Energy Efficiency of Downlink Transmission Strategies for Cloud Radio Access Networks

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Abstract—This paper studies the energy efficiency of the cloud radio access network (C-RAN), specifically focusing on two fundamental and different downlink transmission strategies, namely the data-sharing strategy and the compression strategy. In the data-sharing strategy, the backhaul links connecting the central processor (CP) and the base-stations (BSs) are used to carry user messages – each user’s messages are sent to multiple BSs; the BSs locally form the beamforming vectors then cooperatively transmit the messages to the user. In the compression strategy, the user messages are precoded centrally at the CP, which forwards a compressed version of the analog beamformed signals to the BSs for cooperative transmission. This paper compares the energy efficiencies of the two strategies by formulating an optimization problem of minimizing the total network power consumption subject to user target rate constraints, where the total network power includes the BS transmission power, BS activation power, and load-dependent backhaul power. To tackle the discrete and nonconvex nature of the optimization problems, we utilize the techniques of reweighted $\ell_1$ minimization and successive convex approximation to devise provably convergent algorithms. Our main finding is that both the optimized data-sharing and compression strategies in C-RAN achieve much higher energy efficiency as compared to the non-optimized coordinated multpoint transmission, but their comparative effectiveness in energy saving depends on the user target rate. At low user target rate, data-sharing consumes less total power than compression, however, as the user target rate increases, the backhaul power consumption for data-sharing increases significantly leading to better energy efficiency of compression at the high user rate regime.

Index Terms—Cloud radio access network (C-RAN), data-sharing strategy, compression strategy, energy efficiency, power minimization, base-station activation, base-station clustering, beamforming, backhaul power.

I. INTRODUCTION

Ultra-dense deployment of small cells and cooperative communications are recognized as two promising technologies to meet the ever increasing demand of data traffic for future wireless networks [1]. However, both technologies come at the cost of increase in energy consumption because of the additional energy needed to support the increasing number of base-station (BS) sites and the substantially increased backhaul between the BSs for cooperation. The excessive energy consumption of wireless networks not only has an ecological impact in terms of carbon footprint but also has an economical impact on the operational cost to the mobile operators. Thus, the compelling call for improvement of spectrum efficiency in the fifth-generation (5G) wireless network needs to be accompanied by a call for improvement of energy efficiency to the same extent.

Cloud radio access network (C-RAN) is an emerging network architecture that shows significant promises in improving both the spectrum efficiency and the energy efficiency of current wireless networks [2]. In C-RAN, the BSs are connected to a central processor (CP) through backhaul links. The benefits of the C-RAN architecture in energy saving are several-fold. First, under the C-RAN architecture, most of the baseband signal processing in traditional BSs can be migrated to the cloud computing center so that the conventional high-cost high-power BSs can be replaced by low-cost low-power remote heads (RRHs). Second, the existence of CP also allows for the joint precoding of user messages for interference mitigation. With less interference generated, the transmit power at the BSs can therefore be reduced. Third, as on average (and especially during non-peak time) a significant portion of network resources can be idle [3], the CP can perform joint resource allocation among the BSs to allocate resources on demand and put idle BSs into sleep mode for energy saving [4].

The above-mentioned benefits of C-RAN in energy saving are concerned with the BS side. However, the additional energy consumption due to the increased backhaul between the CP and the BSs also needs to be taken into account [5]. In this paper, we investigate the potential of C-RAN in improving energy efficiency of the communication aspect of the network by considering the energy consumption due to BS activation, transmission, and backhaul provisioning. The backhaul energy consumption depends on the backhaul rate, which further depends on the interface between the CP and the BSs. In this paper, we investigate two fundamental and different transmission strategies for the downlink C-RAN. In the data-sharing strategy, the CP uses the backhaul links to share user messages to a cluster of cooperating BSs. The backhaul cost of the data-sharing strategy depends on the number of BSs that the user messages need to be delivered to: larger cluster size leads to larger cooperative gain, but also higher backhaul rate. In an alternative strategy called the compression strategy, the CP performs joint precoding of the user messages centrally then forwards a compressed version of the precoded signals to the BSs. The backhaul cost of the compression strategy depends on the resolution of the compressed signals: higher-resolution leads to better beamformers, but also larger backhaul rate.

This paper aims to quantify the energy saving of C-RAN while accounting for both the BS and the backhaul energy consumptions, and specifically to answer the question...
of between the data-sharing strategy and the compression strategy, which one is more energy efficient? The answer to this question is nontrivial as there are three factors that can lead to energy reduction: decrease in BS transmit power, turning-off of the BSs, and reduction in backhaul rate. These three factors are interrelated. For example, it may be beneficial to keep more BSs active and to allocate higher backhaul rate in order to allow for better cooperation among the BSs so that more interference can be mitigated. This leads to less transmit power consumption, but it can also lead to higher BS and backhaul power consumption. This paper intends to capture such interplay using an optimization framework. Specifically, we propose a joint design of the BS transmit power, BS activation and backhaul by minimizing network-wide power under given user rate constraints for both the data-sharing strategy and the compression strategy. The resulting optimization problems are nonconvex in nature and are highly nontrivial to solve globally. This paper approximates the problems using reweighted $\ell_1$ minimization technique and successive convex approximation technique, and devises efficient algorithms with convergence guarantee. We identify operating regimes where one strategy is superior to the other, and show that overall optimized C-RAN transmission can lead to more energy efficient network operation than the non-optimized coordinated multi-point (CoMP) transmission.

A. Related Work

The potential of C-RAN in improving the performance for future wireless networks has attracted considerable attentions recently. In the uplink, [7] and [8] show that with the capability of jointly decoding user messages in the CP, the throughput of traditional cellular networks can be significantly improved. A similar conclusion also has been drawn in the downlink. In particular, [9] proposes a joint design of beamforming and multivariate compression to maximize the weighted sum rate for the compression strategy, while [10] and [11] consider joint beamforming and BS clustering design to maximize the weighted sum rate for data-sharing.

This paper focuses on the energy efficiency of C-RAN in the downlink. Several metrics have been proposed in the literature to measure the energy efficiency of a network. For example, the area power consumption metric (watts/unit area) is proposed in [12] to evaluate the energy efficiency of networks of different cell site densities. Another widely adopted measurement in energy efficiency is bits per joule metric, which has been studied in [13] under a simplified single-user-two-BSs model from an information-theoretical point of view and also studied in [14]–[16] for orthogonal frequency division multiple access (OFDMA) based cooperative networks from the practical system design point of view.

In this paper, we formulate the problem of minimizing the total required power for downlink C-RAN in order to provide a given set of quality-of-service (QoS) targets for the scheduled users. Such an optimization problem can also be thought of as minimizing watts per bit (or maximizing the bits per watt) at given user service rates. In this domain, most of the previous works are restricted to the data-sharing strategy [17]–[19]. Specifically, [17] proposes a joint BS selection and beamforming design algorithm to minimize the total power consumption in the downlink, while [18] generalizes to a joint downlink and uplink total power minimization problem. Both [17] and [18] take advantage of the fact that if a BS is not selected to serve any user at the current time slot, it can be put into low-power sleep mode for energy saving purpose. In contrast, [19] assumes fixed BS association but exploits the delay tolerance of the users to improve the energy efficiency in CoMP transmission. In delay-tolerant applications, BSs can aggregate the user messages and transmit them with high rate during a short time frame while remain idle for the rest of the time slots under power-saving sleep mode. Fast deactivation/activation of hardware power-consuming components achieve significant energy reductions [4], [20].

