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Energy Efficient User Association for Cloud Radio Access Networks

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ABSTRACT Cloud radio access network (C-RAN) and massive multiple-input multiple-output (MIMO) are recognized as two key technologies for the fifth-generation mobile networks. In this paper, we consider the energy efficiency-based user association problem in massive MIMO empowered C-RAN, where multiple antennae are clustered at each remote radio head (RRH). We first obtain the deterministic equivalent expression of the energy efficiency, and then propose three user association algorithms, named nearest-based user association (NBUA), single-candidate RRH user association (SCRUA), and multi-candidate RRHs user association (MCRUA), respectively. In NBUA and SCRUA, each user is associated with only one RRH, and in MCRUA, multiple RRHs can serve the same user. In our algorithms, the impact of the power consumption of fronthaul links and antennas is considered by allowing inefficient RRHs to be turned into sleep mode. We provide the numerical comparisons of the proposed algorithms and a state-of-the-art baseline, which associates each user with the nearest RRH. The results show that our proposed algorithms achieve higher energy efficiency than the baseline algorithm. The proposed MCRUA algorithm achieves a good balance between spectral and energy efficiency, and the performance gain is more significant when the number of users is large.

INDEX TERMS Cloud radio access networks, massive MIMO, user association, energy efficiency.

I. INTRODUCTION

Cloud radio access network (C-RAN) is envisioned as a promising architecture to enhance the system performance for the fifth-generation (5G) mobile networks [1]–[3]. Unlike traditional co-located antenna systems (CAS) where the baseband units (BBUs) and radio units are suited together, in C-RAN, the BBUs are placed in a center location and connected with distributed remote radio heads (RRHs) via fronthaul links. By reducing the transmission distance between antennas and users, significant rate improvement can be achieved in C-RAN [4]. On the other hand, massive multiple-input multiple-output (MIMO) has been identified as a promising technology for 5G networks [5]–[10]. By deploying an order of magnitude more antennas than conventional MIMO systems, spectral and energy efficiency can be greatly improved [11], [12]. Along with this architecture, deploying large-scale antennas in C-RAN, known as massive MIMO empowered C-RAN is one of the key evolution solutions for 5G networks [2], [13].

From the viewpoint of green communication, energy efficiency has caught more and more attention in recent years [1], [14], [15]. In C-RAN, a large part of power consumption of the supporting facilities, such as air conditioners, can be reduced. However, unlike traditional co-located antenna systems where the processing unit is close to antennas, the power consumption of fronthaul links in C-RAN might be significant. As well, in massive MIMO systems, the antenna power consumption of electronic components, such as analog electronics, A/D and D/A converters, can not be neglected [16]. The energy efficiency of massive

MIMO systems has been studied in some recent works. For example, in [15], the energy efficiency optimization problem with respect to the number of antennas, users, and transmit power was studied. In [17], the energy efficiency of massive MIMO systems under the impact of transceiver hardware impairments was investigated. The authors of [18] addressed the EE optimization problem by solving the joint beamforming optimization and power allocation problem. For the uplink of single-cell massive MIMO systems, the authors of [19] studied the impact of system parameters on the optimal energy efficiency. Focusing on the downlink of multi-cell distributed massive MIMO systems, the authors of this paper considered the problem of maximizing the energy efficiency with respect to the number of antennas of each RRH, the number of RRHs, and the number of users in [20].

In massive MIMO empowered C-RAN, as users are randomly located in the cell which have different access distance to RRHs, some RRHs contribute significantly to users' communication while others do not. Thus, for each user, rather than being jointly served by all RRHs, only a few surrounding RRHs should be selected to serve the user. More importantly, if all the RRHs are involved in the transmission, the power consumed for fronthaul links and the circuit power consumed for antennas could be large, which consequently results in the degradation of energy efficiency.

Based on the above observations, selecting the serving RRHs for each user, or referred as user association, is a critical problem for C-RAN. But unfortunately, it is a combinatorial problem of high complexity, and the optimal solution requires exhaustive search [21], which is infeasible due to the prohibitively high cost, especially when the number of RRHs and/or users is large [22]. To solve this problem, several user association algorithms based on different performance metrics have been proposed. A common baseline algorithm is the nearest RRH association scheme, where the single nearest RRH or M-nearest RRHs are selected to serve each user [23], [24]. In [13], under the assumption that the network channel state information (CSI) is perfectly known, the optimization problem of user association was solved for maximizing the minimum user rate. Using game theory, a user association algorithm for rate maximization with proportional fairness was considered in [25]. In terms of user association schemes to improve the energy efficiency, the spectral efficiency guided user association algorithms are not desirable, since the behaviors of spectral and energy efficiency are not always coincide. The energy efficiency-based user association problem can be formulated in two forms. One is minimizing the power consumption while satisfying the traffic requirements, and the other is maximizing the overall energy efficiency (bits/Joule), which is defined as the ratio between the sum rate and the total energy consumption [21]. Most of the existing research on energy efficiency-based user association algorithms focused on the former formulation [26]–[28], i.e., minimizing the power consumption. For maximizing the overall energy efficiency, assuming that perfect CSI is available and each user can associate with only one RRH, the authors of [29] proposed a distributed user association algorithm based on the Lagrangian dual analysis.

In this paper, we consider the energy efficiency-based user association problem in massive MIMO empowered C-RAN. Different from the previous works, we consider a more practical situation in two aspects. First, the multi-cell pilot contamination is present in channel estimation, and second, the power consumption of fronthaul links and the circuit power attached to antennas are taken into account in the power consumption model. In such a situation, the user association problem is more complex, which makes the analysis difficult. To solve this problem, we utilize random matrix theory to obtain the deterministic equivalent expression of energy efficiency, which is an accurate approximation for systems in realistic dimensions [30]–[35]. Then, based on the deterministic equivalent expression, we propose three user association algorithms called nearest-RRH based user association (NBUA), single-candidate RRH user association (SCRUA), and multi-candidate RRHs user association (MCRUA), respectively. In NBUA and SCRUA, each user is only associated with one RRH, and in MCRUA, each user can be served by multiple RRHs. In all the three proposed algorithms, the impact of power consumption of fronthaul links and antennas are considered by allowing to switch the inefficient RRHs to sleep mode. Simulation results show that the three proposed user association algorithms achieve higher energy efficiency than the baseline nearest RRH association scheme, and the proposed MCRUA algorithm achieves a good balance between energy and spectral efficiency.

The remainder of the paper is organized as follows. The system model is described in Section II. In Section III, we first analyze the energy efficiency using random matrix theory, and then propose three user association algorithms from the energy efficiency viewpoint. Simulation results are shown in Section IV to verify the performance of the proposed algorithms and the conclusion is given in Section V.

