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Joint Precoding and RRH selection for Green MIMO C-RAN

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***Abstract*—This paper jointly optimizes the precoding matrices and the set of active remote radio heads (RRHs) to minimize the network power consumption for a cloud radio access network (C-RAN) where both the RRHs and users all have multiple antennas. Both users' rate requirements and per-RRH power constraints are considered. Due to these conflicting constraints, this optimization problem may be infeasible. We propose to solve this problem with two phases. In Phase I, a new approach is proposed to check the feasibility of the original problem. If the feasibility is guaranteed, in Phase II, a low-complexity algorithm is proposed to solve the original optimization problem. Simulation results demonstrate the rapid convergence of the proposed algorithms and the benefits of equipping multiple antennas at the user side.**

I. Introduction

Recently, C-RAN has been proposed as a promising solution to support the exponential growth of mobile data traffic [1], [2]. In C-RAN, all the baseband processing is performed at the baseband unit (BBU) pool, while the remote radio heads (RRHs) perform the basic functionalities of signal processing [3], [4] and are connected to the BBU pool via fiber links. Hence, centralized signal processing can be realized and significant performance gains can be achieved. In addition, the RRHs can be densely deployed with low operation cost due to their simple functionalities, which can reduce the average access distance for the users. Despite these merits, the power consumption issue should be resolved. When a large number of RRHs are deployed in the network, the network power consumption of the C-RAN will become considerable due to the increasing circuit power consumption of the RRHs. Fortunately, it was reported in [5] that the traffic load varies substantially over both time and space due to user mobility and varying channel state. Hence, the network power can be significantly reduced by putting some RRHs with light load into sleep mode while maintaining the quality of service (QoS) requirements of the users, which is the focus of this paper.

Recently, the network power minimization problem for C-RAN has been extensively studied in [6]–[11]. However, all of the above researches only considered the single-antenna user (SAU) case. With the increasing development in antenna technology [12], it is possible to equip the wireless devices with multiple antennas. Unfortunately, the above techniques dealing with the SAU case cannot be extended directly to the multiple-antenna user (MAU) case. The reasons are as follows. Firstly, since the rate constraints and power constraints are conflicting with each other, this problem may be infeasible. In the SAU networks, the rate requirements can be equivalently represented as signal-to-interference-plus-noise ratio (SINR) constraints, which can be transformed into an SOCP problem. Hence, the feasibility of the original problem can be easily checked by solving the SOCP feasibility problem. However, the rate constraints in the MAU case is non-convex and much more complex, which cannot be transformed into the SOCP formulation as in the SAU case. Hence, new techniques need to be developed to check the feasibility of the original problem. Secondly, even though the original problem is checked to be feasible, how to solve it is still difficult, since it cannot be transformed into an SOCP problem as in the SAU case. Recently, [13] proposed the weighted minimum mean square error (WMMSE) method to solve the rate maximization problem for multiple-input multiple-output (MIMO) interfering broadcast channels. However, the rate expression is in the objective function, rather than in the constraints.

This paper considers the joint RRH and precoding optimization problem with the objective of minimizing the network power in the MAU based C-RAN. We divide the solution into two phases: feasibility checking and algorithm design. The main contributions of this paper are summarized as follows:

1) In Phase I, a new approach is proposed to check the feasibility of the network power minimization problem by solving an alternative problem, where one auxiliary variable is introduced. This alternative problem is always feasible. The introduced auxiliary variable is proved to be increasing during the iterative procedure of the FBC algorithm.
2) In Phase II, a low-complexity algorithm is proposed to solve the original network power minimization problem if it is declared to be feasible in Phase I. Specifically, the re-weighted l_1-norm minimization method is adopted to convert the original non-smooth optimization problem into a series of smooth weighted power minimization (WPM) problems.

