Antenna Selection for Full-Duplex Distributed Massive MIMO via the Elite Preservation Genetic Algorithm

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***Abstract*— For a full-duplex distributed massive multiple-input multiple-output (MIMO) system, the spectrum efficiency improves significantly over that of a half-duplex system. However, self-interference between all base stations and multiuser interference limit the further improvement of the spectrum efficiency. In this letter, an antenna selection strategy is proposed to address this problem. In particular, the antenna selection problem is formulated as an optimization problem of maximizing the total spectrum efficiency of the system. Since the problem is a nonconvex integer programming problem and it is difficult to find a globally optimal solution, an elite preservation genetic algorithm (EPGA) is utilized to solve this problem, which employs an elite preservation strategy to ensure that the optimal individuals will not be lost due to crossover or mutation in the evolution. The simulation results indicate that the performance of the EPGA is close to the performance of exhaustive search and much better than the performance of random assignment.**

***Index Terms*— Distributed massive MIMO, full-duplex antenna selection, elite preservation genetic algorithm, spectrum efficiency.**

I. Introduction

In recent years, distributed massive multiple-input multiple-output (MIMO) has been foreseen as a promising network architecture for 6th generation (6G) mobile communication systems thanks to its abilities of extending coverage and enhancing throughput [1]. In this architecture, the base stations (BSs) equipped with remote antenna units (RAUs) are separated geographically over a large area and connected to the central processing unit (CPU) by high-bandwidth and low-delay backhaul like fibers. The full-duplex (FD) system, which transmits and receives signals in the same time slot and on the same frequency, is enabled as a result of advanced self-interference cancellation technology, which suppresses the self-interference of each RAU to a very low level [2]. Owing to its potential to double the spectrum efficiency (SE) of the traditional half-duplex (HD) system, the FD system has attracted tremendous attention from the academic world.

In an FD distributed communication system, each antenna at an RAU can be switched between downlink transmitting and uplink receiving modes, and self-interference exists in each RAU. The self-interference of each RAU requires advanced interference mitigation employing analog or digital cancellation, or a combination of analog and digital cancellation [3]. In addition, the interference between uplink and downlink antennas of different RAUs cannot be ignored. Furthermore, it is worth noting that the signal transmitted by the uplink user also interferes with the downlink user. An appropriate antenna selection scheme can effectively reduce the influence on the SE caused by the interference.

In [4], the authors propose the transmit-receive antenna pair selection scheme from the perspective of maximizing sum rate and minimizing the symbol error rate in a point-to-point FD system where each node is only equipped with two antennas. However, the scenario of more antennas and multi-user is not considered in [4]. In [5], the FD antenna selection problem is transformed into an optimization problem to minimize the mean square error (MSE) of the received signal and is solved by the parallel successive convex approximation (PSCA) algorithm, which transforms the nonconvex part of the optimization problem into a solvable convex problem and obtains the approximate solution. Although the PSCA algorithm improves the total spectrum efficiency, there is a large gap compared with exhaustive search. Smart FD architecture with two RF chains for an antenna, which is an intermediate between the separate and shared architectures, is proposed in [6] and the authors investigate its benefits by an assignment problem to optimally assign antennas, beamforming and power to maximize the weighted sum SE. The near-to-optimal solution is obtained with block coordinate descent and advanced semidefinite programming (ASDP) but the number of RF chains may be limited due to the cost constraint and there is room for further improvement of SE as the number of antennas grows.

The works mentioned above differ from ours since an FD distributed massive MIMO system is considered in our letter. Apart from the self-interference of each RAU and UE-to-UE interference between uplink and downlink users, the interference between uplink and downlink antennas of different RAUs also exists. Considering above interference, we endeavor to optimize the antenna selection vector for the maximization of the achievable sum rate. Since it is difficult to address the formulated nonconvex problem, we propose an elite preservation genetic algorithm (EPGA) with lower complexity than exhaustive search to address the problem. The numerical results show that the performance of the proposed algorithm approaches the performance of exhaustive search.