Notation: Boldface uppercase and lowercase letters denote matrices and vectors, respectively. The superscripts $(\cdot)^H$, $(\cdot)^T$, and $(\cdot)^*$ stand for the conjugate-transpose, transpose, and conjugate operations. An $N \times N$ identity matrix is denoted by $\mathbf{I}_N$, while an all-zero matrix is denoted by $\mathbf{0}$. $\mathsf{E}\{\cdot\}$ means the expectation operator, and $\mathsf{var}\{\cdot\}$ denotes the variance. $\mathsf{tr}\,\mathbf{A}$ is used to denote the trace of matrix $\mathbf{A}$. $\mathbf{A}(l,k)$ is the (l,k)-th entry of matrix $\mathbf{A}$. The notation $|\cdot|$ and $\|\cdot\|$ denote the absolute value of a variable and the two-norm of a matrix, respectively. $\mathbf{x} \sim \mathcal{CN}(\mathbf{m}, \mathbf{Q})$ defines a vector of jointly circularly symmetric complex Gaussian random variables with mean value $\mathbf{m}$ and covariance matrix $\mathbf{Q}$.

II. SYSTEM MODEL

A. SIGNAL MODEL

Consider a time-division duplexing (TDD) C-RAN network with L cells, where M RRHs and K single-antenna users are uniformly distributed in each cell, and n antennas are equipped in each RRH. All the cells share the total bandwidth B Hz with universal frequency reuse. The users and RRHs of cell l are labeled as $\mathsf{RRH}_{l1},\ldots,\mathsf{RRH}_{lM}$ and $\mathsf{UE}_{l1},\ldots,\mathsf{UE}_{lK}$, respectively. The RRHs in the same cell are connected to a BBU via fronthaul links. The channel vector between RRH_{lm} and UE_{jk} is given by

$$\mathbf{g}_{lmjk} = \mathbf{R}_{lmjk}^{1/2}\mathbf{h}_{lmjk}, \tag{1}$$

where $\mathbf{h}_{lmjk} \in \mathbb{C}^n$ is the fast-fading channel vector, whose elements follow independent and identically distributed (i.i.d.) $\mathcal{CN}(0,1)$, and $\mathbf{R}_{lmjk} = \mathsf{E}\{\mathbf{g}_{lmjk}\mathbf{g}_{lmjk}^H\} \in \mathbb{C}^{n\times n}$ is a deterministic matrix representing the spatial correlation and large-scale fading. We assume that the long-term channel information $\mathbf{R}_{lmjk}, \forall l, m, j, k$, is known a priori [36], [37].

The downlink communication consists of uplink training phase and downlink data transmission phase. During the uplink training phase, all the L cells reuse the same set of pilot sequences of length $\tau_u = K$ while users within the same cell use mutually orthogonal pilot sequences. The minimum mean-square error (MMSE) estimate of $\mathbf{g}_{jmjk}$ at BBU can be expressed as [38]

$$\hat{\mathbf{g}}_{jmjk} = \mathbf{R}_{jmjk}\mathbf{Q}_{jmk}\left(\mathbf{g}_{jmjk} + \sum_{l\neq j}\mathbf{g}_{jmlk} + \frac{1}{\sqrt{p_u\tau_u}}\mathbf{z}_{jmk}\right), \tag{2}$$

where $\mathbf{z}_{jmk} \sim \mathcal{CN}(0,\sigma^2\mathbf{I}_n)$ is the noise, and $\mathbf{Q}_{jmk} = \left(\frac{\sigma^2}{p_u\tau_u}\mathbf{I}_n + \sum_{l=1}^{L}\mathbf{R}_{jmlk}\right)^{-1}$. The summation in (2) represents the pilot contamination from other cells. With simple calculations, we can obtain that $\hat{\mathbf{g}}_{jmjk}$ follows the distribution of $\mathcal{CN}(\mathbf{0},\mathbf{\Phi}_{jmjk})$ with $\mathbf{\Phi}_{jmjk} = \mathbf{R}_{jmjk}\mathbf{Q}_{jmk}\mathbf{R}_{jmjk}$ [38].

In the considered system, let $\mathcal{A}_l$ be the set of activated RRHs in cell l, $\mathcal{U}_{lm}$ be the set of users associated with RRH_{lm}, and $|\mathcal{U}_{lm}|$ is the cardinality of $\mathcal{U}_{lm}$. In the downlink transmission, the received signal y_{jk} of UE_{jk} is

$$y_{jk} = \sqrt{p_d}\sum_{l=1}^{L}\sum_{m\in\mathcal{A}_l}\mathbf{g}_{lmjk}^T\mathbf{x}_{lm} + z_{jk}, \tag{3}$$

where p_d denotes the transmit power, $\mathbf{x}_{lm} \in \mathbb{C}^n$ is the transmit vector of RRH_{lm}, and $z_{jk} \sim \mathcal{CN}(0,\sigma^2)$ denotes the noise.

The transmit vector of RRH_{lm} is given by

$$\mathbf{x}_{lm} = \sqrt{\lambda_l}\sum_{i\in\mathcal{U}_{lm}}\mathbf{w}_{lmi}s_{lmi}, \tag{4}$$

where λ_l normalizes the transmit power in the cell to $\mathsf{E}\{\frac{1}{K}\sum_{m\in\mathcal{A}_l}\|\mathbf{x}_{lm}\|^2\} = 1$, $\mathbf{w}_{lmi}$ is the precoding vector, and s_{lmi} represents the data symbols with $\mathsf{E}\left\{|s_{lmi}|^2\right\} = 1$.

B. POWER CONSUMPTION MODEL

For downlink transmission, the power consumption of cell l can be modeled as [15], [16]

$$P_l = P_{\mathrm{FIX}} + |\mathcal{A}_l|nP_{\mathrm{RRH}} + P_{\mathrm{T}} + \sum_{m\in\mathcal{A}_l}P_{lm}^{\mathrm{FH}}, \tag{5}$$

where P_{FIX} is the static circuit power consumption, $|\mathcal{A}_l|$ is the number of active RRHs in cell l, P_{RRH} is the power to run the internal radio frequency (RF) components of each antenna at RRHs. P_{T} denotes the RF transmit power. During the coherence time interval T, τ_u symbols are used for pilot transmission and $T-\tau_u$ symbols are used for downlink transmission, hence P_{T} can be expressed as

$$P_{\mathrm{T}} = B\frac{T-\tau_u}{T}\frac{p_d}{\zeta}K, \tag{6}$$

where p_d is the average transmit power normalized to users, and ζ denotes the efficiency of power amplifier.

