select DAs and connect them to the BBU dedicated for the corresponding user [17], and the other is designed to determine the status of DAs according to the connected user. With the considered C-RAN, BBUs can flexibly connect to the DAs and the network has a reconfigurable fronthaul structure. In this paper, in order to simplify our analysis, we actually focus on an interference-limited system without considering the limited fronthaul capacity.

Let $\mathcal{A}_k$ denote the optimal serving DA set for user k, and $|\mathcal{A}_k| = A_k$. The DAs in one set are assumed to jointly process the signals they receive or transmit.

In the UL transmission, if the i-th and j-th users are both UL users, the flat-fading channels between the DAs in $\mathcal{A}_i$ and user j are modeled by

$$\boldsymbol{g}_{i,j} = \left[g_{i,j,1} \cdots g_{i,j,A_i}\right]^{\mathrm{T}}, \tag{1}$$

where $g_{i,j,m}$ denotes the channel between UL user j and the m-th serving DA of UL user i. Without loss of generality, we ignore the shadowing effect, and thus,

$$g_{i,j,m} = c d_{i,j,m}^{-\frac{\alpha}{2}} l_{i,j,m}, \tag{2}$$

where $d_{i,j,m}$ represents the distance, α is the path loss exponent, and c is the median of mean path gain at a reference distance of 1km. Here $l_{i,j,m}$ is the fast fading which is modeled as an independently and identically distributed (i.i.d) zero mean circularly symmetric complex Gaussian (ZMCSCG) random variable with unit variance. Although the CSI acquisition is a key technology which usually brings extra signal overhead and hardware cost, we assume that the CSI is perfectly known at both the transmitter and receiver sides since we mainly focus on studying the DA clustering algorithm. In UL transmission, the received signal of DAs serving user i can be expressed as

$$\begin{aligned} y_i = {} & \sqrt{P_{\mathrm{U}}}\boldsymbol{v}_i^{\mathrm{H}}\boldsymbol{g}_{i,i}x_i + \sqrt{P_{\mathrm{U}}}\sum_{j\in\mathcal{K}_{\mathrm{UL}}}\delta_j\boldsymbol{v}_i^{\mathrm{H}}\boldsymbol{g}_{i,j}x_j \\ & + \sqrt{P_{\mathrm{DA}}}\sum_{k\in\mathcal{K}_{\mathrm{DL}}}\delta_k\boldsymbol{v}_i^{\mathrm{H}}\boldsymbol{B}_{i,k}\boldsymbol{w}_k s_k + \boldsymbol{v}_i^{\mathrm{H}}\boldsymbol{z}_i, \end{aligned} \tag{3}$$

where P_{U} and P_{DA} denote the transmitting power of UL user and DL DA, respectively. x_i and s_k represent the UL symbol transmitted from user i and the DL signal transmitted to user k, respectively, and $\mathcal{E}\left(x_i x_i^{\mathrm{H}}\right) = \mathcal{E}\left(s_k s_k^{\mathrm{H}}\right) = 1$. $\boldsymbol{v}_i^{\mathrm{H}} \in \mathbb{C}^{1\times A_i}$ and $\boldsymbol{w}_k \in \mathbb{C}^{A_k\times 1}$ are the receiving and precoding vectors, respectively. The additive noise $\boldsymbol{z}_i \sim \mathcal{CN}\left(\mathbf{0}, \sigma_{\mathrm{UL}}^2\boldsymbol{I}_{A_i}\right)$. The simultaneous UL and DL transmissions lead to DL-to-UL interference between DL and UL DAs, and the interference channels are denoted by $\boldsymbol{B}_{i,k} \in \mathbb{C}^{A_i\times A_k}$, where

$$\boldsymbol{B}_{i,k} = \begin{bmatrix} b_{i,1,k,1} & \cdots & b_{i,1,k,A_k} \\ \vdots & \ddots & \vdots \\ b_{i,A_i,k,1} & \cdots & b_{i,A_i,k,A_k} \end{bmatrix}. \tag{4}$$

Here $b_{i,j,k,m}$ denotes the channel between the j-th serving DA of user i and the m-th serving DA of user k when user i is an UL user and user k is a DL user. Channel model in (2) can be used to describe $b_{i,j,k,m}$ with a different path loss exponent β. Since our goal is to maximize the SE of the entire network, it is worth inactiving some users that bring less SE gain than the interference they introduced to the whole system. Therefore,

$$\delta_j = \begin{cases} 1, & \text{if user } j \text{ is active} \\ 0, & \text{if user } j \text{ is inactive.} \end{cases} \tag{5}$$

If user i is a DL user, the received signal is

$$\begin{aligned} y_i = {} & \sqrt{P_{\mathrm{DA}}}\boldsymbol{h}_{i,i}^{\mathrm{H}}\boldsymbol{w}_i s_i + \sqrt{P_{\mathrm{DA}}}\sum_{j\in\mathcal{K}_{\mathrm{DL}}}\delta_j\boldsymbol{h}_{i,j}^{\mathrm{H}}\boldsymbol{w}_j s_j \\ & + \sqrt{P_{\mathrm{U}}}\sum_{k\in\mathcal{K}_{\mathrm{UL}}}\delta_k u_{i,k}x_k + n_k, \end{aligned} \tag{6}$$

where the additive noise is modeled as $n_k \sim \mathcal{CN}\left(0, \sigma_{\mathrm{DL}}^2\right)$, $u_{i,k}$ denotes the interference channel between DL user i and UL user k, which can be also modeled as (2) with a path loss exponent κ. Here $\boldsymbol{h}_{i,j} = \left[h_{i,j,1} \cdots h_{i,j,A_j}\right]^{\mathrm{T}}$, where $h_{i,j,m}$

