

Fronthaul Compression and Precoding Design for Full-duplex Cloud Radio Access Network

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Abstract—In this work, joint design of fronthaul compression and precoding is studied for full-duplex (FD) cloud radio access networks (C-RANs). Multiple uplink (UL) and downlink (DL) users equipped with multiple antennas communicate with a control unit (CU) in the “cloud” through a set of multi-antenna FD radio units (RUs) which are connected to the CU through limited capacity fronthaul links. In the first part of the paper, we address the weighted sum-rate maximization problem to compute the optimal precoding and the quantization noise covariance matrices. By exploiting the relationship between weighted-sum-rate maximization and weighted minimum-mean-square-error (WMMSE) minimization problems, and leveraging the successive convex approximation (SCA) method, we propose an iterative algorithm that guarantees convergence to a stationary point. In the second part of the paper, we address the stochastic sum-rate maximization problem under fast-fading channels, where only the statistics of the channel-state-information (CSI) is available. Casting this non-convex problem as a difference of convex (DC) problem, an iterative algorithm based on the combination of stochastic successive upper bound minimization (SSUM) and SCA approaches that guarantees convergence to a stationary point is proposed. Numerical results demonstrate the advantage of the proposed algorithms.

Keywords—Fast fading, fronthaul, full-duplex, MIMO, multi-user, self-interference.

I. INTRODUCTION

In current wireless communication systems, downlink (DL) and uplink (UL) channels are designed to operate in half-duplex (HD) mode, i.e., orthogonal channels. Full-duplex (FD) communication, which enables UL and DL communication at the same time slot on the same frequency, is a promising technique to double the spectral efficiency [1]. Although there are several designs to deal with the self-interference inherent in FD radios, due to the imperfections of radio devices, the self-interference cannot be canceled completely in reality.

On a parallel avenue, cloud radio access networks (C-RANs) have emerged as a novel mobile network architecture for next-generation wireless cellular systems that migrates the baseband operations of a cluster of radio units (RUs) to a centralized

control unit (CU) via finite-capacity fronthaul links [2], [3]. Since the fronthaul links typically have limited capacity and are known to impose a formidable bottleneck to the system performance, it is important to carefully design precoding and fronthaul compression strategies to achieve a high spectral efficiency.

The significant potential advantages of FD in the C-RAN architecture with sufficient fronthaul capacity and appropriate scheduling was analyzed in [4]. Combining the benefits of FD transmission at RUs with the FD fronthaul leads to efficient reuse of RAN spectrum, alleviates the need to obtain dedicated spectrum for fronthaul, and facilitates hardware implementation by enabling the use of same hardware for access links and fronthaul links. While the FD operation can ideally double the spectral efficiency in a link, the network-level gain of exploiting FD transmission in the fronthaul remains unclear due to the complicated interference environment, e.g., self-interference and co-channel interference (CCI) at the fronthaul and access links [5]. Therefore, the usefulness of an FD fronthaul over the popular HD fronthaul is not immediately evident. In this work, we consider an FD C-RAN where RUs operating in FD mode serve multiple UL and DL users simultaneously, and connect to a CU via finite-capacity fronthaul links to transfer the interference management task to be done by the centralized baseband processing effectively. The contributions of the paper are as follows:

- The sum-power minimization problem under quality of service constraints in FD C-RAN systems has been investigated in [6]. However, single antenna users and sufficiently high capacity fronthaul links are assumed in [6]. In this paper, we investigate the impact of finite-capacity fronthaul links in an FD C-RAN and users are equipped with multiple antennas. In particular, in Section III, the weighted sum-rate maximization subject to finite wired fronthaul rate constraints at each RU on the UL and DL channels, and power constraints at the RUs and UL users to find the optimal transmit beamformers and quantization noise covariance matrices (due to compression) is considered. We employ an iterative algorithm converging to a stationary point based on the combination of successive convex approximation (SCA) algorithm [7], [8] and the relationship between weighted-sum-rate maximization and weighted minimum-mean-square-error (WMMSE) minimization problems [9]–[10].
- As discussed in [11], the self-interference channel (even if through an RF circulator for a single antenna) still

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depends on the positions of the nearby moving reflectors, and thus can be modeled as fast-fading. Unlike slow fading channels where instantaneous channel state information (CSI) can be estimated with a reasonable accuracy, here we do not assume any instantaneous CSI feedback from the receiver. Instead, we assume that the receiver feeds the transmitter with statistical CSI (the mean and variance of the channel). In this case, the reliability of the FD system could be decreased due to lack of CSI knowledge in beamforming design and the reduced number of receive antennas for FD transmission [12]. Previous works on the design of fronthaul compression and precoding [2], [5], [6] assume that the knowledge of the instantaneous CSI is available at the CU, which may be impractical due to channel aging, channel estimation errors and nearby reflectors. In contrast, in the second part of Section III, we consider a scenario, where only stochastic CSI (distribution of the channels) is available at the CU and the knowledge of the statistics of the CSI is used at the transmitter to design optimal beamforming schedules. The stochastic (ergodic) sum-rate maximization of the network subject to finite wired fronthaul rate and power constraints on the respective entities is solved. An iterative algorithm converging to a stationary point based on the combination of stochastic successive upper bound minimization (SSUM) approach [13] and SCA approach, which solves a sequence of convex problems obtained by linearizing the non-convex parts in the original problem [8].

The simulation results show the enhancement of the spectral efficiency, thanks to the FD operation of RUs, compared to an HD C-RAN system.

Notation: Matrices and vectors are denoted as bold capital and lowercase letters, respectively. $(\cdot)^T$ is the transpose, and $(\cdot)^H$ is the conjugate transpose. $\mathbb{E}[\cdot]$ denotes the statistical expectation, \mathbf{I}_N is the N by N identity matrix, and $\mathbf{0}_{N \times M}$ is the N by M zero matrix. $\text{tr}\{\cdot\}$ is the trace, $|\cdot|$ is the determinant. $\mathbb{C}^{M \times N}$ denotes the set of complex matrices with a dimension of $M \times N$, $\mathcal{CN}(\mu, \sigma^2)$ denotes complex Gaussian distribution with mean μ and variance σ^2 , and $\text{diag}\{a_1, \dots, a_n\}$ denotes a diagonal matrix with the diagonal elements given by a_1, \dots, a_n . Finally, $\sigma_{max}(\mathbf{A})$ is the largest singular value of matrix \mathbf{A} .

II. SYSTEM MODEL

The general architecture of a C-RAN consists of a centralized CU, RUs with antennas located at the remote sites and a fronthaul (wireless or wired) that connects RUs to the CU. The C-RAN communication can be viewed as a special case of a relay communication with a wireless first-hop (second-hop) and a wireless/wired second-hop (first-hop) in the uplink (downlink) [2], [3]. The RUs are used to provide a high data rate service for the users with a limited coverage, by transmitting radio frequency (RF) signals to the users in the downlink and forwarding the baseband signals from the users to the CU for centralized processing in the uplink.

In practice, the fronthauls are capacity and time (latency) constrained, which affect the spectral efficiency gains obtained

by the usage of C-RANs [2]. To overcome the fronthaul constrains of C-RANs, compression/quantization design over the constrained fronthaul and precoding/decoding over the RUs are deemed to be of critical importance. Moreover, beamformer design taking the constrained fronthaul into account is important to mitigate interference which results in improved spectral efficiency and energy efficiency, and reduced power consumption [2], [3].

In this paper, we assume that the RUs operate in FD mode. In particular, in the uplink channel, the RUs compress and forward the signals received from the uplink users to the centralized CU via the limited-capacity wired fronthaul links. The centralized CU then performs joint decoding of all uplink users based on the compressed data received from all RUs. In the downlink channel, the centralized CU first precodes the data streams of each downlink user in order to mitigate both inter-user interference among downlink users and inter-stream interference among the data streams of a downlink user. The centralized CU then compresses the precoded signals and transmits the compressed data to the RUs via the limited-capacity wired fronthaul links. The RUs decompress the compressed signal received from the centralized CU and forwards it to the downlink users on the wireless downlink channel.

The network-level gain of exploiting FD transmission in the fronthaul remains unclear due to the complicated interference environment, e.g., self-interference and CCI at the fronthaul and access links among the RUs and users. Therefore, the usefulness of an FD fronthaul over the popular HD fronthaul is not immediately evident. As shown in [2], [3], the compression design in both uplink and downlink channels can be transformed into an optimization design of the covariance matrix of the quantization noises across RUs. Therefore, in this paper, we jointly optimize the covariance matrix of the quantization noises across FD RUs and the transmit beamforming matrices to maximize sum-rate of the uplink and downlink users in the FD C-RAN system under the fronthaul capacity constraints and power constraints of the transmitting nodes.

