Lightweight AP selection algorithm for uniform quality everywhere in Cell-Free massive MIMO

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***Abstract*—We propose an AP selection algorithm that is computationally lightweight and feasible for uniform radio quality in wide-area deployment for cell-free massive MIMO (CF-mMIMO). To address the scalability problem in a large-scale CF-mMIMO, recent studies involved the use of distributed CPU architecture and an optimized method of AP selection for each user based on the received signal power, channel state, and user mobility. An AP selection algorithm that achieves uniform quality everywhere with lightweight computation is needed to adapt user mobility and maintain high radio quality. In addition, the algorithm needs to overcome the radio quality degradation of area boundary UEs due to inter-site interference in distributed CPUs. As an algorithm for AP selection, optimization-based methods have been proposed to maximize the throughput sum rate or fairness index. However, these methods require inverse matrix calculations per UE for the objective function, resulting in computational complexity becoming an issue. To address this problem, we propose a list-processing AP selection algorithm that selects APs that contribute to quality improvement to uniform signal power and interference effects among users without inverse matrices calculation for estimating the radio quality and a metaheuristic solution search. Simulation results show that the proposed method can provide uniform and high radio quality in urban environments with a large number of UEs.**

***Index Terms*—6G, Cell-free massive MIMO, RAN management, user-centric RAN.**

I. INTRODUCTION

Various consortiums and standardization task groups have been actively studying use cases for the 6th generation mobile communication system (6G), which is expected to be commercially available around 2030 [1]-[3]. According to these studies, one of the common use cases described is the coexistence of mobile robots and humans, an arrangement that will contribute to addressing the issue of labor shortages. Safety is the most critical factor for the coexistence of mobile robots and humans. For safety, constant monitoring and operation from the cloud via 6G are needed wherever the robot is. Therefore, uniform and high radio quality, anytime and anywhere, is needed in 6G.

The existing mobile communication systems based on the cellular architecture, such as 5th generation (5G), have a problem because the radio quality at the cell edge degrades due to high path loss and inter-cell interference. Cell-free massive MIMO (CF-mMIMO) [4] has attracted attention as an emerging technology that solves the problem and achieves uniform radio quality. In CF-mMIMO, access points (APs) are densely distributed around user equipment (UE), and wireless communication signals are transmitted/received through coordination among APs. A central processing unit (CPU) performs centralized processing for the radio signals from/to the APs. The CPU can remove the cell edges by cooperating with the radio signals and eliminating inter-cell interference. In the initially proposed CF-mMIMO [4], all APs were connected to one CPU, and the CPU processed signals from all UEs. Therefore, there is a scalability issue with the computational load of processing radio signals from all APs and the transmission load between the CPU and APs. To address the scalability problem, recent studies involved using distributed CPU architecture and an optimized method of AP selection for each user based on the received signal power, channel state, and user mobility [5]-[11].

The authors have been studying user-centric radio access network (RAN) architecture toward realizing uniform radio quality with a distributed CPU architecture and aiming for CF-mMIMO deployment in urban areas by a mobile network operator (MNO) [11]-[13]. In the user-centric RAN, the AP cluster is the set of APs that send and receive radio signals and is created per UE. A user-centric RAN intelligent controller (uRIC) needs to manage AP selection according to changes in the wireless environment, which varies from time to time due to user mobility. An AP selection algorithm for AP clusters that achieves uniform quality everywhere with lightweight computation is needed to reduce the number of servers due to the increased computational load. As an algorithm for AP selection, optimization methods have been proposed to maximize the throughput sum rate or fairness index [7]-[11]. However, these methods require inverse matrix calculations per UE for the objective function, resulting in computational complexity becoming an issue. On the other hand, rule-based AP selection algorithms with light computational complexity have also been proposed [5]-[6]. However, these methods do not consider the radio quality degradation of area boundary UEs due to inter-site interference [11] in distributed CPUs. Accordingly, they cannot provide sufficiently uniform radio quality everywhere.

