Joint User Association and Downlink Beamforming for Green Cloud-RANs with Limited Fronthaul

Zhi Yu, Ke Wang, Hong Ji, Xi Li, Heli Zhang
Key Laboratory of Universal Wireless Communications, Ministry of Education
Beijing University of Posts and Telecommunications
Beijing, P.R. China
Email: zhiyu, wangke, jihong, lixi, zhangheli{@bupt.edu.cn}

Abstract—With the explosive growth of smart devices and mobile data traffic, limited fronthaul capacity has become a notable bottleneck of green communication access networks, such as cloud radio access networks (C-RANs). In this paper, we proposed a joint user association and downlink beamforming scheme for green C-RANs to minimize the network power consumption with the limited fronthaul links. We first formulate the design problem as a mixed integer nonlinear programming (MINLP), and then transformed the MINLP problem into a mixed integer second-order cone program (MI-SOCP) which is a convex program when the integer variables are fixed. By relaxing the integer variables to continuous ones, an inflation algorithm, which can be finished within polynomial time, was proposed to solve the problem. The simulation results are presented to validate the effectiveness of our proposed algorithm compared with the scheme adopted by LTE-A.

Index Terms—Cloud-RAN, user association, downlink beamforming design, green communication, mixed integer second-order cone programming.

I. INTRODUCTION

Cloud radio access network (C-RAN) has recently been proposed as a promising network architecture to jointly improve energy efficiency and spectrum efficiency, and reduce both the capital expenses and operation expenses [1]. In C-RANs, baseband data and channel state information (CSI) are processed in a central processor called Baseband Unit (BBU) pool and shared among the densely deployed remote radio heads (RRHs) via fronthaul links, which allows the RRHs to cooperatively transmit the data to the mobile users (MUs) [2]. Unfortunately, with the dense deployment of RRHs, the overall network power consumption, including both transmit and circuit power consumption [3], will increase significantly. Therefore, green C-RAN has quickly attracted wide attention [4]–[6].

The authors in [4] address the problem of downlink beamforming to improve energy efficiency of C-RANs by using weighted mixed norm minimization. A three-stage algorithm based on the group-sparsity inducing norm is presented to minimize the power consumption for multicast C-RANs [5]. Combining virtualized network resources and virtualized functional entities of baseband processing, the authors in [6] propose an energy-saving scheme for C-RANs based on formation of Virtual Base Station. However, these excellent works do not take into account limitation of fronthaul links, which is becoming the a bottleneck for realizing the potential performance gain of C-RANs [7]. Moreover, with the huge number of MUs involved in the network, enormous baseband signals and signaling overheads are required to be transmitted in fronthaul links, which incurs that the fronthaul limited problem becomes more severe. Hence, finding a solution of network power minimization problem under limited fronthaul is critical to achieve green communication and commercial deployment of C-RANs.

Some other excellent works have been done on energy saving with constrained fronthaul links in CRANs. The authors in [8] investigate the tradeoff between total transmit power and sum backhaul capacity over all BSs in a network MIMO system. To minimize downlink transmit power, a efficient algorithm with constraints on fronthaul capacity is presented in [9]. For transmit power minimization, the authors in [10] jointly consider coordinated beamforming and admission control design in fronthaul constrained C-RANs. Nevertheless, all these works assume that all the RRHs are involved to cooperatively transmit data to MUs, i.e., the RRH sleeping mechanism which is closely related to the user association status is not considered. Therefore, the schemes proposed by these works can not efficiently reduce the circuit power consumption, which accounts for a large part of network power consumption [11].

