Robust Layered Transmission and Compression for Distributed Uplink Reception in Cloud Radio Access Networks

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***Abstract*—In the uplink of cloud radio access networks, each base station (BS) compresses the received signal before transmission to the cloud decoder via capacity-limited backhaul links. A major issue in designing the transmission strategy at the mobile stations (MSs) and the compression strategies is the lack of channel state information (CSI) relative to the signal received by BSs in other cells. To tackle this problem, this paper proposes layered transmission and compression strategies that aim at opportunistically leveraging more advantageous channel conditions to neighboring BSs. A competitive robustness criterion is adopted, which enforces the constraint that a fraction of the rate that is achievable when the CSI is perfectly known to the MSs and the BS in the cell under study should be attained also in the absence of CSI. Under competitive robustness and backhaul capacity constraints, the problem is formulated as the minimization of the transmit power. Extensive numerical results confirm the effectiveness of the proposed approaches.**

***Index Terms*—Broadcast coding, cloud radio access networks, distributed uplink reception, robust coding.**

I. Introduction

THE CLOUD radio access network is one of the most promising solutions to address the bandwidth crunch problem in the current cellular systems [1]–[6]. On the uplink of a cloud radio access network, the base stations (BSs) operate by *compressing* and *forwarding* the received signal to a central decoder[1] in the "cloud" [3], [7]. This information is conveyed over the finite-capacity backhaul links that connect each BS with the cloud, as shown in Fig. 1. Since the signals received at different BSs are correlated, distributed compression strategies are generally beneficial, as demonstrated in [8]–[13].

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[1]The cloud decoder may be located in different parts of the operator's network. The cloud decoder is also referred to as "baseband unit pool" and the BSs as "remote radio heads" [2]–[4].

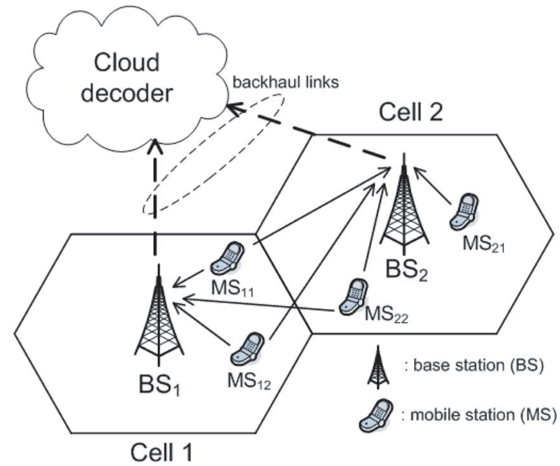

Fig. 1. Uplink of the cloud radio access network under study. The focus is on the design of the transmission strategy for the MSs in cell 1 and of the compression scheme for BS_1 in cell 1.

A major issue in designing the transmission and compression strategies at the mobile stations (MSs) and the BSs, respectively, is that the MSs and the BS in a given cell are generally not informed about the channel state information (CSI) relative to the signal received by BSs in other cells. For instance, in Fig. 1, BS_1 and the MSs in cell 1 are generally not informed about the channel gains toward BS_2 in cell 2. Regarding the design of *transmission* strategies in the presence of uncertain CSI, a well-investigated approach is the use of *layered or broadcast coding* [14]–[16]. With broadcast coding, the transmitter, being uncertain about the CSI, encodes a number of information layers, and the decoder recovers as many as possible depending on the current channel conditions. The conventional performance criterion is the average rate as obtained with respect to the channel state distribution [15], [16]. In contrast, the work in [17] has recently adopted a competitive, rather than average, optimality criterion, whereby the objective is to minimize the worst-case difference between the rate achievable with full CSI and with broadcast coding in the absence of CSI (see [18] and references therein for related discussion on competitive optimality). We emphasize that [14]–[16] focus mostly on point-to-point links and do not consider the issue of compression at the receiver side.

The issue of robustness in distributed *compression* has been tackled in [19] and [20]. Specifically, in [19], the problem of source coding with side information at the decoder is treated in which the compressor is uncertain about the quality of the side information. Assuming that the quality of the side information can be ordered from the least correlated to the most correlated, the work in [19] shows that *layered compression* is optimal in terms of minimizing the distortion of the reconstruction at the receiver. With this approach, each compression layer refines the previous and is designed to be decompressed only if the side information is more correlated than for the previous layer. This strategy is further studied in [21] for the special case of Gaussian fading side information and with the aim of minimizing the average minimum mean square error (MSE) (see below for further discussion). A related model is treated in [20], in which the signal of some compressor might not reach the final decoder. It is emphasized that, in [19]–[21], the goal is to minimize the distortion at the receiver and not to maximize the performance of a digital communication system as for a cloud radio access network.

In contrast to the work reviewed earlier, in cloud radio access networks, one is interested in designing the compression strategy under a performance criterion directly related to transmission of information, such as rate maximization. This problem is studied in [8], [9], and [22] under the assumption of perfect CSI. In [23], instead, the authors studied the problem of compression for rate maximization at a BS under uncertainty about the CSI relative to other cells. The strategy proposed in [23] applies to multiantenna MSs and BSs but is based on single-layer transmission and single-layer compression. Finally, the work in [24] investigated layered transmission and compression as a means to combat uncertainties regarding the quality of the backhaul links while CSI is assumed to be perfect, and the average rate criterion is adopted.

A. Contributions

In this paper, we investigate *layered* transmission and compression strategies for the uplink of a cloud radio access network in the presence of uncertainty regarding the CSI relative to the signal received by other cells. We focus on the design for the MSs and BS of a given cell (e.g., cell 1 in Fig. 1), assuming that the cloud decoder performs joint decoding only within a given cell and treats interference from the MSs in other cells as noise or via successive interference cancelation. We assume single-antenna MSs and BSs and adopt a competitive optimality criterion. Specifically, we enforce the constraint that a given fraction of the rate that is achievable when the CSI relative to other cells is fully known at MSs and BS in the given cell be attained also in the absence of this CSI. Under the said competitive optimality constraints and under backhaul capacity restrictions, we aim at minimizing the overall transmission power. It is noted that, as per the discussion earlier, this formulation has not been studied, to the best of the authors' knowledge, even for the single point-to-point setup.

To obtain fundamental insights into the problem, we first focus on the case with orthogonal intracell resource allocation so that a single MS is active within the spectral resource and cell under study. The setting is thus as in Fig. 1, with only one MS active in the considered cell 1. This scenario, which is sketched in Fig. 2, reduces to a specific relay channel.

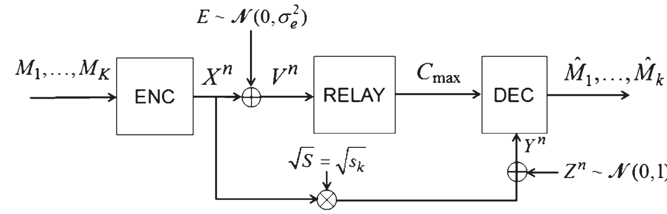

Fig. 2. Block diagram for the system model with one encoder studied in Sections II–VI. With reference to the application to the cloud radio access network in Fig. 1, the encoder (ENC) represents an MS in cell 1, the relay is BS_1, and the decoder (DEC) is the cloud decoder; moreover, $C_{\max}$ is the capacity of the backhaul link between BS_1 and the cloud decoder, and Y^n represents the signal received by the cloud decoder from the other BSs (BS_2 in Fig. 1).

Related works are [25] and [26], in which broadcast coding is studied over a fading relay channel with either a time-division strategy [25] or assuming the absence of a direct link between the encoder and the decoder [26]. It is emphasized that the models considered in [25] and [26] are thus different from the one considered here (see Fig. 1). Moreover, the works in [25] and [26] adopt an average rate criterion and do not consider multilayer compression.

After describing the system model and problem definition in Sections II and III, we investigate *single-layer transmission and compression* (see Section IV), *broadcast coding with single-layer compression* (see Section V), *and broadcast coding with layered compression* (see Section VI). In all cases, efficient algorithms are proposed to obtain locally optimal transmission and compression strategies based on the iterative solution of quadratically constrained quadratic problems (QCQPs) [27]. The main results are then extended to the setup with multiple MSs simultaneously active in the cell under study, i.e., MS_{11} and MS_{12} in Fig. 1 (see Section VII). Numerical results are finally provided that demonstrates the performance advantages of the proposed layered strategies (see Section VIII).

Notation: We adopt standard information-theoretic definitions for the mutual information $I(X;Y)$ between the random variables X and Y, and conditional mutual information $I(X;Y|Z)$ between X and Y conditioned on random variable Z [28]. All logarithms are in base two unless specified. Vector $\mathbf{1}_{a:b}$ represents a column vector of size that is determined from the context and consists of zero elements, except for the positions from a to b. For a sequence U_k, $k = 1, \ldots, K$, we denote a subsequence $U_i, \ldots, U_j$ by $U_{i:j}$ with $1 \le i \le j \le K$.