To address this computational load problem, we propose a lightweight AP selection algorithm that suppresses inter-site interference. The proposed algorithm handles interference clusters as a metric to control the suppression of inter-site interference and reduce the computational processing load. Here, the interference cluster indicates the set of UE-APs to suppress interference among AP clusters, including inter-site interference. To maximize the use of computational resources, the proposed algorithm adds APs with high reference signal received power

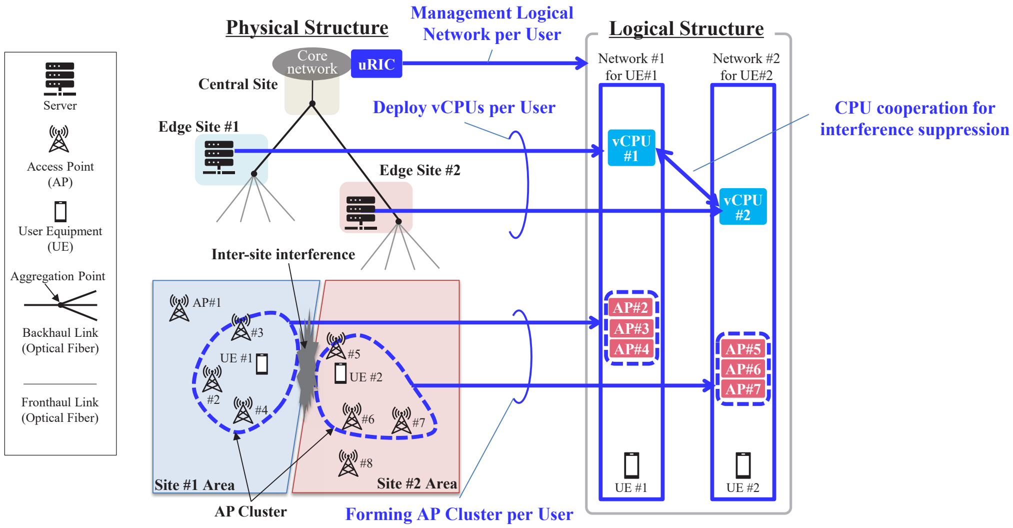

Fig. 1. Architecture of user-centric RAN.

(RSRP) between AP-UE that contribute to quality improvement to the interference clusters and AP clusters up to the upper limit of the resources. In these cluster extensions, we prioritize user groups with low RSRP of the AP cluster and high interference from outside the AP cluster to uniform signal power and interference effects among users. This AP selection process is lightweight because it consists of simple RSRP-based calculations and listing operations and does not require inverse matrix calculations and a metaheuristic solution search for the optimization approach in [7]-[11].

The rest of this paper is organized as follows. Section II describes the architecture of user-centric RAN and problems for AP selection. In Section III, we propose an AP selection method. In Section IV, we evaluate the effectiveness of the proposed method by simulation. In Section V, we conclude the paper.

II. System Model

A. *Architecture of user-centric RAN*

The architecture of user-centric RAN towards achieving uniform and high radio quality everywhere with CF-mMIMO is shown in Fig. 1. The concept of user-centric RAN is to generate a logical network per user on a physical infrastructure based on virtualized base station functions such as vCPU per user which processes signals from APs. We assume a double-star topology, typical in an optical access network [14], as the physical topology. The L APs placed in an area are connected to J edge sites via mobile front haul link such as optical fiber and radio relays. Each edge site is connected to a central site which aggregates all traffic in the area, and traffic from each edge site is aggregated at the central site via a backhaul (BH).

