Received May 19, 2020, accepted June 5, 2020, date of publication June 10, 2020, date of current version June 22, 2020.

Digital Object Identifier 10.1109/ACCESS.2020.3001270

Effective Channel Gain-Based Access Point Selection in Cell-Free Massive MIMO Systems

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This work was supported by the 2020 Research Fund of University of Ulsan.

ABSTRACT In this paper, we investigate the selection problem of access points (APs) in cell-free massive multiple-input multiple-output (MIMO) systems, where APs equipped with a large number of antennas are geographically distributed over a wide area with no cell border. These APs simultaneously serve many users, which are randomly distributed all over the area. We first derive formulas to calculate two proposed metrics used to measure the effective channel gain from all users to all APs and the channel quality of each user. Moreover, these metrics are only based on large-scale fading coefficients, which change very slowly in time. Next, we propose an algorithm to effectively sort and connect users to each AP in a sequential manner using these proposed metrics. Simulation results show that cell-free massive MIMO systems using proposed scheme have better performance compared to existing schemes.

INDEX TERMS Cell-free, massive MIMO, AP selection, AP-user association.

I. INTRODUCTION

Massive multiple-input multiple-output (MIMO) systems where a large number of antennas are equipped on the base stations (BSs) or access points (APs) to simultaneously serve many users in the same frequency resource, is an emerging technology for 5G wireless communication systems and future wireless networks [1], [2]. With a large number of AP antennas, small-scale fading, noise and interference from other users are greatly removed by the effects of channel hardening and favorable propagation [3]. This helps massive MIMO systems significantly improve both spectral efficiency (SE) and energy efficiency (EE). Moreover, APs use simple linear signal processing technique for both uplink signal detection and downlink precoding, such as maximum ratio, zero forcing and so on, but they still achieve nearly optimal performance [1]–[3].

Noticeably, most existing researches on massive MIMO systems have been based on cellular architectures since they are well-studied and can be easily managed cell by cell, and have low backhaul resource requirements [4], [5]. However, some drawbacks of cellular system are cell-edge user performance and user location-related issues [7], [14]. Specifically, an user belongs to a cell but locates in the edge of that cell has bad channel quality since the far distance from its serving cell. That user may have better channel quality if it is connected to other cell than the current serving cell.

On the other hand, distributed or cell-free massive MIMO systems have some advantages in comparison to collocated systems such as more efficient diversity of channels, handover-free, higher probability of coverage, no cost for investigating and deploying cells in particular areas, and so on [8], [9]. The authors of [8] compared cell-free massive MIMO with small cell systems. They focused on max-min power control to provide uniformly good service for every user and pilot assignment with the assumption that all users are served by all APs at the same time. The authors of [9] investigated cell-free massive MIMO systems using an approach called the user centric approach, but APs still serve many users simultaneously. In [10], the authors proposed an energy efficiency maximization scheme using power allocation and user-AP selection. They showed that a fully connected user-AP is not optimal. However, they mainly focused on power allocation and used the results from optimization problem to select APs. This selection scheme is very complicated due to the complexity of the optimization problem, and many users can be connected to one AP. The authors of [11] used the AP selection scheme in [10] to propose a pilot power control design to minimize the mean squared errors of the channel estimation using sequential

The associate editor coordinating the review of this manuscript and approving it for publication was Yiming Huo.

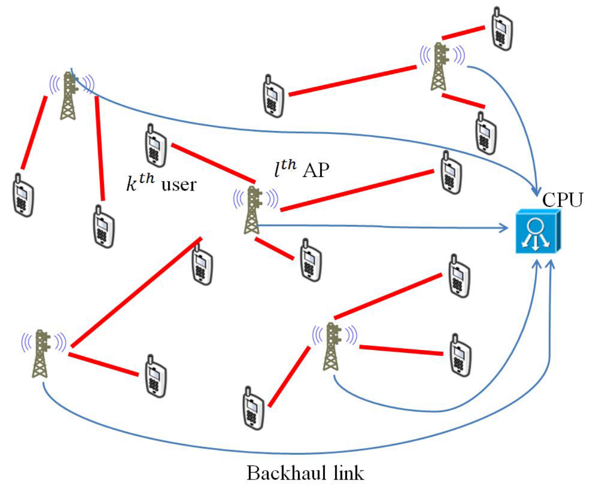

FIGURE 1. System model of a cell-free massive MIMO system.