In this paper, we investigate the network power minimization problem in C-RAN with limited fronthaul. This design problem jointly considers user association and downlink beamforming, which dominate circuit power consumption and transmit power consumption, respectively. To be more specific, we first characterize the problem as a mixed integer nonlinear program (MINLP), which is hard to be solved because of the features of the user association. Then, we transform the problem into a mixed integer second-order cone program (MI-SOCP) by making the objective function plus a sufficient small variable. Finally, we relax the integer variables to continuous ones and adopt a low complexity inflation algorithm to obtain the suboptimal solution. Numerical results verify the effectiveness of the proposed scheme by compared with the scheme adopted by LTE-A.
The rest of this paper is organized as follows. Section II presents the system and power model. In Section III, the network power consumption minimization problem is formulated as a MI-SOCP, followed by some analysis. Section IV presents the low complexity inflation algorithm to obtain the suboptimal solution. Simulation results and discussions are given in section V. Finally, we conclude this paper in section VI.

II. SYSTEM AND POWER MODEL

A. System Model

We consider a downlink Cloud-RAN with $L$ multiple-antenna RRHs and $K$ single-antenna MUs, where the $l$-th RRH with $N_l$ antennas is connected to a BBU Pool by a limited fronthaul link, as shown in Fig. 1. It is assumed that all user data and the perfect CSI is available at the BBU pool. We define $\mathcal{L} = \{1, 2, \ldots, L\}$ and $\mathcal{K} = \{1, 2, \ldots, K\}$ as the set of RRH and MU indices, respectively. In a beamformer design problem, the baseband signals of RRH $l$ can be expressed as

$$x_l = \sum_{k=1}^{K} w_{l,k}s_k, \forall l \in \mathcal{L}$$

(1)

where $w_{l,k} \in \mathbb{C}^{N_l \times 1}, \forall l \in \mathcal{L}, \forall k \in \mathcal{K}$ is the beamforming vector at RRH $l$ for MU $k$ and $s_k \in \mathbb{C}$ is the data symbol for MU $k$ with unit power, i.e., $E[|s_k|^2] = 1$. Specifically, we assume that there is a maximum transmit power constraint for RRH $l$ which is given by:

$$\sum_{k=1}^{K} ||w_{l,k}||_2^2 \leq P_{l}^{MAX}, \forall l \in \mathcal{L}$$

(2)

Moreover, we consider a quasi-static fading environment and denote the channel vector from RRH $l$ to MU $k$ as $h_{l,k} \in \mathbb{C}^{N_l \times 1}, \forall l \in \mathcal{L}, \forall k \in \mathcal{K}$. Then, the received baseband signal at MU $k$ is given by

$$y_k = \sum_{l=1}^{L} h_{l,k}^H w_{l,k} s_k + \sum_{l=1}^{L} \sum_{i \in \mathcal{K}, i \neq k} h_{l,i}^H w_{l,i} s_i + z_k, \forall k \in \mathcal{K}$$

(3)

where $z_k \sim \mathcal{CN}(0, \sigma_k^2)$ is the additive Gaussian noise. Treating the interference in Eqs. (3) as noise, the received signal-to-interference-plus-noise ratio (SINR) at MU $k$ is given by

$$\text{SINR}_k = \frac{\sum_{l=1}^{L} h_{l,k}^H w_{l,k}^2}{\sum_{i \in \mathcal{K}, i \neq k} \sum_{l=1}^{L} h_{l,i}^H w_{l,i}^2 + \sigma_k^2}, \forall k \in \mathcal{K}$$

(4)

B. Power Model

We assume that each RRH in C-RAN may be in one of the two states, which are sleep (SLP) and transmitting (TRA). Then, we define the binary variable tuple $\{a_l, b_{l,k}, \forall l \in \mathcal{L}, \forall k \in \mathcal{K}\}$ as the network state, where $a_l \in \{0, 1\}$ and $b_{l,k} \in \{0, 1\}$. $a_l$ denotes RRH power indicator; $a_l = 1$ indicates that the RRH $l$ is in transmitting state, and $a_l = 0$ otherwise, $\forall l \in \mathcal{L}$. Moreover, $b_{l,k}$ denotes user association indicator: $b_{l,k} = 1$ means that the MU $k$ is served by the RRH $l$, and $b_{l,k} = 0$ otherwise, $\forall k \in \mathcal{K}, \forall l \in \mathcal{L}$. Clearly, according to the relationships among $a_l, b_{l,k}$ and $w_{l,k}, k$, we define the user association constraints as follows:

$$\begin{align*}
\{b_{l,k} = 0, \forall k \in \mathcal{K}\} & \iff a_l = 0, \forall l \in \mathcal{L} \\
{b_{l,k} = 0} & \iff w_{l,k} = 0, \forall l \in \mathcal{L}, \forall k \in \mathcal{K}
\end{align*}$$

(5)

The equivalent form of Eqs. (5) can be written as:

$$\begin{align*}
\{b_{l,k} \neq 0, \exists k \in \mathcal{K}\} & \iff a_l = 1, \forall l \in \mathcal{L} \\
b_{l,k} = 1 & \iff w_{l,k} \neq 0, \forall l \in \mathcal{L}, \forall k \in \mathcal{K}
\end{align*}$$

(6)

According to [12], the power consumption of RRH $l$ in transmitting, denoted by $P_{l}^{TRA}$, consists of both circuit and transmit power consumption. Considering the Eqs. (5), $P_{l}^{TRA}$ can be expressed as:

$$P_{l}^{TRA} = P_{l}^{CIR} + \frac{1}{\eta_l} \sum_{k=1}^{K} b_{l,k} ||w_{l,k}||_2^2$$

(7)

where $P_{l}^{CIR}$ and $\eta_l$ denote the circuit power consumption and the efficiency of the radio frequency power amplifier, respectively. In addition, let the constant $P_{l}^{SLP}$ denote the power consumption when the RRH $l$ is in sleep. For Pico base station, the typical values are $P_{l}^{CIR} = 6.8W$, $P_{l}^{SLP} = 4.3W$, and $\eta_l = 0.25$ [12].

With the Eqs. (5) and Eqs. (7), the power consumption of
RRH \( l \), denoted by \( P_l \), can be expressed as

\[
P_l = a_l P_l^{TRA} + (1 - a_l) P_l^{SLP}
\]

\[
= a_l P_l^{CIR} + \frac{1}{\eta_l} \sum_{k=1}^{K} b_{l,k} \| w_{l,k} \|^2 + (1 - a_l) P_l^{SLP}
\]

\[
= a_l P_l^{CIR} + \frac{1}{\eta_l} \sum_{k=1}^{K} \| w_{l,k} \|^2 + (1 - a_l) P_l^{SLP}
\] (8)

where \( P_l^{CMS} = P_l^{CIR} - P_l^{SLP} \). We denote \( \Phi \) as the parameter tuple \( \{a_l, b_{l,k}, w_{l,k}, \forall l \in L, \forall k \in K\} \). Then, by omitting the constant term \( P_l^{SLP} \), we define the network power consumption function \( F(\Phi) \) as

\[
F(\Phi) = \sum_{l=1}^{L} (a_l P_l^{CMS} + \frac{1}{\eta_l} \sum_{k=1}^{K} \| w_{l,k} \|^2) \] (9)

III. Problem Formulation and Transformation

Based on the power consumption model, we formulate here the network power minimization problem in C-RANs as a MINLP, which jointly consider the QoS requirements of MUs, maximum transmit power and the fronthaul limitation of each RRH.

A. Problem Formulation

Similar to [13]–[16], we employ the QoS constraints for MUs as follows:

\[
SINR_k \geq \gamma_k, \forall k \in K,
\] (10)

where \( \gamma_k > 0 \) denotes the target SINR of MU \( k \).

