Inter-Cluster Design of Precoding and Fronthaul Compression for Cloud Radio Access Networks

Seok-Hwan Park, Osvaldo Simeone, Onur Sahin, and Shlomo Shamai

***Abstract*—This work studies the joint design of precoding and fronthaul compression for the downlink of multi-cluster cloud radio access networks (C-RANs). In these systems, each cluster of radio units (RUs) is managed by a different control unit (CU) through fronthaul links of limited capacity. Each CU performs baseband processing, including channel coding and linear precoding, for all the connected RUs, and then compresses the precoded signals for transmission to the RUs over the corresponding fronthaul links. In a recent work, it was shown that joint, rather than conventional separate, compression of the signals of different RUs leads to significant performance gains. However, the approach therein was limited to the intra-cluster optimization of precoding and joint compression, hence leading to significant performance loss in the presence of mutually interfering clusters. This work proposes instead to perform the inter-cluster optimization of precoding and joint compression. Specifically, the problem of maximizing the weighted sum-rate maximization across multiple clusters is tackled by deriving an iterative algorithm that converges to a locally optimal point of the problem. From numerical results, it is confirmed that the proposed scheme significantly outperforms the existing approach based on intra-cluster optimization.**

***Index Terms*—Cloud radio access networks (C-RANs), inter-cluster interference, constrained fronthaul, multivariate compression.**

I. Introduction

CLOUD radio access networks (C-RANs) enable effective large-scale interference management by migrating baseband processing from distributed radio units (RUs) to centralized control units (CUs) [1], [2]. This migration is realized via the transfer of baseband signals on low-latency fronthaul links between a cluster of RUs and the managing CU. While the current standard for fronthaul communication prescribes the use of conventional scalar quantizers for the baseband signals, it is well known that these solutions require prohibitive fronthaul capacities in typical settings (see, e.g., [3]). Motivated by this observation, industrial and academic work has pursued the design of more performing fronthaul compressors based on vector quantization and possibly multivariate compression strategies (see, e.g., [1], [4]–[8]). Specifically, in [4]–[6], it was shown that joint, rather conventional separate, decompression at the CU is beneficial for the uplink. In a dual manner, [8] demonstrated that *joint compression* of the baseband signals for different RUs at the CU provides performance gains in the downlink.

The work [8] focuses on the optimization of precoding and joint compression only within a given cluster of RUs, neglecting the effect of inter-cluster interference. When applied to practical settings with multiple mutually interfering clusters of RUs, this approach is highly suboptimal (see Section IV for numerical evidence). In this paper, we therefore propose to perform the optimization of precoding and joint compression across multiple clusters of RUs. Specifically, the weighted sum-rate maximization problem is formulated with respect to the precoding matrices and the quantization covariance matrices of multiple clusters subject to the per-RU power constraints and fronthaul capacity constraints. An iterative algorithm is proposed that converges to a locally optimal point of the problem.

Notation: We adopt standard information-theoretic definitions for the mutual information $I(X;Y)$, differential entropy $h(X)$ and conditional differential entropy $h(X|Y)$ [9]. All logarithms are in base two unless specified. The circularly symmetric complex Gaussian distribution with mean $\boldsymbol{\mu}$ and covariance matrix $\mathbf{R}$ is denoted by $\mathcal{CN}(\boldsymbol{\mu},\mathbf{R})$. The set of all $M\times N$ complex matrices is denoted by $\mathbb{C}^{M\times N}$. We use the notation $\mathbf{X}\succeq\mathbf{0}$ to indicate that the matrix $\mathbf{X}$ is positive semidefinite.

II. System Model

We consider the downlink of a C-RAN with N_C mutually interfering clusters. We assume that each ith cluster, $i\in\mathcal{N}_C\triangleq\{1,\ldots,N_C\}$, has a single CU that controls $N_{R,i}$ RUs. The CU communicates with the rth RU through a fronthaul link of capacity $C_{i,r}$ bits/s/Hz, where the normalization is with respect to the downlink bandwidth. The $N_{R,i}$ RUs in the ith cluster transmit signals to serve $N_{M,i}$ Mobile Stations (MSs) located in the cluster. We refer to the rth RU and the kth MS in the ith cluster as RU (i,r) and MS (i,k), respectively, and define the sets $\mathcal{N}_{R,i}\triangleq\{1,\ldots,N_{R,i}\}$ and $\mathcal{N}_{M,i}\triangleq\{1,\ldots,N_{M,i}\}$ of the RUs and the MSs in the cluster. We denote the numbers of antennas of RU (i,r) and MS (i,k) as $n_{R,i,r}$ and $n_{M,i,k}$, respectively. The example of $N_C=2$, $N_{R,i}=N_{M,i}=2$, $n_{R,i,r}=2$ and $n_{M,i,k}=1$ is shown in Fig. 1.