II. System Model

Here, we detail the system model for the setup with orthogonal intracell resource allocation, so that only one MS is active in the cell and spectral resource under study. An example is provided in Fig. 1 with only MS_{11} active in the considered spectral resource. The extension to two active MSs in the same spectral resource (e.g., MS_{11} and MS_{12} in Fig. 1) is considered in Section VII. We focus on the design of the transmission strategy at the active MS and on the compression strategy at the BS serving the cell to which the MS belongs. This is done under the assumption that decoding at the cloud decoder takes place by treating interference from MSs in other cells (e.g., MS_{21} and MS_{22} in Fig. 1) as noise or via successive interference cancelation, as explained in the following.

The problem is modeled as in Fig. 2, where an encoder wishes to communicate with a decoder through a relay that has a capacity-constrained link to the final decoder. With reference to the cloud radio access network application, the encoder represents the active MS, the relay is the BS serving the cell to which the MS belongs, the finite-capacity link is the backhaul link connecting BS to the cloud, and the decoder is the "cloud" decoder.

Assuming a flat-fading channel, the relay receives a signal

$$\tilde{V}_i = \sqrt{H} X_i + \tilde{E}_i \tag{1}$$

for $i = 1, \ldots, n$, where n is the block length, and X_i is the symbol sent by the encoder (i.e., the MS) at time i, with local fading gain H and independent and identically distributed (i.i.d.) additive noise $\tilde{E}_i \sim \mathcal{N}(0, \tilde{\sigma}_e^2)$. We assume that the local fading gain H is estimated at the relay and reported to the encoder, so that the signal $\tilde{V}_i$ can be normalized as

$$V_i = X_i + E_i \tag{2}$$

where $E_i \sim \mathcal{N}(0, \sigma_e^2)$, with $\sigma_e^2 = \tilde{\sigma}_e^2 / H$. We emphasize that the received signal model (2) can be adopted without loss of optimality in terms of capacity since the normalization of (1) as in (2) corresponds to an invertible operation on the received signal (1) (apart from the uninteresting case $H = 0$). Model (2) is thus assumed hereafter for simplicity of notation. The signal V_i is compressed and sent to the decoder via a backhaul link of capacity $C_{\max}$ bits per symbol. We will consider both single-layer compression (see Sections IV and V) and multilayer compression (see Section VI) at the relay. Note that, as discussed earlier, the derived performance metrics are to be considered to be conditioned on a specific realization of the channel H. Average performance criteria can be easily accommodated by performing an expectation over the corresponding distribution of H and, hence, of σ_e^2. This will not be further elaborated on in this paper.

The transmitted signal X_i is assumed to be drawn according to the Gaussian distribution, i.e., $X_i \sim \mathcal{N}(0, P)$, where P is the transmit power. Note that this choice is capacity-achieving for point-to-point Gaussian channels but might not be optimal for the scenario at hand (see [8]). To account for the operation of the BSs in the other cells, we assume that the decoder (i.e., the cloud decoder) has the available side information signal, i.e.,

$$Y_i = \sqrt{S} X_i + Z_i \tag{3}$$

for $i = 1, \ldots, n$, where the additive noise Z_i, $i = 1, \ldots, n$, is an i.i.d. Gaussian random process with $Z_i \sim \mathcal{N}(0, 1)$, and S is the channel state relative to the other BSs. The rationale behind model (3) is that the signal received by the cloud decoder from BSs in other cells can be written as (3), where Z_i accounts for the channel noise, for the effect of the quantization noise due to the finite-capacity backhaul link connecting other-cell BS to the cloud decoder (see Section III), and for the interference due to the MSs active in the given spectral resource in other cells. Note that, if a successive interference cancelation decoder at the cell level is assumed at the cloud decoder, then Z_i only accounts for the residual interference after cancelation.

The quality of the side information is determined by the fading state S, which is modeled as taking a discrete set $\mathcal{S}$ of possible values, i.e., $S \in \mathcal{S} \triangleq \{s_1, \ldots, s_K\}$ with $0 \leq s_1 < s_2 < \cdots < s_K$, and as remaining unchanged through a coding block of length n. Note that, in practice, the set $\mathcal{S}$ is obtained by quantizing the continuous set of values assumed by the fading channel gain as done in, for example, [21, Sec. IV] and [29]. This quantization allows a simplification of the system design. In this regard, we observe that any system designed for the discrete fading model can be also implemented on the continuous fading model. This is accomplished by assigning the continuous interval of fading gains $[0, s_1]$ to the discrete level s_1, the interval $(s_1, s_2]$ to s_2, and so on. Clearly, as K grows large, one can generally improve the system performance. Set $\mathcal{S}$ is predetermined prior to the system deployment and is thus assumed to be known at the relay. Note that the relay also knows the noise variance of Z_i, which can be communicated by the cloud decoder to the relay.

For convenience of notation, we define the side information available in the kth state and time i as

$$Y_{k,i} = \sqrt{s_k} X_i + Z_i. \tag{4}$$

Note that the variables $Y_{K,i}, Y_{K-1,i} \ldots, Y_{1,i}$ are degraded in the given order so that the received signal $Y_{j,i}$ is independent of X_i given any of the variables $Y_{j+1,i}, Y_{j+2,i}, \ldots, Y_{K,i}$. In other words, variables $X_i, Y_{K,i}, Y_{K-1,i} \ldots, Y_{1,i}$ form a Markov chain as $X_i \leftrightarrow Y_{K,i} \leftrightarrow Y_{K-1,i} \leftrightarrow \ldots \leftrightarrow Y_{1,i}$ for all $i = 1, \ldots, n$ (see, e.g., [21]).

We assume a broadcast coding strategy [14]–[16] in which the encoder encodes K independent messages $M_1, \ldots, M_K$ and, if the side information state is $S = s_k$, the decoder is required to receive reliably only the subset of messages $M_1, \ldots, M_k$. Defining the rate of message M_j as R_j for $j = 1, \ldots, K$, this implies that the rate decoded when $S = s_k$ is

$$R^k = \sum_{j=1}^{k} R_j. \tag{5}$$

As a final remark, we observe that, under the assumptions given and with $\sigma_e^2 = 0$, the work in [21] provides the optimal design of multilayer compression at the relay with the aim of minimizing the expected MSE distortion, i.e.,

$$\frac{1}{n} \sum_{k=1}^{K} \Pr[S = s_k] \sum_{i=1}^{n} E\left[(X_i - \hat{X}_{K,i})^2\right] \tag{6}$$

where $\hat{X}_{K,i}$ is the estimate of X_i produced by the decoder based on the message received from the relay and the side information $Y_k^n = (Y_{k,1}, \ldots, Y_{k,n})$. We have adopted the same notation as in [21] for consistency.

In this paper, we are instead interested in the task of reliably communicating[2] to the decoder, rather than enabling the decoder to obtain a good, in the sense of MSE, estimate of the transmitted signal X, as in [21]. Moreover, as detailed in the following, we adopt a competitive, rather than average, optimality criterion [18].

III. Problem Definition

Here, we establish the problem formulation. As we will discuss, our aim is to minimize the transmission power P under competitive optimality constraints on the rate achievable for each fading level s_k, $k \in \{1, \ldots, K\}$. To elaborate, we first define the *informed capacity* $C^k(\hat{P})$, which is the maximum rate achievable when the current fading state $S = s_k$ is known at the encoder and at the relay, and the encoder power constraint is $\hat{P}$. The problem of finding $C^k(\hat{P})$, under the assumption of Gaussian input $X_i \sim \mathcal{N}(0, \hat{P})$, can be formulated as[3]

$$\max_{f(w|v)} I(X; W, Y_k) \quad \text{s.t.} \quad I(V; W|Y_k) \leq C_{\max} \tag{7}$$

where the optimization is over the test channel characterized by the conditional probability density function (pdf) $f(w|v)$ with the variable W being the compressed version of V. Note that the random variables (V, Y_k) in (7) are distributed according to (2) and (4), and the conditional pdf $f(w|v)$ is to be optimized. Test channel $f(w|v)$ describes the compression strategy used at the relay, with W being the compressed description of the received signal V in (2) to be sent to the decoder. The mutual information $I(X; W, Y_k)$ in the objective function of (7) represents the maximum rate at which the encoder can reliably communicate with the decoder [28, Ch. 3]. The left-hand side of the inequality constraint in (7) is the rate required to describe the compressed signal W to the decoder when the side information Y_k is available at the latter [28, Ch. 11]. The following lemma provides an expression for the informed capacity $C^k(\hat{P})$.

Lemma 1: The optimal test channel $f(w|v)$ for problem (7) is given by [22], [31]

$$W = \sqrt{a}V + N \tag{8}$$

where the noise $N \sim \mathcal{N}(0, 1)$ is independent of V, and the gain a is computed as

$$a = \beta \left(\sigma_e^2 + \frac{\hat{P}}{1 + s_k \hat{P}} \right)^{-1} \tag{9}$$

with $\beta = 2^{2C_{\max}} - 1$. Moreover, the resulting informed capacity is given by

$$C^k(\hat{P}) = \frac{1}{2} \log \left(1 + \frac{\hat{P}(s_k + q_k a)}{1 + a\sigma_e^2} \right) \tag{10}$$

where we defined $q_k = 1 + s_k \sigma_e^2$.

