Energy-Efficient Coordinated Multipoint Scheduling in Green Cloud Radio Access Network

Deze Zeng, *Member, IEEE*, Jie Zhang, Lin Gu, *Member, IEEE*, Song Guo, *Senior Member, IEEE*, and Jiangtao Luo, *Senior Member, IEEE*

***Abstract*—The fast development of mobile computing has raised ever-increasing diverse communication needs in wireless networks. To catch up with such needs, cloud radio access networks (CRAN) is proposed to enable efficient radio resource sharing and management. At the same time, the massive deployment of radio access networks has caused huge energy consumption. Incorporating renewable green energy to lower the brown energy consumption also has become a widely concerned topic. In this paper, we are motivated to investigate a green energy aware remote radio head activation problem for coordinated multipoint communications in green energy powered CRAN, aiming at minimizing the network brown energy power consumption. The problem is first formulated into a nonconvex optimization form. By analyzing the characteristics of the formulation, we further propose a heuristic algorithm based on an ordered selection method. Extensive simulation based experiment results show that the proposed green energy aware algorithm provides an effective way to reduce brown energy power consumption, well fitting the goal of developing green communications.**

***Index Terms*—Green energy, cloud radio access networks, energy efficiency, convex optimization.**

I. Introduction

To PURSUE the vision of smart cities, a massive number of wireless devices (e.g., smart meters, various sensors, intelligent transportation devices, etc.) have been penetrated into the cities during the past decades. This results in an exponential growth in both the number of connected user equipments (UE) and the volume of data. According to the report from Ericsson, the number of mobile subscriptions will reach 7.7 billion by 2021. Due to such fact, it is estimated that the total mobile data traffic will reach 30.6 Exabytes by 2020, according to the report from Cicso. To satisfy such huge mobile subscriptions and data traffic, a lot of base stations shall be deployed. The vast deployment of base stations results in huge energy consumption, raising wide concern among the mobile operators [1]. Such trend imposes challenges to both the performance efficiency and power efficiency of radio networks.

To cope with these challenges, a newly emerging technology, named cloud radio access networks (CRAN), has been proposed and shown great potential in promoting the performance efficiency, energy efficiency as well as the network flexibility of future wireless networks. CRAN decouples the baseband processing function from traditional base station and centralizes it into shared baseband unit (BBU) pool, by exploring technologies like network function virtualization (NFV) and software defined network (SDN) [2]–[5]. Via embracing edge computing technology [6]–[11], BBU pool can also reside in the edge cloud, referred as Fog Radio Access Networks (FRAN). By such means, the front-end becomes simple and lightweight remote radio heads (RRHs) that can be densely deployed to provide radio access services for different UEs, well fitting the fast growing communication demands of smart city applications.

Meanwhile, another developing trend on the wireless networks is on the revolution of power provision paradigm, i.e., from traditional non-renewable brown energy to renewable green energy. By powering wireless networks via distributed renewable resources (DER) that harvest green energy from the environment (e.g., solar, geothermal, wind, tide and hydro), it has shown great potential in pursuing high network energy efficiency [12], [13]. By decoupling the baseband processing, the front-end RRHs become simple and lightweight. Therefore, it is natural to power the RRHs with green energy from DERs. This motivates us to consider a green energy powered CRAN architecture, as shown in Fig. 1, where all the RRHs are powered by both green energy from DERs and brown energy from the power grid [14]. In such architecture, how to manage the network resources with the consideration of green energy generation condition therefore becomes a critical issue to be tackled.

CRAN has been widely regarded as an ideal platform to realize coordinated multi-point (CoMP) communications. By centralizing the baseband processing, a BBU can compute the beamforming weight coefficients for different RRHs that serve one UE. Upon the reception of the precoded data, the RRHs then can cooperatively transmit the data to the served UE, which

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D. Zeng and J. Zhang are with the Hubei Key Laboratory of Intelligent Geo-Information Processing, School of Computer Science, China University of Geosciences, Wuhan 430074, China (e-mail: deze@cug.edu.cn; junshan.zhang@asu.edu).

L. Gu is with the School of Computer Science and Technology, Huazhong University of Science and Technology, Wuhan 430074, China (e-mail: linny.gu@gmail.com).

S. Guo is with the Department of Computing, The Hong Kong Polytechnic University, Kowloon Hong Kong (e-mail: cssongguo@comp.polyu.edu.hk).

J. Luo is with the Chongqing University of Posts and Telecommunications, Chongqing 400065, China (e-mail: luojt@cqupt.edu.cn).

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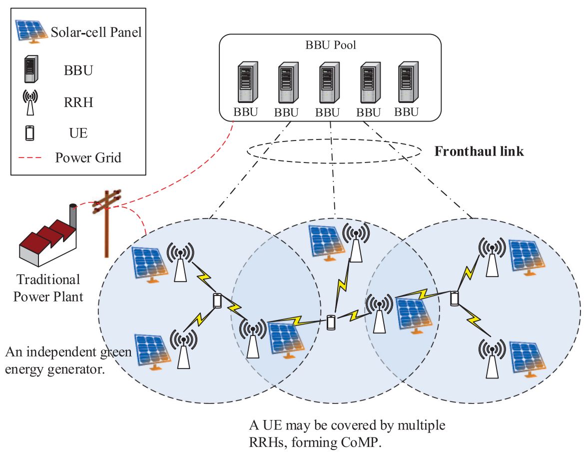

Fig. 1. Green energy powered C-RAN architecture. All the RRHs are powered by both legacy power grid and an independent green energy generator. A UE may be covered by multiple RRHs, forming CoMP.

shall then observe the superposition of multiple signals from the serving RRHs. By coherently combining the signals, a high signal-to-interference-plus-noise ratio (SINR) shall be achieved, potentially improving the network's spectral efficiency and performance efficiency. In order to save energy consumption, it has been shown that not all, but a subset of, RRHs need to be activated, provided that the predefined Quality-of-Service (QoS) is guaranteed. Although energy efficient RRH activation has been widely discussed in the literature, e.g., [15], [16], we notice that none of existing studies take the green energy generation characteristics into consideration. With the consideration of green energy, aggressively shutting down the RRHs to minimize the number of RRHs activated does not always mean high energy efficiency. Instead, we shall carefully choose the RRHs that shall be activated to form a CoMP cluster for each UE. This motivates us to investigate the green energy aware RRH activation for CoMP communications in green energy powered CRAN in this paper. The main contributions of this article are as follows.

