



# An Elite Genetic Algorithm for Power Allocation in Cell-Free Massive MIMO Systems

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**Abstract.** Network-assisted full-duplex (NAFD) cell-free massive MIMO can greatly improve the spectral efficiency and reduce the unmet system capacity ratio (USCR) by simultaneous downlink and uplink transmission with massive access points (APs). As most existing works focus on the system throughput maximization while ignoring the user requirements. In this paper, we jointly study the dynamic power allocation under the constraint of USCR. An elite genetic algorithm for power allocation is proposed to solve the above problems. Simulation results show that the proposed algorithm significantly reduces the USCR of the cell-free massive MIMO while sufficiently meeting the user requirements.

**Keywords:** Massive MIMO · Cell-free · User-centered · Power allocation

## 1 Introduction

Beyond 5G networks are expected to own the ability to handle more access users with great energy efficiency and ultra-low latencies as well as providing exceptionally high transmission rates while supporting more equitable quality of service (QoS) over the coverage area, which can tackle the problems left by 5G [1]. Therefore, cell-free massive MIMO has a strong appeal to the researchers nowadays due to its ability to overcome the inherent intercell-interference in cellular networks through coherent cooperation between APs [2–4]. Specifically, cell-free massive MIMO uses numerous distributed access points (APs) with simple linear processing capability, which can serve many users coherently with the same time and frequency resources [5–7]. The benefits of massive MIMO and full duplex are

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combined. Moreover, cell-free massive MIMO are much more robust to shadow fading correlation than traditional cellular networks [8]. Therefore, it can provide greatly improved services for all users, regardless of their location. However, the cell-free massive MIMO also brings in several challenges including the severe multi-user interference [9]. Therefore, the concept of network-assisted full-duplex (NAFD) system is proposed [10], which aims to reduce the system performance degradation due to self-interference between uplink and downlink. In a NAFD cell-free massive MIMO system, APs with multiple antennas are distributed in an area and connected to a central processor unit (CPU), which can estimate the channel state information (CSI) among APs with pilot arrangement, via fronthaul to serve users with different communication requirements [11]. Since considering only maximizing the total system spectral efficiency (SE) may lead to poor QoS of users, different from the previous works, we investigate the power allocation in NAFD cell-free massive MIMO to find the optimal power allocation to achieve flexible allocation of system resources and improved system performance. Accordingly, we propose a power allocation algorithm based on elite genetic algorithm. Simulation results show that the proposed power allocation scheme has better QoS under various types of user requirements conditions.

## 2 System Model and Problem Formulation

### 2.1 System Model

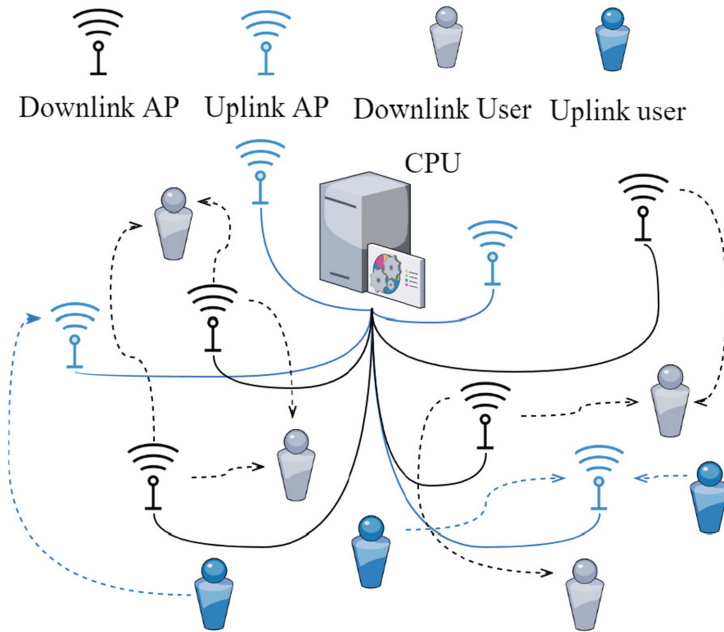


Fig. 1. NAFD cell-free massive MIMO systems.