To manage radio quality for each user and the computational and transmission load in the user-centric RAN, a logical network per user is built by allocating physical resources. The vCPU which processes signals from APs is deployed per user at each edge site. The AP cluster is the set of APs that send and receive radio signals, and it is created per user. The vCPU cooperation is the operation of the suppression of the interference between independent AP clusters, including inter-site interference. uRIC, which is responsible for controlling the RAN, manages radio quality according to each user's mobility and demand. Considering user mobility, it is necessary to change the AP selection for AP clusters in response to changes in the wireless environment, which change from time to time depending on mobility.

B. *Mathematical formulation*

We consider K single-antenna UEs, and each UE k connects to the AP l with the highest power by measuring the periodically broadcasted synchronization signals. This paper assumes that the vCPU of UE k is deployed at an edge site to which the AP l connects. AP clustering is performed based on the method proposed in [6]. The AP index, which belongs to an AP cluster, $\boldsymbol{D}_k$, is defined as the following L-dimensional square matrix,

$$\boldsymbol{D}_k = \begin{bmatrix} D_{k1} & \dots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \dots & D_{kL} \end{bmatrix}, \tag{1}$$

where D_{kl} is defined as

$$D_{kl} = \begin{cases} 1 & \text{if the AP } l \text{ serves UE } k, \\ 0 & \text{otherwise.} \end{cases} \tag{2}$$

Let $\mathcal{M}_k$, which is the set of APs with $D_{kl}=1$, be the AP cluster for UE k. The signal to interference and noise ratio (SINR) of the uplink and downlink for UE k is defined as [6]

$$\mathrm{SINR}_k^{(\mathrm{UL})} = \frac{p_k \left|\boldsymbol{v}_k^H \boldsymbol{D}_k \hat{\boldsymbol{h}}_k\right|^2}{\sum_{i=1, i\neq k}^{K} p_i \left|\boldsymbol{v}_k^H \boldsymbol{D}_k \hat{\boldsymbol{h}}_i\right|^2 + \boldsymbol{v}_k^H \boldsymbol{Z}_k \boldsymbol{v}_k}, \tag{3}$$

$$\mathrm{SINR}_k^{(\mathrm{DL})} = \frac{\rho_k \left|\boldsymbol{D}_k \hat{\boldsymbol{h}}_k \boldsymbol{w}_k\right|^2}{\sum_{i=1, i\neq k}^{K} \rho_i \left|\boldsymbol{D}_k \hat{\boldsymbol{h}}_i \boldsymbol{w}_k\right|^2 + \sigma^2}, \tag{4}$$

where $\boldsymbol{Z}_k = \boldsymbol{D}_k\left(\sum_{i=1}^{K} p_i \boldsymbol{C}_i + \sigma^2 \boldsymbol{I}_L\right)\boldsymbol{D}_k$, p_k and ρ_k are the power of the uplink and downlink signal, respectively, and $\hat{\boldsymbol{h}}_i$ is the estimated channel coefficient. The channel coefficients are estimated with the minimum mean square error (MMSE) based on the pilot assignment method [6]. $\boldsymbol{C}_i$ is a matrix of the channel estimation error for the UE i, which is obtained from the difference between the spatial channel correlation matrix estimated with the MMSE and a real one. σ^2 is the power of thermal noise, and $\boldsymbol{I}_L$ is the L-dimensional identity matrix. $\boldsymbol{v}_k$ and $\boldsymbol{w}_k$ are respectively the combining vector and precoding vector for UE k. In the method proposed in [11], the authors define a new metric, interference cluster, which indicates the combination of APs that handle interfering signals for each user. Let interference cluster $\boldsymbol{E}_k$ belong to the set of APs whose signal power from the UE exceeds the threshold and be defined as the following L-dimensional square matrix.

$$\boldsymbol{E}_k = \begin{bmatrix} E_{k1} & \dots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \dots & E_{kL} \end{bmatrix}, \tag{5}$$

where, E_{kl} is defined as

$$E_{kl} = \begin{cases} 1 & \text{if UE } k \text{ causes interference to the AP } l, \\ 0 & \text{otherwise.} \end{cases} \tag{6}$$