- To our best knowledge, we are the first to investigate the problem of green energy aware RRH activation for CoMP scheduling in CRAN. We formally describe the problem into a non-convex optimization programming problem.
- By reformulating and relaxing the original problem into a convex one, we further propose a heuristic green energy aware RRHs activation algorithm.
- Through extensive simulations, the high energy efficiency of our green energy-aware RRHs selection algorithm is verified by the fact that it indeed outperforms the competitor without the consideration of green energy generation characteristics.

The rest of this paper is organized as follows. Section II introduces the background and preliminaries. Then, Section III reviews some representative related work. Section IV introduces the system model and states the problem to be studied. A non-convex formulation is presented in Section V. Section VI proposes our green energy aware algorithm. The performance is verified by simulations in Section VII. Finally, Section VIII concludes this paper.

II. Background and Preliminaries

In this section, we briefly introduce the background on green energy powered CRAN and CoMP communication.

A. Green Energy Powered Cloud Radio Access Networks

It is noticed that traditional cellular networks consisting of stand-alone base stations suffer many limitations in cost, efficiency and management. To address these limitations, CRAN was first proposed by China Mobile in 2010 [1]. An architecture overview of CRAN is shown in Fig. 1. Obviously, it can be seen that the BBUs are detached from RRHs and centralized into the cloud as BBU pool. After the separation, the hardware-only RRHs respond for simple signal processing while the entire baseband processing is migrated to the BBUs. The lightweight RRHs then are scattered in the network to directly provide radio access services to the user equipments.

In order to alleviate the energy poverty problem and to pursue high network energy efficiency, distributed energy resources (DER) that harvest green energy (e.g., solar energy and wind energy) are introduced. As shown in Fig. 1, all the RRHs are simultaneously powered by both DERs and traditional power grid. The incorporation of green energy substantially reduces carbon footprints resulted from conventional brown energy. It is expected that the integration of green energy can alleviate the energy poverty and sustain the wireless network better. After the introduction of green energy, more advanced green energy aware network resource management is highly demanded.

B. Coordinated Multi-Point Access in CRAN

To migrate the inter-cell interference in dense cellular networks, it has been shown that CoMP has been regarded as one of the most efficient technologies by improving the SINR at the intended receiver [17]. Therefore, it is likely that CoMP would be an essential feature of the fifth generation (5G) networks [18]. As CRAN is also regarded as an essential 5G feature, CoMP in CRAN also has attracted much attention. Wang *et al.* [19] study a CRAN based CoMP example for LTE-A and prove its high spectral efficiency gains. Davydov *et al.* [20] discover that it is possible to realize large CoMP cluster size in CRAN thanks to the centralization of BBUs. Therefore, it is natural to incorporate CoMP into CRAN.

As shown in Fig. 1, a number of RRHs may share a BBU and a UE may connect to multiple RRHs at the same time. Such architecture naturally fits the adoption of CoMP for downlink data communications. The shared BBU can encode the precoded signals with different beamforming weight coefficients to different RRHs, which then cooperatively transmit the precoded signals to the same UE. The UE can then decode the combined signal from multiple RRHs to obtain the data finally.

III. Related Work

In this section, we review some recent progress in the resource management in CRAN and green energy powered wireless networks.

A. Resource Management in CRAN

It is widely agreed that CRAN exhibits spectrum efficiency, performance efficiency, energy efficiency and cost efficiency over traditional architecture. Pioneering researchers have conducted various analytics studies from different aspects. On the performance efficiency, He *et al.* [21] consider distributed antenna system (DAS) in CRAN and analyze the upper and lower bounds of the downlink ergodic capacity in closed-form. On the energy efficiency perspective, Sabella *et al.* [22] theoretically discuss the energy efficiency advantage of CRAN by introducing a generalized holistic power model with the consideration of power consumption at the RRHs, BBUs and the backhaul connections. Alhumaima *et al.* [23] capture the power consumption of individual components and investigate the effect of different parameters, such as the number of antennas and the system bandwidth, to the energy efficiency of CRAN. On the cost efficiency, Suryaprakash *et al.* [24] show that CRAN can save around 10% to 15% less capital expenditure comparing to LTE networks.

Some recent efforts are also devoted to further improving the energy efficiency of CRAN by exploring its inherent features. Liu *et al.* [25] discuss a re-configurable backhaul in CRAN that allows a one-to-many mapping between RRHs and BBUs, thereby resulting in dynamic activation of BBUs and energy saving. Such concept is also practically proved by a prototype designed by Sundaresan *et al.* in [26]. As CoMP can be easily implemented in CRAN, how to promote the performance efficiency and energy efficiency for CoMP communication in CRAN also has attracted much attention. Wang *et al.* [27] study how to jointly allocate the radio and optical resources to improve the network throughput in virtualized CRAN with CoMP communications. Regarding the fronthaul network resource, Qi *et al.* [28] propose to use distributed compression to reduce the fronthaul network congestion for CoMP in CRAN. Regarding energy efficiency, Li *et al.* [29] discuss a queue-aware joint optimization of RRH activation and beamforming towards high energy efficiency of CRAN. Basically, they think that the less RRHs activated, the higher energy efficiency.

B. Green Energy Powered Wireless Networks

Due to the global energy shortage and environment crisis, energy efficiency has been discussed for a long time [30], [31]. Smart grid, featured by renewable green energy and intelligent energy management, has been widely regarded as a promising next-generation electric power system. It is estimated that the green energy from the environment can satisfy more than 50% of the global energy demand. It is therefore highly recommended to incorporate green energy in wireless networks [32], [33]. Pioneering researchers have widely discussed how to apply green energy in wireless networks, e.g., [12], [13], [34], [35]. For example, Niyato *et al.* [12] present an adaptive power management for the wireless base station powered by green energy sources in a smart grid environment. Later on, Li *et al.* [13] investigate a green energy inventory policy in a wireless communication system in which base stations are simultaneously powered by green energy sources and legacy power grids. Although existing studies prove the feasibility and efficiency of utilizing green energy in wireless networks, none of them consider how to manage the green resources in CRAN, especially with the joint consideration of CoMP.