The signal $\mathbf{y}_{i,k}\in\mathbb{C}^{n_{M,i,k}\times 1}$ received by MS (i,k) is given by

$$\mathbf{y}_{i,k}=\sum_{j\in\mathcal{N}_C}\sum_{r\in\mathcal{N}_{R,j}}\mathbf{H}_{i,k,j,r}\mathbf{x}_{j,r}+\mathbf{z}_{i,k}, \tag{1}$$

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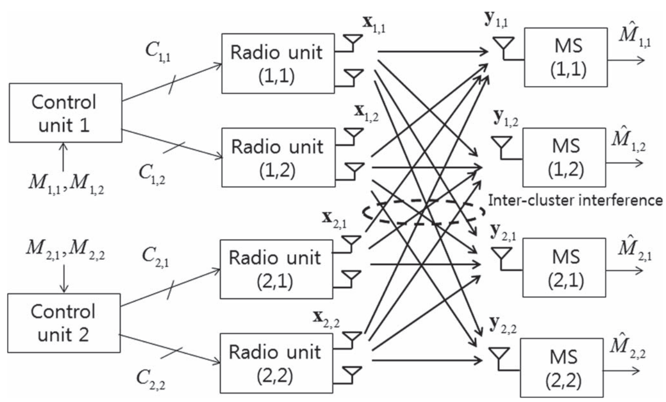

Fig. 1. Illustration of the downlink of C-RAN with $N_C = 2$, $N_{R,i} = N_{M,i} = 2$, $n_{R,i,r} = 2$ and $n_{M,i,k} = 1$.

where $\mathbf{H}_{i,k,j,r} \in \mathbb{C}^{n_{M,i,k} \times n_{R,j,r}}$ represents the channel response matrix from RU (j, r) to MS (i, k); $\mathbf{x}_{j,r} \in \mathbb{C}^{n_{R,j,r} \times 1}$ indicates the signal transmitted by RU (j, r); and $\mathbf{z}_{i,k} \in \mathbb{C}^{n_{M,i,k} \times 1}$ is the additive noise at MS (i, k) distributed as $\mathbf{z}_{i,k} \sim \mathcal{CN}(\mathbf{0}, \mathbf{\Sigma}_{\mathbf{z}_{i,k}})$. Each RU (j, r) is subject to a power constraint stated as

$$\mathbb{E}\|\mathbf{x}_{j,r}\|^2 \leq P_{j,r}. \tag{2}$$

A. Precoding

The CU in the ith cluster first encodes the information message $M_{i,k} \in \{1, \ldots, 2^{nR_{i,k}}\}$ of rate $R_{i,k}$ bits/s/Hz that is to be decoded by MS (i, k), obtaining an encoded signal $\mathbf{s}_{i,k} \in \mathbb{C}^{d_{i,k} \times 1}$ which is distributed as $\mathbf{s}_{i,k} \sim \mathcal{CN}(\mathbf{0}, \mathbf{I})$ for $k \in \mathcal{N}_{M,i}$. We assume that the coding block length n is large enough to justify the use of information-theoretic limits, and that the number $d_{i,k}$ of data streams satisfies the condition $d_{i,k} \leq \min\{n_{R,i}, n_{M,i,k}\}$ with the notation $n_{R,i} \triangleq \sum_{r \in \mathcal{N}_{R,i}} n_{R,i,r}$. To enable the management of the inter-cluster and intra-cluster interference, the CU performs linear precoding with a precoding matrix $\mathbf{A}_i \in \mathbb{C}^{n_{R,i} \times d_i}$, yielding the precoded signal $\tilde{\mathbf{x}}_i = [\tilde{\mathbf{x}}_{i,1}; \ldots; \tilde{\mathbf{x}}_{i,N_{R,i}}] \in \mathbb{C}^{n_{R,i} \times 1}$ with

