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

Wan Nur Suryani Firuz Wan Ariffin, *Student Member, IEEE*, Xinruo Zhang, *Student Member, IEEE*, and Mohammad Reza Nakhai, *Senior Member, IEEE*

***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 ℓ_1-norm approximation for ℓ_0-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

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The authors are with the Department of Informatics, Centre for Telecommunications Research, King's College London, London, WC2R 2LS, U.K. (e-mail: k1206546@kcl.ac.uk; xinruo.zhang@kcl.ac.uk; reza.nakhai@kcl.ac.uk).

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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 ℓ_0-norm optimization problem and handled with reweighted ℓ_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.
- Unlike the latest papers for energy trading with grid, e.g., [13], [14], and [22], that take no consideration of realistic constraints on fronthaul capacity restrictions, this paper formulates more realistic scenarios where RRHs are constrained with limited fronthaul capacities. In practice, the fronthaul resources are highly limited, especially, for joint transmission where all the users data are circulated among all the RRHs. Hence, the designs that take no consideration of fronthaul capacity constraints in problem formulation may lead to infeasible solutions in practical scenarios.
- The problem formulations naturally lead to computationally intractable optimization problems which are dealt with in this paper by reformulating the original problems in their alternative tractable forms using rank relaxation (SDR) technique. The application of SDR adds non-convex unit-rank constraints to the alternative optimization problems, which are subsequently relaxed to find tractable solutions. However, a randomization technique [23] which is a computationally intensive search is required to pick only those feasible solutions that are unit-rank. This paper analytically proves that the solutions to the alternatively reformulated optimization problems using SDR are always unit-rank and, hence, no subsequent search is required to find the unit-rank solutions.

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 ℓ_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, $\mathbf{w}$, $\mathbf{W}$, $(.)^H$ and tr(.), 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. $\mathbb{CN}(\mu, \Gamma)$ represents the circularly symmetric complex normal distribution with mean μ and variance Γ. $\|.\|_p$ is used to denote the ℓ_p-norm of a vector and $\|.\|_0$ indicates the number of non-zero entries in the vector. Note that, the normalized energy unit, i.e., Js^{-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_e 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 $\mathcal{L}_b = \{1, \ldots, N\}$, $\mathcal{L}_e = \{1, \ldots, K_e\}$, $\mathcal{L}_e^{[\text{idle}]} = \{1, \ldots, K_e^{[\text{idle}]}\}$ and $\mathcal{L}_i = \{1, \ldots, K_i\}$ indicate, respectively, the set of indexes of the RHHs, 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.,

$$P_n^{[\text{total}]} = P_n^{[\text{Tx}]} + P_n^{[\text{circuit}]} \leq E_n + B_n^{[\text{ahead}]} + B_n^{[\text{real}]} - S_n. \quad (1)$$

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 $B^{[\text{total}]}$, is given by

$$B^{[\text{total}]} = \pi^{[\text{ahead}]} \sum_{n \in \mathcal{L}_b} B_n^{[\text{ahead}]} + \pi^{[\text{real}]} \sum_{n \in \mathcal{L}_b} B_n^{[\text{real}]} + \pi^{[\text{renew}]} \sum_{n \in \mathcal{L}_b} E_n - \pi^{[\text{sell}]} \sum_{n \in \mathcal{L}_b} S_n. \quad (2)$$

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 $\mathbf{w}_i = [\mathbf{w}_{1i}^H, \ldots, \mathbf{w}_{Ni}^H]^H \in \mathbb{C}^{MN \times 1}$, where $\mathbf{w}_{ni} \in \mathbb{C}^{M \times 1}$ is the beamformer from the n-th RRH towards the i-th IT. $\mathbf{v}_e = [\mathbf{v}_{1e}^H, \ldots, \mathbf{v}_{Ne}^H]^H \in \mathbb{C}^{MN \times 1}$ represents the aggregate beamforming vector from all the RRHs to the e-th active ET. Similarly, let $\mathbf{h}_{ni} \in \mathbb{C}^{M \times 1}$ 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 $\mathbf{h}_i = [\mathbf{h}_{1i}^H, \ldots, \mathbf{h}_{Ni}^H]^H \in \mathbb{C}^{MN \times 1}$. The received signals at the i-th IT, $i \in \mathcal{L}_i$, is then given by

$$y_i = \mathbf{h}_i^H \mathbf{w}_i s_i^{[\text{IT}]} + \sum_{\substack{j \neq i \\ j \in \mathcal{L}_i}} \mathbf{h}_i^H \mathbf{w}_j s_j^{[\text{IT}]} + \sum_{e \in \mathcal{L}_e} \mathbf{h}_i^H \mathbf{v}_e s_e^{[\text{ET}]} + n_i, \quad (3)$$

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., $n_i \sim \mathbb{CN}(0, \sigma_i^2)$, 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 $\mathbb{E}(s_i^{[\text{IT}]}) = \mathbb{E}(s_e^{[\text{ET}]}) = 1$ and σ_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

$$\text{SINR}_i^{[\text{IT}]} = \frac{\left|\mathbf{h}_i^H \mathbf{w}_i\right|^2}{\sum\limits_{j \in \mathcal{L}_i, j \neq i} \left|\mathbf{h}_i^H \mathbf{w}_j\right|^2 + \sum\limits_{e \in \mathcal{L}_e} \left|\mathbf{h}_i^H \mathbf{v}_e\right|^2 + \sigma_i^2}. \quad (4)$$

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

$$C_n^{[\text{fronthaul}]} = \sum_{i \in \mathcal{L}_i} \| \|\mathbf{w}_{ni}\|_2 \|_0 R_i = \sum_{i \in \mathcal{L}_i} \left\| \|\mathbf{w}_{ni}\|_2^2 \right\|_0 R_i, \quad \forall n \in \mathcal{L}_b, \quad (5)$$

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 ℓ_0-norm in (5) is invariant when the input arguments are squared and $\left\| \|\mathbf{w}_{ni}\|_2^2 \right\|_0$ is an indicator function that illustrates the scheduling choices of the individual ITs, i.e.,

$$\left\| \|\mathbf{w}_{ni}\|_2^2 \right\|_0 = \begin{cases} 0, & \text{if } \|\mathbf{w}_{ni}\|_2^2 = 0, \\ 1, & \text{if } \|\mathbf{w}_{ni}\|_2^2 \neq 0. \end{cases} \quad (6)$$

$\|\mathbf{w}_{ni}\|_2^2 = 0$ 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 $\wp_{nm}$
2. **for** $m = 1 : (K_e + K_e^{[\text{idle}]})$
3. **for** $n = 1 : N$
4. CP calculates the hexagonal energy serving areas of the n-th RRH for the m-th ET as follows $A_{nm} = \wp_{nm} * 6(\frac{(D/2)^2}{\sqrt{3}})$;
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 $\{\mathbf{w}_{lm}\}_{\forall l \neq n} = 0$;
7. **end if**
8. **end for**
9. **if** the m-th ET locates outside the area $A_{nm}, \forall n \in \mathcal{L}_b$
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 idle ETs merely harvest energy from the surroundings. The steps of authorization are summarized in Algorithm 1. By adjusting the value of $\wp_{nm}$, 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, $e \in \mathcal{L}_e$, can be expressed as

$$\mathcal{G}_e^{[\text{ET}]} = \eta \left(\left|\mathbf{g}_e^H \mathbf{v}_e\right|^2 + \sum_{j \in \mathcal{L}_e, j \neq e} \left|\mathbf{g}_e^H \mathbf{v}_j\right|^2 + \sum_{i \in \mathcal{L}_i} \left|\mathbf{g}_e^H \mathbf{w}_i\right|^2 \right), \quad (7)$$