As depicted in Fig. 1, we consider a NADF cell-free massive MIMO system containing  $K$  users. Based on the user-centric concept, each user considers itself as the center and selects APs whose distances to the user are smaller than the selection radius  $R_s$ . Then, the system will also contain  $M$  APs, which are connected to a CPU by downlink or uplink fronthaul. Moreover, each AP is equipped with  $L$  antennas, and each user is equipped with single antenna, each DL-AP or uplink user is considered as a transmitter, who allocates its power according to the power allocation method to the corresponding downlink users or UL-APs, which are considered as receivers. Theoretically, each full-duplex AP is considered either a downlink transmitting AP (DL-AP) or an uplink receiving AP (UL-AP), and each user is considered either a downlink user or an uplink user as well [3]. Accordingly, we divide the APs into  $M_d$  DL-APs indexed by  $\mathbf{M}_d = \{1, 2, \dots, m_d\}$ , and  $M_u$  UL-APs indexed by  $\mathbf{M}_u = \{1, 2, \dots, m_u\}$ . Meanwhile, we divide the users into  $K_d$  downlink users indexed by  $\mathbf{K}_d = \{1, 2, \dots, k_d\}$  and  $K_u$  uplink users indexed by  $\mathbf{K}_u = \{1, 2, \dots, k_u\}$ .

## 2.2 Downlink Transmission Model

For downlink transmission, in each scheduled time slot, the CPU computes, compresses and transmits the beamforming signals to each DL-AP. Specifically, the received signal at DL-AP  $m_d$  is given as:

$$\mathbf{x}_{d,m_d} = \sum_{k_d=1}^{K_d} \mathbf{p}_{d,m_d,k_d} s_{d,k_d} + \mathbf{q}_{d,m_d}, \quad (1)$$

where  $\mathbf{p}_{d,m_d,k_d} \in \mathbb{C}^{L \times 1}$  represents the linear transmit beamforming and power allocation vector between DL-AP  $m_d$  and downlink user  $k_d$ , and user  $k_d$ ,  $s_{d,k_d}$  is the download transmitted signal for downlink user  $k_d$  with  $\mathbb{E}[s_{d,k_d} s_{d,k_d}^H] = 1$ .  $\mathbf{q}_{d,m_d} \sim \mathcal{CN}(0, \sigma_{q,d,m_d}^2 \mathbf{I}_L) \in \mathbb{C}^{L \times 1}$  denotes the downlink quantization noise at DL-AP  $m_d$ , where  $\sigma_{q,d,m_d}^2$  is the corresponding compression noise power.

Then, the DL-APs transmit their received signals to the downlink users. The signal received at downlink user  $k_d$  can be expressed as:

$$y_{d,k_d} = \sum_{m_d=1}^{M_d} \mathbf{h}_{d,m_d,k_d}^H \mathbf{x}_{d,m_d} + \sum_{k_u=1}^{K_u} h_{k_u,k_d} \sqrt{p_{u,k_u}} s_{u,k_u} + \mathbf{n}_{d,k_d}, \quad (2)$$

where  $\mathbf{h}_{d,m_d,k_d} \in \mathbb{C}^{L \times 1}$  represents the CSI vector between DL-AP  $m_d$  and downlink user  $k_d$ ,  $h_{k_u,k_d}$  denotes the CSI between uplink user  $k_u$  and downlink user  $k_d$ .  $p_{u,k_u}$  is the uplink transmission power of the uplink user  $k_u$ , and  $s_{u,k_u}$  is the corresponding uplink transmitted signal with  $\mathbb{E}[s_{u,k_u} s_{u,k_u}^H] = 1$ .  $\mathbf{n}_{d,k_d} \sim \mathcal{CN}(0, \sigma_{d,k_d}^2)$  is the additive white gaussian noise (AWGN) at downlink user  $k_d$ . Overall, the downlink SE of downlink user  $k_d$  can be expressed as:

$$R_{k_d} = \log_2 \left( 1 + \frac{|\mathbf{h}_{d,k_d}^H \mathbf{p}_{d,k_d}|^2}{\eta_{d,k_d}} \right) \quad (3)$$

where  $\eta_{d,k_d}$  is the covariance interference at downlink user  $k_d$  and can be expressed as:

$$\eta_{d,k_d} = \sum_{k'_d=1, k'_d \neq k_d}^{K_d} | \mathbf{h}_{d,k_d}^H \mathbf{p}_{d,k'_d} |^2 + \sum_{k_u=1}^{K_u} p_{u,k_u} | h_{k_u,k_d} |^2 + \sigma_{q,d,m_d}^2 \| \mathbf{h}_{d,m_d,k_d} \|^2 + \sigma_{d,k_d}^2, \quad (4)$$