In this paper, we adopt a similar energy saving perspective as in [17] but consider in addition the compression strategy. Compression strategy differs from data-sharing strategy in the way that the backhaul is utilized. We adopt the model proposed in [21] to model the power consumption of backhaul links as a linear function of backhaul rates. This is in contrast to [17], where the backhaul power is modeled as a step function with only two levels of power consumption depending on whether the backhaul link is active or not.

In addition to the backhaul power, we also consider the BS power consumption by adopting the model proposed in [22], which approximates the power consumption of a BS as a piecewise linear function of transmit power. In such model, BS sleep mode corresponds to a constant but lower power consumption with zero transmit power. BS active mode corresponds to a higher constant power plus a nonzero transmit power. The overall framework of this paper is a joint optimization of BS transmit power, BS activation and backhaul rate for both the compression and the data-sharing strategies.

From the optimization perspective, the total power consumption for the data-sharing strategy involves a sum of weighted nonconvex $\ell_0$-norms, which is highly nontrivial to optimize globally. Instead, we adopt the reweighted $\ell_1$ technique [6] to approximate the nonconvex total power into a convex weighted sum of transmit power, where the weights are iteratively updated in a way to reduce not only the number of active BSs but also the backhaul rate. Such technique has also been applied to minimize the total backhaul rate in [23], and to optimize the tradeoff between the total transmit power and total backhaul rate in [24]. On a related note, the discrete $\ell_0$-norm can also be approximated using other tractable continuous functions such as Gaussian-like function in [25] and exponential function in [26]. It has been reported recently in [27] that those approximation methods show similar effectiveness in inducing sparsity.

Further, the mathematical expression of the total power consumption for the compression strategy involves a difference of two logarithmic functions, which is also nonconvex. We propose to approximate the first logarithmic function using the successive convex approximation technique, which transforms the objective function into a convex form. The adopted reweighted $\ell_1$ minimization technique and successive convex approximation technique in this paper are related to...
the majorization-minimization (MM) algorithm \cite{28}, which deals with an optimization problem with nonconvex objective function by successively solving a sequence of optimization problems with approximate objective functions. This paper utilizes the known sufficient conditions of convergence for the MM algorithm in the literature \cite{29} to show the convergence of the proposed algorithms for both the data-sharing and the compression strategies.

Finally, we mention that the data-sharing and compression strategies considered in this paper are not the only possibilities for the downlink of C-RAN. There is a potential to combine these two strategies by sending directly the messages of only the strong users to the BSs and compressing the rest \cite{30}. Also, reverse compute-and-forward strategy that accounts for the lattice nature of the transmitted message is also possible \cite{31}. However, such strategy is difficult to optimize because of the need in choosing the right integer zero-forcing precoding coefficients at the CP so that the effective noise, caused by the non-integer penalty due to practical channels, at each user is minimized.

\section{Main Contributions}

This paper considers energy-efficient design of the data-sharing strategy and the compression strategy for downlink C-RAN by formulating a problem of minimizing the total network power consumption subject to user rate constraints. The first contribution of this paper is the modeling of both the BS power and the backhaul power consumption in the network. The BS power consumption model includes a low-power sleep mode, while the backhaul power consumption is modeled as a linear function of backhaul traffic rate.

For the data-sharing strategy, we propose a novel application of reweighted $\ell_1$ minimization technique to approximate the nonconvex BS activation power and backhaul power. Such approximation technique reduces the nonconvex optimization problem to a conventional convex transmit power minimization problem, which can be solved efficiently using the uplink-downlink duality approach or through transformation as second-order cone programming (SOCP). Moreover, we adopt a reweighting function that enables us to connect the reweighted $\ell_1$ minimization technique with the MM algorithm. This connection allows us to prove the convergence behavior of the proposed algorithm for the data-sharing strategy.

For the compression strategy, in addition to the reweighted $\ell_1$ approximation to the BS activation power as in the data-sharing strategy, we propose a successive convex approximation to the backhaul power, which is in a nonconvex form as a difference of two logarithmic functions. The proposed successive convex approximation technique and the reweighted $\ell_1$ approximation technique can be combined together. The combined algorithm falls into the class of the MM algorithms and has convergence guarantee.

Through simulations, we show that optimized data-sharing and compression strategies in C-RAN can bring much improved energy efficiency as compared to the non-optimized CoMP transmission. However, the comparative energy saving of data-sharing versus compression depends on the user target rates. The energy efficiency of the data-sharing strategy is superior to that of the compression strategy in the low-rate regime. However, the backhaul power consumption of the data-sharing strategy increases significantly with the user rate. Thus, in high user rate regime, the compression strategy may be preferred from an energy saving perspective.

\section{Paper Organization and Notations}

The remainder of this paper is organized as follows. Section II introduces the system model and power consumption model considered throughout this paper. Section III considers the total power minimization under the data-sharing transmission strategy, while Section IV considers the compression strategy. Simulation results are presented in Section V and conclusions are drawn in Section VI.

Throughout this paper, lower-case letters (e.g. $x$) and lower-case bold letters (e.g. $\mathbf{x}$) denote scalars and column vectors respectively. We use $\mathbb{C}$ to represent complex domain. The transpose, conjugate transpose and $\ell_p$-norm of a vector are denoted as $(\cdot)^T$, $(\cdot)^H$ and $\| \cdot \|_p$ respectively. The expectation of a random variable is denoted as $E[\cdot]$. Calligraphy letters are used to denote sets, while $[\cdot]$ stands for either the size of a set or the absolute value of a scalar, depending on the context.

\section{System and Power Consumption Model}

In this section, we describe the overall system model and power consumption model for the downlink C-RAN considered throughout this paper.

\subsection{System Model}

Consider a downlink C-RAN with $L$ BSs serving $K$ users. All the BSs are connected to a CP via backhaul links and each user receives a single independent data stream from the BSs. All the user messages are assumed to be available at the CP and are jointly processed before being forwarded to the BSs through the backhaul links. We assume that the CP has access to global channel state information (CSI) but point out that such assumption can be relaxed so that only the CSI from the neighboring BSs of each user is needed in the CP. To simplify notations and ease analysis, we assume that the BSs and the users are equipped with a single antenna each, although the proposed algorithms in this paper can be easily generalized to the case of multi-antenna BSs as discussed later in the paper. Let $x_k \in \mathbb{C}$ denote the transmit signal at BS $l$, we can write the received signal $y_k \in \mathbb{C}$ at user $k$ as

$$y_k = \mathbf{h}_k^H \mathbf{x} + n_k, \quad k \in \mathcal{K} = \{1, 2, \cdots, K\}$$

where $\mathbf{x} = [x_1, x_2, \cdots, x_L]^T$ is the vector of transmit signals across all the $L$ BSs and $\mathbf{h}_k \in \mathbb{C}^{L \times 1}$ is the vector of channel gains from all the $L$ BSs to user $k$. The received noise $n_k$ is modeled as a complex Gaussian random variable with zero mean $\mathcal{C}(0, \sigma^2)$.

This paper refers the link between CP and BSs as backhaul, which is appropriate if the data-sharing strategy is used. However, in a C-RAN architecture implementing the compression strategy where the BSs are simply RRHs, the connection between RRH and CP can be referred to more appropriately as fronthaul.
mean and variance $\sigma^2$. Each user decodes its own message $s_k \in \mathbb{C}$ from the received signal $y_k$.