For optical fiber based architecture, the power consumption of fronthaul links can be modeled as [39]

$$P_{lm}^{\mathrm{FH}} = P_0 + R_{lm}P_{\mathrm{BT}}, \tag{7}$$

where P_0 is the fixed power consumption part of each fronthaul, R_{lm} is the rate (in bits/s) of data transmission in RRH_{lm}, and P_{BT} is the power consumed for transmitting a single bit.

III. ENERGY EFFICIENCY ANALYSIS AND PROPOSED USER ASSOCIATION ALGORITHMS

In this section, we first apply random matrix theory to investigate the deterministic equivalent energy efficiency, where only the second order channel statistical information are required [36], [38]. Since the deterministic equivalent is an accurate approximation even in non-asymptotic regime, it can be used for designing the user association algorithm of realistic systems. The optimal user association to maximize the energy efficiency is a combinatorial optimization problem, which is in general NP-hard [21]. The optimal solution can be acquired by exhaustive search, but the computational complexity increases exponentially with M and K, and it is prohibitive even for small M and K. To deal with that, we propose three heuristic user association algorithms from the energy efficiency viewpoint. In our proposed algorithms, the "inefficient" RRHs can be turned into sleep mode[1] to improve the energy efficiency.

A. ENERGY EFFICIENCY ANALYSIS AND PROBLEM FORMULATION

We use $\mathcal{R}_{jk}$ to denote the set of RRHs serving UE_{jk}. Following the assumption in [38] and [40] that the channel estimates are known at BBUs while only the channel statistics are available at the users, the received signal at UE_{jk} in (3) can be rewritten as

$$\begin{aligned} y_{jk} = {} & \sqrt{p_d\lambda_j}\sum_{r\in\mathcal{R}_{jk}}\mathsf{E}\left\{\mathbf{g}_{jrjk}^T\mathbf{w}_{jrk}\right\}s_{jrk} \\ & + \sqrt{p_d\lambda_j}\sum_{r\in\mathcal{R}_{jk}}\left(\mathbf{g}_{jrjk}^T\mathbf{w}_{jrk} - \mathsf{E}\left\{\mathbf{g}_{jrjk}^T\mathbf{w}_{jrk}\right\}\right)s_{jrk} \\ & + \sqrt{p_d\lambda_j}\sum_{i\neq k}\sum_{m\in\mathcal{R}_{ji}}\mathbf{g}_{jmjk}^T\mathbf{w}_{jmi}s_{jmi} \\ & + \sum_{l\neq j}\sqrt{p_d\lambda_l}\sum_{i=1}^{K}\sum_{m\in\mathcal{R}_{li}}\mathbf{g}_{lmjk}^T\mathbf{w}_{lmi}s_{lmi} + z_{jk}. \end{aligned} \tag{8}$$

[1] We assume that when the RRH is in sleep mode, the power of running the RF component of each antenna can be approximated to 0.

The resultant SINR is given by

$$\mathrm{SINR}_{jk} = \frac{\lambda_j \left| \sum_{r\in\mathcal{R}_{jk}} \mathsf{E}\left\{ \mathbf{g}_{jrjk}^T \mathbf{w}_{jrk} \right\} \right|^2}{\lambda_j \mathsf{var}\left\{ \sum_{r\in\mathcal{R}_{jk}} \mathbf{g}_{jrjk}^T \mathbf{w}_{jrk} \right\} + \mathrm{SCI}_{jk} + \mathrm{ICI}_{jk} + \frac{\sigma^2}{p_d}}, \tag{9}$$

where the interference from the same cell (SCI), and the inter-cell interference (ICI) are given as

$$\mathrm{SCI}_{jk} = \lambda_j \sum_{i\neq k} \mathsf{E}\left\{ \left| \sum_{m\in\mathcal{R}_{ji}} \mathbf{g}_{jmjk}^T \mathbf{w}_{jmi} \right|^2 \right\}, \tag{10a}$$

$$\mathrm{ICI}_{jk} = \sum_{l\neq j} \lambda_l \sum_{i=1}^{K} \mathsf{E}\left\{ \left| \sum_{m\in\mathcal{R}_{li}} \mathbf{g}_{lmjk}^T \mathbf{w}_{lmi} \right|^2 \right\}. \tag{10b}$$

The spectral efficiency and energy efficiency of cell j can be respectively expressed as

$$S_j = \frac{T-\tau_u}{T} \sum_{k=1}^{K} \log_2\left(1+\mathrm{SINR}_{jk}\right) \text{(in bits/s/Hz)}, \tag{11a}$$

$$\eta_j = \frac{BS_j}{P_j} \text{(in bits/Joule)}. \tag{11b}$$

In this paper, we consider the maximum-ratio transmission, so that $\mathbf{w}_{lmi} = \hat{\mathbf{g}}_{lmli}^*$. Following a similar approach in [38], when M is bounded, $n, K \to \infty$, we have

$$\mathrm{SINR}_{jk} - \overline{\mathrm{SINR}}_{jk} \xrightarrow{a.s.} 0, \tag{12}$$

where the notation "$\xrightarrow{a.s.}$" denotes the almost sure (a.s.) convergence [30], and the deterministic approximation of SINR_{jk} is given by (13), shown at the bottom of this page, with $\bar{\lambda}_l = \left(\frac{1}{K}\sum_{m\in\mathcal{A}_l}\sum_{i\in\mathcal{U}_{lm}} \frac{1}{n}\mathrm{tr}\boldsymbol{\Phi}_{lmli}\right)^{-1}$.

Based on continuous mapping theorem, the approximations of spectral efficiency and energy efficiency are, respectively, given by

$$\bar{S}_j = \frac{T-\tau_u}{T} \sum_{k=1}^{K} \log_2\left(1+\overline{\mathrm{SINR}}_{jk}\right), \tag{14a}$$

$$\bar{\eta}_j = \frac{B\bar{S}_j}{P_j(\bar{S}_j)}. \tag{14b}$$

Therefore, the user association problem for maximizing the energy efficiency can be expressed as

$$\{\mathcal{U}_{jm}, \forall m\} = \underset{\mathcal{U}_{jm}\in\{1,2,\ldots,K\},\forall m}{\mathrm{argmax}} \quad \bar{\eta}_j. \tag{15}$$

TABLE 1. Nearest-based user association (NBUA) algorithm.