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; $\mathbf{g}_e = [\mathbf{g}_{1e}^H, \ldots, \mathbf{g}_{Ne}^H]^H \in \mathbb{C}^{MN \times 1}$ 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 be 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, $z \in \mathcal{L}_e^{[\text{idle}]}$, is given by

$$\mathcal{G}_z^{[\text{ET}-\text{idle}]} = \eta \left(\sum_{i \in \mathcal{L}_i} \left|\mathbf{f}_z^H \mathbf{w}_i\right|^2 + \sum_{e \in \mathcal{L}_e} \left|\mathbf{f}_z^H \mathbf{v}_e\right|^2 \right), \quad (8)$$

where $\mathbf{f}_z = [\mathbf{f}_{1z}^H, \ldots, \mathbf{f}_{Nz}^H]^H \in \mathbb{C}^{MN \times 1}$ 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 fronthaul link capacity relaxation, it will, nevertheless, result in an increase in the total transmit power. In the sequel, a joint strategy of cooperative resource management and real-time energy trading is proposed 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 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 RHHs.

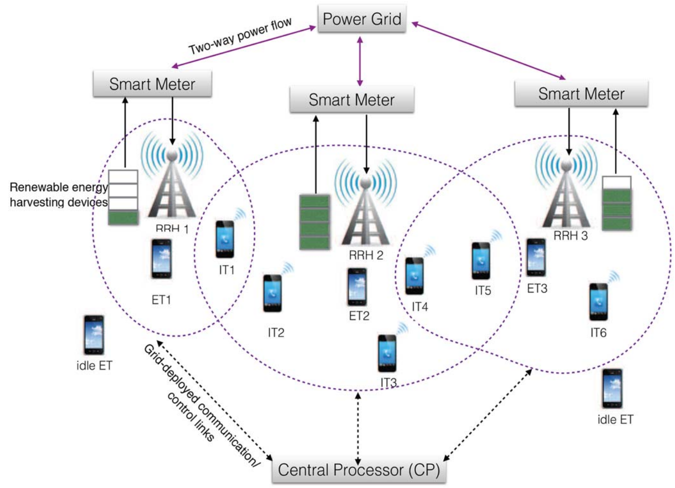


Fig. 1. RRH-centric Clustering embedded with ETs Authorization Algorithm.

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 their maximum real-time energy request at a spot-market under the constraints of supply and demand power balancing at the RRHs, the individual fronthaul link capacity restrictions, the QoS requirements at the ITs, and the transmission energy requirements at the ETs, i.e.,

$$\begin{aligned}
\min_{\substack{\mathbf{w}_{ni}, \\ \mathbf{v}_{ne}, \\ B_n^{[\text{real}]}}} \quad & \alpha \mathcal{P}^{[\text{coop}]} + \beta \sum_{n \in \mathcal{L}_b} P_n^{[\text{Tx}]} + \zeta \max_{n \in \mathcal{L}_b} \left\{ B_n^{[\text{real}]} \right\} \\
\text{s.t.} \quad & \text{C1} : \text{SINR}_i^{[\text{IT}]} \geq \gamma_i, \quad \forall i \in \mathcal{L}_i, \\
& \text{C2} : \mathcal{G}_e^{[\text{ET}]} \geq P_e^{[\min]}, \quad \forall e \in \mathcal{L}_e, \\
& \text{C3} : \mathcal{G}_z^{[\text{ET}-\text{idle}]} \geq P_z^{[\text{idle}]} \quad \forall z \in \mathcal{L}_e^{[\text{idle}]}, \\
& \text{C4} : P_n^{[\text{Tx}]} \leq E_n + B_n^{[\text{ahead}]} + B_n^{[\text{real}]} \\
& \qquad\qquad - S_n - P_n^{[\text{circuit}]}, \quad \forall n \in \mathcal{L}_b, \\
& \text{C5} : P_n^{[\text{Tx}]} \leq P_n^{[\text{Tmax}]}, \quad \forall n \in \mathcal{L}_b, \\
& \text{C6} : C_n^{[\text{fronthaul}]} \leq C_n^{[\text{b}-\text{limit}]}, \quad \forall n \in \mathcal{L}_b, \\
& \text{C7} : \sum_{n \in \mathcal{L}_b} B_n^{[\text{ahead}]} + \sum_{n \in \mathcal{L}_b} B_n^{[\text{real}]} \leq P_{\text{CP}}^{[\max]} - P_{\text{CP}}^{[\text{circuit}]} \\
& \text{C8} : B_n^{[\text{real}]} \geq 0, \qquad \text{C9} : S_n \geq 0, \quad \forall n \in \mathcal{L}_b. \qquad (9)
\end{aligned}$$

where $\mathcal{P}^{[\text{coop}]} = (\sum_{i\in\mathcal{L}_i} \|\|\mathbf{w}_{1i}\|_2^2\|_0 + \cdots + \sum_{i\in\mathcal{L}_i} \|\|\mathbf{w}_{Ni}\|_2^2\|_0) + (\sum_{e\in\mathcal{L}_e} \|\|\mathbf{v}_{1e}\|_2^2\|_0 + \cdots + \sum_{e\in\mathcal{L}_e} \|\|\mathbf{v}_{Ne}\|_2^2\|_0)$ 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 $P_n^{[\text{Tx}]} = \sum_{i\in\mathcal{L}_i} ||\mathbf{w}_{ni}||_2^2 + \sum_{e\in\mathcal{L}_e} ||\mathbf{v}_{ne}||_2^2, n \in \mathcal{L}_b$ is the total transmit power by the n-th RRH to its scheduled receiving terminals. The weighting coefficients $\beta \geq 0$ and $\zeta \geq 0$ model the degrees of CP's emphasis on minimizing the total transmit power, i.e., $\sum_{n\in\mathcal{L}_b} P_n^{[\text{Tx}]}$, and RRHs' maximum real-time energy request at a spot-market, i.e., $\max_{n\in\mathcal{L}_b}\{B_n^{[\text{real}]}\}$, respectively. A larger weighting coefficient results in a more emphasize in minimizing the corresponding term of the objective function. Let γ_i represent the minimum SINR requirement of the i-th IT, then C1 denotes a set of QoS constraints for K_i ITs. $P_e^{[\text{min}]}$ in C2 represents the minimum energy transmission requirements by the active ETs while $P_z^{[\text{idle}]}$ 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 $P_n^{[\text{Tmax}]}$ 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 $P_{\text{CP}}^{[\text{circuit}]}$ and $P_{\text{CP}}^{[\text{max}]}$ 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 ℓ_0-norm in the first term of the objective function and $C_n^{[\text{fronthaul}]}$ in the constraint C6. By using convex relaxation technique [18], the ℓ_0-norm term in the objective function of (9) and C6 can be approximated by their weighted ℓ_1-norm, respectively, as follows