To quantify the fronthaul cost, one obvious metric is the average bits/sec. However, considering that the information exchanged in the fronthaul includes not only user data but also signaling overhead, this metric reveals too much detail, and the associated problem is highly combinatorial [17]. Hence, similar to [10] and [13], we adopt the number of active connection links which gives a first order measurement of fronthaul load as the metric of fronthaul cost instead. Then, we have the following constraints:

\[
\sum_{k=1}^{K} b_{l,k} \leq C_l, \forall l \in L
\] (11)

where \( C_l \) denotes the maximum number of active connection links that RRH \( l \) can serve.

With Eqs. (5), the QoS constraints and the fronthaul capacity constraints, the network power consumption minimization problem can be formulated as follows:

\[
\mathcal{G}^{(pri)}: \min F(\Phi)
\]

s.t. \( SINR_k \geq \gamma_k, \forall k \in K \)

\[
\sum_{k=1}^{K} \| w_{l,k} \|^2 \leq P_l^{MAX}, \forall l \in L
\] (12c)

\[
\sum_{k=1}^{K} b_{l,k} \leq C_l, \forall l \in L
\] (12d)

\[
a_l = 0 \Rightarrow \{ b_{l,k} = 0, \forall k \in K \}, \forall l \in L
\] (12e)

\[
b_{l,k} = 0 \Rightarrow \{ w_{l,k} = 0, \forall l \in L, \forall k \in K \}
\] (12f)

\[
a_l \in \{0, 1\}, b_{l,k} \in \{0, 1\}, \forall l \in L, \forall k \in K
\] (12g)

For the rest of this paper, we assume that problem \( \mathcal{G}^{(pri)} \) is always feasible when all RRHs are active, i.e. the QoS requirement of each MU will be satisfied if \( a_l = 1, \forall l \in L \).

In the following subsection, we will transform problem \( \mathcal{G}^{(pri)} \) into a Mixed-Integer Second-Order Cone Program (MI-SOCP) [19], since the problem with the user association constraints (i.e. Eqs. (12e) and Eqs. (12f)) is hard to be solved.

B. Problem Transformation

We first handle Eqs. (12e). Since the phases of MUs are always feasible when all RRHs are active, i.e. the QoS requirement of each MU will be satisfied if \( a_l = 1, \forall l \in L \).

Then, we define problem \( \mathcal{G}^{(ref)} \) which is a MI-SOCP:

\[
\mathcal{G}^{(ref)}: \min \hat{F}(\Phi) = F(\Phi) + \frac{\zeta}{L \cdot K} \sum_{l=1}^{L} \sum_{k=1}^{K} b_{l,k}
\]

s.t. \( \{13a\}, \{13b\} \)

\[
\sum_{i \neq k} \sum_{l=1}^{L} h_{l,k}^H w_{l,i} \leq 1 / \sqrt{\gamma_k} \Re\{ \sum_{l=1}^{L} h_{l,k}^H w_{l,k} \}, \forall k \in K
\] (13a)

\[
\Im\{ \sum_{l=1}^{L} h_{l,k}^H w_{l,k} \} = 0, \forall k \in K
\] (13b)

Then, we define problem \( \mathcal{G}^{(pri)} \) which is a MI-SOCP:

\[
\mathcal{G}^{(pri)}: \min \hat{F}(\Phi) = F(\Phi) + \frac{\zeta}{L \cdot K} \sum_{l=1}^{L} \sum_{k=1}^{K} b_{l,k}
\]

s.t. \( \{14a\}, \{14b\} \)

\[
\sum_{k=1}^{K} \sum_{k=1}^{K} \| w_{l,k} \|^2 \leq P_l^{MAX}, \forall l \in L
\] (14c)

\[
\sum_{k=1}^{K} b_{l,k} \leq a_l C_l, \forall l \in L
\] (14d)

\[
\| w_{l,k} \|^2 \leq b_{l,k} \sqrt{P_l^{MAX}}, \forall l \in L, \forall k \in K
\] (14e)

\[
a_l \in \{0, 1\}, b_{l,k} \in \{0, 1\}, \forall l \in L, \forall k \in K
\] (14f)

where \( \zeta \) is a constant with \( \zeta \to 0 \).