Algorithm 1: NBUA Algorithm

Initialization:
$\mathcal{U}_{jm} = \emptyset$, $\forall m$, $\mathcal{A}_j = \emptyset$.
Step 1: Associate users with their respectively nearest RRH.
for $k = 1, 2, \ldots, K$
  $\tilde{m} = \underset{m}{\mathrm{argmax}}\, \beta_{jmjk}$, for $m = 1, 2, \ldots, M$.
  $\mathcal{U}_{j\tilde{m}} = \mathcal{U}_{j\tilde{m}} \bigcup \{k\}$.
end for
Step 2: Determine whether to turn "inefficient" RRHs to sleep mode, and re-associate users.
$\mathcal{A}_j = \{m : |\mathcal{U}_{jm}| > 0\}$, $\mathcal{B}_j = \mathcal{A}_j$,
$\bar{m} = \underset{m\in\mathcal{B}_j}{\mathrm{argmin}}\, |\mathcal{U}_{jm}|$.
(If the result of 'argmin' is not unique, randomly select one from the result.)
while ($|\mathcal{U}_{j\bar{m}}| < U_{\mathrm{TH}}$) **do**
  Calculate the deterministic equivalent energy efficiency $\bar{\eta}_j^{\mathrm{on}}$.
  $\bar{\mathcal{A}}_j = \mathcal{A}_j \backslash \{\bar{m}\}$, $\mathcal{B}_j = \mathcal{B}_j \backslash \{\bar{m}\}$,
  $\bar{\mathcal{U}}_{jm} = \mathcal{U}_{jm}$, for $\forall m \in \bar{\mathcal{A}}_j$.
  for $k \in \mathcal{U}_{j\bar{m}}$
    $m' = \underset{m\in\bar{\mathcal{A}}_j}{\mathrm{argmax}}\, \beta_{jmjk}$,
    $\bar{\mathcal{U}}_{jm'} = \mathcal{U}_{jm'} \bigcup \{k\}$.
  end for
  Calculate $\bar{\eta}_j^{\mathrm{s}}$ under $\bar{\mathcal{A}}_j$ and $\bar{\mathcal{U}}_{jm}$.
  if $\bar{\eta}_j^{\mathrm{s}} > \bar{\eta}_j^{\mathrm{on}}$ **then**
    $\mathcal{A}_j = \bar{\mathcal{A}}_j$, $\mathcal{U}_{jm} = \bar{\mathcal{U}}_{jm}$, for $m \in \mathcal{A}_j$.
  end if
  $\bar{m} = \underset{m\in\mathcal{B}_j}{\mathrm{argmin}}\, |\mathcal{U}_{jm}|$.
end while

B. NEAREST-BASED USER ASSOCIATION ALGORITHM

A simple and common practice user association scheme is to associate each user with the nearest RRH [24]. However, this scheme may lead to an inefficient case where some RRHs only serve a very few users. In this part, we propose a nearest-based user association (NBUA) algorithm summarized in Table 1. Here, we take cell j as an example to explain this algorithm, and all the cells are assumed to employ the same scheme.

In Step 1, each user is associated with the nearest RRH in its cell, which can be determined by the large-scale

$$\overline{\mathrm{SINR}}_{jk} = \frac{\bar{\lambda}_j \left(\frac{1}{n} \sum_{r\in\mathcal{R}_{jk}} \mathrm{tr}\boldsymbol{\Phi}_{jrjk} \right)^2}{\bar{\lambda}_l \sum_{l\neq j} \left| \frac{1}{n} \sum_{r\in\mathcal{R}_{lk}} \mathrm{tr}\boldsymbol{\Phi}_{lrjk} \right|^2 + \frac{1}{n} \sum_{l=1}^{L} \sum_{i=1}^{K} \sum_{m\in\mathcal{R}_{li}} \bar{\lambda}_l \frac{1}{n} \mathrm{tr}\mathbf{R}_{lmjk} \boldsymbol{\Phi}_{lmli} + \frac{\sigma^2}{p_d n}} \tag{13}$$

fading channel factors $\beta_{j1jk}, \beta_{j2jk}, \ldots, \beta_{jMjk}$. Then, in Step 2, a greedy method is performed to determine whether to turn the RRHs that serve less than U_{TH} users to sleep mode and re-associate their users to other RRHs. Specifically, the deterministic equivalent energy efficiency under current user association, denoted as $\overline{\eta}_j^{\mathrm{on}}$, is firstly calculated using (14). Then, the RRH that serves the least number of users is assumed to be switched to sleep mode and the users associated to it are assumed to be re-associated to the nearest active RRH. If the RRHs that serve the least number of users is not unique, we randomly select one from them. Next, we calculate the deterministic equivalent energy efficiency under this hypothetical user association, denoted as $\overline{\eta}_j^{\mathrm{s}}$. If $\overline{\eta}_j^{\mathrm{s}} > \overline{\eta}_j^{\mathrm{on}}$, $\mathcal{A}_j$ and $\mathcal{U}_{jm}$ are updated by the hypothetical user association, otherwise they remain unchanged. The above process is repeated until all the RRHs serve less than U_{TH} users have been checked whether or not to be switched to sleep mode.

When switching RRH_{jm} to sleep mode, the power consumption is reduced, however, the change of spectral efficiency and energy efficiency cannot be predicted. This is because that both the intended signal power of the users previously in $\mathcal{U}_{jm}$ and the network interference will decrease, thus we do not know whether or not the sum spectral efficiency will increase, and the change of the energy efficiency cannot be predicted. Thus, we switch the RRH to sleep mode if $\overline{\eta}_j^{\mathrm{s}} > \overline{\eta}_j^{\mathrm{on}}$. The algorithm is based on the deterministic equivalent energy efficiency that only requires channel statistical information and large-scale fading gains, thus the required complexity is acceptable because the need of Monte-Carlo averaging is avoided. Note that the threshold U_{TH} in the above algorithm should be set properly. If U_{TH} is too small, the improvement of energy efficiency might not significant, and if U_{TH} is large, the complexity will be high since more RRHs will be checked whether to be turned to sleep mode. The proper value of U_{TH} can be determined through several simulations.

C. SINGLE-CANDIDATE RRH USER ASSOCIATION ALGORITHM

To improve the energy efficiency further, we propose another user association algorithm called single-candidate RRH user association (SCRUA) algorithm. In NBUA algorithm, each user is associated with the single nearest RRH, and the inefficient RRHs are turned to sleep mode. In this algorithm, we still assume that each user is only associated with a single RRH, and we want to let the number of RRHs in active mode as low as possible when ensuring the performance. The proposed user association algorithm consists of 4 steps, which are presented in Table 2.

