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Sparse Beamforming for Real-Time Resource Management and Energy Trading in Green C-RAN

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Abstract—This paper considers cloud radio access network with simultaneous wireless information and power transfer and finite capacity fronthaul, where the remote radio heads are equipped with renewable energy resources and can trade energy with the grid. Due to uneven distribution of mobile radio traffic and inherent intermittent nature of renewable energy resources, the remote radio heads may need real-time energy provisioning to meet the users’ demands. Given the amount of available energy resources at remote radio heads, this paper introduces two provisioning strategies to strike an optimum balance among the total power consumption in the fronthaul, through adjusting the degree of partial cooperation among the remote radio heads, the total transmit power and the maximum or the overall real-time energy demand. More specifically, this paper formulates two sparse optimization problems and applies reweighted $\ell_1$-norm approximation for $\ell_2$-norm and semidefinite relaxation to develop two iterative algorithms for the proposed strategies. Simulation results confirm that both of the proposed strategies outperform two other recently proposed schemes in terms of improving energy efficiency and reducing overall energy cost of the network.

Index Terms—C-RAN, real-time energy trading, sparse beamforming, SWIPT, fronthaul link capacity constraints.

I. INTRODUCTION

NEXT generation wireless communication networks are expected to support tremendous increasing mobile data and high data rate communications with ubiquitously guaranteed quality of service (QoS) for receiving terminals over the coverage area. Massive multiple-input multiple-output for macro cells [1] as well as ultra-dense heterogeneous networks [2] have been regarded as two key enabling technologies. However, the throughput gain of the former approach is fundamentally limited by the pilot contamination and great capital expenditure (CAPEX) is required for hardware upgrade and deployment, which may result in a revenue threshold of the network [2]. Whereas for the latter approach, the significant inter-cell interference (ICI) may limit the performance of the system. Coordinated multipoint (CoMP) communication has illustrated its considerable advantages in ICI mitigation and system throughput improvement via joint transmission, where multiple base stations (BSs) collaboratively transmit data towards every single receiving terminal. Consequently, in terms of total transmit power, a significant performance gain can be achieved with full cooperation in CoMP systems [3]. A recent emerging deployment trend for CoMP network is to physically detach the baseband processing units (BBUs) from conventional BSs and group them into a BBU pool, i.e., a centralized cloud computing processor (CP). The remaining radio units, i.e., remote radio heads (RRHs), are connected to the CP via high-capacity low-latency fronthaul links, e.g., optical fibre links. This promising network architecture, known as cloud radio access network (C-RAN), reduces both the operating expense (OPEX) and the CAPEX [4]. Supported by the real-time virtualization and greater computational power, the CP is in charge of executing all the scheduling and baseband signal processing, e.g., coordination and energy trading designs, whilst the RRHs are responsible for all radio frequency (RF) operations, e.g., high frequency signal generation and power amplification [5].

On the other hand, enormous demand for energy is raised in both the receiver and the transmitter sides to satisfy the requirements of next generation wireless networks. Recently, the integration of C-RAN and simultaneous wireless information and power transfer (SWIPT), where the signals transmitted from RRHs can be exploited by the battery limited energy receiving terminals (ETs) for self-sustainability, has attracted the attention of researchers [6]. Moreover, since no information is carried by the energy-carrying signals towards the ETs [7], artificial noise generated at the individual RRHs can be used to prevent the ETs from eavesdropping and the physical-layer secrecy is then improved [8], [9]. Another challenge put forward for the network is that the energy cost has become a major OPEX due to dramatic rise of energy consumption by the high density of RRHs deployment [10]. In the case that the energy budgets at the RRHs are insufficient, additional real-time energy provision by the grid may be required to satisfy users’ demand and the network may take a risk of losing profit. Subsequently, equipping the RRHs with renewable energy harvesting devices that can generate local renewable energy from environmental sources, e.g., solar and wind, for green communications has been considered as
a promising technique to benefit both the environment and the network. With the implementation of advanced smart grid technology, two-way energy trading with the grid can be established and the network can maximally benefit from utilizing their local generated renewable energy and selling the excessive energy back to the grid [11]–[14].

A. Related Works

Provided that all of the BSs are equipped with renewable energy harvesters and implemented with two-way energy trading, [13], [14] propose a joint energy trading and full cooperation scheme in CoMP network, where the data of all users is available at the CP and will be distributed to all BSs in the cluster for cooperative transmission via fronthaul links. However, the data circulation between the CP and the BSs requires huge fronthaul signalling overhead when full coordination is enabled. The scheme, nevertheless, takes no account of fronthaul capacity restrictions, which may be infeasible for practical capacity-constrained fronthaul links [15]. Consequently, CoMP with finite fronthaul capacity has been investigated by the research community and sparse beamforming technique for partial cooperation is considered as a viable solution to this issue. Motivated by the literature that sparse beamforming problem is commonly formulated as a $\ell_0$-norm optimization problem and handled with reweighted $\ell_1$-norm method in the field of compressive sensing [16], Dai and Yu [17], Ng et al. [18], Zhao et al. [19], Kim et al. [20], and Hong et al. [21] propose dynamic sparse beamforming designs subject to QoS constraints for capacity-limited fronthaul links in CoMP networks. Ng and Schober [6] integrate the aforementioned works with SWIPT concept and study the resource allocation algorithm, under QoS constraints for information receivers and power constraints at the BSs and the CP. It can be perceived that sparse beamforming technique in joint cooperative real-time resource management and energy trading problem in green C-RAN is firstly tackled in [22].

B. Main Contributions

The main contributions of this paper are summarized as follows.

- In contrast to the energy management model proposed in [22], this paper integrates a real-time energy trading strategy with SWIPT concept, where the RRHs simultaneously transfer information beams to information receiving terminals and energy beams to active energy receiving terminals. Since energy could be highly attenuated over a long distance propagation and in order to maintain the efficiency of SWIPT, an iterative ET authorization algorithm that allows only those ETs situated close enough to the RRHs to receive wireless energy is introduced.