Let the parameter tuples \( \Phi^{(pri)} = \{ a_l^{(pri)}, b_{l,k}^{(pri)}, w_{l,k}^{(pri)} \}, \forall l \in L, \forall k \in K \} \) and \( \Phi^{(ref)} = \{ a_l^{(ref)}, b_{l,k}^{(ref)}, w_{l,k}^{(ref)} \}, \forall l \in L, \forall k \in K \) denote optimal solutions of problem \( \mathcal{G}^{(pri)} \) and
problem $\mathcal{P}^{(ref)}$, respectively. In what follows, we will reveal the relationship between problem $\mathcal{P}^{(pri)}$ and problem $\mathcal{P}^{(ref)}$.

**Lemma 1**: $\Phi^{(ref)}$ is a feasible solution of problem $\mathcal{P}^{(pri)}$. In addition, $\Phi^{(pri)}$ is feasible in problem $\mathcal{P}^{(ref)}$.

**Proof**: Please refer to the Appendix A.

**Theorem 1**: $\Phi^{(ref)}$ is a good approximate solution of problem $\mathcal{P}^{(pri)}$. More specifically, we have

$$0 \leq F(\Phi^{(ref)}) - F(\Phi^{(pri)}) \leq \zeta.$$  \hspace{1cm} (15)

**Proof**: Please refer to the Appendix B.

**IV. The Low Complexity Inflation Algorithm**

In recent years, some commercial software packages such as CPLEX [20] and MOSEK [21] have been adopted to determine the optimal solution of MI-SOCP via the branch-and-cut method [22]. However, the computational complexity may be prohibitive for densely deployed scenarios in practice. Therefore, in this section, we adopt a low complexity inflation algorithm introduced by [23] to obtain the suboptimal solution of problem $\mathcal{P}^{(ref)}$ based on the continuous relaxation of this problem.

By relaxing the integer constraints such as Eqs. (14), we could transform a MI-SOCP into a SOCP, which provides a local lower bound on the optimal objective value of the original problem [19]. Then, the continuous relaxation of problem $\mathcal{P}^{(ref)}$ can be expressed as:

$$\mathcal{P}^{(con)}: \min \tilde{F}(\Phi) \quad \text{s.t.} \quad (13a), \quad (13b), \quad (14c) - (14e)$$

$$a_i \in [0, 1], b_{l,k} \in [0, 1], \forall l \in L, \forall k \in K.$$  \hspace{1cm} (16c)

We denote $\Phi^{(con)} = \{a_{l,k}^{(con)}, b_{l,k}^{(con)}, w_{l,k}^{(con)} : \forall l \in L, \forall k \in K\}$ as the optimal solution of problem $\mathcal{P}^{(con)}$.

In the following, we will describe the low complexity inflation algorithm. Let the parameter tuple $\{a_{l,k}^{(n)}, b_{l,k}^{(n)}, \forall l \in L, \forall k \in K\}$ and $\bar{F}(n)$ denote the network state and optimal objective value in the nth iteration, respectively. The initialization of the algorithm is configured as $a_{l,k}^{(0)} = 0, b_{l,k}^{(0)} = 0, \forall l \in L, \forall k \in K$, and $\bar{F}(0) = \sum_{l=1}^{L} (P_i^{CMSS} + \frac{1}{m} P_i^{MAX}) + \zeta$, which means that the network is shut down at the beginning of iteration and there is no $\bar{F}(n), n = 1, 2, \ldots$ cloud be larger than $\bar{F}(0)$. In addition, $\mathcal{U}^{(n)}$ denotes the indeterminate RRH-MU pair set with $\mathcal{U}^{(0)} = \{(l, k) : \forall l \in L, \forall k \in K\}$. We gradually set one of zero-valued variables in $\{a_{l,k}^{(n-1)}, b_{l,k}^{(n-1)}, \forall (l, k) \in \mathcal{U}^{(n-1)}\}$ to one in the nth iteration.