In step 1, the candidate RRHs of each user are determined by the large-scale fading factors. RRH_{jm} would be a candidate RRH of UE_{jk} if $\beta_{jmjk} \geq \xi\beta_{j\tilde{m}jk}$, where $\xi \in [0, 1]$ is a predefined threshold, and $\beta_{j\tilde{m}jk}$ is the large-scale fading factor between UE_{jk} and its nearest RRH. The $K \times M$ binary matrix $\mathbf{M}$ is used to record the candidate RRHs of each user.

TABLE 2. Single-candidate RRH user association algorithm.

Algorithm 2: SCRUA Algorithm

Initialization:
$\mathcal{U}_{jm} = \emptyset,\ \forall m,\ \mathcal{A}_j = \emptyset,\ \mathbf{M} = \mathbf{0} \in \mathbb{R}^{K\times M}$.
Step 1: Determine candidate RRHs for each user.
for $k = 1, 2, \ldots, K$
  $\tilde{m} = \underset{m}{\operatorname{argmax}}\, \beta_{jmjk}$, for $m = 1, 2, \ldots, M$
  for $m = 1, 2, \ldots, M$
    $\mathbf{M}(k, m) = 1$ if $\beta_{jmjk} \geq \xi\beta_{j\tilde{m}jk}$
  end for
end for
Step 2: Associate users with RRHs.
$\mathrm{cnt}_{jm} = \sum_k \mathbf{M}(k, m),\ m = 1, 2, \ldots, M$.
$c_{\max} = \max\{\mathrm{cnt}_{jm},\ m = 1, 2, \ldots, M\}$.
while $c_{\max} > 0$ **do**
  $\mathcal{R} = \{m : \mathrm{cnt}_{jm} = c_{\max}\}$.
  for $m \in \mathcal{R}$
    $\mathcal{K}_m = \{k : \mathbf{M}(k, m) = 1\}$,
    $t_m = \sum_{k\in\mathcal{K}_m} \beta_{jmjk}$.
  end for
  $\bar{m} = \underset{m\in\mathcal{R}}{\operatorname{argmax}}\, t_m$.
  $\mathcal{U}_{j\bar{m}} = \mathcal{K}_{\bar{m}}$, and $\mathbf{M}(k, :) = \mathbf{0}$, for $k \in \mathcal{K}_{\bar{m}}$.
  Update cnt_{jm}, for $\forall m$, and $c_{\max}$.
end while
Step 3: Reassign user to the nearest active RRH.
$\mathcal{A}_j = \{m : |\mathcal{U}_{jm}| > 0\}$.
for $k = 1, 2, \ldots, K$
  $\tilde{m} = \underset{m\in\mathcal{A}_j}{\operatorname{argmax}}\, \beta_{jmjk}$.
  $\mathcal{U}_{jm'} = \mathcal{U}_{jm'} \backslash \{k\}$, where $m' = \{m : k \in \mathcal{U}_{jm}\}$,
  and set $\mathcal{U}_{j\tilde{m}} = \mathcal{U}_{j\tilde{m}} \bigcup \{k\}$.
end for
Step 4: The same as Step 2 in NBUA algorithm.

The entry $\mathbf{M}(k, m) = 1$ if RRH_{jm} is the candidate RRH of UE_{jk}, and $\mathbf{M}(k, m) = 0$, otherwise.

In step 2, a priority factor of each RRH is calculated according to the number of occurrences in users' candidate set, and the priority factor of RRH_{jm} is calculated as $\mathrm{cnt}_{jm} = \sum_k \mathbf{M}(k, m)$. The RRHs are turned on successively depending on the priority factors cnt_{jm}'s. In each time, the RRH with the highest priority factor, denoted as $\mathrm{RRH}_{j\bar{m}}$, is selected to be turned on to serve the users whose candidate RRHs including $\mathrm{RRH}_{j\bar{m}}$. If the RRH with the highest priority factor is not unique, the RRH with the largest sum of large scale fading factors to the serving users is selected. Then, cnt_{jm}'s are updated by not considering the already associated users, and the above procedures are repeated until all the users are associated with a RRH.

After determining the active RRHs in step 2, in step 3, each user are reassigned to the nearest RRH in active mode to improve the channel gain. Lastly, in step 4, the same as the greedy method in NBUA algorithm, the "inefficient" RRHs are checked whether to be turned to sleep mode.

Note that if the threshold ξ in Step 1 is too small, a lot of RRHs will be included in the candidate set, and the user may associate with a faraway RRH, which will decrease the spectral efficiency. On the other hand, if the threshold is too large, for example, when $\xi = 1$, only the nearest RRH is the candidate RRH, and the algorithm will be equal to NBUA algorithm. Intuitively, when $\beta_{j\tilde{m}jk}$ is large, or when the minimum distance between RRH and user is small, ξ can be small since the surrounding RRHs can provide efficient transmission, and when $\beta_{j\tilde{m}jk}$ is small, ξ should be large to avoid the faraway RRHs being selected. Therefore, we set the minimum value of ξ to be $\xi_{\min}$, and $\xi = \xi_{\min} + (1 - \xi_{\min})d_{j\tilde{m}jk}/(2R_c)$, where $d_{j\tilde{m}jk}$ is the distance between the nearest RRH and user, and R_c is the radius of the cell. Under the large-scale fading model $\beta_{jmjk} = 1/d_{jmjk}^{\gamma}$ (γ is the path-loss exponent), we have $d_{j\tilde{m}jk} = \beta_{j\tilde{m}jk}^{-1/\gamma}$. In this setting, if the user is very close to the nearest RRH, $\xi \approx \xi_{\min}$, and in the extreme case where the distance between user and RRHs is $2R_c$, the threshold $\xi = 1$.

D. MULTI-CANDIDATE RRHs USER ASSOCIATION ALGORITHM

In both NBUA and SCRUA algorithms, each user is only associated with a single RRH. However, in SCRUA algorithm, it is possible that there are more than one candidate RRHs of UE_{jk} are in active mode, and these RRHs can serve UE_{jk} together to improve the channel gain. Therefore, in this part, we propose a multi-candidate RRHs user association (MCRUA) algorithm, which is summarized in Table 3.

Firstly, the same as step 1 and step 2 in SCRUA algorithm, the candidate RRHs for each user are determined by the large-scale fading factors, and the RRHs are successively turned on according to the priority factor cnt_{jm}. After determining the active RRHs in step 2, then in step 3, each user is associated with all of his candidate RRHs that are in active mode. Lastly, similar to NBUA and SCRUA algorithms, if a RRH serves less than U_{TH} users, we check whether the RRHs should be turned to sleep mode to improve the energy efficiency. The only difference is that when $\mathrm{RRH}_{j\bar{m}}$ is assumed to be switched to sleep mode, the set of associated RRHs of UE_{jk} is assumed to be $\bar{\mathcal{R}}_{jk} = \mathcal{R}_{jk} \backslash \{\bar{m}\}$, for $\forall k$, and only if $\bar{\mathcal{R}}_{jk}$ is empty, UE_{jk} will be re-associated with the nearest active RRH.