Note that interference cluster $\boldsymbol{E}_k$ includes AP cluster $\boldsymbol{D}_k$, and if $D_{kl} = 1$, $E_{kl} = 1$. While the AP cluster $\boldsymbol{D}_k$ represents the set of APs that transmit and receive for UE k, the interference cluster $\boldsymbol{E}_k$ indicates the set of APs that perform channel estimation for UE k. In P-MMSE, interference cluster $\boldsymbol{E}_k$ is not defined because $\boldsymbol{E}_k$ is treated as equal to the AP cluster $\boldsymbol{D}_k$. Therefore, interference cluster $\boldsymbol{E}_k$ is defined as a new AP set different from the AP cluster. In the mathematical expression, the combining vector and precoding vector are as follows.

$$\boldsymbol{v}_k = p_k\left(\textstyle\sum_{i\in\mathcal{P}_k} p_i \boldsymbol{D}_k \boldsymbol{E}_i \widehat{\boldsymbol{h}}_i \widehat{\boldsymbol{h}}_i^H \boldsymbol{E}_i \boldsymbol{D}_k + \boldsymbol{Z}_k\right)^{\dagger} \boldsymbol{D}_k \boldsymbol{h}_k. \tag{7}$$

$$\boldsymbol{w}_k = \frac{\boldsymbol{v}_k}{\sqrt{\boldsymbol{v}_k^H \boldsymbol{v}_k}}. \tag{8}$$

Here, $\mathcal{P}_k$ is the set of UEs where the AP cluster for the UE is formed with at least one AP as used in the AP cluster for UE k expressed as $\mathcal{P}_k = \{i : \boldsymbol{D}_k \boldsymbol{E}_i \neq \boldsymbol{O}_L\}$ where $\boldsymbol{O}_L$ is the L-dimensional zero matrix. The user throughput TP_k for UE k is calculated with SINR as $TP_k = W_{\mathrm{RF}} \log_2(1 + \mathrm{SINR}_k)$. Here, W_{RF} is the total bandwidth of the wireless link.

The total computational load involved in the signal processing required for each site is defined as the computer load C_{comp}, which is given by the following equation

$$C_{\mathrm{comp}} = \textstyle\sum_{k\in K}\{C_{\mathrm{est}}(k) + C_{\mathrm{weight}}(k)\}, \tag{9}$$

where C_{est} is the computational load required for the channel estimation of the UE, C_{weight} is the computational load required for the weight vector calculation of UE k, which can be expressed as follows

$$C_{\mathrm{est}}(k) = \left(N\tau_p + N^2\right)|\mathcal{M}_k||\mathcal{P}_k|, \tag{10}$$

$$C_{\mathrm{weight}}(k) = \frac{(N|\mathcal{M}_k|)^2 + N|\mathcal{M}_k|}{2}|\mathcal{P}_k| + (N|\mathcal{M}_k|)^2 + \frac{(N|\mathcal{M}_k|)^3 - N|\mathcal{M}_k|}{3}. \tag{11}$$

Here, N is the number of antennas deployed in the AP, and τ_p is the number of pilot sequences. As the number of UEs increases, C_{comp} also increases because $\mathcal{P}_k$ rises. In order to control the increasing computational load of the RAN as the number of UEs increases, it is necessary to reduce $\mathcal{M}_k$, which indicates the number of APs in AP cluster for UE k [6].

