Charge-then-Forward: Wireless Powered Communication for Multiuser Relay Networks

Mengyu Liu and Yuan Liu, Senior Member, IEEE

Abstract—This paper studies a relay-assisted wireless powered communication network (R-WPCN) consisting of multiple source-destination pairs and a hybrid relay node (HRN). We consider a "charge-then-forward" protocol at the HRN, in which the HRN with constant energy supply first acts as an energy transmitter to charge the sources, and then forwards the information from the sources to their destinations through time division multiple access (TDMA) or frequency division multiple access (FDMA). Processing costs at the wireless-powered sources are taken into account. Our goal is to maximize the sumrate of all transmission pairs by jointly optimizing the time, frequency and power resources. The formulated optimization problems for both TDMA and FDMA are non-convex. For the TDMA scheme, by appropriate transformation, the problem is reformulated as a convex problem and be optimally solved. For the FDMA case, we find the asymptotically optimal solution in the dual domain. Furthermore, suboptimal algorithms are proposed for both schemes to tradeoff the complexity and performance. Finally, the simulation results validate the effectiveness of the proposed schemes.

Index Terms— powered communication network (WPCN), resource allocation, cooperative relay.

I. INTRODUCTION

The rapid growth of high-speed data and multimedia services increases energy consumption for better quality-ofservices. However, conventional battery-powered communications have to replace or recharge batteries manually to extend their lifetime, which is inconvenient, unsafe, and costly. Recently, radio-frequency (RF) signal enabled wireless power transfer (WPT) has drawn great attention as it essentially provides more cost-effective and green energy supplies for wireless devices, where RF signals are used as the carriers to convey wireless energy to low-power wireless devices.

There are two main directions of WPT among the current related researches. One line of WPT focuses on so-called simultaneous wireless information and power transfer (SWIPT), where the same RF signal carries both energy and information at the same time [1], [2]. Due to the practical limitation of receivers that the received signals cannot be used to perform energy harvesting and information decoding simultaneously, two practical receiver architectures, namely time switching (TS) and power splitting (PS), were proposed in [1]. For TS, the received signal is either used for energy harvesting or information decoding, whereas for PS, the received signal is split into two separate streams with one stream for energy harvesting and the other for information decoding at the same time. SWIPT has been investigated extensively in different systems, e.g., the fading channels [3], relay channels [4]–[7] and orthogonal frequency division multiple access (OFDMA) channels [8]–[12].

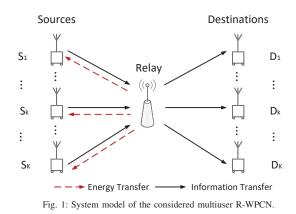
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The newly emerging wireless powered communication network (WPCN) is another line of WPT where ambient RF signals are used to power wireless devices [13]. There are two basic applications about WPCN. One is that energy transmitters and information access points (APs) are located separately where energy transmitters transmit energy to wireless devices and then wireless devices transmit their information to APs using their harvested energy from energy transmitters [14]. Another application is that a hybrid AP (HAP) performs the roles of energy transmitter and AP integrally. For instance, a "harvest-then-transmit" protocol was proposed in [15], where HAP first broadcasts wireless energy to all wireless devices in the downlink and then wireless devices utilize the harvested energy to transmit their independent information to HAP in the uplink based on TDMA. Different from the HAP in SWIPT that coordinates wireless energy and information, the HAP in WPCN only broadcasts wireless energy.

An important application for WPCN lies in relay-assisted WPCN (R-WPCN), where relays are used to assist information transmission in R-WPCN. There are two categories among the current related works about R-WPCN: one is source powering relay [16]–[18] and the second is relay powering source [19], [20]. For the first category, i.e., source powering relay, the authors in [16] proposed a "harvest-then-cooperate" protocol, where both source and relay can harvest energy from the RF signals from a base-station. A two-user R-WPCN was studied in [17] where a nearer user to HAP harvests energy sent by HAP and relays information of the farther user in half-duplex. In [18], the full-duplex relay not only is powered by the source but also harvests energy from itself by energy recycling. As for the category of relay powering source, the throughput maximization problem was investigated in [19], where the source can harvest energy from the access point and/or relay before information transmission. The authors in [20] studied the channel capacity subject to an additional energy transmission cost at the energy harvesting sources. Note that both [19] and [20] considered a single sourcedestination pair.

In this paper, we consider a new R-WPCN consisting of multiple source-destination pairs assisted by a single hybrid relay node (HRN), as shown in Fig. 1. We assume that the HRN in this paper has constant energy supply, while the sources nodes have no embedded power supply so that

The authors are with the School of Electronic and Information Engineering, South China University of Technology, Guangzhou 510641, China (e-mail: liu.mengyu@mail.scut.edu.cn, eeyliu@scut.edu.cn).



they have to be powered by the HRN before information transmission, i.e., "harvest-then-transmit" protocol is applied at the sources. The HRN thus acts double roles, one for an energy transmitter and the other for an information helper. That is, the HRN first charges the sources and then forwards their information, i.e., "charge-then-forward" protocol is considered at the HRN.

