Power Optimization With BLER Constraint for Wireless Fronthauls in C-RAN

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***Abstract*—Cloud radio access network (C-RAN) is a novel architecture for future mobile networks to sustain the exponential traffic growth thanks to the exploitation of centralized processing. In C-RAN, one data processing center or baseband unit (BBU) communicates with users via distributed remote radio heads (RRHs), which are connected to the BBU via high capacity, low latency fronthaul links. In this letter, we study C-RAN with wireless fronthauls due to their flexibility in deployment and management. First, a tight upper bound of the system block error rate (BLER) is derived in closed-form expression via union bound analysis. Based on the derived bound, adaptive transmission schemes are proposed. Particularly, two practical power optimizations based on the BLER and pair-wise error probability (PEP) are proposed to minimize the consumed energy at the RRHs while satisfying the predefined quality of service (QoS) constraint. The premise of the proposed schemes originates from practical scenarios where most applications tolerate a certain QoS, e.g., a nonzero BLER. The effectiveness of the proposed schemes is demonstrated via intensive simulations.**

***Index Terms*—Cloud radio access network, wireless fronthaul, optimization, transmission error.**

I. INTRODUCTION

CLOUD radio access network (C-RAN) is a novel architecture for future mobile networks which can sustain the ever increasing demand in data rate [1]. C-RAN usually consists of one centralized baseband unit (BBU) and a number of distributed remote radio heads (RRHs) which serve users in a geographical area. The RRHs communicate with users through wireless medium and are connected to the BBU via high capacity, low latency fronthaul links. Based on centralized processing at the BBU, C-RAN can provide various benefits as compared with classical distributed network deployment [1], [2].

In order to reap the provisioned benefits of C-RAN, it requires novel network planning and designing methods compared with the conventional techniques for traditional wireless systems. One important problem in C-RAN is how to jointly design access and fronthaul networks. Joint compression techniques have been proposed to optimize quantization noise power [3]–[5]. The compression process is implemented via a test channel in which the quantization noise is modelled as an independent Gaussian random variable. It is shown that, in general, the joint design of precoding and quantization noise matrices can significantly improve the system sum rate, as compared to separate design [3]. A hybrid compression and message-sharing has been proposed in [6]. Practical joint compressions have been proposed to reduce the fronthaul transmission rate in both time and frequency domains [7]. Good compression ratio is achieved by minimizing the redundancy of control information in common public radio interface (CPRI) structure. Such improvement is the result from the transmission of data for only active users and a reduced set of precoding matrices. We note that these works focus on fixed employment of the fronthaul links, e.g., optical fibre.

In contrast to the mentioned-above background, we investigate C-RAN with wireless fronthaul links [1]. The advantages of wireless fronthaul include low investment cost and flexibility in network planning, particularly for area with highly dynamic traffic demand [8]. In this letter, we aim at minimizing the energy consumed by the RRHs subject to some quality of service (QoS) constraints. To the best of our knowledge, this problem is first studied in the present letter and fundamentally different from conventional amplify-and-forward (AF) relay networks [9], [10]. Such problem is motivated by practical systems, in which various applications support different QoS [11], [12]. For example, a video call requires a lower block error rate (BLER) than a text application. Our contribution is as follows. First, a tight bound of the system BLER is derived in closed-form expression by using union bound analysis. Second, based on the derived bounds, two adaptive power minimization schemes are proposed to reduce the consumed energy on the fronthaul links while satisfying the predefined QoS constraint, e.g., the target BLER. Finally, simulation results show the advantages of the proposed optimization schemes.

II. SYSTEM MODEL

We consider a C-RAN system consisting of N RRHs denoted by $\mathrm{R}_1, \ldots, \mathrm{R}_N$, M users denoted by $\mathrm{U}_1, \ldots, \mathrm{U}_M$, and one BBU. The users communicate with the RRHs via multiple access channels. The RRHs connect with the BBU by wireless fronthaul links and there is not direct link between the users and the BBU [8], [13], [14]. In this letter, we assume that each user or RRH is equipped with a single antenna. In practical systems, a multiple-antenna RRH can be seen as a band of single-antenna RRHs (which are subjected to sum fronthaul bandwidth constraint) because all baseband processing are performed at the BBU.