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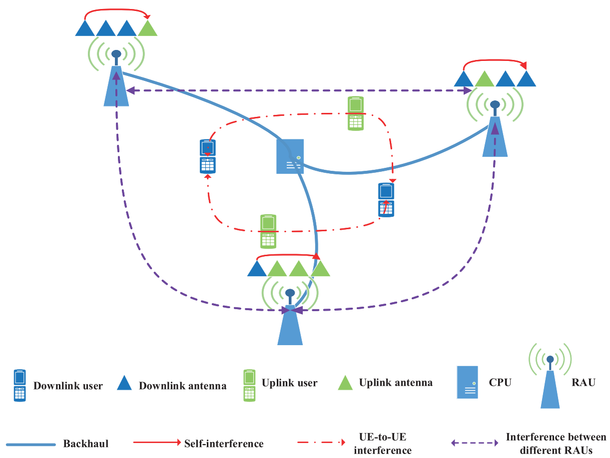

Fig. 1. An architecture diagram of an FD distributed massive MIMO system.

II. System Model and Problem Formulation

Fig. 1 depicts the considered FD distributed massive MIMO system, where each antenna unit at an RAU can be switched between uplink receiving and downlink transmitting. A typical single-cell FD distributed massive MIMO system consisting of M RAUs is considered. Each RAU is equipped with N antenna units and there are K_U uplink HD users and K_D downlink HD users equipped with a single antenna each.

A. Channel Characteristics

The uplink channel vector $\mathbf{g}_i^U \in \mathbb{C}^{MN\times 1}$ between the ith uplink user and the antennas of all RAUs can be expressed as

$$\mathbf{g}_i^U = \sqrt{\mathbf{\Lambda}_i^U}\mathbf{h}_i^U, \tag{1}$$

where $\mathbf{\Lambda}_i^U = \text{diag}([\lambda_{1,i}^U, \ldots, \lambda_{m,i}^U, \ldots, \lambda_{M,i}^U]^T) \bigotimes \mathbf{I}_N$ represents a large-scale fading matrix between the ith uplink user and the antennas of all RAUs and diag$(\mathbf{a})$ represents a diagonal matrix whose diagonal elements are composed by vector $\mathbf{a}$. $\lambda_{m,i}^U$ is a large-scale fading factor between the ith uplink user and the mth RAU. $\mathbf{h}_i^U \in \mathbb{C}^{MN\times 1}$ represents the small-scale fading vector between the ith uplink user and the antennas of all RAUs. $\mathbf{I}_N$ is a $N \times N$ unit matrix, and $\bigotimes$ represents the Kronecker product.

Similarly, the channel vector $\mathbf{g}_j^D \in \mathbb{C}^{MN\times 1}$ between the jth downlink user and the antennas of all RAUs can be written as

$$\mathbf{g}_j^D = \sqrt{\mathbf{\Lambda}_j^D}\mathbf{h}_j^D, \tag{2}$$

where $\mathbf{\Lambda}_j^D = \text{diag}([\lambda_{1,j}^D, \ldots, \lambda_{m,j}^D, \ldots, \lambda_{M,j}^D]^T) \bigotimes \mathbf{I}_N$ represents the large-scale fading matrix between the antennas of all RAUs and the jth downlink user and $\mathbf{h}_j^D \in \mathbb{C}^{MN\times 1}$ is a small-scale fading vector between the antennas of all RAUs and the jth downlink user.

The channel gain $g_{i,j,U}$ between the ith uplink user and the jth downlink user can be expressed as

$$g_{i,j,U} = \sqrt{\lambda_{i,j,U}}s_{i,j,U}, \tag{3}$$

where $\lambda_{i,j,U}$ and $s_{i,j,U}$ represent the large-scale fading factor and small-scale fading factor between the ith uplink user and the jth downlink user, respectively.

Although advanced self-interference cancellation technology has been applied, a low level of residual self-interference also exits between the uplink and downlink antennas of each RAU. The self-interference matrix of the whole system after self-interference cancellation $\mathbf{H}_{SI} \in \mathbb{C}^{MN\times MN}$ can be written as

$$\mathbf{H}_{SI} = \begin{bmatrix} \mathbf{H}_{11} & \ldots & \ldots & \mathbf{H}_{1M} \\ \vdots & \mathbf{H}_{22} & & \vdots \\ \vdots & & \ddots & \vdots \\ \mathbf{H}_{M1} & \ldots & \ldots & \mathbf{H}_{MM} \end{bmatrix} \tag{4}$$