- Instead of designing the energy management for individual RRHs with a shortage of power proposed in [14] and [22], the design strategies introduced in this paper account for all RRHs with or without a shortage of power. The proposed strategies strike an optimum balance among the total power consumption in the fronthaul through adjusting the degree of partial cooperation among RRHs, RRHs’ total transmit power and the maximum or total spot-market energy cost. More specifically, this paper introduces two strategies for optimizing the RRHs’ real-time energy trading with the grid via: (1) minimizing the maximum spot-market energy cost; (2) minimizing the overall spot-market energy cost.

C. Organization and Notations

The remainder of this paper is organized as follows. Section II introduces the system model and an iterative ET authorization algorithm. In Section III, an RRH-centric clustering with Min-Max energy trading strategy is formulated, and then transformed into numerically tractable form using reweighted $\ell_1$-norm method and the SDR. In Section IV, an RRH-centric clustering with overall energy trading minimization strategy is proposed. Numerical simulation results are analyzed in Section V. Finally, Section VI summarizes the paper.

Notations: Throughout the paper, $w$, $\mathbf{w}$, $\mathbf{W}$, $(\cdot)^H$ and tr$(\cdot)$, respectively, represent a scalar $w$, a vector $\mathbf{w}$, a matrix $\mathbf{W}$, the complex conjugate transpose operators and the trace operators. $\mathbf{W} \succeq 0$ denotes that $\mathbf{W}$ is a positive semidefinite matrix and $\mathbb{C}^{n \times m}$ indicates the sets of $n$-by-$m$ dimensional complex matrices. $\mathbb{C}(\mu, \Gamma)$ represents the circularly symmetric complex normal distribution with mean $\mu$ and variance $\Gamma$. $\| \cdot \|_0$ is used to denote the $\ell_0$-norm of a vector and $\| \cdot \|_0$ indicates the number of non-zero entries in the vector. Note that, the normalized energy unit, i.e., $J s^{-1}$, is adopted in this paper and thus the terms ‘power’ and ‘energy’ are mutually convertible.

II. SYSTEM MODEL

This paper considers a downlink C-RAN with SWIPT from $N$ M-antennas RRHs, towards $K_i$ active single-antenna
information receiving terminals (ITs) and $K_i$ active single-antenna ETs, respectively, over same frequency band. A CP is the core processing unit in the network that coordinates all the cooperative energy trading strategies for the RRHs based on perfect knowledge of channel state information, and distributes all ITs’ data along with their beamformers to the corresponding RRHs via the fronthaul links. Besides, the CP also collects the energy information, e.g., the energy harvesting rates and energy trading prices, via the grid-deployed communication/control links from the smart meters installed at RRHs. Let $L_c = \{1, \ldots, N\}$, $L_e = \{1, \ldots, K_e\}$, $L_{\text{iddle}} = \{1, \ldots, K_{\text{iddle}}\}$ and $L_t = \{1, \ldots, K_t\}$ indicate, respectively, the set of indexes of the RRHs, the active ETs, the idle ETs and the active ITs.

A. Energy Management Model

From the CAPEX and OPEXs perspective, at least one renewable energy harvesting devices, e.g., wind turbine and/or solar panel, is assumed to be installed at the individual RRHs in order to generate local renewable energy from environmental sources. Whereas, no RRH is equipped with frequently rechargeable storage devices and the RRHs are obliged to transmit the excessive power back to the grid for sale. In practice, the renewable energy generation is unequal due to different efficiency of renewable energy harvesting devices and various RRHs locations. Let $E_n$, $B_n^{\text{ahead}}$, $B_n^{\text{real}}$, $S_n$ be defined, respectively, as the amount of renewable energy generated at the $n$-th RRH, the amount of energy that has already been purchased from the grid in the day-ahead-market, the amount of energy that is necessary to be maintained from the real-time (spot) market, and the amount of excessive energy sold back to the grid. Furthermore, let $P_n^{\text{[Tx]}}$ and $P_n^{\text{[circuit]}}$ indicate the total transmit power at the $n$-th RRH and the non-transmission hardware circuit power consumption at the $n$-th RRH, respectively. Then, the total energy consumption at the $n$-th RRH, i.e., $P_n^{\text{[total]}}$, is upper-bounded by the total available energy at the $n$-th RRH, i.e.,

$$P_n^{\text{[total]}} = P_n^{\text{[Tx]}} + P_n^{\text{[circuit]}} \leq E_n + B_n^{\text{ahead}} + B_n^{\text{real}} - S_n.$$  

In practice, the price of generating a unit of renewable energy, denoted by $\pi^{\text{[renew]}}$, is much cheaper than the price of buying a unit of energy, denoted by $\pi^{\text{[ahead]}}$, from the day-ahead-market. From the supply and demand’s perspective, it is assumed that the buying price of a unit of energy at the real-time market, i.e., $\pi^{\text{[real]}}$, is higher than the selling price of a unit of excessive (unused) energy, i.e., $\pi^{\text{[sell]}}$. It is typical to assume that $\pi^{\text{[real]}} \geq \pi^{\text{[ahead]}} \geq \pi^{\text{[sell]}} \geq \pi^{\text{[renew]}}$. Consequently, the total energy cost of a RRH, denoted by $\mathcal{C}_n^{\text{[total]}}$, is given by

$$\mathcal{C}_n^{\text{[total]}} = \pi^{\text{[ahead]}} \sum_{n \in \mathcal{L}_b} B_n^{\text{ahead}} + \pi^{\text{[real]}} \sum_{n \in \mathcal{L}_b} B_n^{\text{real}}$$
$$+ \pi^{\text{[renew]}} \sum_{n \in \mathcal{L}_b} E_n - \pi^{\text{[sell]}} \sum_{n \in \mathcal{L}_b} S_n.$$  

In the sequel, we propose provisioning strategies that jointly optimize C-RAN’s resource allocation and energy trading with the grid.