$$\tilde{\mathbf{x}}_i = \mathbf{A}_i \mathbf{s}_i, \tag{3}$$

where $\tilde{\mathbf{x}}_{i,r} \in \mathbb{C}^{n_{R,i,r} \times 1}$ is the signal to be communicated to RU (i, r); $\mathbf{s}_i \triangleq [\mathbf{s}_{i,1}; \ldots; \mathbf{s}_{i,N_{M,i}}]$ is the vector of the signals encoded for the MSs in the ith cluster; and we have defined the notation $d_i \triangleq \sum_{k \in \mathcal{N}_{M,i}} d_{i,k}$. Note that non-linear dirty-paper coding can be similarly considered with a predetermined encoding order of the MSs in the cluster (see [8, Sec. IV-A]).

B. Fronthaul Compression

Since the CU in the ith cluster communicates to RU (i, r) through a fronthaul link of capacity $C_{i,r}$ bits/s/Hz, the precoded baseband signal $\tilde{\mathbf{x}}_{i,r}$ needs to be compressed prior to transmission to the RU. Following standard arguments, we model the impact of compression as the addition of quantization noise as in

$$\mathbf{x}_{i,r} = \tilde{\mathbf{x}}_{i,r} + \mathbf{q}_{i,r}, \tag{4}$$

where the quantization noise $\mathbf{q}_{i,r}$ is independent of the signal $\tilde{\mathbf{x}}_{i,r}$ and is distributed as $\mathbf{q}_{i,r} \sim \mathcal{CN}(\mathbf{0}, \mathbf{\Omega}_{i,r,r})$.

1) Point-to-Point Compression: The standard fronthaul compression approach prescribes the separate point-to-point compression of the baseband signals $\tilde{\mathbf{x}}_{i,r}$ and $\tilde{\mathbf{x}}_{i,q}$ for different RUs with $r \neq q$ (see [10]). As a result, the quantization noises $\mathbf{q}_{i,r}$ and $\mathbf{q}_{i,q}$ are independent, i.e., $\mathbb{E}[\mathbf{q}_{i,r}\mathbf{q}_{i,q}^\dagger] = \mathbf{0}$. Under this assumption, the signal $\mathbf{x}_{i,r}$ can be successfully decompressed at RU (i, r) if the condition

$$\begin{aligned} I(\tilde{\mathbf{x}}_{i,r}; \mathbf{x}_{i,r}) = &\log\det\left(\mathbf{E}_{i,r}^\dagger\left(\mathbf{A}_i\mathbf{A}_i^\dagger + \mathbf{\Omega}_i\right)\mathbf{E}_{i,r}\right) \\ &- \log\det\left(\mathbf{E}_{i,r}^\dagger \mathbf{\Omega}_i \mathbf{E}_{i,r}\right) \leq C_{i,r} \end{aligned} \tag{5}$$

is satisfied, where we have defined the matrices $\mathbf{E}_{i,r} \in \mathbb{C}^{n_{R,i} \times n_{R,i,r}}$ with all-zero elements except for the rows from $(\sum_{q=1}^{r-1} n_{R,i,q} + 1)$ to $(\sum_{q=1}^{r} n_{R,i,q})$ being the identity matrix of size $n_{R,i,r}$ (see, e.g., [9] and also [8, Sec. IV-A]).

2) Multivariate Compression: Assume now that the precoded baseband signals in each cluster, namely $\tilde{\mathbf{x}}_{i,1}, \ldots, \tilde{\mathbf{x}}_{i,N_{R,i}}$, are jointly, and not separately, compressed. As it follows from well known standard network information results (see, e.g., [9, Ch. 9]), joint, or multivariate, compression [9, Ch. 9] allows each ith CU to correlate the quantization noises $\mathbf{q}_{i,1}, \ldots, \mathbf{q}_{i,N_{R,i}}$. This was shown in [8] to provide significant performance gains in the context of a single-cluster C-RAN model (i.e., $N_C = 1$).

