Joint Beamforming and Remote Radio Head Selection in Limited Fronthaul C-RAN

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***Abstract*—This paper considers the power minimization problem in downlink of cloud radio access networks with limited fronthaul capacity. A joint design of beamforming, remote radio head (RRH) selection and RRH-user association that explicitly takes into account per-fronthaul capacity constraints is considered. The problem of interest is in fact a combinatorial program which is generally NP-hard. We naturally write the considered problem as a mixed integer program by introducing binary selection variables. The challenge is that even if these binary selection variables are relaxed to be continuous, the resulting problem is still nonconvex. For such a problem, finding a high-quality solution, rather than an optimal one, is a more realistic goal. Towards this end we propose two iterative algorithms to deal with combinatorial nature of the joint design problem. In the first method, by novel transformations, we iteratively approximate the continuous nonconvex constraints by convex conic ones using successive convex approximation framework. More explicitly the problem arrived at each iteration of the first method is a mixed-integer second order cone program (MI-SOCP) for which dedicated solvers are available. The second method is a simplified variant of the first one where we further relax the binary variables in each iteration to be continuous. That is to say, the second method merely requires solving a sequence of SOCPs. After convergence, we then perform a post-processing procedure on the relaxed selection variables to search for a high-performance solution. Numerical results are presented to demonstrate the superiority of the proposed algorithms over existing methods based on sparse–inducing norm.**

I. Introduction

Over the last few years, cloud radio access networks (C-RAN) have been proposed as a vital technology that provides significant network enhancement to cope with the explosive demand of the foreseen 5G network [1], [2]. By merging the radio access and cloud computing capabilities, C-RAN introduce more alternative to enable centralized computation and more power-saving communications. A C-RAN system basically contains several RRHs with low energy consumption that are all connected to the base band unit (BBU) pool via optical links [1] as illustrated in Fig. 1. In C-RANs, the RRHs with radio frequency (RF) modules only account for transmission/reception radio signals and transport towards/backwards the BBU pool. At the BBU side, the centralized processing task powered by advanced computer processing units (CPUs) is executed to handle all the relevant baseband signals. Although providing significant improvement, C-RAN is critically constrained by the limited fronthaul capacity between RRHs and BBU pool [3]. This creates a bottleneck on the network operation, which requires appropriate management on the selection and transmit power design at RRH to attain the optimal performance.

There have been several works that study the joint design of RRH-user (UE) association and beamforming in C-RAN with limited fronthaul capacity. The works in [4], [5] proposed various compression techniques to minimize the transmitted data delivered over the fronthaul network. In [6], Fan *et. al.* developped a low complexity and efficient algorithm to cluster the RRHs so that the number of centralized processes at BBUs pool was eligibly reduced. In [7], [8], the authors employed the sparse induced-norm to develop a joint beamforming and base station (BS) selection design to minimize the power consumption in C-RAN so that the usage of fronthaul capacity was implicitly minimized. Inspired by these works, [9] further addressed the coupling factor of uplink (UL) and downlink (DL) transmissions in C-RAN to resolve the problem of [7] by exploiting the UL-DL duality and MISOCP framework. Apart from these works, [10], [11] explicitly posed the limited fronthaul constraint in their optimization problems and apply different methods based on group sparsity design to attain the solution.

In this paper, we study the the joint design of beamforming, RRH selection and RRH-UE association on the DL of the C-RAN that minimizes the overall network power consumption. By explicitly considering the per-fronthaul link capacity constraint and naturally introducing binary variables, we write the considered problem as a mixed integer nonlinear program. The problem of interest is in fact a combinatorial nonconvex problem which is generally NP-hard. The challenge is that even if these binary selection variables are relaxed to be continuous, the resulting problem is still nonconvex. For such a problem finding a high-quality solution, rather than an optimal one, is a more realistic goal. Towards achieving this kind of solution, we propose two iterative algorithms to deal with combinatorial nature of the joint design problem. In the first method, unlike the works in [10], [11] where the authors simply assign a fixed achievable rate to overcome the nonconvex fronthaul constraint, we directly tackle it by proposing novel transformation on this difficult constraint to return at an equivalent nonconvex but more tractable problem form. Then, we iteratively approximate the continuous nonconvex constraints by convex conic ones using successive convex approximation (SCA) framework. The problem arrived at each iteration of the first method is a mixed-integer second order cone program (MI-SOCP) for which dedicated solver like MOSEK is available. However, solving the MI-SOCP

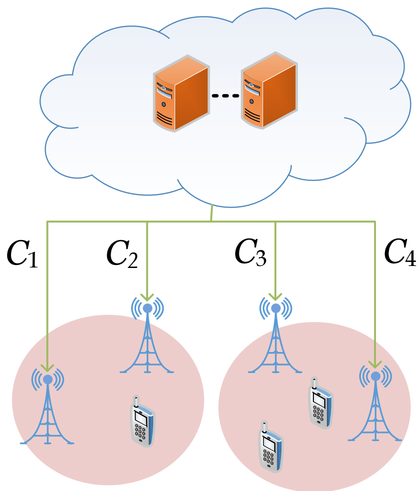

Fig. 1: Limited fronthaul C-RAN.