$$\mathrm{SINR}_i(\boldsymbol{\Delta},\boldsymbol{\Gamma}) = \frac{|\sqrt{P_\mathrm{U}}\boldsymbol{v}_i^\mathrm{H}\boldsymbol{g}_{i,i}|^2}{\sum\limits_{j\in\mathcal{K}_\mathrm{UL}} |\sqrt{P_\mathrm{U}}\delta_j\boldsymbol{v}_i^\mathrm{H}\boldsymbol{g}_{i,j}|^2 + \sum\limits_{k\in\mathcal{K}_\mathrm{DL}} |\sqrt{P_\mathrm{DA}}\delta_k\boldsymbol{v}_i^\mathrm{H}\boldsymbol{B}_{i,k}\boldsymbol{w}_k|^2 + \sigma_\mathrm{UL}^2\|\boldsymbol{v}_i\|^2} \tag{8}$$

denotes the channel between the m-th serving DA of DL user j and the DL user i, which can be modeled by

$$h_{i,j,m} = c r_{i,j,m}^{-\frac{\alpha}{2}} f_{i,j,m}, \tag{7}$$

where $r_{i,j,m}$ is the distance, and $f_{i,j,m}$ denotes the fast fading. By considering the worst case noise, the UL received signal-to-interference-plus-noise ratio (SINR) of the DAs for user i is derived as (8), as shown at the top of this page, where $\boldsymbol{\Delta} = \{\delta_1, \cdots, \delta_K\}$, and $\boldsymbol{\Gamma}$ is a family of sets over $\mathcal{M}$, which is defined as $\boldsymbol{\Gamma} = \{\mathcal{A}_1, \cdots, \mathcal{A}_K\}$.

Similarly, if user i is a DL user, the received SINR is

$$\mathrm{SINR}_i(\boldsymbol{\Delta},\boldsymbol{\Gamma}) = \frac{|\sqrt{P_\mathrm{DA}}\boldsymbol{h}_{i,i}^\mathrm{H}\boldsymbol{w}_i|^2}{\sum\limits_{j\in\mathcal{K}_\mathrm{DL}} |\sqrt{P_\mathrm{DA}}\delta_j\boldsymbol{h}_{i,j}^\mathrm{H}\boldsymbol{w}_j|^2 + \sum\limits_{k\in\mathcal{K}_\mathrm{UL}} |\sqrt{P_\mathrm{U}}\delta_k u_{i,k}|^2 + \sigma_\mathrm{DL}^2}. \tag{9}$$

Different from some previous works [22], [23], we mainly focus on designing a DA clustering method which can be adopted in BDN system with L-DAS, and emphasizing the advantages of BDN compared with traditional time division duplex (TDD) system. Hence, we do not study the precoder design, power allocation, user grouping problems in this paper, and leave them for our future work. We formulate the system SE maximization problem of BDN as follows,

$$\max_{\boldsymbol{\Delta},\boldsymbol{\Gamma}} \mathrm{SE}(\boldsymbol{\Delta},\boldsymbol{\Gamma}) = \sum_{i\in\mathcal{K}} \log_2(1+\mathrm{SINR}_i) \tag{10}$$

$$\text{s.t. } \delta_i \in \{0,1\}, \forall i \in [1,K], \tag{10a}$$

$$\mathcal{A}_i \subseteq \mathcal{M}_i, \bigcup_{i=1}^{K} \mathcal{M}_i \subseteq \mathcal{M}, \quad \forall i \in [1,K], \tag{10b}$$

$$\mathcal{A}_i \cap \mathcal{A}_j = \emptyset, \quad \forall i \neq j. \tag{10c}$$

In reality, communication systems have to guarantee a certain quality of service (QoS) for the mobile user, and $\mathcal{M}_i$ in (10b) is assumed to be the intitial DA candidate set of user i which can ensure the QoS. Different DA candidate sets may overlap, and the combination of them is the subset of universal set $\mathcal{M}$. (10a) follows the fact that some users may be inactive due to the severe interference they bring to the whole system. Since each DA can only work at either UL or DL, the optimal serving DA sets are independent with each other as described in (10c). The objective function in (10) couples all users in $\mathcal{K}$ together, which makes the DA clustering problem very cumbersome. Furthermore, the integer optimization variable set $\boldsymbol{\Delta}$ makes this non-convex objective function more challenging to be solved. One achievable method to find the optimal $\boldsymbol{\Delta}$ and $\boldsymbol{\Gamma}$ is the exhaustive search with the computational complexity related to the search space for each user, $\sum_{i=1}^{M} C_i^M$, where C_M^i denotes the binomial coefficient (i.e., choosing i antennas from M antennas) [21]. Obviously, the entire search space of all the users will be prohibitively large. Furthermore, in L-DAS with hundreds (or even more) of geographically DAs, gaining the best whole system performance would lead to enormous computational complexity, hence the optimal exhaustive search can not be implemented in practice.

III. FAC STRATEGY

Aiming at maximizing the SE for the whole system, we propose a novel and feasible scheme to solve the above optimization problem from the perspective of reducing various kinds of interference, including the homogeneous interference (the interference from UL users to other UL DAs, and DL DAs to other DL users) and heterogeneous interference (the interference from DL DAs to UL DAs, and UL users to DL users). We name the proposed DA clustering method as flexible antenna clustering (FAC) strategy, which includes the following three steps: *Determination of the Initial DA Candidate Sets*, *User ordering*, *DA selection*.