II. System Model and Problem Formulation

A. System model

Consider a downlink C-RAN consisting of I RRHs and K users, where each RRH is equipped with M transmit antennas and each user has N receive antennas, as shown in Fig. 1. In this architecture, there is a BBU pool that centrally controls the whole network. It is assumed that each RRH is connected to the BBU pool via a high-speed transport link and the BBU

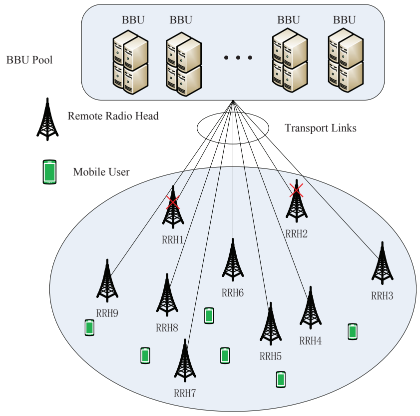

Fig. 1. Illustration of a C-RAN with nine RRHs that are connected to a BBU pool through transport links. In this example, the first RRH and the second RRH can be shut off to save power since they are far away from users.

pool has access to all users' channel state information (CSI), and can distribute all users' data to all the RRHs through transport links by using precoding matrices.

Let $\mathbf{V}_{i,k} \in \mathbb{C}^{M\times d}$ be the precoding matrix used by the ith RRH to transmit data vector $\mathbf{s}_k \in \mathbb{C}^{d\times 1}$ to the kth user, where d is the number of data streams for each user, and $\mathbf{s}_k$ is a Gaussian distribution vector with $\mathbb{E}\left[\mathbf{s}_k\mathbf{s}_k^{\mathrm{H}}\right] = \mathbf{I}_d$ and $\mathbb{E}\left[\mathbf{s}_k\mathbf{s}_l^{\mathrm{H}}\right] = \mathbf{0}$, for $l \neq k$. Let $\mathbf{H}_k = [\mathbf{H}_{1,k}, \cdots, \mathbf{H}_{I,k}] \in \mathbb{C}^{N\times MI}$ be the channel matrix from all the RRHs to the kth user, where $\mathbf{H}_{i,k} \in \mathbb{C}^{N\times M}$ denotes the channel matrix from the ith RRH to the kth user. By introducing a network-wide precoding matrix $\mathbf{V}_k = \left[\mathbf{V}_{1,k}^{\mathrm{H}}, \mathbf{V}_{2,k}^{\mathrm{H}}, \cdots, \mathbf{V}_{I,k}^{\mathrm{H}}\right]^{\mathrm{H}} \in \mathbb{C}^{MI\times d}$, the received signal vector at the kth user, denoted as $\mathbf{y}_k \in \mathbb{C}^{N\times 1}$, is given by

$$\mathbf{y}_k = \mathbf{H}_k\mathbf{V}_k\mathbf{s}_k + \sum_{j\neq k}\mathbf{H}_k\mathbf{V}_j\mathbf{s}_j + \mathbf{n}_k, \tag{1}$$

where $\mathbf{n}_k$ is the noise vector at the kth user, which is an additive Gaussian noise vector following the distribution $\mathcal{CN}\left(\mathbf{0}, \sigma_k^2\mathbf{I}_N\right)$. Then, the achievable rate (nat/s/Hz) of the kth user is given by [14]

$$R_k(\mathbf{V}) = \log\left|\mathbf{I} + \mathbf{H}_k\mathbf{V}_k\mathbf{V}_k^H\mathbf{H}_k^H\mathbf{J}_k^{-1}\right|, \tag{2}$$

where $\log(\cdot)$ is the base of natural logarithm, $\mathbf{J}_k = \sum_{j\neq k}\mathbf{H}_k\mathbf{V}_j\mathbf{V}_j^H\mathbf{H}_k^H + \sigma_k^2\mathbf{I}$ is the interference-plus-noise covariance matrix at the kth user, and $\mathbf{V}$ is the collection of all precoding matrices.