We consider a C-RAN system where a CU is connected to K_R FD RUs serving K_{UL} UL and K_{DL} DL users simultaneously through wired finite-capacity fronthaul links as shown in Fig. 1¹. The k th FD RU is equipped with M_k transmit and N_k receive antennas with a total of $M^{DL} = \sum_{k=1}^{K_R} M_k$ transmit and $N^{UL} = \sum_{k=1}^{K_R} N_k$ receive antennas at the RUs, and the number of antennas at the k th UL and DL users are T_k and R_k , respectively. In wired fronthaul, the sum of data streams of all uplink users should be less than or equal to the transmit antennas at the uplink users and the sum of receive antennas of all RUs. In particular, $\sum_{k=1}^{K_{UL}} d_k^{UL} \leq \sum_{k=1}^{K_{UL}} T_k \leq N^{UL}$. In the downlink channel, sum of data streams of all downlink users should be less than or equal to the receive antennas at

¹In our analysis, we assume that separate physical (wired) links between the CU and the RUs for the uplink and downlink communication are used. The reason is that using the same physical link in the fronthaul for the uplink and downlink can result in co-channel interference, which may lead to more constraint on the already existing capacity constraint of the non-ideal fronthaul links. The usage of separate physical links between the CU and the RUs in FD systems have also been considered in [14].

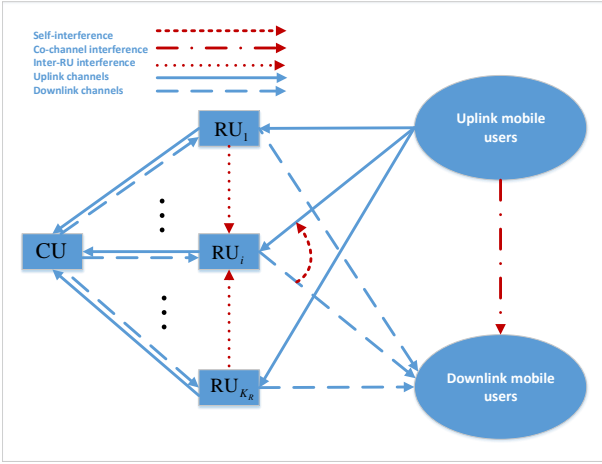


Fig. 1. Full-duplex cloud radio access network. The solid and dashed lines refer to UL and DL transmission, respectively.

the downlink users and the sum of transmit antennas of all RUs. In particular, $\sum_{k=1}^{K_{DL}} d_k^{DL} \leq \sum_{k=1}^{K_{DL}} R_k \leq M^{DL}$. Let us denote \mathcal{S}^{UL} , \mathcal{S}^{DL} and \mathcal{S}^{RU} as the set of all UL users, DL users, and RUs, respectively.

A. Downlink System

In the DL system, the transmit signal vector at the CU $\tilde{\mathbf{x}}^{DL} = [(\tilde{\mathbf{x}}_1^{DL})^T, \dots, (\tilde{\mathbf{x}}_{K_R}^{DL})^T]^T \in \mathbb{C}^{M^{DL} \times 1}$ is expressed as

$$\tilde{\mathbf{x}}^{DL} = \sum_{k=1}^{K_{DL}} \mathbf{V}_k^{DL} \mathbf{s}_k^{DL}. \quad (1)$$

Here $\mathbf{V}_k^{DL} \in \mathbb{C}^{M^{DL} \times d_k^{DL}}$ denotes the precoding matrix for the data symbol of the k th DL user represented as $\mathbf{s}_k^{DL} \in \mathbb{C}^{d_k^{DL} \times 1} \sim \mathcal{CN}(\mathbf{0}, \mathbf{I}_{d_k^{DL}})$, where d_k^{DL} is the number of data streams destined to the k th DL user, $k \in \mathcal{S}^{DL}$. The vector transferred from the CU to the i th RU is the i th subvector of $\tilde{\mathbf{x}}^{DL}$ denoted as $\tilde{\mathbf{x}}_i^{DL} = \mathbf{E}_i^H \tilde{\mathbf{x}}^{DL}$, where \mathbf{E}_i is defined as

$$\mathbf{E}_i = \begin{bmatrix} \mathbf{0}_{\sum_{k=1}^{i-1} M_k \times M_i} & \mathbf{I}_{M_i \times M_i} & \mathbf{0}_{\sum_{k=i+1}^{K_R} M_k \times M_i} \end{bmatrix}^T.$$

The CU compresses the baseband signal $\tilde{\mathbf{x}}_i^{DL}$ by quantizing and forwards on the fronthaul links to the corresponding RUs. The received signal at the i th RU is given as

$$\mathbf{x}_i^{DL} = \tilde{\mathbf{x}}_i^{DL} + \mathbf{q}_i^{DL}, \quad i \in \mathcal{S}^{RU}, \quad (2)$$

where $\mathbf{q}_i^{DL} \sim \mathcal{CN}(\mathbf{0}, \mathbf{\Upsilon}_i^{DL})$ is the quantization noise at the i th RU in the DL channel.

Similar to [15], [16], we assume that the signals are compressed independently so that the quantization noises of different RUs are uncorrelated. The independent quantization noise across RUs can be realized via separate quantizers for the signals of different RUs².

²Note that the possibility to leverage quantization noise correlation across the RUs via joint quantization has been explored in [17] for static channels.

The quantization and forwarding scheme is usually studied under an information-theoretical Gaussian test channel model [2]. According to rate-distortion theory, the Gaussian quantization test channel has a quantization noise modelled as an independent Gaussian random variable with variance linked to the test channel capacity [18].

Given (2), the DL fronthaul rate and power constraints at the i th RU are given, respectively, as

$$\log \left| \mathbf{E}_i^H \sum_{k=1}^{K_{DL}} \mathbf{V}_k^{DL} (\mathbf{V}_k^{DL})^H \mathbf{E}_i + \mathbf{\Upsilon}_i^{DL} \right| - \log \left| \mathbf{\Upsilon}_i^{DL} \right| \leq C_i^{DL}, \quad i \in \mathcal{S}^{RU}, \quad (3)$$

$$\text{tr} \left\{ \mathbf{E}_i^H \sum_{k=1}^{K_{DL}} \mathbf{V}_k^{DL} (\mathbf{V}_k^{DL})^H \mathbf{E}_i + \mathbf{\Upsilon}_i^{DL} \right\} \leq P_i^{DL}, \quad i \in \mathcal{S}^{RU} \quad (4)$$

where C_i^{DL} and P_i^{DL} are the DL fronthaul rate and power constraints at the i th RU, respectively.

The RUs decompress the received signal from the CU and forward it to the downlink users³. The received signal at the k th DL user is expressed as

$$\mathbf{y}_k^{DL} = \mathbf{H}_k^{DL} \mathbf{x}^{DL} + \sum_{l=1}^{K_{UL}} \mathbf{H}_{kl}^{DU} \mathbf{x}_l^{UL} + \mathbf{n}_k^{DL}, \quad k \in \mathcal{S}^{DL}, \quad (5)$$

where $\mathbf{H}_{ki}^{DL} \in \mathbb{C}^{R_k \times M_i}$ represents the channel matrix from the i th RU to the k th DL user, and the stacked matrix $\mathbf{H}_k^{DL} \in \mathbb{C}^{R_k \times M^{DL}}$ is denoted as $\mathbf{H}_k^{DL} = [\mathbf{H}_{k1}^{DL}, \dots, \mathbf{H}_{kK_R}^{DL}]$. Moreover, $\mathbf{H}_{kl}^{DU} \in \mathbb{C}^{R_k \times T_l}$ denotes the co-channel interference (CCI) channel from the l th UL user to the k th DL user. The stacked transmit vector is denoted as $\mathbf{x}^{DL} = [(\mathbf{x}_1^{DL})^T, \dots, (\mathbf{x}_{K_R}^{DL})^T]^T \in \mathbb{C}^{M^{DL} \times 1}$, and $\mathbf{x}_l^{UL} \in \mathbb{C}^{T_l \times 1}$ is the transmit signal vector of the l th UL user. Finally, $\mathbf{n}_k^{DL} \sim \mathcal{CN}(\mathbf{0}, \sigma_{DL}^2 \mathbf{I}_{R_k})$ denotes the additive white Gaussian noise (AWGN) at the k th DL user.

Given (5), the achievable rate at the k th DL user, $k \in \mathcal{S}^{DL}$ is given as

$$R_k^{DL} = \log \left| \mathbf{H}_k^{DL} \mathbf{V}_k^{DL} (\mathbf{V}_k^{DL})^H (\mathbf{H}_k^{DL})^H + \Sigma_k^{DL} \left(\tilde{\mathbf{V}}_k^{DL}, \tilde{\mathbf{\Upsilon}}^{DL}, \tilde{\mathbf{H}}_k^{DL} \right) \right| - \log \left| \Sigma_k^{DL} \left(\tilde{\mathbf{V}}_k^{DL}, \tilde{\mathbf{\Upsilon}}^{DL}, \tilde{\mathbf{H}}_k^{DL} \right) \right|, \quad (6)$$

where $\Sigma_k^{DL} \left(\tilde{\mathbf{V}}_k^{DL}, \tilde{\mathbf{\Upsilon}}^{DL}, \tilde{\mathbf{H}}_k^{DL} \right)$ denotes the interference-plus-noise covariance matrix at the k th DL user, and is given at the top of the following page. In (6), the function

³The RUs operating in FD mode are similar to the decode-and-forward (DF) FD relay nodes, which have been studied extensively in the literature. As in the case for DF FD relay nodes, in our scheme, the FD RU is not receiving from the CU and transmitting to the downlink users the same data streams simultaneously. There is a processing delay associated with the decoding of the signals, which we have omitted as the final optimization will not be affected (i.e., independent of the processing delay). Dropping the processing delay in optimization problems associated with the FD systems can be also seen in [19]-[26].