problem in the first method is computationally costly for large networks. Therefore, in the second method, we develop the polynomial-time algorithm that yields the high-quality solution for practical network. In particular, we further relax the binary variables in each iteration to be continuous so that the second method now only requires solving a sequence of SOCPs. After convergence, we then perform a post-processing procedure based on the proposed incentive metric to refine the relaxed selection variables to a higher-quality solution. Compared to existing methods in [10], [11] based on sparse-inducing-norm, our methods are shown to be more superior to achieve better network performance in the sense of lower power consumption. The rest of the paper is organized as follows. Section II introduces the C-RAN system model. Section III formulates the optimization problem and proposes different algorithms to achieve the solution, respectively. In Section IV, we present our numerical results under different simulation setups. Finally, conclusion of the paper is given in Section V.

Notation: We use bold uppercase letters to denote matrices and bold lowercase letters to denote vectors. $\mathbf{x}^H$ stand for the Hermitian operation of vector $\mathbf{x}$. $|x|$ represents the absolute of $x \in \mathbb{C}$, while $\|\mathbf{x}\|$ is the 2-norm of the vector $\mathbf{x}$. $\mathbb{E}\{\cdot\}$ denotes the expectation operator. x^* represents the complex conjugate of x $\in \mathbb{C}$. $\Re e(.)$ and $\Im m(.)$ stand for the real and imaginary part of the argument, respectively. $\sqrt{-1}$ represents the imaginary number.

II. System Model

We consider the DL of C-RAN consisting of I RRHs and K single antenna UEs. For notational convenience, we denote $\mathcal{I} = \{1, \ldots, I\}$ and $\mathcal{K} = \{1, \ldots, K\}$ as the set of RRHs and UEs, respectively. We assume that each ith RRH is equipped with M_i antennas where $i \in \mathcal{I}$. As shown in Fig. 1, we assume that all the RRHs are connected to BBU pool via the fronthaul links, e.g., high-speed optical ones, where the ith link has a predetermined maximum capacity C_i. Each UE is served by a specific group of RRHs but one RRH can serve more than one users simultaneously. Let us denote s_k as the signal with unit power, e.g., $\mathbb{E}\{s_k s_k^*\} = 1$ intended for the kth UE and $\mathbf{w}_{i,k} \in \mathbb{C}^{M_i \times 1}$ as the transmit beamforming vector from the ith RRH to the kth UE. Then, the received signal at the kth UE is given by

$$y_k = \mathbf{h}_k^H \mathbf{w}_k s_k + \sum_{j \in \mathcal{K} \setminus k} \mathbf{h}_k^H \mathbf{w}_j s_j + z_k \tag{1}$$

where $\mathbf{h}_k \triangleq \{\mathbf{h}_{i,k}\} \in \mathbb{C}^{M \times 1}, \forall i \in \mathcal{I}$, $\mathbf{h}_{i,k} \in \mathbb{C}^{M_i \times 1}$ is the vector of channel coefficients encompassing small-scale fading and pathloss from the ith RRH to the kth UE, and $M = \sum_{i \in \mathcal{I}} M_i$. In addition, $z_k \sim \mathcal{CN}(0, \sigma_k^2)$ is the additive white Gaussian noise (AWGN) and σ_k^2 is the noise power. For brevity, we first assume that each kth UE is connected to all the RRHs. However, the particular ith RRH serves the kth UE is determined when $\|\mathbf{w}_{i,k}\|^2 > 0$, otherwise, the kth UE is not associated with this ith RRH. By denoting the set of beamforming vector intended for the kth UE as $\mathbf{w}_k \triangleq \{\mathbf{w}_{i,k}\} \in \mathbb{C}^{M \times 1}, \forall i \in \mathcal{I}$ and $\mathbf{w} \triangleq \{\mathbf{w}_k\}, \forall k \in \mathcal{K}$. By treating interference as noise, the achievable rate in bits/s/Hz at the kth UE is given by

$$\begin{aligned} R_k(\mathbf{w}) &= \log_2(1 + \Gamma_k(\mathbf{w})) \\ &= \log_2\left(1 + \frac{|\mathbf{h}_k^H \mathbf{w}_k|^2}{\sum_{j \in \mathcal{K} \setminus k} |\mathbf{h}_k^H \mathbf{w}_j|^2 + \sigma_k^2}\right). \end{aligned} \tag{2}$$