Let $\mathcal{I} = \{1, \cdots, I\}$ denote the set of all RRHs, $\mathcal{A}$ the active RRH set. The total power consumption can be modeled as

$$\hat{P}(\mathcal{A}, \mathbf{V}) = \sum_{i\in\mathcal{A}}\frac{1}{\eta_i}P_i^{\mathrm{tr}}(\mathbf{V}) + \sum_{i\in\mathcal{A}}P_i^{\mathrm{c}} + \sum_{i\in\mathcal{I}}P_i^{\mathrm{tl}} + P_{\mathrm{BBU}}, \tag{3}$$

where η_i is a constant accounting for the efficiency of the power amplifier of the ith RRH, $P_i^{\mathrm{tr}}(\mathbf{V})$ is the transmit power at the ith RRH, given by $P_i^{\mathrm{tr}}(\mathbf{V}) = \sum_{k=1}^K\|\mathbf{V}_{i,k}\|_F^2$, P_i^{c} denotes the circuit power consumption of the ith RRH, P_i^{tl} is a constant accounting for the power consumed on the ith transport links, and P_{BBU} is a constant accounting for the power consumed for signal processing in the BBU pool.

B. Problem Formulation

This paper aims to select some RRHs and optimize the precoding matrices to minimize the total network power consumption while guaranteeing all users' rate requirements and each RRH's power constraint, which can be formulated as

$$\begin{aligned}\min_{\mathcal{A},\mathbf{V}} \quad & \sum_{i\in\mathcal{A}}\frac{1}{\eta_i}\sum_{k=1}^K\|\mathbf{V}_{i,k}\|_F^2 + \sum_{i\in\mathcal{A}}P_i^c \\ \text{s.t.} \quad & R_k(\mathbf{V}) \geq R_{k,\min}, \forall k, \\ & \sum_{k=1}^K\|\mathbf{V}_{i,k}\|_F^2 \leq P_{i,\max}, i\in\mathcal{A}, \\ & \sum_{k=1}^K\|\mathbf{V}_{i,k}\|_F^2 = 0, i\in\mathcal{I}\backslash\mathcal{A},\end{aligned} \tag{4}$$

where $R_{k,\min}$ is the rate requirement for the kth user, and $P_{i,\max}$ is the transmit power constraint at the ith RRH.

Problem (4) is an MINLP problem and is NP-hard as proved in [15]. A brute-force solution to this problem is through the exhaustive search. However, the exhaustive search has exponentially prohibitive complexity, which is hard to be implemented in practice. Hence, this motivates us to develop low-complexity algorithms to solve Problem (4).

In addition, Problem (4) may be infeasible even when all RRHs are set in active mode due to the conflicting constraints of rate requirements and per-RRH power limits. Hence, we divide the solution to Problem (4) into two phases: In Phase I, we propose a method to check the feasibility of Problem (4); In Phase II, a low-complexity iterative algorithm is proposed to solve Problem (4).

III. Phase I: Feasibility Check method

We construct an alternative problem by introducing an auxiliary variable α:

$$\begin{aligned}\max_{\alpha\geq 0,\mathbf{V}} \quad & \alpha \\ \text{s.t.} \quad & R_k(\mathbf{V}) \geq \alpha^2 R_{k,\min}, \forall k, \\ & \sum_{k=1}^K\|\mathbf{V}_{i,k}\|_F^2 \leq P_{i,\max}, \forall i.\end{aligned} \tag{5}$$

Obviously, Problem (5) is always feasible. This variable can be regarded as a feasibility indicator of the original Problem (4): if the optimal solution of α is larger than or equal to one, the original Problem (4) is feasible; Otherwise, we claim that it is infeasible. However, due to the first set of constraints in (5), Problem (5) is a non-convex problem, which is difficult to solve. To handle this difficulty, we apply the relationships between WMMSE and the rate expression.