Proof: From [22] and [31], the optimal test channel $f(w|v)$ for problem (7) is Gaussian distributed, as given in (8). Then, problem (7) with test channel (8) is rewritten as

$$\begin{aligned} &\max_{a \geq 0} \frac{1}{2} \log \left(1 + \frac{P\left(s_k + a(1 + s_k \sigma_e^2)\right)}{1 + a\sigma_e^2} \right) \\ &\text{s.t.} \quad \frac{1}{2} \log \left(1 + a \left(\sigma_e^2 + \frac{P}{1 + s_k P} \right) \right) \leq C_{\max}. \end{aligned} \tag{11}$$

Since both the objective and constraints functions are increasing with respect to a, the optimal a is obtained when the constraint is satisfied with equality, which gives (9). ■

With this definition, the competitive optimality constraints are defined as follows.

Definition 1: The coding and compression strategies are said to satisfy the $(\hat{P}, l_o, \gamma)$-*competitive optimality constraints* if the following conditions are satisfied:

$$R^k \geq \gamma C^k(\hat{P}) \quad \forall\, k = l_o + 1, \ldots, K \tag{12}$$

where $\gamma \in [0, 1]$ is a target fraction of the informed capacity that needs to be achieved in the absence of the information about the current fading state S at the encoder and the relay, and $l_o \in \{0, \ldots, K-1\}$ is the allowed outage level.

Constraints (12) impose that a given fraction γ of the informed capacity is attained for all fading states above the outage level l_o. In other words, at any fading state $S = s_k$ with $k > l_o$, the achievable rate is at least a fraction γ of the capacity that would be achieved if $S = s_k$ had been known to the encoder and the relay. No constraint is imposed on the rate achievable in the states with $1 \leq k \leq l_o$ so that l_o is to be considered as the tolerated outage level. We refer to the constraint (12) as the competitive optimality constraint[4] following standard usage in the literature on robust optimization (see, e.g., [18] and [32]). Accordingly, the optimization criterion involves the comparison of the system performance with that of the ideal case with perfect CSI. The aim of this paper is to devise effective strategies to minimize the transmission power under the competitive optimality constraints (12) and the backhaul constraint $C_{\max}$. Throughout this paper, we focus on the case of $l_o = 0$ for brevity of explanation since extension to general $l_o \in \{0, \ldots, K-1\}$ is straightforward. Numerical results for the case $l_o > 0$ are presented in Section VIII.

[2]The communication between the encoder and the decoder is said to be reliable if, when the side information state is $S = s_k$, the probability of erroneous decoding of message M_l goes to zero as $n \to \infty$ for all $l \leq k$.

[3]As it is standard for infinite-length results, the characterization of the achievable rate in (7) is given in terms of random variables, i.e., (X, Y_k, V) that are jointly distributed as any one sample of the process defined by (2) and (4) (see, e.g., [28] and [30]).

[4]The notion of "competitive optimality" used in this paper and in the literature on robust optimization (see, e.g., [18]) should be distinguished from that of competitive noncooperative design used in game-theoretic studies (see, e.g., [33]).

IV. Single-Layer Transmission and Compression

Here, we present a baseline approach to the problem of minimizing transmit power under the competitive optimality constraints (12) that is based on single-layer transmission and single-layer compression. By single-layer transmission, we mean that the messages $(M_1, \ldots, M_K)$ are mapped into an individual codeword $X^n(M_1, \ldots, M_K)$, as opposed to being encoded in a superposition of codewords as done with broadcast coding [14]–[16]. As previously mentioned, we take the codeword X^n to be generated i.i.d. according to $X_i \sim \mathcal{N}(0, P)$. Similarly, by single-layer compression, we refer to standard compression strategies where a single description W of the received signal V is produced by the relay, as discussed earlier, as opposed to multiple successively refined descriptions (see Sections V and VI).

To satisfy the competitive optimality constraints (12) with single-layer transmission, one must impose that the informed capacity $C^K(\hat{P})$ corresponding to the best fading state s_K can be achieved also when the worst-case side information $S = s_1$ is realized. This is because a single-layer transmission does not allow decoding of an increasing number of messages as a function of the current value of S. The codeword $X^n(M_1, \ldots, M_k)$ must be thus decoded also in the worst case $S = s_1$. Thus, the power minimization problem can be formulated as

$$\begin{aligned} &\underset{P\geq 0,\, f(w|v)}{\text{minimize}} && P \\ &\text{s.t.} && I(X; W, Y_1) \geq \gamma C^K(\hat{P}) \\ &&& I(V; W|Y_1) \leq C_{\max}. \end{aligned} \tag{13}$$

In (13), the first constraint reflects the competitive optimality constraints (12) in that $I(X; W, Y_1)$ is the rate achievable in the worst case $S = s_1$. Instead, the second constraint accounts for the backhaul limitation similar to the discussion in Section III. Assuming the Gaussian test channel (8) without a claim of optimality, the problem (13) can be rewritten as

$$\underset{P\geq 0,\, a\geq 0}{\text{minimize}} \; P \tag{14a}$$

$$\text{s.t.} \quad \frac{1}{2}\log\left(1 + \frac{P(s_1 + aq_1)}{1 + a\sigma_e^2}\right) \geq \gamma C^K(\hat{P}) \tag{14b}$$

$$\frac{1}{2}\log\left(1 + a\left(\sigma_e^2 + \frac{P}{1 + s_1 P}\right)\right) \leq C_{\max}. \tag{14c}$$

The solution to problem (14) is given in the following proposition.

Lemma 2: The solution to problem (14) is given by $a^* = \beta(\sigma_e^2 + P^*/(1 + s_1 P^*))^{-1}$ and

$$P^* = \frac{-Q + \sqrt{Q^2 + S}}{2(1 + \beta)q_1 s_1} \tag{15}$$

where $Q = \sigma_e^2 s_1(1 - \eta\beta) + q_1(\beta - \eta)$, and $S = 4(1 + \beta)^2 q_1 s_1 \eta \sigma_e^2$, with $\eta = 2^{2\gamma C^K(\hat{P})} - 1$.

Proof: Reasoning by contradiction, it is easy to see that an optimal solution of (14) requires constraints (14b) and (14c) to be attained with equality. Therefore, we obtain the solution in this proposition via direct calculation from (14b) and (14c). ■

As mentioned, the single-layer approach studied here cannot benefit from better fading states; hence, the encoder and the relay are forced to operate by assuming the worst-case side information $S = s_1$ to satisfy the competitive optimality constraints (12). Motivated by this observation, in the following, we propose two layered approaches that can opportunistically exploit the better fading conditions while still satisfying the constraints (12).

V. Broadcast Coding With Single-Layer Compression

Here, we adopt the broadcast coding approach [14]–[16] while still assuming single-layer compression as earlier. With broadcast coding, layered transmission is employed at the encoder to enable the decoder to reliably decode only messages $M_1, \ldots, M_k$ when the realized fading state is $S = s_k$. This is accomplished via superposition coding as

$$X = \sum_{j=1}^{K} \sqrt{P_j} X_j \tag{16}$$

where the information signals $X_1, \ldots, X_K$ represent independent Gaussian codebooks with zero mean and unit variance, where the codebook corresponding to X_k encodes message M_k. The power of the kth layer is P_k.

Following [14] and [15], signal X_1 and, thus, message M_1, are decoded first by treating all the higher layers as noise. Recalling that it must be decoded in state $S = s_1$, the rate achievable with the first layer is $R_1 = I(X_1; Y_1, W)$. The second layer X_2 is instead decoded only if state $S = s_k$ with $k \geq 2$ is realized and after cancelation of X_1 from the received signal has been performed. This leads to the rate $R_2 = I(X_2; Y_2, W|X_1)$. In general, a rate $R_k = I(X_k; Y_k, W|X_{1:k-1})$ is achievable for layer $k (k = 1, \ldots, K)$.

Under the assumption of Gaussian test channel (8), the power minimization problem is thus given as

$$\underset{P_1,\ldots,P_K,a\geq 0}{\text{minimize}} \; \sum_{j=1}^{K} P_j \tag{17a}$$

$$\text{s.t.} \quad R_k(\mathbf{P}, a) \geq \gamma C_k(\hat{P}), \text{ for all } k = 1, \ldots, K \tag{17b}$$

$$\frac{1}{2}\log\left(1 + a\left(\sigma_e^2 + \frac{\sum_{j=1}^K P_j}{1 + s_1\sum_{j=1}^K P_j}\right)\right) \leq C_{\max} \tag{17c}$$

where we have defined $\mathbf{P} = [P_1, \ldots, P_K]^T$, $C_k(\hat{P}) = C^k(\hat{P}) - C^{k-1}(\hat{P})$, and $R_k(\mathbf{P}, a) = I(X_k; Y_k, W|X_{1:k-1})$ is computed as

$$R_k(\mathbf{P}, a) = \frac{1}{2}\log\left(1 + \frac{P_k}{c_k + \bar{P}_{k+1}}\right) \tag{18}$$

with $c_k = (1 + a\sigma_e^2)/(s_k + q_k a)$, and $\bar{P}_l = \sum_{j=l}^{K} P_j$.