A. Fronthaul constraints

After the BBU pool solves a relevant radio resource management to determine the beamforming vector $\mathbf{w}_k$ for the particular kth UE, only nonzero elements in $\mathbf{w}_k$ are actually transported to the corresponding RRHs through the corresponding fronthaul links. Specifically, if $\|\mathbf{w}_{i,k}\|^2 = 0$ then the ith RRH does not serve the kth UE and the data of the kth UE is not routed from BBU pool to the ith RRH via the ith fronthaul link. In addition, the data rate transported by the ith fronthaul link should be greater or equal to the total rate achieved at the ith RRH. For the purpose of problem formulation, let us introduce binary variables $a_{i,k} \in \{0, 1\}, \forall i \in \mathcal{I}$ and $k \in \mathcal{K}$ to represent the association status between the ith RRH and the kth UE, i.e., $a_{i,k} = 1$ implies that the kth UE is served by the ith RRH and $a_{i,k} = 0$, otherwise. Then, the per-fronthaul capacity constraints can be written as

$$\sum_{k \in \mathcal{K}} a_{i,k} R_k(\mathbf{w}) \leq C_i, \forall i \in \mathcal{I}. \tag{3}$$

B. Power consumption

In this subsection, we present a power consumption model that accounts for the power consumption at RRHs as well as that for transmitting digital data from the BBU pool to the corresponding RRHs. According to [7], the power consumption at a RRH consists of two types, namely, data dependent power and data independent power. The data dependent power is the power dispatched at the power amplifier in RRH which is a function of transmitted signals. On the other hand, the data independent power is mostly due to electronic components in RRH and can be subcategorized into two types, one representing the fixed amount of power P_i^{ra} when the ith RRH is active mode, one denoting the power required to keep the ith RRH in sleep mode, which is denoted by P_i^{ri}. Besides, we denote by $P_{i,k}^{\text{FH}}$ the power consumption for forwarding information data and beamformers related to the transmission from RRH i to UE k via fronthaul tranmission. From the introduction of $a_{i,k}$, it is obvious that when $a_{i,k} = 0$, then $P_{i,k}^{\text{FH}} = 0$. To represent the operation mode of the ith RRH, we introduce a binary variable $b_i = 0, 1, \forall i \in \mathcal{I}$. In particular, $b_i = 0$ states that the ith RRH is in sleep mode and $b_i = 1$ means otherwise. In summary, the sum power consumption at all RRHs and corresponding fronthaul links can be written as

$$\begin{aligned} P^{\text{tot}}(\mathbf{w}, \mathbf{a}, \mathbf{b}) = \frac{1}{\eta_i} \sum_{i \in \mathcal{I}} \sum_{k \in \mathcal{K}} \|\mathbf{w}_{i,k}\|^2 + \sum_{i \in \mathcal{I}} b_i P_i^{ra} \\ + \sum_{i \in \mathcal{I}} (1 - b_i) P_i^{ri} + \sum_{i \in \mathcal{I}} \sum_{k \in \mathcal{K}} a_{i,k} P_{i,k}^{\text{FH}} \end{aligned} \quad (4)$$

where η_i is the power amplifier efficiency, $\mathbf{b} = [b_1, \ldots, b_I]^T$ and $\mathbf{a} = \left[\mathbf{a}_1^T, \ldots, \mathbf{a}_K^T\right]^T$ where $\mathbf{a}_k = [a_{1,k} \ldots, a_{I,k}]^T$.

III. Joint Beamforming, RRH Selection and RRH-UE association in Power Minimization

A. Problem formulation

In this paper, we aim to jointly optimize beamformers and the set of active coordinated RRHs that serve each UE so that the total power consumption is minimized. The considered problem, which is referred as CRAN-SPmin problem, is mathematically stated as

$$\min_{\mathbf{a}, \mathbf{b}, \mathbf{w}, \boldsymbol{\nu} \geq 0} \; P^{\text{tot}}(\mathbf{w}, \mathbf{a}, \mathbf{b}) \quad (5a)$$