In this paper, we investigate two fundamental but different transmission strategies, the data-sharing strategy and the compression strategy, for the downlink C-RAN for delivering the message $s_k$ to user $k$ via the transmit signal $x$ from the BSs. In particular, we compare the potential of these two strategies in improving the energy efficiency. Before discussing the details of the two strategies, we first describe the power consumption model adopted in this paper.

### B. Power Consumption Model

Traditional cellular network transmission strategy design typically only considers transmit power at each BS, which is written as

$$P_{l,tx} = \mathbb{E}[|x_l|^2] \leq P_l, \quad l \in \mathcal{L} = \{1, 2, \ldots, L\},$$

(2)

where $P_l$ is the transmit power budget available at BS $l$. However, a full characterization of power consumption at a BS should also consider the efficiency of the power amplifier and other power-consuming components such as baseband unit, cooling system, etc. In addition, the power consumption of backhaul links connecting the BSs to the CP also needs to be taken into account for the specific C-RAN architecture considered in this paper. In the following, we describe the power consumption model adopted in this paper for the BSs and the backhaul links respectively.

1) Base-Station Power Consumption: The characteristic of power-consuming components in a BS depends on the BS design. We adopt the following unified power consumption model proposed in [22], which is applicable for different types of BSs. This model approximates the BS power consumption as a piecewise linear function of the transmit power $P_{l,tx}$:

$$P_{l,tx}^{BS} = \begin{cases} \eta_l P_{l,tx} + P_{l,active}, & \text{if } 0 < P_{l,tx} \leq P_l, \\ P_{l,sleep}, & \text{if } P_{l,tx} = 0 \end{cases}, \quad l \in \mathcal{L}$$

(3)

where $\eta_l > 0$ is a constant reflecting the amplifier efficiency, feeder loss and other loss factors due to power supply and cooling for BS $l$, $P_{l,tx}$ is the transmit power defined in (2) and $P_{l,active}$ is the minimum power required to support BS $l$ with non-zero transmit power. If BS $l$ has nothing to transmit, it can be put into sleep mode with low power consumption $P_{l,sleep}$. Typically, $P_{l,sleep} < P_{l,active}$ so that it is beneficial to turn BSs into sleep mode, whenever possible, for energy-saving purpose.

2) Backhaul Power Consumption: In C-RAN, the BSs are connected to the CP with the backhaul links. The power consumption due to backhaul links varies with different backhaul technologies. In this paper, we model the backhaul as a set of communication channels, each with capacity $C_l$ and power dissipation $P_{l,BH}^{BH}$, and write the backhaul power consumption as

$$P_{l,BH} = \frac{R_{l,BH}}{C_l} P_{l,BH}^{BH}, \quad l \in \mathcal{L}$$

(4)

where $\rho_l = \frac{P_{l,BH}^{BH}}{C_l}$ is a constant scaling factor and $R_{l,BH}$ is the backhaul traffic between BS $l$ and the CP. This model has been used in [21] for microwave backhaul links and can also be generalized to other backhaul technologies, such as passive optical network, fiber-based Ethernet, etc., as mentioned in [22]. Note that [17] also considers the sleep mode capability for backhaul links. We point out that such consideration can be unified with $P_{l,active}$ and $P_{l,sleep}$ in the BS power consumption model (3).

3) Total Power Consumption: Based on the above BS power consumption model (3) and backhaul power consumption model (4), we can write the total power consumption $P_{total}$ for C-RAN as

$$P_{total} = \sum_{l \in \mathcal{L}} (P_{l,tx}^{BS} + P_{l,BH})$$

$$= \sum_{l \in \mathcal{L}} \left( \eta_l P_{l,tx} + \mathbb{I}_{\{P_{l,tx} \leq P_l\}} (P_{l,active} - P_{l,sleep}) + P_{l,sleep} + \rho_l R_{l,BH} \right)$$

$$= \sum_{l \in \mathcal{L}} \left( \eta_l P_{l,tx} + \mathbb{I}_{\{P_{l,tx} \leq P_l\}} P_{l,\Delta} + \rho_l R_{l,BH} \right) + \sum_{l \in \mathcal{L}} P_{l,sleep}$$

(5)

where $\mathbb{I}_{\{\cdot\}}$ is the indicator function defined as

$$\mathbb{I}_{\{x\}} = \begin{cases} 1, & \text{if } x > 0 \\ 0, & \text{otherwise} \end{cases}$$

and $P_{l,\Delta} = P_{l,active} - P_{l,sleep}$ is the difference between the minimum active BS power consumption and the sleep mode BS power consumption.

As we can see from (5), there are three possibilities in improving the energy efficiency of C-RAN: reducing the transmit power, putting BSs into sleep mode, and decreasing the backhaul traffic. However, these three aspects cannot be realized simultaneously: deactivating more BSs means reduced capability for interference mitigation among the active BSs, which leads to higher transmit power in order to maintain the QoS for the users; higher backhaul rate can allow for more user information being shared among the BSs so that the BSs can better cooperate to mitigate interference, thus less transmit power may be needed. A joint design is necessary in order to balance the roles of transmit power, BS activation and backhaul traffic rate in achieving energy efficiency. In the following, we describe the general problem formulation considered in this paper for such joint design used in both the data-sharing and the compression strategies.

### C. Energy Efficiency Maximization

This paper aims to understand the energy efficiency for downlink C-RAN, which can be defined as the ratio of the achievable sum rate and the sum power consumption, i.e.

$$\frac{R_{total}}{P_{total}}$$

where $R_k$ is the data rate for user $k$ determined by the specific transmission strategy and $P_{total}$ is the total consumed power defined in (5). Towards this end, this paper takes the similar approach as in [19] to fix the service rates of
scheduled users and consider the minimization of total power consumption:

\[ \text{minimize } P_{\text{total}} \]
\[ \text{subject to } R_k \geq r_k, \ \forall k \in K \]
\[ E[|x_l|^2] \leq P_l, \ \forall l \in \mathcal{L} \]

where \( r_k \) is the fixed target rate for user \( k \). The solution to the above problem gives us the energy efficiency \( \frac{E[|x_l|^2]}{F_{\text{total}}} \) of the system at the operating point \((r_1, r_2, \cdots, r_K)\). To maximize energy efficiency, we need to further search over all operating points. For the rest of the paper, we study and compare the minimum required total power for different transmission strategies under the same operating point \((r_1, r_2, \cdots, r_K)\) in the downlink of C-RAN. Note that problem (7) implicitly assumes fixed user scheduling. There also exists a possibility of doing joint user scheduling and power minimization by considering a problem of minimizing the total power consumption across multiple time slots subject to a minimum target for each user’s average rate. Such problem is considerably more complicated.

D. Data-Sharing versus Compression

Data-sharing and compression are two fundamentally different transmission strategies for the downlink of C-RAN for delivering data to the users. These two strategies correspond to alternative functional splits in C-RAN. In the data-sharing transmission strategy, the CP routes each scheduled user’s intended message to a cluster of BSs through the backhaul links; the cluster of BSs then cooperatively serve that user through joint beamforming. In contrast, in the compression strategy, the precoding operation is implemented centrally at the CP, which then forwards a compressed version of the analog beamformed signal to the BSs through the backhaul/fronthaul links. The BSs then simply transmit the compressed beamforming signals to the users [9], [30], [33].