As the considered HRN has double roles, i.e., energy transmitter and information helper, energy charging and information forwarding of the HRN are mutually influenced and restricted since the HRN's total energy is fixed. That is, encouraging the energy charging will increase the transmit power of sources at the first hop but decrease the information forwarding at the second hop. How to find the optimal tradeoff that maximizes the system sum-rate is non-trivial. In addition, based on TDMA and FDMA for multiuser information transmission, the network resources, like time, power, and frequency, are highly coupled and the formulated optimization problems are non-convex and difficult to solve. Moreover, we consider the processing cost at the wireless-powered sources, which further complicates the problems.

The main contributions of this paper are summarized as follows:

- We consider a new multiuser R-WPCN based on a "charge-then-forward" relaying protocol, where the HRN first powers the energy-free sources and then forwards the information from the sources to their destinations by TDMA and FDMA. Processing cost is considered at the wireless-powered sources.
- Depending on whether TDMA or FDMA is adopted, we formulate two optimization problems respectively for sum-rate maximization, which are both non-convex. We propose efficient algorithms to find the optimal solutions. In addition, suboptimal algorithms are proposed for both schemes to tradeoff the complexity and performance.
- We provide some useful insights into the R-WPCN. For example, the time of WPT should be as small as possible so that the time for wireless information transmission (WIT) can be maximized for sum-rate maximization. In addition, due to the doubly distance-dependent signal attenuation for both WPT and the first hop of WIT, it is shown that the sum-rate decreases when the HRN moves from the sources to the destinations.

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The remainder of this paper is organized as follows. In Section II, we introduce the system model of multiuser R-WPCN and problem formulations based on TDMA and FDMA, respectively. Section III presents the optimal and suboptimal resource allocation algorithms for the TDMA based problem. In the next, the asymptotically optimal and suboptimal algorithms for the FDMA based problem are presented in Section IV. In Section V, we evaluate the performance of proposed algorithms by simulations. Finally, Section VI concludes the paper.

II. SYSTEM MODEL AND PROBLEM FORMULATION

As shown in Fig. 1, we consider a general two-hop R-WPCN with multiple source-destination pairs as well as a HRN which not only transfers energy to the sources but also forwards information from the sources to the destinations. All nodes are equipped with a single antenna. We assume that the HRN is half-duplex due to the practical consideration, and there is no direct link between each source-destination pair due to the shielding effect caused by obstacles. As a result, each pair needs the assistance of the HRN to forward information. In this paper, we consider that the HRN has a constant energy supply while the source nodes have no embedded energy and thus have to harvest energy for information transmission. In addition, we assume that each source has the energy harvesting function to store the energy. In particular, we consider the "charge-then-forward" relaying protocol to coordinate power and information transfer, in which the HRN first acts as a wireless power beacon to charge the sources then as a helper for forwarding their information. Specifically, the whole transmission is divided into two continuous phases. The first phase is used for WPT conducted by the HRN. The second phase is WIT, i.e., the sources use the harvested energy to transmit their independent information to their destinations via the assistance of the HRN in the second phase based on TDMA or FDMA. The sources do not store the harvested energy for future, i.e., all the energy harvested during WPT phase is used for WIT.

The global channel state information (CSI) of the network is assumed to be known at the HRN where the central processing task is embedded. RF power transfer crucially depends on the available CSI of the nodes, which needs additional resources to acquire and the straightforward way is channel estimation via pilot signals, similar to conventional wireless communication systems. In our R-WPCN, whether the sources transmit pilots and the HRN estimates CSI, or the HRN transmits pilots and the sources estimate CSI, the sources are required to have initial energy to transmit/decode the pilot signals at the beginning of the training phase (before WPT in transmission phase). Thus it is reasonable to assume that the wirelesspowered sources reserve some circuit power at the beginning for channel estimation, since the energy used to channel estimation is much smaller than that of information transmission in practice. CSI acquisition in WPT systems is very important but seems to be beyond of the scope of this paper. In this paper, we consider a block fading wireless environment so that the channel impulse response can be treated as time invariant in the block duration. As a result, the channel gains

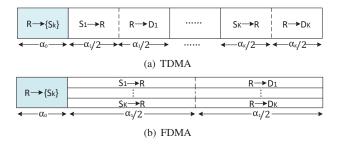


Fig. 2: The "charge-then-forward" relaying protocol based on (a) TDMA and (b) FDMA information transmission.

within the block duration remain unchanged (but can vary in different block durations). For convenience, we assume that the transmission time of each block is normalized to be unit.