where  $\mathbf{h}_{d,k_d} = [\mathbf{h}_{d,1,k_d}^T, \dots, \mathbf{h}_{d,M_d,k_d}^T]^T \in \mathbb{C}^{LM_d \times 1}$  denotes the CSI matrix between all DL-APs and downlink user  $k_d$ ,  $\mathbf{p}_{d,k_d} = [\mathbf{p}_{d,1,k_d}^T, \dots, \mathbf{p}_{d,M_d,k_d}^T]^T \in \mathbb{C}^{LM_d \times 1}$  denotes the transmit beamforming and power allocation vector between DL-APs and downlink user  $k_d$ .

### 2.3 Uplink Transmission Model

For uplink transmission, in each scheduled time slot,  $M_u$  UL-APs jointly receive signals from uplink users. The received signal by UL-AP  $m_u$  can be expressed as:

$$y_{u,m_u} = \sum_{k_u=1}^{K_u} \mathbf{h}_{u,k_u,m_u} \sqrt{p_{u,k_u}} s_{u,k_u} + \sum_{k_d=1}^{K_d} \mathbf{H}_{m_u} \mathbf{p}_{d,k_d} s_{d,k_d} + \mathbf{n}_{u,m_u}, \quad (5)$$

where  $\mathbf{h}_{u,k_u,m_u} \in \mathbb{C}^{L \times 1}$  represents the CSI vector between UL-AP  $m_u$  and downlink user  $k_u$ , and  $\mathbf{n}_{u,m_u}$  denotes the AWGN at UL-AP  $m_u$ .  $\mathbf{H}_{m_u} \in \mathbb{C}^{L \times LM_d}$  denotes the CSI between UL-AP  $m_u$  and all DL-APs. Then, the UL-APs compress the received signals and transmit them to the CPU. The received signal at the CPU can be expressed as:

$$y_u = \sum_{k_u=1}^{K_u} \mathbf{h}_{u,k_u} \sqrt{p_{u,k_u}} s_{u,k_u} + \mathbf{H} \mathbf{x}_d + \mathbf{n}_u + \mathbf{q}_u, \quad (6)$$

where  $\mathbf{h}_{u,k_u} = [\mathbf{h}_{u,k_u,1}^T, \dots, \mathbf{h}_{u,k_u,M_u}^T]^T \in \mathbb{C}^{LM_u \times 1}$  denotes the CSI between the uplink user  $k_u$  and all UL-APs.  $\mathbf{H} = [\mathbf{H}_1^T, \dots, \mathbf{H}_{M_u}^T]^T \in \mathbb{C}^{LM_u \times LM_d}$  denotes the CSI between all UL-APs and DL-APs,  $\mathbf{x}_d = [\mathbf{x}_{d,1}^T, \dots, \mathbf{x}_{d,M_d}^T]^T \in \mathbb{C}^{LM_d \times 1}$  represents the received signal at all DL-APs,  $\mathbf{n}_u = [\mathbf{n}_{u,1}^T, \dots, \mathbf{n}_{u,M_u}^T]^T \in \mathbb{C}^{LM_u \times 1}$  is the AWGN at all UL-APs,  $\mathbf{q}_u = [\mathbf{q}_{u,1}^T, \dots, \mathbf{q}_{u,M_u}^T]^T \in \mathbb{C}^{LM_u \times 1}$  is the uplink compression noise at all UL-APs,  $\mathbf{q}_{u,m_u} \sim \mathcal{CN}(0, \sigma_{q,u,m_u}^2 \mathbf{I}_L) \in \mathbb{C}^{L \times 1}$  denotes the quantization noise at UL-AP  $m_u$ , where  $\sigma_{c,u,m_u}^2$  is the corresponding compression noise power. In order to detect the transmitted signal  $s_{u,k_u}$ , the CPU employs a receive beamforming and power allocation vector  $\mathbf{p}_{u,k_u} = [\mathbf{p}_{u,k_u,1}^T, \dots, \mathbf{p}_{u,k_u,M_u}^T]^T \in \mathbb{C}^{LM_u \times 1}$ .