B. Downlink Transmission Model

The aggregate beamforming vector from all the RRHs towards the $i$-th IT, $i \in \mathcal{L}_i$, is denoted as $w_i = \{w_i^H, \ldots, w_i^{N}\}^H \in \mathbb{C}^{MN \times 1}$, where $w_{ni} \in \mathbb{C}^{M \times 1}$ is the beamformer from the $n$-th RRH towards the $i$-th IT. $v_i = \{v_i^H, \ldots, v_i^{N}\}^H \in \mathbb{C}^{MN \times 1}$ represents the aggregate beamforming vector from all the RRHs to the $e$-th active ET. Similarly, let $h_n \in \mathbb{C}^{M \times 1}$ represent the channel vector between the $n$-th RRH and the $i$-th IT, the aggregate channel vector between all the RRHs and the $i$-th IT is denoted by $h_i = \{h_i^H, \ldots, h_i^{N}\}^H \in \mathbb{C}^{MN \times 1}$. The received signals at the $i$-th IT, $i \in \mathcal{L}_i$, is then given by

$$y_i = h_i^H w_i s_i^{[\text{IT}]} + \sum_{j \neq i} h_i^H w_j s_j^{[\text{IT}]} + \sum_{e \in \mathcal{L}_e} h_i^H v_e s_e^{[\text{ET}]} + n_i,$$  

where the terms at the right hand side of (3), respectively, represent the intended information-carrying signal for the $i$-th IT, the inter-user interference caused by all other non-desired information beams, the interference caused by energy beams for all active ETs and the additive white Gaussian noise, i.e., $n_i \sim \mathcal{CN}(0, \sigma_i^2)$, at the $i$-th IT. Since no information is carried by the energy-carrying signals, they can be any arbitrary random signals. Without loss of generality, it is assumed that $\mathbb{E}(s_i^{[\text{IT}]}) = \mathbb{E}(s_i^{[\text{ET}]}) = 1$ and $\sigma_i^2$ is identical at all receiving terminals. Then, the signal-to-interference-plus-noise ratio (SINR) at the $i$-th IT, $i \in \mathcal{L}_i$, is formulated as

$$\text{SINR}_i^{[\text{IT}]} = \frac{|h_i^H w_i|^2}{\sum_{j \neq i} |h_i^H w_j|^2 + \sum_{e \in \mathcal{L}_e} |h_i^H v_e|^2 + \sigma_i^2}.$$  

The fronthaul capacity consumption for the $n$-th RRH is given by

$$C_n^{[\text{fronthaul}]} = \sum_{i \in \mathcal{L}_i} \|w_{ni}\|_2^2 R_i = \sum_{i \in \mathcal{L}_i} \|w_{ni}\|_2^2 = 0,$$  

where $R_i = \log_2(1 + \text{SINR}_i^{[\text{IT}]}))$ is the achievable data rate (bit/s/Hz) for the $i$-th IT. Note that the quantity of $\ell_0$-norm in (5) is invariant when the input arguments are squared and $\|w_{ni}\|_2^2 = 0$ is an indicator function that illustrates the scheduling choices of the individual ITs, i.e.,

$$\|w_{ni}\|_2^2 = 0 \implies \{0, \text{ if } \|w_{ni}\|_2^2 = 0, 1, \text{ if } \|w_{ni}\|_2^2 \neq 0\}.$$  

$$\|w_{ni}\|_2^2 = 0$$ indicates partial cooperation, where the CP will not deliver data for the $i$-th IT to the $n$-th RRH via the corresponding fronthaul link and the $n$-th RRH is not participating in the joint transmission to the $i$-th IT.

Motivated by the fact that energy is highly attenuated during long-distance propagation and in order to improve the energy efficiency, an ET authorization algorithm that can be implemented in the CP to authorize the RRHs to transmit energy directly towards the ETs located within their hexagonal energy serving area and set as active ETs is considered, whilst other ETs will be set as idle ETs. Note that only the active ETs will be assigned with dedicated beamformers for power transmission. Consequently, the active ETs can harvest energy not only from the RRHs, but also from the ambient RF signals whilst
Algorithm 1 An Iterative ET Authorization Algorithm

1. Initialize: RRH-to-RRH distance $D$ and constant $\phi_{nm}$
2. for $m = 1$ to $(K_e + K_{idle})$
3. for $n = 1$ to $N$
4. CP calculates the hexagonal energy serving areas of the $n$-th RRH for the $m$-th ET as follows
   \[ A_{nm} = \phi_{nm} \times (D/2)^2; \]
5. if the $m$-th ET locates within the area $A_{nm}$
6. then the $m$-th ET is set as an active ET and is permitted to harvest energy from the $n$-th RRH, set \{$w_{lm}\}_{l\in L_n} = 0$;
7. end if
8. end for
9. if the $m$-th ET locates outside the area $A_{nm}, \forall n \in L_b$
10. then the $m$-th ET is prohibited to harvest energy from any RRH, set as an idle ET;
11. end if
12. end for

The steps of authorization are summarized in Algorithm 1. By adjusting the value of $\phi_{nm}$, the size of the hexagonal energy serving area can be controlled by the CP as per practical situations, e.g., capacity restrictions and power budgets. Then, the total energy harvested by the $e$-th active ET, $e \in L_e$, can be expressed as
\[
G_{\text{ET}} = \eta \left( |g_{eH}^H v_{e\text{idle}}|^2 + \sum_{j \in L_e, j \neq e} |g_{eH}^j v_{e\text{idle}}|^2 + \sum_{i \in L_e} |g_{eH}^i w_{e\text{idle}}|^2 \right),
\]
where $0 \leq \eta \leq 1$ indicates the conversion efficiency from the harvested RF energy to the electrical energy and is assumed to be constant and identical for all ETs; $g_{eH} = [g_{eH}^1, \ldots, g_{eH}^N]^H \in \mathbb{C}^{MN \times 1}$ represents the aggregate channel vector from all the RRHs to the $e$-th active ET. Note that only one RRH is serving the $e$-th active ET and all the beamformers from other RRHs to the $e$-th ET are set to zero as per step 6 in the Algorithm 1. Besides, the total amount of energy that can be harvested from surroundings by the $z$-th idle ET, $z \in L_{\text{idle}}$, is given by
\[
G_{\text{ET-idle}} = \eta \left( \sum_{i \in L_e} |f_{eH}^i v_{e\text{idle}}|^2 + \sum_{e \in L_e} |f_{eH}^i v_{e\text{idle}}|^2 \right),
\]
where $f_e = [f_{eH}^1, \ldots, f_{eH}^N]^H \in \mathbb{C}^{MN \times 1}$ denotes the aggregate channel vector from all the RRHs to the $z$-th idle ET.