A. TDMA Case

We first consider the case of TDMA-based information transmission as shown in Fig. 2(a). The total transmission time is divided into K + 1 time slots where the first time slot, say slot 0 with time duration α_0 , is allocated for WPT and all source nodes harvest energy from the HRN, while the rest K slots are assigned to WIT of the K pairs where each pair k is allocated α_k time duration. Moreover, for each pair's information transmission, α_k is further divided into two equal sub-slots with $\alpha_k/2$ for the first hop and the rest $\alpha_k/2$ for the second hop. By normalizing the whole time to be unit, we have

$$\sum_{k=0}^{K} \alpha_k \le 1, \quad 0 \le \alpha_k \le 1, \quad k = 0, 1, \cdots, K.$$
 (1)

In addition, the power of the HRN used at slot k is denoted as p_k . Besides, we consider that there is a peak power constraint on p_k , i.e., $0 \le p_k \le P_{\text{peak}}$. Denote the maximum transmit power of the HRN as P, then the energy constraint at the HRN is given by

$$\alpha_0 p_0 + \sum_{k=1}^K \frac{\alpha_k}{2} p_k \le P,\tag{2}$$

where $\alpha_k/2$ is the transmission time of the HRN in the second hop for each pair k. Note that the terms of power and energy are interchangeably used here since the duration of each block is normalized to be T = 1 unit.

We consider energy accumulation for TDMA case, i.e., source k harvests and accumulates energy from the previous slots, i.e., slot 0 to slot k - 1. The channel power gain from HRN to source k for WPT and the channel power gain from source i to source k are denoted by $g_{r,k}$ and $g_{i,k}$, respectively. Denote source i's transmit power at slot i as q_i . Then the harvested energy of source k can be expressed as

$$E_{k} = \begin{cases} \eta \alpha_{0} p_{0} g_{\mathrm{r},k}, & k = 1\\ \eta \left(\alpha_{0} p_{0} g_{\mathrm{r},k} + \sum_{i=1}^{k-1} \frac{\alpha_{i}}{2} p_{i} g_{\mathrm{r},k} \\ + \sum_{i=1}^{k-1} \frac{\alpha_{i}}{2} q_{i} g_{i,k} \right), & k = 2, \cdots, K, \end{cases}$$
(3)

which comprises three parts: the first term is the energy harvested in WPT phase, and the last two terms correspond to the energy harvested from the HRN and sources in the previous WIT phase. Here $0 < \eta < 1$ is the energy conversion efficiency at the sources. As a result, the energy causality constraint at source k is given by

$$\frac{\alpha_k}{2}q_k + E_k^c \le E_k, \quad k = 1, \cdots, K, \tag{4}$$

where $\alpha_k/2$ is the time of the first hop for the information transmission of pair k and E_k^c is the non-zero energy processing cost at source k. Moreover, the additional White Gaussian noise (AWGN) at each node is modeled as circularly symmetric complex Gaussian (CSCG) random variable with zero mean and variance σ^2 . Denote the channel power gains for the first and second hops of WIT for pair k as $h_{1,k}$ and $h_{2,k}$, respectively. Using decode-and-forward (DF) relaying strategy, the achievable rate for each pair k is given by

$$R_k = \frac{\alpha_k}{2} \min\left\{ \log_2\left(1 + \frac{q_k h_{1,k}}{\sigma^2}\right), \log_2\left(1 + \frac{p_k h_{2,k}}{\sigma^2}\right) \right\}.$$
(5)

Our objective is to maximize the sum-rate of all pairs by jointly optimizing the time allocation, the transmit power of sources and HRN. Let $p = \{p_k\}, q = \{q_k\}, \alpha = \{\alpha_k\}$ and $R = \{R_k\}$, the problem can be mathematically formulated as

(P1):
$$\max_{\{p,q,\alpha,R\}} \sum_{k=1}^{K} R_k$$
(6a)
s.t. (1), (2), (4), (5)

$$0 \le p_k \le P_{\text{peak}}, k = 0, 1, \cdots, K.$$
 (6b)

Problem (P1) is non-convex since the rate expression (5) is not jointly concave in the variables. We will optimally solve this problem in Section III.

B. FDMA Case

We also consider the case of FDMA-based information transmission for the multiple pairs as shown in Fig. 2(b), where the total time is divided into two time slots, i.e., slot 0 and slot 1 utilized for WPT (using energy signals) and WIT, respectively. The time duration of slot 0 and slot 1 are denoted by α_0 and α_1 with

$$\alpha_0 + \alpha_1 \le 1, \quad 0 \le \alpha_0, \alpha_1 \le 1. \tag{7}$$

We assume that the HRN broadcasts energy signals over the entire bandwidth in the phase of WPT, while information signals are conveyed by using FDMA over N subcarriers (SCs) in the next phase of WIT. For information transmission, we define a binary SC allocation variable $x_{k,n}$ with $x_{k,n} = 1$ representing that SC n is allocated to pair k for WIT and $x_{k,n} = 0$ otherwise. Each SC is allocated to at most one pair at slot 1 for WIT to avoid interference. The constraint can be expressed as

$$\sum_{k=1}^{K} x_{k,n} \le 1, \forall n, \quad x_{k,n} \in \{0,1\}, \quad \forall n, k = 1, \cdots, K.$$
(8)