Define the correlation matrix of the quantization noises within the ith cluster as

$$\mathbf{\Omega}_i \triangleq \mathbb{E}[\mathbf{q}_i\mathbf{q}_i] = \begin{bmatrix} \mathbf{\Omega}_{i,1,1} & \mathbf{\Omega}_{i,1,2} & \cdots & \mathbf{\Omega}_{i,1,N_{R,i}} \\ \mathbf{\Omega}_{i,2,1} & \mathbf{\Omega}_{i,2,2} & \cdots & \mathbf{\Omega}_{i,2,N_{R,i}} \\ \vdots & \vdots & \ddots & \vdots \\ \mathbf{\Omega}_{i,N_{R,i},1} & \mathbf{\Omega}_{i,N_{R,i},2} & \cdots & \mathbf{\Omega}_{i,N_{R,i},N_{R,i}} \end{bmatrix}, \tag{6}$$

where we have defined the notations $\mathbf{q}_i \triangleq [\mathbf{q}_{i,1}; \ldots; \mathbf{q}_{i,N_{R,i}}]$ and $\mathbf{\Omega}_{i,r,q} \triangleq \mathbb{E}[\mathbf{q}_{i,r}\mathbf{q}_{i,q}^\dagger]$ for all $i \in \mathcal{N}_C$,. The following lemma provides a sufficient condition on the capacities of the fronthaul links of the ith cluster that guarantees that quantization noises with the given covariance matrix $\mathbf{\Omega}_i$ can be realized.

Lemma 1: A joint compressor exists that produces the compressed signals (4) with the given quantization noise covariance $\mathbf{\Omega}_i$ if the conditions

$$\begin{aligned} g_{i,\mathcal{S}}(\mathbf{A}, \mathbf{\Omega}) &\triangleq \sum_{r \in \mathcal{S}} h(\mathbf{x}_{i,r}) - h(\mathbf{x}_{i,\mathcal{S}}|\tilde{\mathbf{x}}_i) \\ &= \sum_{r \in \mathcal{S}} \log\det\left(\mathbf{E}_{i,r}^\dagger\left(\mathbf{A}_i\mathbf{A}_i^\dagger + \mathbf{\Omega}_i\right)\mathbf{E}_{i,r}\right) \\ &\quad - \log\det\left(\mathbf{E}_{i,\mathcal{S}}^\dagger \mathbf{\Omega}_i \mathbf{E}_{i,\mathcal{S}}\right) \leq \sum_{r \in \mathcal{S}} C_{i,r} \end{aligned} \tag{7}$$

are satisfied for all subsets $\mathcal{S} \subseteq \mathcal{N}_{R,i}$, where we have defined the matrix $\mathbf{E}_{i,\mathcal{S}}$ obtained by stacking the matrices $\mathbf{E}_{i,r}$ for $r \in \mathcal{S}$ horizontally, the set $\mathbf{x}_{i,\mathcal{S}} \triangleq \{\mathbf{x}_{i,r}\}_{r \in \mathcal{S}}$, and the variables $\mathbf{A} \triangleq \{\mathbf{A}_i\}_{i \in \mathcal{N}_C}$ and $\mathbf{\Omega} \triangleq \{\mathbf{\Omega}_i\}_{i \in \mathcal{N}_C}$.

Proof: See [8, Lemma 2] and [9, Ch. 9] for a proof. □

Comparing the constraints (7) with (5), we observe that introducing correlation among the quantization noises for different RUs imposes more stringent requirements on the fronthaul capacities. This penalty must thus be counterbalanced by the advantages of correlating the quantization noises to make the multivariate compression strategy preferable to the point-to-point compression.

C. Achievable Rates

Each RU (i,r) decompresses the baseband signal $\mathbf{x}_{i,r}$ based on the bit stream received from the managing CU on the fronthaul link, and then upconverts the decompressed baseband signals for transmission in downlink. Accordingly, the received signal $\mathbf{y}_{i,k}$ in (1) can be written as

$$\mathbf{y}_{i,k} = \mathbf{H}_{i,k,i}\mathbf{A}_{i,k}\mathbf{s}_{i,k} + \sum_{l\in\mathcal{N}_{M,i}\setminus\{k\}} \mathbf{H}_{i,k,i}\mathbf{A}_{i,l}\mathbf{s}_{i,l} + \sum_{j\in\mathcal{N}_C\setminus\{i\}}\sum_{l\in\mathcal{N}_{M,j}} \mathbf{H}_{i,k,j}\mathbf{A}_{j,l}\mathbf{s}_{j,l} + \sum_{j\in\mathcal{N}_C}\mathbf{H}_{i,k,j}\mathbf{q}_j + \mathbf{z}_{i,k}, \quad (8)$$