We consider the linear receiver filter so that the estimated signal vector is given by

$$\hat{\mathbf{s}}_k = \mathbf{U}_k^H\mathbf{y}_k, \forall k. \tag{6}$$

where $\mathbf{U}_k \in \mathbb{C}^{N\times d}$ is the receiver filter of the kth user. Since the signal vectors $\mathbf{s}_k$'s and noise $\mathbf{n}_k$'s are mutually independent, the mean square error (MSE) matrix at the kth user is given by

$$\begin{aligned}\mathbf{E}_k \;=\; & \left(\mathbf{U}_k^H\mathbf{H}_k\mathbf{V}_k - \mathbf{I}_d\right)\left(\mathbf{U}_k^H\mathbf{H}_k\mathbf{V}_k - \mathbf{I}_d\right)^H \\ & + \sum_{j\neq k}\mathbf{U}_k^H\mathbf{H}_k\mathbf{V}_j\mathbf{V}_j^H\mathbf{H}_k^H\mathbf{U}_k + \sigma_k^2\mathbf{U}_k^H\mathbf{U}_k.\end{aligned} \tag{7}$$

By introducing a set of auxiliary matrices $\{\mathbf{W}_k \succeq \mathbf{0}\}$, we define the following functions

$$h_k\left(\mathbf{V}, \mathbf{U}_k, \mathbf{W}_k\right) = \log|\mathbf{W}_k| - \mathrm{Tr}\left(\mathbf{W}_k\mathbf{E}_k\right) + d, \forall k. \tag{8}$$

The following lemma establishes the relationships between the rate expression and function $h_k\left(\mathbf{V}, \mathbf{U}_k, \mathbf{W}_k\right)$.

Lemma 1 [13] : $h_k(\mathbf{V}, \mathbf{U}_k, \mathbf{W}_k)$ is a concave function for each set of the matrices $\mathbf{V}$, $\mathbf{U}_k$ and $\mathbf{W}_k$ when the other two are given. Given $\mathbf{V}$, $h_k(\mathbf{V}, \mathbf{U}_k, \mathbf{W}_k)$ is the lower-bound of the data rate $R_k(\mathbf{V})$ in (2). The optimal $\mathbf{U}_k, \mathbf{W}_k$ for $h_k(\mathbf{V}, \mathbf{U}_k, \mathbf{W}_k)$ to achieve the data rate is given by

$$\mathbf{U}_k^{\star} = \left(\sum_{j=1}^{K} \mathbf{H}_k \mathbf{V}_j \mathbf{V}_j^H \mathbf{H}_k^H + \sigma_k^2 \mathbf{I}\right)^{-1} \mathbf{H}_k \mathbf{V}_k, \mathbf{W}_k^{\star} = \mathbf{E}_k^{\star -1}, \forall k, \tag{9}$$

where $\mathbf{E}_k^{\star}$ is obtained by plugging the expression of $\mathbf{U}_k^{\star}$ into the kth user's MSE in (7)

$$\mathbf{E}_k^{\star} = \mathbf{I}_d - \mathbf{V}_k^H \mathbf{H}_k^H \left(\sum_{j=1}^{K} \mathbf{H}_k \mathbf{V}_j \mathbf{V}_j^H \mathbf{H}_k^H + \sigma_k^2 \mathbf{I}\right)^{-1} \mathbf{H}_k \mathbf{V}_k.$$

□

By replacing the first set of constraints in (5) with its lower-bound $h_k(\mathbf{V}, \mathbf{U}_k, \mathbf{W}_k)$, Problem (5) becomes

$$\begin{aligned} \max_{\alpha \geq 0, \mathbf{V}, \mathbf{W}, \mathbf{U}} \quad & \alpha \\ \text{s.t.} \quad & h_k(\mathbf{V}, \mathbf{U}_k, \mathbf{W}_k) \geq \alpha^2 R_{k,\min}, \forall k, \\ & \sum_{k=1}^{K} \|\mathbf{V}_{i,k}\|_F^2 \leq P_{i,\max}, \forall i, \end{aligned} \tag{10}$$

where $\mathbf{U}$ and $\mathbf{W}$ are the collection of matrices $\mathbf{U}_k, \forall k$ and $\mathbf{W}_k, \forall k$, respectively.