As described in Section II, we do not focus on the design of the precoder and receiver, and the precoder and receiver design do not affect the efficiency of our proposed scheme. In order to simplify the system analysis and make sure that the transmit power of each DL DA is P_DA, we use the equal gain precoding as in [25] and [26], which is given by

$$\boldsymbol{w}_i = \left[\frac{h_{i,i,1}}{|h_{i,i,1}|} \cdots \frac{h_{i,i,A_i}}{|h_{i,i,A_i}|}\right]^\mathrm{T}. \tag{11}$$

In the UL transmission, it is well known that the maximum ratio combination (MRC) receiver is the simplest combiner because it only requires the knowledge of the desired information. Hence, we use MRC as the receiver.

A. DETERMINATION OF THE INITIAL DA CANDIDATE SETS

Considering the initial DA candidate set $\mathcal{M}_i$, we propose a simple-yet-reasonable way to determine $\mathcal{M}_i$ by treating each user as an isolated terminal without interference among them. Since the goal of the proposed antenna clustering algorithm is to maximize the spectral efficiency, we use two predefined selection thresholds of received signal to noise (SNR) in UL and DL, denoted as γ_UL and γ_DL, are given to derive the initial DA candidate sets. From the channel models described in Section II, we can obtain the following inequalities,

$$\frac{cP_\mathrm{DA}R_\mathrm{DL}^{-\alpha}}{\sigma_\mathrm{DL}^2 W} > \gamma_\mathrm{DL} \Rightarrow R_\mathrm{DL} < \left(\frac{cP_\mathrm{DA}}{\gamma_\mathrm{DL}\sigma_\mathrm{DL}^2 W}\right)^{\frac{1}{\alpha}} \tag{12}$$

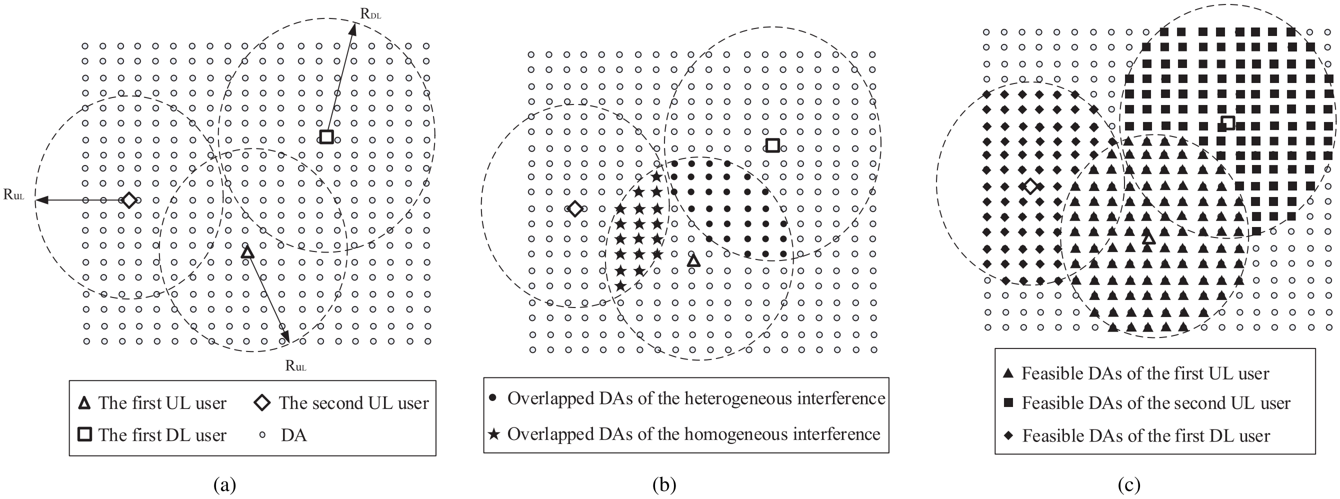

FIGURE 2. Ilustration of various kinds of DA sets, $M = 400$, $K_{\mathrm{UL}} = 2$, $K_{\mathrm{DL}} = 1$. (a) Initial DA candidate sets. (b) Overlapped DA sets. (c) Feasible DA sets.

and

$$\frac{cP_{\mathrm{U}}R_{\mathrm{UL}}^{-\alpha}}{\sigma_{\mathrm{DL}}^{2}W} > \gamma_{\mathrm{UL}} \Rightarrow R_{\mathrm{UL}} < \left(\frac{cP_{\mathrm{U}}}{\gamma_{\mathrm{UL}}\sigma_{\mathrm{UL}}^{2}W}\right)^{\frac{1}{\alpha}}, \tag{13}$$

where W denotes the available bandwidth. In order to simplify the description, let e be a transmission indicator, and $e = \mathrm{UL}$ or $e = \mathrm{DL}$. Hence, the DAs whose distances to user i are smaller than R_e become the elements of $\mathcal{M}_i$, as they can serve this user with a preferable SNR. As shown in Fig. 2(a), given the predefined threshold γ_{UL} and γ_{DL}, the initial DA candidate sets are the DAs placed in the dashed circles, and the three users fail to connect to the DAs outside the areas.