The data-sharing strategy differs from the compression strategy in backhaul utilization. In data-sharing, the backhaul rate is a function of the user message rate and the BS cluster size, while in the compression strategy the backhaul cost is determined by the compression resolution. Intuitively, as the user target rate and BS cluster size increase, the backhaul rate for the data-sharing strategy would increase significantly, leading to high energy consumption. However, in the low user rate regime where the BS cluster size is small, data-sharing can be more efficient than compression as the latter suffers from quantization noise. Therefore, there exists a tradeoff between data-sharing and compression in terms of backhaul rate and energy efficiency at different user target rate operating points. In the following two sections, we describe in details the data-sharing strategy and the compression strategy, and propose corresponding algorithms to find the minimum required total power for each strategy.

Throughout this paper, we primarily account for the energy consumption due to communications in either the backhaul or the transmission front-end at the BSs, rather than the energy consumption due to computing. There is significant additional energy saving due to migrating signal processing from the BSs to the cloud computer center in the C-RAN architecture. We refer the readers to [34].

III. DATA-SHARING STRATEGY

In this section, we study the minimum total power required for the data-sharing strategy in order to support the given scheduled users at guaranteed service rates.

A. Problem Formulation

Consider the data-sharing transmission strategy for the downlink of C-RAN as illustrated in Fig. 1, where the each user’s message is shared among a cluster of serving BSs. Let \( w_{lk} \in \mathbb{C} \) be the beamforming coefficient for BS \( l \) to serve user \( k \). If BS \( l \) is not part of user \( k \)’s serving cluster, \( w_{lk} \) is set to be zero. The transmit signal \( x_l \) at BS \( l \) can be written as
\[ x_l = \sum_{k \in K} w_{lk}s_k. \]
We model the user messages \( s_k \)’s as independent and identically distributed complex Gaussian random variables with zero mean and unit variance. The transmit power \( P_{l,tx} \) formulated in (2) can be written as
\[ P_{l,tx} = \sum_{k \in K} |w_{lk}|^2, \quad l \in \mathcal{L}. \]

Substituting \( x_l = \sum_{k \in K} w_{lk}s_k \) into (1), the received signal \( y_k \) at user \( k \) is
\[ y_k = h_k^H w_k s_k + \sum_{j \neq k} h_k^H w_j s_j + n_k, \quad k \in K, \]
where \( w_k = [w_{1k}, w_{2k}, \cdots, w_{lk}]^T \) is the network beamformer for user \( k \). Based on (9), the received signal-to-interference-plus-noise ratio (SINR) at user \( k \) can be expressed as
\[ \text{SINR}_k = \frac{|h_k^H w_k|^2}{\sum_{j \neq k} |h_k^H w_j|^2 + \sigma^2}, \quad k \in K \]
and the achievable rate for user $k$ is then
\[
R_k = \log_2 \left( 1 + \frac{\text{SINR}_k}{\Gamma_m} \right), \quad k \in \mathcal{K},
\] (11)
where $\Gamma_m$ stands for the signal-to-noise ratio (SNR) gap due to practical modulation scheme.

For the data-sharing strategy, if user $k$ is served by BS $l$, then the CP needs to send user $k$’s message $s_k$, along with the beamforming coefficient $w_{lk}$, to BS $l$ through the backhaul link. In this paper, we assume that the backhaul capacity is slow varying and ignore the backhaul required for sharing CSI and beamformers, and only consider the backhaul capacity consumption due to data-sharing. Hence, the backhaul rate for BS $l$, $R_l^{BH}$, is the accumulated data rates of those users served by BS $l$, which can be formulated as
\[
R_l^{BH} = \sum_{k \in \mathcal{K}} \mathbb{1}_{\{|w_{lk}|^2\}} R_k, \quad l \in \mathcal{L},
\] (12)
where $\mathbb{1}_{\{|w_{lk}|^2\}}$ is the indicator function defined in (6) and indicates whether or not BS $l$ serves user $k$.

Substituting (8) and (12) into (3), the total power minimization problem (7) can be formulated for the data-sharing strategy as
\[
\begin{align*}
\min_{\{w_{lk}\}} & \quad \sum_{l \in \mathcal{L}} \left( \eta_l \sum_{k \in \mathcal{K}} |w_{lk}|^2 + \mathbb{1}_{\{|\sum_{k \in \mathcal{K}} |w_{lk}|^2\}} P_{l,\Delta} ight. \\
& \quad \left. + \rho_l \sum_{k \in \mathcal{K}} \mathbb{1}_{\{|w_{lk}|^2\}} R_k \right) \\
\text{subject to} & \quad R_k = \log_2 \left( 1 + \frac{\text{SINR}_k}{\Gamma_m} \right) \geq r_k, \quad k \in \mathcal{K} \quad (13a) \\
& \quad \sum_{k \in \mathcal{K}} |w_{lk}|^2 \leq P_l, \quad l \in \mathcal{L}. \quad (13b)
\end{align*}
\]
Note that the $\sum_{l \in \mathcal{L}} P_{l,\text{sleep}}$ term in (3) is a constant and has been dropped in the objective function (13a). It is easy to see that the minimum rate constraint (13b) is met with equality at the optimal point. Hence, problem (13) can be equivalently formulated as
\[
\begin{align*}
\min_{\{w_{lk}\}} & \quad \sum_{l \in \mathcal{L}} \left( \eta_l \sum_{k \in \mathcal{K}} |w_{lk}|^2 + \mathbb{1}_{\{|\sum_{k \in \mathcal{K}} |w_{lk}|^2\}} P_{l,\Delta} ight. \\
& \quad \left. + \rho_l \sum_{k \in \mathcal{K}} \mathbb{1}_{\{|w_{lk}|^2\}} r_k \right) \\
\text{subject to} & \quad \text{SINR}_k \geq \gamma_k, \quad k \in \mathcal{K} \quad (14a) \\
& \quad \sum_{k \in \mathcal{K}} |w_{lk}|^2 \leq P_l, \quad l \in \mathcal{L}. \quad (14b)
\end{align*}
\]
where the variable $R_k$ in (13a) is replaced by the target rate $r_k$ in (14a) and $\gamma_k = \Gamma_m (2^{r_k} - 1)$ in (14b). The new SINR constraint (14b) is also met with equality at the optimality. However, we keep (14b) as an inequality constraint, so that it can be reformulated as a convex second-order cone (SOC) constraint [35]. Note that problem (14) is equivalent to problem (13) in the sense that they have the same optimal solutions and the same feasibility region.

Note that the above optimization is over the beamforming coefficients and also implicitly over the BS cluster for each user. The overall optimization problem (14) aims to choose the optimal cluster of serving BSs for each scheduled user for minimizing the total power consumption while satisfying the user QoS constraints. Due to the indicator functions in the objective function (14a), problem (14) is nonconvex (discrete), so finding its global optimum solution is challenging. In the following, we propose to approximate the nonconvex indicator function using reweighted convex $\ell_1$-norm and show that with a particular reweighting function the proposed algorithm always converges.