The channel power gains for WPT of source k, the first and second hops of pair k over SC n for WIT are denoted as $g_{r,k}$, $h_{1,k,n}$ and $h_{2,k,n}$, respectively. The transmit power of HRN for WPT at slot 0 is denoted as p_0 , and the power of the HRN for forwarding pair k's information on SC n at slot 1 is $p_{k,n}$. Note that WPT is conducted over the entire bandwidth, thus there is no index n for $g_{r,k}$ and p_0 . The total transmit energy constraint of the HRN is thus given by

$$\alpha_0 p_0 + \sum_{n=1}^N \sum_{k=1}^K \frac{\alpha_1}{2} p_{k,n} \le P,$$
(9)

where $\alpha_1/2$ represents the transmission time of the HRN in the second hop.

Moreover, we define source k's transmit power on SC n at slot 1 as $q_{k,n}$. Different from TDMA case, since all sources transmit their information at the same time in slot 1, the harvested energy of sources are only from HRN during WPT phase. Therefore, the energy constraint at source k is given by

$$\sum_{n=1}^{N} \frac{\alpha_1}{2} q_{k,n} + E_k^c \le \eta \alpha_0 p_0 g_{\mathbf{r},k}, \quad k = 1, \cdots, K, \quad (10)$$

where the $\alpha_1/2$ represents the time of the first hop during information transmission.

The achievable rates of the first and second hops for pair k over SC n can be respectively written as:

$$R_{1,k,n} = \frac{\alpha_1}{2N} \log_2\left(1 + \frac{q_{k,n}h_{1,k,n}}{\sigma^2}\right), \forall n, k, \qquad (11)$$

$$R_{2,k,n} = \frac{\alpha_1}{2N} \log_2\left(1 + \frac{p_{k,n}h_{2,k,n}}{\sigma^2}\right), \forall n, k.$$
(12)

The achievable rate of pair k by using DF relaying strategy is the minimum of the rates achieved in the two hops, which can be expressed as

$$R_{k,n} = \min\{R_{1,k,n}, R_{2,k,n}\}, \quad \forall n, k = 1, \cdots, K.$$
(13)

Our goal is maximizing the sum-rate of all transmission pairs by varying the transmit power of the sources and HRN, SC assignment and time allocation. Let $p = \{p_0, p_{k,n}\}$, $q = \{q_{k,n}\}$, $x = \{x_{k,n}\}$, $\alpha = \{\alpha_0, \alpha_1\}$ and $R = \{R_{k,n}\}$, the optimization problem can be mathematically formulated as

(P2):
$$\max_{\{p,q,x,\alpha,R\}} \sum_{k=1}^{K} \sum_{n=1}^{N} x_{k,n} R_{k,n}$$
(14a)

s.t. (7), (8), (9), (10)

$$R_{k,n} \le R_{1,k,n}, R_{k,n} \le R_{2,k,n}, \forall n, k = 1 \cdots, K,$$
(14b)

$$0 \le p_0, p_{k,n} \le P_{\text{peak}}, \forall n, k = 1, \cdots, K.$$
(14c)

Problem (P2) is also non-convex since both binary and continuous variables are involved, which is a mixed-integer programming problem. The asymptotically optimal solution for Problem (P2) will be obtained in Section IV.

III. RESOURCE ALLOCATION IN TDMA CASE

In this section, we study the TDMA case by solving Problem (P1). Problem (P1) is not convex and cannot be solved in its original form. Therefore, to make the problem tractable, we introduce a set of new variables $m = \{\alpha_k q_k/2\}$ and $s = \{\alpha_0 p_0, \alpha_k p_k/2\}$. Clearly, m and s can be viewed as the actual transmit energy of the sources and HRN, respectively. Problem (P1) is equivalent to the following problem:

$$(P1'): \max_{\{\boldsymbol{\alpha}, \boldsymbol{m}, \boldsymbol{s}, \boldsymbol{R}\}} \quad \sum_{k=1}^{K} R_k \tag{15a}$$

s.t.
$$\sum_{k=0}^{K} \alpha_k \le 1, \quad 0 \le \alpha_k \le 1, \quad k = 0, 1, \cdots, K,$$
 (15b)

$$\sum_{k=0}^{K} s_k \le P,\tag{15c}$$

$$R_k \le R_{1,k}, R_k \le R_{2,k}, \quad k = 1, \cdots, K,$$
 (15d)

$$m_k + E_k^c \le \eta s_0 g_{\mathbf{r},k}, \quad k = 1, \tag{15e}$$

$$m_k + E_k^c \le \eta \left(\sum_{i=0}^{\kappa-1} s_i g_{\mathbf{r},k} + \sum_{i=1}^{\kappa-1} m_i g_{i,k}\right), k = 2, \cdots, K,$$
(15f)

$$0 \le s_0 \le \alpha_0 P_{\text{peak}}, 0 \le s_k \le \frac{\alpha_k}{2} P_{\text{peak}}, k = 1, \cdots, K.$$
(15g)

where

$$R_{1,k} = \frac{\alpha_k}{2} \log_2 \left(1 + \frac{2m_k h_{1,k}}{\alpha_k \sigma^2} \right), \quad k = 1, \cdots, K, \quad (16)$$

$$R_{2,k} = \frac{\alpha_k}{2} \log_2 \left(1 + \frac{2s_k h_{2,k}}{\alpha_k \sigma^2} \right), \quad k = 1, \cdots, K.$$
(17)

