
Jing Gao,1 Xin Guan,2 Shuyue Zhang,2 and Xiao Meng2

1School of Control Engineering, Northeastern University at Qinhuangdao, Qinhuangdao 066004, China
2School of Computer Science and Engineering, Northeastern University, Shenyang 110819, China

Correspondence should be addressed to Jing Gao; gaojing@neuq.edu.cn

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1. Introduction

With the rapid development of next-generation mobile communication technology, user equipments (UEs) expect higher data rates, lower delays, higher energy efficiency, and higher reliability [1]. Due to the continuous growth of user traffic, a large number of small base stations are deployed in small areas to provide high-speed data transmission. However, such a network deployment might cause serious cell interference among base stations (BSs) [2].

C-RAN is recognized as a promising solution to reduce interference and save energy. As shown in Figure 1, the traditional BS is divided into three parts: RRH, BBU pool, and fronthaul link connecting RRH and BBU pool in C-RAN. The function of the BBU pool is to process baseband signals, estimate channel state information, calculate precoding matrices, and so on [3]. Compared with traditional wireless access networks, C-RAN is considered to reduce operation and maintenance expenditures, as well as energy consumption, and alleviate interference among base stations [4]. However, the separate architecture of BBU and RRH puts forward strict capacity demand on the fronthaul link that is used to transmit baseband signals. Therefore, the fronthaul capacity constraint should be considered when we are studying C-RAN issues.

With the development of the times, millimeter wave technology has become more mature, and the deployment strategy of wireless fronthaul solutions has been studied by a wide range of researchers [5, 6]. A problem of downlink power allocation considering the limited BS fronthaul
capacity to maximize energy efficiency is proposed [7]. But the work is limited to the dense network with traditional network architecture. A joint association control and cooperative precoding algorithm in the downlink C-RAN is considered, and a goal of minimizing system transmission energy consumption under the limitation of the fronthaul capacity is proposed in [8]. The author analyzes the C-RAN scenario considering the fronthaul limitation to achieve the goal of minimizing cost by optimizing resource allocation in [9]. Therefore, the fronthaul capacity is an indispensable constraint when designing an energy-saving network.

At the same time, EE plays an important role in green communication performance indicators. The energy-harvesting technology in RRH, that is, to equip RRH with solar panels or wind generators, is expected by a large number of researchers. The scenario where the cell is powered by only one energy source, grid-connected or green energy is studied [10]. However, studies have shown that the amount of green energy collected is uncertain, and sometimes, the energy collected by the RRH may not match its traffic load. In order to solve the problem of the volatility of the collected energy, more researchers choose to use a hybrid energy composed of green energy and on-grid energy as the power source. The problem of energy sharing in a traditional network powered by hybrid energy sources is studied, and an objective function to minimize the total network cost is constructed in [11]. In addition, as the density of wireless devices increases, the energy consumption of wireless devices is valued by a lot of researchers. For the sake of extending the battery life, simultaneous wireless information and power transfer (SWIPT) is recognized as a potential solution. The power transmission problem of traditional cellular networks is studied; besides, a dynamic location-based power allocation ratio algorithm with the purpose of optimizing the performance of wireless charging is proposed in [12]. We consider the problem of constructing power supply model, the sleep strategy for fronthaul link, and the algorithm of power and RB allocation in order to maximize the energy efficiency of the C-RAN in this paper.

The rest of this paper is organized as follows. Related work of this paper is introduced in Section 2. The system model of C-RAN, the objective function, and constraints of the optimization problem are described in Section 3. The ERM scheme is designed, and the process of solving the problem is given in Section 4. The algorithm and extensive simulations are given, and the effectiveness of the solution is analyzed in Section 5. Finally, the work of this paper is summarized in Section 6.

2. Related Work

In recent years, green communication has become one of the main challenges of the 5G system communication network [13]. A survey studied different works related to hybrid renewable energy system (HRES), and a discussion on the challenges and future research directions on the subject of HRES is also presented in [14]. In this topic, some researchers use renewable energy hybrid power supplies to improve network energy efficiency. The literature [15] proposes an optimal strategy for user scheduling and resource allocation in a heterogeneous network with the goal of maximizing energy efficiency and powered by hybrid energy sources. However, renewable energy is unstable and cannot provide reliable services to users. There is also a problem that the distribution of renewable energy does not match...
the distribution of users’ business. Therefore, the power supply method that mixes renewable and nonrenewable energy has become an important research topic. The problem of resource allocation driven by renewable energy is studied in C-RAN. RRH uses solar panels to obtain energy, and the optimization goal is to maximize the user’s utility function in this C-RAN [16]. An optimization algorithm is proposed for a two-tier heterogeneous cloud radio access network (H-CRAN) where macro cells are powered by on-grid power and RRHs are empowered by renewable energy. The optimization goal is to maximize the use of green energy [17].

As one of the key standard technologies for realizing software-defined and green communication technologies in 5G cellular networks, C-RAN has been extensively studied by the academic community. The joint optimization problem of uplink power control and resource block allocation is studied in C-RAN. The goal of optimization is to maximize the spectrum efficiency of the network, and the article uses greedy algorithm (GA) to solve the optimization problem [18]. A network energy consumption model is proposed to optimize the energy efficiency in H-CRAN by joint user association and resource allocation algorithms in [19]. The authors put forward a joint optimization scheme of RB allocation and power allocation in H-CRAN based on orthogonal frequency division multiple access (OFDMA); the goal of this document is to maximize EE performance [20]. The joint uplink (UL) and downlink (DL) resource allocation in the user-centric OFDMA Cloud Radio Access Network is studied. The purpose of the article is to maximize system throughput by jointly optimizing RRH clustering and power allocation under the constraints of maximum power and fronthaul capacity in [21].

Based on the above research, many existing works only consider on-grid supply or green energy supply in the C-RAN scenario. However, the result of the former is that energy saving is not significant and the latter cannot ensure the QoS of users. In addition, some works do not consider the actual fronthaul capacity constraint, which is indispensable in the resource allocation of C-RAN. To deal with these problems, the energy-saving user association and power allocation with green energy supply and on-grid supply simultaneously should be investigated.

2.1. Main Contributions. In order to save energy consumption, a comprehensive network energy efficiency model which considers innovatively green energy is established in this paper. Specifically, a comprehensive energy consumption model, which includes the energy consumption of the RRH, the wireless fronthaul link, the BBU pool, and the wireless charging equipment of user terminal, is considered. It is worth emphasizing that new fronthaul capacity constraint is considered by the network energy efficiency model in this paper. Multiple practical constraints are considered in the optimization problem which is a mixed integer nonlinear programming (MINLP) problem and cannot be solved directly. In order to solve the difficult problem, an energy-saving resource management (ERM) algorithm is developed. The ERM algorithm firstly uses the Dinkelbach algorithm to convert the objective function from a fractional form to a subtractive form. Next, the interference value of the objective function is set to a constant value within the tolerable interference level, and then, the ERM algorithm obtains the optimal solution of RB and power value by the Lagrangian dual method. The contributions of this paper can be summarized as follows.