B. Proposed Algorithm

We make an observation that the indicator function defined in (6) is equivalent to the $\ell_0$-norm of a scalar. The $\ell_0$-norm of a vector is defined as the number of nonzero entries in the vector, so it reduces to the indicator function in the scalar case. In compressive sensing literature [6], nonconvex $\ell_0$-minimization problem can be approximated as convex reweighted $\ell_1$ minimization problem. We take advantage of this technique and propose to approximate the indicator functions in the objective function (14a) as
\[
\mathbb{1}_{\{|w_{lk}|^2\}} = \left\| \sum_{k \in \mathcal{K}} |w_{lk}|^2 \right\|_0 \approx \mu_l \sum_{k \in \mathcal{K}} |w_{lk}|^2 \quad (15)
\]
\[
\mathbb{1}_{\{|w_{lk}|^2\}} = \left\| |w_{lk}|^2 \right\|_0 \approx \nu_l |w_{lk}|^2 \quad (16)
\]
with weights $\mu_l$ and $\nu_l$ iteratively updated according to
\[
\begin{align*}
\mu_l &= f \left( \sum_{k \in \mathcal{K}} |w_{lk}|^2, \tau_1 \right) = \frac{c_1}{\sum_{k \in \mathcal{K}} |w_{lk}|^2 + \tau_1} \quad (17a) \\
\nu_l &= f \left( |w_{lk}|^2, \tau_2 \right) = \frac{c_2}{|w_{lk}|^2 + \tau_2} \quad (17b)
\end{align*}
\]
where $\{w_{lk}\}$ is the beamformer from the previous iteration, $\tau_1 > 0$ and $\tau_2 > 0$ are some constant regularization factors, and $c_1, c_2$ are constants.

Note that in the above iterative updates of $\mu_l$ and $\nu_l$, the BSs with small transmit power, $\sum_{k \in \mathcal{K}} |w_{lk}|^2$, or small transmit power to user $k$, $|w_{lk}|^2$, at current iteration are given larger weights $\mu_l$ or $\nu_l$ in the next iteration. This further decreases $\sum_{k \in \mathcal{K}} |w_{lk}|^2$ or $|w_{lk}|^2$ in the next iteration, and eventually forces BS $l$ toward sleep mode (i.e., $\sum_{k \in \mathcal{K}} |w_{lk}|^2 = 0$) or to be removed from user $k$’s serving cluster (i.e., $|w_{lk}|^2 = 0$). The weight $\mu_l$ has the effect of putting appropriate BSs to sleep mode, while $\nu_l$ has the effect of determining the BS cluster size for user $k$, which in turn affects the backhaul capacity consumption of user $k$.

The resulting optimization problem after the $\ell_1$-norm approximation is formulated as follows:
\[
\begin{align*}
\min_{\{w_{lk}\}} & \quad \sum_{l \in \mathcal{L}} \sum_{k \in \mathcal{K}} \alpha_{lk} |w_{lk}|^2 \\
\text{subject to} & \quad (14b), \quad (14c)
\end{align*}
\]
In fact, it converges to the stationary point solution of an approximation to problem (14).
Algorithm 1 Total Power Minimization for Data-Sharing Strategy

Initialization: Set the initial values for \( \{ \mu_l, \nu_l \} \) according to (17) with the \( \{ w_{lk} \} \) chosen as a feasible point of problem (14);

Repeat:

1) Fix \( \{ \mu_l, \nu_l \} \), find the optimal \( \{ w_{lk} \} \) by solving problem (18) using the uplink-downlink duality approach [36] or by transforming it into an SOCP problem [35];

2) Update \( \{ \mu_l, \nu_l \} \) according to (17).

Until convergence

where \( \alpha_{lk} = \eta_l + \mu_l P_{l,0} \Delta + \rho_l \nu_l r_k \). Problem (18) is a weighted sum transmit power minimization problem, which can be solved efficiently through the uplink-downlink duality approach [36] or by transforming it into an SOCP problem [35]. We now summarize the proposed algorithm to solve the total power minimization problem (14) for the data-sharing strategy in Algorithm 1.

Note that a similar problem as to (14) is considered in our previous work [24], where we formulate the problem as a tradeoff between the BS transmit power and the backhaul capacity. This paper considers a more realistic BS power consumption model with sleep mode capability, and also accounts for backhaul power consumption. The considered problem (14) in this paper can also be thought of as providing a tradeoff between the per-BS power consumption and the per-BS backhaul capacity consumption, where the tradeoff constant \( \rho_l \) is specifically chosen according to the backhaul power consumption model [4].

C. Convergence Analysis

Algorithm 1 relies on the reweighting heuristic (17) to deactivate BSs and reduce the BS cluster size for energy saving purpose. To establish the convergence proof for Algorithm 1 under arbitrary reweighting function is challenging, however, we show in the following that if the reweighting function is chosen as

\[
 f(x, \tau) = \frac{1}{(x + \tau) \ln(1 + \tau^{-1})},
\]

i.e. the constants in (17) are chosen as \( c_1 = \frac{1}{\ln(1+\tau_0^{-1})} \), \( c_2 = \frac{1}{\ln(1+\tau_0^{-1})} \). Algorithm 1 can be seen as a special case of the MM algorithms [28] and is guaranteed to converge.

**Theorem 3.1:** Starting with any initial point, the sequence \( \{ w_{lk}^{(n)} \}_{n=1}^{\infty} \) generated by Algorithm 1 with the reweighting function chosen as (19) is guaranteed to converge.

**Proof:** See Appendix A.

Finally, we point out that the choice of the reweighting function (19) is not unique. There exist other reweighting functions that may work well in different problem setups [6]. Recently, [27] has experimented with other approximation functions to the \( \ell_0 \)-norm, e.g. exponential function and arc-tangent function, in addition to the logarithmic function [32] used in this paper, and observed similar effectiveness of these functions in inducing sparsity.

D. Complexity Analysis

Algorithm 1 is an iterative procedure between updating the weights \( \{ \mu_l, \nu_l \} \) and solving the weighted transmit power minimization problem (18). The problem (18) can be formulated as an SOCP and solved using the interior-point method, e.g. using the convex optimization solver [37]. The total number of variables in problem (18) is \( L \times K \) and the total number of SOC constraints is \( L + K \). The complexity order for solving such a problem through interior-point method is given as \( O\left( (L + K)(LK)^3 \right) \) [38]. Assuming that Algorithm 1 requires a total number of \( T_1 \) weight updates, the overall complexity order for Algorithm 1 is then \( O\left( T_1 (L + K)(LK)^3 \right) \).

Note that in the above complexity order, \( K \) is the number of scheduled users, which is comparable to the number of active BSs in the network. In addition, instead of considering all the \( L \) BSs in the entire network, we can set the nearest \( L_c \) BSs around each scheduled user as its candidate serving BS cluster. This further reduces the computational complexity for Algorithm 1 with negligible performance loss.

E. Generalization to the Multi-Antenna System

Algorithm 1 can be readily generalized to the case with multiple transmit antennas at each BS. In such case, one only needs to replace the beamforming coefficient \( w_{lk} \) with the beamforming vector \( \mathbf{w}_{lk} \in \mathbb{C}^{N_t \times 1} \) from BS \( l \) to user \( k \), where \( N_t \) is the number of antennas at BS \( l \). The rest of the optimization parameters are straightforward extensions based on \( w_{lk} \) [24].