III. STRATEGY 1: DYNAMIC RRH-CENTRIC CLUSTERING WITH MIN-MAX REAL-TIME ENERGY COST

In the practical downlink C-RAN, the tremendous information exchange between the CP and the RRHs via capacity-constrained fronthaul links may result in the infeasibility of full cooperation. Therefore, it is necessary to take into account of the fronthaul capacity restrictions and employ sparse beamforming technique to enable partial cooperation. However, the degree of partial cooperation among the RRHs in serving the receiving terminals and the total transmit power minimization conflict with each other. In particular, reducing the receiving terminal-RRH cooperative links may be beneficial for the idle ETs merely harvest energy from the surroundings. The steps of authorization are summarized in Algorithm 1. By adjusting the value of $\phi_{nm}$, the size of the hexagonal energy serving area can be controlled by the CP as per practical situations, e.g., capacity restrictions and power budgets. Then, the total energy harvested by the $e$-th active ET, $e \in L_e$, can be expressed as
\[
G_{\text{ET}} = \eta \left( |g_{eH}^H v_{e\text{idle}}|^2 + \sum_{j \in L_e, j \neq e} |g_{eH}^j v_{e\text{idle}}|^2 + \sum_{i \in L_e} |g_{eH}^i w_{e\text{idle}}|^2 \right),
\]
where $0 \leq \eta \leq 1$ indicates the conversion efficiency from the harvested RF energy to the electrical energy and is assumed to be constant and identical for all ETs; $g_{eH} = [g_{eH}^1, \ldots, g_{eH}^N]^H \in \mathbb{C}^{MN \times 1}$ represents the aggregate channel vector from all the RRHs to the $e$-th active ET. Note that only one RRH is serving the $e$-th active ET and all the beamformers from other RRHs to the $e$-th ET are set to zero as per step 6 in the Algorithm 1. Besides, the total amount of energy that can be harvested from surroundings by the $z$-th idle ET, $z \in L_{\text{idle}}$, is given by
\[
G_{\text{ET-idle}} = \eta \left( \sum_{i \in L_e} |f_{eH}^i v_{e\text{idle}}|^2 + \sum_{e \in L_e} |f_{eH}^i v_{e\text{idle}}|^2 \right),
\]
where $f_e = [f_{eH}^1, \ldots, f_{eH}^N]^H \in \mathbb{C}^{MN \times 1}$ denotes the aggregate channel vector from all the RRHs to the $z$-th idle ET.

A. Problem Formulation

Strategy 1 is formulated as a linear combination of the total power consumption in the fronthaul through adjusting the degree of partial cooperation among RRHs, the RRHs’ total transmit power and the maximum real-time energy cost at a spot-market under the constraints of fronthaul link capacity restrictions. As shown in Fig 1, the optimal receiving terminal cluster to be served by each RRH is determined by the CP through evaluation of actual situations, e.g., the location of active receiving terminals, the associated channel conditions, the available resources, power budgets, and fronthaul link capacity constraints of the individual RRHs.

\[
\min \alpha P_{\text{coop}} + \beta \sum_{n \in L_b} P_{n[Tx]} + \zeta \max_{n \in L_b} \left( B_n^{\text{real}} \right)
\]
\begin{align*}
\text{s.t.} & \quad C_{1}: |S_n^{\text{fronthaul}}| \geq \gamma_i, \quad \forall i \in L_i, \\
& \quad C_{2}: \eta G_{\text{ET}} \geq P_{\text{min}}, \quad \forall e \in L_e, \\
& \quad C_{3}: G_{\text{ET-idle}} \geq P_{\text{idle}}, \quad \forall z \in L_{\text{idle}}, \\
& \quad C_{4}: P_{n[Tx]} \leq E_n + P_{n[\text{ahead}]} + B_n^{\text{real}} - S_n - P_{n[\text{circuit}]}, \quad \forall n \in L_b, \\
& \quad C_{5}: P_{n[Tx]} \leq P_{n[\text{max}]}, \quad \forall n \in L_b, \\
& \quad C_{6}: C_{(b-\text{limit})} \leq C_{\text{fronthaul}}, \quad \forall n \in L_b, \\
& \quad C_{7}: \sum_{n \in L_b} B_n^{\text{ahead}} + \sum_{n \in L_b} B_n^{\text{real}} \leq P_{\text{max}} - P_{\text{circuit}}, \quad \forall n \in L_b, \\
& \quad C_{8}: B_n^{\text{real}} \geq 0, \quad C_{9}: S_n \geq 0, \quad \forall n \in L_b.
\end{align*}
where $\mathcal{P}^{[\text{coop}]} = \left( \sum_{i \in \mathcal{L}_i} \| \mathbf{w}_{1i} \|_2^2 \right) + \cdots + \left( \sum_{i \in \mathcal{L}_i} \| \mathbf{w}_{ni} \|_2^2 \right) + \left( \sum_{\ell \in \mathcal{L}_\ell} \| v_{1\ell} \|_2^2 \right) + \cdots + \left( \sum_{\ell \in \mathcal{L}_\ell} \| v_{n\ell} \|_2^2 \right)$ indicates the number of total active cooperative links between the RRHs and the receiving terminals, $\alpha \geq 0$ is the maximum power cost in the fronthaul due to the transportation of an active receiving terminal’s data from the CP to a serving RRH and $P_{\ell}^{[\text{Tx}]} = \sum_{i \in \mathcal{L}_i} \| \mathbf{w}_{ni} \|_2^2 + \sum_{\ell \in \mathcal{L}_\ell} \| v_{n\ell} \|_2^2$.)