In addition, since the CPU has the full information of the downlink signal  $s_{d,k_d}$ , the inter-AP interference (IAI) can be modeled as  $\mathbf{H} = \widehat{\mathbf{H}} + \widetilde{\mathbf{H}}$ , where  $\widehat{\mathbf{H}} \in \mathbb{C}^{LM_u \times LM_d}$  denotes the imperfect channel and  $\widetilde{\mathbf{H}} \in \mathbb{C}^{LM_u \times LM_d}$  denotes the

channel estimation error, and since the IAI power can be much stronger than the others, we assume that only the IAI channel is imperfect, and other channel estimates are perfect.

Overall, the uplink SE of uplink user  $k_u$  can be expressed as:

$$R_{k_u} = \log_2 \left( 1 + \frac{p_{u,k_u} | \mathbf{p}_{u,k_u}^H \mathbf{h}_{u,k_u} |^2}{\eta_{u,k_u}} \right), \quad (7)$$

where  $\eta_{u,k_u}$  is the interference-plus-noise at uplink user  $k_u$  and can be expressed as:

$$\begin{aligned} \eta_{u,k_u} = & \sum_{k'_u=1, k'_u \neq k_u}^{K_u} p_{u,k'_u} | \mathbf{p}_{u,k'_u}^H \mathbf{h}_{u,k'_u} |^2 + \mathbf{p}_{u,k_u}^H \sum_{m_d=1}^{M_d} p_{d,m_d} \tilde{\mathbf{H}}_{m_d} \mathbf{p}_{u,k_u} \\ & + \mathbf{p}_{u,k_u}^H (\mathbf{N}_u + \mathbf{Q}_u) \mathbf{p}_{u,k_u}, \end{aligned} \quad (8)$$

where  $p_{d,m_d} = \sum_{k'_d=1}^{K_d} \| \mathbf{h}_{d,m_d,k_d} \|^2 + L \sigma_{q,d,m_d}^2$ ,  $\tilde{\mathbf{H}}_{m_d} = \text{diag}(\sigma_{1,m_d}^2 \mathbf{I}_L, \dots, \sigma_{M_u,m_d}^2 \mathbf{I}_L)$ ,  $\mathbf{N}_u = \mathbf{n}_u \mathbf{n}_u^H = \text{diag}(\sigma_{u,1}^2 \mathbf{I}_L, \dots, \sigma_{u,m_u}^2 \mathbf{I}_L)$  and  $\mathbf{Q}_u = \mathbf{q}_u \mathbf{q}_u^H = \text{diag}(\sigma_{q,u,1}^2 \mathbf{I}_L, \dots, \sigma_{q,u,m_u}^2 \mathbf{I}_L)$ .

## 2.4 Problem Formulation

Most existing works focused on maximizing the sum SE of users in the system, i.e.  $\sum_1^K R_k$ , which ignores user requirements, leads to poor insufficient user satisfaction and waste of resources. To solve this problem, we define the unmet system capacity ratio (USCR) in Eq. 9 (note that there is no extra benefit in providing data rate that exceeds the requirements) [12]:

$$USCR = \sum_1^K \max(R_{r,k} - R_k, 0) / \sum_1^K R_{r,k}, \quad (9)$$

where  $R_{r,k}$  indicates the SE requirement of  $k$ -th user at the current time slot. In terms of constraints, we assume that both the uplink and downlink transmissions are limited by the maximum transmit power. To maximize QoS, our object is to minimize USCR by allocating power subject to the constraints, as mentioned before, this can be formulated as the following mathematical program:

$$\begin{aligned} \min \quad & USCR \\ \text{s.t.} \quad & 0 \leq p_{d,m_d} \leq P_d, \\ & 0 \leq p_{u,k} \leq P_u, \end{aligned} \quad (10)$$

where Ineq. 10 indicates the lower and upper limits of transmission power of each DL-AP and user respectively.

### 3 The Power Allocation Based on Elite Genetic Algorithm

Due to the high computational cost of finding the optimal solution to solve the resource allocation problem, we turn to the metaheuristic optimization method. Genetic algorithm is one of the effective ways to address these problems, and in this section, we will briefly introduce the genetic algorithm. Genetic algorithm searches for optimal solutions by simulating natural evolutionary processes. The process of solving the problem is transformed into a process similar to the intersection and mutation of chromosomal genes in biological evolution. The basic framework of genetic algorithm includes encoding, initial population selection, genetic operations, and fitness function evaluation. The initial individuals are changed by genetic operators such as selection, crossover and variation. Finally, the individual with the greatest fitness will be selected as the optimal solution through the evaluation and the judgment of termination criterion.