$$\begin{aligned}
\mathcal{P}^{[\text{coop}]} &\approx \sum_{i\in\mathcal{L}_i}\left\|\left[\xi_{1i}\|\mathbf{w}_{1i}\|_2^2\right]\right\|_1 + \cdots + \sum_{i\in\mathcal{L}_i}\left\|\left[\xi_{Ni}\|\mathbf{w}_{Ni}\|_2^2\right]\right\|_1 \\
&\quad + \sum_{e\in\mathcal{L}_e}\left\|\left[\kappa_{1e}\|\mathbf{v}_{1e}\|_2^2\right]\right\|_1 + \cdots + \sum_{e\in\mathcal{L}_e}\left\|\left[\kappa_{Ne}\|\mathbf{v}_{Ne}\|_2^2\right]\right\|_1 \\
&= \sum_{n\in\mathcal{L}_b}\left(\sum_{i\in\mathcal{L}_i}\xi_{ni}\|\mathbf{w}_{ni}\|_2^2\right) + \sum_{n\in\mathcal{L}_b}\left(\sum_{e\in\mathcal{L}_e}\kappa_{ne}\|\mathbf{v}_{ne}\|_2^2\right), \\
&= \sum_{n\in\mathcal{L}_b}\left(\sum_{i\in\mathcal{L}_i}\xi_{ni}\mathrm{tr}\left(\mathbf{w}_i\mathbf{w}_i^H\mathbf{D}_n\right) + \sum_{e\in\mathcal{L}_e}\kappa_{ne}\mathrm{tr}\left(\mathbf{v}_e\mathbf{v}_e^H\mathbf{D}_n\right)\right), \\
C_n^{[\text{fronthaul}]} &= \sum_{i\in\mathcal{L}_i}\left\|\|\mathbf{w}_{ni}\|_2^2\right\|_0 R_i \approx \sum_{i\in\mathcal{L}_i}\left\|\left[\xi_{ni}\|\mathbf{w}_{ni}\|_2^2\right]\right\|_1 R_i \\
&= \sum_{i\in\mathcal{L}_i}\xi_{ni}\|\mathbf{w}_{ni}\|_2^2 R_i = \sum_{i\in\mathcal{L}_i}\xi_{ni}\mathrm{tr}\left(\mathbf{w}_i\mathbf{w}_i^H\mathbf{D}_n\right)R_i,
\end{aligned}$$

Algorithm 2 Reweighted ℓ_1-Norm Method

1: **Initialize**: constant $\mu \to 0$, iteration count $t = 0$, weighting factor $\xi_{ni}(t) = 1$, $\kappa_{ne}(t) = 1$, maximum number of iterations $t_{\max}$, $\hat{R}_i(t) = \log_2(1+\gamma_i)$.
2: **while** ξ_{ni} and κ_{ne} 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 $\xi_{ni}(t+1)$ as follows, $\xi_{ni}(t+1) = \frac{1}{\mathrm{tr}(\mathbf{W}_i^*(t)\mathbf{D}_n)+\mu}, \quad \forall n \in \mathcal{L}_b, i \in \mathcal{L}_i$;
5: Update the weight factor $\kappa_{ne}(t+1)$ as follows, $\kappa_{ne}(t+1) = \frac{1}{\mathrm{tr}(\mathbf{V}_e^*(t)\mathbf{D}_n)+\mu}, \quad \forall n \in \mathcal{L}_b, e \in \mathcal{L}_e$;
6: Calculate the achievable rate $R_i(t)$ as follows,
$$R_i(t) = \log_2\Big[1 + \frac{\mathrm{tr}(\mathbf{H}_i\mathbf{W}_i^*(t))}{\sum_{j\in\mathcal{L}_i, j\neq i}\mathrm{tr}(\mathbf{H}_i\mathbf{W}_j^*(t)) + \sum_{e\in\mathcal{L}_e}\mathrm{tr}(\mathbf{H}_i\mathbf{V}_e^*(t)) + \sigma_i^2}\Big];$$
7: Update $\hat{R}_i(t+1) = R_i(t)$;
8: Increment the iteration number $t = t+1$;
9: **end while**

where $\mathbf{D}_n \triangleq \mathrm{Bdiag}(\mathbf{0}_1 \cdots \mathbf{0}_i \ldots \mathbf{I}_n \cdots \mathbf{0}_N) \succeq 0, \forall n \in \mathcal{L}_b$ is a block diagonal matrix, $\mathbf{0}_i$ is an $M \times M$ matrix with all-zero elements and $\mathbf{I}_n$ is an $M \times M$ identity matrix. $\xi_{ni} \geq 0$ and $\kappa_{ne} \geq 0$, respectively, are the weighting factors associated with the n-th RRH and the i-th IT/the e-th active ET. It has been argued in [16] that weights could counteract the influence of the signal magnitude on the ℓ_1 norm surrogate to ℓ_0 norm, as ℓ_0 norm simply counts the number of nonzero elements of a vector and is not sensitive to their actual values. Thus, this paper introduces a *reweighted ℓ_1-norm method* in Algorithm 2, where the weights are set to be inversely proportional to the true signal magnitude in steps 4 and 5. Since obtaining a valid set of weights depends on knowing the optimal beamformers, i.e., $\mathbf{w}_{ni}^*, \forall n, \forall i$, the proposed Algorithm 2 alternates between computing the beamformers and redefining the weights by first solving the optimization problem (10) in step 3 and then updating the weights in steps 4 and 5. In particular, the RRH transmitting with low transmit power to a particular receiving terminal in the t-th iteration results in a large weighting factor, which will force further reduction in the transmit power of the same RRH in the $(t+1)$-th iteration until the solution sparsity is attained. Consequently, the cooperative links between the RRHs and the active receiving terminals are iteratively removed on the basis of the power budgets and fronthaul link capacity restrictions at the individual RRHs.