where $\mathbf{H}_{ii} \in \mathbb{C}^{N\times N}$ is defined to represent the self-interference channel matrix of the ith RAU. The elements in the matrix are independent and all obey the distribution $\mathcal{CN}(\sqrt{\sigma_{SI}^2 K_r/(1+K_r)}, \sigma_{SI}^2/(1+K_r))$, where K_r is the Rician factor, and σ_{SI}^2 represents self-interference variance, which is the ratio of the average self-interference power after and before the cancellation process [7]. $\mathbf{H}_{ij} \in \mathbb{C}^{N\times N}$ with $i \neq j$, represents the interference channel matrix between the ith RAU and the jth RAU, whose element $h_{p,q,B}$ in pth row and qth column is expressed as

$$h_{p,q,B} = \sqrt{\lambda_{p,q,B}}s_{p,q,B}. \tag{5}$$

where $\lambda_{p,q,B}$ and $s_{p,q,B}$ represent the large-scale fading factor and small-scale fading factor between the pth antenna of the ith RAU and the qth antenna of the jth RAU, respectively [8].

B. Signal Model

The CSI is assumed known at the RAUs, which is also in accordance with some works in the FD literature [6], [7]. Here, we will temporarily forget the antenna selection and we will consider shared FD antennas, which can work as transmitter and receiver at the same time. Then, the signal $\mathbf{y}^U$ received at all the RAUs can be expressed as

$$\mathbf{y}^U = \sum_{i=1}^{K_U}\sqrt{p_i^U}\mathbf{g}_i^U s_i^U + \mathbf{H}_{SI}\left(\sum_{j=1}^{K_D}\sqrt{p_j^D}\mathbf{w}_j^D s_j^D\right) + \mathbf{n}, \tag{6}$$

where p_i^U is the transmission power of the ith uplink user, and p_j^D is the transmission power for the jth downlink user. s_i^U and s_j^D are the symbols of the ith uplink user and the jth downlink user, respectively, and $\mathbf{w}_j^D \in \mathbb{C}^{MN\times 1}$ represents the precoding vector for the jth downlink user. $\mathbf{n}$ is white Gaussian noise, and $\mathbf{n} \sim \mathcal{CN}(0, \sigma_u^2 \mathbf{I}_{MN})$. Similarly, the received signal y_j^D of the jth downlink user can be written as

$$y_j^D = (\mathbf{g}_j^D)^H \sum_{k=1}^{K_D}\sqrt{p_k^D}\mathbf{w}_k^D s_k^D + \sum_{i=1}^{K_U}\sqrt{p_i^U}g_{i,j,U}s_i^U + n_j, \tag{7}$$

where $\mathbf{g}_j^D$ represents the channel vector between the jth downlink user and the RAUs and $\mathbf{w}_k^D$ is the precoding vector for the kth downlink user. n_j is white Gaussian noise, and $n_j \sim \mathcal{CN}(0, \sigma_d^2)$.

When considering antenna working mode selection, the signal model needs to be modified to some extent. For convenience of description, we define $\mathbf{x}_i^U \in \{0,1\}^{N\times 1}$ as the uplink channel assignment vector of the ith RAU, each element of which is selected as 0 or 1. If the jth element of $\mathbf{x}_i^U$ is set to 1, then the jth antenna of the ith RAU works in the uplink receiving mode. Otherwise, the jth antenna of the ith RAU works in the downlink transmitting mode. Similarly, we define $\mathbf{x}_i^D \in \{0,1\}^{N\times 1}$ as the downlink channel assignment vector of the ith RAU. Clearly, $\mathbf{x}_i^U + \mathbf{x}_i^D = \mathbf{1}^{N\times 1}$, where $\mathbf{1}^{N\times 1}$ represents an $N \times 1$ vector whose elements are all 1. Then, we can obtain the uplink antenna assignment vector $\mathbf{x}^U$ and assignment matrix $\mathbf{X}^U$ of the whole system, as shown below.

$$\mathbf{x}^U = [(\mathbf{x}_1^U)^H, \ldots, (\mathbf{x}_M^U)^H]^H, \quad \mathbf{X}^U = \mathrm{diag}(\mathbf{x}^U). \tag{8}$$