To solve Problem (10), we apply the block coordinate descent method: given $\mathbf{V}$, update $\mathbf{U}$ and $\mathbf{W}$ by using (9); update α and $\mathbf{V}$ with given $\mathbf{U}$ and $\mathbf{W}$. We only need to solve the latter one. Putting the MSE expression in (7) into the first set of constraints in Problem (10) yields

$$\begin{aligned} \max_{\alpha \geq 0, \mathbf{V}} \quad & \alpha \\ \text{s.t.} \operatorname{Tr} & \left(\left(\tilde{\mathbf{H}}_k \mathbf{V}_k - \mathbf{I}_k\right)^H \mathbf{W}_k \left(\tilde{\mathbf{H}}_k \mathbf{V}_k - \mathbf{I}_k\right)\right) + \alpha^2 R_{k,\min} \\ & + \sum_{j \neq k} \operatorname{Tr}\left(\mathbf{V}_j^H \tilde{\mathbf{H}}_k^H \mathbf{W}_k \tilde{\mathbf{H}}_k \mathbf{V}_j\right) \leq t_k, \forall k, \\ & \sum_{k=1}^{K} \|\mathbf{V}_{i,k}\|_F^2 \leq P_{i,\max}, \forall i. \end{aligned} \tag{11}$$

where $\tilde{\mathbf{H}}_k = \mathbf{U}_k^H \mathbf{H}_k, \forall k$ and $t_k = \log|\mathbf{W}_k| + d - \sigma_k^2 \operatorname{Tr}\left(\mathbf{U}_k^H \mathbf{U}_k \mathbf{W}_k\right)$. Problem (11) can be equivalently transformed into the following problem

$$\begin{aligned} \max_{\alpha \geq 0, \mathbf{V}} \quad & \alpha \\ \text{s.t.} & \|\mathbf{x}_k\|_2 \leq \sqrt{t_k}, \forall k, \\ & \|\mathbf{y}_i\|_2 \leq \sqrt{P_{i.\max}}, \forall i, \end{aligned} \tag{12}$$

where $\mathbf{x}_k$ is given by

$$\mathbf{x}_k = \left[\operatorname{vec}\left(\mathbf{V}_1^H \tilde{\mathbf{H}}_k^H \mathbf{W}_k^{1/2}\right)^H, \cdots, \operatorname{vec}\left(\left(\mathbf{V}_k^H \tilde{\mathbf{H}}_k^H - \mathbf{I}_k\right) \mathbf{W}_k^{1/2}\right)^H, \right. \\ \left. \cdots, \operatorname{vec}\left(\mathbf{V}_K^H \tilde{\mathbf{H}}_k^H \mathbf{W}_k^{1/2}\right)^H, \alpha \sqrt{R_{k,\min}}\right]^H$$

and $\mathbf{y}_i$ is given by

$$\mathbf{y}_i = \left[\operatorname{vec}(\mathbf{V}_{i,1})^H, \cdots, \operatorname{vec}(\mathbf{V}_{i,K})^H\right]^H. \tag{13}$$

Problem (12) is an SOCP that can be efficiently solved.

Based on the above analysis, the FBC algorithm for checking the feasibility of the original optimization problem (4) is formally described in Algorithm 1.