Algorithm 1 can also be applied to the case with multiple receive antennas at each user but with fixed receive beamformer. In this case, the only change is to replace the channel gain vector \( \mathbf{h}_k \) with the effective channel gain \( \tilde{\mathbf{h}}_k = \mathbf{h}_k \mathbf{u}_k \), where \( \mathbf{H}_k \in \mathbb{C}^{L \times M_k} \) and \( \mathbf{u}_k \in \mathbb{C}^{M_k \times 1} \) are the channel matrix seen by user \( k \) and the receive beamformer at user \( k \), \( M_k \) is the number receive antennas at user \( k \). However, the joint design of transmit beamformer and receive beamformer for the multiple receive antennas case is more complicated. One possible way is to iteratively design the transmit beamformer assuming fixed receive beamformer and update the receiver as the optimal minimum mean square error (MMSE) beamformer.

IV. COMPRESSION STRATEGY

In this section, we aim to minimize the total power consumption for downlink C-RAN under the compression strategy.

A. Problem Formulation

Consider the compression transmission strategy for downlink C-RAN as illustrated in Fig. 2. Let \( \hat{x}_l = \sum_{k \in K} w_{lk}s_{lk} \) denote the beamformed signal formed in the CP for BS \( l \). The CP compresses \( \hat{x}_l \) into \( x_l \) and sends \( x_l \) to BS \( l \). In this paper, we assume that each \( \hat{x}_l \) is compressed independently and model the compression procedure as the following forward test channel:

\[
x_j = \hat{x}_l + e_l, \quad l \in \mathcal{L},
\]

\( ^3 \)Correlated compression is also possible and has been considered in [9].
where $e_l \in \mathbb{C}$ is the quantization noise independent of $\hat{x}_l$ and is assumed to be Gaussian distributed with zero mean and variance $q^2_l$. Substituting (20) into (2), the transmit power at BS $l$ under the compression strategy can be written as

$$P_{l,tx} = \sum_{k \in K} |w_{lk}|^2 + q^2_l, \quad l \in \mathcal{L}. \quad (21)$$

Comparing (21) with (8), we can see that different from the data-sharing strategy, the BS transmit power in the compression strategy involves a quantization noise power in addition to the beamforming power.

Substituting (20) into (4), the received signal $y_k$ at user $k$ under the compression strategy can be written as

$$y_k = h^H_k w_k s_k + \sum_{j \neq k} h^H_k w_j s_j + h^H_k e + n_k, \quad k \in K, \quad (22)$$

where $e = [e_1, e_2, \ldots, e_L]^T$ is the quantization noise vector transmitted from all the $L$ BSs. As we can see, besides the inter-user interference and background noise, each user now also receives an additional quantization noise term $h^H_k e$ from the BSs. The user received SINR is expressed as

$$\text{SINR}_k = \frac{|h^H_k w_k|^2}{\sum_{j \neq k} |h^H_k w_j|^2 + \sum_{l \in \mathcal{L}} |h_{lk} q_l|^2 + \sigma^2}, \quad k \in K. \quad (23)$$

The backhaul capacity consumption for the compression strategy is related to the level of quantization noise $q^2_l$; lower quantization noise requires higher backhaul rate. Under the forward test channel (20), the achievable compression rate is the mutual information between $x$ and $\hat{x}$, according to rate-distortion theory [39], given as $\log_2 \left( 1 + \frac{\sum_{k \in K} |w_{lk}|^2}{q^2_l} \right)$, where $\sum_{k \in K} |w_{lk}|^2$ is the power of the signal to be compressed, i.e. $\hat{x}_l$. However, practical quantizer may be far from the theoretically ideal quantizer. Similar to (33), we introduce a notion of gap to rate-distortion limit, denote as $\Gamma_q > 1$, to account for the loss due to practical quantizer and formulate the backhaul capacity consumption for BS $l$ as

$$R^{BH}_l = \log_2 \left( 1 + \frac{\Gamma_q \sum_{k \in K} |w_{lk}|^2}{q^2_l} \right), \quad l \in \mathcal{L}. \quad (24)$$

Substituting (27) and (24) into (5), the total power minimization problem for the compression strategy is formulated as follows

$$\min_{\{w_{lk}, q_l\}} \sum_{l \in \mathcal{L}} \left( \eta_l \left( \sum_{k \in K} |w_{lk}|^2 + q^2_l \right) + \left\{ \sum_{k \in K} |w_{lk}|^2 + q^2_l \right\} P_{l,\Delta} \right)$$

$$+ \rho_l \log_2 \left( 1 + \frac{\Gamma_q \sum_{k \in K} |w_{lk}|^2}{q^2_l} \right) \quad (25a)$$

s.t. $\text{SINR}_k \geq \gamma_k, \quad k \in K \quad (25b)$

$$\sum_{k \in K} |w_{lk}|^2 + q^2_l \leq P_{l,\Delta}, \quad l \in \mathcal{L} \quad (25c)$$

where the SINR in (25b) is defined in (23). Due to the indicator function as well as the backhaul rate expression in (25a), the optimization problem (25) is nonconvex. In the following, we describe the techniques to approximate (25a) in a convex form.

**B. Proposed Algorithm**

The difficulties in solving problem (25) lie in both the indicator function and the nonconvex backhaul rate expression in the objective function (25a). For the indicator function, we can utilize the similar technique used in the previous section to approximate it using reweighted $\ell_1$-norm:

$$\| \{ \sum_{k \in K} |w_{lk}|^2 + q^2_l \} \|_0 \approx \beta_l \left( \sum_{k \in K} |w_{lk}|^2 + q^2_l \right) \quad (26)$$

where $\beta_l$ is iteratively updated according to the following reweighting function

$$\beta_l = f \left( \sum_{k \in K} |w_{lk}|^2 + q^2_l, \tau_3 \right) = \frac{c_3}{\sum_{k \in K} |w_{lk}|^2 + q^2_l + \tau_3} \quad (27)$$

where $\{w_{lk}, q_l\}$ come from the previous iteration, $\tau_3 > 0$ is some constant regularization factor, and $c_3$ is a constant.

For the backhaul rate (24), we can express it as a difference of two logarithmic functions: $\log_2 \left( \frac{q^2_l + \Gamma_q \sum_{k \in K} |w_{lk}|^2}{q^2_l - 2\rho_l \log_2 q_l} \right)$. Although the second term $-2\rho_l \log_2 q_l$ is convex in $q_l$, the first term is still nonconvex. To deal with the nonconvexity of the backhaul rate, we propose to successively approximate the first logarithmic function using the following inequality

$$\log_2 \left( \frac{q^2_l + \Gamma_q \sum_{k \in K} |w_{lk}|^2}{q^2_l - \frac{1}{\ln 2} \rho_l \ln 2} \right) \leq \log_2 \lambda_l + \frac{q^2_l + \Gamma_q \sum_{k \in K} |w_{lk}|^2}{\lambda_l \ln 2} - \frac{1}{\ln 2} \quad (28)$$
Algorithm 2 Total Power Minimization for Compression Strategy

**Initialization:** Set the initial values for \( \{ \beta_l \} \) and \( \{ \lambda_l \} \) according to (27) and (29) respectively with \( \{ w_{lk}, q_l \} \) chosen as a feasible point of problem (25).

**Repeat:**
1. Fix \( \{ \beta_l, \lambda_l \} \), find the optimal \( \{ w_{lk}, q_l \} \) by solving the convex optimization problem (30);
2. Update \( \{ \beta_l \} \) and \( \{ \lambda_l \} \) according to (27) and (29) respectively.