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#### Algorithm 1. Elite Genetic Algorithm-based Power Allocation

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1:  $pop \leftarrow \text{INITPOPULATION}(N_{ind})$ 
2: for  $gen = 1$  to  $N_{gen}$  do
3:   for  $ind$  in  $pop$  do
4:      $ind.fitness \leftarrow \text{EVALUATESOLUTIONFITNESS}(ind, env)$ 
5:   end for
6:
7:    $elites, pop' \leftarrow \text{SORTBYFITNESS}(pop)$ 
8:    $pop'' \leftarrow \text{MAINTAINPOPULATION}(pop')$ 
9:
10:   $stop \leftarrow \text{TERMINATIONCRITERION}()$ 
11:  if  $stop$  then
12:    break
13:  end if
14:
15:   $offspring \leftarrow \text{TOURNAMENTSELECTION}(pop'')$ 
16:   $offspring' \leftarrow \text{CROSSOVERANDMUTATION}(offspring)$ 
17:   $pop \leftarrow offspring' + elites$ 
18:
19: end for
20: return  $pop.top$ 
21:
22: function  $\text{EVALUATESOLUTIONFITNESS}(ind, env)$ 
23:    $ind \leftarrow \text{CONSTRAINTHANDLING}(ind)$ 
24:    $scheme \leftarrow \text{DEPLOYMENT}(ind, env)$ 
25:    $USCR \leftarrow \text{CALCULATEUSCR}(scheme)$ 
26:   return  $-USCR$ 
27: end function

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Algorithm 1 presents details of our proposed algorithm. Initially, a population of individuals is created by assigning random values of power allocation vectors, and in practice, in order to avoid invalid search and speed up convergence, we take some proven excellent power allocation vectors as part of the initial individuals. Then, for each generation, all individuals will be evaluated and ranked. Next, to protect individuals with better fitness, the top ranked individuals will be set as elites according to the elite rate. In addition, to maintain the stability of the size of population, the last few individuals will be eliminated, while the others, a subset of individuals from the population will be selected and applied through the crossover and mutation operators. To be specific, crossover operations randomly combine the characteristics (some elements in the power distribution vector) of two individuals (parents) to produce a pair of new individuals (offspring), and mutation operations assign new values randomly to the power allocation vector, making it possible for the algorithm to derive different solutions. Finally, the offspring are born, and they will form a new population with the elites in the next generation. In order to ensure that the solution can be obtained in time, we set the maximum number of iterations of the algorithm, which means the process will continue until generation  $N_{gen}$  is reached. Furthermore, to avoid the algorithm falling into invalid iterations, we set termination criterion as well which will terminate the iterations when the convergence criterion in Ineq. 11 is met.

$$\frac{\max(USCR_{i-1}, \dots, USCR_{i-20}) - USCR_i}{USCR_i} \leq threshold, \quad (11)$$

where  $USCR_i$  indicates the  $i$ -th generation lowest USCR and the convergence criterion ensures that the algorithm will stop when the optimization beyond the threshold cannot be achieved in all last 20 generations. In this paper, we generate new power allocation vectors through initialization, crossover and mutation. Then, the negative value of USCR is set as the fitness function to iteratively select the optimal power allocation vector that can minimize USCR. In addition, due to the limitation of uplink and downlink transmission power, when the total power allocated by the new power allocation vector is greater than the corresponding upper power limit, the allocated power needs to be reduced proportionally to ensure that the total power is no more than the corresponding upper power limit. Similarly, the allocated power will not be less than the lower power limit to ensure that it will not allocation negative power.