$$\begin{aligned}\Sigma_k^{DL}(\tilde{\mathbf{V}}_k^{DL}, \tilde{\mathbf{Y}}^{DL}, \tilde{\mathbf{H}}_k^{DL}) &= \mathbf{H}_k^{DL} \left(\sum_{l=1, l \neq k}^{K_{DL}} \mathbf{V}_l^{DL} (\mathbf{V}_l^{DL})^H + \tilde{\mathbf{Y}}^{DL} \right) (\mathbf{H}_k^{DL})^H + \sum_{l=1}^{K_{UL}} \mathbf{H}_{kl}^{DU} \mathbf{V}_l^{UL} (\mathbf{V}_l^{UL})^H (\mathbf{H}_{kl}^{DU})^H + \sigma_{DL}^2 \mathbf{I}_{R_k}, \\ \Sigma_k^{UL}(\tilde{\mathbf{V}}_k^{UL}, \tilde{\mathbf{Y}}^{UL}, \tilde{\mathbf{H}}_k^{UL}) &= \sum_{l=1, l \neq k}^{K_{UL}} \mathbf{H}_l^{UL} \mathbf{V}_l^{UL} (\mathbf{V}_l^{UL})^H (\mathbf{H}_l^{UL})^H + \mathbf{H}^{UD} \left(\sum_{l=1}^{K_{DL}} \mathbf{V}_l^{DL} (\mathbf{V}_l^{DL})^H + \tilde{\mathbf{Y}}^{DL} \right) (\mathbf{H}^{UD})^H \\ &\quad + \tilde{\mathbf{Y}}^{UL} + \sigma_{UL}^2 \mathbf{I}_{N^{UL}}.\end{aligned}$$

variables are denoted as $\tilde{\mathbf{Y}}^X = \text{diag} \{ \mathbf{Y}_1^X, \dots, \mathbf{Y}_{K_R}^X \}$, $X \in \{UL, DL\}$, $\tilde{\mathbf{V}}_k^{DL} = \left[\{ \mathbf{V}_l^{UL} \}_{l=1}^{K_{UL}}, \{ \mathbf{V}_l^{DL} \}_{l=1, l \neq k}^{K_{DL}} \right]$, and $\tilde{\mathbf{H}}_k^{DL} = \left[\{ \mathbf{H}_{kl}^{DU} \}_{l=1}^{K_{UL}}, \mathbf{H}_k^{DL} \right]$.

B. Uplink System

In the UL channel, the received signal at the i th RU is given as

$$\mathbf{y}_i^{UL} = \sum_{k=1}^{K_{UL}} \mathbf{H}_{ik}^{UL} \mathbf{V}_k^{UL} \mathbf{s}_k^{UL} + \sum_{j=1}^{K_R} \mathbf{H}_{ij}^{UD} \mathbf{x}_j^{DL} + \mathbf{n}_i^{UL}, \quad i \in \mathcal{S}^{RU} \quad (7)$$

where $\mathbf{V}_k^{UL} \in \mathbb{C}^{T_k \times d_k^{UL}}$ denotes the precoding matrix for the data symbol of the k th UL user represented as $\mathbf{s}_k^{UL} \in \mathbb{C}^{d_k^{UL} \times 1} \sim \mathcal{CN}(\mathbf{0}, \mathbf{I}_{d_k^{UL}})$, where d_k^{UL} is the number of data streams of the k th UL user. Here, $\mathbf{H}_{ik}^{UL} \in \mathbb{C}^{N_i \times T_k}$ represents the channel matrix from k th UL user to the i th RU, and $\mathbf{H}_{ij}^{UD} \in \mathbb{C}^{N_i \times M_j}$ represents the residual self-interference channel matrix from the j th RU to the i th RU. Finally, the vector $\mathbf{n}_i^{UL} \sim \mathcal{CN}(\mathbf{0}, \sigma_{UL}^2 \mathbf{I}_{N_i})$ denotes the AWGN at the i th RU. The power constraint at the k th UL user is given as

$$\text{tr} \left\{ \mathbf{V}_k^{UL} (\mathbf{V}_k^{UL})^H \right\} \leq P_k^{UL}, \quad k \in \mathcal{S}^{UL}, \quad (8)$$

where P_k^{UL} is the maximum allowed transmit power at the k th UL user.

Upon receiving the signal (7), the i th RU forwards the compressed version of the signal (7) to the CU, given as

$$\tilde{\mathbf{y}}_i^{UL} = \mathbf{y}_i^{UL} + \mathbf{q}_i^{UL}, \quad i \in \mathcal{S}^{RU}, \quad (9)$$

where $\mathbf{q}_i^{UL} \sim \mathcal{CN}(\mathbf{0}, \mathbf{Y}_i^{UL})$ is the quantization noise at the i th RU in the UL channel. Given (9), the CU can recover the signal of the i th RU only when the following UL fronthaul rate condition is satisfied:

$$\log \left| \Phi_i^{UL} + \mathbf{Y}_i^{UL} \right| - \log \left| \mathbf{Y}_i^{UL} \right| \leq C_i^{UL}, \quad i \in \mathcal{S}^{RU}, \quad (10)$$

where C_i^{UL} is the UL fronthaul rate constraint at the i th RU, and Φ_i^{UL} is the covariance matrix of the received signal \mathbf{y}_i^{UL}

in (7) given as

$$\begin{aligned}\Phi_i^{UL} &= \sum_{k=1}^{K_{UL}} \mathbf{H}_{ik}^{UL} \mathbf{V}_k^{UL} (\mathbf{V}_k^{UL})^H (\mathbf{H}_{ik}^{UL})^H + \sigma_{UL}^2 \mathbf{I}_{N_i} \\ &\quad + \tilde{\mathbf{H}}_i^{UD} \left(\sum_{k=1}^{K_{DL}} \mathbf{V}_k^{DL} (\mathbf{V}_k^{DL})^H + \tilde{\mathbf{Y}}^{DL} \right) (\tilde{\mathbf{H}}_i^{UD})^H,\end{aligned}$$

where $\tilde{\mathbf{H}}_i^{UD} = [(\mathbf{H}_{i1}^{UD}), \dots, (\mathbf{H}_{iK_R}^{UD})]$.

Stacking the received signal vectors at the CU as $\tilde{\mathbf{y}}^{UL} = \left[(\tilde{\mathbf{y}}_1^{UL})^T, \dots, (\tilde{\mathbf{y}}_{K_R}^{UL})^T \right]^T$, and applying the linear minimum mean squared error (MMSE) decoding, the achievable rate for k th UL user is given as [16]:

$$\begin{aligned}R_k^{UL} &= \log \left| \mathbf{H}_k^{UL} \mathbf{V}_k^{UL} (\mathbf{H}_k^{UL} \mathbf{V}_k^{UL})^H \right. \\ &\quad \left. + \Sigma_k^{UL}(\tilde{\mathbf{V}}_k^{UL}, \tilde{\mathbf{Y}}^{UL}, \tilde{\mathbf{H}}_k^{UL}) \right| \\ &\quad - \log \left| \Sigma_k^{UL}(\tilde{\mathbf{V}}_k^{UL}, \tilde{\mathbf{Y}}^{UL}, \tilde{\mathbf{H}}_k^{UL}) \right|,\end{aligned} \quad (11)$$

where $\Sigma_k^{UL}(\tilde{\mathbf{V}}_k^{UL}, \tilde{\mathbf{Y}}^{UL}, \tilde{\mathbf{H}}_k^{UL})$ denotes the interference-plus-noise covariance matrix and is expressed at the top of the page. Here, the stacked channel matrices in $\Sigma_k^{UL}(\tilde{\mathbf{V}}_k^{UL}, \tilde{\mathbf{Y}}^{UL}, \tilde{\mathbf{H}}_k^{UL})$ are denoted as $\mathbf{H}_k^{UL} = \left[(\mathbf{H}_{1k}^{UL})^T, \dots, (\mathbf{H}_{K_R k}^{UL})^T \right]^T$ and $\mathbf{H}^{UD} = [\mathbf{H}_1^{UD}, \dots, \mathbf{H}_{K_R}^{UD}]$, where $\mathbf{H}_j^{UD} = \left[(\mathbf{H}_{1j}^{UD})^T, \dots, (\mathbf{H}_{K_R j}^{UD})^T \right]^T$. Moreover, the function variables are denoted as $\tilde{\mathbf{V}}_k^{UL} = \left[\{ \mathbf{V}_l^{UL} \}_{l=1, l \neq k}^{K_{UL}}, \{ \mathbf{V}_l^{DL} \}_{l=1}^{K_{DL}} \right]$, and $\tilde{\mathbf{H}}_k^{UL} = \left[\mathbf{H}^{UD}, \{ \mathbf{H}_l^{UL} \}_{l=1, l \neq k}^{K_{UL}} \right]$.