1. In order to reduce network energy consumption and improve network energy efficiency, a supply mode powered by hybrid energy which includes green energy and on-grid energy is proposed. To make full use of green energy, the wireless charging function which can store the remaining green energy to provide energy when the green energy is insufficient is also considered.

2. After considering the new constraints which includes fronthaul capacity and energy harvesting, the optimization problem is reconstructed. Besides, the optimization problem considers many practical constraints of QoS. In order to further save network energy consumption and improve energy efficiency, the fronthaul link sleep strategy is considered.

3. The proposed optimization problem with many practical constraints is regarded as a MINLP and cannot be solved directly. An effective ERM scheme which constructs the nonconvex objective function as an equivalent convex optimization problem is proposed. In addition, an iterative algorithm consisting of outer loop and inner loop is proposed to obtain the global optimal solution.

3. System Model and Problem Formulation

3.1. System Model

3.1.1. Network Architecture and Communication Model. The traditional C-RAN is usually composed of a BBU pool, $M$ users, $N$ RRHs, and fronthaul communication links connecting RRHs to the BBU pool. Let $\mathcal{N} = \{1, 2, \cdots, N\}$ and $\mathcal{M} = \{1, 2, \cdots, M\}$ denote the set of RRHs and users respectively. In the proposed C-RAN, each of RRHs is equipped with renewable energy collecting equipment, e.g., solar panels in Figure 1. In addition, each of RRHs is considered as having both green and on-grid energy, and the green energy is usually stored in batteries with limited storage capacity. C-RAN is based on OFDMA system; i.e., the time is divided into unit time slots $t \in \mathcal{T} = \{1, 2, \cdots, T\}$. All RRHs share resource blocks (RBs) over $T$ time intervals and each with bandwidth $W$. The service of $M_i(t)$ UEs in time interval $t$ is provided by each RRH $i$. Besides, large-scale channel fading, such as distance-related path loss and shadow, is considered, and assume that channel state information (CSI) can be obtained through the BBU pool to optimize radio resource allocation. UEs are equipped with wireless charging devices and power splitting receiver. The received power of each UE can be split into parts $\rho$ and $\rho^f$ for information decoding and wireless charging, respectively, in
Figure 1. The $\rho^E = \{\rho^E_{i,k,r}(t) \in [0,1]|vi,Vk,\forall r,\forall t\}$ and $\rho^G = \{\rho^G_{i,k,r}(t) \in [0,1]|vi,Vk,\forall r,\forall t\}$ are the power splitting policies.

Assuming CSI is perfectly known by RRHs, the channel assignment will be considered to avoid mutual interference among UEs in the same RRH, whereas there has intercell interference because all the RRHs share the same spectrum resource. Therefore, the signal-to-interference-plus-noise ratio (SINR) of UE $k$ served by RRH $i$ on RB $r$ in time interval $t$ can be calculated as

$$S_{i,k,r}(t) = \frac{\rho^G_{i,k,r}(t)\rho^H_{i,k,r}(t)h_{i,k,r}(t)}{\rho^G_{i,k,r}(t)(I_{i,k,r} + N_rW + N_P)}.$$  \hspace{1cm} (1)

Denote $p_{i,k,r}(t)$ and $h_{i,k,r}(t)$ as the transmission power and channel gain from the $i$th RRH to the $k$th UE on the $r$th RB, where $p_{i,k,r}(t) = p^G_{i,k,r}(t) + p^H_{i,k,r}(t)$ and $p^G_{i,k,r}(t)$ denoting variable of on-grid and $p^H_{i,k,r}(t)$ denoting variable of green energy, respectively, are the transmission power from RRH $i$ to UE $k$ on RB $r$ in time interval $t$. As shown in the above formula, $i'$ indicates other RRHs except the $i$th RRH. $N_r$ denotes thermal noise and $N_P$ represents the signal processing noise at receiver [22]. $I_{i,k,r}$ represents the intercell interference which can be denoted as

$$I_{i,k,r} = \sum_{i'\neq i}^{N_m(t)} \sum_{k'=1}^{M_i(t)} n_{i',k',r}(t)(p^G_{i',k',r}(t) + p^H_{i',k',r}(t))h_{i',k',r}(t).$$ \hspace{1cm} (2)

Denote $n_{i',k',r}(t)$ as the RB assignment factor. If the $r$th RB of the $i'$th RRH is assigned to the $k'$th UE, $n_{i',k',r}(t) = 1$; otherwise, $n_{i',k',r}(t) = 0$. Then, the maximum achievable data rate [23] of the $k$th UE using the $r$th RB in the $i$th RRH is formulated as

$$R_{i,k}(t) = \sum_{r=1}^{B} n_{i,k,r}(t)W \log_2(1 + S_{i,k,r}(t)).$$ \hspace{1cm} (3)

Based on (3), the total achievable capacity for C-RAN over $T$ time intervals can be calculated as

$$R^T = \sum_{t=1}^{T} \sum_{r=1}^{B} \sum_{k=1}^{N_m(t)} R_{i,k}(t).$$ \hspace{1cm} (4)

3.1.2. Fronthaul Model. The digitized in-phase and quadrature samples of the baseband signals are forwarded over the common public radio interface (CPRI) in the communications network [24], and the fronthaul may be the bottleneck of the C-RAN. The wireless fronthaul link plays an important role in C-RAN. Since the wireless fronthaul link is out-of-band, there will be no interference between the wireless fronthaul link and the wireless access link. The focus of our discussion is that even wireless fronthaul links can provide huge capacity, which is mainly due to the development of millimeter wave technology, but due to the limitation of spectrum bandwidth, the overall capacity of wireless fronthaul links is still limited. Therefore, a new fronthaul capacity constraint is modeled as

$$\sum_{k=1}^{M_i(t)} n_{i,k,r}(t)R_{i,k,r}(t) \leq R_i^{\text{max}}(t), \forall t,i,$$ \hspace{1cm} (5)

where $R_i^{\text{max}}$ is defined as the effective fronthaul capacity of the $i$th RRH and the value of $R_i^{\text{max}}$ depends on the fronthaul transmission technology.

3.1.3. Network Energy Consumption Model. In order to maintain stable energy conversion control between grid energy and green energy, it is assumed that controllable on-grid energy is used for transmission circuit of the RRH. The battery power consumption of RRH $i$ in time interval $t$ can be calculated as

$$p^B_i(t) = p_i^{RS} + \Delta t \sum_{k=1}^{M_i(t)} \sum_{r=1}^{B} n_{i,k,r}(t)p^G_{i,k,r}(t),$$ \hspace{1cm} (6)

where $p_i^{RS}$ represents the static energy consumption of the $i$th RRH and $\Delta t$ is the energy factor of the $i$th RRH characterizing the relationship between the dynamic power consumption and the traffic load.