Note that, in problem (17), the competitive optimality constraints (17b) are expressed in terms of the incremental rates R_k and C_k, rather than the cumulative rates, as done in (12). This is done to simplify the analysis below and is without loss of optimality. We now put forth a definition that will be useful to tackle problem (17) and related problems in this paper.

Definition 2: A QCQP is defined as [34]

$$\begin{aligned}&\underset{\mathbf{x}}{\text{minimize}}\ \mathbf{x}^T\mathbf{B}_0\mathbf{x}+\mathbf{b}_0^T\mathbf{x}\\ &\text{s.t.}\qquad \mathbf{x}^T\mathbf{B}_i\mathbf{x}+\mathbf{b}_i^T\mathbf{x}+b_i\le 0,\quad \text{for } i=1,\dots,m \end{aligned}\tag{19}$$

where $\mathbf{x}$ and $\mathbf{b}_i$ for $i=0,\dots,m$ are $d\times 1$ vectors, and $\mathbf{B}_i$ for $i=0,\dots,m$ are $d\times d$ matrices.

A QCQP (19) is nonconvex if any of the $\mathbf{B}_i$ matrices, for $i=1,\dots,m$, is not semidefinite positive. The next proposition shows that problem (17) can be formalized as a nonconvex QCQP.

Proposition 1: Defining $\mathbf{x}=[\mathbf{P}^T\ a]^T$, problem (17) is a QCQP (19) with $d=K+1$, $m=K+J$, and coefficients given as $\mathbf{B}_0=\mathbf{0}$, $\mathbf{b}_0=\mathbf{1}_{1:K}$ and

$$b_k=\eta_k,\ \mathbf{b}_k=\mathbf{f}_k,\ \mathbf{B}_k=\mathbf{F}_k,\ \text{for } k=1,\dots,K \tag{20}$$

$$b_{K+k}=-\beta_k,\ \mathbf{b}_{K+k}=\mathbf{g}_k,\ \mathbf{B}_{K+k}=\mathbf{G}_k,\ \text{for } k=1,\dots,J \tag{21}$$

where $\mathbf{f}_k$, $\mathbf{F}_k$, $\mathbf{g}_k$, and $\mathbf{G}_k$ are defined as

$$\mathbf{f}_k=\eta_k s_k\mathbf{1}_{k+1:K}+\eta_k\sigma_e^2\mathbf{f}'_k-s_k\mathbf{1}_k \tag{22}$$

$$\mathbf{F}_k=\left(\mathbf{F}'_k+\mathbf{F}'^T_k\right)/2, \tag{23}$$

with

$$\begin{aligned}\mathbf{F}'_k&=q_k(\eta_k\mathbf{1}_{k+1:K}-\mathbf{1}_k)\mathbf{f}'^T_k\\ \mathbf{g}_k&=\sigma_e^2\mathbf{g}'_k-\beta_k s_k\mathbf{g}''_k+\mathbf{g}'''_k \qquad (24)\\ \mathbf{G}_k&=\left(\mathbf{G}'_k+\mathbf{G}'^T_k\right)/2 \qquad (25)\end{aligned}$$

with

$$\mathbf{G}'_k=q_k\mathbf{G}''_k+\mathbf{G}'''_k$$

with $J=1$, $\eta_k=2^{2\gamma C_k(\hat{P})}-1$, $\beta_1=2^{2C_{\max}}-1$, $\mathbf{f}'_k=\mathbf{1}_{K+1}$, $\mathbf{g}'_k=\mathbf{1}_{K+1}$, $\mathbf{g}''_k=\mathbf{1}_{1:K}$, $\mathbf{g}'''_k=\mathbf{0}$, $\mathbf{G}''_k=\mathbf{1}_{K+1}\mathbf{1}^T_{1:K}$, and $\mathbf{G}'''_k=\mathbf{0}$.

Proof: It follows by direct calculation from (17). ■

The QCQP in Proposition 1 is nonconvex because the symmetric matrices $\mathbf{F}_k$ and $\mathbf{G}_k$ appearing in the quadratic terms in (20) and (21) are generally not positive semidefinite [27]. Nonconvex QCQPs are well studied, and various approaches exist to obtain locally optimal solution. Here, we adopt the approach reviewed in [27, Sec. 4], which is based on solving a series of (convex) semidefinite programming (SDP) problems (see, e.g., [34]), which leads to a monotonically decreasing objective function along the iterations. Due to its monotonicity property, the approach is guaranteed to converge to a local minimum of the problem. The algorithm is summarized in Algorithm 1. Note that the algorithm is based on the decomposition of symmetric matrix $\mathbf{B}_i$ into positive semidefinite matrices $\mathbf{B}_i^+$ and $\mathbf{B}_i^-$ as $\mathbf{B}_i=\mathbf{B}_i^+-\mathbf{B}_i^-$ (see, e.g., [27, Sec. 4]), and each iteration of the algorithm has polynomial-time complexity with respect to the dimension d [35, Sec. II]. Since we assumed in Section II that the local fading state affects only the noise variance σ_e^2 and the coefficients $b_{K+1},\dots,b_{K+J}$ that do not depend on σ_e^2 can be computed offline before obtaining the information about σ_e^2. We remark that another approach for finding a locally optimal point for problem (17) can be found in [36] in which the monotonic properties of the functions in (17b) and (17c) with respect to the variables $P_1,\dots,P_K,a$ are exploited to guarantee that the cost function monotonically decreases with respect to the number of iterations. However, we do not employ this approach in this paper since it cannot be extended to the case with multiple users (see Section VII).

Algorithm 1 Iterative algorithm for finding a locally optimal point of problem (19)

Step 1. Find a feasible point for problem (19), and set it as an initial point $\mathbf{x}^{(0)}$. Set iteration index $t=1$.

Step 2. For each iteration t, solve the following SDP and store the solution $\mathbf{x}$ into $\mathbf{x}^{(t)}$, i.e.,

$$\begin{aligned}&\min_{\mathbf{x}\in\mathbb{R}_+^d}\ \mathbf{x}^T\mathbf{B}_0\mathbf{x}+\mathbf{b}_0^T\mathbf{x}\\ &\text{s.t.}\quad b_i+\mathbf{b}_i^T\mathbf{x}+\mathbf{x}^T\mathbf{B}_i^+\mathbf{x}\\ &\qquad\le \mathbf{x}^{(t-1)T}\mathbf{B}_i^-\mathbf{x}^{(t-1)}+2\mathbf{x}^{(t-1)T}\mathbf{B}_i^-\left(\mathbf{x}-\mathbf{x}^{(t-1)}\right)\\ &\qquad\text{for } i=1,\dots,m\end{aligned}\tag{26}$$

where $\mathbf{B}_i=\mathbf{B}_i^+-\mathbf{B}_i^-$, and $\mathbf{B}_i^+$ and $\mathbf{B}_i^-$ are positive semidefinite matrices.

Step 3. Stop the iterations if a convergence criterion is satisfied, and go back to Step 2 with $t\leftarrow t+1$ otherwise.

VI. Broadcast Coding With Layered Compression

Here, we combine broadcast coding with layered compression at the relay. We assume that the encoder performs superposition coding in (16), but unlike single-layer compression, the relay sends a set of descriptions $W_1,\dots,W_K$ to the decoder. The decoder works as follows. It first decompresses the description W_1, which is then used to decode the first layer X_1 and, thus, M_1. Since these steps should be successful in state $S=s_1$, the rate necessary to convey W_1 is $I(V;W_1|Y_1)$ [28, Ch. 11], and the achievable rate for message M_1 is $R_1=I(X_1;W_1,Y_1)$. The second description W_2 is assumed to be recovered only if state $S=s_k$ with $k\ge 2$ is realized and after the signals X_1 and W_1 are decoded first. To this end, the relay should allocate the rate $I(V;W_2|Y_2,W_1,X_1)$ to describe W_2. After recovering W_2, the decoder can utilize the signals Y_2 and W_2 to decode the second-layer signal X_2 by taking X_1 and W_1 as side information. This leads to the rate $R_2=I(X_2;Y_2,W_1,W_2|X_1)$ delivered by X_2 in state $S = s_k$ with $k \geq 2$. More generally, the rate $I(V; W_k | Y_k, W_{1:k-1}, X_{1:k-1})$ is required to describe W_k, and the rate $R_k = I(X_k; Y_k, W_{1:k} | X_{1:k-1})$ is achievable by decoding X_k in state $S = s_l$ with $l \geq k$.

Unlike the single-layer compression given earlier, layered compression is defined by a set of test channels, i.e., one for each layer. Assuming Gaussian test channels (without claim of optimality), we express the description W_k corresponding to the kth layer as

$$W_k = \sqrt{a_k} V + N_k \tag{27}$$

for a given $a_k \geq 0$ and with quantization noise $N_1, \ldots, N_K$ being independent and Gaussian distributed random variables with zero mean and unit variance, independent of V.