III. JOINT DESIGN OF FRONTHAUL COMPRESSION AND PRECODING

As discussed in Section II, the design of covariance matrix of quantization noises across all RUs is important to overcome the capacity constraints of the fronthaul links. Moreover, the precoding design taking the constrained fronthaul into account is important to mitigate the interference among RUs and users which results in improved spectral efficiency. Therefore, in this section, we jointly optimize the precoding and quantization noise covariance matrices to maximize the sum-rate of the uplink and downlink users in the FD C-RAN system subject

to power constraints in (4) and (8), and wired fronthaul rate constraints in (3) and (10). We consider two scenarios, i) the CU has perfect instantaneous information about the channel matrices, where the design of the precoding matrix and the covariance matrix of quantization noises can be adapted to the channel realization, and ii) the CU is only aware of the stochastic CSI, i.e., distribution of the channel matrices such as mean, variance, spatial correlation of the channels. The knowledge of the statistics of the CSI is used at the CU to design optimal precoding matrices and covariance matrices of quantization noises. The CSI acquisition is practically limited by how fast the channel conditions are changing. In fast fading systems where channel conditions vary rapidly under the transmission of a single information symbol, only statistical CSI is reasonable. On the other hand, in slow fading systems, instantaneous CSI can be estimated with reasonable accuracy and can be used in transmission adaptation for some time before being outdated.

A. Instantaneous CSI

In this section, we jointly optimize the precoding and quantization noise covariance matrices to maximize the weighted sum-rate of the FD C-RAN system subject to power constraints in (4) and (8), and fronthaul rate constraints in (3) and (10). The problem is formulated as:

$$\max_{\mathbf{V}, \mathbf{Y}} \sum_{k=1}^{K_{DL}} \alpha_k^{DL} R_k^{DL} + \sum_{k=1}^{K_{UL}} \alpha_k^{UL} R_k^{UL} \quad (12a)$$

$$\text{s.t.} \quad (3), (4), (8), (10), \quad (12b)$$

$$\mathbf{R}_i^X \succeq \mathbf{0}, \quad i \in \mathcal{S}^{RU}, \quad X \in \{UL, DL\}, \quad (12c)$$

where α_k^X denote the weights representing the priorities associated with the mobile users. Here, the optimization variables $\mathbf{V} \triangleq \{\mathbf{V}_k^X : \forall k \in \mathcal{S}^X, X \in \{UL, DL\}\}$ and $\mathbf{Y} \triangleq \{\mathbf{Y}_i^X : \forall i \in \mathcal{S}^{RU}, X \in \{UL, DL\}\}$ denote the set of all precoding and quantization noise covariance matrices, respectively.

Since the objective function (12a), and the fronthaul constraints (3) and (10) are non-convex, solving the problem (12) is challenging. To that end, firstly, we will use Lemma 1, which is described below, to approximate the fronthaul constraints (3) and (10), and secondly apply the WMMSE approach in [9], [10] to approximate the objective function (12a) in a MMSE matrix form. Finally, we will use the SCA algorithm [7], [8] in order to find a suboptimal solution of (12) by solving a sequence of resulting approximate problems iteratively.

Before we move on, we will first state the following lemma obtained via Fenchel conjugate arguments [27].

Lemma 1: Let d be any integer and $\mathbf{E} \in \mathbb{C}^{d \times d}$ be any positive definite Hermitian matrix. Consider the function $f(\mathbf{W}) = \log |\mathbf{W}| - \text{tr}\{\mathbf{E}\mathbf{W}\} + d$. Then,

$$\log |\mathbf{E}^{-1}| = \max_{\mathbf{W} \in \mathbb{C}^{d \times d}, \mathbf{W} \succeq \mathbf{0}} f(\mathbf{W}).$$

From Lemma 1, we have the inequality $f(\mathbf{W}) \leq \log |\mathbf{E}^{-1}|$, and the equality is achieved at the optimal $\tilde{\mathbf{W}} = \mathbf{E}^{-1}$. Using

this inequality, the fronthaul rate constraints in (3) and (10) can be rewritten as

$$\begin{aligned} & \text{tr} \left\{ \left(\Theta_i^{DL} \right)^{-1} \left(\mathbf{E}_i^H \sum_{k=1}^{K_{DL}} \mathbf{V}_k^{DL} (\mathbf{V}_k^{DL})^H \mathbf{E}_i + \mathbf{Y}_i^{DL} \right) \right\} \\ & + \log |\Theta_i^{DL}| - \log |\mathbf{Y}_i^{DL}| \leq C_i^{DL} + M_i, \quad i \in \mathcal{S}^{RU}, \end{aligned} \quad (13)$$

$$\begin{aligned} & \text{tr} \left\{ \left(\Theta_i^{UL} \right)^{-1} \left(\Phi_i^{UL} + \mathbf{Y}_i^{UL} \right) \right\} + \log |\Theta_i^{UL}| \\ & - \log |\mathbf{Y}_i^{UL}| \leq C_i^{UL} + N_i, \quad i \in \mathcal{S}^{RU}. \end{aligned} \quad (14)$$

The constraints (3) and (10) are equivalent to (13) and (14), respectively when the auxiliary matrices are

$$\Theta_i^{DL} = \mathbf{E}_i^H \sum_{k=1}^{K_{DL}} \mathbf{V}_k^{DL} (\mathbf{V}_k^{DL})^H \mathbf{E}_i + \mathbf{Y}_i^{DL}, \quad (15)$$

$$\Theta_i^{UL} = \Phi_i^{UL} + \mathbf{Y}_i^{UL}. \quad (16)$$

Now we approximate the objective function (12a) using the WMMSE approximation. Let $\mathbf{U}_k^{UL} \in \mathbb{C}^{N^{UL} \times d_k^{UL}}$ and $\mathbf{U}_k^{DL} \in \mathbb{C}^{R^k \times d_k^{DL}}$ be the linear receiver applied at the CU and k th DL user, respectively. By applying Lemma 1, the following relationship for the rates in (6) and (11) was established in [9], [10]:

$$R_k^X = \max_{\mathbf{U}_k^X, \mathbf{W}_k^X} (\log |\mathbf{W}_k^X| - \text{tr}\{\mathbf{F}_k^X \mathbf{W}_k^X\} + d_k^X), \quad (17)$$

where $\mathbf{W}_k^X \in \mathbb{C}^{d_k^X \times d_k^X}$ is the weight matrix, and \mathbf{F}_k^X is the MSE matrix defined as

$$\begin{aligned} \mathbf{F}_k^X &= \left((\mathbf{U}_k^X)^H \mathbf{H}_k^X \mathbf{V}_k^X - \mathbf{I}_{d_k^X} \right) \left((\mathbf{U}_k^X)^H \mathbf{H}_k^X \mathbf{V}_k^X - \mathbf{I}_{d_k^X} \right)^H \\ &+ (\mathbf{U}_k^X)^H \Sigma_k^X \left(\tilde{\mathbf{V}}_k^X, \tilde{\mathbf{Y}}^X, \tilde{\mathbf{H}}_k^X \right) \mathbf{U}_k^X. \end{aligned} \quad (18)$$

Using the fronthaul rate approximations in (13) and (14), objective function reformulation (17), the weighted sum-rate maximization problem (12) can be reformulated as:

$$\begin{aligned} & \max_{\substack{\mathbf{V}, \mathbf{Y}, \mathbf{U} \\ \mathbf{W}, \Theta}} \sum_{k=1}^{K_{DL}} \alpha_k^{DL} (\log |\mathbf{W}_k^{DL}| - \text{tr}\{\mathbf{F}_k^{DL} \mathbf{W}_k^{DL}\}) \\ & + \sum_{k=1}^{K_{UL}} \alpha_k^{UL} (\log |\mathbf{W}_k^{UL}| - \text{tr}\{\mathbf{F}_k^{UL} \mathbf{W}_k^{UL}\}) \quad (19a) \\ & \text{s.t.} \quad (4), (8), (12c), (13), (14), \quad (19b) \end{aligned}$$

where $(\mathbf{U}, \mathbf{W}, \Theta)$ are the additional optimization variables, and $(\mathbf{U}, \mathbf{W}) \triangleq \{(\mathbf{U}_k^X, \mathbf{W}_k^X) : \forall k \in \mathcal{S}^X, X \in \{UL, DL\}\}$ denote the set of all receive beamforming and weight matrices, and $\Theta \triangleq \{\Theta_i^X : \forall i \in \mathcal{S}^{RU}, X \in \{UL, DL\}\}$ denote the set of all auxiliary matrices.

Although the optimization problem (19) is still non-convex, it is component-wise convex, i.e., it is convex with respect to any one of the optimization variables when the other optimization variables are fixed. In particular, when the other variables are fixed, the optimal auxiliary matrices is given

in (15) and (16); the optimal receive beamforming matrix is MMSE receiver given as

$$\tilde{\mathbf{U}}_k^X = \left(\mathbf{H}_k^X \mathbf{V}_k^X (\mathbf{H}_k^X \mathbf{V}_k^X)^H + \Sigma_k^X \right)^{-1} \mathbf{H}_k^X \mathbf{V}_k^X, \quad (20)$$

and the optimal weight matrix is given as

$$\tilde{\mathbf{W}}_k^X = (\mathbf{F}_k^X)^{-1}. \quad (21)$$

The steps of the proposed algorithm⁴ is illustrated in Algorithm 1.