On modeling the energy consumption of the fronthaul, the strategy of the fronthaul which can be switched to sleep mode is proposed. The main factor affecting the power consumption of the fronthaul is the static power consumption. The fronthaul power consumption of the $i$th RRH in time interval $t$ can be calculated as

$$P_i^F(t) = \begin{cases} P_i^{FA}(t), & I_i(t) \neq 0, \\ P_i^{FS}, & I_i(t) = 0, \end{cases}$$ \hspace{1cm} (7)

where $P_i^{FA}(t)$ and $P_i^{FS}(t)$ denote the fronthaul power consumption of the $i$th RRH in the active and sleep mode, respectively. $I_i = \sum_{k \in \mathbb{R}} \sum_{r \in \mathbb{R}} n_{i,k,r}(t)p_{i,k,r}(t)$ reflects whether the fronthaul link in the $i$th RRH carries traffic loads. If $I_i(t) = 0$, it represents the fronthaul link carries no traffic loads, and therefore, the fronthaul link is in the sleep mode; otherwise, the fronthaul link is in the active mode. We can also rewrite the equation as

$$P_i^F(t) = P_i^{FS} + \left( P_i^{FA}(t) - P_i^{FS} \right) ||I_i(t)||_0.$$ \hspace{1cm} (8)

The processing of the baseband signal is performed in the BBU pool, so the power consumption of the BBU pool depends on the computing workloads of the signal processing. We assume that each RRH has a corresponding virtual machine (VM), and the power consumption of the VM in the BBU pool depends on the traffic load in its corresponding RRH. Therefore, the power consumption of the VM...
served by the \(i\)th RRH in time interval \(t\) is modeled as

\[
P^B_i(t) = P^{BS}_i + \sigma i \sum_{k=1}^{M_i(t)} \sum_{l=1}^{B} n_{ikr}(t),
\]

where \(P^{BS}_i\) is the static power of the \(i\)th RRH’s corresponding VM. \(\sigma i\) is an energy factor which represents the relationship between the VM power consumption and the radio resource utilization.

Since the wireless charging of UEs is added, the battery power consumption for UE \(k\) served by RRH \(i\) over time interval \(t\) can be expressed as

\[
P^{UE}_{ik}(t) = \max \left\{ P^{UE}_C - Q_{ik}(t), 0 \right\},
\]

where \(P^{UE}_C\) is the power consumption for data reception used by each UE. \(Q_{ik}(t)\) is the amount of wireless charging that UE \(k\) can harvest during time interval \(t\), which is referred as charging capacity and can be expressed as

\[
Q_{ik}(t) = \frac{b}{r} P^{E}_{ikr}(t) n_{ikr}(t) \left( (P^{C}_{ikr}(t) + P^{H}_{ikr}(t)) h_{ikr}(t) \right) + \frac{b}{r} P^{E}_{ikr}(t) n_{ikr}(t) (I_{ikr} + N_o W),
\]

where in wireless charging, \(0 < \eta < 1\) is the efficiency for energy converted to electricity storage.

For the sake of simplicity, the total power consumption of \(i\)th RRH in time interval \(t\) in the above analysis can be calculated as

\[
P^{RRH}_i(t) = \sum_{l=1}^{N} \left( P^{FS}_i + P^{FS}_i + P^{FS}_i \right) + \sum_{l=1}^{N} \sigma i \sum_{k=1}^{M_i(t)} \sum_{l=1}^{B} n_{ikr}(t) \right) + \sum_{l=1}^{N} \left( \Delta I_i(t) + \left( P^{FA}_i(t) - P^{FS}_i \right) \| I_i(t) \|_0 \right).
\]

Based on (5)–(7), the total system on-grid power consumption can be expressed as

\[
P^T = \sum_{t=1}^{T} P^{RRH}_i(t) + \sum_{t=1}^{T} \sum_{t=1}^{N} M_i(t) \sum_{l=1}^{B} P^{UE}_{ik}(t).
\]

3.2. Problem Formulation. The objective of decision policies of RB assignment \(n = \{n_{ikr}^G(t) | \forall i, \forall k, \forall r, \forall t\}\), power allocation \(p = \{P_{ikr}(t), \forall i, \forall k, \forall r, \forall t\}\), and power splitting ratio adjustment \(p = \{P^S, P^F\}\) is to maximize EE of the C-RAN. The optimization problem can be formulated as

\[
U(P, n, p) = \frac{R^T(P, n, p)}{P^T(P, n, p)},
\]

Note that the green energy transmitted power is not counted in (9) since it is renewable.

The optimization problem can be formulated as follows:

\[
\begin{align*}
\max_{P, n, p} U(P, n, p) \\
\text{s.t.} \quad & C_1: R_{ikr}(t) \geq R_{ikr}^{min}(t), \forall t, i, k \\
& C_2: Q_{ik}(t) \geq P_{ikr}^{min}(t), \forall t, i, k \\
& C_3: \sum_{i=1}^{I} E_i(t) - \sum_{i=1}^{I} \sum_{k=1}^{M_i(t)} \sum_{l=1}^{B} en_{ikr}(t) P_{ikr}^{A}(t) \leq E_{max}, \forall t, i, l \in \{1, \ldots, T\} \\
& C_4: \sum_{i=1}^{I} \sum_{k=1}^{M_i(t)} \sum_{l=1}^{B} en_{ikr}(t) P_{ikr}^{A}(t) \leq \sum_{i=1}^{I} E_i(t), \forall t, i \in \{1, \ldots, T\}
\end{align*}
\]

\[
\begin{align*}
& C_5: \sum_{k=1}^{M_i(t)} n_{ikr}(t) \leq 1, \forall t, i, k \\
& C_6: \sum_{k=1}^{M_i(t)} \sum_{l=1}^{B} en_{ikr}(t) (P_{ikr}^{G}(t) + P_{ikr}^{H}(t)) \leq P_{ikr}^{T}, \forall t, i \\
& C_7: \sum_{k=1}^{M_i(t)} n_{ikr}(t) R_{ikr}(t) \leq R_{ikr}^{max}(t), \forall t, i \\
& C_8: P_{ikr}^{G}(t) + P_{ikr}^{E}(t) = 1, \forall t, i, k, r \\
& C_9: 0 < P_{ikr}^{G}(t), P_{ikr}^{F}(t) < 1, \forall t, i, k
\end{align*}
\]

where \(R_{ikr}^{min}(t)\) is the minimum required data rate for UE \(k\) served by RRH \(i\) during time interval \(t\) and \(C_1\) acts as the QoS constraint for each UE. \(P_{ikr}^{min}(t)\) in \(C_2\) describes the minimum required charging capacity for each UE \(k\) served by RRH \(i\) over time interval \(t\). In the proposed C-RAN model, \(E_i(t)\) is the green power harvested by RRH \(i\) during time interval \(t\). Hence, \(C_3\) denotes that the amount of green energy of RRH \(i\) will not exceed battery capacity \(E_{max}\). \(C_4\) represents that the transmitted power using green energy in each RRH cannot exceed the amount it stored. To avoid intracell interference, \(C_5\) restricts that each RB can only be assigned to one UE. \(C_6\) indicates that the transmitted power in RRH \(i\) cannot exceed its maximum power limitation \(P_{ikr}^{T}\). \(C_7\) are the fonthaul capacity constraint, and the fronthaul capacity in RRH \(i\) cannot exceed its maximum capacity limitation \(R_{ikr}^{max}(t)\). \(C_8\) and \(C_9\) are the boundary constraints for power splitting ratios.