Based on the earlier assumption, we can formulate the power minimization problem as

$$\underset{\substack{P_1,\ldots,P_K,\\ a_1,\ldots,a_K \geq 0}}{\text{minimize}} \quad \sum_{j=1}^{K} P_j \tag{28a}$$

$$\text{s.t.} \quad R_k(\mathbf{P}, \mathbf{a}) \geq \gamma C_k(\hat{P}), \ \text{ for all } k=1,\ldots,K \tag{28b}$$

$$\sum_{k=1}^{K} \frac{1}{2} \log \left(1 + \frac{a_k \left(\sigma_e^2 + q_k \bar{P}_k\right)}{1 + s_k \bar{P}_k + \left(\sigma_e^2 + q_k \bar{P}_k\right) \bar{a}_{k-1}} \right) \leq C_{\max} \tag{28c}$$

with $\mathbf{a} = [a_1, \ldots, a_K]^T$, $\bar{a}_j = \sum_{l=1}^{j} a_l$, and $R_k(\mathbf{P}, \mathbf{a})$ defined as

$$R_k(\mathbf{P}, \mathbf{a}) = \frac{1}{2} \log \left(1 + \frac{P_k (s_k + q_k \bar{a}_k)}{1 + \bar{P}_{k+1} s_k + \left(\sigma_e^2 + q_k \bar{P}_{k+1}\right) \bar{a}_k} \right). \tag{29}$$

Constraint (28c) can be shown to result in a polynomial expression in terms of the optimization variables with order generally larger than two. To simplify the problem, we substitute constraint (28c) with the following K constraints:

$$\frac{1}{2} \log \left(1 + \frac{a_k \left(\sigma_e^2 + q_k \bar{P}_k\right)}{1 + s_k \bar{P}_k + \left(\sigma_e^2 + q_k \bar{P}_k\right) \bar{a}_{k-1}} \right) \leq \alpha_k C_{\max}, \quad \text{for all } k = 1, \ldots, K \tag{30}$$

where we have introduced additional optimization variables $\alpha_1, \ldots, \alpha_K$ with $0 \leq \alpha_k \leq 1$, $k = 1, \ldots, K$, and $\sum_{j=1}^{K} \alpha_j = 1$ to represent backhaul capacity allocation across the layers.

Similar to Proposition 1, the following proposition demonstrates that problem (28) can be related to a nonconvex QCQP.

Proposition 2: Define $\mathbf{x} = [\mathbf{P}^T \, \mathbf{a}^T]^T$. For given $\alpha_1, \ldots, \alpha_K$, problem (28) is a QCQP (19) with $d = 2K$, $m = K + J$, and coefficients given as $\mathbf{B}_0 = \mathbf{0}$, $\mathbf{b}_0 = \mathbf{1}_{1:K}$, and (20)–(25), where $J = K$, $\eta_k = 2^{2\gamma C_k(\hat{P})} - 1$, $\beta_k = 2^{2\alpha_k C_{\max}} - 1$, $\mathbf{f}'_k = \mathbf{1}_{K+1:K+k}$, $\mathbf{g}'_k = \mathbf{1}_{K+k}$, $\mathbf{g}''_k = \mathbf{1}_{k:K}$, $\mathbf{g}'''_k = -\beta_k \sigma_e^2 \mathbf{1}_{K+1:K+k-1}$, $\mathbf{G}''_k = \mathbf{1}_{k:K} \mathbf{1}_{K+k}^T$, and $\mathbf{G}'''_k = -\beta_k q_k \mathbf{1}_{k:K} \mathbf{1}_{K+1:K+k-1}^T$.

Proposition 2 states that, for given backhaul allocation variables $\{\alpha_1, \ldots, \alpha_K\}$, the optimization over $\mathbf{x}$ in (28) consists of a nonconvex QCQP (19). Therefore, for fixed $\{\alpha_1, \ldots, \alpha_K\}$, we can employ Algorithm 1 to find a locally optimal $\mathbf{x}$. Optimization over $\{\alpha_1, \ldots, \alpha_K\}$ for a fixed $\mathbf{x}$ can be instead tackled using global optimization methods in the simplex $\mathcal{S}_\alpha = \{\alpha_1, \ldots, \alpha_K | 0 \leq \alpha_k \leq 1, \, k = 1, \ldots, K, \, \sum_{j=1}^{K} \alpha_j = 1\}$. It is noted that this search can be efficiently done using, e.g., branch-and-bound strategies [37, Sec. 5.5.2], unlike the original problem (28) over a $2K$-dimensional orthant. In the branch-and-bound approach, the feasible simplex $\mathcal{S}_\alpha$ is partitioned into smaller subsets and then bounds on the cost functions within each subset are calculated to eliminate inappropriate subsets from consideration (see, e.g., [37, Sec. 5.5.2] for more detail).

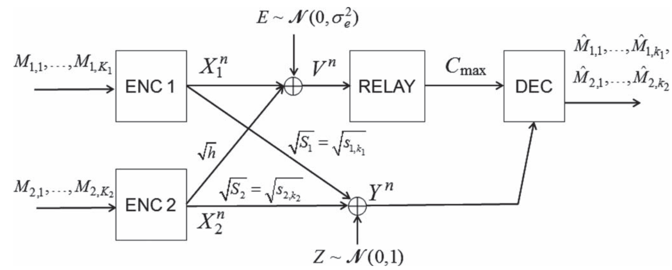

Fig. 3. Block diagram for the system model with two encoders studied in Section VII. With reference to the application to the cloud radio access network in Fig. 1, two encoders (i.e., ENC 1 and ENC 2) represent MSs in cell 1 (i.e., MS_{11} and MS_{12} in Fig. 1), the relay is BS_1, and the decoder (DEC) is the cloud decoder; moreover, $C_{\max}$ is the capacity of the backhaul link between BS_1 and the cloud decoder, and Y^n represents the signal received by the cloud decoder from the other BSs (BS_2 in Fig. 1).

VII. Multiuser Case

Here, we extend our discussion to the case in which two MSs are active in the spectral resource and cell under study. Following the discussion in Section II, this scenario is modeled as in Fig. 3, in which two encoders communicate with a decoder through a relay connected to the decoder via a capacity-constrained link. With reference to the cloud radio access network application, the encoders stand for the two MSs in the cell at hand (e.g., MS_{11} and MS_{12} in Fig. 1), the relay is the BS of the cell, and the decoder is the "cloud" decoder. Similar to Section II, to account for the signal received by the cloud decoder from the BSs in other cell, we assume that the decoder has available side-information signal Y, where

$$Y_i = \sqrt{S_1} X_{1,i} + \sqrt{S_2} X_{2,i} + Z_i \tag{31}$$

with $X_{u,i}$ representing the signal transmitted by encoder u at time i for $u = 1, 2$ and $i = 1, \ldots, n$. The fading coefficients S_1 and S_2 are assumed to be known to the decoder, whereas the encoders and the relay know only the fact that $S_u \in \mathcal{S}_u = \{s_{u,1}, \ldots, s_{u,K_u}\}$ with $s_{u,1} < \cdots < s_{u,K_u}$ for $u = 1, 2$. The additive noise $Z_i \sim \mathcal{N}(0, 1)$, $i = 1, \ldots, n$, is an i.i.d. Gaussian random process.

The signal received by the relay at time i is given as

$$V_i = X_{1,i} + \sqrt{h} X_{2,i} + E_i \tag{32}$$

with $E_i \sim \mathcal{N}(0, \sigma_e^2)$, and h being the channel gain from encoder 2 to the relay, which is assumed to be fixed for the current transmission block and known to the encoders, the relays, and the decoder. Without claim of optimality, Gaussian codebooks are assumed for both transmitted signals X_1 and X_2, i.e., $X_u \sim \mathcal{N}(0, P_u)$ for $u = 1, 2$. We remark that, if $P_2 = 0$, the model at hand reduces to the one considered earlier.

Similar to Section II, we assume a broadcast strategy [14]–[16] in which each encoder u, $u = 1, 2$, encodes K_u independent messages $M_{u,1}, \ldots, M_{u,K_u}$, and if the side information state is $S_u = s_{u,k}$, the cloud decoder is required to decode reliably only the subset of messages $M_{u,1}, \ldots, M_{u,k}$. Note that this requirement holds, regardless of the current realization of the fading channel $S_{\bar{u}}$ of the other encoder, i.e., $\bar{u} \in \{1, 2\}$ and $\bar{u} \neq u$. Defining the rate of message $M_{u,j}$ as $R_{u,j}$, the rate decoded when the state is $S_u = s_{u,k}$ is then given as

$$R_u^k = \sum_{j=1}^{k} R_{u,j}. \tag{33}$$

To simplify the analysis and in light of its practicality, we assume that the cloud decoder carries out successive decoding as detailed in the following. Moreover, we focus on single-layer compression strategies at the relay for simplicity. Extension to multilayer compression is possible following the previous sections.

A. Informed Capacity and Competitive Optimality Constraints

To simplify the comparison with the single-encoder case considered earlier, we define the informed capacity $C_u^k(\hat{P}_u)$ as in Section III, namely, as the maximum rate achievable by encoder u when the current fading state $S_u = s_{u,k}$ is known at the relay and at encoder u, and encoder u is subject to the power constraint $\hat{P}_u$, whereas the other encoder is inactive, i.e., $P_{\bar{u}} = 0$, $\bar{u} \in \{1, 2\}$, with $\bar{u} \neq u$. The informed capacity $C_u^k(\hat{P}_u)$ can be thus immediately obtained as in Lemma 1.