IV. System Model and Problem Statement

In this section, we first introduce the system model for our work on green energy aware RRH activation for CoMP in green energy powered CRAN and then formally formulate the problem into a non-convex form.

A. System Model

1) Network Model: We consider a CRAN, as shown in Fig. 1, with a set $\mathcal{L} = \{1, 2, \ldots, L\}$ of RRHs randomly scattered in the network, where RRH $l \in \mathcal{L}$ is equipped with N_l antennas. All the RRHs are simultaneously powered by legacy power grid with brown energy and DER with renewable green energy. We assume that the average green energy generation rate at DER on RRH l is $P_{g,l}$. Due to the separation of RRH and BBU, the fronthaul network connecting RRHs and BBUs requires a extremely high bandwidth to transport the digital I-Q samples [36]. Usually, high-speed medium is adopted by the fronthaul network. It could be in either wired or wireless way, e.g., fiber or microwave. We assume that a fixed amount of fronthaul network capacity is shared by the RRHs and the maximum allowable fronthaul network capacity on RRH $l \in \mathcal{L}$ is $C_{l,\max}$ [37].

A set $\mathcal{K}$ of single-antenna UEs are randomly distributed and are connected to these RRHs to acquire network access service. In this paper, we mainly consider downlink data communications. To ensure the QoS, UE $k \in \mathcal{K}$ requires a minimum achievable data rate r_k. As we have known, CRAN is a natural platform to easily adopt CoMP for QoS promotion. Therefore, a UE may simultaneously connect to multiple active RRHs to acquire network service. For traceability on the RRH activation, we follow the channel model widely used in the literature (e.g., [19], [22], [25], [28], [29], [38]), without the consideration of fading, shadowing, and path loss. By treating interference as noise, we assume that single user detection is employed in the network. Such assumption actually is widely accepted in the literature with the consideration of low-complexity and energy-efficient structure of antenna.

2) Power Model: In this paper, we are mainly interested in minimizing the energy consumption on the RRHs, which consists of three parts.

The first part is for the wireless signal transmission to the UEs and is proportional to the beamforming vector, i.e., $P_l^{\mathrm{tr}} = \sum_{k\in\mathcal{K}} \| \mathbf{w}_{lk} \|_{\ell_2}^2$. It is widely noted that a RRH $l \in \mathcal{L}$ is with a predefined transmission power limitation P_l that cannot be surpassed, regardless of the usage of brown energy or green energy.

A high-capacity fronthaul connection is established between a RRH and its associated BBU. It is noticed that the power consumption on the high-speed fronthaul links is comparable to the one for wireless transmissions [39]. Therefore, the fronthaul network energy consumption is un-ignorable. As each activated RRH must associate with its BBU via one fronthaul link, we calculate the fronthaul energy consumption due to RRH l as $P_l^{\text{fr}} = \sum_{k\in\mathcal{K}} \frac{1}{\eta_l} \| \mathbf{w}_{lk} \|_{\ell_2}^2$, where η_l is the drain efficiency of the radio frequency power amplifier on RRH l [40].

Besides the above two kinds of energy consumption, another un-ignorable part is known as the static energy consumption, independent of the signal received and sent. Whenever a RRH $l \in \mathcal{R}$ is activated, a fixed amount P_l^c of energy, mainly depending on the number of antennas, is consumed.

As a result, we can express the energy consumption on a RRH $l \in \mathcal{L}$ as

$$P_l = \sum_{k\in\mathcal{K}} \| \mathbf{w}_{lk} \|_{\ell_2}^2 + \sum_{k\in\mathcal{K}} \frac{1}{\eta_l} \| \mathbf{w}_{lk} \|_{\ell_2}^2 + P_l^c, \forall l \in \mathcal{L}. \quad (1)$$

B. Problem Statement

With respect to energy efficiency, there is no need to activate all RRHs provided that the predefined QoS of all users get satisfied. Intuitively, the less RRHs activated, the higher energy efficiency can be achieved. However, by taking the green energy into consideration, we are mainly interested in maximizing the usage of green energy so as to minimize the brown energy consumption. Appropriate selection of the active RRH set with the consideration of diverse green energy generation rates is critical to the energy efficiency of the network. Besides, as the RRHs cooperatively send the signal with different weights to the users. It is also of great importance to appropriately set the weight on each RRHs for a UE. As a result, our problem can be stated as: how to appropriately choose a subset $\mathcal{A} \subseteq \mathcal{L}$ and set the weight on the active RRHs for different users, so as to minimize the brown energy consumption, while still guaranteeing the predefined QoS of all users.

V. Problem Formulation and Analysis

Based on the above discussion, in this section, we formally formulate our problem and make analysis to comprehensively understand it.

A. Problem Formulation

1) QoS Constraints: By enabling CoMP, a UE may associate with multiple active RRHs at the same time. With respect to energy efficiency, not all RRHs need to be active but a subset $\mathcal{A} \subseteq \mathcal{L}$ shall be activated provided the predefined QoS requirements of all users get satisfied. Hence, the baseband received signal at UE $k \in \mathcal{K}$ is given by

$$y_k = \sum_{l\in\mathcal{A}} \mathbf{h}_{kl}^{\text{H}} \mathbf{w}_{lk} s_k + \sum_{i\neq k} \sum_{l\in\mathcal{A}} \mathbf{h}_{kl}^{\text{H}} \mathbf{w}_{li} s_i + z_k, \forall k \in \mathcal{K}, \quad (2)$$

where s_k is a complex scalar denoting the data symbol for user k, $\mathbf{w}_{lk} \in \mathbb{C}^{N_l}$ is the beamforming vector at RRH l for user k, $\mathbf{h}_{kl} \in \mathbb{C}^{N_l}$ is the channel channel state information (CSI) vector from RRH l to user k, and $z_k \in \mathcal{CN}(0, \sigma_k^2)$ is the additive Gaussian noise.