Since constraint (15d) is convex and the other constraints of Problem (P1') are affine, Problem (P1') is convex in its current form. In the literature [21]–[24], the first-order method can be used to solve these non-convex problems by approximating the non-convex objective functions and constraints into convex ones. However, in this paper, by appropriate variable transformation, Problem (P1) is reformulated to be convex, which can thus be optimally solved by applying the Lagrange duality method, as will be shown next.

We first introduce non-negative Lagrangian multipliers $\lambda = \{\lambda_k\} \succeq 0$ and $\beta = \{\beta_k\} \succeq 0$ associated with the rate constraint (15d), $\nu = \{\nu_k\} \succeq 0$ associated with the energy causality constraints (15e) and (15f). In addition, non-negative Lagrangian multipliers $\mu \ge 0$ and $\xi \ge 0$ are associated with the total time constraint (15b) and total energy constraint at HRN (15c). Then, the Lagrangian of Problem (P1') is given by

$$\mathcal{L}(s, m, \alpha, R, \lambda, \beta, \nu, \mu, \xi) = \sum_{k=1}^{K} [R_k + \lambda_k (R_{1,k} - R_k) + \beta_k (R_{2,k} - R_k)] + \mu \left(1 - \sum_{k=0}^{K} \alpha_k\right) + \xi \left(P - \sum_{k=0}^{K} s_k\right) + \nu_1 (\eta s_0 g_{r,1} - E_1^c - m_1) + \sum_{i=2}^{K} \nu_i \left(\sum_{k=0}^{i-1} \eta s_k g_{r,i} + \sum_{k=1}^{i-1} \eta m_k g_{k,i} - E_i^c - m_i\right).$$
(18)

Denote \mathcal{D} as the set of $\{s, m, \alpha, R\}$ satisfying the primary constraints, then the dual function of Problem (P1') is given by

$$g(\boldsymbol{\lambda}, \boldsymbol{\beta}, \boldsymbol{\nu}, \boldsymbol{\mu}, \boldsymbol{\xi}) = \max_{\{\boldsymbol{s}, \boldsymbol{m}, \boldsymbol{\alpha}, \boldsymbol{R}\} \in \mathcal{D}} \mathcal{L}\left(\boldsymbol{s}, \boldsymbol{m}, \boldsymbol{\alpha}, \boldsymbol{R}, \boldsymbol{\lambda}, \boldsymbol{\beta}, \boldsymbol{\nu}, \boldsymbol{\mu}, \boldsymbol{\xi}\right).$$
(19)

To compute the dual function $g(\lambda, \beta, \nu, \mu, \xi)$, we need to find the optimal $\{s^*, m^*, \alpha^*, R^*\}$ to maximize the Lagrangian under the given dual variables $\{\lambda, \beta, \nu, \mu, \xi\}$. In the following we present the derivations in detail.

A. Optimizing $\{s, m, \alpha, R\}$ for Given $\{\lambda, \beta, \nu, \mu, \xi\}$

1) Maximizing Lagrangian over $\{R_k\}$: The part of the dual function with respect to the rate variable $\{R_k\}$ is given by

$$g_R(\boldsymbol{\lambda},\boldsymbol{\beta}) = \max_{\boldsymbol{R} \succeq 0} \sum_{k=1}^{K} (1 - \lambda_k - \beta_k) R_k.$$
(20)

To make sure that the dual function is bounded, we have $1 - \lambda_k - \mu_k \equiv 0$. In such case, $g_R(\lambda, \beta) \equiv 0$ [25] and we obtain that $\beta_k = 1 - \lambda_k$. Note that $0 \leq \lambda_k \leq 1$ such that β_k is non-negative. By substituting these results above into (18), the Lagrangian can be rewritten as:

$$\mathcal{L}(\boldsymbol{s}, \boldsymbol{m}, \boldsymbol{\alpha}, \boldsymbol{\lambda}, \boldsymbol{\nu}, \boldsymbol{\mu}, \boldsymbol{\xi}) = \sum_{k=1}^{K} [\lambda_k R_{1,k} + (1 - \lambda_k) R_{2,k}] + \mu \left(1 - \sum_{k=0}^{K} \alpha_k \right) \\ + \xi \left(P - \sum_{k=0}^{K} s_k \right) + \nu_1 (\eta s_0 g_{\mathbf{r},1} - E_1^c - m_1) \\ + \sum_{i=2}^{K} \nu_i \left(\sum_{k=0}^{i-1} \eta s_k g_{\mathbf{r},i} + \sum_{k=1}^{i-1} \eta m_k g_{k,i} - E_i^c - m_i \right). \quad (21)$$