An illustration of user association results of different algorithms is shown in Fig. 1. The results are obtained by applying the baseline nearest RRH association algorithm and the three proposed user association algorithms under a $M = 10,\ K = 20$ topology. We set $U_{\mathrm{TH}} = 3$ in the proposed three user association algorithm.

In the baseline nearest RRH association scheme, two RRHs are not activated since they are not the nearest RRH to any user. By applying the proposed NBUA algorithm, an "inefficient" RRH is turned to sleep mode (highlighted by a red circle). For the SCRUA algorithm, one more RRH is in sleep mode. In MCRUA algorithm, 8 users (represented by red squares) are associated with multiple RRHs, and the association with multiple RRHs are indicated by dashed arrows.

TABLE 3. Multi-candidate RRHs User association algorithm.

Algorithm 3: MCRUA Algorithm

Initialization:
$\mathcal{U}_{jm} = \emptyset, \forall m, \mathcal{A}_j = \emptyset, \mathbf{M} = \mathbf{0} \in \mathbb{R}^{K \times M}, \mathcal{R}_{jk} = \emptyset, \forall k.$
Step 1& Step 2: The same as Step 1 and Step 2 in SCRUA Algorithm.
Step 3: Associate each user with all of his candidate RRHs in active mode.
$\mathcal{A}_j = \{m : |\mathcal{U}_{jm}| > 0\}.$
for $k = 1, 2, \ldots, K$
  $\mathcal{R}_{jk} = \{m : m \in \mathcal{A}_j, \mathbf{M}(k, m) = 1\}.$
  for $m \in \mathcal{R}_{jk}$
    $\mathcal{U}_{jm} = \mathcal{U}_{jm} \bigcup \{k\}.$
  end for
end for
Step 4: Determine whether to turn "inefficient" RRHs to sleep mode and re-associate users.
$\bar{m} = \operatorname*{argmin}_{m \in \mathcal{B}_j} |\mathcal{U}_{jm}|.$
(If the result of 'argmin' is not unique, randomly select one from the result.)
while ($|\mathcal{U}_{j\bar{m}}| < U_{\mathrm{TH}}$) **do**
  Calculate the deterministic equivalent energy efficiency $\overline{\eta}_j^{\mathrm{on}}$.
  $\bar{\mathcal{A}}_j = \mathcal{A}_j \backslash \{\bar{m}\}, \mathcal{B}_j = \mathcal{B}_j \backslash \{\bar{m}\}, \bar{\mathcal{R}}_{jk} = \mathcal{R}_{jk}, \forall k,$
  $\bar{\mathcal{U}}_{jm} = \mathcal{U}_{jm}, \forall m \in \bar{\mathcal{A}}_j.$
  for $k \in \mathcal{U}_{j\bar{m}}$
    $\bar{\mathcal{R}}_{jk} = \mathcal{R}_{jk} \backslash \{\bar{m}\}.$
    if $\bar{\mathcal{R}}_{jk} = \emptyset$
      $m' = \operatorname*{argmax}_{m \in \bar{\mathcal{A}}_j} \beta_{jmjk},$
      $\bar{\mathcal{R}}_{jk} = \{m'\}, \bar{\mathcal{U}}_{jm'} = \mathcal{U}_{jm'} \bigcup \{k\}.$
    end if
  end for
  Calculate $\overline{\eta}_j^{\mathrm{s}}$ under $\bar{\mathcal{A}}_j$, $\bar{\mathcal{U}}_{jm}$, and $\bar{\mathcal{R}}_{jk}$.
  if $\overline{\eta}_j^{\mathrm{s}} > \overline{\eta}_j^{\mathrm{on}}$ **then**
    $\mathcal{A}_j = \bar{\mathcal{A}}_j, \mathcal{U}_{jm} = \bar{\mathcal{U}}_{jm}$, for $m \in \mathcal{A}_j$,
    $\mathcal{R}_{jk} = \bar{\mathcal{R}}_{jk}$, for $\forall k$.
  end if
  $\bar{m} = \operatorname*{argmin}_{m \in \mathcal{B}_j} |\mathcal{U}_{jm}|.$
end while

IV. SIMULATION RESULTS

In this section, we show the performance of the proposed user association algorithms. A 7-cell network where the center cell surrounding by 6 interfering cells is considered in our simulations. The cell radius $R_c = 2$ km, and the performance of the center cell is evaluated as a typical example. The large-scale fading is modeled as $\beta_{lmjk} = 1/d_{lmjk}^{\gamma}$, where d_{lmjk} is the distance between RRH_{lm} and UE_{jk},

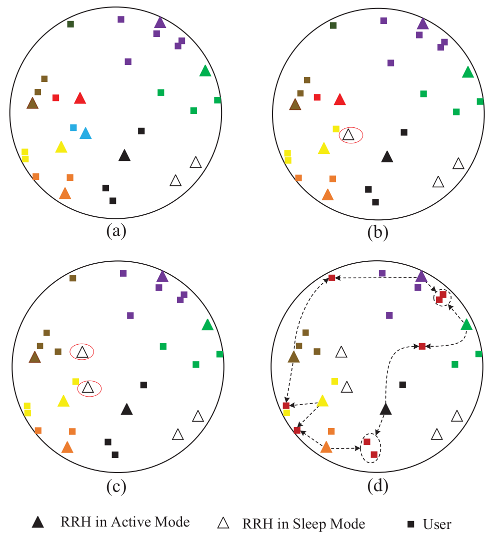

FIGURE 1. **Illustration of user association results of different algorithms under the same topology ($M = 10$ and $K = 20$). The squares represent the users, solid triangles represent the RRHs in active mode, and the empty triangles represent the RRH in sleep mode. The users are associated with RRHs in the same color. In (b) and (c), the difference of RRHs in sleep mode are highlighted in red circles. In (d), the users served by multiple RRHs are represented by red squares, and the association with multiple RRHs are indicated by dashed arrows.**