In the EE optimization problem, the objective function in fractional form is nonconvex, and it is difficult to find the optimal solution. For binary RB allocation, the optimization problem is a MINLP problem. The \(l_0\) norm in the consumption model cannot be solved directly. In the following sections, we will solve the problem and analyze the performance of the solution.
4. The ERM Algorithm

In this section, an energy-saving resource management (ERM) algorithm to solve the network EE effectively is proposed. Through nonlinear fractional programming to transform the objective function firstly, an effective iterative algorithm to solve the EE performance maximization problem is developed. In the following, the details about the improved ERM algorithm are provided.

4.1. Problem Transformation. The objective function of the EE optimization problem defined in (17) is in the fractional form, which makes the problem nonconvex. Dinkelbach method is exploited to solve this problem effectively. Define the maximum EE $U^*$ of the considered system as

$$U^* = \frac{R^T(P^*, n^*, \rho^*)}{P^T(P^*, n^*, \rho^*)},$$  \hspace{1cm} (17)$$

where $P^*$, $n^*$, $\rho^*$ are the optimal decision policies of power allocation, RB assignment, and power splitting ratio adjustment. We denote $(P^*, n^*, \rho^*)$ as the optimal solution to the following problem:

$$\max_{P,n,\rho} R^T(P, n, \rho) - U \cdot P^T(P, n, \rho)$$  \hspace{1cm} (18)

s.t.  \hspace{1cm} C_1 \leq C_9  \hspace{1cm} (19)$$

**Theorem 1.** When $R^T(P^*, n^*, \rho^*) - U^*P^T(P^*, n^*, \rho^*) = 0$, $(P^*, n^*, \rho^*)$ is the optimal solution to the EE optimization problem.

If the optimal $U^*$ is obtained, the EE optimization problem can be transformed to the problem in Equation (18) according to Lemma 1. Therefore, the optimal $U^*$ is obtained through the Dinkelbach algorithm iteratively in outer loop. At the beginning, the $U$ is initialized, and then, the problem in Equation (18) with fixed $U$ will be solved in each iteration. By solving the problem in Equation (18), $U$ will be updated and converged to the optimal EE $U^*$.

In order to simplify the solution of the optimization problem in this paper, the definition domain of discrete-related variables is relaxed to continuous definition domain $[0,1]$. The values of discrete variables are obtained by the algorithm. It can be seen that when the transformed problem reaches the optimal value, it is actually the upper bound of the original problem [19]. Therefore, the binary factor $n_{i,k,r}(t)$ is released as a continuous variable $0 \leq n_{i,k,r}(t) \leq 1$. Then, $P_{i,k}^{\text{UE}}(t)$ in (10) can be rewritten as

$$P_{i,k}^{\text{UE}}(t) = P_C^{\text{UE}} - Q_{i,k}(t),$$  \hspace{1cm} (20)$$

with an additional constraint

$$Q_{i,k}(t) \leq P_C^{\text{UE}}, \quad \forall t, i, k.$$  \hspace{1cm} (21)$$

4.2. $l_0$-Norm Approximation. The EE optimization problem is still nonconvex because the model $P_{i,k}^{T}(P, n, \rho)$ includes $l_0$-norm. The $l_0$-norm of a vector calculates the number of nonzero entries in the vector and can be approximated as

$$\|X\|_0 = \sum_{m=1}^{|X|} \mu_m |X_m|,$$  \hspace{1cm} (22)$$

where $X_m$ is the $m$th component of vector $X$ and $\mu_m$ is the weight of $X_m$ [25].

Since $I_{i} \geq 0$, in order to eliminate the norm in the model, we rewrite $I_{i}$ into the following equation:

$$\|I_{i}\|_0 = \mu_i I_{i},$$  \hspace{1cm} (23)$$

where $\mu_i$ is the weight of the fronthaul link of the $i$th RRH.

After approximating, the energy consumption of network optimization can be expressed as

$$p_i^T = \sum_{t=1}^T \sum_{i=1}^N \left(p_{i,t}^{\text{RF}} + p_{i,t}^{\text{PA}} + p_{i,t}^{\text{PS}}\right) + \sum_{t=1}^T \sum_{i=1}^N \sum_{k=1}^B M_{i,k}(t) + \sum_{t=1}^T \sum_{i=1}^N \sum_{k=1}^B P_{i,k}^{\text{UE}}(t).$$  \hspace{1cm} (24)$$

In addition, $\mu_i$ in Equation (24) is formulated as

$$\mu_i = h(I_i, \omega) = \frac{\xi}{I_i + \omega},$$  \hspace{1cm} (25)$$

where $I_i$ is the previous iteration. $\omega$ and $\xi$ are constant regularization factors which regulate the stability and control precision. The value of $\mu_i$ is iteratively updated based on Equation (25) until it converges in the ERM algorithm.

In the above iterative updates of $\mu_i$, the fronthaul with lighter traffic loads (smaller $I_i$) will be assigned larger weights. This weight distribution will continue to increase the weight of the lightly loaded fronthaul link in the next iteration, making the load flow in the fronthaul link smaller, and eventually the fronthaul link will enter the dormant state.

4.3. Optimal Decision Policies. The next challenge is the nonconvexity due to consideration of complex interference distribution. In order to meet the challenge, an approximate of transmission rate $R_{i,k}(t)$ in (3) is used as [23] and given by

$$R_{i,k}(t) \leq \sum_{r=1}^W n_{i,k,r}(t) W(a_{i,k,r}(t) \cdot \log_2 S_{i,k,r}(t) + b_{i,k,r}(t)).$$  \hspace{1cm} (26)$$
The coefficients $a_{i,k,r}(t)$ and $b_{i,k,r}(t)$ can be iteratively obtained as

\[
\begin{align*}
    a^{(c)}_{i,k,r}(t) &= \frac{S_{i,k,r}(t)}{1 + S_{i,k,r}(t)}, \\
    b^{(c)}_{i,k,r}(t) &= \log \left( 1 + S_{i,k,r}(t) \right) - \frac{S_{i,k,r}(t)}{1 + S_{i,k,r}(t)} \log S_{i,k,r}(t),
\end{align*}
\]

(27)

where $c \geq 1$ is the iteration index.

Furthermore, it is assumed that a constant value of interference $I_{i,k,r}$ is adopted, which plays an important role in solving the optimization problem. Then, the achievable data rate for UE $k$ served by RRH $i$ in (3) can be approximated as

\[
\bar{R}_{i,k}(t) = \sum_{r=1}^{R} n_{i,k,r}(t) W(a_{i,k,r}(t) \cdot \log_2 \bar{S}_{i,k,r}(t) + b_{i,k,r}(t)).
\]

(28)

where

\[
\bar{S}_{i,k,r}(t) = \frac{p_{i,k,r}(t) p_{i,k,r}(t) h_{i,k,r}(t)}{p_{i,k,r}(t) \left( I_{i,k,r} + N_0 W \right)}.
\]

(29)

Note that the implementing value of $I_{i,k,r}$ can be set as a fixed tolerable interference level.