2) Maximizing Lagrangian over $\{m_k\}_{k=1}^K$, $\{s_k\}_{k=1}^K$ and $\{\alpha_k\}_{k=1}^K$: Observing the Lagrangian in (21), we find that the dual function in (19) can be decomposed into K + 1 independent functions:

$$g(\boldsymbol{\lambda}, \boldsymbol{\nu}, \boldsymbol{\mu}, \boldsymbol{\xi}) = \sum_{k=0}^{K} g_k(\boldsymbol{\lambda}, \boldsymbol{\nu}, \boldsymbol{\mu}, \boldsymbol{\xi}) + \boldsymbol{\mu} + \boldsymbol{\xi} P - \sum_{i=1}^{K} \nu_i E_i^c,$$
(22)

where

$$g_k(\boldsymbol{\lambda}, \boldsymbol{\nu}, \boldsymbol{\mu}, \boldsymbol{\xi}) \triangleq \max_{\{\boldsymbol{s}, \boldsymbol{m}, \boldsymbol{\alpha}\} \in \mathcal{D}} \mathcal{L}_k(\boldsymbol{s}, \boldsymbol{m}, \boldsymbol{\alpha}, \boldsymbol{\lambda}, \boldsymbol{\nu}, \boldsymbol{\mu}, \boldsymbol{\xi}) \quad (23)$$

with

$$\mathcal{L}_{k}(\boldsymbol{s}, \boldsymbol{m}, \boldsymbol{\alpha}, \boldsymbol{\lambda}, \boldsymbol{\nu}, \mu, \xi) = \begin{cases}
-\mu_{k}\alpha_{k} - \xi s_{k} + \sum_{i=1}^{K} \eta \nu_{i}g_{\mathrm{r},i}s_{k}, & k = 0, \\
\lambda_{k}R_{1,k} + (1 - \lambda_{k})R_{2,k} & \\
-\mu\alpha_{k} - \xi s_{k} - \nu_{k}m_{k} & \\
+ \sum_{i=k+1}^{K} \eta \nu_{i}(g_{\mathrm{r},i}s_{k} + g_{k,i}m_{k}), & k = 1, \cdots, K - 1, \\
\lambda_{k}R_{1,k} + (1 - \lambda_{k})R_{2,k} - \mu\alpha_{k} - \xi s_{k} - \nu_{k}m_{k}, & k = K.
\end{cases}$$
(24)

For given dual point $\{\lambda, \nu, \mu, \xi\}$, maximizing (21) over $\{m_k\}_{k=1}^K, \{s_k\}_{k=1}^K, \{\alpha_k\}_{k=1}^K$ is equivalent to solving (23) for $k = 1, \dots, K$. From (24), the partial derivatives of \mathcal{L}_k with respect to s_k and m_k can be given by (25) and (26) on the top of the next page. Given $\alpha_k, k = 1, \dots, K$, the optimal energy variables s_k and m_k that maximize \mathcal{L}_k can be obtained by setting $\frac{\partial \mathcal{L}_k}{\partial s_k} = 0$ and $\frac{\partial \mathcal{L}_k}{\partial m_k} = 0$ and are given by (27) and (28) on the top of the next page.

With given s_k and m_k , we can easily prove that $\frac{\partial \mathcal{L}_k}{\partial \alpha_k}$ is a decreasing function of α_k . As a result, the optimal α_k with given s_k and m_k can be found by a simple bisection search over $0 \le \alpha_k \le 1$.

To summarize, for $k = 1, \dots, K$, Problem (23) can be solved by iteratively optimizing between $\{s_k, m_k\}$ and α_k with one of them fixed at one time, which is known as blockcoordinate descent (BCD) method.

3) Maximizing Lagrangian over s_0 and α_0 : Next, we study the solution of Problem (23) for k = 0, which is a linear programming problem (LP). From (24), to maximize \mathcal{L}_0 we have

$$s_0 = \begin{cases} \alpha_0 P_{\text{peak}}, & \text{if } -\xi + \sum_{i=0}^K \eta \nu_i g_{\mathbf{r},i} > 0, \\ 0, & \text{otherwise.} \end{cases}$$
(29)

$$\alpha_0 = \begin{cases} 1, & \text{if } -\mu - \xi P_{\text{peak}} + \sum_{i=0}^{K} \eta \nu_i g_{\text{r},i} P_{\text{peak}} > 0, \\ 0, & \text{otherwise.} \end{cases}$$
(30)