In the same way, we can define the downlink antenna assignment vector $\mathbf{x}^D$ and assignment matrix $\mathbf{X}^D$ of the whole system, expressed as follows:

$$\mathbf{x}^D = \mathbf{1} - \mathbf{x}^U, \quad \mathbf{X}^D = \mathrm{diag}(\mathbf{x}^D) = \mathbf{I} - \mathbf{X}^U. \tag{9}$$

According to the antenna assignment vector, the effective channel vectors of the ith uplink user and the jth downlink user can be defined as $\bar{\mathbf{g}}_i^U$ and $\bar{\mathbf{g}}_j^D$, and the effective self-interference matrix at the base station can be defined as $\bar{\mathbf{H}}_{SI}$; then,

$$\bar{\mathbf{g}}_i^U = \mathbf{X}^U \mathbf{g}_i^U, \quad \bar{\mathbf{g}}_j^D = \mathbf{X}^D \mathbf{g}_j^D, \tag{10}$$

$$\bar{\mathbf{H}}_{SI} = \mathbf{X}^U \mathbf{H}_{SI} \mathbf{X}^D. \tag{11}$$

Therefore, with an effective channel vector and effective self-interference matrix, the effective signal received at the base station can be expressed as

$$\bar{\mathbf{y}}^U = \sum_{i=1}^{K_U} \sqrt{p_i^U}\bar{\mathbf{g}}_i^U s_i^U + \overline{\mathbf{H}}_{SI}\left(\sum_{j=1}^{K_D}\sqrt{p_j^D}\mathbf{w}_j^D s_j^D\right) + \mathbf{X}^U\mathbf{n}, \tag{12}$$

Similarly, the effective signal $\bar{y}_j^D$ received by the jth downlink user is modified as

$$\bar{y}_j^D = (\bar{\mathbf{g}}_j^D)^H \sum_{k=1}^{K_D}\sqrt{p_k^D}\mathbf{w}_k^D s_k^D + \sum_{i=1}^{K_U}\sqrt{p_i^U} g_{i,j,U} s_i^U + n_j. \tag{13}$$

C. Uplink and Downlink Spectrum Efficiency

Based on the above analysis, the signal received at the RAU from the ith uplink user mainly consists of three parts: the effective signal transmitted by the ith uplink user, the interference signal transmitted by other uplink users as well as the interference signal transmitted by the base station to all downlink users, and noise. Therefore, the signal-to-interference and noise ratio (SINR) of the ith uplink user received by the RAU is

$$\gamma_i^U = \frac{p_i^U \left\|\bar{\mathbf{g}}_i^U\right\|_2^2}{\sum\limits_{k=1,k\neq i}^{K_U} p_k^U \left\|\bar{\mathbf{g}}_k^U\right\|_2^2 + \sum\limits_{j=1}^{K_D} p_j^D \left\|\overline{\mathbf{H}}_{SI}\mathbf{w}_j^D\right\|_2^2 + \sigma_u^2}. \tag{14}$$

Then, the uplink spectral efficiency of the whole system can be expressed as

$$R_U = \sum_{i=1}^{K_U} \log(1+\gamma_i^U). \tag{15}$$

Similarly, the signal received by the jth downlink user also consists of three parts: the effective signal transmitted by the base station to the jth downlink user, the interference signal transmitted by the base station to other downlink users as well as the interference signal transmitted by all uplink users, and noise. Thus, the SINR of the jth downlink user is

$$\gamma_j^D = \frac{p_j^D \left\|(\bar{\mathbf{g}}_j^D)^H \mathbf{w}_j^D\right\|_2^2}{\sum\limits_{k=1,k\neq j}^{K_D} p_k^D \left\|(\bar{\mathbf{g}}_j^D)^H \mathbf{w}_k^D\right\|_2^2 + \sum\limits_{i=1}^{K_U} p_i^U |g_{i,j,U}|^2 + \sigma_d^2}. \tag{16}$$