Assume that all nodes are perfectly time synchronized and denote c_m as a modulated symbol emitted by user U_m. The modulated symbol c_m, $1 \le m \le M$, thus belongs to the source codebook $\mathcal{S} = \{s_1, \ldots, s_{|\mathcal{S}|}\}$, where $|\cdot|$ denotes the cardinality of a set. Without loss of optimality, the source codebook is

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normalized to satisfy an unit power constraint, e.g., $\mathbb{E}_{s\in\mathcal{S}}|s|^2 = 1$. The signal received at R_n is given as follows:

$$r_n = \sum_{m=1}^{M} h_{nm}\sqrt{E_m}c_m + z_n, \tag{1}$$

where E_m is the average transmitted power at U_m, h_{nm} is the channel fading coefficient from U_m to R_n, including the path loss, which is a complex Gaussian variable with zero mean and variance σ_{nm}^2, and z_n is an independent and identically distributed (i.i.d.) complex Gaussian noise with zero mean and variance σ_1^2.

Upon receiving the aggregated signal from all users, the RRHs forward the received signal to the BBU by using AF relaying protocol [10]. We assume that the BBU is equipped with a large number of antennas to form orthogonal beams to the RRHs, thus inter-RRH interference is negligible. The signal received from the n-th RRH at the BBU is given as follows:

$$y_n = g_n\sqrt{P_n}\beta_n r_n + v_n, \tag{2}$$

where P_n is the transmit power at the n-th RRH, g_n is the channel fading coefficient between the n-th RRH and the BBU, including the path loss, which is a complex Gaussian variable with zero mean and variance σ_{mB}^2, $\beta_n = 1/\sqrt{\sum_{m=1}^{M}|h_{nm}|^2E_m + \sigma_1^2}$ is the AF factor satisfying the energy normalization constraint, and v_n is an i.i.d. complex Gaussian noise at the BBU with zero mean and variance σ_2^2.

The received signal in (2) can be rewritten as

$$y_n = \sqrt{P_n}g_n\beta_n\mathbf{h}_n\mathbf{E}\mathbf{c} + \bar{z}_n, \tag{3}$$

where $\mathbf{h}_n = [h_{n1},\ldots,h_{nM}]$, $\mathbf{c} = [c_1,\ldots,c_M]^T$, $\mathbf{E} = \mathrm{diag}(\sqrt{E_1},\ldots,\sqrt{E_M})$, and $\bar{z}_n = \sqrt{P_n}g_n\beta_n z_n + v_n \sim \mathcal{CN}(0, \frac{P_n|g_n|^2\sigma_1^2}{\|\mathbf{h}_n\mathbf{E}\|^2+\sigma_1^2} + \sigma_2^2)$, where $\|\cdot\|$ denotes the l_2 norm.

A. Joint Decoding at the BBU

In order to optimally exploit spatial diversity gain, maximum likelihood (ML) receiver is deployed at the BBU. Although ML receiver imposes high decoding complexity, it provides the best performance and serves as the benchmark scheme. The complexity can significantly be reduced by using low-complexity receiver, e.g., sphere decoding. The BBU is assumed to know the channel state information (CSI) of all wireless links. In practical systems, the CSI can be obtained via pilot-assisted training period. The BBU optimally estimates the source codeword using the maximum a posteriori (MAP) decoding rule as follows:

$$\hat{\mathbf{c}} = \arg\max_{\mathbf{c}} \Pr\{\mathbf{c}\}\prod_{n=1}^{N}\Pr\{y_n|\mathbf{c}\}, \tag{4}$$

where (4) is because $\Pr\{y_1,\ldots,y_N\}$ is constant for any codeword and the noise $\bar{z}_n$'s are independent for the given codeword. Since $\bar{z}_n$ is a Gaussian noise, we obtain

$$\Pr\{y_n|\mathbf{c}\} = \frac{1}{\pi\sigma_{\bar{z}_n}^2}\exp\left(-\frac{|y_n - \sqrt{P_n}g_n\beta_n\mathbf{h}_n\mathbf{E}\mathbf{c}|^2}{\sigma_{\bar{z}_n}^2}\right), \tag{5}$$

where $\sigma_{\bar{z}_n}^2 = \frac{P_n|g_n|^2\sigma_1^2}{\|\mathbf{h}_n\mathbf{E}\|^2+\sigma_1^2} + \sigma_2^2$. Substituting (5) into (4), we obtain the decoded codeword.