$$\text{s.t.} \; \Gamma_k(\mathbf{w}) \geq \Gamma_k^{\min} \quad (5b)$$

$$\sum_{k \in \mathcal{K}} \|\mathbf{w}_{i,k}\|^2 \leq b_i P_{\max} \quad (5c)$$

$$\|\mathbf{w}_{i,k}\|^2 \leq a_{i,k} \nu_{i,k} \quad (5d)$$

$$\nu_{i,k} \leq a_{i,k} P_{\max} \quad (5e)$$

$$a_{i,k} \leq b_i \quad (5f)$$

$$\sum_{i \in \mathcal{I}} a_{i,k} \geq 1 \quad (5g)$$

$$\sum_{k \in \mathcal{K}} a_{i,k} R_k(\mathbf{w}) \leq C_i \quad (5h)$$

$$b_i \in \{0, 1\}, a_{i,k} \in \{0, 1\} \quad (5i)$$

$$\forall i \in \mathcal{I}, \forall k \in \mathcal{K}$$

where $\boldsymbol{\nu} = \{\nu_{i,k}\}, \forall i \in \mathcal{I}, k \in \mathcal{K}$ is the set of introduced variables representing the soft power transmitted from the ith RRH to UE k. The constraints in (5b) ensure the QoS requirement for the kth user, where $\Gamma_k^{\min}$ is the given SINR requirements for the kth user, $\forall k \in \mathcal{K}$. (5c) represents the limited total transmit power at each RRH. With this presentation, we find that when RRH is in sleep mode, e.g., $b_i = 0$, there is no power transmitted from the ith RRH to its user, e.g., the sum $\sum_{k \in \mathcal{K}} \|\mathbf{w}_{i,k}\|^2 = 0$ in (5c) and there is no power consummed to transport data from the cloud towards the ith RRH, e.g., $a_{i,k} = 0$ in (5f). Similarly, in (5d) we also guarantee that the transmit power $\|\mathbf{w}_{i,k}\|^2$ from the ith RRH to the kth user is forced to zero if $a_{i,k} = 0$. The constraint in (5e) to limit the soft power from the ith RRH to the kth user. We also impose the constraint (5g) to make sure that each user k is served by at least one RRH. Finally, the per-fronthaul capacity constraint is explicitly imposed in (5h) since each fronthaul link has the predetermined maximum capacity C_i.

It is worth to mention that the formulated optimization problem is a mixed integer non-linear programming (MINLP) problem, which is generally NP-hard. Moreover, when the binary variables $\mathbf{b}$ and $\mathbf{a}$ are relaxed to be continuous, the problem is still nonconvex due to the existence of the non-convex constraint (5h). In mathmetical programming terminology, problem (5) is classified as a non-convex mixed integer program for which such methods as the one in [12] are not applicable to find an optimal solution. The above dicussions imply that computing a global optimal solution to (5) is very difficult and even if possible, it is of little practical use. In this paper we propose to solve (5) by converting it into more tractable form that can leverage advanced optimization techniques. In particular we employ sequential convex approximation (SCA) method to approximate non-convex continuous constraints arrive at a series of MI-SOCPs. We also consider a simplifed method where all binary variables to allowed to take continuous values. This is done with a post-processing scheme to search for a good feasible solution.

B. Problem transformation

We quickly observe that without constraints (5i), the objective function (5) is a convex function with respect to all variables. In addition, the constraints (5f), (5e) and (5g) are linear with variables $\mathbf{a}$ and $\mathbf{b}$. Similar to [12], we remark that the beamforming vector $\mathbf{w}_{i,k}$ are phase-invariant so that if $\mathbf{w}_{i,k}$ is feasible for the SINR constraint in (5b), its rotated version $\mathbf{w}_{i,k} e^{\sqrt{-1}\theta_{i,k}}$ is also a feasible solution that satisfies (5b). Moreover, $\mathbf{w}_{i,k} e^{\sqrt{-1}\theta_{i,k}}$ and $\mathbf{w}_{i,k}$ result in the same value of objective function in (5). Hence, the SINR constraint (5b) can be written in the SOC constraint as

$$\sqrt{\left(\frac{1}{\Gamma_k^{\min}} + 1\right)} \Re e(\mathbf{h}_k^H \mathbf{w}_k) \geq \left\| \mathbf{h}_k^H \mathbf{w}_1, \ldots, \mathbf{h}_k^H \mathbf{w}_K, \sigma_0 \right\| \quad (6)$$

$$\Im m(\mathbf{h}^{\mathscr{H}} \mathbf{w}) = 0 \quad (7)$$

Furthermore, we notice that (5c) and (5d) can also be rewritten in the form of MI-SOCP as

$$(b_i + P_{\max})/2 \geq \|\mathbf{w}_{i,1}, \ldots, \mathbf{w}_{i,K}, (b_i - P_{\max})/2\| \quad (8)$$

$$(a_{i,k} + \nu_{i,k})/2 \geq \|\mathbf{w}_{i,k}, (a_{i,k} - \nu_{i,k})/2\| \quad (9)$$

At this point, it is obvious to see that the difficulty in solving (5) lies in constraint (5h) due to its non-convexity. To obtain a more tractable form, we first rewrite (5h) as

$$\sum_{k=1}^{K} a_{i,k} \log(1 + t_k) \leq C_i \quad (10a)$$

$$\frac{|\mathbf{h}_k^H \mathbf{w}_k|^2}{\sum_{j \neq k}^{K} |\mathbf{h}_k^H \mathbf{w}_j|^2 + \sigma_0^2} \leq t_k \quad (10b)$$

where $t_k \geq 0, \forall k \in \mathcal{K}$ are the newly introduced variables and $\mathbf{t} = [t_1, \ldots, t_K]^T$. Moreover, we can rewrite (10a) as

$$\sum_{k \in \mathcal{K}} a_{i,k}^2 / z_k \leq C_i \tag{11}$$

$$1 + t_k \leq e^{1/(z_k \log_2 e)} \tag{12}$$

where $z_k \geq 0, \forall k \in \mathcal{K}$ are the newly introduced variables and $\mathbf{z} = [z_1, \ldots, z_K]^T$. In (11), we have used the fact that $a_{i,k} = a_{i,k}^2$ for $a_{i,k} \in \{0, 1\}$. Note that constraint (11) can be easily transformed into SOC constraints by introducing slacks variables $c_{i,k} \geq 0, \forall i, k$ and rewritting it as