convex optimization. In [12], the authors investigated the energy efficiency in downlink transmission by optimizing power allocation, user-AP association, and antenna activation on each AP in a combinational manner. This algorithm had very high computational complexity since they combined three challenging problems in cell-free massive MIMO into a mixed integer nonlinear problem. Moreover, to solve this problem, the authors need to approximate the original problem two times, and the solution is only a local optimum. In this paper, we focus on AP-user selection problem in a cell-free massive MIMO system. The main contributions of this paper are as follows.

- We derive two metrics, one is to measure the channel quality of each user to all APs, and another one is to calculate the effective channel gain between every user and AP in the system. These two metrics are calculated only using large-scale fading coefficients that do not change quickly in time so that we do not need to re-run the algorithm frequently.
- We propose an effective channel gain-based algorithm to assign users to each AP sequentially to reduce the interference between users and consequently improve the sum rate of the system.

The remainder of this paper is organized as follows. We briefly describe the system model and assumption in Section II. In Section III, we show the details of proposed metrics and AP-user selection algorithm. Simulation results and discussion are provided in Section IV. Finally, we give our conclusion in Section V.

II. SYSTEM MODEL

We consider a multi-user cell-free massive MIMO system containing L geographically distributed APs serving K users in the same time-frequency resource. The system operates in time division duplex (TDD) mode, which means the channels in the uplink and downlink are reciprocal, and we only need to estimate the channel in uplink. Each AP is equipped with M antennas ($M \gg K$) while each user has single antenna. Assume that all APs are located without any cell-border and all users are distributed randomly in a wide area. Moreover, all L APs are connected to a central processing unit via a backhaul network as in Fig. (1). The channel vector between the k^{th} user and the l^{th} AP, $\mathbf{h}_{kl} \in C^{M\times 1}$, is a combination of two factors, small-scale fading $\mathbf{g}_{kl}$ and large-scale fading β_{kl}:

$$\mathbf{h}_{kl} = \mathbf{g}_{kl}\sqrt{\beta_{kl}}, \tag{1}$$

where elements of $\mathbf{g}_{kl}$ are independent and identically distributed (i.i.d) Complex Normal $\mathcal{CN}(0, 1)$ random variables (RVs). We further assume block fading where large-scale fading does not change over multiple coherent time intervals and thus can be easily tracked at the BS, while small-scale fading remains unchanged within one coherence interval [1].

With TDD mode, there are three phases within each coherence interval: uplink pilot transmission (or training phase), uplink data transmission, and downlink data transmission. In this paper, we focus on the downlink and do not discuss the uplink data transmission. We assume that time duration of each coherent interval is τ_c, in which τ_p is used for the uplink pilot signals, and the remaining $\tau_c - \tau_p$ is used for downlink data transmission.

A. UPLINK TRAINING & CHANNEL ESTIMATION

In the training phase, all users simultaneously transmit their pilot signals to APs to estimate channels. A set of mutually orthogonal pilot sequences Ψ is assigned randomly to each user. This set contains K pilot sequences with pilot length τ_p, $\tau_p \geq K$, which is shown as

$$\Psi = [\boldsymbol{\psi}_1, \boldsymbol{\psi}_2, \ldots, \boldsymbol{\psi}_K]^T \in C^{K\times\tau_p},$$
$$\boldsymbol{\psi}_i^H\boldsymbol{\psi}_i = \tau_p, \boldsymbol{\psi}_i^H\boldsymbol{\psi}_j = 0, \quad \forall i \neq j. \tag{2}$$