In C7, we also model the degree of CP’s emphasis on minimizing the total transmit power, i.e., $\sum_{\ell \in \mathcal{L}_\ell} P_{\ell}^{[\text{Tx}]}$, and RRH’s maximum real-time energy request at a spot-market, i.e., $\max_{\ell \in \mathcal{L}_\ell} \{ b_{\ell}^{[\text{real}]} \}$, respectively. A larger weighting coefficient results in a more emphasize in minimizing the corresponding term of the objective function. Let $\gamma_i$ represent the minimum SINR requirement of the $i$-th IT, then C1 denotes a set of QoS constraints for $K_i$ ITs. $P_{\ell}^{[\text{min}]}$ in C2 represents the minimum energy transmission requirements by the active ETs while $P_{\ell}^{[\text{sidle}]}$ in C3 are the requirements of minimum energy harvested from the surroundings by the idle ETs. C4 indicates that the total transmit power of each RRH is constrained by its power budget. C5 denotes that the total transmit power should not exceed the maximum transmit power allowance $P_{\ell}^{[\text{max}]}$ at the $n$-th RRH. C6 denotes the fronthaul link capacity restrictions for the individual RRHs. C7 specifies the constraint for the total power supplied by the grid to the RRHs, where $P_{\ell}^{[\text{CP}]}$ and $P_{\ell}^{[\text{max}]}$ are the hardware circuit power consumption and the maximum power provision by grid at the CP, respectively. C8 and C9 are the non-negative optimization variables.

### B. Resource Management Algorithm Design

The optimization problem in (9) is NP-hard due to the non-convexity of the constraint C1, the $\ell_0$-norm in the first term of the objective function and $C_{\ell_1}^{[\text{fronthaul}]}$ in the constraint C6. By using convex relaxation technique [18], the $\ell_0$-norm term in the objective function of (9) and C6 can be approximated by their weighted $\ell_1$-norm, respectively, as follows

$$
\mathcal{P}^{[\text{coop}]} \approx \sum_{i \in \mathcal{L}_i} \left( \sum_{\ell \in \mathcal{L}_\ell} \| \mathbf{w}_{1i} \|_2^2 \right) + \cdots + \left( \sum_{\ell \in \mathcal{L}_\ell} \| \mathbf{w}_{ni} \|_2^2 \right) + \left( \sum_{\ell \in \mathcal{L}_\ell} \| v_{1\ell} \|_2^2 \right) + \cdots + \left( \sum_{\ell \in \mathcal{L}_\ell} \| v_{n\ell} \|_2^2 \right)
$$

Algorithm 2 Reweighted $\ell_1$-Norm Method

1. **Initialize**: constant $\mu \rightarrow 0$, iteration count $t = 0$, weighting factor $\xi_n(t) = 1$, $\kappa_n(t) = 1$, maximum number of iterations $t_{\max}$, $R_i(t) = \log_2(1 + \gamma_i)$.
2. **while** $\xi_n(t)$ and $\kappa_n(t)$ are not converged or $t \neq t_{\max}$ do
3. **Find** the optimal beamformers $\mathbf{W}_i(t)$ and $\mathbf{V}_e(t)$ by solving (10);
4. **Update** the weight factor $\xi_n(t+1)$ as follows,
   $\xi_n(t+1) = \frac{1}{\mathbf{w}_n^H \mathbf{D}_n \mathbf{w}_n + \mu}, \quad \forall n \in \mathcal{L}_b, i \in \mathcal{L}_i$;
5. **Update** the weight factor $\kappa_n(t+1)$ as follows,
   $\kappa_n(t+1) = \frac{1}{\mathbf{v}_e^H \mathbf{D}_n \mathbf{v}_e + \mu}, \quad \forall n \in \mathcal{L}_b, e \in \mathcal{L}_e$;
6. **Calculate** the achievable rate $R_i(t)$ as follows,
   $$R_i(t) = \log_2[1 + \frac{\mathbf{w}_i^H \mathbf{D}_n \mathbf{w}_i}{\sum_{j \in \mathcal{L}_i, j \neq i} \mathbf{W}_j(t)^H (\mathbf{H}_j \mathbf{H}_j^H) + \sum_{e \in \mathcal{L}_e} \mathbf{V}_e(t)^H (\mathbf{H}_e \mathbf{H}_e^H) + \sigma_i^2}]$$;
7. **Update** $R_i(t+1) = R_i(t)$;
8. **Increment** the iteration number $t = t + 1$;
9. **end while**

Let us set $\mathbf{H}_e = \mathbf{h}_e^H \mathbf{G}_e = \mathbf{g}_e^H \mathbf{F}_e = \mathbf{f}_e^H \mathbf{H}_e$ and define the unit-rank semidefinite matrices as $\mathbf{W}_i = \mathbf{w}_i \mathbf{w}_i^H$ and $\mathbf{V}_e = \mathbf{v}_e \mathbf{v}_e^H$. Then the second term of objective function of problem (9) can be expressed as $\sum_{n \in \mathcal{L}_b} P_{\ell}^{[\text{Tx}]} = \sum_{i \in \mathcal{L}_i} \sum_{\ell \in \mathcal{L}_\ell} \mathbf{w}_n^H \mathbf{D}_n \mathbf{v}_n^H + \sum_{e \in \mathcal{L}_e} \sum_{\ell \in \mathcal{L}_\ell} \mathbf{v}_{ne}^H \mathbf{D}_n \mathbf{v}_{ne}^H$. The original optimization problem in (9) can be transformed to a semidefinite programming (SDP) problem after relaxing the unit-rank constraints.
of rank($W_i$) = 1 and rank($V_e$) ≤ 1, as

$$\min_{W_i, V_e, \chi} \alpha \sum_{n \in L_b} \left( \sum_{i \in L_i} \xi_i \text{tr}(W_i D_n) + \sum_{e \in L_e} \kappa_e \text{tr}(V_e D_n) \right) + \beta \left( \sum_{i \in L_i} \text{tr}(W_i) + \sum_{e \in L_e} \text{tr}(V_e) \right) + \chi,$$

s.t. $C1 : \text{tr}(H_i W_i) \geq \gamma_i \sum_{j \in L_i, i \neq j} \text{tr}(H_i W_j) + \gamma_i \alpha_i^2, \forall i \in L_i,$

$$C2 : \text{tr}(G_i V_e) + \sum_{j \in L_e, j \neq e} \text{tr}(G_e V_j) + \sum_{i \in L_i} \text{tr}(G_i W_i) \geq P_e^{\text{real}} \eta^{-1}, \forall e \in L_e,$$  