The corresponding signal-to-interference-plus-noise ratio (SINR) for UE k is hence given by

$$\text{SINR}_k = \frac{\left|\sum_{l\in\mathcal{A}} \mathbf{h}_{kl}^{\text{H}} \mathbf{w}_{lk}\right|^2}{\sum_{i\neq k} \left|\sum_{l\in\mathcal{A}} \mathbf{h}_{kl}^{\text{H}} \mathbf{w}_{li}\right|^2 + \sigma_k^2}, \forall k \in \mathcal{K}. \quad (3)$$

Note that we theoretically consider that a UE can be served by any RRH in (3).

In order to ensure the minimum achievable data rate of UE $k \in \mathcal{K}$, according to the Shannon's theorem, the SINR value of UE k shall be larger than a predefined value γ_k [16]. That is,

$$\text{SINR}_k \geq \gamma_k, \forall k \in \mathcal{K}. \quad (4)$$

2) RRH Transmission Power Constraints: As we have known, the maximum transmission power consumption each RRH that can tolerate is limited. Therefore, the total transmission power consumption for all users on a RRH is constrained by the maximum allowable power P_l, i.e.,

$$\sum_{k\in\mathcal{K}} \| \mathbf{w}_{lk} \|_{\ell_2}^2 \leq P_l, \forall l \in \mathcal{A}. \quad (5)$$

3) Fronthaul Network Capacity Constraints: The fronthaul link is used to carry the signal from the BBUs to RRHs. For each UE $k \in \mathcal{K}$, the fronthaul network capacity consumption on a RRH is proportional to its data rate, i.e., the number of data symbols to be carried by the fronthaul link from BBU to RRH l for UE k. By adopting CoMP, a number of RRHs may cooperate with each other to serve one user. If a UE k is served by RRH $l \in \mathcal{L}$, it indicates that its corresponding beamforming vector $\mathbf{w}_k$ is nonzero. To this end, we define an indicator function as

$$f\left(\|\mathbf{w}_{lk}\|_{\ell_2}^2\right) = \begin{cases} 0, & \text{if } \|\mathbf{w}_{lk}\|_{\ell_2}^2 = 0, \\ 1, & \text{if otherwise.} \end{cases} \quad (6)$$

Now, following [41], we can describe the fronthaul network bandwidth requirement of an active RRH $l \in \mathcal{A}$ as the accumulated data rates to be transmitted between the BBU pool and RRH l for all UEs, i.e.,

$$C_l = \sum_{k\in\mathcal{K}} f\left(\|\mathbf{w}_{lk}\|_{\ell_2}^2\right) \cdot r_k, \forall l \in \mathcal{A}. \quad (7)$$

As we have known, the fronthaul network capacity for each RRH is limited. As a result, the total bandwidth requirement on a RRH shall not exceed its capacity, i.e.,

$$\sum_{k\in\mathcal{K}} f\left(\|\mathbf{w}_{lk}\|_{\ell_2}^2\right) \cdot r_k \leq C_{l,\max}, \forall l \in \mathcal{A}. \quad (8)$$

4) Problem Formulation: The RRHs are simultaneously powered by brown energy from legacy power grid and green energy from DERs. Our objective to maximize the energy efficiency is equivalent to minimizing the brown energy usage. For each RRH $l \in \mathcal{A}$, the brown energy consumption $P_{b,l}$ can be calculated as

$$\begin{aligned} P_{b,l} &= \max\{0, P_l - P_{g,l}\} \\ &= \max\left\{0, \sum_{k\in\mathcal{K}} \left(1+\frac{1}{\eta_l}\right) \| \mathbf{w}_{lk} \|_{\ell_2}^2 + P_l^c - P_{g,l}\right\}, \forall l \in \mathcal{A}, \end{aligned} \quad (9)$$

by which we can express the total brown energy consumption on all RRHs as

$$p_b(\mathcal{A}, \mathbf{w}) = \sum_{l\in\mathcal{A}} \max\left\{0, \sum_{k\in\mathcal{K}} \left(1+\frac{1}{\eta_l}\right) \| \mathbf{w}_{lk} \|_{\ell_2}^2 + P_l^c - P_{g,l}\right\},$$

where $\mathbf{w} = [\mathbf{w}_{11}^T, \ldots, \mathbf{w}_{1k}^T, \ldots, \mathbf{w}_{L1}^T, \ldots, \mathbf{w}_{LK}^T]^T$.

Now, we can formulate the brown energy consumption problem as

$$\mathscr{P}: \quad \min_{\mathbf{w},\mathcal{A}} \; p_b(\mathcal{A}, \mathbf{w})$$
$$\text{s.t.} \quad (4), (5), (8).$$

It can be seen that problem $\mathscr{P}$ is with variables $\mathbf{w}$ and $\mathcal{A}$, referring to the active RRH set selection and the beamforming weight settings, respectively. It is an NP-hard non-convex problem and is difficult to solve in general. We will further analyze it and try to reformulate it in the next section.

B. Problem Reformulation and Analysis

1) Problem Reformulation: We notice that the objective function, transmission power and fronthaul network capacity constraints are all not affected by any phase rotation of the beamforming vector, i.e., $\mathbf{w}_k = [\mathbf{w}_{1k}^T, \ldots, \mathbf{w}_{lk}^T, \ldots, \mathbf{w}_{Lk}^T]^T \in \mathbb{C}^{\sum_{l\in\mathcal{A}} N_l}$. As a result, according to [42], we can rewrite the QoS constraint for user $k \in \mathcal{K}$ in a second-order cone (SOC) form as:

$$C_1(\mathcal{A}, \mathbf{w}): \sqrt{\sum_{i\neq k} \left|\mathbf{h}_k^{\mathrm{H}} \mathbf{w}_i\right|^2 + \sigma_k^2} \leq \frac{1}{\sqrt{\gamma_k}} \left|\mathbf{h}_k^{\mathrm{H}} \mathbf{w}_k\right|^2, \forall k \in \mathcal{K}, \tag{10}$$

where $\mathbf{h}_k^H = [\mathbf{h}_{k1}^{\mathrm{H}}, \ldots, \mathbf{h}_{kl}^{\mathrm{H}}, \ldots, \mathbf{h}_{kL}^{\mathrm{H}}] \in \mathbb{C}^{\sum_{l\in\mathcal{A}} N_l}$.