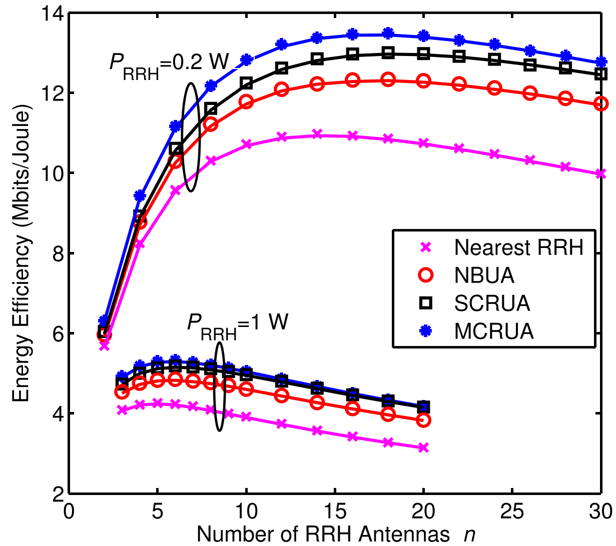

FIGURE 2. **Energy efficiency comparison versus n ($M = 10$ and $K = 20$). The solid curves depict analytical results, while the markers depict simulation results.**

and path-loss exponent $\gamma = 2.5$. We assume $\mathbf{R}_{lmjk} = \beta_{lmjk}\mathbf{I}_n$. Taking into account that the large scale fading is a function of user and RRH locations, we generate 1000 random user and RRH locations to complete the Monte-Carlo simulation. We assume that the system bandwidth $B = 20$ MHz, with the coherence interval $T = 196$, and the thermal noise density $N_0 = -174$ dBm/Hz. Based on [15] and [39], the parameters related to power consumption model are set as follows: amplifier efficiency $\zeta = 0.4$, fixed power consumption of fronthaul $P_0 = 0.825$W, traffic dependent fronthaul power $P_{\mathrm{BT}} = 0.25$ W/(Gbits/s), fixed power consumption of system $P_{\mathrm{FIX}} = 9$ W, and the downlink transmit power $p_d = 20$ dBm. In our proposed user association algorithm, we set $\xi_{\min} = 0.3$ and $U_{\mathrm{TH}} = 2$.

In Fig. 2, we present the energy efficiency achieved by the three proposed user association algorithms and the baseline nearest RRH association algorithm via both analytical deterministic equivalent results and Monte-Carlo method. $K = 20$ users and $M = 10$ RRHs are uniformly distributed in each cell. According to the parameters given in [41] and the predicted parameters in the year 2020 [42], the power attached to each RRH antenna are set to be $P_{\mathrm{RRH}} = 1$ W and $P_{\mathrm{RRH}} = 0.2$ W, respectively.

We firstly observe that the deterministic equivalent results (solid curves) perfectly agree with the simulation results (markers) obtained by Monte-Carlo method, even for small number of RRH antennas n. Secondly, when n is increasing, the behavior of the energy efficiency is "rise and drop". This is because when n goes up, the spectral efficiency can be improved due to the array gain, but the power consumption of running antennas increases correspondingly. If the spectral efficiency is low, the proportion of the increased spectral efficiency is greater than that of the increased power consumption, then the energy efficiency increases, and vice versa. Thirdly, the three proposed user association algorithms achieve better energy efficiency than the baseline nearest RRH association scheme, since the inefficient RRHs are switched to sleep mode to reduce the power consumption of antenna and fronthaul links. We can see that the proposed MCRUA algorithm outperforms the other algorithms, but when n is large, the gap between the performance of SCRUA and MCRUA is reduced. The reason is that in MCRUA algorithm, it is possible that more RRHs are in active mode for multiple RRHs transmission. When n is small, the circuit power of antennas is small, and the MCRUA algorithm outperforms the others algorithms due to a higher array gain, but when n is large, the circuit power is significant so that the energy efficiency decreases with n more rapidly in MCRUA. Lastly, comparing the two groups of curves, when $P_{\mathrm{RRH}} = 1$ W, less antennas should be deployed to achieve the maximal energy efficiency.

In Fig. 3, we show the average number of active RRHs in the center cell versus the number of RRH antennas n when $P_{\mathrm{RRH}} = 0.2$ W. It is shown that when n is increasing, the number of active RRHs with nearest RRH algorithm is unchanged and larger than that of other algorithms. The number of active RRHs with NBUA and SCRUA algorithms are decreasing with n, while the number of active RRHs with MCRUA is slightly changed with n. Compared with SCRUA algorithm, in MCRUA, more RRHs are in active mode, but due to multiple RRHs transmission, the energy efficiency achieved by MCRUA is more satisfactory as shown in Fig. 2.

Fig. 4 and Fig. 5 show the energy efficiency of employing the four user association algorithms at different number of RRHs M and different number of users K

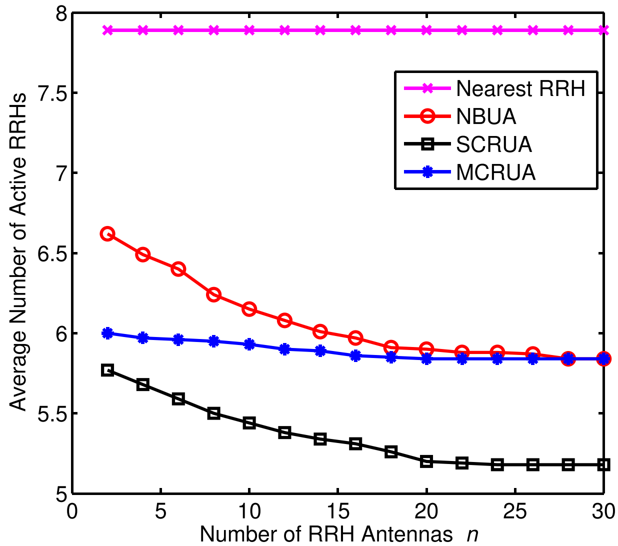

FIGURE 3. Average number of active RRHs versus n ($M = 10$ and $K = 20$).

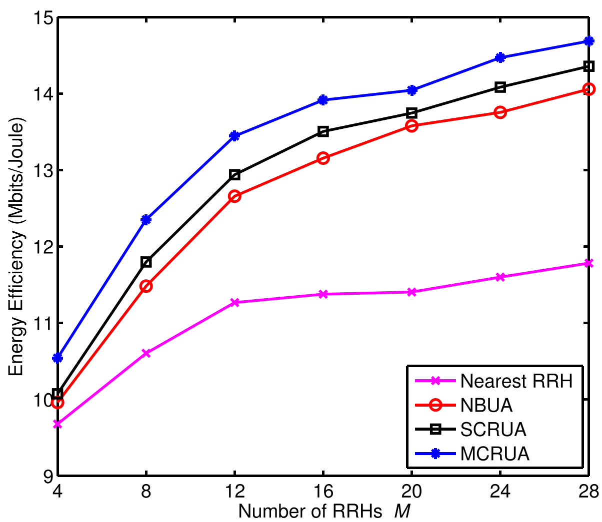

FIGURE 4. Energy efficiency comparison versus M ($n = 10$ and $K = 20$).

when $P_{\mathrm{RRH}} = 0.2$ W. In Fig. 4, we fix $n = 10$, $K = 20$, and investigate the energy efficiency as a function of the number of RRHs M. From the results we can see that the energy efficiency of nearest RRH algorithm is not satisfactory, and the proposed three user association algorithms achieve better energy efficiency than the nearest RRH algorithm. When M is larger than a certain number, the growth of energy efficiency is slower since more power may be consumed for antennas and fronthaul links. Note that the M RRHs may not be fully activated since some of them are in sleep node. In Fig. 5, we fix $n = 10$, $M = 10$, and increase K from 5 to 30. It can be seen that the energy efficiency generally first increases with K and then decreases. This is due to the fact that when scheduling more users, more RRHs are activated to serve users, and more interference arise. The effectiveness of the proposed algorithms can also be observed.