Algorithm 1 FBC Algorithm

1: Initialize iterative number $n = 1$, the maximum number of iterations $n_{\max}$. Initial precoding matrices $\mathbf{V}^{(0)}$ such that the per-RRH power constraints are satisfied. Calculate $\mathbf{U}^{(0)}$ and $\mathbf{W}^{(0)}$ by using (9) with $\mathbf{V}^{(0)}$;
2: With $\mathbf{U}^{(n-1)}$ and $\mathbf{W}^{(n-1)}$, update $\alpha^{(n)}$ and $\mathbf{V}^{(n)}$ by solving the SOCP problem (12);
3: Update $\mathbf{U}^{(n)}$ and $\mathbf{W}^{(n)}$ as in (9) with $\mathbf{V}^{(n)}$;
4: If $\alpha^{(n)} \geq 1$, declare that Problem (4) is feasible and output $\mathbf{V}^{(n)}$ for the initialization of Phase II and terminate; If $\alpha^{(n)} < 1$ and $n \geq n_{\max}$, declare that Problem (4) is infeasible and terminate; Otherwise, set $n \leftarrow n + 1$ and go to step 2.

Theorem 1: The sequence of α generated during the iterative procedure of the FBC algorithm is monotonically increasing.

Proof: The details are omitted due to space limit. □

IV. Phase II: A Low-complexity Algorithm to Solve Problem (4)

In this section, we provide a low-complexity algorithm to solve Problem (4) if it is claimed to be feasible in Phase I.

A. Reweighted l_1-norm minimization

By using the l_0-norm, the objective function of Problem (4) is equivalent to

$$\sum_{i=1}^{I} \frac{1}{\eta_i} \sum_{k=1}^{K} \|\mathbf{V}_{i,k}\|_F^2 + \sum_{i=1}^{I} \left\| \sum_{k=1}^{K} \|\mathbf{V}_{i,k}\|_F^2 \right\|_0 P_i^c. \tag{14}$$

Then the non-smooth l_0-norm objective can often be approximated by a re-weighted l_1-norm,

$$\left\| \sum_{k=1}^{K} \|\mathbf{V}_{i,k}\|_F^2 \right\|_0 \approx a_i^{(n)} \sum_{k=1}^{K} \|\mathbf{V}_{i,k}\|_F^2 \tag{15}$$

where $a_i^{(n)}$ is a weight factor of the ith RRH at the nth iteration that is iteratively updated as

$$a_i^{(n)} = \frac{1}{\sum_{k=1}^{K} \left\|\mathbf{V}_{i,k}^{(n)}\right\|_F^2 + \delta}, \forall i, \tag{16}$$

where δ is a small constant parameter and $\mathbf{V}_{i,k}^{(n)}$ is the solution in the nth iteration.

By using the approximation in (15), we have the following problem that should be solved in the n-th iteration

$$\begin{aligned} \min_{\mathbf{V}} \quad & \sum_{i=1}^{I} \omega_i^{(n-1)} \sum_{k=1}^{K} \|\mathbf{V}_{i,k}\|_F^2 \\ \text{s.t.} \quad & R_k(\mathbf{V}) \geq R_{k,\min} \forall k, \\ & \sum_{k=1}^{K} \|\mathbf{V}_{i,k}\|_F^2 \leq P_{i,\max}, \forall i \end{aligned} \tag{17}$$

where

$$\omega_i^{(n-1)} = \frac{1}{\eta_i} + a_i^{(n-1)} P_i^c. \tag{18}$$

Based on the above analysis, the re-weighted l_1-norm (RLN) algorithm to solve Problem (4) is given in Algorithm 2. Problem (17) can be similarly solved as Problem (5) by using the WMMSE method.

Algorithm 2 RLN algorithm

1: Initialize a small δ, the iterative number $n = 1$, the maximum number of iterations $N_{\max}$. Initialize $\mathbf{V}^{(0)}$ with the outputs given by Phase I, calculate $\{\omega_i^{(0)}, \forall i\}$ in (18);
2: Given $\{\omega_i^{(n-1)}, \forall i\}$, solve Problem (17) to get $\mathbf{V}^{(n)}$ by using the WMMSE algorithm;
3: Update $\{\omega_i^{(n)}, \forall i\}$ as in (18) with $\mathbf{V}^{(n)}$;
4: If $n \geq N_{\max}$, terminate. Otherwise, set $n \leftarrow n + 1$ and go to step 2.