The RRH transmission power constraints can be also rewritten into SOC form as:

$$C_2(\mathcal{A}, \mathbf{w}): \sqrt{\sum_{k\in\mathcal{K}} \|\mathbf{w}_{lk}\|_{\ell_2}^2} \leq \sqrt{P_c^l}, \forall l \in \mathcal{A}. \tag{11}$$

For the fronthaul network capacity constraints, we first equivalently rewrite the indicator function $f(\|\mathbf{w}_{lk}\|_{\ell_2}^2)$ as

$$f\left(\|\mathbf{w}_{lk}\|_{\ell_2}^2\right) = \left\|\|\mathbf{w}_{lk}\|_{\ell_2}^2\right\|_{\ell_0}. \tag{12}$$

According to [43], we can approximate the non-convex ℓ_0-norm expressions by a convex ℓ_1-norm to deal with the discrete indicator function in constraints (8) as follows

$$\|\mathbf{w}\|_{\ell_0} \approx \sum_{i\in\mathcal{K}} \beta_i |w_i|, \tag{13}$$

where w_i is the i-th element in vector $\mathbf{w}$ with weight β_i. Then, following [41], the constraints (8) in $\mathscr{P}$ can be rewritten as

$$C_3(\mathcal{A}, \mathbf{w}): \sum_{k\in\mathcal{K}} \beta_{lk} \|\mathbf{w}_{lk}\|_{\ell_2}^2 \cdot r_k \leq C_{l,\max}, \forall l \in \mathcal{A}, \tag{14}$$

where

$$\beta_{lk} = \frac{1}{\|\mathbf{w}_{lk}\|_{\ell_2}^2 + \tau}, \forall k \in \mathcal{K}, l \in \mathcal{A} \tag{15}$$

and τ is a small positive factor to ensure stability and can be set as $\tau = 10^{-10}$ [41].

Now, problem $\mathscr{P}$ can be transformed into

$$\mathscr{P}_1: \quad \min_{\mathbf{w},\mathcal{A}} \; p_b(\mathcal{A}, \mathbf{w})$$
$$\text{s.t.} \quad C_1(\mathcal{A}, \mathbf{w}), C_2(\mathcal{A}, \mathbf{w}), C_3(\mathcal{A}, \mathbf{w})$$

Similarly, $\mathcal{A}$ and $\mathbf{w}$ are the variables to be derived. Let us first consider the case where the active RRH set $\mathcal{A}$ is given and fixed. This shall result in a brown energy consumption minimization problem $\mathscr{P}_1(\mathcal{A})$. Thereafter, we can search over all the possible active RRH sets based on the solution of $\mathscr{P}_1(\mathcal{A})$ in a brute-force manner. Therefore, we have

$$p_{opt} = \min_{\mathcal{A}^* \in \{\mathcal{A}_1, \ldots, \mathcal{A}_n\}} \quad p_{opt}(\mathcal{A}^*) \tag{16}$$

where $p_{opt}(\mathcal{A}^*)$ is the optimal value of the problem $\mathscr{P}_1(\mathcal{A}^*)$. $\{\mathcal{A}_1, \ldots, \mathcal{A}_n\}$ is the set of fixed RRH sets.

2) Complexity Analysis: The number of set $\mathcal{A}^*$ for a given RRH set with cardinality m is $\binom{L}{m}$, which can be very large. Besides, note that the value of m could range between 1 and L in theory. As a result, the searching space discussed above shall exponentially increase with the number of RRHs L. Therefore, brute-force searching method is not feasible in practice. Therefore, we propose a heuristic algorithm in the next Section.

VI. Green Energy Aware Algorithm Design

In order to avoid treating $\mathcal{A}$ as variables or brute-force searching of all the feasible active RRH set $\mathcal{A}$, we propose a heuristic green energy aware RRH activation algorithm in this Section.

By analyzing $\mathscr{P}_1$, we notice that $p_b(\mathcal{A}, \mathbf{w})$ is a convex function if the active RRH set $\mathcal{A}$ is given. However, even with given $\mathcal{A}$, it is still difficult to solve $\mathscr{P}_1$ due to the involvement of the fronthaul network capacity constraints C_3, where the value of r_k is also related with variables $\mathbf{w}$. To address this problem, we plan to further temporarily exclude the fronthaul network capacity constraints C_3. By such means, we can obtain a solvable SOC problem as

$$\mathscr{P}_{soc}(\mathcal{A}): \quad \min_{\mathbf{w}} \; p_b(\mathbf{w})$$
$$\text{s.t.} \quad C_1(\mathbf{w}), C_2(\mathbf{w}),$$

where $\mathbf{w}$ is the optimization variable to be derived for a given $\mathcal{A}$. The above observations motivate the main concept of our algorithm as: we first treat all RRHs as active and then try to iteratively switch off the RRHs with certain rule and solve $\mathscr{P}_{soc}(\mathcal{A})$ with the updated $\mathcal{A}$ until we find out a feasible solution that can minimize the brown energy consumption, without violating any constraints discussed in Section V. Our proposed heuristic algorithm is summarized in Algorithm 1 and will be detailed as follows.

We first initialize $\mathcal{A}$ as the whole RRH set, i.e., $\mathcal{A} = \mathcal{L}$, and the inactive RRH set is accordingly initialized as empty, i.e., $\mathcal{D} = \emptyset$, as shown in line 1. We first solve $\mathscr{P}_{soc}(\mathcal{A})$ to obtain an initial solution on the beamforming vector $\mathbf{w}$ in line 2. If the problem is feasible, we then try to iteratively switch off RRHs in $\mathcal{A}$ until finding out a feasible solution that can minimize the brown energy consumption.

To this end, we propose a RRH ordering rule based on several factors (e.g., the beamforming vector already obtained, the fronthaul network capacity, RRH power consumption and the

Algorithm 1: Green Energy aware RRH Activation Algorithm Towards Energy Efficient CoMP in CRAN.