The competitive optimality constraints for the multiuser case are defined similar to Definition 1 as follows.

Definition 3: The transmission and compression strategies are said to satisfy the $(\hat{P}_1, \hat{P}_2, l_1, l_2, \gamma)$-competitive optimality constraints if the following conditions are satisfied:

$$R_u^{k_u} \geq \gamma_u C_u^{k_u}(\hat{P}_u) \tag{34}$$

for all $k_u = l_u + 1, \ldots, K_u$ and $u = 1, 2$, where $\gamma_u \in [0, 1]$ is a target fraction, and $l_u \in \{0, \ldots, K_u - 1\}$ is the allowed outage level for encoder u.

In the following, we aim at devising transmission and compression strategies to minimize the transmit power under the competitive optimality constraints (34) and the backhaul constraint $C_{\max}$. As for the single-user case, we focus on $l_1 = l_2 = 0$ for brevity of explanation.

B. Single-Layer Transmission

Here, we extend the single-layer transmission and compression studied in Section IV to the multiuser case at hand. For convenience of notation, we define the side information in state (s_{j_1}, s_{j_2}) and time i as

$$Y_{j_1,j_2,i} = \sqrt{s_{j_1}} X_{1,i} + \sqrt{s_{j_2}} X_{2,i} + Z_i.$$

Moreover, we assume successive decoding, whereby the decoder decodes encoder 1's signal X_1 first and then decodes encoder 2's signal X_2 after canceling the effect of X_1. Under this assumption, the power minimization problem is formulated as

$$\begin{aligned} \underset{P_1,P_2 \geq 0, f(w|v)}{\text{minimize}} \quad & P_1 + P_2 \\ \text{s.t.} \quad & I(X_1; W, Y_{j_1,j_2}) \geq \gamma_1 C_1^{K_1}(\hat{P}_1) \\ & \quad \text{for all } (j_1, j_2) \in \mathcal{K}_1 \times \mathcal{K}_2 \\ & I(X_2; W, Y_{j_1,j_2} | X_1) \geq \gamma_2 C_2^{K_2}(\hat{P}_2) \\ & \quad \text{for all } j_2 \in \mathcal{K}_2 \\ & I(V; W | Y_{j_1,j_2}) \leq C_{\max} \\ & \quad \text{for all } (j_1, j_2) \in \mathcal{K}_1 \times \mathcal{K}_2 \end{aligned} \tag{35}$$

where $\mathcal{K}_u = \{1, \ldots, K_u\}$ for $u = 1, 2$. The first two constraints in (35) reflect the competitive optimality constraints (34). The last constraint accounts for the backhaul constraint $C_{\max}$. We remark that the constraints in (35) reflect the fact that states (s_{1,j_1}, s_{2,j_2}) cannot be globally ordered. Therefore, for instance, one needs to impose that the description W of the received signal V be decompressed for all possible states (s_{j_1}, s_{j_2}) as imposed by the third constraint. Assuming Gaussian test channel (8) without claim of optimality, we can rewrite the problem (35) as

$$\begin{aligned} \underset{P_1,P_2,a \geq 0}{\text{minimize}} \quad & P_1 + P_2 \\ \text{s.t.} \quad & R_1(P_1, P_2, a) \geq \gamma_1 C_1^{K_1}(\hat{P}_1) \\ & \quad \text{for all } (j_1, j_2) \in \mathcal{K}_1 \times \mathcal{K}_2 \\ & R_2(P_1, P_2, a) \geq \gamma_2 C_2^{K_2}(\hat{P}_2), \text{ for all } j_2 \in \mathcal{K}_2 \\ & R_c(P_1, P_2, a) \leq C_{\max}, \text{ for all } (j_1, j_2) \in \mathcal{K}_1 \times \mathcal{K}_2 \end{aligned} \tag{36}$$

where the functions $R_1(P_1, P_2, a)$, $R_2(P_1, P_2, a)$, and $R_c(P_1, P_2, a)$ are defined as

$$\begin{aligned} & R_1(P_1, P_2, a) \\ & = \frac{1}{2} \log \left(1 + \frac{\rho_{j_1,j_2} P_1 P_2 a + q_{1,j_2} P_1 a + s_{1,j_1} P_1}{q_{2,j_2} P_2 a + P_2 s_{2,j_2} + a\sigma_e^2 + 1} \right) \\ & R_2(P_1, P_2, a) \\ & = \frac{1}{2} \log \left(1 + P_2 \left(\frac{ah}{a\sigma_e^2 + 1} + s_{2,j_2} \right) \right) \\ & R_c(P_1, P_2, a) \\ & = \frac{1}{2} \log \left(1 + a \frac{\rho_{j_1,j_2} P_1 P_2 + q_{1,j_1} P_1 + q_{2,j_2} P_2 a + \sigma_e^2}{s_{1,j_1} P_1 + s_{2,j_2} P_2 + 1} \right) \end{aligned}$$

with $\rho_{j_1,j_2} = (\sqrt{s_{2,j_2}} - \sqrt{s_{1,j_1} h})^2$, $q_{1,j_1} = 1 + \sigma_e^2 s_{1,j_1}$, and $q_{2,j_2} = h + \sigma_e^2 s_{2,j_2}$. Note that the rate $R_1(P_1, P_2, a)$ of the signal X_1 decreases as the interference power P_2 from the signal X_2 increases.

Unlike the single-user case, problem (36) is not a QCQP. To find a locally optimal solution, we iteratively repeat the following two steps: 1) Optimize P_1 and a for fixed P_2; and 2) optimize P_2 and a for fixed P_1. Note that the optimization problems at each step are QCQPs discussed in Section V; thus, we can use the technique in [27] to obtain a locally optimal solution of each step (see Algorithm 1). With this approach, convergence to a stationary point is guaranteed since we obtain a decreasing sequence of cost functions $P_1 + P_2$ with respect to the number of iterations.

C. Broadcast Coding

Here, we consider superposition coding at encoder u as

$$X_u = \sum_{j=1}^{K_u} \sqrt{P_{u,j}} X_{u,j} \tag{37}$$

where the information signals $X_{u,1}, \ldots, X_{u,K_u}$ are independently obtained from Gaussian codebooks with zero mean and unit variance for $u = 1, 2$. The relay is still assumed to employ single-layer compression. To satisfy the competitive optimality constraints, we impose that the messages $M_{u,1}, \ldots, M_{u,K_u}$ are reliably decoded by the decoder for all $u = 1, 2$ when $S_u = s_{j_u}$ with $j_u \geq k_u$. Moreover, it is assumed that the decoder carries out successive decoding by first decoding the message of encoder 1 and then that of encoder 2 for each decoded layer. This enforces that the rate $R_{1,k}$ of message $M_{1,k}$ is bounded as

$$R_{1,k} \leq I\left(X_{1,k}; W, Y_{j_1,j_2} | X_{1,1:k-1}, X_{2,1:\min\{k-1,j_2\}}\right) \tag{38}$$

for all (j_1, j_2) such that $j_1 \in \{k, k+1, \ldots, K_1\}$ and $j_2 \in \mathcal{K}_2$. Similarly, decoding of $M_{2,k}$ is subjected to the constraints

$$R_{2,k} \leq I\left(X_{2,k}; W, Y_{j_1,j_2} | X_{1,1:\min\{k,j_1\}}, X_{2,1:k-1}\right) \tag{39}$$

for all (j_1, j_2) such that $j_1 \in \mathcal{K}_1$ and $j_2 \in \{k, k+1, \ldots, K_2\}$. With these assumptions and the Gaussian test channel (8) at the relay, the power minimization problem is then formulated as

$$\begin{aligned}
\underset{\{P_{1,k}\},\{P_{2,k}\},a\geq 0}{\text{minimize}} \quad & \sum_{j=1}^{K_1} P_{1,j} + \sum_{j=1}^{K_2} P_{2,j} \\
\text{s.t.} \quad & R_{1,k}(\mathbf{P}_1, \mathbf{P}_2, a) \geq \gamma_1 C_{1,k}(\hat{P}_1) \\
& \quad \text{for all } (j_1, j_2) \in \{k, k+1, \ldots, K_1\} \times \mathcal{K}_2 \\
& \quad \text{and } k \in \mathcal{K}_1 \\
& R_{2,k}(\mathbf{P}_1, \mathbf{P}_2, a) \geq \gamma_2 C_{2,k}(\hat{P}_2) \\
& \quad \text{for all } (j_1, j_2) \in \mathcal{K}_1 \times \{k, k+1, \ldots, K_2\} \\
& \quad \text{and } k \in \mathcal{K}_2 \\
& R_c\left(\sum_{j=1}^{K_1} P_{1,j}, \sum_{j=1}^{K_2} P_{2,j}, a\right) \leq C_{\max} \\
& \quad \text{for all } (j_1, j_2) \in \mathcal{K}_1 \times \mathcal{K}_2
\end{aligned} \tag{40}$$