III. PERFORMANCE ANALYSIS

This section analyzes the BLER of the studied system, which is defined as the probability of receiving codeword $\hat{\mathbf{c}}$ when a codeword $\mathbf{c} \neq \hat{\mathbf{c}}$ was transmitted. A block error event occurs when at least one out of M symbols c_m, $1 \le m \le M$, is decoded with error. Since the BLER is difficult to investigate, we instead resort to the union bound on the BLER and consider the average pairwise error probability (APEP) given as follows:

$$\mathrm{BLER} \le \mathrm{APEP} = \frac{1}{|\mathcal{S}|^M}\sum_{\mathbf{c}\in\mathcal{S}^M}\sum_{\tilde{\mathbf{c}}\in\mathcal{S}^M,\tilde{\mathbf{c}}\neq\mathbf{c}}\Pr\{\mathbf{c}\to\tilde{\mathbf{c}}\}, \tag{6}$$

where $\Pr\{\mathbf{c}\to\tilde{\mathbf{c}}\}$ is the instantaneous pair-wise error probability (PEP) of receiving $\tilde{\mathbf{c}}$ when $\mathbf{c}$ was transmitted and $\tilde{\mathbf{c}}$ is the only candidate, which depends on the channel fading coefficients.

A pair-wise error occurs if the metric of the transmitted codeword is smaller than that of the candidate:

$$\Pr\{\mathbf{c}\to\tilde{\mathbf{c}}\} = \Pr\{\mathbb{M}(\mathbf{c}) < \mathbb{M}(\tilde{\mathbf{c}})\}. \tag{7}$$

Substituting (5) into (4) we obtain $\mathbb{M}(\mathbf{c}) = K\exp(-\mathbb{D}(\mathbf{c}))$, where $K = \prod_{n=1}^{N}1/(\pi\sigma_{\bar{z}_n}^2)$ is a constant and $\mathbb{D}(\mathbf{c}) = \sum_{n=1}^{N}\frac{|y_n-\sqrt{P_n}g_n\beta_n\mathbf{h}_n\mathbf{E}\mathbf{c}|^2}{\sigma_{\bar{z}_n}^2}$. Then the PEP is written as

$$\Pr\{\mathbf{c}\to\tilde{\mathbf{c}}\} = \Pr\{\mathcal{J}(\mathbf{c},\tilde{\mathbf{c}}) > 0\} \tag{8}$$

where $\mathcal{J}(\mathbf{c},\tilde{\mathbf{c}}) \triangleq \mathbb{D}(\mathbf{c}) - \mathbb{D}(\tilde{\mathbf{c}})$.

After some algebraic manipulations, we obtain $\mathcal{J}(\mathbf{c},\tilde{\mathbf{c}}) = Z + \psi$, where $Z = \sum_{n=1}^{N}(\bar{z}_n^T\Xi_n + \Xi_n^T\bar{z}_n)/\sigma_{\bar{z}_n}^2$ and $\psi = \sum_{n=1}^{N}|\Xi_n|^2/\sigma_{\bar{z}_n}^2$, where $\Xi_n = \sqrt{P_n}g_n\beta_n\mathbf{h}_n\mathbf{E}(\tilde{\mathbf{c}}-\mathbf{c})$.

Because each $\bar{z}_n$ is a Gaussian random variable and $\bar{z}_n$'s are mutually independent, Z is also a Gaussian random variable with mean zero and variance

$$\sigma_Z^2 = 2\sum_{n=1}^{N}\mathrm{Var}[\bar{z}_n]\frac{|\Xi_n|^2}{\sigma_{\bar{z}_n}^4} = 2\sum_{n=1}^{N}\frac{|\Xi_n|^2}{\sigma_{\bar{z}_n}^2}. \tag{9}$$

Therefore, the PEP is given as

$$\begin{aligned}\Pr\{\mathbf{c}\to\tilde{\mathbf{c}}\} &= \Pr\{Z > \psi\} = \frac{1}{2}\mathrm{erfc}\left(\sqrt{\frac{|\psi|^2}{2\sigma_Z^2}}\right)\\ &= \frac{1}{2}\mathrm{erfc}\left(\sqrt{\sum_{n=1}^{N}\frac{P_n|g_n|^2\mathbf{h}_n\mathbf{E}(\tilde{\mathbf{c}}-\mathbf{c})|^2}{4\left(P_n|g_n|^2\sigma_1^2 + \sigma_2^2(\|\mathbf{h}_n\mathbf{E}\|^2+\sigma_1^2)\right)}}\right).\end{aligned} \tag{10}$$

Substituting (10) into (6), we obtain the upper bound of BLER.