1: Initialization: the active RRH set $\mathcal{A} \leftarrow \mathcal{L}$, inactive RRH set $\mathcal{D} = \emptyset$
2: Take $\mathcal{A}$ into $\mathscr{P}_{soc}(\mathcal{A})$ and solve the convex optimization problem
3: **if** $\mathscr{P}_{soc}(\mathcal{A})$ is feasible **then**
4: Obtain the corresponding beamforming vector $\mathbf{w}$
5: Sort the RRHs in $\mathcal{A}$ in an ascending order $\theta_{\pi_1} \leq \cdots \leq \theta_{\pi_{|\mathcal{A}|}}$ according to the ordering criteria defined in (17)
6: **repeat**
7: Remove the first element, i.e., π_1, from active RRH set $\mathcal{A}$
8: Solve $\mathscr{P}_{soc}(\mathcal{A})$ with updated $\mathcal{A}$
9: **if** it is feasible **then**
10: Insert π_1 into $\mathcal{D}$
11: **end if**
12: **until** $\mathscr{P}_{soc}(\mathcal{A})$ is infeasible
13: Obtain the RRHs that shall be activated and the corresponding transmission beamformers for all users
14: **else if** $\mathscr{P}_{soc}$ is infeasible **then**
15: go to **end**
16: **end if**
17: **end**

green energy generation rate, etc.) as:

$$\theta_l = \sqrt{\frac{\eta_l \sum_{k\in\mathcal{K}} \|\mathbf{h}_{kl}\|_{\ell_2}^2}{P_l^c + \sum_{k\in\mathcal{K}} \beta_{lk}} \left(\sum_{k\in\mathcal{K}} \|\mathbf{w}_{lk}\|_{\ell_2}^2\right)} + P_{g,l}, \forall l \in \mathcal{L}, \tag{17}$$

where the RRH with lower value of θ_l shall have higher priority to be switched off. It is obvious that θ_l is proportional to the channel power gain $\sum_{k\in\mathcal{K}} \|\mathbf{h}_{kl}\|_{\ell_2}^2$, which is related to the sum capacity of the whole network. The RRHs with higher channel power gain contribute more to the total capacity and therefore shall have lower priority to be switched off. Note that we should reconsider the fronthaul constraint $C_3(\mathbf{w})$, so we regard β_{lk} as one of the key system parameters to choose RRHs to be switched off. As for the heuristic weight updating rule (15), β_{lk} is inversely proportional to the transmit power level $\|\mathbf{w}_{lk}\|_{\ell_2}^2$. Switching off the RRH with lower transmit power, i.e., higher value of β_{lk}, shall have less impact on the QoS of the UEs, but more significant to the energy efficiency. Meanwhile, the fixed energy consumption P_c^l of an active RRH has similar effect as β_{lk}, i.e., a RRH with higher P_l^c should be encouraged to be switched off. Many existing studies, e.g., [44]–[46], show that a RRH l with small coefficient $r_l = (\sum_{k\in\mathcal{K}} \|\mathbf{w}_{kl}\|_{\ell_2}^2)^{1/2}$ contributes little beamforming gain and therefore shall be given high priority to be switched off. When green energy is take into consideration, one more important factor to the switch-off decision is the green energy generation rate $P_{g,l}$. There is no doubt that a RRH with higher green energy rate shall be encouraged to be active. Based on the above analysis, we design the ordering criteria as shown in (17).

After obtaining an initial active RRH set $\mathcal{A}$, we first sort the RRHs in an ascending order where the RRHs with lower θ_l shall have a higher priority to be switched off (line 5). According to (17), the RRHs in lower order shall have higher priority to be switched off. As a result, we then try to iteratively and greedily switch off RRHs until the problem $\mathscr{P}_{soc}(\mathcal{A})$ is infeasible any more, in order to minimize the brown energy as much as possible (lines 6–12). During each iteration, we first remove the RRH with the lowest value of θ_l from $\mathcal{A}$ and then try to solve $\mathscr{P}_{soc}(\mathcal{A})$ with the updated $\mathcal{A}$ to check its feasibility. When no RRH can be switched off any more, we terminate the iteration and finally obtain the RRHs that shall be activated, as well as their beamformers to all users (line 13).

Computational Complexity: As shown in Algorithm 1, we shall iteratively solve the SOCP convex optimization problem $\mathscr{P}_{soc}(\mathcal{A})$ with computation complexity $\mathcal{O}((L - |\mathcal{D}|)^{3.5} N^{3.5} K^{3.5})$. Considering an extremely worst case, we need to go over all the RRHs, i.e., solving $\mathscr{P}_{soc}(\mathcal{A})$ with $L-1$ times. As a result, the proposed green energy aware RRH activation algorithm is with computation complexity $\mathcal{O}(L^{4.5} N^{3.5} K^{3.5})$.

VII. Simulation Results

In this section, we present our simulation-based performance evaluation results to verify the correctness and efficiency of our proposed green energy aware algorithm (Aware). Specially, in order to show the advantage of our proposed algorithm, we compare the performance of our proposal against the state-of-the-art energy efficient RRH activation algorithm (Unaware) proposed in [15], which also intends to minimize the energy consumption but do not take the green energy generation rate into consideration. The unaware scheme also treats all RRHs as active to obtain the corresponding beamforming vector $\mathbf{w}$. Next, it tries to deactivate the RRHs for energy saving by ordering the RRH according to the criteria related to the coefficient, channel power and the transport link power consumption. For more details, please refer to reference [15].

Following the same environment settings as [15], we simulate a square region 1000×1000, where a number of RRHs and UEs are randomly distributed. Two different scales of networks are considered. In both network scales, the path and penetration loss is defined as $148 + 37.6 \log_2(d_{kl})$, where d_{kl} denotes the propagation distance between RRH l and UE k. The small scale fading is described as independent circularity symmetric complex Gaussian random variables with distribution $\mathcal{CN}(0, 1)$. The noise power spectral density is -102 dBm. The maximum allowable transmission power on any RRH is limited by $P_l = 1W$, $l \in \mathcal{L}$. All the transport link power consumption is $P_l^c = (5 + l)W, l \in \mathcal{L}$ and the power amplifier coefficients is 4. To verify the feasibility and efficiency of our work in large-scale network, we further consider large-scale networks where the number of users ranges from 20 to 50 and the number of RRHs also ranges from 20 to 50.