Then, the downlink spectrum efficiency of the whole system can be expressed as

$$R_D = \sum_{j=1}^{K_D} \log(1+\gamma_j^D). \tag{17}$$

D. Problem Statement

When the channel condition and user position are determined, the spectrum efficiency of the system is only related to the working mode of the antennas. In this letter, the sum spectrum efficiency of the system is maximized by finding the best antenna selection scheme, and the optimization problem is stated as follows:

$$\max_{\mathbf{x}^U} \; R_U(\mathbf{x}^U) + R_D(\mathbf{x}^U), \tag{18a}$$

$$\text{s.t. } \mathbf{x}^U \in \{0,1\}^{MN\times 1}. \tag{18b}$$

III. Elite Preservation Genetic Algorithm Optimization

In this letter, an intelligent optimization method that employs an elite preservation genetic algorithm is proposed to achieve the maximum spectrum efficiency of the distributed FD system.

A. Algorithm Principle

1) Population Initialization: In (18a), $\mathbf{x}^U$ is a binary solution vector that meets the requirements of the genetic algorithm coding space and is directly used as the individual in the genetic space. The population set at the uth evolution is defined as

$$\mathbf{X}_u^U = \{\mathbf{x}_{u,1}^U, \mathbf{x}_{u,2}^U, \ldots, \mathbf{x}_{u,pop}^U\}, \tag{19}$$

where $\mathbf{x}_{u,r}^U$ is the rth individual of the population set and pop is the population size. The initial population is $\mathbf{X}_1^U$.

2) Fitness Function: The fitness function is an indicator used to judge the pros and cons of individuals in the group. In this letter, the value of the objective function in (18a) can effectively reflect the performance of the antenna working mode selection scheme. Thus, the sum spectrum efficiency is chosen as the fitness function, and the larger the fitness is, the better the individual is. The fitness function $fit(\mathbf{x}^U)$ of the individuals is defined as follows:

$$fit(\mathbf{x}^U) = R_U(\mathbf{x}^U) + R_D(\mathbf{x}^U). \tag{20}$$

3) Selection: The purpose of selection is to select excellent individuals from the current population so that they have the opportunity to breed as parents. The tournament selection strategy is utilized. This strategy first selects n individuals from the population randomly and then compares their fitness. The individual with the highest fitness of these n individuals is chosen as the parent to pass on to the next generation. The above selection process is repeated pop times; then, we can obtain a new population $\mathbf{X}_{u,s}^U$, expressed as follows:

$$\mathbf{X}_{u,s}^U = \left\{\mathbf{x}_{u,s,1}^U, \mathbf{x}_{u,s,2}^U, \ldots, \mathbf{x}_{u,s,pop}^U\right\}. \tag{21}$$

where $\mathbf{x}_{u,s,r}^U$ is the rth individual of the population set after selection.

4) Crossover: Crossover is the main genetic operation in genetic algorithms. A new generation of individuals can be obtained by a crossover operation, which combines the characteristics of parents. In our algorithm, the probability of crossover is P_c. When crossover occurs, a new population $\mathbf{X}_{u,c}^U = \left\{\mathbf{x}_{u,c,1}^U, \mathbf{x}_{u,c,2}^U, \ldots, \mathbf{x}_{u,c,pop}^U\right\}$ is produced based on the following rule:

$$\begin{aligned}\mathbf{x}_{u,c,2v-1}^U = [&\mathbf{x}_{u,s,2v-1}^U(1), \ldots, \mathbf{x}_{u,s,2v-1}^U(k),\\ &\mathbf{x}_{u,s,2v}^U(k+1), \ldots, \mathbf{x}_{u,s,2v}^U(pop)]^T,\end{aligned} \tag{22}$$

$$\begin{aligned}\mathbf{x}_{u,c,2v}^U = [&\mathbf{x}_{u,s,2v}^U(1), \ldots, \mathbf{x}_{u,s,2v}^U(k),\\ &\mathbf{x}_{u,s,2v-1}^U(k+1), \ldots, \mathbf{x}_{u,s,2v-1}^U(pop)]^T,\end{aligned} \tag{23}$$

where $\mathbf{x}_{u,c,r}^U$ is the rth individual of the population set after crossover, k obeys a discrete uniform distribution in $[1, pop]$ and $v = 1, 2, \ldots, \frac{pop}{2}$.