B. USER SELECTION ORDER

We notice that the initial DA candidate sets for users may overlap each other. Intuitively, it seems that the closer any two users are, the more intersected elements of their initial DA sets have, and the heavier interference exists between them. Hence, we use the intersected DA information to investigate the user order from the perspective of interference. At first, the initial DA candidate set of the j-th user is renamed as $\mathcal{D}_i^e$ when this user is the i-th e user in $\mathcal{K}$, which means $\mathcal{D}_i^e = \mathcal{M}_j$. Let us define the intersection set referred to the homogeneous interference for the j-th e user as

$$\mathcal{O}_j^e = \mathcal{D}_j^e \bigcap \left(\bigcup_{\substack{i \neq j,\\ i=1}}^{K_e} \mathcal{D}_i^e \right). \tag{14}$$

The overlapped DA set related to the heterogeneous interference is defined as

$$\mathcal{Q}_i^e = \mathcal{D}_i^e \bigcap \left(\bigcup_{j=1}^{K_{!e}} \mathcal{D}_j^{!e} \right), \tag{15}$$

where

$$!e = \begin{cases} \mathrm{DL}, & \textit{if } e = \mathrm{UL} \\ \mathrm{UL}, & \textit{if } e = \mathrm{DL}. \end{cases} \tag{16}$$

Fig. 2(b) demonstrates the DAs related to the homogeneous and the heterogeneous interference. More specifically, $\mathcal{O}_1^{\mathrm{UL}}$ and $\mathcal{O}_2^{\mathrm{UL}}$ are depicted with stars, $\mathcal{O}_1^{\mathrm{DL}}$ is an empty set, $\mathcal{Q}_1^{\mathrm{UL}}$ and $\mathcal{Q}_1^{\mathrm{DL}}$ are shown with solid dots, and $\mathcal{Q}_2^{\mathrm{UL}}$ is an empty set.

Therefore, for the j-th e user, the number of overlapped DAs with other e users is

$$\Delta o_j^e = \left|\mathcal{O}_j^e\right|. \tag{17}$$

The number of overlapped DAs causing heterogeneous interference is

$$\Delta q_i^e = \left|\mathcal{Q}_i^e\right|. \tag{18}$$

In this paper, we propose a novel and effective order metric for the users ordering before DA selection

$$\tau_i^e = \mu^e \Delta o_i^e + \varphi^e \Delta q_i^e, \tag{19}$$

where μ^e and φ^e denote the weight coefficients of the homogeneous interference and the heterogeneous interference parts, respectively. Motivated by the fact that we intend to reduce various kinds of interference, we should thoughtfully consider the design of these weight coefficients. From the above analysis, to some extent, the variables Δo_j^e and Δq_j^e are related to the geographical locations between users, as their values will grow when the j-th e user get closer to other users. According to the channel model, the interference consists of the transmitting power and the distance information, hence, the following values are introduced

$$\mu^{\mathrm{UL}} = 1, \quad \varphi^{\mathrm{UL}} = \frac{P_{\mathrm{DA}}}{P_{\mathrm{U}}}, \quad \mu^{\mathrm{DL}} = \frac{P_{\mathrm{DA}}}{P_{\mathrm{U}}}, \quad \varphi^{\mathrm{DL}} = 1. \tag{20}$$

Note that the above four coefficients are normalized by P_{U}, which is reasonable as we want a dimensionless order metric for each user. Therefore, the users can be arranged in an ascending or descending order of τ_i^e, and the ordered user set is named as $\mathcal{K}^{\mathrm{ord}} = \{u_1, \cdots, u_{\mathrm{K}}\}$, where u_k denotes the k-th ordered user. Furthermore, we renumber the indices of the initial DA candidate sets according to the user order. Now, $\mathcal{M}_i$ denotes the initial DA candidate set of the i-th user in $\mathcal{K}^{\mathrm{ord}}$. Needless to say, the order rule (descending or ascending according to this order metric) is an essential part for the whole clustering problem. Descending rule means the user surrounded by most users chooses the DAs at first, and the user who is located far away from other users is the last one scheduled to select DAs. Ascending rule is the opposite situation to descending rule. Section IV will discuss the impact of different order rules on the DA selection results.

C. DA SELECTION SCHEME

Once $\mathcal{K}^{\mathrm{ord}}$ is obtained, in this section, we propose a DA selection algorithm. Unlike some previous works, e.g. [17] that analyzed the random DA selection and nearest DA selection, an effective and feasible algorithm is introduced which does not need any information of the small scale fading or set any threshold to decide whether the DA should be selected.

Before proceeding, the initial DA candidate sets can be further shrunk. The feasible shrinking DA sets is given by

$$\mathcal{C}_i = \mathcal{M}_i \backslash \left(\bigcup_{k=1}^{i-1} \mathcal{M}_k \right). \tag{21}$$

In Fig. 2(c), the descending user selection order is assumed to be adopted, and the first UL user has the highest order to choose DAs. Then, the feasible DA sets for the three users are shown in Fig. 2(c). In this paper, we do not consider the cooperation of different DA sets to serve several users, the reason is that the operation mode of the overlapped DAs can not be easily determined in BDN when the overlapped DAs belong to both the UL and DL users. Meanwhile, cooperative L-DAS always introduces higher overhead due to the information exchange among DA clusters.

In this way, the higher-ordered user holds the overlapped DAs exclusively. Therefore, it reduces the computational complexity in DA selection. In order to obtain the optimal DA selection to maximize the SE, a feasible way is to try all the possible DAs greedily, however, due to the high computational complexity, it is not practical in L-DAS even the feasible DA sets are already shrunk. If the feasible DAs in $\mathcal{C}_i$ are also ordered according to a proper metric, we can try to select the ordered DA in turn until adding some DA leads to performance degradation in SE. In this way, terminating the DA selection in time and starting the next user selection can further reduce the computation cost.