C. *Problem statement and related works*

In this section, we design the problem of providing uniform and high radio quality and present the existing approaches and challenges to be addressed. The optimization problem of providing uniform and high radio quality in a user-centric RAN can be designed as follows.

$$\max_{D_{k,l}, E_{k,l}} \; FI, TP, \tag{12a}$$

$$\text{s.t.:} \quad C_{Th} \geq C_{comp}, \tag{12b}$$

Here, $TP = \sum_{k\in K} TP_k$ and denotes the throughput of the entire area. FI is the fairness index [15] as a metric for uniformity, described as follows, with throughput per user as a variable.

$$FI = \frac{\left(\sum_{k\in K} TP_k\right)^2}{K \sum_{k\in K}(TP_k)^2} \tag{13}$$

(12a) presents a multi-objective optimization problem that maximizes the throughput of the entire area and the Fairness index between users, respectively. (12b) shows the constraint that is less than or equal to the deployed computer resource C_{Th}. Approaches in existing methods for the problem (12) have proposed heuristic methods to search for quasi-optimal solutions [7]-[11]. In the search for a solution, inverse matrix calculation is required to calculate the SINR for each UE for the objective function. The complexity in inverse matrix calculation is proportional to the third power with respect to the number of UE and AP [6], so the computational complexity is an issue when the number of UEs increases. In addition, the problem (12) is a nonlinear and nonconvex optimization problem, so it is necessary to heuristically search for a quasi-optimal solution as the number of UEs increases. Assuming a large-scale deployment of CF-mMIMO, a large number of searches are required to find a high-quality suboptimal solution, resulting in an increase in computational complexity. In [11], the authors use a genetic algorithm, one of the metaheuristic algorithms, to search for a solution of this type of optimization problem. However, the authors pointed out that the high computational complexity of the algorithm is an issue. On the other hand, lightweight rule-based methods that do not use SINR calculation or solution search have also been proposed [5]-[6]. These methods, however, do not consider the radio quality degradation of area boundary UEs due to inter-site interference [11] in distributed CPUs. Accordingly, they cannot provide sufficiently uniform radio quality.

III. PROPOSED ALGORITHM

We propose a lightweight AP selection algorithm that suppresses inter-site interference for large-scale deployment in CF-mMIMO. The proposed algorithm does not require a metaheuristic search or the high computational load incurred in calculating inverse matrices for estimating the radio quality of users because the AP selection is based on the distribution of RSRPs and listing operations. To control the suppression of inter-site interference, the proposed algorithm defines interference clusters as a metric to be handled. The proposed AP selection algorithm suppresses inter-site interference and does not require metaheuristic search or high computation of inverse matrices calculation for estimating the radio quality of users.

Specifically, to uniform the signal power of the AP cluster for each user, we classify user groups based on the distribution of RSRPs that form the AP cluster, and gradually expand the AP cluster for the user group with low RSRP. At the same time, to uniform the interference effects, the interference clusters are gradually expanded, prioritizing user groups with low total interference from outside the AP cluster. By repeating the operation of expanding these two clusters up to the upper limit of computational resources for signal processing, we achieve uniformity of radio quality while utilizing computational resources to the maximum extent possible.

Next, we present the proposed AP selection algorithm in detail in Algorithm 1.