We investigate how our algorithm performs under different network settings, as well as how various parameters affect the brown energy power consumption, by varying the settings of SINR requirement SINR_k, the number of RRHs L and the

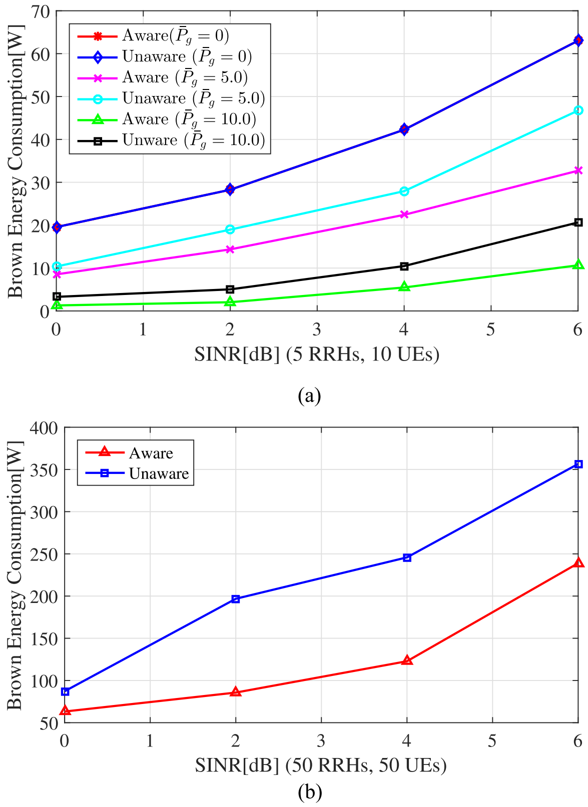

Fig. 2. Brown energy consumption on different SINR requirements. (a) Small-scale network. (b) Large-scale network.

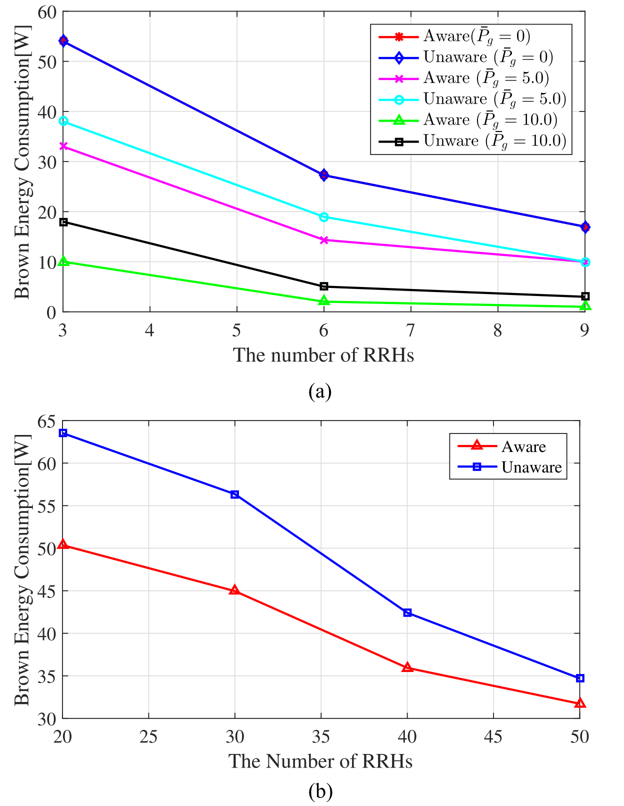

Fig. 3. Brown energy consumption on different number of RRHs. (a) Small-scale network. (b) Large-scale network.

number of UEs K. For each group of experiments, we compare the two algorithms under different values of average green energy generation rate $\bar{P}_g = \frac{\sum_{l \in \mathcal{L}} P g,l}{|\mathcal{L}|}$, i.e., $\bar{P}_g = 0, 5$, and 10, and run the simulation for 50 times to obtain the average brown energy consumption.

A. On the effect of SINR Requirements

We first vary the value of SINR requirements for all users from 0 dB to 6 dB and report the average brown energy consumption with different SINR requirements in Fig. 2. From both Fig. 2(a) on small-scale network and Fig. 2(b) on large-scale network, we can see that the the brown energy consumption shows as an increasing function of the SINR requirement. This is due to the fact that higher transmit power is needed to guarantee the higher QoS requirement, definitely resulting in higher transmit power. And, if the green energy is not enough to satisfy such needs, we need to use the brown energy from the power grid, incurring the increasing of brown energy consumption. While, thanks to the efficient use of green energy, our proposed algorithm always requires less brown energy than the unaware algorithm, under any value of SINR requirement. Furthermore, by checking the brown energy consumption under different values of green energy generation rates $\bar{P}_g$, we can see that the brown energy consumption decreases with the increasing of green energy generation. Specially, we can see that the two curves for our "aware" algorithm and the "unaware" competitor overlap when $\bar{P}_g = 0$, this further verify that our algorithm can well adapt to the green energy generation rates and still performs as well as the state-of-the-art energy efficient RRH activation algorithm in [15].

B. On the Effect of Number of RRHs

Next, we investigate the energy efficiency of the two algorithms under different number of RRHs varying from 3 to 9 when the number of UEs is fixed as 10. All the UEs are with the same SINR requirement as 4 dB. Fig. 3 presents the brown energy consumption on different number of RRHs. Similarly, the results for both small-scale and large-scale networks are shown. In either network scale, we notice that the brown energy consumption decreases with the increase of the number of RRHs. This is because we may have more feasible CoMP structure that can guarantee the QoS of all UEs when there are more RRHs, potentially enlarging the solution space leading to lower brown energy consumption. Once again, we notice that when $\bar{P}_g = 0$, the two algorithms show similar performance. While, in other cases, we can always observe the higher energy efficiency of our proposed green energy "aware" algorithm.