$$\sum_{k=1}^{K} c_{i,k} \leq C_i, \forall i \in \mathcal{I} \tag{13}$$

$$\|a_{i,k}, (c_{i,k} - z_k)/2\| \leq (c_{i,k} + z_k)/2 \tag{14}$$

At this point, we can equivalently rewrite (5) as

$$\min_{\substack{\mathbf{a},\mathbf{b},\mathbf{w},\\ \boldsymbol{\nu}\geq 0,\mathbf{t}\geq\mathbf{0}\\ \mathbf{z}\geq 0,\mathbf{c}\geq 0}} \quad P^{\text{tot}}(\mathbf{w}, \mathbf{a}, \mathbf{b}) \tag{15a}$$

$$\text{s.t.} \sqrt{\frac{1}{\Gamma_k^{\min}} + 1}\,\Re\left(\mathbf{h}_k^H \mathbf{w}_k\right) \geq \left\|\mathbf{h}_k^H \mathbf{w}_1, \ldots, \sigma_0\right\|, \tag{15b}$$

$$(b_i + P_{\max})/2 \geq \left\|\mathbf{w}_i^T, (b_i - P_{\max})/2\right\|, \tag{15c}$$

$$\frac{a_{i,k} + \nu_{i,k}}{2} \geq \left\|\mathbf{w}_{i,k}^T, (a_{i,k} - \nu_{i,k})/2\right\|, \tag{15d}$$

$$\|a_{i,k}, (c_{i,k} - z_k)/2\| \leq (c_{i,k} + z_k)/2, \tag{15e}$$

$$\sum_{k \in \mathcal{K}} c_{i,k} \leq C_i, \tag{15f}$$

$$1 + t_k \leq e^{1/(z_k \log_2 e)}, \tag{15g}$$

$$\frac{|\mathbf{h}_k^H \mathbf{w}_k|^2}{\sum_{j \neq k}^{K} |\mathbf{h}_k^H \mathbf{w}_j|^2 + \sigma_0^2} \leq t_k, \tag{15h}$$

$$(5e), (5f), (5g), (5i). \tag{15i}$$

Observe that problem (15) is still nonconvex due to the nonconvex constraints (10b) and (12). In the following, we apply the SCA method to convexify (10b) and (12) and based on that to develop an efficient algorithm to achieve a high-quality solution.

C. SCA-MISOCP Algorithm

We first observe that wihout (10b) and (12), the transformed problem (15) will admit the form of general MI-SOCP, which can be solved optimally by some powerful convex solvers such as MOSEK. Motivated by this observation, we propose to replace each of these non-convex constraints by its convex approximation. In (12), we can see that the right side of this inequality is a convex function with respect to z_k, while the left side is also a convex function with respect to t_k. Thus, we apply the first order Taylor's approximation of $\exp\left(1/\left(z_k \log_2 e\right)\right)$, around the point $z_k^{(n)}$ by

$$F_k\left(z_k, z_k^{(n)}\right) = e^{1/\left(z_k^{(n)} \log_2 e\right)} - \frac{e^{1/\left(z_k^{(n)} \log_2 e\right)}}{\left(z_k^{(n)}\right)^2 \log_2 e}\left(z_k - z_k^{(n)}\right) \tag{16}$$

Next, we quickly rewrite the constraint (10b) as

$$\frac{|\mathbf{h}_k^H \mathbf{w}_k|^2}{t_k} \leq \sum_{j \neq k}^{K} |\mathbf{h}_k^H \mathbf{w}_j|^2 + \sigma_0^2 \tag{17}$$

Then, we also observe that the non-convexity of the constraint (17) lies in the right side of the inequality. Thus, we apply the first order Taylor's approximation around the point $\mathbf{w}^{(n)}$ by

$$G_k\left(\mathbf{w}, \mathbf{w}^{(n)}\right) = \sum_{j \neq k}^{K} 2\Re\left(\left(\mathbf{w}_j^{(n)}\right)^H \mathbf{H}_k \mathbf{w}_j\right) - \sum_{j \neq k}^{K} \left(\mathbf{w}_j^{(n)}\right)^H \mathbf{H}_k \mathbf{w}_j^{(n)} + \sigma_0^2 \tag{18}$$

where we denote $\mathbf{H}_k = \mathbf{h}_k \mathbf{h}_k^H$ for brevity. By applying these approximation, we can formulate the upper bounded MI-SOCP approximation of problem (5) at iteration $n+1$ as below