Algorithm 1

Input: $P_{l,k}, x_{ini}, y_{ini}$

1: **for** k = 1 to K **do** #Initial state decision
2: **for** l=1 to x_{ini} **do**
3: $D_{kl} = 1$ ($l = \text{Argmax}_{l \in D_{kl}=0} P_{l,k}$)
4: **end for**
5: **for** l=1 to y_{ini} **do**
6: $E_{kl} = 1$ ($l = \text{Argmax}_{l \in E_{kl}=0} P_{l,k}$)
7: **end for**
8: **end for**
9: x_k=x_{ini} , y_k=y_{ini}
10: **while true** #Expand clusters per UE.
11: **for** k=1 to K **do**
12: $P_k^s = \sum_{l \in (D_{kl}=1)} P_{l,k}$, $P_k^i = \sum_{l \in (E_{kl}=0)} P_{l,k}$
13: **end for**
14: $P_{r,k} \sim N(\mu_x, \sigma_s^2)$, $P_{i,k} \sim N(\mu_y, \sigma_i^2)$
15: $\mathcal{X}_{low} = \{k| -\sigma_x > P_{r,k}\}$, $\mathcal{X}_{mid} = \{k| -\sigma_x < P_{r,k} < \sigma_x\}$
16: $\mathcal{Y}_{low} = \{k\,|\sigma_y < P_{i,k}\}$, $\mathcal{Y}_{mid} = \{k| -\sigma_y < P_{i,k} < \sigma_y\}$
17: **for** k=1 to K **do** #Prioritize of UE.
18: **if** ($k \in \mathcal{X}_{low}$): $x_k = x_k + N_{low}$
19: **if** ($k \in \mathcal{Y}_{low}$): $y_k = y_k + N_{low}$
20: **if** ($k \in \mathcal{X}_{mid}$): $x_k = x_k + N_{mid}$
21: **if** ($k \in \mathcal{Y}_{mid}$): $y_k = y_k + N_{mid}$
22: **for** l=1 to x_k **do**
23: $D_{kl} = 1$ ($l = \text{Argmax}_{l \in D_{kl}=0} P_{l,k}$)
24: **end for**
25: **for** l=1 to y_k **do**
26: $E_{kl} = 1$ ($l = \text{Argmax}_{l \in E_{kl}=0} P_{l,k}$)
27: **end for**
28: **end for**
29: **if** $C_{comp} > C_{max}$ #Utilize computational resources
Restore D_{kl} and E_{kl} to the values one loop ago, **break**
30: **end while**

Output: D_{kl}, E_{kl}

$P_{l,k}$, which is the value of the RSRP between UE k and AP l, and the initial values x_{ini} and y_{ini} of the number of APs x_k associated with the AP cluster and the number of APs y_k associated with the interference cluster are entered. x_{ini} and y_{ini} are the minimum AP values required for phase control for interference suppression. In Steps 1-8, initial values for AP clusters and interference clusters are formed. The AP clusters and interference clusters are associated with the APs in order of increasing $P_{l,k}$. In Step12, calculate the total signal power P_k^s from the AP cluster and the total interference power P_k^i outside the interference cluster. The next operation is to expand the AP cluster and the interference cluster so that this P_k^r and P_k^i are uniform. If a large number of APs are associated with a particular UE, the amount of signal processing for the UE will increase significantly, and the system throughput TP will decrease. Therefore, we divide UEs into multiple groups and expand clusters for each group to achieve balanced AP selection among UEs. In Steps 14-16, assume that P_k^s follow a normal distribution and calculate the user group $\mathcal{X}_{\text{low}}$ with low P_k^s and middle user group $\mathcal{X}_{\text{low}}$ with middle P_k^s based on the standard

TABLE I
SIMULATION PARAMETERS

Parameter	Value
The number of APs, L	100
Location of APs and UEs	Random with uniform distribution
User traffic	Full buffer
Carrier frequency, Bandwidth	3.5 GHz, 100MHz
Transmission power of UE	100 mW
Subcarrier spacing	30 kHz
Number of pilot sequences	24
Quantization bit rate	16 bits/symbol
Path loss and Channel fading	3GPP-UMi [16], Rayleigh fading
Channel estimation	MMSE [17]
Shadowing deviation	10 dB
Noise figure	7 dB
C_{Th}	30 GFLOPs