It is obvious that how to select the proper RRH-MU pair in the set $\mathcal{U}^{(n-1)}$ is critical for the performance of the inflation algorithm. Among the various QoS requirements, therefore, the priority level of each pair can be always obtained by calculating Eq. (17). In nth iteration, the $(l^*, k^*)$ denotes the RH-MU pair with largest priority level in $\mathcal{U}^{(n-1)}$, and we will set $b_{l^*,k^*}^{(n)} = 1$ and $a_{l^*,k^*}^{(n)} = 1$. Then, we will remove $(l^*, k^*)$ from $\mathcal{U}^{(n-1)}$. Moreover, if the number of MUs served by RH $(l^*, k^*)$ reaches the capacity, all the RRH-MU pairs except $(l^*, k^*)$ will be removed from $\mathcal{U}^{(n-1)}$.

When parameter tuple $\{a_{l,k}^{(n)}, b_{l,k}^{(n)}, \forall l \in L, \forall k \in K\}$ in the nth iteration is fixed, the MI-SOCP $\mathcal{P}^{(ref)}$ is transformed into a SOCP, which can be expressed as:

$$\mathcal{P}^{(n)}: \min \bar{F}(\Phi) \quad \text{s.t.} \quad (13a), \quad (13b), \quad (14a) - (14e)$$

$$\sum_{k=1}^{K} ||w_{l,k}||_2^2 \leq a_{l,k}^{(n)} P_i^{MAX}, \forall l \in L$$

$$w_{l,k} = b_{l,k}^{(n)} w_{l,k}, \forall l \in L, \forall k \in K.$$  \hspace{1cm} (18d)

If problem $\mathcal{P}^{(n)}$ is infeasible, we will set $\bar{F}(n) = \bar{F}(0)$ and proceed to the next iteration. If problem $\mathcal{P}^{(n)}$ is feasible and $\bar{F}(n) > \bar{F}(n-1)$, we will stop and go back to the previous iteration, i.e., we set $\bar{F}(n) = \bar{F}(n-1), b_{l,k}^{(n)} = 0$ and $a_{l,k}^{(n)} = \max\{b_{l,k}^{(n-1)}, \forall k \in K\}$. Otherwise, we proceed to the next iteration. The pseudo-code of the low complexity inflation algorithm is presented in Algorithm 1.

The computational complexity of the inflation algorithm in Algorithm 1 mainly consists in solving $(\sum C_l + 1)$ SOCP problems, since a RH can not serve any MU if the fronthaul reaches its limitation. For each of the SOCP problem $\mathcal{P}^{(n)}$, the computational complexity is $O((K \sum_{l \in L} N_l)^{3.5})$ by using the interior-point method [24]. Therefore, Algorithm 1 is a polynomial time algorithm and it converges in finite iterations.

**V. Simulation Results and Discussions**

| Parameter | Value |
|-----------|-------|
| Path-loss at distance $d$ (km) | $148.1 + 38.5 \log_{10}(d)$ dB |
| Standard deviation of log-norm shadowing | 8 dB |
| Small-scale fading distribution | $\mathcal{CN}(0, 1)$ |
| Noise power density | $-174$ dBm/Hz |
| System bandwidth | 10 MHz |
| Maximum transmit power of RRH $P_i^{MAX}$ | 10W |
| Transmitting antenna power gain | 9 dB |
| Constant $\zeta$ | $10^{-3}$ |

In this section, we simulate the performance of Algorithm 1. For comparison, the scheme adopted by LTE-A is used...
Algorithm 1 Low Complexity Inflation Algorithm

1: **Initialization:** \( \mathcal{U}^{(0)} = \{(l,k)\} | \forall l \in \mathcal{L}, \forall k \in \mathcal{K} \}; \quad a^{(0)}_i = 0, b^{(0)}_i = C_i, \quad \alpha^{(0)}_{l,k} = 0, \alpha^{(0)}_{l,k} = 0; \quad \text{a sufficiently large } \hat{F}^{(0)}; \quad n = 1.