$$\min_{\substack{\mathbf{b},\mathbf{a},\mathbf{w},\\ \boldsymbol{\nu}\geq 0,\mathbf{t}\geq\mathbf{0}\\ \mathbf{z}\geq 0,\mathbf{c}\geq 0}} \quad P^{\text{tot}}(\mathbf{w}, \mathbf{a}, \mathbf{b}) \tag{19a}$$

$$1 + t_k \leq F_k\left(z_k, z_k^{(n)}\right), \tag{19b}$$

$$\left|\mathbf{h}_k^H \mathbf{w}_k\right|^2 / t_k \leq G_k\left(\mathbf{w}, \mathbf{w}^{(n)}\right), \tag{19c}$$

$$(15b) - (15f), (5e), (5f), (5g), (5i). \tag{19d}$$

where $\mathbf{w}^{(n)}, \mathbf{z}^{(n)}$ are the parameters that are updated at the $(n+1)$th iteration. Note that (19) can be optimally solved at each iteration by using the available MI-SOCP solver, namely MOSEK. The pseudo-code to solve (19) is summarized in Algorithm 1.

Algorithm 1 SCA-MISOCP based Algorithm.

1: Initialize starting points of $\mathbf{z}^{(n)}, \mathbf{w}^{(n)}$;
2: Set $n := 0$;
3: **repeat**
4: Solve the MI-SOCP problem (19) with $\mathbf{z}^{(n)}, \mathbf{w}^{(n)}$ to achieve the optimal solution $\mathbf{b}^\star, \mathbf{a}^\star, \mathbf{w}^\star, \boldsymbol{\nu}^\star, \mathbf{t}^\star, \mathbf{z}^\star, \mathbf{c}^\star$;
5: Set $n := n + 1$;
6: Update $\mathbf{z}^{(n)} = \mathbf{z}^\star, \mathbf{w}^{(n)} = \mathbf{w}^\star$;
7: **until** Convergence;

D. Inflation based Algorithm

Solving the MISOCP problem (19) is computationally costly due to its combinatorial nature, especially when the number of RRHs and/or UEs becomes large. This motivates us to develop a more practically appealing algorithm, i.e., with much lower complexity, to find a good feasible solution of (5). A simple approach is to consider the continuous relaxation of (5i), e.g., $0 \leq b_i \leq 1, 0 \leq a_{i,k} \leq 1$ for $\forall i \in \mathcal{I}, \forall k \in \mathcal{K}$. According to this, the continuous relaxation of (19), denoted as $(\mathcal{P}^r)$, can be reduced to an SOCP and can be solved by Algorithm 1, where at Step 4, we replace the MI-SOCP problem by its continuous relaxed SOCP problem. However, this results in a poor performance in a sense that the most of b_i and $a_{i,k}$ are infeasible for the MI-SOCP problem (19) after convergence. Therefore, we propose to apply the inflation procedure as in [12] to refine the achieved solution of the relaxed SOCP problem so that $\mathbf{a}$ and $\mathbf{b}$ can finally take binary values. In particular, we choose the value of the solution at convergence of the relaxed SCA-SOCP as the incentive measure to make decision on the value of $\mathbf{a}$ and $\mathbf{b}$. Let us denote $\tilde{\mathbf{a}}, \tilde{\mathbf{b}}$ and $\tilde{\mathbf{w}}$ as the solution achieved at the convergence of Algorithm (1) for the relaxed SOCP problem. Intuitively, the connection between the ith RRH and the kth UE is more likely to be chosen, $a_{i,k} = 1$ if the channel between this pair of RRH-UE is better and the power consummed to transmit fronthaul data $P^{\text{FH}}_{i,k}$ is smaller than the others. Consequently, solving the relaxed SOCP problem yields higher $\widetilde{b}_i$ for the ith RRH and higher $\widetilde{a}_{i,k}$ for the link of the ith RRH and the kth UE. Based on the above remarks, we propose an iterative procedure to determine the set of active RRHs and RRH-UE association by relying on the incentive measure $\tilde{\mathbf{a}}, \tilde{\mathbf{b}}$. The process initiates by assuming that all the RRHs are off and there is no association between RRH and UE. In each iteration, $(\mathcal{P}^r)$ is solved with a candidate set of RRHs and RRH-UE association that might be inactive and not connected, respectively. The candidate RRH-UE association will be chosen to be connected with the largest $\tilde{a}_{i,k}$ and the candidate RRH will be set active by following the relationship in (5f). The overall algorithm is presented in Algorithm 2.