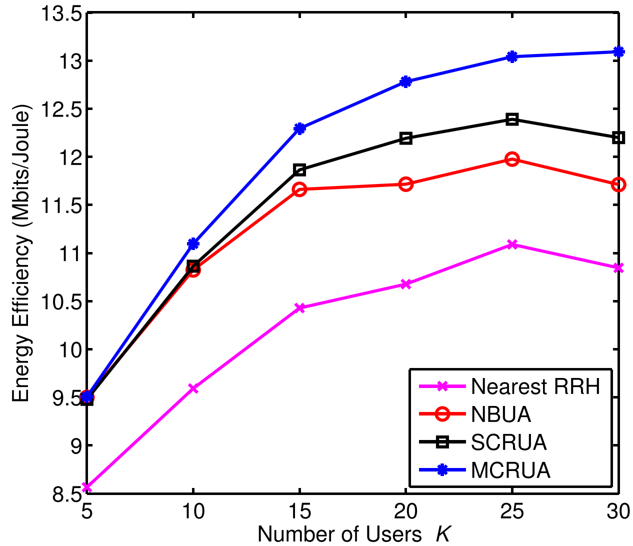

FIGURE 5. Energy efficiency comparison versus K ($n = 10$ and $M = 10$).

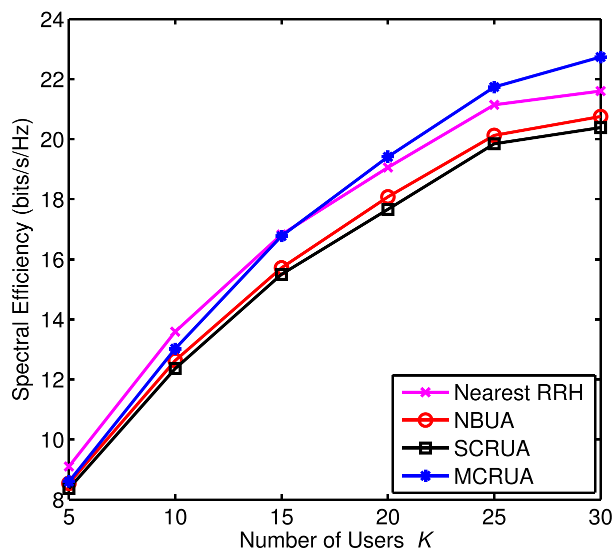

FIGURE 6. Spectral efficiency comparison versus K ($n = 10$ and $M = 10$).

We also present the spectral efficiency achieve by different association algorithms in Fig. 6. We see that NBUA and SCRUA algorithms achieve a slightly lower spectral efficiency than the nearest RRH scheme. The nearest RRH scheme achieves higher spectral efficiency than MCRUA when K is small, however, when K is large, MCRUA algorithm is preferred since the nearby multiple RRHs can improve the array gain and reduce the inter-user interference.

Finally, we indicate the trade-off between energy efficiency and spectral efficiency achieved by different algorithms. A unified metric is proposed in [43] as $U = S_{\mathrm{norm}}^{w} \times \eta_{\mathrm{norm}}^{(1-w)}$, where S_{norm} is the spectral efficiency normalized to its max value, i.e., $S_{\mathrm{norm}} = S/S^{\max}$, and similarly $\eta_{\mathrm{norm}} = \eta/\eta^{\max}$, $w \in [0, 1]$ is the preference factor for spectral efficiency, and $(1 - w)$ is the preference factor for energy efficiency.

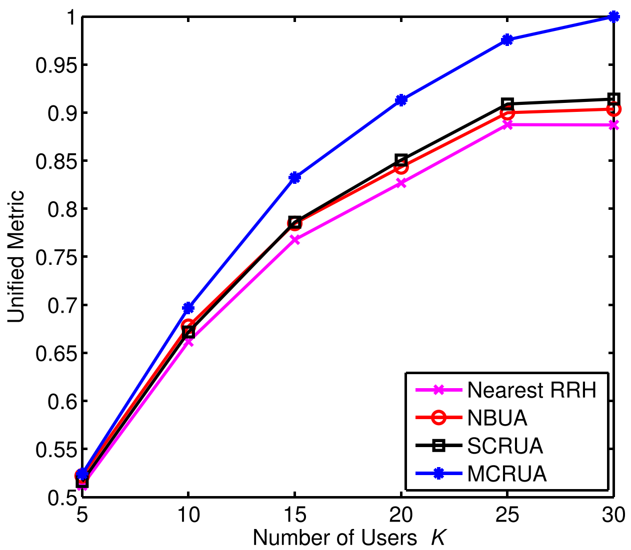

FIGURE 7. **Unified metric comparison versus K ($n = 10$ and $M = 10$).**

The unified metric comparison with $w = 0.5$ is shown in Fig. 7. We can find that MCRUA algorithm achieves the best trade-off, and the gap is more significant when K is larger. Thus, we draw the conclusion that MCRUA can achieve a good balance between spectral and energy efficiency.

V. CONCLUSION

In this paper, we have studied the user association problem of massive MIMO empowered C-RAN from the energy efficiency viewpoint. We first obtained the deterministic equivalent energy efficiency, and then proposed three user association algorithms to improve the energy efficiency. The proposed NBUA and SCRUA algorithms allow each user associate with only one RRH, while the proposed MCRUA algorithm allows multiple RRHs serve the same user together. Since the proposed algorithms are based on the deterministic equivalent of the energy efficiency, only channel statistical information is required. Numerical results show that the three proposed user association schemes outperform the nearest RRH algorithm, and MCRUA algorithm achieves a good balance between spectral and energy efficiency. The performance gain of MCRUA algorithm over other algorithms is more significant when the number of users is large.

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