The training pilot signal received at the l^{th} AP is

$$\mathbf{Y}_l = \sum_{k=1}^{K}\sqrt{p_p}\mathbf{h}_{kl}\boldsymbol{\psi}_k^H + \mathbf{N}_l, \tag{3}$$

where p_p is the pilot power, which is the same for all users. $\mathbf{N}_l \in C^{M\times\tau_p}$ presents Gaussian noise at the $l^{th}AP$ with i.i.d zero-mean and unit-variance elements. To estimate the channel vector from the k^{th} user, the received training signal in (3) is correlated with the k^{th} pilot sequence as

$$\mathbf{y}_{kl} = \mathbf{Y}_l\boldsymbol{\psi}_k = \tau_p\sqrt{p_p}\mathbf{h}_{kl} + \mathbf{n}_{kl}, \tag{4}$$

where $\mathbf{n}_{kl} = \mathbf{N}_l\boldsymbol{\psi}_k$ is the equivalent noise after being correlated with the k^{th} pilot, and its elements follow complex Gaussian distributions with zero-mean. Finally, the MMSE estimated channel [15] between the k^{th} user and the l^{th} AP is calculated as

$$\hat{\mathbf{h}}_{kl} = \frac{\sqrt{p_p}\beta_{kl}}{\tau_p p_p\beta_{kl} + 1}\mathbf{y}_{kl}, \tag{5}$$

Error between true channel and estimated channel is given as $\boldsymbol{\epsilon}_{kl} = \mathbf{h}_{kl} - \hat{\mathbf{h}}_{kl}$. Both estimated channel and estimated error follow complex Gaussian distribution [10]–[12] as follows.

$$\begin{aligned}\hat{\mathbf{h}}_{kl} &\sim \mathcal{CN}(0, \eta_{kl}\mathbf{I}_M),\\ \boldsymbol{\epsilon}_{kl} &\sim \mathcal{CN}(0, (\beta_{kl}-\eta_{kl})\mathbf{I}_M),\end{aligned} \tag{6}$$

where $\eta_{kl} = \frac{p_p\tau_p\beta_{kl}^2}{\tau_p p_p \beta_{kl}+1}$ follows the property of MMSE estimator in (5).

B. DOWNLINK DATA TRANSMISSION

After the training phase, all APs have all estimated channels from all users and can start transmitting data. In downlink, we assume that one user can only connect to one AP, but one AP can simultaneously serve multiple users. U_l denotes the set of users served by the l^{th} AP, and the transmitted signal vector from the l^{th} AP is given as

$$s_l = \sum_{k=1}^{|U_l|} \sqrt{p_d}\mathbf{w}_{kl} d_k, \tag{7}$$

where d_k denotes the transmitted data for the k^{th} user with $\mathbb{E}\{|d_k|^2\} = 1$; p_d denotes the transmit data power, which is same for all users; $|U_l|$ is number of elements in set U_l; and $\mathbf{w}_{kl}$ is the precoding vector. In this paper, we use a simple and general maximum ratio transmission precoding technique, which is calculated as

$$\mathbf{w}_{kl} = \hat{\mathbf{h}}_{kl}. \tag{8}$$

After APs transmit their corresponding data signal to users, the received signal at the k^{th} user served by the l^{th} AP can be given as

$$\begin{aligned} u_k = \sqrt{p_d}\mathbf{h}_{kl}^H\mathbf{w}_{kl}d_k &+ \sum_{m=1,m\neq k}^{|U_l|}\sqrt{p_d}\mathbf{h}_{kl}^H\mathbf{w}_{ml}d_m\\ &+ \sum_{j=1,j\neq l}^{L}\sum_{t=1}^{|U_j|}\sqrt{p_d}\mathbf{h}_{kl}^H\mathbf{w}_{tj}d_t + n_k, \end{aligned} \tag{9}$$

where $n_k \sim \mathcal{CN}(0,1)$ is additive noise at k^{th} user. The first term $\sqrt{p_d}\mathbf{h}_{kl}^H\mathbf{w}_{kl}d_k$ is the desired signal from the k^{th} user, the second term $\sum_{m=1,t\neq k}^{|U_l|}\sqrt{p_d}\mathbf{h}_{kl}^H\mathbf{w}_{ml}$ is intra-AP interference which comes from other users connected to the same l^{th} AP as the k^{th} user, and the third term $\sum_{j=1,j\neq l}^{L}\sum_{t=1}^{|U_j|}\sqrt{p_d}\mathbf{h}_{kl}^H\mathbf{w}_{tj}d_t$ is inter-AP interference from other APs. In the next section, we will propose an algorithm to select an AP for each user in order to mitigate the effect of intra-AP interference.