Since BDN facilitates simultaneous UL and DL communications, when selecting an UL DA, it suffers the interference from other UL users and DL DAs. On the other hand, when adding a DL DA, it brings interference to other DL users and UL DAs. From the perspective of the trade-off between system gain and the interference introduced by the m-th DA in $\mathcal{C}_k$, we propose a novel metric called benefit to interference ratio (BIR) to specify the DA order, which is defined as

$$\xi_{k,m} = \frac{d_{k,k,m}^{-\alpha}}{\sum\limits_{\substack{i \in \mathcal{K}_{\mathrm{UL}}, \\ i \neq k}} d_{k,i,m}^{-\alpha}}, \tag{22}$$

if user k is an UL user. When user k is a DL user,

$$\xi_{k,m} = \frac{r_{k,k,m}^{-\alpha}}{\sum\limits_{\substack{i \in \mathcal{K}_{\mathrm{DL}}, \\ i \neq k}} r_{i,k,m}^{-\alpha}}. \tag{23}$$

Since the final DA sets are not decided yet, BIRs do not consider the interference related to DAs. It is noticeable that BIRs only depends on the distance between users and DAs when given the path loss exponent, and to some extent, they reflect the contributions of the DAs made to the system performance. Meanwhile, it is obvious that the DAs with larger BIRs should have the higher probability to be chosen. Hence, the feasible DAs in set $\mathcal{C}_i$ should be rearranged in descending order of BIRs, and the ordered set is denoted as $\mathcal{C}_i^{\mathrm{ord}} = \{m_{i,1}^{\mathrm{ord}}, \cdots, m_{i,C_i}^{\mathrm{ord}}\}$, where $m_{i,k}^{\mathrm{ord}}$ indicates the k-th ordered DA of the i-th ordered user, and $C_i = |\mathcal{C}_i|, \forall i \in [1, K]$.

The DA selection algorithm is summarized in Algorithm 1. In Algorithm 1, the detailed derivation of SINR for each user in line 8 will be introduced in the following Algorithm 2. In order to mitigate the optimality loss of the DA selection, it is worth studying additional DAs assignment to the lower-ordered users if they are unselected finally, i.e. $A_k < C_k$, where $A_k = |\mathcal{A}_k|$. For the unselected DAs, the re-allocation is described in Algorithm 3.

After arranging the users in Section III-B, the first user has the highest priority to own the overlapped DAs as described in (21). Hence, if user k is surrounded by many higher-ordered users, it might have an empty $\mathcal{C}_k$ because all the DAs in $\mathcal{M}_k$ also belong to the feasible DA sets of higher-ordered users. Accordingly, user k is initialized by setting its activity indicator δ_k to zero, which is listed in the initial steps of Algorithm 1. Although we intend to maximize the performance of the entire system, it is worth attempting to guarantee a relative fairness of resources among users. Here L is used to ensure the balance of DA resources, and it is reasonable to set $L = M/K$ since M/K is the average number of DAs for one user.

As shown in line 3 of Algorithm 1, if the current user is an active user, the feasible DA set $\mathcal{C}_i$ needs to be re-ordered according to BIRs. After that, we exhaust the ordered DAs until adding a certain DA leads to the SE decreasing. Note that when studying the DA selection of user k, other lower-ordered users do not participate in the system, which means $\mathcal{K} = \{u_1, \cdots, u_k\}$. The k-th BBU is aware of the decisions made by the former $k-1$ BBUs by exchanging information among them, and will choose its preferred DAs according to

Algorithm 1 DA Selection Algorithm of FAC Strategy

Input: L, $\mathcal{K}^{\mathrm{ord}}$, $\mathcal{C}_i$ and $\mathcal{M}_i$ $\forall i \in [1, \cdots, K]$
Output: $\mathbf{\Delta} = \{\delta_1, \cdots, \delta_K\}$, $\mathbf{\Gamma} = \{\mathcal{A}_1, \cdots, \mathcal{A}_K\}$, SE
Initial setup: SE $= 0$, tempSE $= 0$, $\mathcal{A}_1 = \emptyset$, $k = 1$, $\mathcal{K} = \emptyset$, $\mathcal{K}_{\mathrm{UL}} = \emptyset$, $\mathcal{K}_{\mathrm{DL}} = \emptyset$, $\mathbf{\Delta} = \{\delta_i | \delta_i = 1 \text{ if } C_i \neq 0, \text{ else } \delta_i = 0 \ \forall i \in [1, \cdots, K]\}$
while $k \leq K$ *and* $\delta_k = 1$ **do**
  $j \leftarrow 1$, tempSINR$_k \leftarrow 0$, SINR$_k \leftarrow 0$, and derive $\mathcal{C}_k^{\mathrm{ord}}$ by the values of BIR in (22) and (23);
  while $j \leq C_k$ *and* $A_k < L$ **do**
    if $k = 1$ **then**
      calculate SNR$_1$ and SE by considering the added DA $m_{1,j}^{\mathrm{ord}}$ according to (8) and (9) , $\mathcal{A}_1 \leftarrow \mathcal{A}_1 \bigcup \{m_{1,j}^{\mathrm{ord}}\}$;
    else
      calculate tempSNR$_k$ and tempSE when adding the DA $m_{k,j}^{\mathrm{ord}}$, see Algorithm 2;
    end
    if *tempSE* $<$ *SE* **then**
      tempSE $\leftarrow$ SE, tempSNR$_i \leftarrow$ SNR$_i$ $\forall i \in [1, k]$, break;
    else
      SE $\leftarrow$ tempSE, SNR$_i \leftarrow$ tempSNR$_i$ $\forall i \in [1, k]$, $\mathcal{A}_k \leftarrow \mathcal{A}_k \bigcup \{m_{k,j}^{\mathrm{ord}}\}$;
    end
    $j \leftarrow j + 1$;
  end
  if $A_k < C_k$ **then**
    add the unselected DAs in $\mathcal{C}_k^{\mathrm{ord}}$ to other lower-ordered users, see Algorithm 3;
  end
  if u_k *is an UL user* **then**
    $\mathcal{K}_{\mathrm{UL}} \leftarrow \mathcal{K}_{\mathrm{UL}} \bigcup \{u_k\}$;
  else
    $\mathcal{K}_{\mathrm{DL}} \leftarrow \mathcal{K}_{\mathrm{DL}} \bigcup \{u_k\}$;
  end
  $\mathcal{K} \leftarrow \mathcal{K} \bigcup \{u_k\}$, $k \leftarrow k + 1$;
end