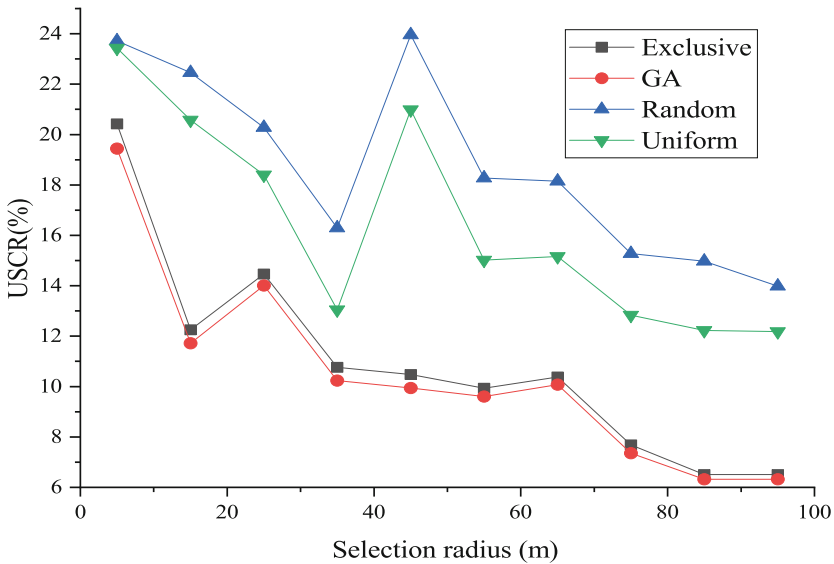
## 4 Numerical Results and Discussion

In this section, some numerical results are provided to validate the performance of our proposed scheme under different system parameters. We consider a cell-free system in a circular area, and in order to simplify the system, the density of uplink and downlink APs is equal to  $\rho_{AP}$ . Besides, we model the variance and mean value of user requirements as  $\sigma^2(R_r)$  and  $R_r$  respectively. Moreover, the detailed system configurations are listed in Table 1 [13].

**Table 1.** Simulation parameters

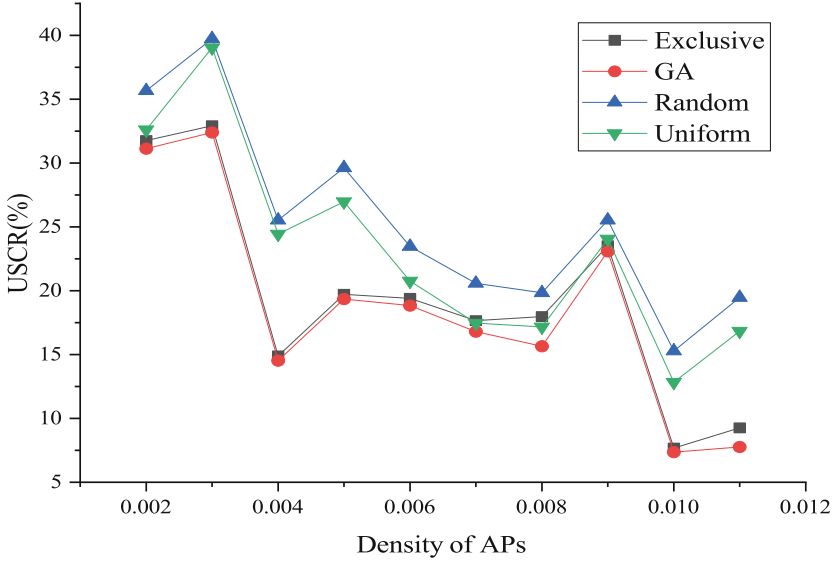
Parameter	Value
Radius	120 m
Density of downlink/uplink users	0.001
Number of antennas	4
The maximum power of the DL-APs	30 dBm
The maximum power of the users	20 dBm
Path loss	$128.1+27.6\lg(d)$
Lognormal shadowing	8 dB
Rayleigh fading	0 dB
Size of population	2000
Threshold	0.1%

Three commonly used algorithms are compared with ours: In Uniform Allocation, each transmitter allocates power uniformly to all receivers. While in Random Allocation, the transmitter randomly allocates power to the receivers. In Exclusive Allocation, the transmitter allocates all its power to a particular receiver which has the best channel state.



**Fig. 2.** USCR versus user selection radius with  $\sigma^2(R_r) = 10, \overline{R_r} = 7bps/Hz$  and  $\rho_{AP} = 0.01$