III. AP SELECTION SCHEME

In this section, we derive the SE formula of an user and from that we derive a closed-form of that SE. The closed form of user SE inspires us to propose two proposed metrics and how we use them in the proposed algorithm to effectively select an AP for every user in the system to improve the sum SE, instead of just connecting user to its largest large-scale fading coefficient AP as in [10].

A. SPECTRAL EFFICIENCY

The received data signal in (9) can be rewritten as

$$\begin{aligned} u_k = \mathbb{E}\{\sqrt{p_d}\mathbf{h}_{kl}^H\mathbf{w}_{kl}\}d_k &+ (\sqrt{p_d}\mathbf{h}_{kl}^H\mathbf{w}_{kl}\\ &- \mathbb{E}\{\sqrt{p_d}\mathbf{h}_{kl}^H\mathbf{w}_{kl}\})d_k + \sum_{m=1,m\neq k}^{|U_l|}\sqrt{p_d}\mathbf{h}_{kl}^H\mathbf{w}_{ml}d_m\\ &+ \sum_{j=1,j\neq l}^{L}\sum_{t=1}^{|U_j|}\sqrt{p_d}\mathbf{h}_{kl}^H\mathbf{w}_{tj}d_t + n_k. \end{aligned} \tag{10}$$

Using lower bounding technique as in [3], the spectral efficiency of k^{th} user is given as (11), which is shown at the bottom of this page, where

$$\begin{aligned} X_k &= \mathbb{E}\{\sqrt{p_d}\mathbf{h}_{kl}^H\mathbf{w}_{kl}\},\\ Y_k &= \sqrt{p_d}\mathbf{h}_{kl}^H\mathbf{w}_{kl} - \mathbb{E}\{\sqrt{p_d}\mathbf{h}_{kl}^H\mathbf{w}_{kl}\},\\ Z_{ml} &= \sqrt{p_d}\mathbf{h}_{kl}^H\mathbf{w}_{ml},\\ T_{tj} &= \sqrt{p_d}\mathbf{h}_{kl}^H\mathbf{w}_{tj}. \end{aligned} \tag{12}$$

Using properties in (6), we calculate the closed form of user SE as follows.

$$|X_k|^2 = p_d\left|\mathbb{E}\{(\hat{\mathbf{h}}_{kl}+\boldsymbol{\epsilon}_{kl})\hat{\mathbf{h}}_{kl}\}\right|^2 = M^2\, p_d\eta_{kl}^2, \tag{13}$$

$$\begin{aligned} \mathbb{E}\{|Y_k|^2\} &= \mathbb{E}\{|\sqrt{p_d}\mathbf{h}_{kl}^H\hat{\mathbf{h}}_{kl}|^2\} - |\mathbb{E}\{\sqrt{p_d}\mathbf{h}_{kl}^H\hat{\mathbf{h}}_{kl}\}|^2\\ &= p_d\left(\mathbb{E}\{|\boldsymbol{\epsilon}_{kl}^H\hat{\mathbf{h}}_{kl}|^2\} + \mathbb{E}\{\|\hat{\mathbf{h}}_{kl}\|^4\} - M^2\eta_{kl}^2\right)\\ &= p_d\left(M\eta_{kl}(\beta_{kl}-\eta_{kl}) + (M^2+M)\eta_{kl}^2 - M^2\eta_{kl}^2\right)\\ &= Mp_d\eta_{kl}\beta_{kl}, \end{aligned} \tag{14}$$

$$\begin{aligned} \mathbb{E}\{|Z_{ml}|^2\} &= p_d\,\mathbb{E}\{|\mathbf{h}_{kl}^H\hat{\mathbf{h}}_{ml}|^2\}\\ &= p_d\,\mathbb{E}\{|(\hat{\mathbf{h}}_{kl}+\boldsymbol{\epsilon}_{kl})^H\hat{\mathbf{h}}_{ml}|^2\}\\ &= p_d\left(\mathbb{E}\{|\hat{\mathbf{h}}_{kl}^H\hat{\mathbf{h}}_{ml}|^2\} + \mathbb{E}\{|\boldsymbol{\epsilon}_{kl}^H\hat{\mathbf{h}}_{ml}|^2\}\right)\\ &= p_d\left(M\eta_{ml}(\beta_{kl}-\eta_{kl}) + M\eta_{ml}\eta_{kl}\right)\\ &= Mp_d\eta_{ml}\beta_{kl}, \end{aligned} \tag{15}$$

$$\mathbb{E}\{|T_{tj}|^2\} = p_d\,\mathbb{E}\{|\mathbf{h}_{kl}^H\hat{\mathbf{h}}_{tj}|^2\} = Mp_d\eta_{tj}\beta_{kj}. \tag{16}$$