In addition, it is assumed that an ideal receiver is used to eliminate the complexity associated with solving optimization problems. The upper bound of $Q_{i,k}(t)$ can be obtained and given as

\[
\tilde{Q}_{i,k}(t) = \sum_{r=1}^{B} \eta P_{i,k,r}(t) n_{i,k,r}(t) (P_{i,k,r}^E(t) + P_{i,k,r}^H(t)) h_{i,k,r}(t)
\]

\[
+ \sum_{r=1}^{B} \eta P_{i,k,r}(t) n_{i,k,r}(t) (I_{i,k,r} + N_0 W),
\]

(30)

where (30) is acquired by letting $P_{i,k,r}^E(t)$ of desired signal power as 1.

Based on the above analysis, the original optimization problem (16) is transformed into the following form:

\[
\max_{P,n,p} \bar{R}^T(P,n,p) - U \cdot \tilde{P}^T(P,n,p)
\]

(31)

s.t. $\bar{R}_{i,k}(t) \geq R_{i,k}^{\text{min}}(t), \forall t, i, k$

$C_2 \sim C_3$

where

\[
\bar{R}^T(P,n,p) = \sum_{i=1}^{T} \sum_{k=1}^{N} \sum_{t=1}^{M(t)} \bar{R}_{i,k}(t).\]

(33)

The lower bound of on-grid power consumption can be expressed as

\[
\bar{P}^T = \sum_{i=1}^{T} p_i^{\text{RRH}}(t) + \sum_{i=1}^{T} \sum_{k=1}^{N} \sum_{t=1}^{M(t)} \bar{P}_{i,k}^{\text{UE}}(t),
\]

(34)

where

\[
\bar{P}_{i,k}^{\text{UE}}(t) = P_{i,k}^{\text{UE}} - \tilde{Q}_{i,k}(t).
\]

(35)

The solution of decision policies will further be obtained by adopting the Lagrange dual method in inner loop. Defining the effective policies of power allocation and power splitting ratios on each RB as $P_{i,k,r}^{\text{E}}(t) = P_{i,k,r}^{\text{E}}(t) n_{i,k,r}(t)$, $P_{i,k,r}^{\text{H}}(t) = P_{i,k,r}^{\text{H}}(t) n_{i,k,r}(t), \tilde{P}_{i,k,r}(t) = P_{i,k,r}^E(t) n_{i,k,r}(t)$, and $\tilde{P}_{i,k,r}(t) = P_{i,k,r}^E(t) n_{i,k,r}(t)$. The Lagrangian function used to solve (31) can be written as

\[
L(\Omega, P, n, p) = \bar{R}^T(P,n,p) - U \cdot \tilde{P}^T(P,n,p)
\]

\[
+ \sum_{i=1}^{T} \sum_{k=1}^{N} \sum_{t=1}^{M(t)} \alpha_{i,k}(t) (\tilde{Q}_{i,k}(t) - \tilde{Q}_{i,k}^{\text{min}}(t))
\]

\[
+ \sum_{i=1}^{T} \sum_{k=1}^{N} \sum_{t=1}^{M(t)} \sum_{l=1}^{R} \delta_{i,k,r}(t) (n_{i,k,r}(t) - \tilde{P}_{i,k,r}(t) - \tilde{P}_{i,k,r}(t))
\]

\[
- \sum_{i=1}^{T} \sum_{k=1}^{N} \sum_{t=1}^{M(t)} \sum_{l=1}^{R} \tau_{i,k,r}(t) (1 - n_{i,k,r}(t)) + \sum_{i=1}^{T} \sum_{k=1}^{N} \sum_{t=1}^{M(t)} \lambda_{i,k,r}(t)
\]

\[
\cdot \left( P_{i,k,r}^{\text{E}} - \sum_{k=1}^{M(t)} \sum_{t=1}^{M(t)} n_{i,k,r}(t) P_{i,k,r}^{\text{E}}(t) - \sum_{k=1}^{M(t)} \sum_{t=1}^{M(t)} n_{i,k,r}(t) P_{i,k,r}^{\text{H}}(t) \right)
\]

\[
+ \sum_{i=1}^{T} \sum_{k=1}^{N} \sum_{t=1}^{M(t)} \sum_{l=1}^{R} \gamma_{i,k,r}(t) (n_{i,k,r}(t) - \tilde{P}_{i,k,r}(t) - \tilde{P}_{i,k,r}(t))
\]

\[
\cdot \left( P_{i,k,r}^{\text{E}} - \sum_{k=1}^{M(t)} \sum_{t=1}^{M(t)} n_{i,k,r}(t) P_{i,k,r}^{\text{E}}(t) - \sum_{k=1}^{M(t)} \sum_{t=1}^{M(t)} n_{i,k,r}(t) P_{i,k,r}^{\text{H}}(t) \right)
\]

\[
+ \sum_{i=1}^{T} \sum_{k=1}^{N} \sum_{t=1}^{M(t)} \sum_{l=1}^{R} \eta_{i,k,r}(t) (Q_{i,k}(t) - \tilde{Q}_{i,k}(t))
\]

(36)

where $\Omega = \{ \alpha_{i,k}(t), \beta_{i,k}(t), y_{i,k}(t), \delta_{i,k,r}(t), \tau_{i,k,r}(t), \lambda_{i,k,r}(t), \gamma_{i,k,r}(t), \theta_{i,k}(t), \eta_{i,k,r}(t) \}$ is the nonnegative set of Lagrange multipliers associated with the corresponding constraints.

The Lagrange dual function is

\[
g(\Omega) = \max_{P,n,p} L(\Omega, P, n, p),
\]

(37)
and the Lagrange dual problem can be expressed as

$$
\max_{P, \rho} g(\Omega). 
$$

(38)

It is worth noting that the Lagrangian multipliers in $\Omega$ must be greater than or equal to zero.

According to Karush-Kuhn-Tucker (KKT) conditions, the on-grid power allocation policy can be derived as

$$
P^G_{i,k,r}(t) = \left[ \frac{\alpha_{i,k,r}(t) W (1 + \alpha_{i,k,r}(t) - \nu_i(t))}{\ln(2)} \frac{\psi_{i,k,r}(t)}{\ln(2)} - P^H_{i,k,r}(t) \right]^+, \quad (39)
$$

where

$$
\psi_{i,k,r}(t) = (\pi_{i,k}(t) - \theta_{i,k}(t) - U \eta) h_{i,k,r}(t) + U \Delta_k^E + \lambda_i(t).
$$

(40)

$[x]^+$ is generally defined as $[x]^+ = \max \{0, x\}$ and

$$
\Delta_i^E = \Delta_i + \mu_i \left( p_{i}^{FA}(t) - p_{i}^{FS}(t) \right),
$$

(41)