5) Mutation: With the mutation operation, an individual in the population is randomly selected, and the value of a chromosome node of this individual may be changed with a certain probability. The mutation probability is P_m, and the population obtained via mutation is $\mathbf{X}_{u,m}^U = \left\{\mathbf{x}_{u,m,1}^U, \mathbf{x}_{u,m,2}^U, \ldots, \mathbf{x}_{u,m,pop}^U\right\}$ where $\mathbf{x}_{u,m,r}^U$ is the rth individual of the population set after mutation. For each element of $\mathbf{x}_{u,m,r}^U$ with $r = 1, 2, \ldots, pop$, the mutation rule is:

$$\mathbf{x}_{u,m,r}^U(q) = \begin{cases} \mathbf{x}_{u,c,r}^U(q) & p > P_m \\ 1 - \mathbf{x}_{u,c,r}^U(q) & p \leq P_m, \end{cases} \tag{24}$$

where $p \in [0, 1]$ is a uniformly distributed random number and regenerated for each q.

B. Elite Preservation Strategy

To select a new generation of individuals, an elite preservation strategy is employed in our algorithm since this method can obtain the solution close to the globally optimal solution efficiently. When evolving to a new generation by exploiting this strategy, the individuals with the highest fitness are copied directly to the next generation without crossover, mutation or other genetic operations. The main purpose of elite preservation strategy is maintaining the optimal individual found by the population evolution so far. We can preserve the best individual (only one) or a group of the best of the previous generation as long as the main purpose is reached. Here, we preserve the best individual (only one) in our algorithm. Assuming $l_1 = \underset{r=1,2,\ldots,pop}{\arg\max}\ fit(\mathbf{x}_{u,r}^U)$ and $l_2 = \underset{r=1,2,\ldots,pop}{\arg\max}\ fit(\mathbf{x}_{u,m,r}^U)$, the $(u+1)$th generation is produced as follows:

$$\mathbf{X}_{u+1}^U = \begin{cases} \{\mathbf{x}_{u,l_1}^U, \ldots, \mathbf{x}_{u,m,k-1}^U, \mathbf{x}_{u,m,k+1}^U, \ldots\} & f_1 \geq f_2 \\ \mathbf{X}_{u,m}^U & f_1 < f_2, \end{cases} \tag{25}$$

where $f_1 = fit(\mathbf{x}_{u,l_1}^U)$, $f_2 = fit(\mathbf{x}_{u,m,l_2}^U)$ and $\mathbf{x}_{u,m,k}^U$ is the lowest-fitness individual in $\mathbf{X}_{u,m}^U$.

TABLE I

SIMULATION PARAMETERS

Parameter	Value
Cell radius	500 m
Distance between RAUs and center of the circle	200 m
Number of antennas for each RAU N	4,16
Population size pop	50
Crossover probability P_c	0.6
Mutation probability P_m	0.01
Evolution iterations L_{it}	50

C. Complexity Analysis

The detailed steps of the elite preservation genetic algorithm can be found in Algorithm 1. For a given population size pop and iteration number L_{it}, the number of evaluations of the fitness function is equal to $L_{it} \times pop$. The complexity of the proposed algorithm is $\mathcal{O}(L_{it}pop)$, which grows linearly with L_{it} and pop. By contrast, the computational complexity of exhaustive search is $\mathcal{O}(2^{MN})$, which grows exponentially. If MN is large, the complexity savings of our algorithm are significant.

Algorithm 1 Working Mode Selection Algorithm

Input: $\mathbf{g}_i^U, \mathbf{g}_j^D, \mathbf{H}_{SI}, g_{i,j,U}, \mathbf{w}_j^D, p_i^U, p_j^D, N, P_c, P_m, L_{it}$
Initialization:
Initialize the random population set $\mathbf{X}_1^U$ and $u = 1$
Evolution:
while $u \leq L_{it}$ **do**
  Calculate the fitness value of individuals using (20) in $\mathbf{X}_u^U$
  Perform selection and produce $\mathbf{X}_{u,s}^U$ according to (21)
  Perform crossover according to (22) and (23) and produce $\mathbf{X}_{u,c}^U$
  Perform mutation according to (24) and produce $\mathbf{X}_{u,m}^U$
  Generate a new population $\mathbf{X}_{u+1}^U$ with (25)
  $u++$
end while
Output: $\mathbf{x}_{L_{it}+1,l_1}^U$ as the solution for problem (18)

IV. SIMULATION RESULTS

In this section, the performance of the proposed elite preservation genetic algorithm is analyzed through Monte Carlo simulations. A single-cell distributed FD MIMO system is considered, where the users are randomly distributed and $M = 6$ RAUs are uniformly distributed on a circle whose center is the center of the cell. The beamformer $\mathbf{w}_j^D$ is generated by maximum ratio transmission (MRT) precoding. In addition, the downlink power p_j^D is 30 dBm and the uplink power p_i^U is 20 dBm for each user. The other required parameters are listed in Table I.