$$C3 : \sum_{i \in L_i} \text{tr}(F_i V_i) + \sum_{e \in L_e} \text{tr}(F_e V_e) \geq P_e^{\text{idle}} \eta^{-1}, \forall e \in L_e,$$ 

$$C4 : \sum_{i \in L_i} \text{tr}(W_i D_n) + \sum_{e \in L_e} \text{tr}(V_e D_n) \leq [E_n - S_n + B_n^{\text{ahead}} + B_n^{\text{real}} - P_n^{\text{circuit}}], \forall n \in L_b,$$

$$C5 : \sum_{i \in L_i} \text{tr}(W_i D_n) + \sum_{e \in L_e} \text{tr}(V_e D_n) \leq P_n^{\text{Tmax}},$$

$$C6 : \sum_{i \in L_i} \xi_i \text{tr}(W_i D_n) \hat{R}_i \leq C_n^{\text{b-limit}}, \forall n \in L_b,$$ 

$$C7 - C9, \quad C10 : \sum_{i \in L_i} \text{tr}(W_i D_n) \hat{R}_i \leq C_n^{\text{b-limit}}, \forall n \in L_b,$$ 

$$C11 : W_i \geq 0, \forall i \in L_i, \quad C12 : V_e \geq 0, \forall e \in L_e.$$

IV. STRATEGY 2: DYNAMIC RRH-CENTRIC CLUSTERING WITH MINIMAL OVERALL REAL-TIME ENERGY COST

A. Problem Formulation

This section proposes a different approach for energy trading optimization by jointly minimizing the total power consumption in the fronthaul through adjusting the degree of partial cooperation among RRHs, the RRHs’ total transmit power and the RRHs’ overall real-time energy requests at a spot-market, under the constraints of satisfying the QoS/energy transmission requirements of the ITs/ETs, respectively. The proposed strategy 2 can be formulated as

$$\min_{W_i, V_e, B_n^{\text{real}}} \alpha \sum_{n \in L_b} \left( \sum_{i \in L_i} \xi_i \text{tr}(W_i D_n) + \sum_{e \in L_e} \kappa_e \text{tr}(V_e D_n) \right) + \beta \left( \sum_{i \in L_i} \text{tr}(W_i) + \sum_{e \in L_e} \text{tr}(V_e) \right) + \chi \sum_{n \in L_b} \left\{ B_n^{\text{real}} \right\},$$

s.t. $C1 - C9$ in (9).  

(11)

where $\alpha \geq 0$ is the maximum power cost in the fronthaul due to the transportation of an active receiving terminal’s data from the CP to a serving RRH. The weighting coefficients $\beta \geq 0$ and $\chi \geq 0$ model the degrees of CP’s emphasis on minimizing the RRHs’ total transmit power and their overall real-time energy demands, respectively.

B. Resource Management Algorithm Design

Following the similar SDR approach as in the strategy 1, the problem of strategy 2 in (11) can be transformed as

$$\min_{W_i, V_e, B_n^{\text{real}}} \alpha \sum_{n \in L_b} \left( \sum_{i \in L_i} \xi_i \text{tr}(W_i D_n) + \sum_{e \in L_e} \kappa_e \text{tr}(V_e D_n) \right) + \beta \left( \sum_{i \in L_i} \text{tr}(W_i) + \sum_{e \in L_e} \text{tr}(V_e) \right) + \chi \sum_{n \in L_b} \left\{ B_n^{\text{real}} \right\}$$

s.t. $C1 - C9$, $C11 - C12$ in (10).  

(12)

Note that, if the obtained solutions $W_i^*$ and $V_e^*$ are rank-one, the problems (10) and (12) yield same optimal solutions as problems (9) and (11), respectively.

**Lemma 1:** The optimal solutions to the problems (10) and (12) satisfy $\text{rank}(W_i^*) = 1$ and $\text{rank}(V_e^*) \leq 1$ with probability one.