Let us set $\mathbf{H}_i = \mathbf{h}_i\mathbf{h}_i^H$, $\mathbf{G}_e = \mathbf{g}_e\mathbf{g}_e^H$, $\mathbf{F}_z = \mathbf{f}_z\mathbf{f}_z^H$ 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 $\sum_{n\in\mathcal{L}_b} P_n^{[\text{Tx}]} = \sum_{i\in\mathcal{L}_i}\sum_{n\in\mathcal{L}_b}\mathrm{tr}(\mathbf{w}_i\mathbf{w}_i^H\mathbf{D}_n) + \sum_{e\in\mathcal{L}_e}\sum_{n\in\mathcal{L}_b}\mathrm{tr}(\mathbf{v}_e\mathbf{v}_e^H\mathbf{D}_n) = \sum_{i\in\mathcal{L}_i}\mathrm{tr}(\mathbf{W}_i) + \sum_{e\in\mathcal{L}_e}\mathrm{tr}(\mathbf{V}_e)$. The original optimization problem in (9) can be transformed to a semidefinite programming (SDP) problem after relaxing the unit-rank constraints of $\text{rank}(\mathbf{W}_i) = 1$ and $\text{rank}(\mathbf{V}_e) \leq 1$, as

$$\begin{aligned}
\min_{\substack{\mathbf{W}_i,\\ \mathbf{V}_e,\chi}} \ & \alpha \sum_{n\in\mathcal{L}_b}\left(\sum_{i\in\mathcal{L}_i}\xi_{ni}\text{tr}(\mathbf{W}_i\mathbf{D}_n) + \sum_{e\in\mathcal{L}_e}\kappa_{ne}\text{tr}(\mathbf{V}_e\mathbf{D}_n)\right) \\
& + \beta\left(\sum_{i\in\mathcal{L}_i}\text{tr}(\mathbf{W}_i) + \sum_{e\in\mathcal{L}_e}\text{tr}(\mathbf{V}_e)\right) + \chi, \\
\text{s.t.}\ & \text{C1} : \text{tr}(\mathbf{H}_i\mathbf{W}_i) \geq \gamma_i \sum_{j\in\mathcal{L}_i, j\neq i}\text{tr}\big(\mathbf{H}_i\mathbf{W}_j\big) \\
& \qquad + \gamma_i\sum_{e\in\mathcal{L}_e}\text{tr}(\mathbf{H}_i\mathbf{V}_e) + \gamma_i\sigma_i^2, \ \forall i \in \mathcal{L}_i, \\
& \text{C2} : \text{tr}(\mathbf{G}_e\mathbf{V}_e) + \sum_{j\in\mathcal{L}_e, j\neq e}\text{tr}\big(\mathbf{G}_e\mathbf{V}_j\big) \\
& \qquad + \sum_{i\in\mathcal{L}_i}\text{tr}(\mathbf{G}_e\mathbf{W}_i) \geq P_e^{[\min]}\eta^{-1}, \ \forall e \in \mathcal{L}_e, \\
& \text{C3} : \sum_{i\in\mathcal{L}_i}\text{tr}(\mathbf{F}_z\mathbf{W}_i) + \sum_{e\in\mathcal{L}_e}\text{tr}(\mathbf{F}_z\mathbf{V}_e) \geq P_z^{[\text{idle}]}\eta^{-1} \\
& \qquad \forall z \in \mathcal{L}_e^{[\text{idle}]}, \\
& \text{C4} : \sum_{i\in\mathcal{L}_i}\text{tr}(\mathbf{W}_i\mathbf{D}_n) + \sum_{e\in\mathcal{L}_e}\text{tr}(\mathbf{V}_e\mathbf{D}_n) \leq \big[E_n - S_n \\
& \qquad + B_n^{[\text{ahead}]} + B_n^{[\text{real}]} - P_n^{[\text{circuit}]}\big], \ \forall n \in \mathcal{L}_b, \\
& \text{C5} : \sum_{i\in\mathcal{L}_i}\text{tr}(\mathbf{W}_i\mathbf{D}_n) + \sum_{e\in\mathcal{L}_e}\text{tr}(\mathbf{V}_e\mathbf{D}_n) \leq P_n^{[\text{Tmax}]}, \\
& \qquad \forall n \in \mathcal{L}_b, \\
& \text{C6} : \sum_{i\in\mathcal{L}_i}\xi_{ni}\text{tr}(\mathbf{W}_i\mathbf{D}_n)\hat{R}_i \leq C_n^{[\text{b-limit}]}, \ \forall n \in \mathcal{L}_b, \\
& \text{C7} - \text{C9}, \qquad \text{C10} : \zeta B_n^{[\text{real}]} \leq \chi, \quad \forall n \in \mathcal{L}_b, \\
& \text{C11} : \mathbf{W}_i \succeq 0, \forall i \in \mathcal{L}_i, \quad \text{C12} : \mathbf{V}_e \succeq 0, \forall e \in \mathcal{L}_e. \qquad (10)
\end{aligned}$$

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

$$\begin{aligned}
\min_{\mathbf{w}_{ni},\mathbf{v}_{ne},B_n^{[\text{real}]}} \ & \alpha\mathcal{P}^{[\text{coop}]} + \beta\sum_{n\in\mathcal{L}_b}P_n^{[\text{Tx}]} + \zeta\sum_{n\in\mathcal{L}_b}\left\{B_n^{[\text{real}]}\right\} \\
\text{s.t.}\ & \text{C1} - \text{C9 in (9).} \qquad (11)
\end{aligned}$$

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 $\zeta \geq 0$ model the degrees of CP's emphasis on minimizing the RRHs' total transmit power and their overall real-time energy demands, respectively.

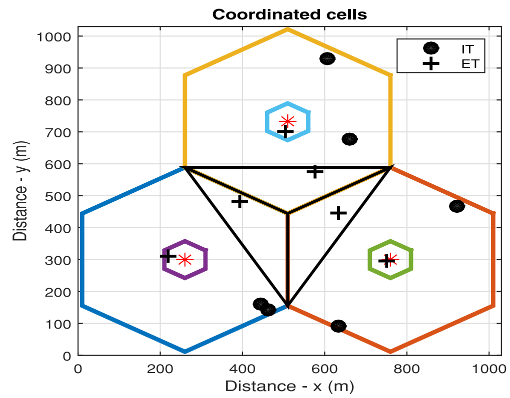


Fig. 2. A Multi-user Downlink SWIPT C-RAN Simulation Topology.

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

$$\begin{aligned}
\min_{\substack{\mathbf{W}_i,\\ \mathbf{V}_e,\\ B_n^{[\text{real}]}}} \ & \alpha \sum_{n\in\mathcal{L}_b}\left(\sum_{i\in\mathcal{L}_i}\xi_{ni}\text{tr}(\mathbf{W}_i\mathbf{D}_n) + \sum_{e\in\mathcal{L}_e}\kappa_{ne}\text{tr}(\mathbf{V}_e\mathbf{D}_n)\right) \\
& + \beta\left(\sum_{i\in\mathcal{L}_i}\text{tr}(\mathbf{W}_i) + \sum_{e\in\mathcal{L}_e}\text{tr}(\mathbf{V}_e)\right) + \zeta\sum_{n\in\mathcal{L}_b}\left\{B_n^{[\text{real}]}\right\} \\
\text{s.t.}\ & \text{C1} - \text{C9},\ \text{C11} - \text{C12 in (10).} \qquad (12)
\end{aligned}$$