Algorithm 1 Weighted-Sum-Rate Maximization Algorithm

- 1: Set the iteration number $n = 0$ and initialize the precoding $\mathbf{V}^{[n]} \leftarrow \epsilon \mathbf{1}$ and the quantization noise covariance matrices $\Upsilon^{[n]} \leftarrow \mathbf{I}$, $\epsilon = 0.001$.
 - 2: **repeat**
 - 3: $n \leftarrow n + 1$.
 - 4: Update $\Theta^{[n]}$ from (15) and (16).
 - 5: Update the receive matrices $\mathbf{U}^{[n]}$ from (20).
 - 6: Update the weight matrices $\mathbf{W}^{[n]}$ from (21).
 - 7: Update the precoding $\mathbf{V}^{[n]}$ and the quantization noise covariance matrices $\Upsilon^{[n]}$ by solving the convex problem (19) when $\Theta^{[n]}$, $\mathbf{U}^{[n]}$, and $\mathbf{W}^{[n]}$ are fixed.
 - 8: **until** convergence or maximum number of iterations is reached.
-

The proposed algorithm in Algorithm 1 yields a non-decreasing sequence of objective values for problem (19). Particularly, due to the use of convex approximations at each iteration of Algorithm 1, the optimal solution obtained at iteration n is a feasible point of the convex problem at iteration $n + 1$. Therefore, the objective value for (19) obtained at iteration $n + 1$ is equal to or larger than that of at iteration n . This results in a non-decreasing sequences of objectives for (19). Moreover, since the objective is upper bounded due to the power constraints, the iterative algorithm converges.

B. Statistical CSI

In this section, we jointly optimize the precoding and quantization noise covariance matrices to maximize the ergodic sum-rate of the FD C-RAN system subject to power constraints in (4) and (8), and fronthaul rate constraints in (3) and (10) under the knowledge of statistical CSI. To this end, we first denote $\mathbf{Q}_k^X = \mathbb{E} \left[\mathbf{V}_k^X (\mathbf{V}_k^X)^H \right]$. The statistical problem is formulated as:

$$\max_{\mathbf{Q}, \Upsilon} \sum_{k=1}^{K_{DL}} \mathbb{E} [R_k^{DL}] + \sum_{k=1}^{K_{UL}} \mathbb{E} [R_k^{UL}] \quad (22a)$$

$$\text{s.t.} \quad (3), (4), (8), (12c), \quad (22b)$$

$$\mathbb{E} \left[\log \left| \Phi_i^{UL} + \Upsilon_i^{UL} \right| \right] - \log \left| \Upsilon_i^{UL} \right| \leq C_i^{UL}, \quad i \in \mathcal{S}^{RU}, \quad (22c)$$

$$\mathbf{Q}_k^X \succeq \mathbf{0}, \quad k \in \mathcal{S}^X, \quad X \in \{UL, DL\}, \quad (22d)$$

where the variable \mathbf{Q} denotes $\mathbf{Q} \triangleq \{\mathbf{Q}_k^X : \forall k \in \mathcal{S}^X, X \in \{UL, DL\}\}$. The expectation in (22a) is taken over the distribution of the channels.

⁴Please note that if the used initialization matrices violate the maximum power constraint for a users or a BS, they are scaled down to comply with the power limitations.

Observing that the objective function (22a), and the fronthaul constraints (3) and (10) are in difference of convex (DC) form, we can apply an iterative algorithm based on SSUM [13], [28] and SCA methods [7], [8], which solves a sequence of locally tight (stochastic) convex lower bounds by linearizing the non-convex functions in the optimization problem (22) at each iteration [8].

The proposed SSUM algorithm has two nested loops. At each outer iteration n , a new channel matrix realization $\mathbf{H}^{[n]}$ is drawn based on the availability of stochastic CSI at the CU, where \mathbf{H} includes all the channels in the network under investigation. The outer loop aims at maximizing a stochastic lower bound on the objective function. The inner loop tackles the nonconvex DC constraints (3) and (10) via the SCA algorithm, i.e., by applying successive locally tight convex lower bounds to the left-hand side of the constraints. Specifically, at the r th inner iteration of the n th outer iteration, the convex problem (23) given at the top of the following page is solved. In (23), the function $f(\mathbf{A}, \mathbf{B})$ is the first-order Taylor approximation of log-det function, and is given as

$$f(\mathbf{A}, \mathbf{B}) \triangleq \log |\mathbf{B}| + \frac{1}{\ln 2} \text{tr} \{ \mathbf{B}^{-1} (\mathbf{A} - \mathbf{B}) \}.$$

The idea of convex approximation in wireless communications has been previously used in [29], [30]. In our optimization problem, the fronthaul constraints (3) and (10) are in the form $\log |\mathbf{A} + \mathbf{B}| - \log |\mathbf{B}|$. This function is non-convex due to the presence of the second term $\log |\mathbf{B}|$, which is indeed a concave function. An approximate solution is found in [29] via an iterative scheme where the term $\log |\mathbf{B}|$ is approximated using a first-order Taylor expansion. With the approximation, the nonconvex part of the optimal problem can locally linearized to its first-order Taylor expansion. Thus, the nonconvex optimization problem can be iteratively solved through successive convex programming of its convexified version.

The steps of the proposed algorithm is illustrated in Algorithm 2.

Algorithm 2 Sum-Rate Maximization Algorithm under Statistical CSI

- 1: Set the iteration number $n = 0$ and initialize the precoding $\mathbf{V}^{[n]} \leftarrow \epsilon \mathbf{1}$ and the quantization noise covariance matrices $\Upsilon^{[n]} \leftarrow \mathbf{I}$, $\epsilon = 0.001$.
 - 2: **repeat**
 - 3: $n \leftarrow n + 1$.
 - 4: Generate a channel matrix realization $\mathbf{H}^{[n]}$ using the available stochastic CSI.
 - 5: Set the iteration number $r = 0$ and initialize the source covariance $\mathbf{Q}^{[n,r]} = \mathbf{Q}^{[n-1]}$ and the quantization noise covariance matrices $\Upsilon^{[n,r]} = \Upsilon^{[n-1]}$.
 - 6: **repeat**
 - 7: $r \leftarrow r + 1$.
 - 8: Update $\mathbf{Q}^{[n,r]}$ and $\Upsilon^{[n,r]}$ by solving the problem (23).
 - 9: **until** convergence.
 - 10: Update $\mathbf{Q}^{[n]} = \mathbf{Q}^{[n,r]}$ and $\Upsilon^{[n]} = \Upsilon^{[n,r]}$.
 - 11: **until** convergence or maximum number of iterations is reached.
 - 12: Calculate the precoding matrices \mathbf{V}_k^X from the source covariance matrices \mathbf{Q}_k^X via rank reduction method [31] as $\mathbf{V}_k^X = \lambda_k^X g(\mathbf{V}_k^X, d_k^X)$, $\forall k \in \mathcal{S}^X, X \in \{UL, DL\}$, where the function $g(\mathbf{V}, d)$ is a unitary matrix containing the d eigenvectors as columns corresponding to the largest d eigenvalues of the semi-positive definite matrix \mathbf{V} , and λ_k^X is the normalization factor computed from the power constraints.
-

Remarks: In addition to the sum-rate maximization design under power constraints considered in subsections III-A

$$\max_{\mathbf{Q}, \mathbf{Y}} \frac{1}{n} \sum_{X \in \{UL, DL\}} \sum_{k=1}^{K_X} \sum_{l=1}^n \left(\log \left| \mathbf{H}_k^{X,[l]} \mathbf{Q}_k^X \left(\mathbf{H}_k^{X,[l]} \right)^H + \boldsymbol{\Sigma}_k^X \left(\tilde{\mathbf{Q}}_k^X, \tilde{\mathbf{Y}}^X, \tilde{\mathbf{H}}_k^{X,[l]} \right) \right| \right. \\ \left. - f \left(\boldsymbol{\Sigma}_k^X \left(\tilde{\mathbf{Q}}_k^X, \tilde{\mathbf{Y}}^X, \tilde{\mathbf{H}}_k^{X,[l]} \right), \boldsymbol{\Sigma}_k^X \left(\tilde{\mathbf{Q}}_k^{X,[l-1]}, \tilde{\mathbf{Y}}^{X,[l-1]}, \tilde{\mathbf{H}}_k^{X,[l]} \right) \right) \right) \quad (23a)$$

$$\text{s.t. } f \left(\mathbf{E}_i^H \sum_{k=1}^{K_{DL}} \mathbf{Q}_k^{DL} \mathbf{E}_i + \mathbf{Y}_i^{DL}, \mathbf{E}_i^H \sum_{k=1}^{K_{DL}} \mathbf{Q}_k^{DL,[n,r-1]} \mathbf{E}_i + \mathbf{Y}_i^{DL,[n,r-1]} \right) - \log \left| \mathbf{Y}_i^{DL} \right| \leq C_i^{DL}, \quad i \in \mathcal{S}^{RU}, \quad (23b)$$

$$\sum_{l=1}^n f \left(\boldsymbol{\Phi}_i^{UL,[l]} + \mathbf{Y}_i^{UL}, \boldsymbol{\Phi}_i^{UL,[l-1]} + \mathbf{Y}_i^{UL,[l-1]} \right) - \log \left| \mathbf{Y}_i^{UL} \right| \leq C_i^{UL}, \quad i \in \mathcal{S}^{RU}, \quad (23c)$$