**Proof:** Please refer to Appendix A.

V. SIMULATION RESULTS

As shown in Fig. 2, we consider a SWIPT C-RAN scenario with 3 neighbouring 8-antennas RRHs, located 500m away from each other. 6 ITs and 6 ETs are randomly generated in the network and the weight factor of energy serving area for ETs is $\phi_{\text{ET}} = 0.2$. The renewable energy generation at each RRH is assumed to be $E_1 = 1.5 \ W$, $E_2 = 0.2 \ W$ and $E_3 = 0.05 \ W$, respectively, at a price of $\pi^{\text{renew}} = 0.02/W$ and the RRHs can sell excessive energy back to the grid at a price of $\pi^{\text{sell}} = 0.05/W$. It is further assumed that amounts of $B_1^{\text{ahead}} = B_2^{\text{ahead}} = B_3^{\text{ahead}} = 0.7 \ W$ energy have already been purchased from the day-ahead market for the RRHs at a price of $\pi^{\text{ ahead}} = 0.07/W$ and that the buying energy price at a spot-market is at $\pi^{\text{real}} = 0.15/W$. Besides, the channel vectors $h_1$, $g_r$ and $f$ are assumed to be independently distributed and a correlated channel model $h_{\text{int}} = R^{1/2} h_1$ is adopted [24], where $h_{\text{int}} \in \mathbb{C}^{M \times 1} \sim \mathcal{CN}(0, 1)$, $R \in \mathbb{C}^{M \times M}$ is the spatial covariance matrix and its $(m, n)$-th element is given by $G_{mk} \sigma^2 \left( e^{-0.5 \sin^2 \theta \cos^2 \phi} + \frac{1}{e^{-2 \tan^2 \phi \sin \phi \sin \theta} \left( (n - m) \sin \phi \sin \theta \right) } \right)^2$, where antenna gain $G_{mk} = 15 \ \text{dBi}$, $L_{\text{p}} \ (\text{dB}) = 125.2+$
$36.3 \log_{10}(d)$ is the path loss model over a distance of $d$ km, $\sigma^2_F$ is the variance of complex Gaussian fading coefficient, log-normal shadowing standard deviation $\sigma_s = 8$ dB, antenna spacing $\delta = \lambda/2$, angular offset standard deviation $\sigma = 2^\circ$ and $\theta$ is the estimated angle of departure. The channel bandwidth, noise figure at receiving terminals and noise power spectral density are set to be 20 MHz, 5 dB and $-174$ dBm/Hz, respectively. Besides, the parameters for optimization constraints are set, unless otherwise stated, to be $P^{[\text{circuit}]} = 40$ dBm, $P^{[\text{max}]} = 50$ dBm, $P^{[\text{circuit}]} = 30$ dBm, $P^{[\text{max}]} = 46$ dBm, $C^{[\text{b-limit}]} = 40$ bit/s/Hz, $P^{[\text{min}]} = -60$ dBm, $P^{[\text{idle}]} = -90$ dBm and $\eta = 0.5$, respectively. The simulation results are efficiently obtained via CVX [25] and are averaged over 200 independent channel realizations. Note that in simulations, the power in the objective function and the constraints of the optimization problems in (9) and (11), has been normalized with respect to $\alpha$, i.e., $\alpha = 1$. Further in the simulations, the same preference on the second and the third terms of the optimization problems in (9) and (11) is given by setting equal values for the weighting coefficients $\beta$ and $\zeta$, i.e., $\beta = \zeta = 1$. Five strategies are employed in this paper as comparison group and identical constraints are applied to all of the strategies for fair comparison. They are, respectively, 1. the strategy in [6] that jointly optimizes the fronthaul capacity via partial cooperation and the total transmit power; 2. the joint minimization of cooperative energy trading and full cooperation among RRHs in [13]; 3. the proposed strategy 1 without ET authorization algorithm; 4. a special case of the proposed strategy 1 by setting ($\alpha = 0$, $\beta = \zeta = 1$) for jointly optimizing the full cooperation and the energy trading with the grid, and 5. a special case of the proposed strategy 1 by setting ($\alpha = 1$, $\beta = 0$, $\zeta = 1$) for jointly optimizing the fronthaul power consumption via partial cooperation and the energy trading with the grid. The comparison of total energy cost of the RRH as per (2) for different strategies is presented in Fig. 3. One can conclude that in terms of total energy cost reduction, overwhelming performance gain can be achieved by both of the proposed joint cooperative energy trading strategies as compared to the baseline strategy in [6] that separately designs the partial cooperation and energy trading. The strategy 2 has the lowest total energy cost in terms of achieving higher SINR targets and closely follows strategy $1(\alpha = \beta = \zeta = 1)$ and $1(\alpha = 1$, $\beta = 0$, $\zeta = 1$) at low and medium SINR requirements. It is noticeable that both of the proposed strategies outperform the strategy in [13] in the medium and high target SINR range since full cooperation in [13] may be infeasible for medium and high target SINR due to fronthaul capacity restrictions. The comparison of the total transmit power versus various SINR targets for different strategies is illustrated in Fig. 4. It can be observed from the figure that a significant performance gap exists between the proposed strategies 1, 2 that embedded with ET authorization algorithm, and the strategies in [6] and [13] that have no implementation of ET authorization algorithm. As expected, the strategy $1(\alpha = 0$, $\beta = \zeta = 1$) and strategy in [13] that enable full cooperation in C-RAN, consume lower transmit power as compared to their counterparts up to medium SINR range and then become infeasible due to fronthaul capacity restrictions.
Fig. 6. Clustering behaviour of RRH 3 at $\gamma = 20$ dB target SINR.

Fig. 7. Optimal energy trading for proposed strategies at $\gamma = 30$ dB.

Transmit power variation of the individual RRHs using reweighted $\ell_1$-norm method proposed in Algorithm 2 for serving the 3rd IT for different strategies at target SINR of $\gamma = 20$ dB is presented in Fig. 5. One can conclude that for the proposed strategies 1 and 2 that apply sparse beamforming for partial cooperation, the transmit power of all the RRHs converge within 12 iterations. In addition, it is illustrated by the figure that only RRH 2 is participating in serving the 3rd IT while RRH 1 and 3 release their cooperative links by iteratively forcing its transmit power close to zero. Whereas, for the full cooperation, i.e., the strategy 1 ($\alpha = 0$, $\beta = \zeta = 1$), all the cooperation links are preserved for the 3rd IT.

Fig. 6 illustrates the clustering behaviour of RRH 3 for different strategies at $\gamma = 20$ dB target SINR. It can be observed that for the proposed strategies 1($\alpha = 1$, $\beta = 0$, $\zeta = 1$), 1($\alpha = \beta = \zeta = 1$) and 2, only the cooperative links between RRH 3 and the 5th, the 6th ITs are preserved while the transmit power from RRH 3 to the other ITs are dropped close to zero due to its backhaul capacity restriction. Meantime, the strategies with full cooperation retain all the joint transmission links between RRH 3 and the ITs.

Fig. 7 presents in details the comparison of the optimal energy trading for the proposed strategy 1 and 2 at target SINR of $\gamma = 30$ dB. It is noticeable that even though both of the proposed strategies have similar performance in terms of total energy cost of the RRH at $\gamma = 30$ dB, the proposed strategy 1 tends to provision equal amount of energy from real-time market for individual RRHs, as a result of minimizing the maximum real-time energy demand among the RRHs. Whereas, for the proposed strategy 2, all the RRHs utilize all amount of energy without selling back to the grid.

VI. CONCLUSION

This paper proposes two joint real-time resource management and energy trading strategies based on sparse beamforming technique in downlink green C-RAN with SWIPT, taking into account the individual fronthaul capacity restrictions, to strike an optimum balance among the total power consumption in the fronthaul through adjusting the degree of partial cooperation among RRHs, RRHs’ total transmit power and their maximum or overall spot-market energy demand. To further improve the energy efficiency, an iterative ET authorization algorithm is proposed to design energy beamformers only for the ETs located within the energy serving area of RRHs. By employing the reweighted $\ell_1$-norm approximation for $\ell_0$-norm and SDR, the solution sparsity to the original non-convex optimization problems in (9) and (11) can be obtained. Simulation results confirm that both of the proposed strategies outperform two other recently proposed schemes in terms of improving the energy efficiency and reducing total energy cost of the RRHs in a realistic C-RAN scenario.