IV. POWER MINIMIZATION UNDER QOS CONSTRAINT

In this section, we aim at minimizing the RRH's transmit power while guaranteeing some predefined QoS constraints, e.g., a non-zero BLER. The RRHs can significantly save their energy by adjusting the transmit power as long as the BLER satisfying the target QoS, e.g., a predefined threshold γ_{tag}. Particularly, two practical optimization schemes are proposed based on the BLER and the maximum PEP, respectively.

A. BLER-Based Power Minimization

For the given target BLER γ_{tag}, we would like to minimize the RRHs' energy as follows:

$$\begin{aligned} \underset{\{P_n : P_n \geq 0\}_{n=1}^N}{\text{minimize}} \; & \sum_{n=1}^{N} P_n \\ \text{s.t.} \; & \frac{1}{|\mathcal{S}|^M} \sum_{\mathbf{c}\in\mathcal{S}^M} \sum_{\tilde{\mathbf{c}}\neq\mathbf{c}} \Pr\{\mathbf{c} \to \tilde{\mathbf{c}}\} \leq \gamma_{tag}, \\ & \sum_{n=1}^{N} P_n \leq P_{sum}, \end{aligned} \tag{11}$$

where $\Pr\{\mathbf{c} \to \tilde{\mathbf{c}}\}$ is given in (10).

It is observed that problem in (11) is difficult to solve due to high complexity of its first constraint (see (10) with respect to variable P_n). By introducing arbitrary variable $x_{\mathbf{c},\tilde{\mathbf{c}}}$, we reformulate (11) as:

$$\begin{aligned} \underset{\{P_n\}_{n=1}^N, \{x_{\mathbf{c},\tilde{\mathbf{c}}}\}}{\text{minimize}} \; & \sum_{n=1}^{N} P_n \\ \text{s.t.} \; & \frac{1}{|\mathcal{S}|^M} \sum_{\mathbf{c}\in\mathcal{S}^M} \sum_{\tilde{\mathbf{c}}\neq\mathbf{c}} \frac{1}{2}\text{erfc}\left(\sqrt{x_{\mathbf{c},\tilde{\mathbf{c}}}}\right) \leq \gamma_{tag}, \\ & \Phi_{\mathbf{c},\tilde{\mathbf{c}}} \geq x_{\mathbf{c},\tilde{\mathbf{c}}}, \forall \mathbf{c} \neq \tilde{\mathbf{c}}, \\ & \sum_{n=1}^{N} P_n \leq P_{sum}; \; P_n \geq 0, \forall n, \end{aligned} \tag{12}$$

where $\Phi_{\tilde{\mathbf{c}},\mathbf{c}} = \sum_{n=1}^{N} \frac{|\mathbf{h}_n \mathbf{E}(\tilde{\mathbf{c}}-\mathbf{c})|^2}{4\sigma_1^2} \frac{P_n}{P_n + \frac{\sigma_2^2(\|\mathbf{h}_n\mathbf{E}\|^2+\sigma_1^2)}{|g_n|^2\sigma_1^2}}$.

Define $a_{n,\mathbf{c},\tilde{\mathbf{c}}} = \frac{|\mathbf{h}_n \mathbf{E}(\tilde{\mathbf{c}}-\mathbf{c})|^2}{4\sigma_1^2}$ and $b_n = \frac{\sigma_2^2(\|\mathbf{h}_n\mathbf{E}\|^2+\sigma_1^2)}{|g_n|^2\sigma_1^2}$, we can rewrite the second condition of (12) as $\sum_{n=1}^{N} \frac{a_{n,\mathbf{c},\tilde{\mathbf{c}}} b_n}{P_n+b_n} + x_{\mathbf{c},\tilde{\mathbf{c}}} \leq \sum_{n=1}^{N} a_{n,\mathbf{c},\tilde{\mathbf{c}}}$.