$$\text{tr} \left\{ \mathbf{E}_i^H \sum_{k=1}^{K_{DL}} \mathbf{Q}_k^{DL} \mathbf{E}_i + \mathbf{Y}_i^{DL} \right\} \leq P_i^{DL}, \quad i \in \mathcal{S}^{RU}, \quad \text{tr} \left\{ \mathbf{Q}_k^{UL} \right\} \leq P_k^{UL}, \quad k \in \mathcal{S}^{UL}, \quad (12c), (22d). \quad (23d)$$

and III-B, we can also include a target rate for each UL/DL user as a constraint. The motivation behind this design as will be seen in the simulations is that even if FD outperforms HD in terms of total throughput, this does not guarantee that all UL/DL users are served evenly in every time slot. In some instances an UL user may achieve a lower rate in order to reduce the amount of interference present in the system. To that end, QoS-constrained optimization problem is reformulated as

$$\max_{\mathbf{V}, \mathbf{Y}} \sum_{k=1}^{K_{DL}} \alpha_k^{DL} R_k^{DL} + \sum_{k=1}^{K_{UL}} \alpha_k^{UL} R_k^{UL} \quad (24a)$$

$$\text{s.t. } (3), (4), (8), (10), \quad (24b)$$

$$\mathbf{Y}_i^X \geq \mathbf{0}, \quad i \in \mathcal{S}^{RU}, \quad X \in \{UL, DL\}, \quad (24c)$$

$$R_k^{DL} \geq r^{DL}, \quad k = 1, \dots, K_{DL}, \quad (24d)$$

$$R_k^{UL} \geq r^{UL}, \quad k = 1, \dots, K_{UL}, \quad (24e)$$

where r^{DL} and r^{UL} are the minimum data rates required by the DL and UL users, respectively. The key difficulty in solving the problem (24) is the rate constraints (24d) and (24e). However, we can use the local approximation used in (23a) to approximate these nonlinear and non-concave functions and then solve the problem (24) successively using SCA, which we will not repeat due to space limitations. The simulation results corroborate the importance of fairness introduced with this QoS constrained problem⁵.

Remarks: The acquisition of an accurate CSI in a C-RAN communication is vital to the optimal design of precoding matrices and covariance matrices of quantization noises. In this paper, the proposed algorithms for wired fronthauls (Section III) assume the availability of perfect CSI at the centralized CU. In particular, all the channel matrices are estimated and reported to the CU. Similar to the FD channel estimation in [19], [20], we assume that before the FD data transmission

period, an HD channel training period (e.g., time-division duplexing (TDD)) is used to exploit the existing channel estimation methods and to estimate the additional interference terms introduced with the FD data transmission (e.g., self-interference, co-channel interference). For example, an RU can estimate the channel matrices of uplink and downlink users based on standard uplink training. The channel matrices between the downlink users and the RUs can be estimated by the RUs using the reciprocity existing in TDD systems. Upon the channel estimation of the users, the RU can forward (or feed back) the estimated channel to the CU via the fronthaul links.

As C-RAN systems are similar to relaying systems, the existing literature on the channel estimation of the relaying systems can be reused for the channel estimation of the C-RAN systems. An overview of channel estimation techniques proposed for C-RANs has been discussed in [33]. For example, the superimposed training scheme in [34] is a promising solution to estimate the channels in C-RANs, in which the RU superimposes its own training sequence on the received one from the users such that the individual CSIs can be estimated at the CU.

Although we have assumed perfect CSI acquisition in our work, obtaining perfect CSI is very challenging resulting in estimation errors, quantization errors, and feedback delays. Therefore, an analysis of FD C-RANs under the assumption of imperfect CSI is an interesting direction to explore.

IV. SIMULATION RESULTS

In this section, we compare the sum-rate performance of the proposed FD C-RAN scheme with that of the HD C-RAN scheme, under various system conditions. Unless otherwise stated, the following parameters are used in our simulations: $K_R = 4$, $M_k = N_k = 2$, $\forall k \in \mathcal{S}^{RU}$, $K_{DL} = K_{UL} = 4$, $\alpha_k^{UL} = \alpha_k^{DL} = 1$, and $T_k = R_k = 2$, $\forall k$. Moreover, we assume that every RU and every UL user have the same power constraints, i.e., $P_i^{DL} = P^{DL} = 26$ dBm, $i \in \mathcal{S}^{RU}$ and $P_k^{UL} = P^{UL} = 23$ dBm, $k \in \mathcal{S}^{UL}$, and the noise powers in both UL and DL channels are equal $\sigma_{DL}^2 = \sigma_{UL}^2 = -107$ dBm. The fronthaul constraints are assumed to be the same for all RUs in both UL and DL channels, i.e., $C_i^X = C_{FH} = 10^7$ bits/sec, $\forall i \in \mathcal{S}^{RU}$, $X \in \{UL, DL\}$, and the wireless system

⁵Please note that the previously given initialization in Algorithm 1 may lead to infeasibility, due to the additional QoS constraints. In this regard, the algorithm is firstly executed by replacing the objective with the rate deficiencies. For a standard optimization problem, $\min f(x)$ s.t. $g_i(x) \geq 0$, $\forall i$, this is formulated as: $\min_{x, c_i} \sum_i c_i$ s.t. $g_i(x) + c_i \geq 0$, $c_i \geq 0$, where c_i represents the rate deficiencies. The algorithm declares infeasibility if converges to a non-zero objective. The obtained solution will then serve as an initialization point. For the variations of the popular penalty methods please see [32].

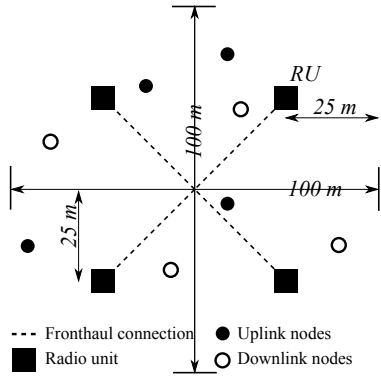


Fig. 2. The simulated setup. RUs are located at the center of each small square (50×50), where the UL and DL users are located randomly.

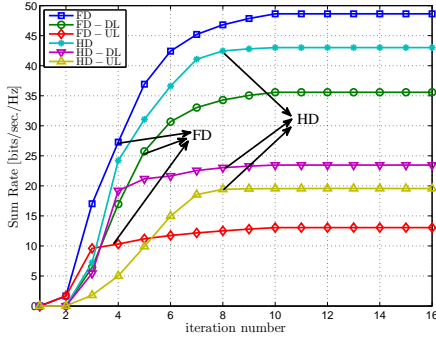


Fig. 3. Sum rate [bits/sec./Hz] vs. algorithm iterations. The convergence is obtained in average within 8-12 optimization iterations.

operates on the bandwidth of 10 MHz. The users are randomly located in a square area of side length 100 m. Dividing this square into 4 equal small squares with a side length 50m, each of $K_R = 4$ RUs is located at the center of these 4 small squares, see Fig. 2. The position of the UL and DL users within each square area is chosen randomly for each channel realization. For the self-interference channel, we adopt the model in [1], in which the self-interference channel $\mathbf{H}_{ii}^{UL/D}$ at the i th RU is distributed as Rician with mean $\sqrt{\frac{\sigma_{SI}^2 \kappa}{1+\kappa}}$ and variance $\frac{\sigma_{SI}^2}{1+\kappa}$, where κ and σ_{SI}^2 represent the Rician factor and the residual self-interference power, respectively. The rest of the channel matrices follows a complex Gaussian distribution with path-loss defined as $PL = 22.9 + 37.5 \log_{10} d$ in dB where d is the distance in meters between relevant entities. For the statistical design, we assume a channel estimation error model in the form of $\mathbf{H} = \hat{\mathbf{H}} + \mathbf{Z}$, where \mathbf{H} is the actual channel and $\hat{\mathbf{H}}$ is the estimated channel. In this regard, \mathbf{Z} represents the estimation error such that $\mathbf{Z} = \mathbf{Z}_0 \tilde{\mathbf{Z}}$, where the elements of $\tilde{\mathbf{Z}}$ are zero-mean complex Gaussian i.i.d. with unit variance, and \mathbf{Z}_0 represents the matrix with all elements equal to 0.1, and builds the spatial correlation for the estimation error. Unlike the FD setup, where UL and DL users can be active simultaneously, a time-division-duplexing (TDD) scheme is considered for an equivalent HD setup to connect the UL and DL users in the subsequent time slots. In the Figs. 3-6, the resulting sum rate of the users are depicted

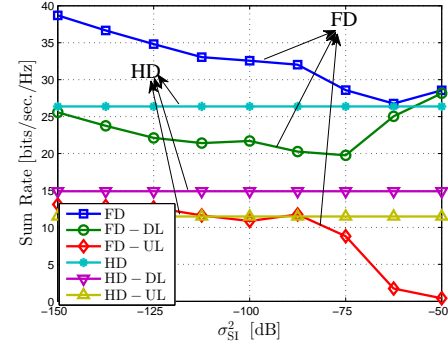


Fig. 4. Sum rate [bits/sec./Hz] vs. residual self-interference intensity. The sum rate of the FD system decreases as σ_{SI}^2 increases.