The green power allocation policy can be derived as

$$
P^H_{i,k,r}(t) = \left[ \frac{\alpha_{i,k,r}(t) W (1 + \alpha_{i,k,r}(t) - \nu_i(t))}{\ln(2)} \frac{\phi_{i,k,r}(t)}{\ln(2)} - P^G_{i,k,r}(t) \right]^+, \quad (42)
$$

where

$$
\phi_{i,k,r}(t) = \sum_{t=1}^{T} \Delta_k^E (\gamma_{i,k,r}(t) - \beta_{i,k,r}(t)) + \lambda_i(t) + (\pi_{i,k}(t) - \theta_{i,k}(t) - U \eta) h_{i,k,r}(t).
$$

(43)

In addition, the power splitting ratio for information decoding can be obtained as

$$
\rho_{i,k,r}(t) = \left[ 1 - \frac{\sqrt{\kappa_{i,k,r}(t)} - \ln(2) \delta_{i,k,r}(t) N_p}{2 \ln(2) \delta_{i,k,r}(t) \left( \hat{I}_{i,k,r}(t) + N_0 W \right)} \right]^+, \quad (44)
$$

where

$$
\kappa_{i,k,r}(t) = N_p^2 (\ln(2))^2 \delta_{i,k,r}(t)^2 + 4 \ln(2) W N_p \delta_{i,k,r}(t) N_p a_{i,k,r}(t) \cdot \left( \hat{I}_{i,k,r}(t) + N_0 W \right) (1 + \alpha_{i,k,r}(t)), \quad (45)
$$

Algorithm 1: The ERM algorithm.

**Table 1: Simulation parameters setting.**

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of RRHs $N$</td>
<td>3</td>
</tr>
<tr>
<td>Number of UEs $M_i(t), \forall i, t$</td>
<td>10</td>
</tr>
<tr>
<td>Number of RB $B$</td>
<td>30</td>
</tr>
<tr>
<td>Number of time intervals $T$</td>
<td>5</td>
</tr>
<tr>
<td>RB bandwidth $W$</td>
<td>180 kHz</td>
</tr>
<tr>
<td>RRH static circuit power $P_{i}^{RS}$</td>
<td>30 dBm</td>
</tr>
<tr>
<td>Fronthaul static circuit power $P_{i}^{FS}$</td>
<td>37 dBm</td>
</tr>
<tr>
<td>Fronthaul active circuit power $P_{i}^{FA}$</td>
<td>40 dBm</td>
</tr>
<tr>
<td>BBU pool circuit power $P_{i}^{PS}$</td>
<td>38 dBm</td>
</tr>
<tr>
<td>UE static circuit power $P_{i}^{UE}$</td>
<td>20 dBm</td>
</tr>
<tr>
<td>Maximum transmit power $P_{i}^{T}$, $\forall i$</td>
<td>21 dBm</td>
</tr>
<tr>
<td>Power amplifier efficiency $\epsilon$</td>
<td>6.25</td>
</tr>
<tr>
<td>Wireless charging efficiency $\eta$</td>
<td>0.9</td>
</tr>
<tr>
<td>Green power source $E_i(t)$</td>
<td>Rand (0,1) watt</td>
</tr>
<tr>
<td>Battery capacity $E_i^{max}$, $\forall i$</td>
<td>40 dBm</td>
</tr>
<tr>
<td>Minimum transmission rate $R_{i,k}^{min}$, $\forall t, i, k$</td>
<td>5 mbps</td>
</tr>
<tr>
<td>Minimum wireless charging power $P_{i,k}^{min}$</td>
<td>-15 dBm</td>
</tr>
<tr>
<td>Energy factor between VM and RRH $\sigma_i$</td>
<td>5.676</td>
</tr>
<tr>
<td>Energy factor $\Delta i$</td>
<td>4.75</td>
</tr>
</tbody>
</table>
and \([x]_0^1\) is defined as

\[
[x]_0^1 = \begin{cases} 
0, & \text{if } x < 0, \\
 x, & \text{if } 0 \leq x \leq 1, \\
1, & \text{if } x > 1.
\end{cases}
\]  

As shown in the following formula, we can use \(\rho_{i,k,r}(t)\) to obtain the power splitting ratio for wireless charging.

\[
\rho_{i,k,r}^E(t) = 1 - \rho_{i,k,r}^I(t). 
\]  

Then, the optimal RB assignment can be determined as

\[
n_{i,k',r}^*(t) = \begin{cases} 
1, & \text{if } k' = \arg\max_k M_{i,k,r}(t), \\
0, & \text{otherwise.}
\end{cases}
\]  

Figure 2: EE comparison of proposed ERM algorithm with baselines.
where

\[ M_{i,k,r}(t) = W a_{i,k,r}(t)(1 + \alpha_{i,k,r}(t)) \]

\[
\log_2 \left[ \frac{\left( p_{i,k,r}^b(t) + p_{i,k,r}^w(t) \right) h_{i,k,r}(t)}{I_{i,k,r}(t) + N_0 W + N_p / \rho_{i,k,r}(t)} \right] \]

\[- \frac{\rho_{i,k,r}(t) (I_{i,k,r}(t) + N_0 W)}{\ln 2 \left( I_{i,k,r}(t) (I_{i,k,r}(t) + N_0 W) + N_p \right)} \]

\[ + \delta_{i,k,r}(t) - \tau_{i,r}(t) + W_{b_{i,k,r}}(t)(1 + \alpha_{i,k,r}(t)) \]

It is worth mentioning that this article uses the subgradient method to update the Lagrangian multiplier through an iterative process.

### 4.4. The Pseudocode of the ERM Algorithm

In this section, we provide simulation experiments to verify the performance of the proposed ERM algorithm. In the simulations, consider a C-RAN in which all the RRHs and UEs are equally distributed in the service area. The system bandwidth \( B_T \) is 180 kHz. The carrier frequency is

![Figure 3: The EE versus the minimum data rate requirement.](image_url)
881.5 MHz, and path loss exponent is 2.8. The maximum transmit power $P_T^i$ of RRHs is 21 dBm. The static circuit power of RRHs and UEs is 30 dBm and 20 dBm, respectively. The parameters $\sigma^i$ and $\Delta^i$ are 5.676 and 4.75, respectively. The RRH fading is a Rayleigh distribution. \( \hat{I}_{k,r}(t) \) assumed in (29) is given as the worst-case interference Table 1. Note that the harvested green power of each RRH $E^i(t)$ is assumed to be identical and the value of $E^i(t)$ is evenly distributed between 0 and 1 watt. As shown as Table 1, it summarizes the default values of important parameters in the simulations.

In the simulations, we compare the proposed ERM algorithm with the following algorithms: joint wireless charging and hybrid power-based resource allocation (JWHRA) algorithm [26]: the HRA algorithm also considers the help of green energy power supply and wireless charging. But the sleep mode of the fronthaul link is not considered.

Wireless charging-based resource allocation (WRA) algorithm [27]: the WRA algorithm only considers wireless charging in the network and does not consider the assistance of renewable energy. At the same time, the fronthaul link is not changed to the sleep mode if it carries no traffic load.

As shown in Figure 2, EE performances are compared among proposed ERM algorithm, the JWHRA algorithm and the WRA algorithm. It can be observed that as the number of iterations increases, the energy efficiency of the network gradually rises, and the energy efficiency of the network stabilizes within a few iterations. Compared with the WRA algorithm that does not consider renewable energy power supply and wireless charging, the proposed ERM algorithm can achieve higher energy efficiency.