Note that, if the obtained solutions $\mathbf{W}_i^*$ and $\mathbf{V}_e^*$ 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 $\text{rank}(\mathbf{W}_i^*) = 1$ and $\text{rank}(\mathbf{V}_e^*) \leq 1$ 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 $\wp_{nm} = 0.2$. 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 price of $\pi^{[\text{renew}]} = £0.02/\text{W}$ and the RRHs can sell excessive energy back to the grid at price of $\pi^{[\text{sell}]} = £0.05/\text{W}$. 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 $\pi^{[\text{ahead}]} = £0.07/\text{W}$ and that the buying energy price at a spot-market is at $\pi^{[\text{real}]} = £0.15/\text{W}$. Besides, the channel vectors $\mathbf{h}_i$, $\mathbf{g}_e$ and $\mathbf{f}_z$ are assumed to be independently distributed and a correlated channel model $\mathbf{h}_{ni} = \mathbf{R}^{1/2}\mathbf{h}_w$ is adopted [24], where $\mathbf{h}_w \in \mathbb{C}^{M\times 1} \sim \mathbb{CN}(0, 1)$, $\mathbf{R} \in \mathbb{C}^{M\times M}$ is the spatial covariance matrix and its (m, n)-th element is given by $G_a L_p \sigma_F^2 e^{-0.5\frac{(\sigma_s \ln 10)^2}{100}} e^{j\frac{2\pi\delta}{\lambda}[(n-m)sin\theta]} e^{-2[\frac{\pi\delta\sigma}{\lambda}(n-m)cos\theta]^2}$, where antenna gain $G_a = 15$ dBi, $L_p(\text{dB}) = 125.2+$

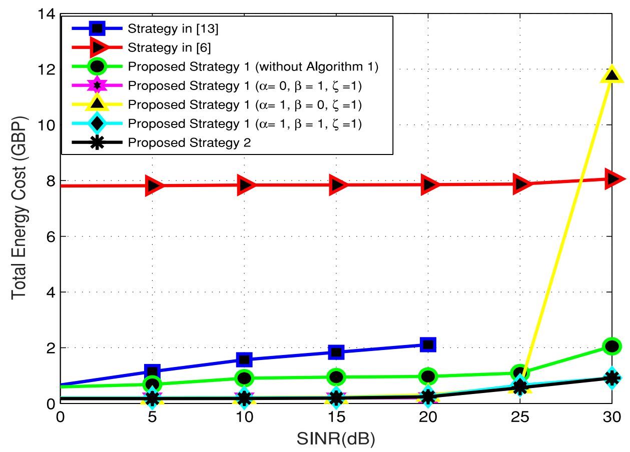


Fig. 3. Total energy cost versus various target SINR for different strategies.

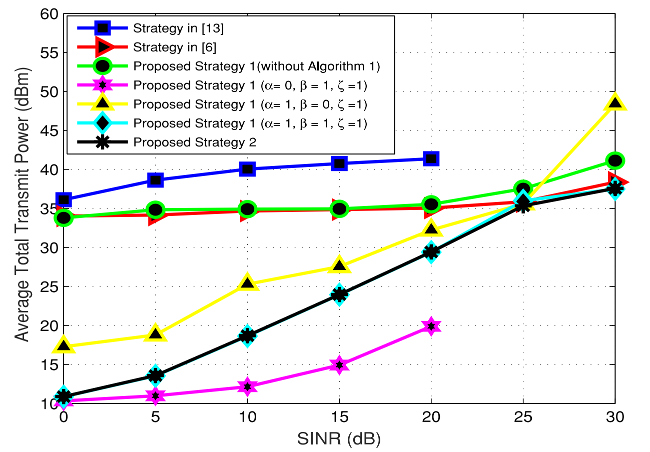


Fig. 4. Total transmit power versus various target SINR for different strategies.

$36.3\log_{10}(d)$ is the path loss model over a distance of d km, σ_F^2 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 $\sigma = 2°$ and θ 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 $P_{\text{CP}}^{[\text{circuit}]} = 40$ dBm, $P_{\text{CP}}^{[\max]} = 50$ dBm, $P_n^{[\text{circuit}]} = 30$ dBm, $P_n^{[\text{Tmax}]} = 46$ dBm, $C_n^{[\text{b-limit}]} = 40$ bit/s/Hz, $P_e^{[\min]} = -60$ dBm, $P_z^{[\text{idle}]} = -90$ 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 α, 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 β and ζ, 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.

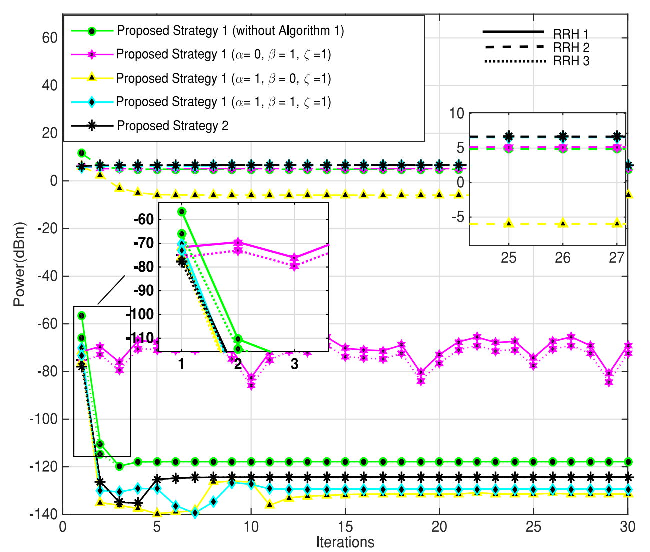


Fig. 5. Transmit power variation of RRHs using reweighted ℓ_1-norm method proposed in Algorithm 2 for serving the 3rd IT at $\gamma = 20$ dB.

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.

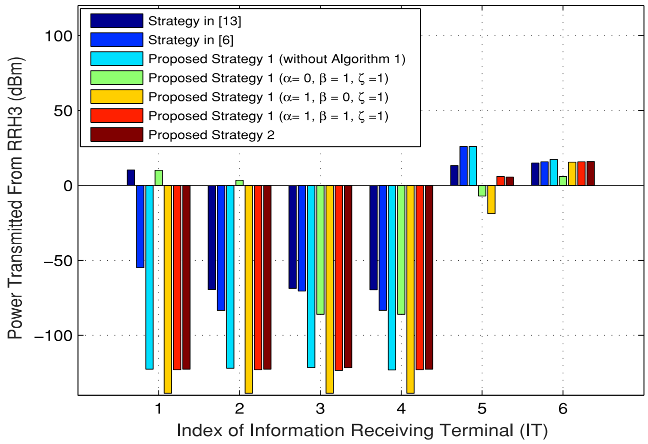
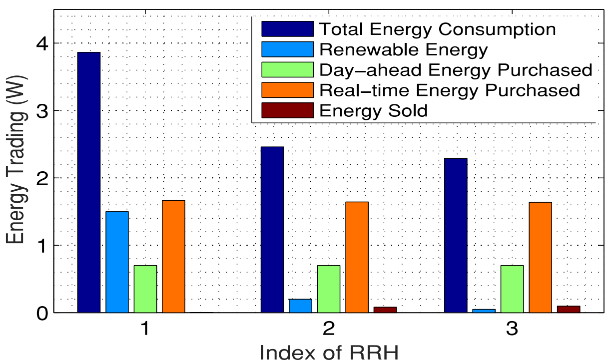
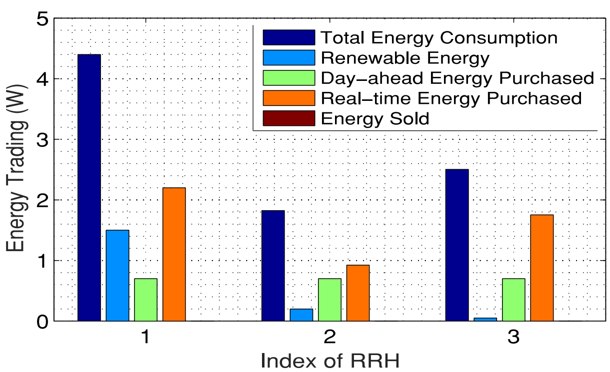


Fig. 6. Clustering behaviour of RRH 3 at $\gamma = 20$ dB target SINR.