C. On the Effect of Number of UEs

Finally, we vary the number of UEs in the network to investigate how the brown energy consumption is influenced by the number of UEs. We set the number of RRHs as 5 and 50 in small-scale network and large-scale network, respectively. The SINR requirements on all UEs are set as 4 dB. The performance

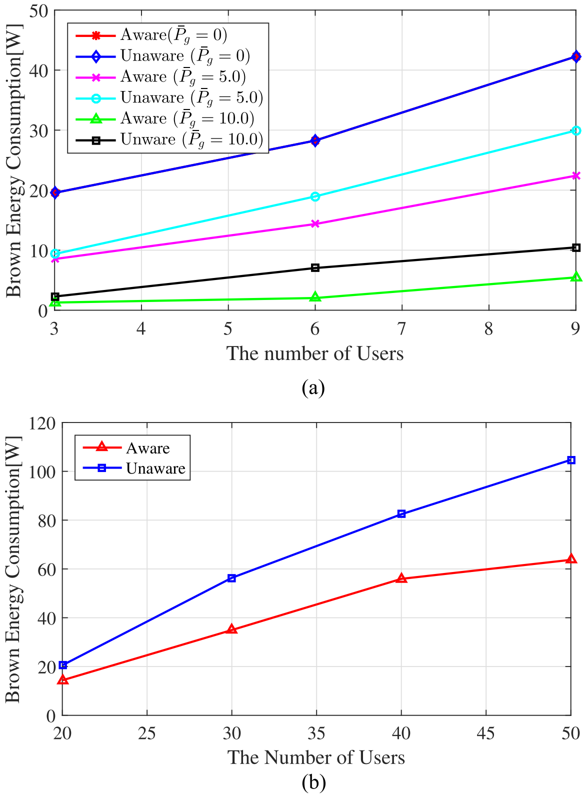

Fig. 4. Brown energy consumption on different number of Users. (a) Small-scale network. (b) Large-scale network.

evaluation results are reported in Fig. 4, from which we notice that the brown energy consumption shows as an increasing function of the number of UEs. This is because more users indicate more QoS requirements to be satisfied and henceforth higher energy consumption is needed. When the green energy fails to satisfy such needs, more brown energy consumption is needed. Nevertheless, the high energy efficiency of our proposal algorithm can be observed once again in Fig. 4. This further validates the high efficiency of our proposed algorithm.

VIII. Conclusion

CRAN has already shown promising potential in both the performance efficiency and energy efficiency in the next-generation wireless networks for smart cities. By adopting renewable green energy to power the lightweight RRHs, we think that it can further promote the network energy efficiency. With respect to the green energy generation rate diversity, it is significant to carefully activate the RRHs to maximize the green energy usage and hence minimize the brown energy consumption. Specially, as CRAN is an ideal platform to realize CoMP, we specially investigate how to activate the RRHs in a green energy aware way for CoMP in CRAN. We first formulate the problem into a non-convex optimization problem. By analyzing the characteristics of the original problem, we then propose a heuristic algorithm based on an ordered selection method. Simulation-based studies have conducted to verify the correctness and efficiency of our proposed approximation algorithm. The results show that our proposed green energy aware algorithm indeed exhibit higher energy efficiency in comparison with the state-of-the-art competitor.

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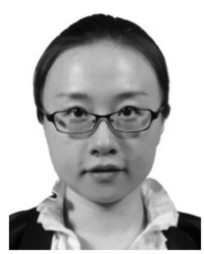
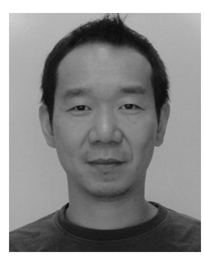
Deze Zeng is currently a Professor with the School of Computer Science, China University of Geosciences, Wuhan, China. His current research interests include network function virtualization, software-defined networking, cloud computing, and edge computing. He has authored one book and more than 80 papers in refereed journals and conferences in these areas. He is the recipient of three Best Paper Awards from IEEE/ACM conferences and the IEEE Systems Journal Annual Best Paper Award of 2017. He is on the editorial boards of *Journal of Network and Computer Applications* and Guest Editor of many prestigious journals. He has been on the organizing or program committees of many international conferences including ICPADS, ICA3PP, CollaberateCom, MobiQuitous, ICC, and Globecom.

Jie Zhang received the B.S. degree in computer science from China University of Geosciences, Wuhan, China, where she is currently working toward the M.S. degree in the School of Computer Science. Her current research interests mainly include software-defined networking and network functions virtualization.



Lin Gu received the M.S. and Ph.D. degrees in computer science from University of Aizu, Fukushima, Japan, in 2011 and 2015, respectively. She is currently a Lecturer with the School of Computer Science and Technology, Huazhong University of Science and Technology, Wuhan, China. Her current research interests include cloud computing, vehicular cloud computing, big data, and software-defined networking.



Song Guo is currently a Full Professor with the Department of Computing, The Hong Kong Polytechnic University, Kowloon, Hong Kong. His research interests include big data, cloud computing and networking, and distributed systems. His work was recognized by the 2016 Annual Best of Computing in *ACM Computing Reviews*. He is the recipient of the 2017 IEEE Systems Journal Annual Best Paper Award and other five Best Paper Awards from IEEE/ACM conferences. He was an Associate Editor for IEEE TRANSACTIONS ON PARALLEL AND DISTRIBUTED SYSTEMS and an IEEE ComSoc Distinguished Lecturer. He is currently on the editorial board of IEEE TRANSACTIONS ON CLOUD COMPUTING, IEEE TRANSACTIONS ON EMERGING TOPICS IN COMPUTING, IEEE TRANSACTIONS ON SUSTAINABLE COMPUTING, IEEE TRANSACTIONS ON GREEN COMMUNICATIONS AND NETWORKING, IEEE NETWORK, etc. He was also the General and TPC Chair for numerous IEEE conferences. He is currently a Director and Member of the Board of Governors of ComSoc.

Jiangtao Luo (SM'03) received the B.S. and Ph.D. degrees from Nankai University, Tianjin, China, and the Chinese Academy of Sciences, Beijing, China, in 1993 and 1998, respectively. He is currently a Full Professor, Ph.D. Supervisor, and Deputy Dean of the Electronic Information and Networking Research Institute, Chongqing University of Posts and Telecommunications, Chongqing, China. His major research interests include network protocol analysis, network data mining, urban computing, and future Internet architecture. He has published more than 100 papers and owned 21 patents in these fields. He was the recipient of the Chinese State Award of Scientific and Technological Progress in 2011, the Chongqing Provincial Award of Scientific and Technological Progress twice in 2010 and 2007, respectively, and the Chongqing Science and Technology Award for Youth in 2010. He has been an ACM member since Nov 2013.