Algorithm 2 Inflation based Algorithm

1: Set $m := 0$, $\pi^{(m)}$ is significantly large, and initialize the set $\mathcal{R}^{(m)}_{\text{off}} = \{(i,k) \times i \in (\mathcal{I},\mathcal{K}) \times \mathcal{I}\}$.
2: **repeat**
3: Set $m := m + 1$;
4: Solve $(\mathcal{P}^r)$ with $a_{i',k'} = 1$ and $b_{i'} = 1, \forall \{(i',k') \times i'\} \notin \mathcal{R}^{(m-1)}_{\text{off}}$;
5: Update $\mathcal{R}^{(m)}_{\text{off}} = \mathcal{R}^{(m-1)}_{\text{off}} \setminus \left\{(i',k') \times i' = \arg\max_{i,k \in \mathcal{R}^{(m-1)}_{\text{off}}} \widetilde{a}_{i,k}\right\}$;
6: Solve (19) with $a_{i',k'} = 1, b_{i'} = 1, \forall \{(i',k') \times i'\} \notin \mathcal{R}^{(m)}_{\text{off}}$ and $a_{i,k} = 0, b_i = 0, \forall \{(i,k) \times i\} \in \mathcal{R}^{(m)}_{\text{off}}$, and set $\pi^{(m)}$as the value of objective function achieved at convergence.
7: **until** $(\mathcal{P}^r)$ starts to be infeasible or (19) is feasible and $\pi^{(m)} > \pi^{(m-1)}$;
8: Solve (19) with $a_{i',k'} = 1, b_{i'} = 1, \forall \{(i',k') \times i'\} \notin \mathcal{R}^{(m-1)}_{\text{off}}$ and $a_{i,k} = 0, b_i = 0, \forall \{(i,k) \times i\} \in \mathcal{R}^{(m-1)}_{\text{off}}$ to obtain $\mathbf{w}^\star, \boldsymbol{\nu}^\star, \mathbf{t}^\star, \mathbf{z}^\star, \mathbf{c}^\star$;

We realize that in the worst case of the Algorithm 2, it mainly runs $N(I-1)K$ times to solve the SOCP of relaxed (19) and therefore, our SCA-SOCP method to solve (5) is a polynomial-time algorithm and it converges in the finite iteration [13]. In the later, the illustrated numerical results show that our solution obtained from Algorithm 2 is very close to that of SCA-MISOCP Algorithm but with very low computational complexity.

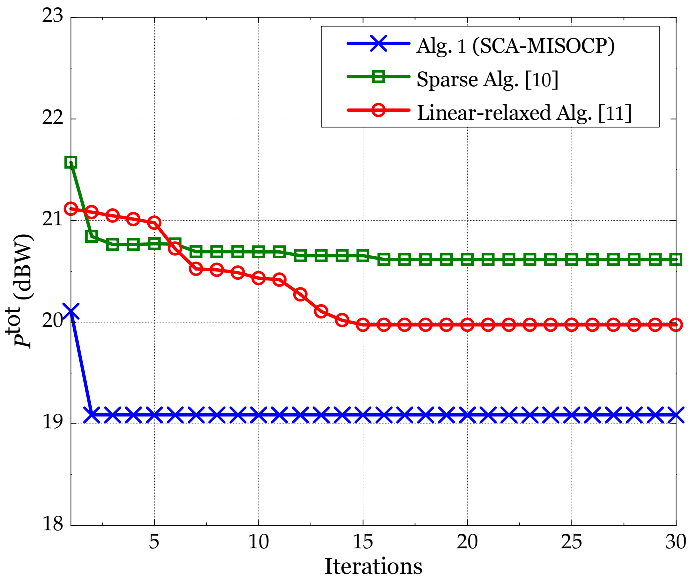

Fig. 2: Total power consumption versus number of iterations.

IV. Numerical Results

In this section, we present our numerical results on the performance of the proposed algorithms. In our network setting, we consider that there are$I = 6$ RRHs and $K = 4$ UEs. In addition, the antenna number at each RRH is equally set to $M_i = 2$, the relative static power consumption of RRH is equal to 10 dB (e.g., $P^{ra}_i - P^{ri}_i = 10$ dB,$\forall i \in \mathcal{I}$), the power amplifier inefficiency $\eta = 0.35$ and $P_{\max} = 10$dB. Moreover, we assume that the channel fading is distributed according the Rayleigh distribution while the RHHs and UEs are randomly scattered across the considered network coverage.

In Fig. 2, we show the performance of Algorithm 1 in comparison with the Sparsity based algorithm in [10] and linear-relaxed algorithm in [11], where the required minimum SINR for each user k as $\Gamma^{\min}_k = 6$ dB and the fronthaul power consumption $P^{\text{FH}}_{i,k} = 0$ dB, $\forall i \in \mathcal{I}, k \in \mathcal{K}$. The convergence of the objective function (5) is represented in this figure. From the figure, we can observe that our SCA-MISOCP algorithm converge very fast after only 3 iterations, while linear-relaxed algorithm and sparse algorithm converge after more than 15 and 20 iterations, respectively. Moreover, our proposed algorithm achieves a better objective function value compared to the other algorithms referred, which again shows the effectiveness of our proposed approach.

The superiority of our algorithms is further shown in Fig. 3, where the total transmission power versus the fronthaul transmission power P^{FH} is achieved by applying different algorithms at two different $\Gamma^{\min}_k = 2, 6$ dB. Again, our algorithms outperform the other ones in the sense of achieving small total power consumption. Moreover, when P^{FH} increases, more power is required to transport the data via the fronthaul link, thus results in the increment of P^{tot}. At higher $\Gamma^{\min}_k$, the system consumes more power to achieve the required target SINR.