B. Optimizing Dual Variables $\{\lambda, \nu, \mu, \xi\}$

As a dual function is always convex [26], we adopt the ellipsoid method to simultaneously iterate the dual variables $\{\lambda, \nu, \mu, \xi\}$ to the optimal ones by using the defined subgradients as follows:

$$\Delta = \begin{bmatrix} \Delta \lambda_k = R_{1,k} - R_{2,k}, k = 1, \cdots, K \\ \Delta \mu = 1 - \sum_{k=0}^{K} \alpha_k \\ \Delta \xi = P - \sum_{k=0}^{K} s_k \\ \Delta \nu_1 = \eta s_0 g_{r,1} - E_1^c - m_1 \\ \Delta \nu_k = \sum_{\substack{i=0\\i=0\\-E_k^c}} \eta s_i g_{r,k} - \sum_{\substack{i=1\\i=1\\i=1\\-E_k^c}} \eta m_i g_{i,k} \end{bmatrix}$$
(31)

C. Discussion on Optimality and Complexity

The optimal s_k^* , m_k^* and α_k^* for $k = 1, \dots, K$ are obtained at optimal $\{\lambda^*, \nu^*, \mu^*, \xi^*\}$, then the optimal α_0^* is given by $\alpha_0^* = 1 - \sum_{k=1}^K \alpha_k^*$. With $\{\alpha_k^*\}_{k=0}^K$, $\{s_k^*\}_{k=1}^K$ and $\{m_k^*\}_{k=1}^K$, Problem (P1') becomes a LP with variable s_0 . The optimal value of s_0^* is obtained by solving this LP.

To summarize, the algorithm to solve Problem (P1') is given in Algorithm 1. The time complexity of steps 3-7 is of order K^2 . The complexity of step 9 is $\mathcal{O}(K^2)$. Therefore, the complexity of steps 3-9 is given by $\mathcal{O}(K^2)$. Note that step 10 iterates $\mathcal{O}(q^2)$ to converge, where q is the number K. of dual variables and q = 2K + 2 in our case. Thus the (24) complexity of steps 1-10 is $\mathcal{O}(q^2K^2)$. The time complexity

$$\frac{\partial \mathcal{L}_k}{\partial s_k} = \begin{cases} \frac{(1-\lambda_k)\alpha_k h_{2,k}}{(\alpha_k \sigma^2 + 2s_k h_{2,k})\ln 2} + \sum_{i=k+1}^K \eta \nu_i g_{\mathbf{r},i} - \xi, \quad k = 1, \cdots, K-1 \\ (1-\lambda_i)\alpha_i h_{2,k} & = 1, \cdots, K-1 \end{cases}$$
(25)

$$\frac{\partial \mathcal{L}_k}{\partial m_k} = \begin{cases} \frac{\lambda_k \alpha_k h_{1,k}}{(\alpha_k \sigma^2 + 2m_k h_{1,k}) \ln 2} + \sum_{i=k+1}^K \eta \nu_i g_{k,i} - \nu_k, & k = 1, \cdots, K-1 \\ \frac{\lambda_k \alpha_k h_{1,k}}{(\alpha_k \sigma^2 + 2m_k h_{1,k}) \ln 2} - \nu_k, & k = K \end{cases}$$
(26)

$$s_{k} = \begin{cases} \frac{\alpha_{k}}{2} \min\left\{ \left[\frac{1 - \lambda_{k}}{\left(\xi - \sum_{i=k+1}^{K} \eta \nu_{i} g_{\mathrm{r},i}\right) \ln 2} - \frac{\sigma^{2}}{h_{2,k}} \right]^{+}, P_{\mathrm{peak}} \right\}, \quad k = 1, \cdots, K - 1 \\ \frac{\alpha_{k}}{2} \min\left\{ \left(\frac{1 - \lambda_{k}}{\xi \ln 2} - \frac{\sigma^{2}}{h_{2,k}} \right)^{+}, P_{\mathrm{peak}} \right\}, \quad k = K \end{cases}$$

$$n_{k} = \begin{cases} \frac{\alpha_{k}}{2} \left[\frac{\lambda_{k}}{\left(\nu_{k} - \sum_{i=k+1}^{K} \eta \nu_{i} g_{k,i}\right) \ln 2} - \frac{\sigma^{2}}{h_{1,k}} \right]^{+}, \quad k = 1, \cdots, K - 1 \end{cases}$$
(27)

$$m_{k} = \begin{cases} 2 \left[\left(\nu_{k} - \sum_{i=k+1}^{i} \eta \nu_{i} g_{k,i} \right) \ln 2 & \mu_{1,k} \right] \\ \frac{\alpha_{k}}{2} \left(\frac{\lambda_{k}}{\nu_{k} \ln 2} - \frac{\sigma^{2}}{h_{1,k}}, \right)^{+}, \qquad k = K \end{cases}$$
(28)

Algorithm 1 Optimal Algorithm for Problem (P1')

- 1: Initialize $\{\lambda, \nu, \mu, \xi\}$.
- 2: repeat
- Initialize $\alpha_k = 1/K, k = 1, \cdots, K$. 3:
- repeat 4:
- Compute $\{s_k\}_{k=1}^K$ and $\{m_k\}_{k=1}^K$ by (27) and (28), 5: respectively.