APPENDIX

PROOF OF LEMMA 1

This section provides a proof for lemma 1 in the context of optimization problem in (10), which can be similarly extended to the context of the optimization problem in (12). Since the optimization problem in (10) is convex and satisfies the Slater’s condition, strong duality holds [26] and its Lagrangian is given by

$$L(W_i, V_e, \chi, Y_i, Z_e, \psi_e, \pi_e, \varphi_e, \theta_e, \tau_e, \psi_e, \xi_e, \rho_e, \beta_e, \delta_e) = \sum_{i \in \mathcal{L}_i} \text{tr}(Q_i W_i) - \sum_{i \in \mathcal{L}_i} \text{tr}\left(W_i \left( Y_i + \frac{v_i H_i}{\gamma_i} \right) \right) + \sum_{e \in \mathcal{L}_e} \text{tr}(Q_e V_e) - \sum_{e \in \mathcal{L}_e} \text{tr}\left(V_e \left( Z_e + \frac{\rho_e G_e}{P_{ee}^{\min}} \right) \right) + \Xi. \quad (13)$$
where

\[ Q_i = \alpha \sum_{n \in L_b} \xi_n D_n + \beta I + \sum_{i \in L_i} v_i H_j - \sum_{e \in L_e} \frac{\rho_e G_e}{P_{e_{\text{min}}}} \]

\[- \sum_{\xi \in \xi_{\text{dead}}} F_\xi \psi \ast \sum_{n \in L_b} (\psi_n + \phi_n + \tau_n \xi_n \tilde{R}_i) D_n. \tag{14} \]

\[ Q_e = \alpha \sum_{n \in L_b} \xi_n D_n + \beta I + \sum_{i \in L_i} v_i H_j - \sum_{e \in L_e} \frac{\rho_e G_e}{P_{e_{\text{min}}}} \]

\[- \sum_{\xi \in \xi_{\text{dead}}} F_\xi \psi \ast \sum_{n \in L_b} (\psi_n + \phi_n) D_n. \tag{15} \]

\[ \Xi = \sum_{n \in L_b} (\psi - \phi_n) B_n^{\text{abond}} + \sum_{n \in L_b} (\psi - \phi_n - \epsilon_n) B_n^{\text{ideal}} \]

\[ + \sum_{i \in L_i} \frac{\psi_i \sigma_i^2 + \sum_{\xi \in \xi_{\text{dead}}} \rho_e \vartheta_{\xi \text{dead}} \sum_{n \in L_b} (\psi_n + \phi_n \tilde{F}_n^{\text{max}})}{\sum_{\xi \in \xi_{\text{dead}}} \vartheta_{\xi \text{dead}}} \sum_{n \in L_b} (\psi_n + \phi_n \tilde{F}_n^{\text{max}}) + \psi \sum_{e \in L_e} F_{e_{\text{CP}}} \]

\[ - \sum_{n \in L_b} \left( \tau_n C_n^{\text{limit}} + \psi_n S_n - \varsigma_n \chi - \varsigma_n \xi \right) + \chi. \tag{16} \]

\[ \Xi \] is the summation of the terms that does not involve any \( W_i \) and \( V_e \). The matrices \( Y_i, Z_e \) and the set \( \Theta = \{ v_i, p_e, \psi, \varphi, \phi_n, \tau_n, \psi, \epsilon_n, \Theta_n, \varsigma_n \} \) denote, respectively, the matrix dual variable of C11, C12 and the set of scalar Lagrange multipliers of the primal constraints C1-C10. Then, the dual problem can be written as

\[ \max_{\Theta \geq 0, Y_i, Z_e} \min_{W_i, V_e, \chi} \mathcal{L}(W_i, V_e, \chi, Y_i, Z_e, \Theta), \tag{17} \]

where \( \Theta \geq 0 \) implies that all of the scalar dual variables within the set \( \Theta \) are non-negative, for the sake of notational simplicity. Let \( \{ W_i^*, V_e^*, \chi^* \} \) and \( \{ Y_i, Z_e, \Theta^* \} \) be defined as the set of optimal primal and dual variables of (10), respectively. The dual problem in (17) can be expressed as

\[ \min_{W_i} \mathcal{L}(W_i, V_e^*, \chi^*, Y_i, Z_e, \Theta^*), \tag{18} \]

\[ \min_{V_e} \mathcal{L}(W_i, V_e^*, \chi^*, Y_i, Z_e, \Theta^*), \tag{19} \]

and the Karush-Kuhn-Tucker (KKT) conditions are given by

\[ \Theta^* \geq 0, Y_i^* \geq 0, V_e^* W_i = 0, \forall i \in L_i, \tag{20} \]

\[ Z_e^* \geq 0, Z_e^* V_e = 0, \forall e \in L_e, \tag{21} \]

\[ Q_i^* - (Y_i^* + v_i H_i) \gamma_i^* = 0, \forall i \in L_i, \tag{22} \]

\[ Q_e^* - (Z_e^* + \rho_e G_e P_{e_{\text{min}}}) = 0, \forall e \in L_e. \tag{23} \]

where \( Q_i^* \) and \( Q_e^* \) are obtained by substituting the optimal dual variables into the expressions in (14) and (15), respectively. In the sequel, it is shown by contradiction that rank\((V_e^*) \leq 1 \) holds with probability one. It is first proved by contradiction that \( Q_e^* \) is a positive definite matrix with probability one. Assuming \( Q_e^* \) is a non-positive definite matrix, one of the optimal solutions of (19) can be chosen as \( V_e = h v_e v_e^H, \) where \( h > 0 \) is a scaling factor and \( v_e \) is the eigenvector corresponding to one of the non-positive eigenvalues of \( Q_e^* \). Substituting \( V_e = h v_e v_e^H \) into (19) gives

\[ \min_{V_e} \mathcal{L}(V_e, W_i^*, \chi^*, Y_i^*, Z_e^*, \Theta^*), \]
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J. Zhao, T. Q. S. Quek, and Z. Lei, “Coordinated multipoint transmission

M. Hong, R. Sun, H. Baligh, and Z.-Q. Luo, “Joint base station clus-

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