(a) Proposed Strategy 1



(b) Proposed Strategy 2

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

Transmit power variation of the individual RRHs using reweighted ℓ_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 backhual 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 ℓ_1-norm approximation for ℓ_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

$$\begin{aligned}
&\mathcal{L}(\mathbf{W}_i, \mathbf{V}_e, \chi, \mathbf{Y}_i, \mathbf{Z}_e, \nu_i, \rho_e, \pi_z, \varphi_n, \phi_n, \tau_n, \psi, \epsilon_n, \varrho_n, \varsigma_n) \\
&= \sum_{i\in\mathcal{L}_i} \mathrm{tr}(\mathbf{Q}_i\mathbf{W}_i) - \sum_{i\in\mathcal{L}_i} \mathrm{tr}\left(\mathbf{W}_i\left(\mathbf{Y}_i + \frac{\nu_i\mathbf{H}_i}{\gamma_i}\right)\right) \\
&\quad + \sum_{e\in\mathcal{L}_e} \mathrm{tr}(\mathbf{Q}_e\mathbf{V}_e) - \sum_{e\in\mathcal{L}_e} \mathrm{tr}\left(\mathbf{V}_e\left(\mathbf{Z}_e + \frac{\rho_e\mathbf{G}_e}{P_e^{[\min]}}\right)\right) + \Xi, \qquad (13)
\end{aligned}$$

where

$$\mathbf{Q}_i = \alpha \sum_{n\in\mathcal{L}_b} \xi_{ni}\mathbf{D}_n + \beta\mathbf{I} + \sum_{i\in\mathcal{L}_i, j\neq i} \nu_j\mathbf{H}_j - \sum_{e\in\mathcal{L}_e} \frac{\rho_e\mathbf{G}_e}{P_e^{[\min]}} - \sum_{z\in\mathcal{L}_e^{[\text{idle}]}} \mathbf{F}_z\pi_z + \sum_{n\in\mathcal{L}_b}\Big(\varphi_n + \phi_n + \tau_n\xi_{ni}\hat{R}_i\Big)\mathbf{D}_n, \quad (14)$$

$$\mathbf{Q}_e = \alpha \sum_{n\in\mathcal{L}_b} \kappa_{ne}\mathbf{D}_n + \beta\mathbf{I} + \sum_{i\in\mathcal{L}_i} \nu_i\mathbf{H}_i - \sum_{e\in\mathcal{L}_e, j\neq e} \frac{\rho_e\mathbf{G}_j}{P_e^{[\min]}} - \sum_{z\in\mathcal{L}_e^{[\text{idle}]}} \mathbf{F}_z\pi_z + \sum_{n\in\mathcal{L}_b}(\varphi_n + \phi_n)\mathbf{D}_n, \quad (15)$$

$$\begin{aligned}\Xi = &\sum_{n\in\mathcal{L}_b}(\psi - \varphi_n)B_n^{[\text{ahead}]} + \sum_{n\in\mathcal{L}_b}(\psi - \varphi_n - \epsilon_n)B_n^{[\text{real}]} \\ &+ \sum_{i\in\mathcal{L}_i}\nu_i\sigma_i^2 + \sum_{e\in\mathcal{L}_e}\rho_e\eta^{-1} + \sum_{z\in\mathcal{L}_e^{[\text{idle}]}}\pi_z P_z^{[\text{idle}]}\eta^{-1} - \psi P_{\text{CP}}^{[\max]} \\ &- \sum_{n\in\mathcal{L}_b}\Big[\varphi_n\Big(E_n - S_n - P_n^{[\text{circuit}]}\Big) + \phi_n P_n^{[\text{Tmax}]}\Big] + \psi P_{\text{CP}}^{[\text{circuit}]} \\ &- \sum_{n\in\mathcal{L}_b}\Big(\tau_n C_n^{[\text{b-limit}]} + \varrho_n S_n - \varsigma_n\chi - \varsigma_n\zeta B_n^{[\text{real}]}\Big) + \chi. \end{aligned} \quad (16)$$

Ξ is the summation of the terms that does not involve any $\mathbf{W}_i$ and $\mathbf{V}_e$. The matrices $\mathbf{Y}_i$, $\mathbf{Z}_e$ and the set $\Theta = \{\nu_i, \rho_e, \pi_z, \varphi_n, \phi_n, \tau_n, \psi, \epsilon_n, \varrho_n, \varsigma_n\}$ 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

$$\max_{\Theta\geq 0, \mathbf{Y}_i, \mathbf{Z}_e \succeq 0}\ \min_{\mathbf{W}_i, \mathbf{V}_e, \chi} \mathcal{L}(\mathbf{W}_i, \mathbf{V}_e, \chi, \mathbf{Y}_i, \mathbf{Z}_e, \Theta), \quad (17)$$

where $\Theta \geq 0$ implies that all of the scalar dual variables within the set Θ are non-negative, for the sake of notational simplicity. Let $\{\mathbf{W}_i^*, \mathbf{V}_e^*, \chi^*\}$ and $\{\mathbf{Y}_i^*, \mathbf{Z}_e^*, \Theta^*\}$ be defined as the set of optimal primal and dual variables of (10), respectively. The dual problem in (17) can be expressed as

$$\min_{\mathbf{W}_i} \mathcal{L}\big(\mathbf{W}_i, \mathbf{V}_e^*, \chi^*, \mathbf{Y}_i^*, \mathbf{Z}_e^*, \Theta^*\big), \quad (18)$$

$$\min_{\mathbf{V}_e} \mathcal{L}\big(\mathbf{V}_e, \mathbf{W}_i^*, \chi^*, \mathbf{Y}_i^*, \mathbf{Z}_e^*, \Theta^*\big), \quad (19)$$