**Until** convergence due to the concavity of \( \log_2(x) \). The above inequality achieves equality if and only if

\[ \lambda_l = q_l^2 + \Gamma_q \sum_{k \in K} |w_{lk}|^2. \tag{29} \]

The right-hand side of (28) is a convex quadratic function in \( \{ w_{lk}, q_l \} \) for fixed \( \lambda_l \). This fact motivates us to successively solve the problem (25) with \( \log_2 \left( q_l^2 + \Gamma_q \sum_{k \in K} |w_{lk}|^2 \right) \) replaced by the right-hand side of (28) for fixed \( \lambda_l \), then to iteratively update \( \lambda_l \) according to (29).

Combining the above described \( l_1 \)-norm reweighting and successive convex approximation techniques, we get the resulting optimization problem under fixed \( \beta_l \) and \( \lambda_l \) as

\[
\begin{align*}
\text{minimize} \quad & \sum_{l \in L} \sum_{k \in K} \phi_l |w_{lk}|^2 + \sum_{l \in L} (\psi_l q_l^2 - 2 \rho_l \log_2 q_l) \\
& + \sum_{l \in L} \rho_l \left( \log_2 \lambda_l - \frac{1}{\ln 2} \right) \quad \text{constant} \\
\text{subject to} \quad & (25b), \quad (25c)
\end{align*}
\]

where \( \phi_l = \eta_l + \beta_l P_{l,\Delta} + \frac{\rho_l \gamma_l}{\lambda_l} \) and \( \psi_l = \eta_l + \beta_l P_{l,\Delta} + \frac{\rho_l}{\lambda_l} \).

Similar to the SINR constraint in (14b), the constraint (25b) can also be equivalently reformulated as an SOC constraint. Thus, problem (30) is a convex optimization problem and can be solved efficiently using standard convex optimization solver, e.g. [17], with polynomial complexity.

We summarize the proposed algorithm for solving problem (25) in Algorithm 2, which admits guaranteed convergence property as stated in the following theorem.

**Theorem 4.1:** Starting with any initial point, the sequence \( \{ w_{lk}^{(n)}, q_l^{(n)} \}_{n=1}^\infty \) generated by Algorithm 2 with the reweighting function in (27) chosen as (19) is guaranteed to converge.

**Proof:** See Appendix B.

Algorithm 2 shows a similar computational complexity as Algorithm 1 but with additional \( L \) quantization noise variables to be optimized in each iteration. Assuming that Algorithm 2 converges in \( T_2 \) iterations, its complexity order is then given as \( O \left( T_2 (L + K) (LK + L)^3 \right) \).

C. Generalization to the Multi-Antenna System

Algorithm 2 can be readily applied to the scenario where multiple transmit antennas are available at the BSs assuming that the CP performs independent compression for each antenna. Joint compression among the antennas may improve the performance but results in a different optimization problem. Similar to Algorithm 1, generalization of Algorithm 2 to multiple receive antennas at the user side is also straightforward if the receive beamformer is assumed to be fixed, however, joint design of transmit and receive beamformer is by no means trivial and requires additional efforts.

V. Numerical Evaluation of Energy Efficiency

In this section, we evaluate the energy efficiency of the data-sharing and compression strategies for downlink C-RAN using the proposed algorithms for a 7-cell network with wrapped-around topology. Each cell here refers to a geographic area with 4 RRHs as shown in Fig. 3. Equivalently, the network consists of 28 BSs. The out-of-cell interference combined with background noise is set as \(-150 \text{ dBm/Hz}\). The gap to rate-distortion limit is set as \( \Gamma_q = 4.3 \text{ dB} \) corresponding...
serving BSs for each user, we set the initial BS cluster for each of considering all the different number of scheduled users are simulated. Instead are listed in Table I. (4) are from [21]. All the parameters related to the simulations from [22] while the parameters for the backhaul power model reweighting technique in turning off BSs. We plot the number of active BSs remained in each iteration for both data-sharing (Algorithm 1) and compression (Algorithm 2) strategies in Fig. 4. The user target rate is set to be 20 Mbps for every user.

We first evaluate the effectiveness of the proposed algorithms in Fig. 5. As in Fig. 4, different number of scheduled users are tested and each user’s target rate is set to be 20 Mbps. As we can see, the objective values monotonically decrease and converge for both the data-sharing (Algorithm 1) and the compression (Algorithm 2) strategies. Similar to Fig. 4, we also observe faster convergence speed for data-sharing than for compression in Fig. 5. This is possibly due to the fact that compression strategy involves more variables to be optimized.

We now compare the performance of the data-sharing strategy and the compression strategy in terms of power saving in Fig. 6. In addition, we consider two reference schemes. In the first scheme, each user is only served by its strongest BS that is not already associated with another user. This scheme is termed as “Single BS Association”, for which the transmit power for each user can be minimized using the strategy in [41]. In the second scheme, each user’s message is shared among the 4 RRHs in its own cell and is cooperatively served by the 4 RRHs using the coordinated beamforming strategy of [46]. Such scheme is termed as “Per-Cell CoMP”. The “Single BS Association” and “Per-Cell CoMP” are two extreme cases in terms of number of active BSs: the former only has K (number of scheduled users) active BSs while in the latter all the 28 BSs in the entire network remain active. Each point in Fig. 6 is averaged over 100 channel realizations.

As we can see from Fig. 6, “Per-Cell CoMP” consumes the most power since all the BSs are active in this scheme. “Single BS Association” consumes the least power, similar to the data-sharing strategy, but only at low user rate regime because the minimum number of BSs are selected to serve the users in this scheme. However, as the user rate or the number of scheduled users increases, “Single BS Association” becomes infeasible very quickly. For instance, in Fig. 6(b) where there are 2 users per cell, “Single BS Association” can only support each user with 10 Mbps service rate, while in Fig. 6(c) the case of 3 users per cell, “Single BS Association” is not feasible even at 10 Mbps per user.

It is worth noting that “Single BS Association” consumes the same amount of power as data-sharing in the low user target rate regime in Fig. 6 as the latter essentially reduces to single BS association at low user rates. However, there is still significant advantage in migrating signal processing to the cloud in a C-RAN as compared to the conventional cellular architecture in term of computation power saving, which is not included in the model in this paper. It is also worth noting that the optimized data-sharing and compression strategies outperform the non-optimized per-Cell CoMP significantly in Fig. 6 highlighting the importance of optimization approaches.
proposed in this paper. Other optimized CoMP schemes with larger cooperation cluster may consume less BS transmission power, however, the overall power consumptions can be still very high if all the BSs remain active.

We also observe from Fig. 6 that neither the data-sharing nor the compression strategy dominates the other over the entire user target rate regime. For example in Fig. 6(b), although data-sharing consumes less power than compression when the user target rate is below 30 Mbps, its power consumption increases dramatically with the user rate and eventually crosses over the total power consumed by compression after 40 Mbps target rate. Similar trend can be observed from Fig. 6(a) and 6(c). This trend is parallel to the observation made in [33], in which these two downlink strategies are compared from the utility maximization perspective with limited backhaul constraint. It is observed in [33] that with low backhaul rate, data-sharing produces higher utility than compression while with high backhaul rate, compression outperforms data-sharing.