Algorithm 2 Calculation of tempSINRs and tempSE When Adding the DA $m_{k,j}^{\mathrm{ord}}$

Input: $\mathcal{A}_i$ $\forall i \in [1, \cdots, k]$, j, k, $\mathcal{K}$, $\mathcal{K}_{\mathrm{UL}}$, $\mathcal{K}_{\mathrm{DL}}$
Output: tempSE, tempSINR$_i$ $\forall i \in [1, \cdots, k]$
1 **if** u_k *is an UL user* **then**
2   **if** *j=1* **then**
3   update the values of tempSINR$_n$ for all active higher-ordered users, where $\forall n \in [1, k-1]$;
4   **end**
5   Calculate the tempSINR$_k$ according to (8) or (9) when adding the DA $m_{k,j}^{\mathrm{ord}}$;
6 **else**
7   update the values of tempSINR$_i$ for all active higher-ordered users, where $\forall i \in [1, k-1]$ and calculate tempSINR$_k$;
8 **end**

Algorithm 3 Complementary DAs for the Lower-Ordered Users

Input: $\mathcal{A}_k$, $\mathcal{M}_i$ $\forall i \in [k+1, \cdots, K]$
Output: $\mathcal{C}_i$, δ_i $\forall i \in [k+1, \cdots, K]$
1 Initial setup: let the unselected DAs in $\mathcal{C}_k^{\mathrm{ord}}$ be the set $\mathcal{F} = \mathcal{C}_i \backslash \mathcal{A}_k$, $q = k$;
2 **while** $\mathcal{F} \neq \emptyset$ *and* $q < K$ **do**
3   $q \leftarrow q + 1$;
4   **if** $\mathcal{F} \bigcap \mathcal{M}_q \neq \emptyset$ **then**
5     $\mathcal{C}_q \leftarrow \mathcal{C}_q \bigcup (\mathcal{F} \bigcap \mathcal{M}_q)$, $\mathcal{F} \leftarrow \mathcal{F} \backslash (\mathcal{F} \bigcap \mathcal{M}_q)$;
6   **if** $\delta_q = 0$ **then**
7       $\delta_q \leftarrow 1$;
8   **end**
9   **end**
10 **end**

these decisions. Therefore, we do not consider the interference caused by other lower-ordered users. Moreover, if this user is the first user, there is no need to discuss whether an extra DA should be selected, since more DAs will always increase the SE in single user MISO system.

If the current discussed user k is not the first user, it is necessary to check whether this is the first time for it to select DAs. If user k makes its first DA selection and it is an UL user as listed in lines 2-4 of Algorithm 2, we have to update the values of SINR$_i$ $\forall i \in [1, \cdots, k-1]$ as the new UL user brings extra interferences to the DL users and the DAs serving other UL users. Likewise, if the discussed user is a DL user, adding an additional DA gives rise to interferences to other DL users and UL DAs. Although updating the SINRs of higher ordered users increases the computational complexity, all we need to do is adding this new introduced interference part to the interference part of the original values of SINRs, and the useful signal power is still the same. Accordingly, this will not lead to an extra overhead with very high computational complexity.

Once user k finishes the DA choosing procedure, it is beneficial to assign the additional DAs to lower-ordered users if they are unselected by user k. As described in lines 6-8 of Algorithm 3, it is possible that some inactive user may turn into an active one when certain unselected DAs is reallocated to its feasible DA set. Hence, the optimality loss can be mitigated as much as possible.

IV. NUMERICAL RESULTS

In this section, simulations are conducted to validate the performance of FAC strategy in BDN with L-DAS. Furthermore, the advantages of the BDN is discussed compared with TDD systems. Some interesting and meaningful results

TABLE 1. System parameters.

Parameters	Value
Focus area: R	1km
Median of mean path gain: c	-128.1dB
Noise figure:	5
Path loss exponent between DA and users: α	3.7
Path loss exponent between DAs: β	3
Path loss exponent between users: κ	4
UL user power: P_{U}	15 dBm
DL DA power: P_{DA}	27 dBm
Thermal noise: $\sigma_{UL}^2 = \sigma_{\mathrm{DL}}^2$	-174dBm/Hz
Available bandwidth: W	20MHz
UL SNR threshold: γ_{UL}	5dB
DL SNR threshold: γ_{DL}	10dB
Minimum distance to DA: R_0	15m

can be observed from the numerical results. Any type of DA layouts, e.g. random and circular DA arrangements can be adopted, but for simple demonstration, a grid DA layout is adopted with the side length R. R_0 denotes the closest access distance from users to DAs. The detailed simulation parameters given in Table 1 are inspired by a variety of prior works [13], [26]–[28]. According to the modified COST231 propagation model, we set $\alpha = 3.7$. Furthermore, with the fact that DAs have the height advantage over users in an open area and mobile users are always at ground height, we set $\beta = 3$ and $\kappa = 4$.