In Fig. 4, we show the total transmission power versus the fronthaul link capacity $C_i = C, \forall i \in \mathcal{I}$ with $\Gamma^{\min}_k$ =4 dB

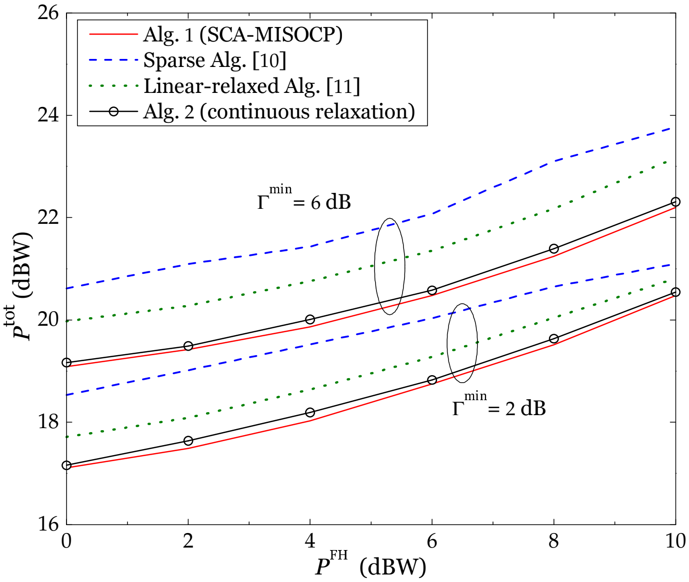

Fig. 3: Total power consumption versus P^{FH}.

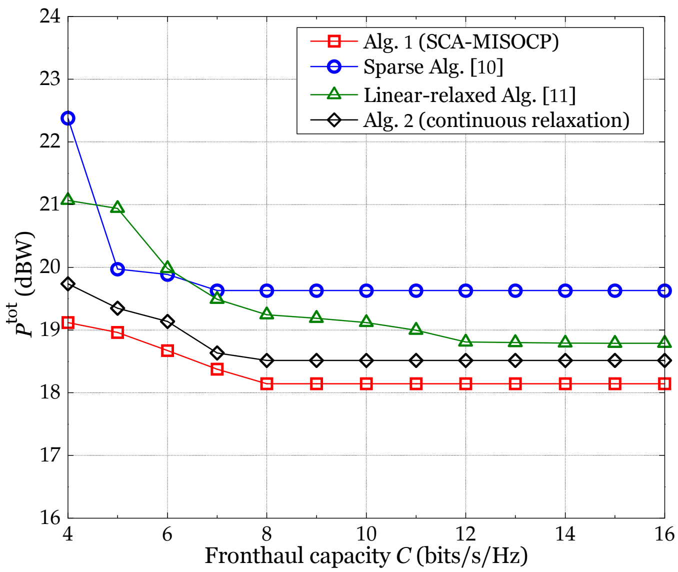

Fig. 4: Total power consumption versus maximum capacity of per-fronthaul link.

and $P^{\mathrm{FH}} = 0$ dB. As shown in the figure, P^{tot} decreases with the increment of fronthaul maximum capacity C. This can be explained as when the fronthaul capacity becomes higher, the number of UEs which are served by each RRH is larger. Moreover, this figure again shows that our proposed algorithms outperform the two algorithms used in [10] and [11]. Alternatively, we list the number of active RRHs and number of RRH-UE associations versus the fronthaul transmission power in Table I. We observe that our proposed algorithms switch off 50% number of RRHs and 54.17% number of user-RRHs associations to further reduce the total transmission power, while other algorithms only switch off 33.33% and 16.67% number of RRHs, respectively.

V. Conclusion

In this paper, a joint beamforming, RRHs selection and RRH-UE association design has been proposed to minimize

TABLE I: Active RRH-UE associations (No. RRH-UE) and active RRHs (No. RRHs) number.

P^{FH}		Alg. 1	Relaxed Alg.	[10]	[11]
2	No. RRH-UE	11	11	9	17
	No. RRHs	3	3	4	6
8	No. RRH-UE	9	9	8	14
	No. RRHs	3	3	4	5

the total transmission power, which includes not only the RRHs power but also the fronthaul transmission power. The nonconvexity of user rate and nonsmooth of user-RRHs association in per-fronthaul capacity constraints were explicitly formulated. Then, we proposed the SCA method to approximate the combinatorial and non-convex problem into a MI-SOCP problem, which was then solved by our proposed iterative algorithms. We also developed the inflation based SCA-SOCP algorithm with much lower complexity to yield the integer feasible solutions that were shown very close to that of MI-SOCP algorithm. The numerical results have confirmed that our proposed algorithms significantly outperform other existing algorithms.

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