![Figure 4: The EE versus the fronthaul capacity.](image-url)
energy power supply, the network energy efficiency of our proposed ERM algorithm is much higher than that of WRA. The reason is that the use of green energy and on-grid energy to supply power at the same time greatly saves on-grid energy consumption and increases network energy efficiency. The algorithm proposed in this paper also considers the fronthaul link sleep mode. Compared with the JWHRA algorithm that considers hybrid energy and wireless charging but does not consider fronthaul link sleep, the network energy efficiency is also improved. This is because the fronthaul link is switched to sleep mode when the fronthaul link does not carry any traffic load, which reduces the total energy consumption of the network and improves the energy efficiency of the network.

Figure 3 shows a graph of the network energy efficiency values of different strategies versus the minimum data rate requirements. As the minimum data rate requirement increases, network energy efficiency is showing a downward trend. This is because the smaller the minimum rate requirement of users, the smaller the transmission power required by users. However, as the minimum rate requirement increases, on the one hand, higher transmission power is required to meet the users’ needs, which will increase the energy consumption of the network and reduce the energy efficiency of the network. On the other hand, the RRHs closer to the users may not be able to meet the users’ minimum rate requirement; therefore, the users must be associated with the farther RRHs, which will further increase the energy consumption of the network. Obviously, it can be seen from Figure 3 that no matter what the value of the minimum data rate is, the network energy efficiency of the proposed scheme is still higher than the other two schemes.

The network EE versus the fronthaul capacity is shown in Figure 4. As the figure shows, x-axis is the capacity of high-capacity fronthaul and y-axis is the network energy efficiency. Figure 5: Power allocation in different time intervals.
efficiency. From Figure 4, we can easily observe that as the fronthaul capacity increases, the value of network energy efficiency also shows an upward trend. This is because the resource allocation scheme is difficult to achieve optimal allocation under the small fronthaul capacity limit. As the fronthaul capacity increases, the constraints become slacking, so the best network energy efficiency value is easier to obtain. With the increase of the fronthaul capacity, the network energy efficiency will not be restricted by the fronthaul capacity. Therefore, when the fronthaul capacity is large enough, the network energy efficiency will not be affected.

In order to better observe the respective usage of grid energy and green energy in different time intervals, we derive the new formulas. Assuming that the number of UEs $M_i(t)$ served by each RRH $i$ is assumed to be identical as $M(t)$ but varied from each time interval $t$. By using the proposed ERM algorithm, the total on-grid power allocated in each time interval $t$ can be calculated as

$$P^G(t) = \frac{1}{N} \sum_{i=1}^{N} \sum_{k=1}^{M_i(t)} \sum_{r=1}^{B} n_{i,k,r}(t) P^G_{i,k,r}(t).$$

The total green power allocated in each time interval $t$ can be, respectively, calculated as

$$P^H(t) = \frac{1}{N} \sum_{i=1}^{N} \sum_{k=1}^{M_i(t)} \sum_{r=1}^{B} n_{i,k,r}(t) P^H_{i,k,r}(t).$$

In Figure 5, the result of power allocation in different time intervals is described. It can be observed from the figure that the use of renewable energy increases with the increase of connected users. When 12 UEs...
served by each RRH, the utilization rate of renewable energy is about 85%. As the proportion of green energy power distribution in RRHs increases, the power distribution of the grid is reduced accordingly, which is more helpful to reduce grid consumption and improve network energy efficiency. The ERM algorithm we proposed will give different allocation strategies at different time intervals; the algorithm will store renewable energy in the battery when the number of users is small and allocate the renewable energy to the time interval with a higher number of UEs, which maximize the energy efficiency of the network.

In Figure 6, the result of wireless charging capacity in different time intervals is illustrated. As we know, when the number of UEs is large, more power needs to be consumed to satisfy the QoS requirements of UEs. $Q(t)$ is the average charging capacity of $Q_{ik}(t)$. As the number of UEs increases, the power consumed by users also increases significantly. More green energy is used not only for signal transmission but also for wireless charging to improve network performance. Therefore, it can be observed from Figure 6 that $Q(t)$ will increase with $M(t)$.

In order to explore the relationship between available green energy and power, the variable available green energy is considered in this paper. Out of fairness, $E_{i}(t)$ of each RRH $i$ in each time interval $t$ is assumed to be identical as $E$; at the same time, we give the value of available green energy for each time interval $E$ and $E = \{0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8\}$ watt is used for performance comparison. By using the proposed ERM algorithm, the average on-grid...
The average green power allocated in each case of $E$ can be formulated as

$$P_{G_i}^G(t) = \frac{1}{TN} \sum_{t=1}^{T} \sum_{i=1}^{N} \sum_{r=1}^{M_i(t)} \sum_{k=1}^{B} n_{i,k,r}(t) P_{i,k,r}^G(t).$$

The average green power allocated in each case of $E$ can be formulated as

$$P_{H}^H(t) = \frac{1}{TN} \sum_{t=1}^{T} \sum_{i=1}^{N} \sum_{k=1}^{B} \sum_{r=1}^{M_i(t)} n_{i,k,r}(t) P_{i,k,r}^H(t).$$

Figure 7 shows the impact of the amount of available green energy on power allocation. Obviously, we can observe that the on-grid power allocation gradually increases with the increase of the available green energy $E$. On the contrary, the green power allocation gradually decreases with the increase of the available green energy $E$ in Figure 5. The reason is that when the available green energy $E$ is greater, more green power $P_{H}^H(t)$ can replace the on-grid power $P_{G}^G(t)$ for data and power.

In Figure 8, the result of average power splitting and average charge capacity is shown. $Q(t)$ and $\rho^E$ are the average charging capacity of $Q_{i,k}(t)$ and the average splitting ratio for wireless charging during $i$, $k$, and total time interval $T$. $\rho^E$ is the average splitting ratio for wireless charging over all $i$, $k$, and total time interval $T$. Intuitively, the average power splitting and average charging capacity both increase with the increase of the available green energy $E$; in the meantime, they have the same growth trend. This is mainly because as the available green energy increases, a large amount of green energy can be used for information decoding and wireless charging. In summary, it can be seen that $Q(t)$ is proportional to $\rho^E$.

6. Conclusion

EE performance optimization in C-RAN supplied by hybrid energy sources has been analyzed in this paper. We
reconstruct the optimization problem after considering the new constraints which includes fronthaul capacity and energy harvesting in C-RAN. The optimization which includes RB assignment, power allocation, and power splitting ratio adjustment is formulated as a MINLP problem. To deal with the optimization of resource allocations, the ERM scheme that is composed of Dinkelbach method and Lagrange dual decomposition method was proposed. We prove the convergence and optimality of the ERM algorithm and verify its performance through extensive simulations. Simulation results confirm that the proposed resource allocation solution can provide higher energy efficiency for the C-RAN compared to solutions that do not consider hybrid energy power supply and fronthaul capacity constraint. To maximize EE performance further, the advanced ERM scheme with considering the transfer of available green energy between RRHs should be researched, and the corresponding optimal solution of RB, power allocation, and power splitting ratio should be obtained in the future.