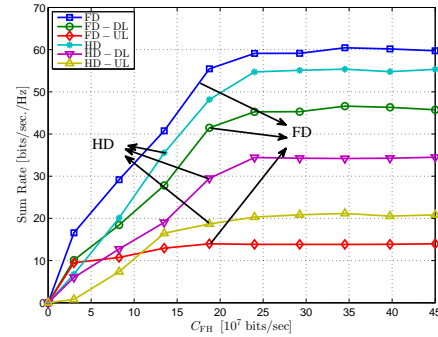


Fig. 5. Sum rate [bits/sec./Hz] vs. available fronthaul capacity. Higher C_{FH} results in a higher network sum rate in both UL and DL.

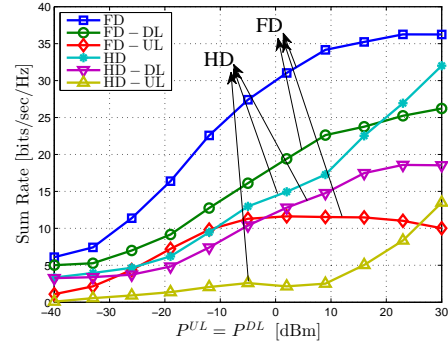


Fig. 6. Sum rate [bits/sec./Hz] vs. available power ($P^{UL} = P^{DL}$). A higher transmit power results in a higher network performance.

in terms of the different system parameters, evaluating both FD and the HD systems. In this respect, "FD-DL", "FD-UL" and "FD" represent the network sum rate for DL, UL and for all users, respectively. Moreover, "HD-DL", "HD-UL" and "HD" respectively represent the same concept for the equivalent HD setup⁶. Both UL and DL rates, as well as the sum user rate of

⁶The HD system benchmarks for both exact CSI and the statistical cases are obtained by separating the UL and DL communications in two subsequent time periods, and to apply the Algorithms 1, 2 in order to obtain the solution. This is implemented by adding zero-enforcing constraints on the transmit precoders, i.e., $\mathbf{V} = \mathbf{0}$ within the optimization routines, for the communications which are turned-off due to the HD operation. The time periods for the UL and DL are assumed to be equal.

the network are evaluated. For each realization of the network the location of UL and DL users are chosen randomly, and the channels are randomly obtained as described. The resulting performance is then averaged over 100 channel realizations.

As explained in Algorithm 1, due to the non-convex nature of the resulting optimization problem an iterative solution is proposed with a guaranteed convergence. In this regard, the average convergence behavior of the network is depicted in Fig. 3. As observed, the convergence is obtained in average after 8-12 number of iterations. Note that the convergence speed is an important factor regarding the efficiency of the optimization method in terms of the computational complexity.

In Fig. 4, the resulting sum rate for UL and DL users are depicted for different levels of the residual self-interference intensity. It is observed that as σ_{SI}^2 increases the resulting sum rate decreases for the FD system, where the performance of the HD system remains unchanged, as it employs a TDD scheme to avoid simultaneous operation of UL and DL users. On the other hand, it is observable that as σ_{SI}^2 increases, the performance of overall FD system reaches close to that of the HD system. This is perceivable, since for a system with high residual self-interference intensity, only one communication direction is activated to avoid severe self-interference effect. Moreover, the DL communication links has the advantage of higher transmit power and the coordinated transmit beamforming compared to the UL counterparts which results in a higher sum rate for DL users⁷.

In Fig. 5, the resulting sum rate is depicted for different levels of fronthaul capacity. Since the fronthaul connection is the necessary connection link from the RUs to the CU, the limitations on fronthaul link results in a severe damage on the overall network performance. In this respect, it is observable that as C_{FH} increases the user sum rate increases in both FD and HD setups⁸. Nevertheless, the resulting sum rate saturates after a certain point, due to the other limitations on the network performance, i.e., noise, interference. Moreover, an FD system can simultaneously make use of fronthaul links in both UL and DL. This results in a higher relative gain of an FD system, compared to the TDD-based HD counterpart, when the value of C_{FH} becomes small.

In Fig. 6, the impact of the maximum transmit power on the system sum rate is depicted. As expected, a higher transmit power results in a higher network performance. On the other hand, as $P^{UL} = P^{DL}$ increases, the relative gain of the FD setup in comparison to the HD counterpart decreases. This is since, a higher transmit power results in a higher interference intensity, e.g., self-interference and CCI, which are inherent to the simultaneous operation in UL and DL, and pushes the optimal operation of an FD system towards a HD operation.

⁷It is worth mentioning that a successive interference cancellation decoding can be considered as a gainful measure to reduce the impact of interference. In particular, it can be implemented at the DL users in order to mitigate the impact of co-channel interference, or mitigating the residual self-interference signal at the RUs when self-interference cancellation is limited to passive suppression [35], [36].

⁸It can be also interpreted as a larger C_{FH} results in a larger feasible space imposed by the constraints (13) and (14) which leads to a higher sum rate performance.

Nevertheless, the resulting sum rate performance is saturated after a certain level of transmit power due to the other network limitations, e.g., limited fronthaul capacity.

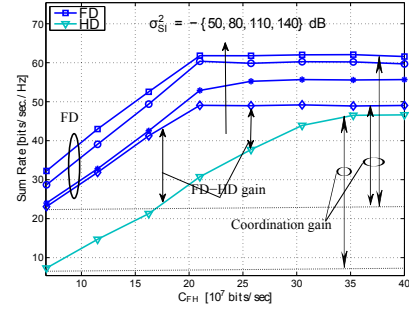


Fig. 7. Joint coordination and full-duplexing gain.

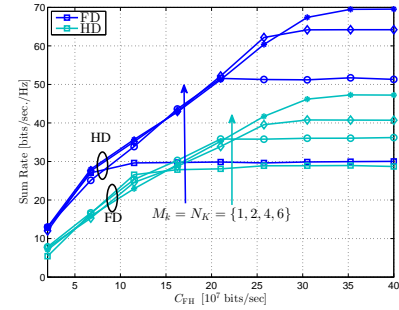


Fig. 8. Coordination gain for various antenna array size, $T_k = R_k = 1$.

In Figs. 7 the joint impact of coordination, as well as the self-interference cancellation at the RUs are depicted. Please note that when the fronthaul capacity is low (and hence appears as the bottleneck), the system automatically switches to a single RU association, in order to reduce the fronthaul traffic. Similarly, when self-interference cancellation capability is low (σ_{SI}^2 is high) the system automatically switches to the traditional half-duplex (HD) operation. However, the full-duplexing (coordination) gain is evident, as the self-interference cancellation capability (fronthaul capacity) increases. Moreover, it is observed that the FD-HD gain is more significant for a system with a limited backhaul.

In Fig. 8, the impact of different array size is depicted. As expected, a higher antenna array size results in a high network performance, due to the better beamforming accuracy. It is particularly apparent for a system with a high fronthaul capacity, where the signal arrays (obtained from multiple transmit/receive antennas) can be accurately communicated to the central unit. Moreover, it is observed that the gain obtained via full-duplexing is increased when the number of antennas increase. This is expected, since a higher beamforming accuracy result in a better control of the interference paths which appear as a result of FD operation, e.g., interference among BSs and the self-interference.

A. QoS consideration

In this part we consider the QoS constrained design discussed in (24). In Figs. 9-11 the network behavior is studied

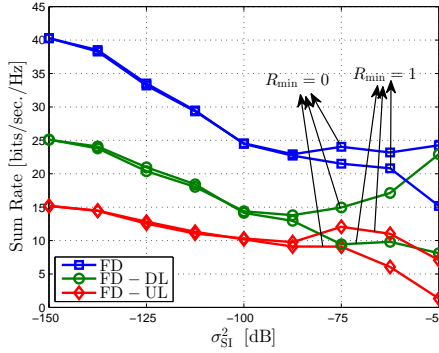


Fig. 9. Sum rate [bits/sec./Hz] vs. residual self-interference intensity. Imposition of R_{\min} results in a higher fairness between UL and DL users, specially as σ_{SI}^2 increases.

TABLE I. COMPARISON OF THE REQUIRED CPU TIME.

	CPU Time (SCA-SCA)	CPU Time (SCA-WMMSE)
$T = R = 1$	61.1 [sec]	9.2 [sec]
$T = R = 2$	138.5 [sec]	32.8 [sec]

under the effect of minimum required rate, where $R_{\min} := r^{UL} = r^{DL}$, see (24).

In Fig. 9, the sum rate of the network is depicted, with and without the imposition of minimum rate constraints. It is observed that for a small value of σ_{SI}^2 , where the self-interference is effectively eliminated, the imposition R_{\min} does not impact the sum network performance. However, as σ_{SI}^2 increases, the network sacrifices the quality of DL users to preserve the QoS requirement in UL, hence, promoting fairness. However, the improved fairness is obtained at the cost of a reduced network sum rate.

In Fig. 10, the rate of the weakest link, as an indication of network fairness, is depicted for different values of R_{\min} . It is observed that a higher R_{\min} results in a stronger weakest link. This is particularly effective among the UL users, where the link quality is severely degraded under poor interference conditions. However, the aforementioned enhancement comes at the expense of occasional infeasibility of the rate constraints. In this respect, a higher portion of network realizations fail to satisfy the minimum rate requirement constraints as R_{\min} increases.