Replace (13), (14), (15) and (16) into (11), we have the closed-form of SE of k^{th} user as

$$\mathrm{S}_k = \frac{\tau_c-\tau_p}{\tau_c}\log\left(1+\frac{M^2p_d\eta_{kl}^2}{\sum_{j=1}^{L}\sum_{t=1}^{|U_j|}Mp_d\eta_{tj}\beta_{kj}+1}\right). \tag{17}$$

$$\mathrm{S}_k = \frac{\tau_c-\tau_p}{\tau_c}\log\left(1+\mathrm{SINR}_k\right) = \frac{\tau_c-\tau_p}{\tau_c}\log\left(1+\frac{|X_k|^2}{\mathbb{E}\{|Y_k|^2\}+\sum_{m=1,m\neq k}^{|U_l|}\mathbb{E}\{|Z_{ml}|^2\}+\sum_{j=1,j\neq l}^{L}\sum_{t=1}^{|U_j|}\mathbb{E}\{|T_{tj}|^2\}+1}\right), \tag{11}$$

B. PROPOSED METRICS

1) SELF-PRICE METRIC

From the closed-form SE in (17), we see that the numerator of k^{th} user SINR contains $\eta_{kl}^2 = \left(\frac{p_p \tau_p \beta_{kl}^2}{\tau_p p_p \beta_{kl}+1}\right)^2$, which contains only large-scale fading of the intended k^{th} user. Put aside interference from other users in the denominator of SINR in (17), we can define a metric for each user as self price metric δ using η_{kl}^2. This metric is used to measure channel quality from that user to all APs, without caring about other user interference. The metric δ_k of the k^{th} user is measured as

$$\delta_k = \sum_{l=1}^{L} \eta_{kl}^2. \tag{18}$$

δ_k is summation of all η_{kl}^2 from all k^{th} user to all APs and this can help us to roughly evaluate the channel quality of k^{th} user in the system.

2) EFFECTIVE CHANNEL QUALITY METRIC

Assume that the k^{th} user is assigned to connect to the l^{th} AP, and l^{th} AP already connected to some other users. Clearly, SE of k^{th} user is interfered by these users. As in the denominator of (17), the interference from other users, who are connected to the same AP as k^{th} user, can be roughly measured by $\eta_{tl}\beta_{kl}, t \neq k$.

Eventually, the effective channel gain from the k^{th} user to the l^{th} AP can be measured by its self-channel quality η_{kl}^2 minuses summation of other users interference, which also are connected to the same AP as k^{th} user. We propose the effective channel quality metric as

$$\pi_{kl} = \eta_{kl}^2 - \sum_{t=1,t\neq k}^{|U_l|} \eta_{tl}\beta_{kl}. \tag{19}$$

From (19), we can see that although large-scale fading coefficient β_{kl} is large, which means the channel quality from k^{th} user to l^{th} AP is good, it might not be proper to assign the k^{th} user to connect to the l^{th} AP. Since the other users, which are already connected to the l^{th} AP prior to the k^{th} user, may also have large β_{tl}, and it causes large interference to k^{th} user.

C. PROPOSED AP SELECTION ALGORITHM

In this subsection, we propose an effective channel gain-based algorithm to choose the most suitable AP for each user in a sequential way until all users in the system are connected to its AP. The entire process of AP selection is summarized in **Algorithm 1** below.

At the beginning of the selection process, there is no user connected to any AP. Thus, steps 1 and 2 are to sort all users in descending order of total channel gain as in (18) to ensure that users with best channel qualities are connected to AP first.