In this section, the TDD system is simulated as a comparison to study the performance improvement of BDN with FAC scheme in L-DAS. In the TDD simulation scenario, K_{UL} and K_{DL} users are supported in different time intervals, and ξ represents the ratio of the UL transmission time period to the whole time period T, where $0 < \xi < 1$. Then, it takes $(1-\xi)T$ for the system to operate DL communications. Some heuristic algorithms in DA selection can also reduce the computational complexity, i.e. channel-gain-based (CGB)-greedy DA selection and minimum distance-based (MDB)-greedy DA selection [16], [22] are utilized in TDD. CGB plans to assign the DA whose channel gain is the strongest to a corresponding user, while MDB attempts to pair a user with the nearest DA. Here CGB and MDB schemes are both extended, in which the DAs are first ordered according to their channel gains and distances to users, respectively, and then users decide whether to choose a certain DA or not according to the SE performance. However, these works do not point out the selection order of users, and thus we use the random order for CGB and MDB schemes, where the users carry out the DA selection in a random order. In TDD, to keep a relative balance of DA resources among users, we set $L = M/K_{\mathrm{UL}}$ and $L = M/K_{\mathrm{DL}}$ when operating UL and DL transmissions, respectively. Meanwhile, this also guarantees the comparison fairness with the BDN. Typically, TDD can serve $10\% - 60\%$ of the transmission time interval for UL communication [29], hence $0.1 \leq \xi \leq 0.6$.

Fig. 3 and 4 both compare the SE performance in BDN and TDD over the number of DAs. Obviously, these two

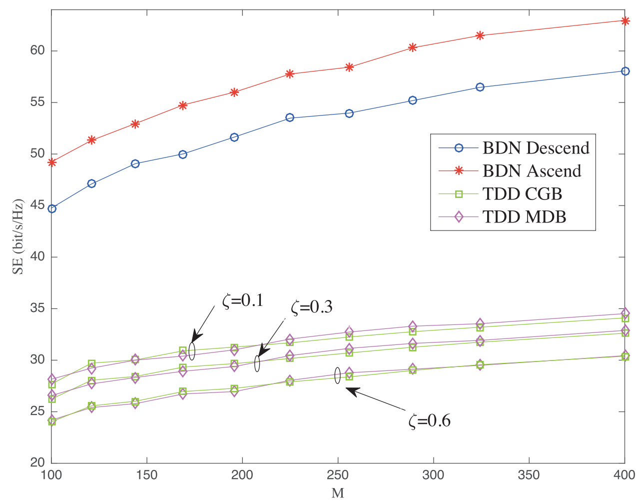

FIGURE 3. SE vs. M when $K_{\mathrm{UL}} = 2, K_{\mathrm{DL}} = 3$.

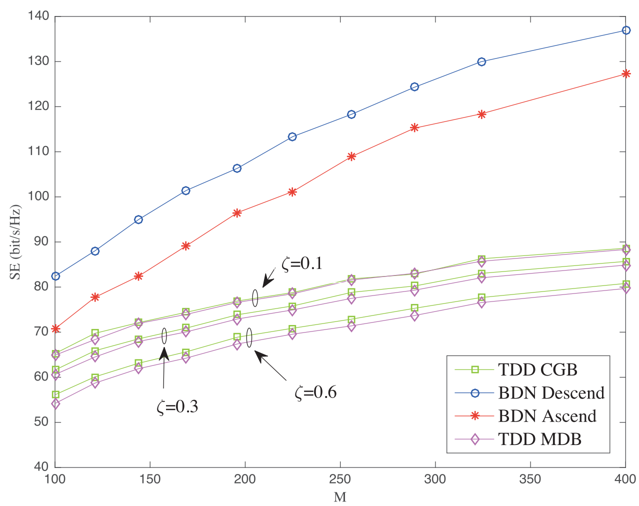

FIGURE 4. SE vs. M when $K_{\mathrm{UL}} = K_{\mathrm{DL}} = 10$.

figures indicate that the more DAs in this area, the better SE can be gained in both BDN and TDD. It can also be seen from Fig. 3 and 4, although CGB and MDB act in different ways, they bring almost the same results in terms of SE. Furthermore, we can see that no matter how ξ changes, the proposed FAC scheme in BDN always has a much better performance than TDD systems in terms of SE. Consequently, it is beneficial to form a BDN rather than considering a TDD when improving SE of the entire system is the main target. Although BDN introduces the extra interference between DL and UL DAs, the FAC scheme can effectively limit the interference according to the geographical separation and proper DA scheduling, and thus can fully release the advantages of BDN in making full use of the spatial resources.

Section III-B only offers a metric for the user selection order, however, the specific order is not analyzed yet. In the follows, the user selection order is dicussed in descending or ascending order by the value of τ_i^e. Interestingly, we

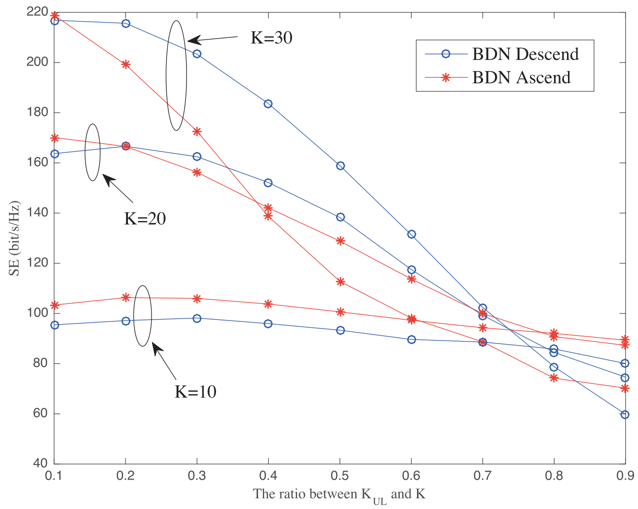

FIGURE 5. SE vs. the ratio between K_{UL} and K, $M = 400$.