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

$$\Theta^* \geq 0,\ \mathbf{Y}_i^* \succeq 0,\ \mathbf{Y}_i^*\mathbf{W}_i^* = 0,\ \forall i \in \mathcal{L}_i, \quad (20)$$

$$\mathbf{Z}_e^* \succeq 0,\ \mathbf{Z}_e^*\mathbf{V}_e^* = 0,\ \forall e \in \mathcal{L}_e, \quad (21)$$

$$\mathbf{Q}_i^* - \left(\mathbf{Y}_i^* + \frac{\nu_i^*\mathbf{H}_i}{\gamma_i}\right) = 0,\ \forall i \in \mathcal{L}_i, \quad (22)$$

$$\mathbf{Q}_e^* - \left(\mathbf{Z}_e^* + \frac{\rho_e^*\mathbf{G}_e}{P_e^{[\min]}}\right)\Bigg) = 0,\ \forall e \in \mathcal{L}_e, \quad (23)$$

where $\mathbf{Q}_i^*$ and $\mathbf{Q}_e^*$ 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 $\text{rank}(\mathbf{V}_e^*) \leq 1$ holds with probability one. It is first proved by contradiction that $\mathbf{Q}_e^*$ is a positive definite matrix with probability one. Assuming $\mathbf{Q}_e^*$ is a non-positive definite matrix, one of the optimal solutions of (19) can be chosen as $\mathbf{V}_e = \hbar\mathbf{v}_e\mathbf{v}_e^H$, where $\hbar > 0$ is a scaling factor and $\mathbf{v}_e$ is the eigenvector corresponding to one of the non-positive eigenvalues of $\mathbf{Q}_e^*$. Substituting $\mathbf{V}_e = \hbar\mathbf{v}_e\mathbf{v}_e^H$ into (19) gives

$$\begin{aligned}&\min_{\mathbf{V}_e} \mathcal{L}\big(\mathbf{V}_e, \mathbf{W}_i^*, \chi^*, \mathbf{Y}_i^*, \mathbf{Z}_e^*, \Theta^*\big) \\ &= \sum_{e\in\mathcal{L}_e}\text{tr}\big(\hbar\mathbf{Q}_e^*\mathbf{v}_e\mathbf{v}_e^H\big) - \hbar\sum_{e\in\mathcal{L}_e}\text{tr}\left(\mathbf{v}_e^H\left(\mathbf{Z}_e^* + \frac{\rho_e^*\mathbf{G}_e}{P_e^{[\min]}}\right)\mathbf{v}_e\right) \\ &\quad + \left(\sum_{i\in\mathcal{L}_i}\text{tr}\big(\mathbf{Q}_i^*\mathbf{W}_i^*\big) - \sum_{i\in\mathcal{L}_i}\text{tr}\left(\mathbf{W}_i^*\left(\mathbf{Y}_i^* + \frac{\nu_i^*\mathbf{H}_i}{\gamma_i}\right)\right) + \Theta^*\right), \end{aligned} \quad (24)$$

where $\sum_{e\in\mathcal{L}_e}\text{tr}(\hbar\mathbf{Q}_e^*\mathbf{v}_e\mathbf{v}_e^H)$ is non-positive and as $\hbar \to \infty$, $-\hbar\sum_{e\in\mathcal{L}_e}\text{tr}(\mathbf{v}_e^H(\mathbf{Z}_e^* + \frac{\rho_e^*\mathbf{G}_e}{P_e^{[\min]}})\mathbf{v}_e)$ may go to negative infinity, which results in an unbounded dual optimal value. However, the optimal value of the primal problem is non-negative, thus strong duality does not hold which induces a contradiction. Therefore, $\mathbf{Q}_e^*$ is a positive definite matrix with probability one and $\text{rank}(\mathbf{Q}_e^*) = MN$, provided that channel vectors $\mathbf{h}_i$, $\mathbf{g}_e$ and $\mathbf{f}_z$ are independently distributed. Then the following inequality holds as per (23) and properties of rank of matrix:

$$\begin{aligned}\text{rank}\big(\mathbf{Q}_e^*\big) = MN &= \text{rank}\left(\mathbf{Z}_e^* + \frac{\rho_e^*\mathbf{G}_e}{P_e^{[\min]}}\right) \\ &\leq \text{rank}\big(\mathbf{Z}_e^*\big) + \text{rank}\left(\frac{\rho_e^*\mathbf{G}_e}{P_e^{[\min]}}\right) \\ &\Rightarrow \text{rank}\big(\mathbf{Z}_e^*\big) \geq MN - 1. \end{aligned} \quad (25)$$

Furthermore, the KKT condition in (21), i.e., $\mathbf{Z}_e^*\mathbf{V}_e^* = 0$, implies

$$\text{rank}\big(\mathbf{Z}_e^*\big) \leq MN - \text{rank}\big(\mathbf{V}_e^*\big). \quad (26)$$

If the desired $P_e^{[\min]}$ is larger than the power that can be transferred to the ET by the ambient interference, then $\mathbf{V}_e^* \neq 0$, otherwise $\mathbf{V}_e^* = 0$. On the other hand, an inspection of the results in (25) and (26) implies that for $\mathbf{V}_e^* \neq 0$, $\text{rank}(\mathbf{Z}_e^*) = MN - 1$ must hold. Note also that according to the KKT condition in (21), the columns of $\mathbf{V}_e^*$ are in the null space of $\mathbf{Z}_e^*$. Therefore, when $\mathbf{V}_e \neq 0$, $\text{rank}(\mathbf{V}_e^*) = 1$ holds with probability one, whereas $\mathbf{V}_e^* = 0$ implies $\text{rank}(\mathbf{V}_e^*) = 0$. Hence, $\text{rank}(\mathbf{V}_e^*) \leq 1$ holds with probability one.

By following the similar steps, it can be easily shown that in order to satisfy the minimum SINR requirements in the constraint C1 of (12), $\text{rank}(\mathbf{W}_i^*) = 1$ must hold with probability one. This thus completes the proof of *Lemma1* for problem (10). Furthermore, *Lemma1* also holds for the optimization problem in (12) and can be proven straightforwardly by following the similar steps as stated for the optimization problem in (10).

References

[1] F. Rusek *et al.*, "Scaling up MIMO: Opportunities and challenges with very large arrays," *IEEE Signal Process. Mag.*, vol. 30, no. 1, pp. 40–60, Jan. 2013.

[2] I. Hwang, B. Song, and S. S. Soliman, "A holistic view on hyper-dense heterogeneous and small cell networks," *IEEE Commun. Mag.*, vol. 51, no. 6, pp. 20–27, Jun. 2013.

[3] R. Irmer *et al.*, "Coordinated multipoint: Concepts, performance, and field trial results," *IEEE Commun. Mag.*, vol. 49, no. 2, pp. 102–111, Feb. 2011.

[4] P. Rost *et al.*, "Cloud technologies for flexible 5G radio access networks," *IEEE Commun. Mag.*, vol. 52, no. 5, pp. 68–76, May 2014.

[5] (Oct. 2011). *C-RAN: The Road Towards Green Ran*. [Online]. Available: http://labs.chinamobile.com/cran/wp-content/uploads/CRAN_white_paper_v2_5_EN.pdf

[6] D. W. K. Ng and R. Schober, "Resource allocation for coordinated multipoint networks with wireless information and power transfer," in *Proc. IEEE Glob. Commun. Conf.*, Austin, TX, USA, Dec. 2014, pp. 4281–4287.

[7] J. Xu, L. Liu, and R. Zhang, "Multiuser MISO beamforming for simultaneous wireless information and power transfer," in *Proc. IEEE Int. Conf. Acoust. Speech Signal Process.*, Vancouver, BC, Canada, May 2013, pp. 4754–4758.