where we have defined the channel matrix $\mathbf{H}_{i,k,j} \triangleq [\mathbf{H}_{i,k,j,1}\ldots \mathbf{H}_{i,k,j,N_{R,j}}]$ from all the RUs in the jth cluster to MS (i,k) and the matrix partition $\mathbf{A}_i = [\mathbf{A}_{i,1}\ldots\mathbf{A}_{i,N_{M,i}}]$ with $\mathbf{A}_{i,k}\in\mathbb{C}^{n_{R,i}\times d_{i,k}}$. The first term in (8) indicates the desired signal to be decoded by the receiving MS (i,k), and the second and third terms represent the intra-cluster and inter-cluster interference signals, respectively.

Assuming that each MS (i,k) decodes the message $M_{i,k}$ based on the signal $\mathbf{y}_{i,k}$ in (8) while treating the interference signals as noise, the achievable rate $R_{i,k}$ for MS (i,k) is given as

$$\begin{aligned} R_{i,k} &= f_{i,k}(\mathbf{A},\mathbf{\Omega}) \triangleq I(\mathbf{s}_{i,k};\mathbf{y}_{i,k}) \\ &= \log\det\Bigg(\sum_{j\in\mathcal{N}_C}\sum_{l\in\mathcal{N}_{M,j}}\mathbf{H}_{i,k,j}\mathbf{R}_{j,l}\mathbf{H}_{i,k,j}^{\dagger} + \sum_{j\in\mathcal{N}_C}\mathbf{H}_{i,k,j}\mathbf{\Omega}_j\mathbf{H}_{i,k,j}^{\dagger} + \mathbf{\Sigma}_{\mathbf{z}_{i,k}}\Bigg) \\ &\quad - \log\det\Bigg(\sum_{l\in\mathcal{N}_{M,i}\setminus\{k\}}\mathbf{H}_{i,k,i}\mathbf{R}_{i,l}\mathbf{H}_{i,k,i}^{\dagger} + \sum_{j\in\mathcal{N}_C\setminus\{i\}}\sum_{l\in\mathcal{N}_{M,j}}\mathbf{H}_{i,k,j}\mathbf{R}_{j,l}\mathbf{H}_{i,k,j}^{\dagger} + \sum_{j\in\mathcal{N}_C}\mathbf{H}_{i,k,j}\mathbf{\Omega}_j\mathbf{H}_{i,k,j}^{\dagger} + \mathbf{\Sigma}_{\mathbf{z}_{i,k}}\Bigg), \quad (9)\end{aligned}$$

where we have defined $\mathbf{R}_{i,k} \triangleq \mathbf{A}_{i,k}\mathbf{A}_{i,k}^{\dagger}$.

III. Problem Definition and Optimization

We aim at optimizing the precoding matrices $\mathbf{A}$ and the quantization covariance matrices $\mathbf{\Omega}$ across all clusters with the goal of maximizing the weighted sum-rate $\sum_{i\in\mathcal{N}_C}\sum_{k\in\mathcal{N}_{M,i}} w_{i,k}R_{i,k}$ subject to the per-RU power constraints (2) and the fronthaul capacity constraints (7). The problem is stated as

$$\begin{aligned} &\underset{\mathbf{A},\mathbf{\Omega}\succeq\mathbf{0}}{\text{maximize}} \sum_{i\in\mathcal{N}_C}\sum_{k\in\mathcal{N}_{M,i}} w_{i,k}f_{i,k}(\mathbf{A},\mathbf{\Omega}) \\ &\text{s.t. } g_{i,\mathcal{S}}(\mathbf{A},\mathbf{\Omega}) \le \sum_{r\in\mathcal{S}} C_{i,r}, \text{ for all } i\in\mathcal{N}_C,\ \mathcal{S}\subseteq\mathcal{N}_{R,i}, \\ &\quad\ \mathrm{tr}\Big(\mathbf{E}_{i,r}^{\dagger}\mathbf{A}_i\mathbf{A}_i^{\dagger}\mathbf{E}_{i,r}\Big) \le P_{i,r}, \text{ for all } i\in\mathcal{N}_C,\ r\in\mathcal{N}_{R,i}. \quad (10)\end{aligned}$$