To investigate further, we plot the individual power consumption of BSs and backhaul links for both the data-sharing and the compression strategies in Fig. 7 for the case of 2 users per cell. As seen from Fig. 7 although the BS power consumptions for data-sharing and compression are similar in each case of the user target rate, the backhaul power consumptions are significantly different and are the determining factor in the choice of strategies. As the user target rate increases, the backhaul power consumption for data-sharing increases significantly and crosses over the compression strategy at around 30 Mbps. This is because in data-sharing, each user’s message needs to be delivered to each one of its serving BSs through backhaul links. So, the backhaul rate directly depends on both the user target rate and the BS cluster size. Note that as user target rate increases, the size of serving BS cluster also increases. The two factors together contribute to a much higher backhaul rate. In contrast, the backhaul rate of compression strategy depends on the logarithm of the signal-to-quantization-noise ratio, which only increases gradually as user target rate increases. Also, note that in the low user rate regime, data-sharing consumes less backhaul power than compression in Fig. 7. This is because it is more efficient to share data directly than to compress when only a few BSs are involved.

In Fig. 8 we compare the percentage of active BSs in the data-sharing strategy versus in the compression strategy. Similar to Fig. 6 each point in Fig. 8 is averaged over 100 channel realizations. As we can see, with higher user target rate and more users to be served, more BSs need to remain active for transmission. Also, from Fig. 8 it is observed that the compression strategy tends to turn off more BSs than the data-sharing strategy.
VI. CONCLUSION

This paper compares the energy efficiency between the data-sharing strategy and the compression strategy in downlink C-RAN. We formulate the problem as that of minimizing the total network power consumption subject to user target rate constraints, with both the BS power consumption and the backhaul power consumption taken into account. By taking advantage of the $\ell_1$-norm reweighting technique and successive convex approximation technique, we transform the nonconvex optimization problems into convex form and devise efficient algorithms with provable convergence guarantees.

The main conclusions of this paper are that C-RAN significantly improves the range of feasible user data rates in a wireless cellular network, and that both data-sharing and compression strategies bring much improved energy efficiency to downlink C-RAN as compared to non-optimized CoMP. Moreover, between the data-sharing strategy and the compression strategy, either may be preferred depending on the different target rate regimes: at low user target rate, data-sharing consumes less power, while at high user target rate compression is preferred since the backhaul rate for data-sharing increases significantly as user rate increases.

APPENDIX A

PROOF FOR THEOREM 3.1

The idea is to show that Algorithm 1 converges to the stationary point solution of the following problem:

$$\min_{\{w_{lk}\}} \sum_{l \in \mathcal{L}} \left( \eta_l \sum_{k \in \mathcal{K}} |w_{lk}|^2 + P_l \Delta \frac{\ln \left( 1 + \tau_1^{-1} \sum_{k \in \mathcal{K}} |w_{lk}|^2 \right)}{\ln \left( 1 + \tau_1^{-1} \right)} \right)$$

s.t. \[ (14b), (14c) \]

First, we note that problem (31) differs from the original problem (14) in that the $\ell_0$-norms in the objective function are approximated by the logarithmic functions in (31). This approximation stems from the relation that with $x \geq 0$,

$$\|x\|_0 = \lim_{\tau \to 0} \frac{\ln \left( 1 + x \tau^{-1} \right)}{\ln \left( 1 + \tau^{-1} \right)}.$$  \hspace{1cm} (32)

Now, due to the concavity of $\ln x$, the inequality $\ln x \leq \ln x_0 + x_0^{-1} x - 1$ holds for any $x > 0$, $x_0 > 0$ and achieves equality if and only if $x = x_0$. Hence, we have

$$\sum_{l \in \mathcal{L}} \left( \eta_l \sum_{k \in \mathcal{K}} |w_{lk}|^2 + P_l \Delta \frac{\ln x_l + x_l^{-1} \left( 1 + \tau_1^{-1} \sum_{k \in \mathcal{K}} |w_{lk}|^2 \right) - 1}{\ln \left( 1 + \tau_1^{-1} \right)} \right) + \rho_l \sum_{k \in \mathcal{K}} \frac{\ln y_{lk} + y_{lk}^{-1} \left( 1 + \tau_2^{-1} |w_{lk}|^2 \right) - 1}{\ln \left( 1 + \tau_2^{-1} \right)} r_{lk} \right),$$

where equality if and only if

$$x_l = 1 + \tau_1^{-1} \sum_{k \in \mathcal{K}} |w_{lk}|^2, \quad y_{lk} = 1 + \tau_2^{-1} |w_{lk}|^2.$$  \hspace{1cm} (33)

Although problem (31) is nonconvex due to the logarithmic objective function, the function on the right-hand side of (33) is a convex quadratic function in $\{w_{lk}\}$. Based on this fact, we can develop an MM algorithm to solve problem (31) by solving a sequence of convex optimization problems with the objective function in (31) replaced by the convex function in (33) and iteratively updating the parameters $x_l$, $y_{lk}$ according to (34). Comparing such MM algorithm with Algorithm 1, it is easy to see that Algorithm 1 reduces to the MM algorithm if the reweighting function in (17) is chosen as (19).

It is known in the literature [29] that an MM algorithm is guaranteed to converge to the stationary point solutions of the original problem if the approximate function satisfies the following conditions: 1) it is continuous, 2) it is a tight upper
bound of the original objective function and 3) it has the same first-order derivative as the original objective function at the point where the upper bound is tight. It is easy to check that the function in (33) satisfies all these sufficient conditions. Thus, Algorithm 1 which is equivalent to an MM algorithm, must converge.

**APPENDIX B PROOF FOR THEOREM 4.1**

Similar to the proof for Theorem 3.1, the idea is show that Algorithm 2 converges to the stationary point solution of the following optimization problem:

\[
\begin{align*}
\text{minimize} & \quad \sum_{l \in L} \left( \eta_l \left( \sum_{k \in K} |w_{lk}|^2 + q_l^2 \right) + P_l,_{\Delta} \left( 1 + \tau_3^{-1} \left( \sum_{k \in K} |w_{lk}|^2 + q_l^2 \right) \right) \right) \\
& \quad + \rho_l \log_2 \left( 1 + \frac{\Gamma_g \sum_{k \in K} |w_{lk}|^2}{q_l^2} \right)
\end{align*}
\]

subject to (25b), (25c),

which is a logarithmic approximation to the original problem (25).

Problem (35) is nonconvex due to the logarithmic functions in its objective function. However, we can develop an MM algorithm to solve (35) by solving a sequence of convex optimization problems with the objective function in (35) replaced by its upper bound shown below:

\[
\begin{align*}
\sum_{l \in L} & \left( \eta_l \left( \sum_{k \in K} |w_{lk}|^2 + q_l^2 \right) - 2\rho_l \log_2 q_l \right) \\
& + P_l,_{\Delta} \ln \left( 1 + \tau_3^{-1} \left( \sum_{k \in K} |w_{lk}|^2 + q_l^2 \right) \right) - 1 \\
& + \rho_l \left( \log_2 q_l + \frac{\Gamma_g \sum_{k \in K} |w_{lk}|^2}{\lambda_l \ln 2} - \frac{1}{\ln 2} \right)
\end{align*}
\]

and iteratively updating the parameters \(z_l\) as \(z_l = 1 + \tau_3^{-1} \left( \sum_{k \in K} |w_{lk}|^2 + q_l^2 \right)\) and \(\lambda_l\) as (29). It is easy to see that such MM algorithm is equivalent to Algorithm 2 with the reweighting function in (27) chosen as (19). We can also easily verify that the majorizing function in the right-hand side of (36) satisfies all the sufficient conditions in (29) for the convergence guarantee of MM algorithm. Hence, Algorithm 2 must converge.

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