[8] H. Xing, L. Liu, and R. Zhang, "Secrecy wireless information and power transfer in fading wiretap channel," in *Proc. IEEE Int. Conf. Commun.*, Sydney, NSW, Australia, Jun. 2014, pp. 5402–5407.

[9] H. Xing, K.-K. Wong, Z. Chu, and A. Nallanathan, "To harvest and jam: A paradigm of self-sustaining friendly jammers for secure AF relaying," *IEEE Trans. Signal Process.*, vol. 63, no. 24, pp. 6616–6631, Dec. 2015.

[10] A. Fehske, G. Fettweis, J. Malmodin, and G. Biczok, "The global footprint of mobile communications: The ecological and economic perspective," *IEEE Commun. Mag.*, vol. 49, no. 8, pp. 55–62, Aug. 2011.

[11] Y. Wang, W. Saad, Z. Han, H. V. Poor, and T. Başar, "A game-theoretic approach to energy trading in the smart grid," *IEEE Trans. Smart Grid*, vol. 5, no. 3, pp. 1439–1450, May 2014.

[12] J. Leithon, T. J. Lim, and S. Sun, "Online energy management strategies for base stations powered by the smart grid," in *Proc. IEEE SmartGridComm*, Vancouver, BC, Canada, Oct. 2013, pp. 199–204.

[13] J. Xu and R. Zhang, "Cooperative energy trading in comp systems powered by smart grids," in *Proc. IEEE Glob. Commun. Conf.*, Austin, TX, USA, Dec. 2014, pp. 2697–2702.

[14] W. N. S. F. W. Ariffin, X. Zhang, and M. R. Nakhai, "Real-time power balancing in green comp network with wireless information and energy transfer," in *Proc. IEEE Int. Symp. Pers. Indoor Mobile Radio Commun. (PIMRC)*, Aug. 2015, pp. 1574–1578.

[15] T. A. Le, S. Nasseri, A. Zarrebini-Esfahani, M. R. Nakhai, and A. Mills, "Power-efficient downlink transmission in multicell networks with limited wireless backhaul," *IEEE Wireless Commun.*, vol. 18, no. 5, pp. 82–88, Oct. 2011.

[16] E. J. Candès, M. B. Wakin, and S. P. Boyd, "Enhancing sparsity by reweighted ℓ_1 minimization," *J. Fourier Anal. Appl.*, vol. 14, no. 5, pp. 877–905, 2008.

[17] B. Dai and W. Yu, "Sparse beamforming and user-centric clustering for downlink cloud radio access network," *IEEE Access*, vol. 2, pp. 1326–1339, Oct. 2014.

[18] D. W. K. Ng, E. S. Lo, and R. Schober, "Energy-efficient resource allocation in multi-cell OFDMA systems with limited backhaul capacity," *IEEE Trans. Wireless Commun.*, vol. 11, no. 10, pp. 3618–3631, Oct. 2012.

[19] J. Zhao, T. Q. S. Quek, and Z. Lei, "Coordinated multipoint transmission with limited backhaul data transfer," *IEEE Trans. Wireless Commun.*, vol. 12, no. 6, pp. 2762–2775, Jun. 2013.

[20] S.-J. Kim, S. Jain, and G. B. Giannakis, "Backhaul-constrained multi-cell cooperation using compressive sensing and spectral clustering," in *Proc. IEEE Int. Workshop SPAWC*, Çeşme, Turkey, Jun. 2012, pp. 65–69.

[21] M. Hong, R. Sun, H. Baligh, and Z.-Q. Luo, "Joint base station clustering and beamformer design for partial coordinated transmission in heterogeneous networks," *IEEE J. Sel. Areas Commun.*, vol. 31, no. 2, pp. 226–240, Feb. 2013.

[22] W. N. S. F. W. Ariffin, X. Zhang, and M. R. Nakhai, "Real-time energy trading with grid in green cloud-RAN," in *Proc. IEEE Int. Symp. Pers. Indoor Mobile Radio Commun. (PIMRC)*, Hong Kong, Aug. 2015, pp. 748–752.

[23] A. Shaverdian and M. R. Nakhai, "Robust distributed beamforming with interference coordination in downlink cellular networks," *IEEE Trans. Commun.*, vol. 62, no. 7, pp. 2411–2421, Jun. 2014.

[24] T. A. Le and M. R. Nakhai, "A decentralized downlink beamforming algorithm for multicell processing," in *Proc. IEEE Glob. Commun. Conf.*, Anaheim, CA, USA, Dec. 2012, pp. 3924–3929.

[25] M. Grant and S. P. Boyd. (Mar. 2013). *CVX: MATLAB Software for Disciplined Convex Programming, Version 2.0 (Beta)*. [Online]. Available: http://cvxr.com/cvx/

[26] S. P. Boyd and L. Vandenberghe, *Convex Optimization*. Cambridge, U.K.: Cambridge Univ. Press, 2004.

Wan Nur Suryani Firuz Wan Ariffin (S'15) received the B.Eng. degree in computer and communication systems engineering from Universiti Putra Malaysia, Malaysia, in 2004, and the M.Eng. degree in communication and computer engineering from Universiti Kebangsaan Malaysia, Malaysia, in 2006. She is currently pursuing the Ph.D. degree with the Department of Informatics, Centre for Telecommunications Research, King's College London, U.K.

Since 2005, she has been a Faculty Member with Universiti Malaysia Perlis, Malaysia, where she is currently a Lecturer with the School of Computer and Communication Engineering. Her research interests fall into the areas of sparse beamforming and cooperative energy trading and management in wireless networks and smart energy grids.

Xinruo Zhang (S'15) received the B.Sc. degree in electronics engineering from Beihang University, Beijing, China, in 2010, and the M.Sc. degree in satellite communications engineering from the University of Surrey, U.K., in 2012. She is currently pursuing the Ph.D. degree with the Centre for Telecommunications Research, King's College London, University of London.

Her research interests include in beamforming and interference management as well as cooperative energy trading in 5G cellular network.

Mohammad Reza Nakhai (M'88–SM'07) received the B.Sc. and M.Sc. degrees in electrical engineering from the Sharif University of Technology, Tehran, Iran, in 1984 and 1987, respectively, and the Ph.D. degree in electronic engineering from King's College London, University of London, U.K., in 2000.

From 1988 to 1995, he was a Research Faculty Member with the Sharif University of Technology, where he worked on communications signal processing. In 2000, he was a Post-Doctoral Research Fellow with the Centre for Communication Systems Research, University of Surrey, U.K. He joined as the Academic Staff Member with the Department of Electronic Engineering, King's College London, in 2001. He is currently with the Department of Informatics, Centre for Telecommunications Research, King's College London. His current research interests include learning and decision making in wireless networks, optimization theory and its application in wireless communications, massive MIMO and ultra-dense wireless networks, green radio communications, statistical signal processing, and communications theory. He serves as an Editor for the IEEE TRANSACTIONS ON WIRELESS COMMUNICATIONS.