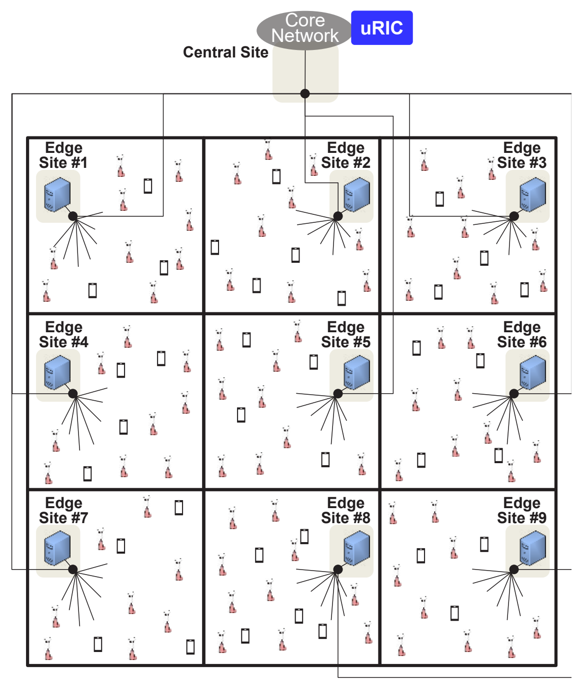

Fig. 2. Evaluation environment. The figure shows that the number of edge sites is nine.

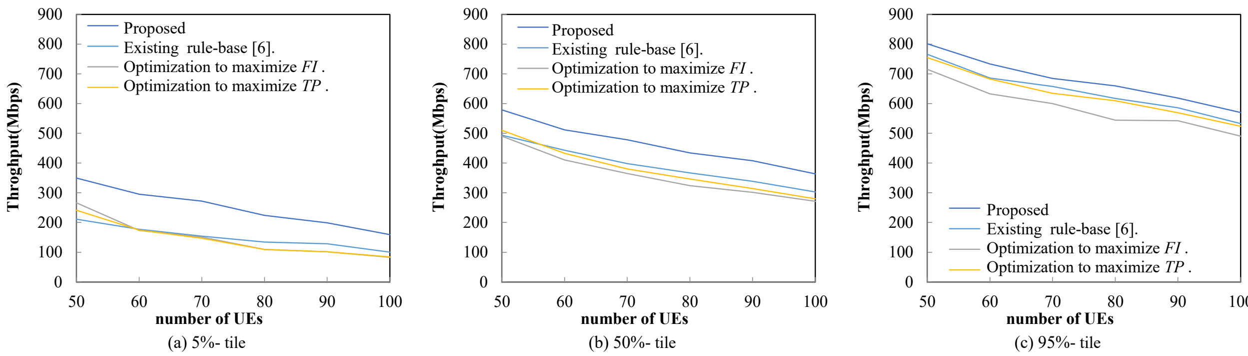

Fig. 3. Comparison of the 5th, 50th and 95th percentile user throughput.

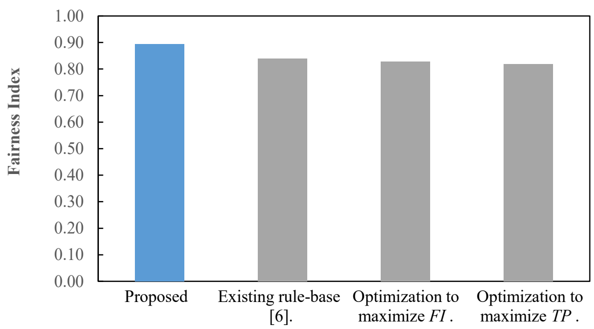

Fig. 4. Comparison of the average fairness index.

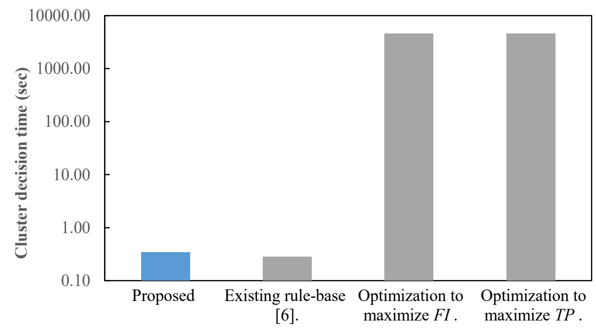

Fig. 5. Comparison of the average cluster decision time.