Note that it is not easy to solve the problem (10) due to the non-convexity in the objective function and of the first constraint. However, solving the problem with respect to the variables $\mathbf{R}\triangleq\{\mathbf{R}_{i,k}\}_{i\in\mathcal{N}_C,k\in\mathcal{N}_{M,i}}$ and $\mathbf{\Omega}$ is a difference-of-convex problem whose stationary point can be found via Majorization Minimization (MM) approach [11]. The detailed algorithm is summarized in Table Algorithm 1, where we have defined the functions

$$\begin{aligned} &f'_{i,k}\left(\left\{\mathbf{R}^{(t+1)},\mathbf{\Omega}^{(t+1)}\right\},\left\{\mathbf{R}^{(t)},\mathbf{\Omega}^{(t)}\right\}\right) \\ &\triangleq \log\det\Bigg(\sum_{j\in\mathcal{N}_C}\sum_{l\in\mathcal{N}_{M,j}}\mathbf{H}_{i,k,j}\mathbf{R}_{j,l}^{(t+1)}\mathbf{H}_{i,k,j}^{\dagger} + \sum_{j\in\mathcal{N}_C}\mathbf{H}_{i,k,j}\mathbf{\Omega}_j^{(t+1)}\mathbf{H}_{i,k,j}^{\dagger} + \mathbf{\Sigma}_{\mathbf{z}_{i,k}}\Bigg) \\ &\quad - \varphi\Bigg(\sum_{l\in\mathcal{N}_{M,i}\setminus\{k\}}\mathbf{H}_{i,k,i}\mathbf{R}_{i,l}^{(t+1)}\mathbf{H}_{i,k,i}^{\dagger} + \sum_{j\in\mathcal{N}_C\setminus\{i\}}\sum_{l\in\mathcal{N}_{M,j}}\mathbf{H}_{i,k,j}\mathbf{R}_{j,l}^{(t+1)}\mathbf{H}_{i,k,j}^{\dagger} + \sum_{j\in\mathcal{N}_C}\mathbf{H}_{i,k,j}\mathbf{\Omega}_j^{(t+1)}\mathbf{H}_{i,k,j}^{\dagger} + \mathbf{\Sigma}_{\mathbf{z}_{i,k}}, \\ &\qquad \sum_{l\in\mathcal{N}_{M,i}\setminus\{k\}}\mathbf{H}_{i,k,i}\mathbf{R}_{i,l}^{(t)}\mathbf{H}_{i,k,i}^{\dagger} + \sum_{j\in\mathcal{N}_C\setminus\{i\}}\sum_{l\in\mathcal{N}_{M,j}}\mathbf{H}_{i,k,j}\mathbf{R}_{j,l}^{(t)}\mathbf{H}_{i,k,j}^{\dagger} + \sum_{j\in\mathcal{N}_C}\mathbf{H}_{i,k,j}\mathbf{\Omega}_j^{(t)}\mathbf{H}_{i,k,j}^{\dagger} + \mathbf{\Sigma}_{\mathbf{z}_{i,k}},\Bigg), \quad (11)\end{aligned}$$

$$\begin{aligned} &g'_{i,\mathcal{S}}\left(\left\{\mathbf{R}^{(t+1)},\mathbf{\Omega}^{(t+1)}\right\},\left\{\mathbf{R}^{(t)},\mathbf{\Omega}^{(t)}\right\}\right) \\ &\triangleq \sum_{r\in\mathcal{S}}\varphi\Big(\mathbf{E}_{i,r}^{\dagger}\Big(\mathbf{R}_i^{(t+1)}+\mathbf{\Omega}_i^{(t+1)}\Big)\mathbf{E}_{i,r},\mathbf{E}_{i,r}^{\dagger}\Big(\mathbf{R}_i^{(t)}+\mathbf{\Omega}_i^{(t)}\Big)\mathbf{E}_{i,r}\Big) \\ &\quad - \log\det\Big(\mathbf{E}_{i,\mathcal{S}}^{\dagger}\mathbf{\Omega}_i^{(t+1)}\mathbf{E}_{i,\mathcal{S}}\Big), \quad (12)\end{aligned}$$

with the function $\varphi(\mathbf{X},\mathbf{Y})$ defined as

$$\varphi(\mathbf{X},\mathbf{Y}) \triangleq \log\det(\mathbf{Y}) + \frac{1}{\ln 2}\mathrm{tr}\left(\mathbf{Y}^{-1}(\mathbf{X}-\mathbf{Y})\right). \quad (13)$$