Fig. 2 shows the cumulative distribution functions (CDFs) of the sum spectrum efficiency of different selection schemes,

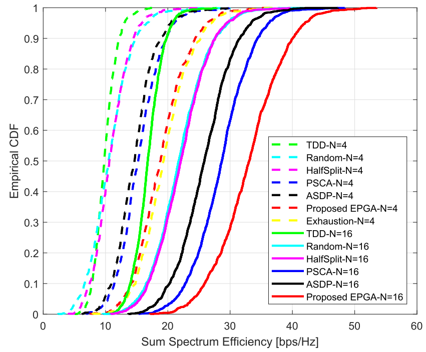

Fig. 2. Comparison of the CDFs of different assignment schemes at $N = 4$ and $N = 16$. The self-interference variance σ_{SI}^2 is -80dB and the Rician factor K_r is set as 0dB.

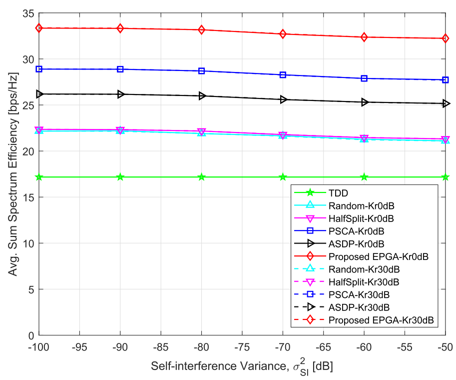

Fig. 3. Average sum spectrum efficiency versus self-interference variance σ_{SI}^2 of different assignment schemes at $N = 16$. The Rician factor K_r is set as 0dB and 30dB.

where the number of users is 16 with 8 uplink and 8 downlink users, and the SNR is set as 10 dB. Since exhaustive search when $N = 16$ has a complexity of $2^{(MN)} = 2^{96}$, which is extremely high, it is impossible for the computer to solve it now. Thus, we make the CDFs figure for different schemes except exhaustive search when $N = 16$.

From Fig. 2, it can be seen that the performance of the proposed EPGA is close to that of the exhaustive search at $N = 4$ and better than the PSCA algorithm mentioned in [5] as well as the A-SDP algorithm mentioned in [6] at $N = 4$ and $N = 16$. Additionally, its performance is much better than that of the random assignment scheme and half-split assignment scheme, where $\mathbf{x}^U = [\mathbf{0}_{MN/2}, \mathbf{1}_{MN/2}]$. The performance of all above schemes in FD system is better than that of TDD system, which shows the great potential of FD system. Furthermore, the growth on the number of antennas per RAU increases the sum SE of all different schemes including TDD.

The performance of the proposed EPGA and other algorithms at different self-interference variance σ_{SI}^2 and Rician factor K_r is illustrated in Fig. 3. As self-interference variance increases, the sum SE of different schemes in FD system gradually declines since the residual self-interference limits the improvement of the sum SE. As the Rician factor grows in FD massive MIMO system, the sum SE of different schemes is nearly unchanged, which shows the Rician factor has less influence than self-interference variance. In addition, our proposed EPGA is better than other schemes in FD system regardless of the self-interference variance and Rician factor.

V. Conclusion

This letter presented an elite preservation genetic algorithm to design an antenna selection scheme in an full-duplex distributed massive MIMO system. The self-interference of each RAU, the interference between different RAUs, and UE-to-UE interference were analyzed, and the antenna selection problem was transformed into an optimization problem maximizing the total spectrum efficiency. Then, the elite preservation genetic algorithm was utilized to solve this optimization problem. The simulation results show that our algorithm is much better than a random assignment and close to an exhaustive search.

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