2: **while** \( \mathcal{U}^{n-1} \) is non-empty **do**

3: \quad Compute \((l^*, k^*) = \arg\max_{(l,k) \in \mathcal{U}^{(n-1)}} \alpha_{l,k}. \)

4: \quad Set \( b^{(n)}_{l,k} = \alpha^{(n-1)}_{l,k}, a^{(n)}_l = a^{n-1}_l. \)

5: \quad Set \( b^{(n)}_{l^*, k^*} = 1, a^{(n)}_{l^*} = 1. \)

6: \quad Update \( \mathcal{U}^{(n)} = \mathcal{U}^{(n-1)} \setminus \{(l^*, k^*)\}. \)

7: \quad \text{if} \quad \sum_{j=1}^{K} b^{(n)}_{l,k} = C_i \quad \text{then}

8: \quad \quad \mathcal{U}^{(n)} = \mathcal{U}^{(n)} \setminus \{(l^*, k^*) \} \quad \forall k \in K, k \neq k^*.

9: \quad \text{end if}

10: \quad \text{if Problem } \mathcal{P}^{(n)} \text{ is infeasible. then}

11: \quad \quad \hat{F}^{(n)} = \hat{F}^{(0)}.

12: \quad \text{else}

13: \quad \quad \text{if } \hat{F}^{(n)} > \hat{F}^{(n-1)} \quad \text{then}

14: \quad \quad \quad \hat{F}^{(n)} = \hat{F}^{(n-1)}.

15: \quad \quad \quad \text{Set } \hat{b}^{(n)}_{l,k} = 0, a^{(n)}_{l^*} = \max_{k \in K} b^{(n)}_{l,k}.

16: \quad \quad \text{end if}

17: \quad \text{end if}

18: \quad \text{The iteration number } n = n + 1.

19: **end while**

as a benchmark, where the network is divided into non-overlapping clusters according to the locations of RRHs and MUs, and the RRHs in each cluster coordinately serve all the users within the coverage area \([25] \). We consider a network comprising \( L = 10 \) 2-antenna RRHs and \( K = 10 \) or \( K = 15 \) single-antenna MUs uniformly distributed in the square region \([-1500 \ 1500] \times [-1500 \ 1500] \) meters. The channel model is shown in Table I. The numerical results are averaged over 100 randomly generated network realization. According to \([12] \), we set \( P^C_{TH} = 6.81W, P^S_{LP} = 4.31W \) and \( \eta_l = 0.25 \).

Fig 2 shows the variation in network power consumption versus target SINR when fronthaul capacity equals 6. We observe from this figure that the performance of Algorithm 1 is better than that of LTE-A beamforming algorithm and the gap between the two algorithms increases with the target SINR, since the RRHs serving each MU in Algorithm 1 are overlapping and adopt CoMP to jointly transmit data, which converts the ICI into useful signals. In addition, it is easy to understand that the network consumption with \( K = 10 \) is lower than that with \( K = 15 \), since higher transmitpower and more active RRHs are required to serve the excess MUs.

Fig 3 depicts the variation in network power consumption versus fronthaul capacity when target SINR is 6dB. As we can see, the network power consumption decreases with the fronthaul capacity. This is because the RRH can serve more MUS and more diversity gain can be obtained. Moreover, the curves descends slowly when each RRH can serve more MUs, as the fronthaul capacity is not the primary limitation on the network performance.