Let us define a constant $L = |\mathcal{S}|^M \times (|\mathcal{S}|^M - 1)$, $\mathbf{x} \in \mathbb{R}^{(L+N)\times 1}$, and $A \in \mathbb{R}^{L\times(L+N)}$ as

$$\mathbf{x} = \left[x_1, \ldots, x_L, \frac{1}{P_1 + b_1}, \ldots, \frac{1}{P_N + b_N}\right];$$

$$A = \begin{bmatrix} 1 & 0 & \ldots & 0 & a_{1,1}b_1 & \ldots & a_{N,1}b_N \\ 0 & 1 & \ldots & 0 & a_{1,2}b_1 & \ldots & a_{N,2}b_N \\ \ldots & & & & & & \\ 0 & 0 & \ldots & 1 & a_{1,L}b_1 & \ldots & a_{N,L}b_N \end{bmatrix}.$$

Then the optimization (12) is equivalent to the following problem:

$$\begin{aligned} \underset{\mathbf{x}}{\text{minimize}} \; & \sum_{n=L+1}^{L+N} \frac{1}{x[n]} \\ \text{s.t.} \; & \frac{1}{2|\mathcal{S}|^M} \sum_{l=1}^{L} \text{erfc}\left(\sqrt{x[l]}\right) \leq \gamma_{tag}, \\ & A[l,:] * \mathbf{x} \leq \sum_{n=1}^{N} a_{n,l}, \; 1 \leq l \leq L, \\ & \sum_{n=1}^{N} \frac{1}{x[L+n]} \leq P_{sum} + \sum_{n=1}^{N} b_n, \\ & x[L+n] \leq \frac{1}{b_n}, \; 1 \leq n \leq N. \end{aligned} \tag{13}$$

It is observed that the problem (13) is a convex optimization, hence it can be efficiently solved by standard methods, e.g., gradient descent [15].

Remark 1: In order to leverage the computation, the first constraint in problem (13) can be computed using a tight approximation of erfc(.) function $\text{erfc}(x) \simeq e^{-x^2}/6 + e^{-\frac{4x^2}{3}}/2$.

B. PEP-Based Power Minimization

In this subsection, we propose an alternative approach which gives us an upper-bound of (11) as follows:

$$\begin{aligned} \underset{\{P_n : P_n > 0\}_{n=1}^N}{\text{minimize}} \; & \sum_{n=1}^{N} P_n \\ \text{s.t.} \; & \frac{1}{2}\text{erfc}\left(\sqrt{\Phi_{\tilde{\mathbf{c}},\mathbf{c}}}\right) \leq \frac{\gamma_{tag}}{|\mathcal{S}|^M - 1}, \forall \tilde{\mathbf{c}} \neq \mathbf{c}, \\ & \sum_{n=1}^{N} P_n \leq P_{sum}. \end{aligned} \tag{14}$$

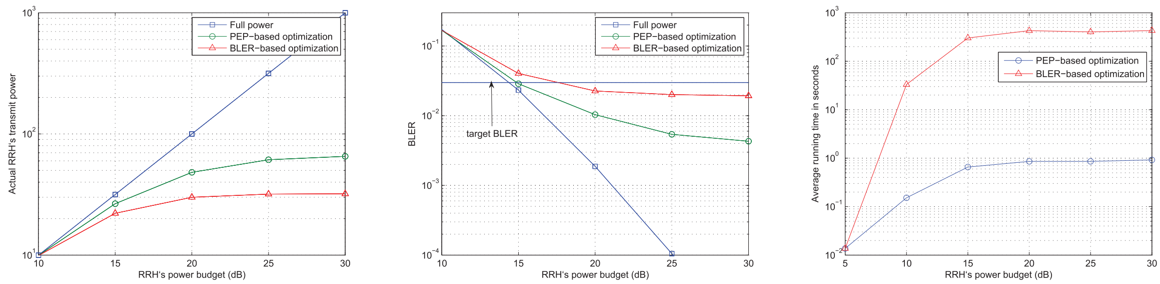
We note that the optimal solution of (14) always satisfies (11), i.e., the optimal objective value of (14) is an upper-bound for that of (11). The proof is as follows. Let $\text{Pe}(\mathbf{c})$ be error probability when $\mathbf{c}$ was transmitted and $\hat{\mathbf{c}} \neq \mathbf{c}$ is received, i.e., $\text{Pe}(\mathbf{c}) = \Pr\{\hat{\mathbf{c}} \in \mathcal{S}^M \setminus \mathbf{c}|\mathbf{c}\}$, where $\mathcal{S}^M \setminus \mathbf{c}$ denotes the set of codewords except $\mathbf{c}$. Obviously, $\Pr\{\hat{\mathbf{c}} \in \mathcal{S}^M \setminus \mathbf{c}|\mathbf{c}\} \leq \sum_{\hat{\mathbf{c}}\neq\mathbf{c}} \Pr\{\mathbf{c} \to \hat{\mathbf{c}}\}$.