For each user from the descending list, we calculate the effective channel gain from it to all APs as in (19) and choose the AP with the highest value, as in steps 3 and 4. A scenario where many users are located closely to a specific AP happens frequently, and it is not good if many users are connected to the same AP. Steps 3 and 4 guarantee that each user is connected to the most suitable AP, not just the AP with the highest large scale fading coefficient, or channel gain. As the proposed algorithm keeps going on, effective channel gain of each user is recalculated and changes since the user set U_l of each AP changes after every time steps 3 and 4 are executed.

Algorithm 1 Effective Channel Gain-Based AP Selection Algorithm

Initialize: $\delta_k = 0, \pi_{kl} = 0\ \forall k = 1, 2, \ldots, K; l = 1, 2, \ldots L.$

1: Calculate δ_k as in (18) $\forall k = 1, 2, \ldots, K$
2: Sort δ_k $\forall k = 1, 2, \ldots, K$ in descending order.
3: Calculate the effective channel gain π_{kl} of each user in order as determined in step 2 as in (19) $\forall l = 1, 2, \ldots L$.
4: Choose the AP with highest effective channel gain π_{kl} and connect this user to that AP.
5: Keep running the process from step 3 until all users have been assigned an AP.

It is worth noting that **Algorithm 1** has low complexity since it uses only sorting, comparison, and simple mathematic operations. Moreover, the proposed algorithm is based on large scale fading, which does not change in many coherent intervals so we do not have to re-run the algorithm frequently. Algorithms based on heuristic observations have been proposed in many other researches such as pilot assignment based on graph coloring algorithm in [5]–[7], or smart pilot assignment algorithm in [14].

IV. NUMERICAL RESULTS

In this section, we evaluate the performance of the proposed AP selection scheme using Monte-Carlo simulations with 500 realizations for each figures. In each realization, APs and users are randomly located on a square area. The coherence length is 200 symbols, system bandwidth is 20 MHz, and noise variance is −94 dBm. The large-scale fading coefficient is simulated using the 3GPP LTE model [16]

$$\beta_{kl} = -35.3 - \gamma \log_{10}(d_{kl}) + z_{kl}, \tag{20}$$

where γ is the path-loss exponent, and −35.3 denotes the average channel gain at 1m reference distance. d_{kl} is the distance from the k^{th} user to the l^{th} AP, and z_{kl} is the shadow fading that follows a log-normal distribution with a standard deviation of 5 dB. Pilot power p_p and data power p_d are 200mW and are the same for all users.

All system parameters are summarized in Table 1 below.

Our proposed algorithm is compared to three other reference schemes:

- Random Selection: each user is randomly connected to one AP. Since there is a chance that some AP will not serve any users, in simulation, we make sure that each AP serves at least one user to be fair in comparison. This scheme is marked as "Random" in figures.

TABLE 1. System parameters.

Area	1 km^2
Number of APs L	5, 10, 20
Number of users K	10,20,30
Number of AP antennas M	100
Path loss γ	3.76
Bandwidth	20MHz
log normal standard deviation	5dB
Pilot and data power p_p, p_d	200mW

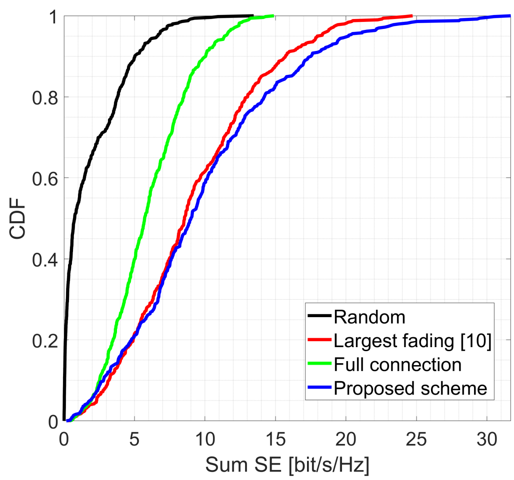

FIGURE 2. CDF of the sum rate of system with $L = 5, K = 20$.

- AP selection based on largest fading in [10]: In this scheme, an user is connected to an AP to which this user has the highest large scale fading coefficient. This scheme is marked as "Largest fading [10]" in figures.
- Full connection scheme: AP selection in which one user is connected to all APs. This scheme is marked as "Full connection" in figures.