Algorithm 1 MM Algorithm for problem (10)

1. Initialize the matrices $\mathbf{R}^{(1)}$ and $\mathbf{\Omega}^{(1)}$ to arbitrary feasible positive semidefinite matrices for problem (10) and set $t=1$.
2. Update the matrices $\mathbf{R}^{(t+1)}$ and $\mathbf{\Omega}^{(t+1)}$ as a solution of the convex problem

$$\begin{aligned} &\underset{\mathbf{R}^{(t+1)},\mathbf{\Omega}^{(t+1)}\succeq\mathbf{0}}{\text{maximize}} \sum_{i\in\mathcal{N}_C}\sum_{k\in\mathcal{N}_{M,i}} w_{i,k} \times f'_{i,k}\left(\left\{\mathbf{R}^{(t+1)},\mathbf{\Omega}^{(t+1)}\right\},\left\{\mathbf{R}^{(t)},\mathbf{\Omega}^{(t)}\right\}\right) \\ &\text{s.t. } g'_{i,\mathcal{S}}\left(\left\{\mathbf{R}^{(t+1)},\mathbf{\Omega}^{(t+1)}\right\},\left\{\mathbf{R}^{(t)},\mathbf{\Omega}^{(t)}\right\}\right) \le \sum_{i\in\mathcal{S}} C_i, \\ &\quad \text{for all } i\in\mathcal{N}_C,\ \mathcal{S}\subseteq\mathcal{N}_{R,i}, \\ &\quad \sum_{k\in\mathcal{N}_{M,i}}\mathrm{tr}\left(\mathbf{E}_{i,r}^{\dagger}\mathbf{R}_{i,k}^{(t+1)}\mathbf{E}_{i,r}\right) \le P_{i,r}, \\ &\quad \text{for all } i\in\mathcal{N}_C,\ r\in\mathcal{N}_{R,i}. \quad (14)\end{aligned}$$

3. Go to Step 4 if a convergence criterion is satisfied. Otherwise, set $t\leftarrow t+1$ and go back to Step 2.
4. Calculate the precoding matrices $\mathbf{A}_{i,k}\leftarrow\mathbf{V}_{i,k}\mathbf{D}_{i,k}^{1/2}$ for $i\in\mathcal{N}_C$ and $k\in\mathcal{N}_{M,i}$, where $\mathbf{D}_{i,k}$ is a diagonal matrix whose diagonal elements are the nonzero eigenvalues of $\mathbf{R}_{i,k}^{(t)}$ and the columns of $\mathbf{V}_{i,k}$ are the corresponding eigenvectors.

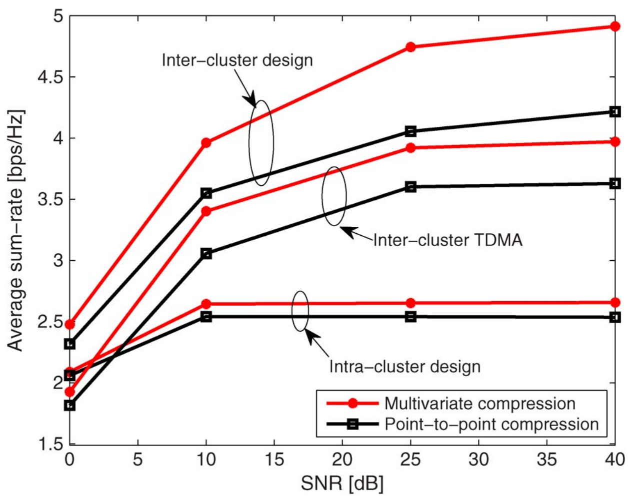

Fig. 2. Average sum-rate versus the SNR for the downlink system with $N_C = 2$, $N_{R,i} = N_{M,i} = 2$, $n_{R,i,r} = n_{M,i,k} = 1$ and $C_{i,r} = 2$ bits/s/Hz.