In Fig. 11, the average rate of the network is depicted for different values of R_{\min} . It is observed that the average UL performance increases for a higher R_{\min} , promoting fairness among DL and UL users. However this comes at the expense of degrading the DL performance. Note that the average network performance degrades as R_{\min} increases, due to the imposition of an additional constraint in the sum rate maximization problem. However, it shows an increasing behavior for large values of R_{\min} . This is grounded in the fact that large values of R_{\min} lead to the infeasibility of a meaningful portion of channel realizations, see Fig. 10, leaving only *good* channel realizations in the averaging process. In all of the studied cases, the imposition of a higher R_{\min} results in a higher fairness among the UL and DL average performance, as well as among the individual links.

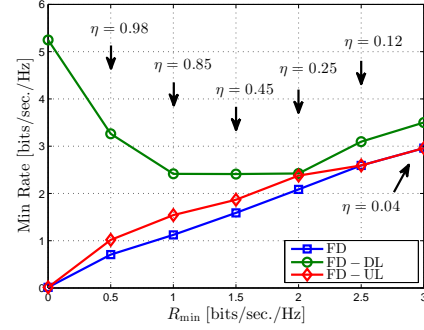


Fig. 10. Rate of the weakest link vs. minimum required rate, i.e., R_{\min} . A higher R_{\min} results in a stronger weakest link. The parameter η represents the ratio of feasible network realizations. $\sigma_{SI}^2 = -50$ dB.

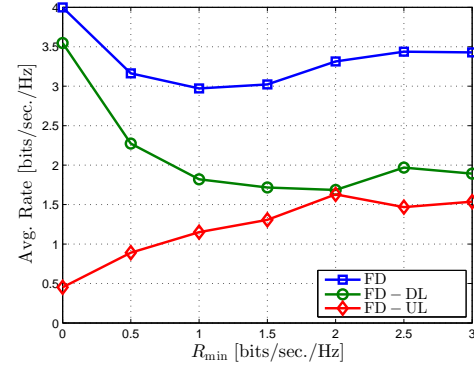


Fig. 11. Average rate vs. minimum required rate. A higher R_{\min} results in a higher average rate in UL, where resulting in a reduced average rate at DL. $\sigma_{SI}^2 = -50$ dB.

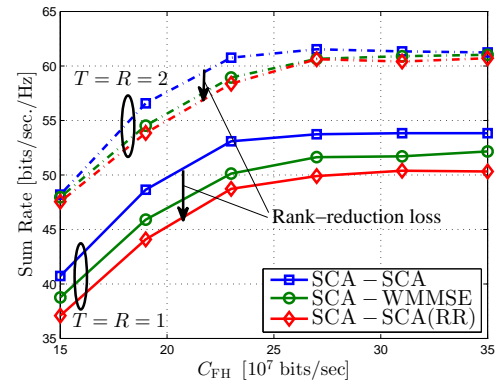


Fig. 12. Performance comparison of Algorithm 1 to the SCA-SCA framework in [14], $T_k = T, R_k = R$.

In Fig 12, the performance of the proposed joint SCA framework in [14] is evaluated in comparison to the Algorithm 1 (WMMSE-SCA). In particular, the SCA-SCA curve represents the performance of the SCA framework with rank relaxation. However, please consider that the obtained general-rank covariance may not be linearly constructed, hence resulting in an infeasible solution. Hence, decomposition based rank reduction is applied to obtain a (feasible) linear precoder similar to [14,

Alg. 1], i.e., SCA-SCA RR. An observable performance loss is observed as a result of the introduced rank-reduction, which effectively results in a slightly better system performance for the proposed WMMSE-SCA method. Moreover, it is observed from Table I that the SCA-SCA method results in a higher CPU time. This is perceivable, since the SDP variable dimension is reduced due to the WMMSE structure, and the closed-form expression given in (21).

B. Statistical CSI

For the case that the statistical knowledge of the channels are available, the proposed design in Subsection III.B is employed. In this respect, the statistical behavior of the network performance in both FD and HD cases are evaluated, over different realizations of channel matrices. Due to the iterative nature of the proposed design, where a number of channel realizations are drawn randomly with a known distribution, the statistical convergence behavior of the design is of interest. In Fig. 13, the cumulative probability distribution (CDF) of the network sum rate is depicted where 1000 realizations of channel matrices are considered with the defined distribution in the previous subsection. It is observed that the network performance is enhanced by employing a higher number of channel realizations in terms of the rate statistics. This is expected, since the channel statistics is better captured by employing a higher number of realizations. Moreover, the network performance converges after employing around 20 channel realizations⁹. This is particularly important since the application of a high number of channel realizations results in a higher design complexity.

In Fig. 14, it is observed that knowledge of the CSI statistics can result in a significant gain, compared to a setup where the erroneous instantaneous CSI is used. In this regard, "Inst-Sum", "Inst-DL" and "Inst-UL" respectively represent the obtained total, DL, and UL users sum rate using the design proposed in Subsection II.A, where "Stat-Sum", "Stat-DL" and "Stat-UL" represent the same concept with the application of the design proposed in Subsection III.B. In particular, it is observed that a positive gain results for the sum rate of both UL and DL users. Nevertheless, as expected, the system performance is degraded compared to the scenario where the exact instantaneous values for CSI matrices where available.

In Fig. 15-16, the CDF of the network sum rate is evaluated for different values of fronthaul link capacity, as well as the residual self-interference intensity.

Similar to the scenario with deterministic CSI, it is observed in Fig. 15 that the network performance for the FD setup enhances as the σ_{SI}^2 decreases. Moreover, where the residual self-interference intensity is adequately high, the network performance is close to that of the HD system, since in such a case simultaneous operation of UL and DL users results in a high residual self-interference intensity.

In Fig. 16, the CDF of network sum rate is depicted for different levels of C_{FH} . Similar to the case with deterministic

⁹The average performance information can be also obtained from the CDF curves, however, CDF also indicates information regarding the performance variance, and also how the obtained overall performance is distributed among the evaluated population.

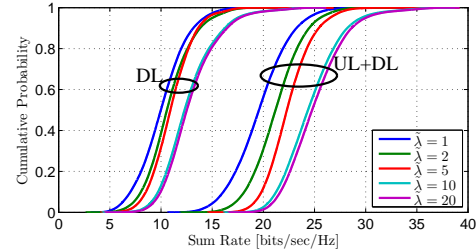


Fig. 13. Cumulative probability distribution (CDF) of the network sum rate for different number of iterations. λ represents the number of the used channel realizations.

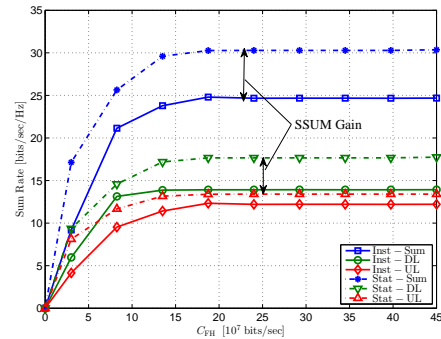


Fig. 14. Average network sum rate for different values of fronthaul capacity. A significant gain is obtained via the application of CSI statistics.

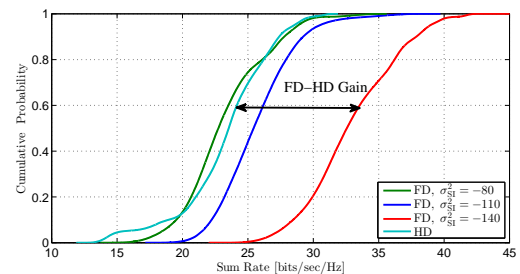


Fig. 15. Cumulative probability distribution (CDF) of the network sum rate for different values of residual self-interference intensity.

channel knowledge, it is observed that a higher fronthaul capacity results in a higher network performance for both HD and FD setups.

V. CONCLUSION

In this work, joint design of fronthaul compression and precoding is studied for single-cell FD MIMO C-RANs. We first address the weighted sum-rate maximization problem for this setup and show that FD C-RAN system with sufficient self-interference cancellation at the RUs brings significant sum-rate gains over the HD scheme. In the second part of the paper, we address the stochastic sum-rate maximization problem under fast-fading channels, and show the importance of accurate channel estimation in FD systems.

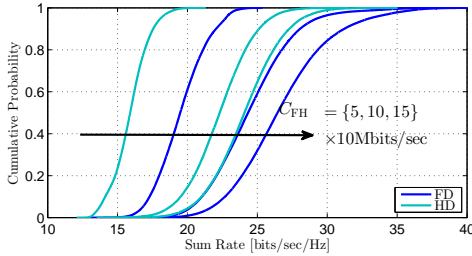


Fig. 16. Cumulative probability distribution (CDF) of the network sum rate for different values of fronthaul capacity.

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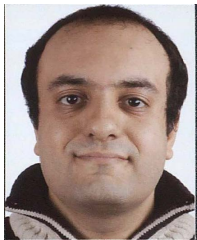
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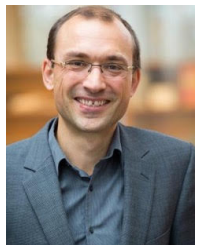


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