In fact, if there is only one AP available, all aforementioned schemes are the same and any user-AP connection scheme is useless. Since this extreme case is truism, it is unnecessary to investigate further.

Fig. 2 shows the cumulative distribution function (CDF) ofa the system's sum rate with the four aforementioned schemes where $L = 5, K = 20$. In fig. 1, the proposed algorithm outperforms the others, at nearly 2.5 bit/s/Hz higher than the scheme in [10] at a probability of 0.9. The improvement in our proposed scheme comes from the fact that the largest large-scale fading based scheme only connects an user to its highest largest-scale fading AP, while our proposed scheme smartly chooses a suitable AP instead of the highest large scale fading AP if this AP already connects to too many users prior to the current user. Interestingly, the full connection scheme does not work well in this situation since number of users is four times larger than number of APs. This causes a high intra-AP interference for each user since many users have to be connected to the same AP. Random scheme shows the worst performance since users are randomly connected to APs.

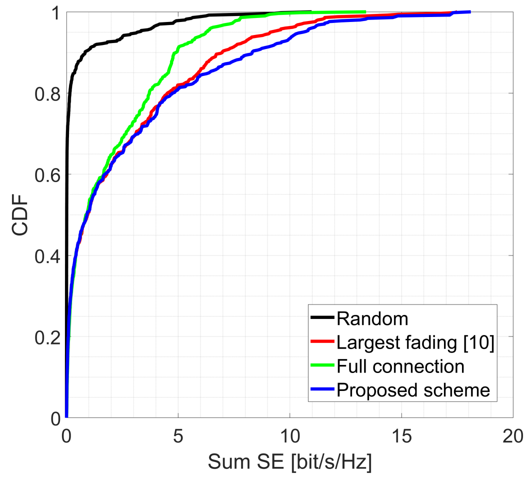

FIGURE 3. CDF of the sum rate of system with $L = 10, K = 20$.

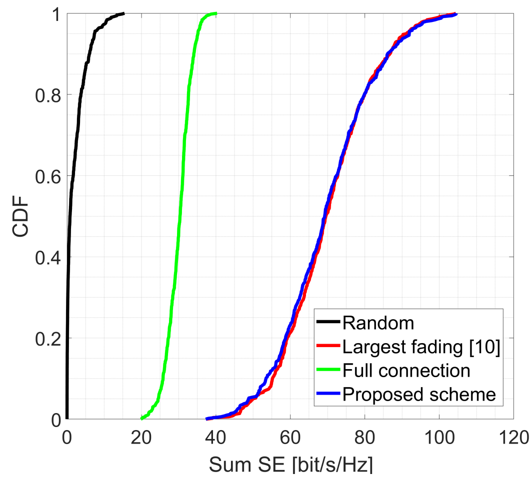

FIGURE 4. CDF of the sum rate of system with $L = 20, K = 30$.

Fig. 3 shows the simulation results when $L = 10$, and number of users is two times larger than number of APs. In this case, the proposed scheme still outperforms the others, but the gain becomes smaller. Since users have more APs to choose from for connection, the number of users connected to the same AP decreases. Therefore, the scheme in [10] performs better than in the previous situation and produces results closer to those of the proposed scheme.

The simulation results when number of users is only 1.5 times higher than number of APs with $L = 20$, $K = 30$ are shown in fig. 4. Obviously, the proposed algorithm performs similarly to the scheme in [10]. In conclusion, our proposed scheme performs very well in a scenario where the ratio of number of users to number of APs is high.

V. CONCLUSION

In cell-free massive MIMO research, full connection is commonly assumed between users and APs. Another common assumption is connection of an user to its highest large-scale fading AP. However, both these schemes cannot have good performance when the number of APs are much fewer than the number of users. Motivated by that, in this paper, we propose two metrics to measure the channel quality of users and the effective channel gain between users and APs. After that, we propose an effective channel gain-based algorithm to smartly select AP for each user to be connected in a cell-free massive MIMO system using these metrics. Compared to existing schemes, our proposed algorithm offers better performance when the ratio of number of users to number of APs is high. Practically, our proposed scheme should be applied to cell-free massive MIMO system which is deployed in crowed area where the number of user is much higher than number of APs.