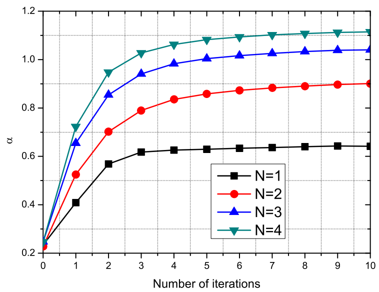

Fig. 2. Convergence performance of the FBC algorithm under different numbers of receive antennas.

V. Simulation Results

In this section, we present simulation results to evaluate the performance of the proposed algorithms. Consider one square C-RAN network with $[-1000\ 1000] \times [-1000\ 1000]$ meters. It is assumed that all the users and RRHs are uniformly and independently distributed in this region. We adopt the channel model that consists of four parts: 1) the long term evolution (LTE) standard path loss model: $PL_{i,k} = 148.1 + 37.6\log_{10} d_{i,k}$ (dB), where $d_{i,k}$ (in km) is the distance from the ith RRH to the kth user; 2) Log-normal shadowing with zero mean and 8 dB standard derivation; 3) Rayleigh fading with zero mean and unit variance [16]–[18]; 4) transmit antenna power gain of 9 dBi. Each user is assumed to have the same rate requirement, i.e., $R_{\min} = R_{k,\min}, \forall k$. The number of data streams is set as $d = \min\{M, N\}$. Unless stated otherwise, the system parameters are set as follows: error tolerance is $\varepsilon = 10^{-3}$, system bandwidth is 10 MHz, thermal noise power density is -174 dBm/Hz, $I = 10$, $K = 8$, $M = 2$, $N = 2$, $P_{i,\max} = 5W$, $\eta_i = 25\%$ [19], $P_i^{\rm c} = 5.6W$, $P_i^{\rm tl} = 5.05W, \forall i$, $P_{\rm BBU} = 20W$ [8], [20].

Fig. 2 shows the convergence behaviour of the FBC algorithm for different numbers of receive antennas N when $M = 4$ and $R_{\min} = 10$ nats/s/Hz. It can be seen from Fig. 2 that the value of α monotonically increases during the iterative procedure, which verifies the theoretical results in Theorem 1. It is also observed that the convergence speed is slightly affected by the number of receive antennas. As expected, the converged value of α increases with the number of receive antennas since more degrees of freedom are available with more receive antennas. This means that more receive antennas can support more users.

To show the benefits of equipping multiple antennas at each user, Fig. 3 shows the effect of the number of receive antennas

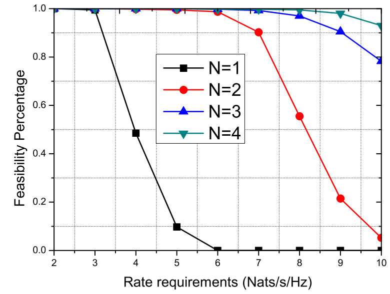

Fig. 3. Feasibility probabilities under different numbers of receive antennas with $M = 4$.

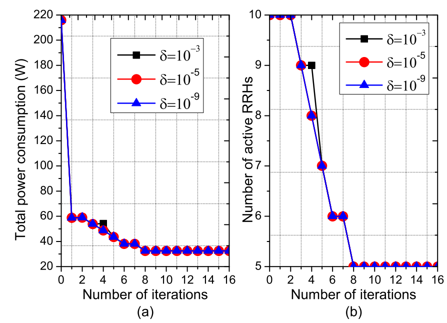

Fig. 4. (a) Total power consumption versus the number of iterations; (b) The number of active RRHs versus the number of iterations. The rate requirement for each user is set as $R_{\min} = 2$ nats/s/Hz.

on the feasibility percentage, which is defined as the ratio of the number of feasible channel realizations to the total number of channel realizations. For each number of receive antennas, 500 randomly generated channels are checked. As seen from Fig. 3, the feasibility percentage dramatically increases with the number of receive antennas, which means more receive antennas can admit more users.