Define $\sqrt{\delta} = \text{erfc}^{-1}\left(\frac{2\gamma_{tag}}{|\mathcal{S}|^M - 1}\right)$. It is straightforward to verify that problem (14) is equivalent to the following problem

$$\begin{aligned} \underset{\{P_n : P_n > 0\}_{n=1}^N}{\text{minimize}} \; & \sum_{n=1}^{N} P_n \\ \text{s.t.} \; & \sum_{n=1}^{N} \frac{a_{n,\mathbf{c},\tilde{\mathbf{c}}} b_n}{P_n + b_n} \leq \sum_{n=1}^{N} a_{n,\mathbf{c},\tilde{\mathbf{c}}} - \delta, \forall \tilde{\mathbf{c}} \neq \mathbf{c}, \\ & \sum_{n=1}^{N} P_n \leq P_{sum}. \end{aligned} \tag{15}$$

We observe that problem (15) is a convex optimization problem, and therefore it can be effectively solved by standard methods, e.g., gradient descent [15].

Remark 2: The BLER-based minimization is expected to achieve smaller consumed energy with the trade-off high computing complexity. On the other hand, the PEP-based minimization is sustainably simpler and practically preferable for its low complexity. This is because the PEP-based solution guarantees all PEP satisfying the target QoS, which can result in a far smaller BLER than necessary. Consequently, the PEP-based solution requires more RRHs' power to achieve a smaller BLER. Due to space limit, the complexity analysis of the proposed optimization is excluded in this letter. We instead illustrate the advantage of the PEP-based optimization over the BLER-based scheme via simulation in Section V.



(a) (b) (c)

Fig. 1. Performance comparison between different optimizations: (a) actual power consumption at the RRHs, (b) BLER performance, and (c) average running time. The target BLER $\gamma_{tag} = 0.03$. The SNR on user-RRH links is equal to 20dB.

V. Simulation Results

The proposed algorithms are evaluated for a network topology consisting of $M = 4$ users and $N = 4$ RRHs under block Rayleigh fading channel. The path loss exponent is equal to 3.5. Symmetric network is assumed, e.g., $E_m = E, \forall m$ and $\sigma_{nm}^2 = \sigma_{mB}^2 = 1, \forall n, m$. QPSK modulation is used, e.g., the codebook $\mathcal{S} = \{-1 - 1i, -1 + 1i, 1 - 1i, 1 + 1i\}/\sqrt{2}$. The noise power is set as $\sigma_1^2 = \sigma_2^2 = 1$. Full CSI is assumed to be available at the BBU.

Fig. 1a presents the energy consumption at the RRHs in different schemes. The SNR on the user-RRH link is set equal to 20 dB. The two proposed optimizations are compared with the full power scheme, which uses all the RRHs' power budget. It is shown in the figure that the proposed optimization schemes significantly reduce the consumed energy at the RRHs. Particularly, the BLER-based scheme reduces 90% and the PEP-based scheme saves 80% energy consumption as compared with the scheme without optimization at 25 dB. Compared with the BLER-based scheme, the PEP-based scheme consumes slightly more energy. Such expected result is explained from the fact that the PEP-based scheme guarantees all PEPs below the target BLER. One important observation is that the consumed energy of the proposed optimizations becomes stable even when the budget increases.

Fig. 1b plots the BLER performance of different schemes under the similar setting. At the small RRHs' power budget regime, all schemes do not satisfy the target BLER because of the dominance of thermal noise. When the budget increases, both proposed optimizations achieve the BLER smaller than the QoS threshold. As expected, the BLER-based does exactly it is required, e.g., achieving a BLER slightly smaller than the target, but no more. The PEP-based optimization achieves a smaller BLER with the cost of consuming more energy than the BLER-based scheme, which is in line with the result in Fig. 1a. We note that there is a gap between the target BLER and the actual performance of the BLER-based optimization since (6) provides the upper bound of BLER.

Fig. 1c presents the average running time of the proposed optimizations. At very low SNRs, both schemes consume the same amount of time because the channels are very poor that the optimizations are inactive. At the high SNR regime, the PEP-based optimization reveals a huge gain in running times over the BLER-based optimization. In particular, the PEP-based scheme is 400 times faster than the BLER-based one.

VI. Conclusions and Discussions

We have studied the performance of a cloud radio access network which employs wireless fronthaul connections. The system block error rate has been derived in closed-form expression. Based on the derived bounds, two practical power minimization schemes with BLER constraint have been proposed to reduce the energy consumed on the fronthaul links.

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