Fig 4 and Fig 5 show the variation in number of active RRHs versus target SINR and fronthaul capacity, respectively. The fronthaul capacity and target SINR are 6 and 6dB in the two figures, respectively. These two figures illustrate that more RRHs have to be active with high SINR requirement or small fronthaul capacity, and more RRHs can be in sleep if there are fewer MUs when we adopt Algorithm 1. In addition, Fig 4 shows that all RRHs are active in LTE-A beamforming algorithm, even if the number of MUs is small and the target SINR is low.
VI. CONCLUSION

In this paper, we proposed a joint user association and downlink beamforming scheme for C-RANs with limited fronthaul to minimize the network power consumption. To be more specific, the design problem is formulated as a mixed integer nonlinear program at first. We then transform the problem into a MI-SOCP which is a SOCP when the integer variables are fixed. At last, we adopt a low complexity inflation algorithm to obtain the suboptimal solution. According to the simulation results, it has been observed that the adopted algorithm can effectively lower the network consumption compared with the scheme used by LTE-A. Since too many users served by the network will incurs problem $\mathcal{P}^{(pri)}$ is infeasible, our future work is in progress to consider the user admission control in the proposed scheme.

APPENDIX A

PROOF OF LEMMA 1

We can easily observe that the feasible region of problem $\mathcal{P}^{(pri)}$ is a subset of that of problem $\mathcal{P}^{(ref)}$. Hence, $\Phi^{(pri)}$ is a feasible solution of problem $\mathcal{P}^{(ref)}$. In addition, $\Phi^{(ref)}$ satisfies the constraints (12b), (12d) and (12e). Accordingly, in the following, we will prove $\Phi^{(ref)}$ satisfies the constraints (12a) and (12c).

In case that $a_i^{(ref)} = 0$, the equalities $\{b_{l,k}^{(ref)} = 0, \forall k \in K\}$ hold according to constraints (14d). In turn, if $b_{l,k}^{(ref)} = 0, \forall k \in K$, we can easily know that both $a_i = 0$ and $b_i$ are feasible. If $a_i^{(ref)} = 1$, we have $\hat{F}(\Phi^{(ref)})|_{a_i=1} > \hat{F}(\Phi^{(ref)})|_{a_i=0} = 0$, which is in contradiction to the assumption that $\Phi^{(ref)}$ is the optimal solution of problem $\mathcal{P}^{(ref)}$. Hence, we have $a_i^{(ref)} = 0$. Moreover, through Eqs. (14c), we have $w_{l,k}^{(ref)} = 0$ if $b_{l,k}^{(ref)} = 0$. We adopt similar contradicting argument to prove that $b_{l,k}^{(ref)}$ equals 0 if $w_{l,k}^{(ref)} = 0$ as well. Therefore, $\Phi^{(ref)}$ is feasible in problem $\mathcal{P}^{(pri)}$.

The proof is completed.

APPENDIX B

PROOF OF THEOREM 1

With the Lemma 1, we have

$$\hat{F}(\Phi^{(ref)}) - \hat{F}(\Phi^{(pri)}) \leq 0$$

$$(F(\Phi^{(ref)}) - F(\Phi^{(pri)})) + \frac{\zeta}{L \cdot K}$$. $\sum_{l=1}^{L} \sum_{k=1}^{K} (b_{l,k}^{(ref)} - b_{l,k}^{(pri)}) \leq 0$$

$$F(\Phi^{(ref)}) - F(\Phi^{(pri)}) \leq \frac{\zeta}{L \cdot K}$$. $\sum_{l=1}^{L} \sum_{k=1}^{K} (b_{l,k}^{(pri)} - b_{l,k}^{(ref)})$$

(19)

$\Phi^{(pri)}$ is a optimal solution of problem $\mathcal{P}^{(pri)}$, so

$$0 \leq F(\Phi^{(ref)}) - F(\Phi^{(pri)}) \leq \frac{\zeta}{L \cdot K}$$. $\sum_{l=1}^{L} \sum_{k=1}^{K} (b_{l,k}^{(pri)} - b_{l,k}^{(ref)})$$

$$\leq \frac{\zeta}{L \cdot K} \cdot L \cdot K = \zeta$$

(20)

The proof is completed.

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