Appendix

A. Proof of Theorem 1

Denote \( (P, n, \rho) \) as any feasible solution to the problem in Equation (18). Since \( (P^*, n^*, \rho^*) \) is the optimal solution to the problem,

\[
R^T(P^*, n^*, \rho^*) - U^*P^T(P^*, n^*, \rho^*) \geq R^T(P, n, \rho) - U^*P^T(P, n, \rho).
\]

(54)

Because \( R^T(P^*, n^*, \rho^*) - U^*P^T(P^*, n^*, \rho^*) = 0 \), \( R^T(P, n, \rho) - U^*P^T(P, n, \rho) \leq 0 \). \( P^T(P, n, \rho) \) is the CRAN power consumption which is larger than zero. Therefore,

\[
\frac{R^T(P, n, \rho)}{P^T(P, n, \rho)} \leq U^*.
\]

(55)

Hence,

\[
\frac{R^T(P, n, \rho)}{P^T(P, n, \rho)} \leq \frac{R^T(P^*, n^*, \rho^*)}{P^T(P^*, n^*, \rho^*)}.
\]

(56)

Thus, \( (P^*, n^*, \rho^*) \) maximizes \( R^T(P, n, \rho)/P^T(P, n, \rho) \) while satisfying all the constraints in the EE optimization problem. That is, \( (P^*, n^*, \rho^*) \) is the optimal solution to the EE optimization problem. Then, the lemma is proved.

B. The convergence of \( U^* \)

The convergence of \( U^* \) is as follows:

Define \( F(U) = \max_{(P, n, \rho)} \{ R^T(P, n, \rho) - UP^T(P, n, \rho) \} \).

(57)

Proposition 2. \( F(U) \) is a strictly monotonic decreasing function with respect to \( U \).

Proof. Denote \( \{P^1, n^1, \rho^1\} \) and \( \{P^2, n^2, \rho^2\} \) as the solutions to \( F(U^1) \) and \( F(U^2) \), respectively. Then,

\[
F(U^1) = \max_{(P, n, \rho)} \{ R^T(P, n, \rho) - U^1P^T(P, n, \rho) \}
\]

\[
= R^T(P^1, n^1, \rho^1) - U^1P^T(P^1, n^1, \rho^1)
\]

(58)

\[
> R^T(P^2, n^2, \rho^2) - U^1P^T(P^2, n^2, \rho^2).
\]

□

Assume \( U^2 > U^1 \). Since \( P^T(P^2, n^2, \rho^2) \geq 0 \),

\[
R^T(P^2, n^2, \rho^2) - U^1P^T(P^2, n^2, \rho^2) \geq R^T(P^2, n^2, \rho^2)
\]

(59)

\[
- U^2P^T(P^2, n^2, \rho^2) = F(U^2)
\]

Therefore, \( F(U^1) > F(U^2) \). Hence, \( F(U) \) is a strictly monotonic decreasing function with respect to \( U \).

Proposition 3. \( F(U) \) is a nonnegative function when \( U \) is determined by any feasible RB assignment and power allocation.

Proof. Denote \( \{P^1, n^1, \rho^1\} \) as any feasible RB assignment and power allocation. According to the Dinkelbach algorithm [28],

\[
U^1 = \frac{R^T(P^1, n^1, \rho^1)}{P^T(P^1, n^1, \rho^1)}.
\]

(60)

Therefore,

\[
F(U^1) = \max_{(P, n, \rho)} \{ R^T(P, n, \rho) - U^1P^T(P, n, \rho) \}
\]

\[
\geq R^T(P^1, n^1, \rho^1) - U^1P^T(P^1, n^1, \rho^1) = 0.
\]

(61)

Hence, \( F(U) \) is larger than zero when \( U \) is determined by any feasible RB assignment and power allocation. □

Notations

\( N \): The set of RRHs
\( M \): The set of UEs
\( \mathcal{T} \): The set of slots
\( \rho^F \): The set of splitting ratios for wireless charging
\( \rho^I \): The set of splitting ratios for information decoding
\( p_{i,k,s}(t) \): The transmission power from \( i \) th RAP to \( k \) th UE on \( s \) th RB in time interval \( t \)
\( h_{i,k,s}(t) \): The channel gain from \( i \) th RAP to \( k \) th UE on \( s \) th RB in time interval \( t \)
\( p_{o,i,k,s}^G(t) \): The on-grid the transmission power from \( i \) th RAP to \( k \) th UE on \( s \) th RB in time interval \( t \)
\( p_{i,k,s}^H(t) \): The green energy the transmission power from \( i \) th RAP to \( k \) th UE on \( s \) th RB in time interval \( t \)
\( I_{i,k,s}(t) \): The intercell interference
\( N_e \): The thermal noise
\( N_{p} \): The signal processing noise
\( n_{i,k,s}(t) \): The RB assignment indicator
\( R^T: \) The total achievable capacity of network
\( P^B_i(t): \) The battery power consumption of RRH \( i \) in time interval \( t \)
\( P^S_{iR}(t): \) The static energy consumption of the \( i \)th RRH
\( P^F_i(t): \) The fronthaul power consumption of the \( i \)th RRH in time interval \( t \)
\( P^F_A(i): \) The fronthaul power consumption of the \( i \)th RRH in the active mode
\( P^S_i(t): \) The fronthaul power consumption of the \( i \)th RRH in the sleep mode
\( P^B_i(t): \) The power consumption of the VM served by the \( i \)th RRH in time interval \( t \)
\( P^U_{ik}(t): \) The battery power consumption for UE \( k \) served by RRH \( i \) over time interval \( t \)
\( P_C^U: \) The power consumption for data reception used by each UE
\( Q_{ik}(t): \) The amount of wireless charging that UE \( k \) can harvest during time interval \( t \)
\( p^{RRH}_i(t): \) The total power consumption of \( i \)th RRH in time interval \( t \)
\( P_T: \) The total system on-grid power consumption
\( n: \) The RB assignment matrix
\( P: \) The power allocation matrix
\( \rho: \) The power splitting ratio matrix
\( \Delta i: \) The energy factor between the dynamic power consumption and the traffic load
\( \sigma i: \) The energy factor between the VM power consumption and the radio resource utilization.

**Data Availability**

All data used to support the findings of this study are included within the article.

**Conflicts of Interest**

The authors declare no conflicts of interest.

**Authors’ Contributions**

J.G. conceptualized and supervised the study and was responsible for the data curation, project administration, and validation; X.G. was responsible for the formal analysis, methodology, and software and wrote the original draft; X.M. was responsible for the investigation; S.Z. was responsible for the methodology, and software and wrote the original draft; X.G. was responsible for the formal analysis, and validation; J.Z. was responsible for the investigation; S.Z. was responsible for the visualization; S.Z. and X.G. wrote, reviewed, and edited the manuscript. All authors have read and agreed to the published version of the manuscript.

**References**