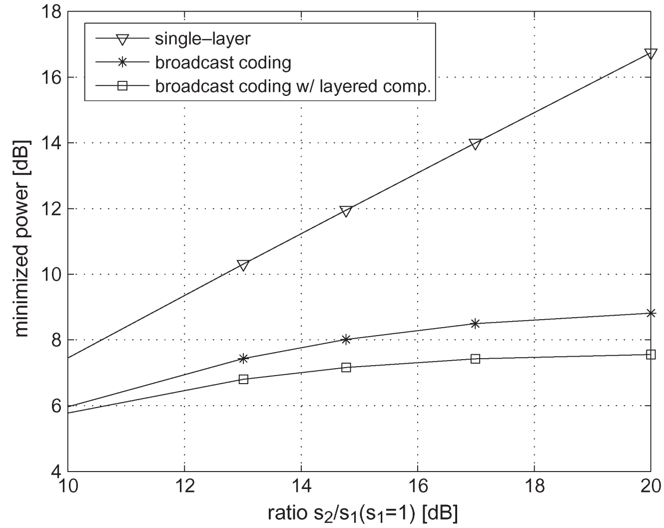

Fig. 4. Minimized power versus the ratio s_2/s_1 ($s_1 = 1$) with $K = 2$, $C_{\max} = 2$, $\hat{P} = 1$, $\gamma = 0.9$, and $\sigma_e^2 = 0$.

where we have defined $C_{u,k}(\hat{P}_u) = C_u^k(\hat{P}_u) - C_u^{k-1}(\hat{P}_u)$, $\mathbf{P}_u = [P_{u,1}, \ldots, P_{u,K_u}]^T$, and the rates $R_{1,k}(\mathbf{P}_1, \mathbf{P}_2, a)$ and $R_{2,k}(\mathbf{P}_1, \mathbf{P}_2, a)$ as (41) and (42), shown at the bottom of the page, with $\bar{P}_{u,j} = \sum_{l=j}^{K_u} P_{u,l}$.

For the solution of (40), we employ a similar approach to that given earlier, i.e., we repeat the following two steps: 1) Optimize $\{P_{1,k}\}$ and a for fixed $\{P_{2,k}\}$; and 2) optimize $\{P_{2,k}\}$ and a for fixed $\{P_{1,k}\}$. It is straightforward to see that optimization at each step is QCQP. Thus, we can employ the same approach as before to find a locally optimal point to problem (40). Details are omitted but can be easily worked out similar to Algorithm 1.

VIII. Numerical Results

Here, we present some numerical results to validate the analysis. We start with the single-user scenario in Fig. 2. In Fig. 4, we compare three possible approaches: 1) a single-layer approach (see Section IV); 2) broadcast coding with single-layer

$$R_{1,k}(\mathbf{P}_1, \mathbf{P}_2, a) = \frac{1}{2}\log\left(1 + \frac{P_{1,k}\left(\rho_{j_1,j_2}\bar{P}_{2,\min\{k-1,j_2\}+1}a + q_{1,j_1}a + s_{1,j_1}\right)}{\bar{P}_{2,\min\{k-1,j_2\}}(\rho_{j_1,j_2}\bar{P}_{1,k+1}a + q_{2,j_2}a + s_{2,j_2}) + \bar{P}_{1,k+1}(q_{1,j_1}a + s_{1,j_1}) + \sigma_e^2 a + 1}\right) \tag{41}$$

$$R_{2,k}(\mathbf{P}_1, \mathbf{P}_2, a) = \frac{1}{2}\log\left(1 + \frac{P_{2,k}\left(\rho_{j_1,j_2}\bar{P}_{1,\min\{k-1,j_1\}+1}a + q_{2,j_2}a + s_{2,j_2}\right)}{\bar{P}_{1,\min\{k-1,j_1\}+1}\left(\rho_{j_1,j_2}\bar{P}_{2,k+1}a + q_{1,j_1}a + s_{1,j_1}\right) + \bar{P}_{2,k+1}\left(q_{2,j_2}a + s_{2,j_2}\right) + \sigma_e^2 a + 1}\right) \tag{42}$$

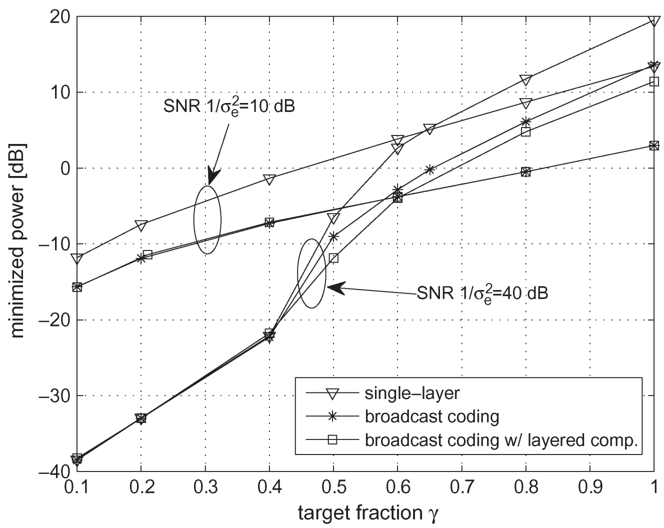

Fig. 5. Minimized power versus the target fraction γ with $K = 2, C_{\max} = 3, \hat{P} = 1$, and $[s_1, s_2] = [1, 200]$.

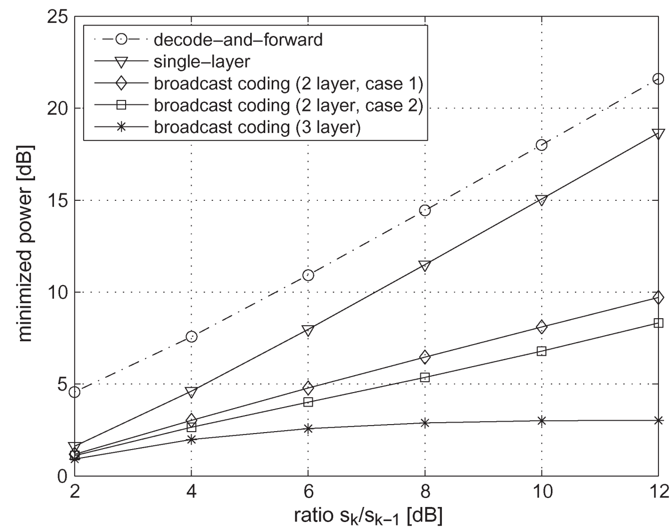

Fig. 7. Minimized power versus the ratio s_k/s_{k-1} (for $k = 2, \ldots, K$) with $K = 3, C_{\max} = 3, \hat{P} = 1, \gamma = 0.9, \sigma_e^2 = 1$ and $s_1 = 1$.

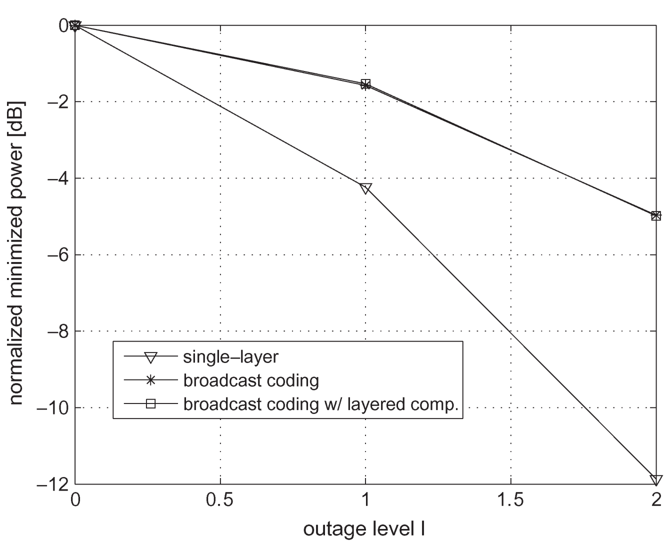

Fig. 6. Normalized minimized power versus the allowed outage level $l_o \in \{0, 1, 2\}$ with $K = 3$, $C_{\max} = 2$, $\hat{P} = 1$, $\gamma = 0.8$, $\sigma_e^2 = 0.1$, and $[s_1, s_2, s_3] = [1, 10, 100]$.

compression (see Section V); and 3) layered compression (see Section VI) in terms of minimized power for $K = 2, C_{\max} = 2$, $P_0 = 1$, and $\sigma_e^2 = 0$ versus the ratio s_2/s_1 between the side information fading levels. As expected, layered approaches are particularly advantageous if the difference between the fading levels in the two states becomes more pronounced. In Fig. 5, we observe the effect of the target fraction γ in the competitive optimality constraints (12) when $K = 2$, $C_{\max} = 3$, $\hat{P} = 1$, and $[s_1, s_2] = [1, 200]$. It is seen that increasing the target fraction γ results in a more relevant gain of layered approaches. This shows that more demanding system constraint calls for the more flexible layered approaches. In Fig. 6, we investigate the impact of the allowed outage level l_o introduced in Definition 1 by plotting the minimized power for each level l_o as normalized by the minimum power with no outage, i.e., $l_o = 0$. In Fig. 6, we can see that allowing for outage is significantly beneficial to the single-layer transmission scheme due to its lack of robustness, whereas the broadcast approaches are relatively insensitive to the outage level l_o. In Figs. 4–6, we conclude that most of the gain is achieved through broadcast coding rather than through layered compression.