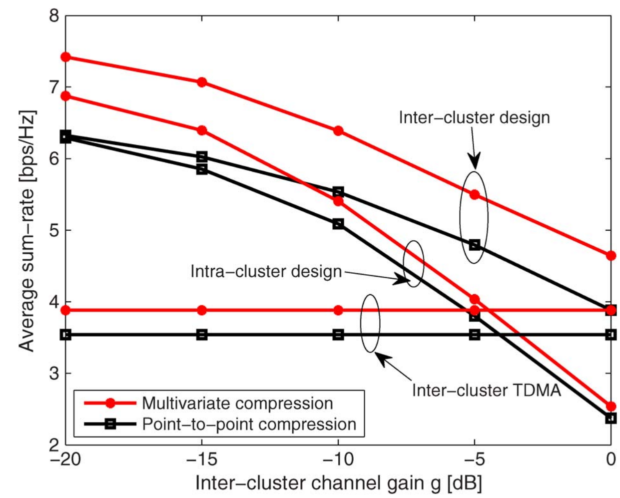

Fig. 3. Average sum-rate versus the inter-cluster channel gain g for the downlink system with $N_C = 2$, $N_{R,i} = N_{M,i} = 2$, $n_{R,i,r} = n_{M,i,k} = 1$, $C_{i,r} = 2$ bits/s/Hz and $P_{i,r} = 20$ dB.

IV. Numerical Results

In this section, we present numerical results that show the effectiveness of the proposed inter-cluster design based on multivariate compression compared to the approach in [8] based on intra-cluster optimization. Specifically, we compare three difference strategies: *i*) Inter-cluster design: The problem (10) is solved using Algorithm I; *ii*) Inter-cluster TDMA: The problem (10) is tackled for a single cluster while deactivating the other clusters; *iii*) Intra-cluster design: The problem (10) is solved in parallel for each cluster by assuming that there is no inter-cluster interference. For reference, we also consider schemes based on point-to-point compression [10].

Fig. 2 plots the average sum-rates versus the signal-to-noise ratio (SNR) defined as P/N_0, where we assume $P_{i,r} = P$ and $\mathbf{\Sigma}_{\mathbf{z}_{i,k}} = N_0\mathbf{I}$ for all $i \in \mathcal{N}_C$, $r \in \mathcal{N}_{R,i}$ and $k \in \mathcal{N}_{M,i}$, for the downlink system with $N_C = 2$, $N_{R,i} = N_{M,i} = 2$, $n_{R,i,r} = n_{M,i,k} = 1$ and $C_{i,r} = 2$ bits/s/Hz. We assume that the elements of the channel matrices $\mathbf{H}_{i,k,j,r}$ are independent and identically distributed (i.i.d.) as $\mathcal{CN}(0,1)$. From the figure, it is observed that the performance gain of the inter-cluster design with multivariate compression, compared to intra-cluster design and/or point-to-point compression, increases with the SNR. This is because, in this regime, inter-cluster interference and the quantization noises become dominant with respect to the additive noise. It is also noted that multivariate compression is particularly effective when optimized using the proposed inter-cluster design, since, with the intra-cluster design, the corresponding performance gain is masked by the effect of the inter-cluster interference. Comparing the performance of the intra-cluster design to that of the inter-cluster TDMA, we learn that it is desirable to activate both clusters at low SNR regime instead of avoiding inter-cluster interfernece.

Fig. 3 shows the average sum-rate versus the inter-cluster channel gain g for the downlink system with $N_C = 2$, $N_{R,i} = N_{M,i} = 2$, $n_{R,i,r} = n_{M,i,k} = 1$, $C_{i,r} = 2$ bits/s/Hz and $P_{i,r} = 20$ dB, where we assume the elements of the channel matrices $\mathbf{H}_{i,k,j,r}$ are i.i.d. random variables distributed as $\mathcal{CN}(0,1)$ and $\mathcal{CN}(0,g)$ for $i = j$ and $i \neq j$, respectively. This implies that the parameter g measures the channel power between the MSs and the RUs belonging to different clusters. The figure validates and quantifies the larger gains obtained with the proposed inter-cluster design as the power of the inter-cluster interference increases.

V. Conclusion

In this paper, we have studied the joint design of precoding and fronthaul compression for the downlink of C-RANs in the presence of inter-cluster interference. Via numerical results, it was confirmed that the proposed approach based on multivariate compression and inter-cluster design outperforms the existing approaches based on independent compression and intra-cluster design.

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