REFERENCES

[1] T. L. Marzetta, "Noncooperative cellular wireless with unlimited numbers of base station antennas," *IEEE Trans. Wireless Commun.*, vol. 9, no. 11, pp. 3590–3600, Nov. 2010.

[2] L. Lu, G. Y. Li, A. L. Swindlehurst, A. Ashikhmin, and R. Zhang, "An overivew of massive MIMO: Benefits and challenges," *IEEE J. Sel. Topics Signal Process.*, vol. 8, no. 5, pp. 742–758, Oct. 2014.

[3] E. Bjornson, J. Hoydis, and L. Sanguinetti, *Massive MIMO Networks: Spectral, Energy, and Hardware Efficiency*. Boston, MA, USA: NOW Publisher, 2017.

[4] X. Zhu, Z. Wang, C. Qian, L. Dai, J. Chen, S. Chen, and L. Hanzo, "Soft pilot reuse and multicell block diagonalization precoding for massive MIMO systems," *IEEE Trans. Veh. Technol.*, vol. 65, no. 5, pp. 3285–3298, May 2016.

[5] X. Zhu, L. Dai, Z. Wang, and X. Wang, "Weighted-graph-coloring-based pilot decontamination for multicell massive MIMO systems," *IEEE Trans. Veh. Technol.*, vol. 66, no. 3, pp. 2829–2834, Mar. 2017.

[6] Z. Wang, P. Zhao, C. Qian, and S. Chen, "Location-aware channel estimation enhanced TDD based massive MIMO," *IEEE Access*, vol. 4, pp. 7828–7840, 2016.

[7] H. T. Dao and S. Kim, "Vertex graph-coloring-based pilot assignment with location-based channel estimation for massive MIMO systems," *IEEE Access*, vol. 6, pp. 4599–4607, 2018.

[8] H. Q. Ngo, A. Ashikhmin, H. Yang, E. G. Larsson, and T. L. Marzetta, "Cell-free massive MIMO versus small cells," *IEEE Trans. Wireless Commun.*, vol. 16, no. 3, pp. 1834–1850, Mar. 2017.

[9] S. Buzzi and C. D'Andrea, "Cell-free massive MIMO: User-centric approach," *IEEE Wireless Commun. Lett.*, vol. 6, no. 6, pp. 706–709, Dec. 2017.

[10] H. Q. Ngo, L.-N. Tran, T. Q. Duong, M. Matthaiou, and E. G. Larsson, "On the total energy efficiency of cell-free massive MIMO," *IEEE Trans. Green Commun. Netw.*, vol. 2, no. 1, pp. 25–39, Mar. 2018.

[11] T. C. Mai, H. Q. Ngo, M. Egan, and T. Q. Duong, "Pilot power control for cell-free massive MIMO," *IEEE Trans. Veh. Technol.*, vol. 67, no. 11, pp. 11264–11268, Nov. 2018.

[12] G. Dong, H. Zhang, S. Jin, and D. Yuan, "Energy-efficiency-oriented joint user association and power allocation in distributed massive MIMO systems," *IEEE Trans. Veh. Technol.*, vol. 68, no. 6, pp. 5794–5808, Jun. 2019.

[13] Z. Gao, L. Dai, D. Mi, Z. Wang, M. A. Imran, and M. Z. Shakir, "MmWave massive-MIMO-based wireless backhaul for the 5G ultra-dense network," *IEEE Wireless Commun.*, vol. 22, no. 5, pp. 13–21, Oct. 2015.

[14] X. Zhu, Z. Wang, L. Dai, and C. Qian, "Smart pilot assignment for massive MIMO," *IEEE Commun. Lett.*, vol. 19, no. 9, pp. 1644–1647, Sep. 2015.

[15] S. M. Kay, *Fundamentals of Statistical Signal Processing: Estimation Theory*. Upper Saddle River, NJ, USA: Prentice-Hall, 1993.

[16] *Further Advancements for E-UTRA Physical Layer Aspects (Release 9)*, Standard 3GPP TS 36.814, 2010.

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