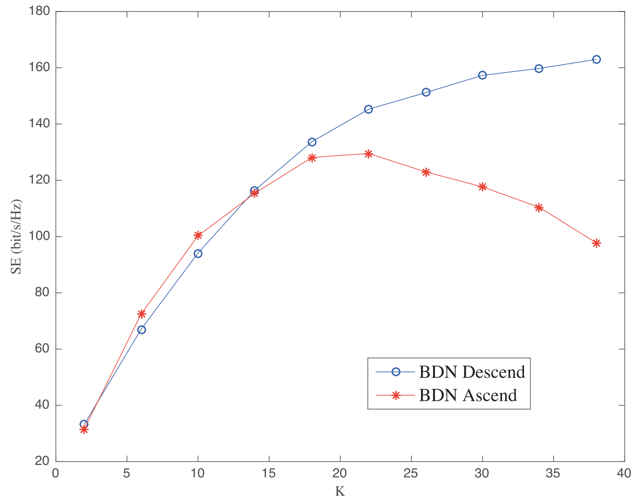

FIGURE 6. SE vs. K when the ratio between UL and DL user numbers equals 1/2, and $M = 400$.

note that the performance of user selection order varies with the number of users. In Fig. 3 which supports two UL users and three DL users, arranging users in ascending order of τ_i^e has a better performance than operating the descending order in terms of SE. However, when $K_{\text{UL}} = K_{\text{DL}} = 10$, the results are opposite. Rethinking the definition of τ_i^e, it is related to the number of overlapped DAs. In some degree, τ_i^e indicates the interference degree caused by user i. Consequently, from Fig. 3 and 4, it can be concluded that when considering a sparse network with fewer users, it will lead to a higher SE if the user that has the least overlapped DAs picks DA first. On the contrary, considering a dense network, giving the highest DA selection priority to the user which is surrounded by most users can gain a better SE performance. This provides meaningful insights for deciding the order of user selection. In Fig. 5 and 6, we will further discuss the reason for this.

Fixing the total number of users $K = 10$, $K = 20$, and $K = 30$, Fig. 5 plots the SE versus the the ratio of K_{UL} to K with descending and ascending user orders, respectively. Fig. 5 indicates that ascending order always achieves better SE performance than descending order in sparse networks (e.g. $K = 10$). However, when the number of users increases, the performance advantage of descending order over ascending order becomes more and more obvious. Notice that when $K = 20$ and $K = 30$, there are two crossovers for each scenario, and these crossovers divide the entire interval into three subintervals. Obviously that the first and the third subintervals indicate a relatively heavier asymmetric network of user types (UL and DL). Often, heavier asymmetry leads to more heterogeneous interference between DL DAs to UL DAs. In such situations, it is usually beneficial to consider the users with less interference (the number of overlapped serving DA is less) to choose DA first. However, when the number disparity in UL and DL users is not obvious, the SE performance of descending order in user selection performs better than that of ascending order. Interestingly, when $\frac{K_{\text{UL}}}{K} = 0.9$, more users lead to lower SE for both ascending and descending orders. This is due to the growing interference with the increasing number of users.

In addition to the ratio of user types, we also investigate the SE versus the total number of users when half of K users operate UL communications and the other half work at DL transmissions in Fig.6. As observed, when there is fewer users, the gap between descending and ascending orders are not so obvious. According to the above analysis that fewer users usually leads to a sparse network, therefore, there barely exists overlapped DAs. In this way, ascending order for users to select DAs may achieve better SE performance. However, with the growth of K, and ascending order even leads to SE reduction. In a fixed area, supporting more users means the users are closer to each other, and thus there would be more overlapped DAs for the users. If the user which has the fewest overlapped DAs selects its serving DA first, there is a large chance that other lower-ordered users will be inactive as their DA candidates are already chosen by higher-ordered users. Hence, the number of active users may be very small, which incurs the performance degradation in terms of SE for the entire network. Furthermore, we can improve the active fairness among users by introducing a fairness scheduling parameter to the order metric in (19), and this is our future work. On the contrary, in a dense network with a large number of users, it can achieve better performance in terms of SE by giving the highest priority to the user whose DA candidates have the most serious overlapped issue. This is because the lower-ordered users will always have some DAs which are not overlapped by higher-ordered users, there is a relatively less chance for lower-ordered users to be inactive than that with ascending order. Therefore, descending order of user selection can gain better performance in SE for dense networks.

V. CONCLUSIONS

In this paper, we have proposed a novel DA clustering scheme named FAC for BDN with L-DAS to obtain a satisfying SE. By exploiting the geographical location information among users and DAs, we judiciously designed FAC such that the novel user selection order and the DA selection algorithm can be obtained for BDN with complex interference.

By utilizing FAC, the operating mode of each DA can be flexibly changed according to the requirements of users, and the computational complexity of the DA clustering problem can be reduced. Numerical results show that FAC in BDN with L-DAS achieves higher SE compared with the TDD systems. It further supports the application of BDN in practical communication systems. In addition, we reached some specific suggestions for the network configuration, e.g., how to choose the user selection order for dense and sparse systems, respectively.

In practical systems, there are some more needs to be considered in DA clustering, e.g., the limited-fronthaul capacity and resource allocation between DAs. Therefore, we will investigate these issues in BDN for the future study.

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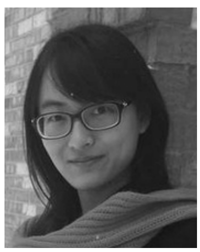

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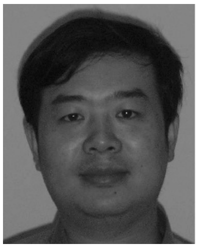

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