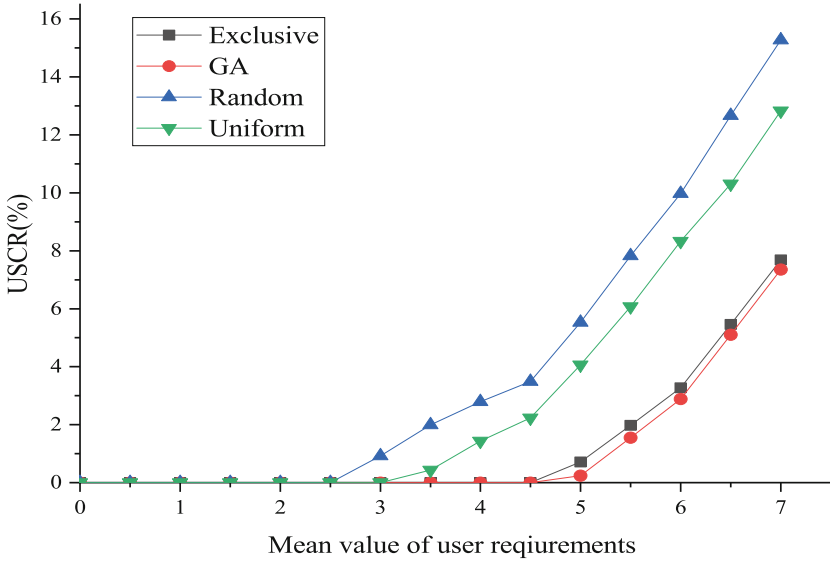
Figure 2 and Fig. 3 depict the user selection radius and density of AP versus USCR respectively. As we can see, the proposed scheme is superior to other



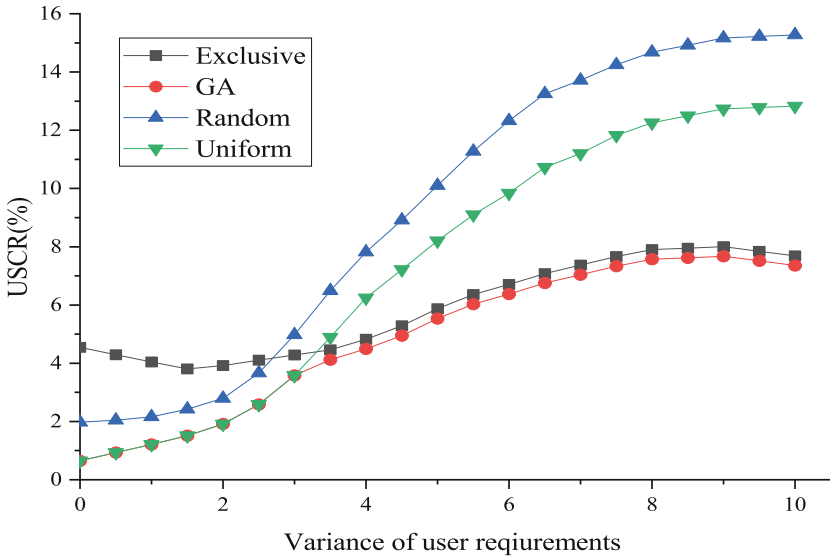
**Fig. 3.** USCR versus density of AP with  $\sigma^2(R_r) = 10$ ,  $\overline{R_r} = 7\text{bps/Hz}$  and  $R_s = 75\text{m}$

schemes under various conditions. Specifically, as the user selection radius and density of AP increase, which means the number of APs increase, USCRs have the overall declining trend for all four schemes, which indicates that the increase in the number of APs can enhance the data rates and thus decrease the USCRs. However, all curves in the two figures do not monotonically decrease similarly also suggests that simply increasing the number of APs is not a panacea for our problems, it is because that as the number of APs increases, the complexity of the system increases as well, which leads to more interference that offsets the data rates it provides.

Figure 4 and Fig. 5 illustrate the mean value and variance of user requirements verse USCR respectively. As expected, the proposed scheme outperforms the traditional schemes under each user requirements case. In addition, the USCR of all four schemes increases with the mean value and variance of user requirements, but the proposed scheme increases more slowly and has a more significant advantage over the traditional allocation scheme especially when the mean value and variance of user requirements are large due to the ability to dynamically select a better power allocation method to meet the current user requirements and to achieve lower USCR.



**Fig. 4.** USCR versus mean value of user requirements with  $\sigma^2(R_r) = 10$ ,  $R_s = 75m$  and  $\rho_{AP} = 0.01$



**Fig. 5.** USCR versus variance of user requirements with  $\overline{R_r} = 7bps/Hz$ ,  $R_s = 75m$  and  $\rho_{AP} = 0.01$

## 5 Conclusion

In this paper, the power allocation problem in NAFD cell-free massive MIMO systems is investigated. The USCR is minimized by adjusting the power distribution method according to the dynamic user requirements. An elite genetic algorithm-based power allocation algorithm is proposed to solve this problem. Simulation results show that the proposed scheme achieves higher improvements than the uniform, exclusive and random allocations under various user requirements. In future work, we will study the power allocation method with user fairness in continuous communication scenarios.

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