Next, we consider an example with $K = 3$ possible fading states and plot the minimized power versus the ratio s_k/s_{k-1} assumed to be the same for all $k = 2, \ldots, K$ in Fig. 7 with $C_{\max} = 3$, $\hat{P} = 1$, $\gamma = 0.9$, and $\sigma_e^2 = 1$. For comparison, we also show the performance of approaches that use only two layers. Specifically, to meet the competitive optimality constraints, we consider the following options: *case 1*, where the design is based on the fading levels (s_1, s_2), and it is imposed that the desired γ fraction of the informed capacity for $S = s_1$ is attained for s_1 and that for $S = s_3$ is met at s_2; and *case 2*, where the design is based on the fading levels (s_1, s_3), and it is imposed that the desired γ fraction of the informed capacity for $S = s_2$ is attained for s_1 and that for $S = s_3$ is met at s_3. In Fig. 7, it is observed that the most general schemes that employ three layers in accordance with the number of fading levels provide significant gains due to their flexibility in satisfying the competitive optimality constraints. Moreover, we compare the proposed layered scheme also with a decode-and-forward (DF) scheme in which the signals X_i transmitted by the encoder are decoded at the relay and then forwarded to the destination via the backhaul link. Note that this scheme models the BS operations in the conventional cellular systems. The achievable rate with this scheme is given by $R_{\rm DF} = \min\{(1/2)\log(1 + P/\sigma_e^2), C_{\max}\}$, and the minimum power required to satisfy the competitive optimality constraints (12) is derived as $P^* = \sigma_e^2(2^{2\gamma C^M(\hat{P})} - 1)$. It is shown that the performance of the DF scheme is even worse than that of the single-layer scheme since the decoding at the relay should be done without utilizing the side information Y_i. We remark that this figure demonstrates the importance of the joint decoding at the cloud decoder.

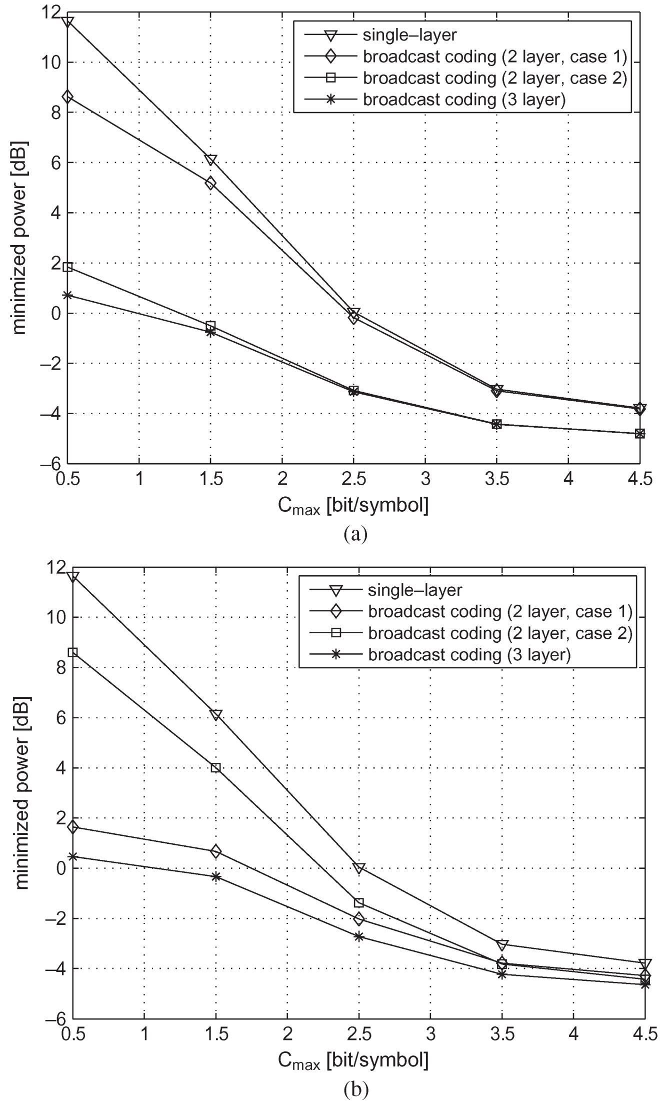

Fig. 8. Minimized power versus the backhaul capacity $C_{\max}$ with $K=3$, $\hat{P}=1$, $\gamma=0.7$ and $\sigma_e^2=0.01$. (a) $(s_1,s_2,s_3)=(0,5,20)$ dB. (b) $(s_1,s_2,s_3)=(0,15,20)$ dB.

In Fig. 8, the minimized power is plotted versus the backhaul capacity $C_{\max}$ with $K=3$, $\hat{P}=1$, $\gamma=0.7$, and $\sigma_e^2=0.01$ for two different fading sets $\mathcal{S}$: 1) $[s_1,s_2,s_3]=[0,5,20]$ dB; and 2) $[s_1,s_2,s_3]=[0,15,20]$ dB. In Fig. 8, it is shown that the gain obtained by layered transmission decreases as the backhaul capacity increases. This implies that the robust design with respect to the uncertainty on the side information Y_i becomes less critical when the quality of the compressed signal W_i, which is determined by the SNR $1/\sigma_e^2$ and the backhaul $C_{\max}$, is of sufficiently high quality. Moreover, compared with Fig. 8(a) and (b), we observe that, in the presence of three states, i.e., $K=3$, two-layer approaches are sensitive to the value of s_2 unlike the single-layer and three-layer approaches.

In Fig. 9, we consider the multiuser setup studied in Section VII and plot the minimized power versus the target fraction γ_2 of encoder 2 for fixed target fraction $\gamma_1=0.4$ of encoder 1 with $K_1=K_2=3$, $C_{\max}=3$, $\hat{P}_1=\hat{P}_2=1$,

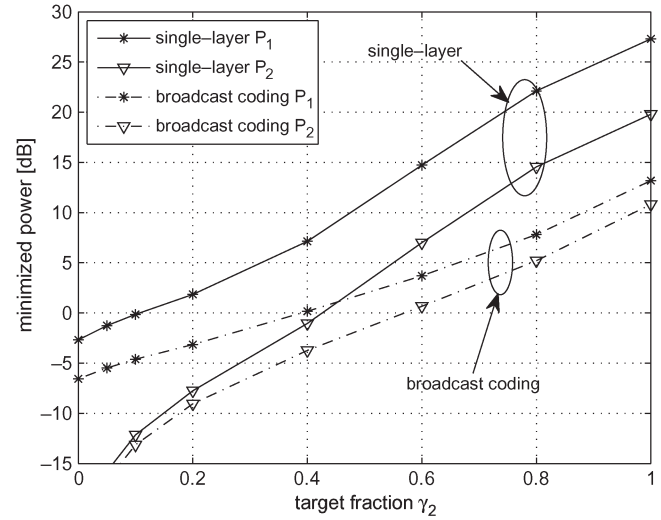

Fig. 9. Minimized power versus the target fraction γ_2 in the two-encoder model with $K_1=K_2=3$, $C_{\max}=3$, $\hat{P}_1=\hat{P}_2=1$, $\gamma_1=0.4$, $\sigma_e^2=0.1$, $h=1$, and $[s_{u,1},s_{u,2},s_{u,3}]=[1,10,100]$ for $u=1,2$.

$\sigma_e^2=0.1$, $h=1$, and $[s_{u,1},s_{u,2},s_{u,3}]=[1,10,100]$ for $u=1,2$. As the target γ_2 increases, the required power for encoder 2 is necessarily boosted, and this induces increased interference to encoder 1. As a result, we observe that both encoders' power grows with γ_2. Moreover, the broadcast coding outperforms the single-layer transmission scheme and the gain is more significant for encoder 1 since the interference from encoder 2 can be partially canceled due to broadcast coding and successive decoding.

IX. Conclusion

In this paper, we have studied the uplink of a cloud radio access network, in which each BS receives a superposition of the signals transmitted by the MSs in different cells, compresses it, and sends it to the cloud decoder via a capacity-constrained backhaul link. Motivated by the fact that the MSs and the BS in a given cell are generally not informed about the CSI relative to the signal received by BSs in other cells, we have proposed layered transmission and compression strategies at the MSs and BS of a cell, respectively, which aim at opportunistically leveraging more advantageous channel conditions in neighboring cells. We adopted a competitive optimality criterion so that a fraction of the rate that is achievable when the CSI is perfectly known to the MSs and BSs can be attained also in the absence of CSI. The proposed layered strategies have been shown to significantly outperform single-layer approaches. Moreover, most of the gain was seen to be accessed due to layered transmission rather than layered compression. Relevant future work includes the analysis of joint decoding across multiple cells, which calls for a joint design of the transmission and compression strategies across multiple cells. Another interesting open issue is the assessment of the tradeoffs between performance and delay that can be accrued by allowing coding over multiple-fading blocks (see, e.g., [38], [39]).

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