deviation σ_s. Perform the same operation for interference P_k^i. In Steps 17-28, the AP cluster is expanded by N_{low} or N_{mid} for each UE group. Here, N_{low}>N_{mid}, and the user group $\mathcal{X}_{\text{low}}$ is prioritized to expand the AP cluster. The same operation is performed for the interference clusters, and the UE group $\mathcal{Y}_{\text{low}}$ with high interference is prioritized to expand the interferer cluster. Repeating Steps 10-30 allows uniformity and system throughput improvement with no bias among UEs while uniforming P_k^s and P_k^i among users not to exceed the computational upper limit. According to Steps 10-30 in algorithm 1, the proposed AP selection process consists of quadratic calculations based on the SS-RSRP, defined as measurement information in 3GPP. In other words, the proposed method does not estimate SINR using P-MMSE, the computational complexity of which increases with the cube of the number of UEs and APs. In addition, the number of searches in the proposed algorithm is at most *LK*, which reduces the increase in computational load with respect to the increase in the number of users compared to heuristic approaches that search in the range of $2^{(L+K)}$.

IV. Performance Evaluation

Table I shows the computer simulation conditions and Fig. 2 shows evaluation environment. These simulation parameters assume a service deployment of CF-mMIMO with sub-6 frequency range in urban areas. One hundred APs are placed at random in an area of 1 km^2. Based on the user-centric RAN architecture, one central site covers the area, and $J = 9$ edge sites are placed to divide the area into four sections in a grid pattern. Each AP is connected to the edge site of the deployed divided area. Since the terminal is stationary, the calculation is repeated ten times to allow a statistical evaluation to be made. We show that the proposed method can provide uniform and high radio quality with a light computational load by comparing the proposed method with existing methods in terms of user throughput, fairness index, and computation time for determining AP selection. As a comparison, we choose three methods: an existing rule-based method [5] and two methods that search for a quasi-optimal solution to the optimization problem (12) by the objective function.

First, we show the simulation results of the comparison of the downlink 5th, 50th and 95th percentile user throughput, in Fig. 3 when the number of UEs is 50. Figure 3 shows that the proposed method provides higher *TP*, especially for UEs with low throughput, compared to the existing methods. Figure 4 shows a comparison of the mean values of the fairness index. We find that the proposed method provides the highest *FI*, indicating that the radio quality is uniform. This is because the proposed method increases the AP cluster and interference cluster of UEs with low signal power or high interference, thereby improving the radio quality of UEs. This is because the optimization problem (12) is a nonlinear and non-convex problem with two variables, the AP cluster and the interference cluster. The solution search range is extensive, and a suboptimal solution with sufficiently high *TP* has not been obtained.

Next, a comparison of the average computation time per run to determine the AP clusters and interference clusters for all UEs is shown in Fig 5 for a case with 100 UEs. We use MATLAB and a personal computer (PC) with a Core i9-7900X, 64 GB of memory, and SSD storage. The proposed method and the rule-based method [5] can determine clusters in less than 1 second even with a general-purpose PC and a scripting language such as MATLAB, indicating that they can be sufficiently adapted to user mobility. On the other hand, optimization-based methods require a large amount of computation. This is because the objective function calculation in (14a) requires an inverse matrix calculation for each UE, which need the same amount of computation as the C_{weight} in (11), and the amount of computation per search is high. In addition, Fig. 3 shows that the optimization method does not provide a high-quality suboptimal solution. Additional computation time or computational resources are required to find a solution equivalent to the proposed method. From the above, it is clear that the proposed lightweight computational algorithm can provide uniform and high radio quality in urban environments with a large number of UEs, where we are aiming to deploy CF-mMIMO.

V. Conclusion

We presented a lightweight AP selection algorithm that suppresses inter-site interference. The proposed list-processing based AP selection algorithm prefers to select APs that contribute to quality improvement to uniform signal power and interference effects among users without inverse matrices calculation for estimating the radio quality and a metaheuristic solution search. Simulation results show that the proposed method can provide uniform and high radio quality in urban environments with a large number of UEs compared to existing methods.

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