The convergence performances of the RLN algorithm are shown in Figs. 4 (a) and (b) for the total power consumption and the number of the remaining RRHs in each iteration, respectively. Three different values of δ are tested, i.e., $\delta = 10^{-3}, 10^{-5}$ and 10^{-9}. One randomly generated channel that is checked to be feasible by the FBC algorithm is used to obtain the convergence behaviour. It can be seen from the figures that for all considered values of δ, both the number of active RRHs and the total power consumption decrease rapidly. At the converged state, only six RRHs are active. Compared to the full cooperation strategy where all RRHs are active, we can save large amount of power as seen from Fig. 4 (a).

Next, we compare the performance of the RLN algorithm with the following RRH selection methods:

- Exhaustive search (Exhau-search) method: In this method, we check all possible $\mathcal{A}$ and choose one with the least power consumption. It has an exponential complexity, which serves as the performance benchmark.
- Successive RRH selection (Succesive-sel) method: This method first lets all the RRHs be active and then gradually removes the RRHs according to their transmit power from the lowest to the highest until the problem becomes infeasible.

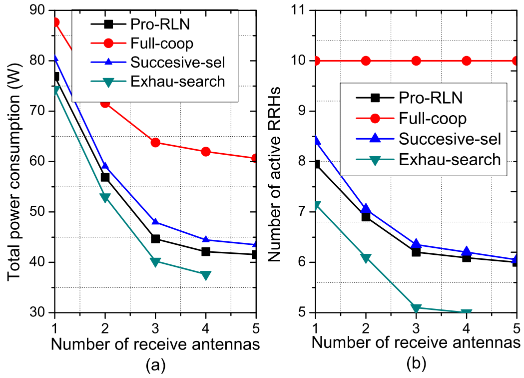

Fig. 5. (a) Total power consumption versus the number of receive antennas N; (b) The corresponding average number of active RRHs versus the number of receive antennas N. The rate requirements for each user are set as $R_{\min} = 3$ nats/s/Hz.

- Full cooperative (Full-coop) method: In this method, all the RRHs are active.

Figs. 5 (a) and (b) show the average total power consumption and their corresponding number of active RRHs respectively versus the number of receiver antennas. It is seen the total power consumption of the RLN algorithm is very close to that of the exhaustive search method, especially when the number of receive antennas is small. Also, the RLN algorithm is observed to require lower total power consumption and fewer active RRHs than the successive RRH selection method. As expected, the RLN algorithm outperforms the full cooperative transmission scheme significantly and the performance gain increases with the number of receive antennas. It is observed that there is a dramatic decrease in the total power consumption when the number of receive antennas increases from 1 to 2, i.e., the total power reduction is roughly 36%. However, when the number of receive antennas increases from 3 to 5, the reduction in both the total power consumption and the number of active RRHs is small. This is due to the fact that enough spatial degrees of freedom become available to regulate the multi-user interference and the additional receive antennas can only achieve some diversity gain rather than spatial multiplexing gain.

VI. Conclusion

In this paper, a joint selection of active RRHs and optimization of the precoding matrices which minimizes the network power consumption for the MIMO C-RAN, while guaranteeing users' rate requirements and per-RRH power constraints, has been studied. A novel approach was proposed to check the feasibility of this problem by solving an alternative problem with one introduced variable. Then a low-complexity iterative algorithm, based on the reweighted l_1-norm minimization method and WMMSE algorithm was proposed to solve the original network power minimization problem. Simulation results show that the proposed algorithms converge fast, which is attractive for practical implementation. Also, more antennas at the user side can admit more users. Moreover, our proposed algorithm was shown to achieve much greater power savings than the full cooperation method, and the performance loss compared with the optimal approach is insignificant.

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