 $(\alpha_k \sigma^2 + 2m_k h_{1,k}) \ln 2$

- Obtain $\{\alpha_k\}_{k=1}^K$ with given $\{s_k\}$ and $\{m_k\}$ by 6: bisection search.
- **until** improvement of $\mathcal{L}_k, k = 1, \cdots, K$ converges to a 7: prescribed accuracy.
- Compute s_0 and α_0 by (29) and (30), respectively. 8:
- Update $\{\lambda, \nu, \mu, \xi\}$ according to the ellipsoid method 9. via (31).
- 10: **until** { λ, ν, μ, ξ } converge to a prescribed accuracy.
- 11: Set $s_k^* = s_k$, $m_k^* = m_k$, $\alpha_k^* = \alpha_k$ for $k = 1, \dots, K$, and $\alpha_0^* = 1 - \sum_{k=1}^K \alpha_k^*.$
- 12: Obtain $s_0^{\kappa=1}$ solving Problem (P1') with $\{s_k^*\}_{k=1}^K$, $\{m_k^*\}_{k=1}^K$ and $\{\alpha_k^*\}_{k=0}^K$.

of the LP is $\mathcal{O}(K)$. Therefore, the complexity of Algorithm 1 is $\mathcal{O}(q^2K^2 + K)$.

Proposition 3.1: For the TDMA case with K sourcedestination pairs and $P_{\text{peak}} \rightarrow \infty$, the maximum sum-rate by solving Problem (P1') is achieved by $\alpha_0^* \to 0$.

Proof: Clearly, we have $\alpha_0 > 0$ and $s_0 > 0$; otherwise, no energy will be harvested at the sources. Since the objective function of Problem (P1') is an increasing function of α_k for $k = 1, \dots, K$ from constraint (15d), when it comes to the extreme case with $P_{\text{peak}} \rightarrow \infty$, for any given s_k and m_k satisfying constraints (15c), (15e) and (15f), the optimal solution must be achieved by $\sum_{k=1}^{K} \alpha_k \to 1$ according to constraint (15b). In this case, $\alpha_0^* \to 0$ and $p_0^* \to \infty$ are required to guarantee positive harvested energy at the sources. The proof is thus completed.

Proposition 3.2: For the TDMA case with K sourcedestination pairs and finite P_{peak} , the maximum sum-rate for Problem (P1') is achieved by $p_0^* = P_{\text{peak}}$.

Proof: Please refer to Appendix A.

By Proposition 3.1 and Proposition 3.2, it can be inferred that Problem (P1') is actually a problem of energy and time allocation at the HRN, i.e., allocating energy and time for WPT and each WIT. Therefore, for any given energy allocated for WPT (i.e., $s_0 = \alpha_0 p_0$), the HRN should charge the sources at its maximum available power (i.e., $p_0 = P_{\text{peak}}$), so that the time used for WPT $\alpha_0 = s_0/p_0$ can be as small as possible and more time $1 - \alpha_0$ can be allocated to WIT due to the sum-rate maximization goal. In particular, when $P_{\rm peak} \rightarrow \infty$, the portion of transmission time α_0 for WPT should asymptotically go to zero, which means that the sources can harvest sufficient energy in a sufficiently small time and almost whole time is allocated to WIT.

D. Suboptimal Algorithm

The complexity of the optimal algorithm becomes high as the number of pairs increases, mainly due to the dual updates. By simplifying the system model and eliminating the dual updates, in this section, we present an efficient suboptimal algorithm which significantly reduces the complexity.

At first, in WIT phase, the received power at each source in other periods is from the relay and other sources, which are both small. Specifically, the received energy from other sources is negligible due to the double energy decay, i.e., the energy decay of relay-to-source and then source-to-source. As DF relaying protocol is adopted, the transmission power of the relay could relatively match the source's transmit power, and thus the relay's transmit power for forwarding is also small. As a result, in this section, we consider that the harvested energy

Algorithm 2 Suboptimal Algorithm for Problem (P1)

- 1: Divide α_0 in [0, 1] with fixed step ϵ .
- 2: for each $\alpha_0 P_{\text{peak}} \leq P$ do
- 3: Compute the time allocation for WIT $\{\alpha_k\}_{k=1}^K$ according to (36).
- 4: Compute the power allocation for WIT $\{p_k\}_{k=1}^K$ and $\{q_k\}_{k=1}^K$ according to (33) and (35), respectively.
- 5: Compute the sum-rate according to (5) with given α₀.
 6: end for
- 7: Choose the optimal α_0^* that has the maximum sum-rate.

at the sources is only from the WPT phase. With give α_0 , the transmit power of source k can be given by

$$q_k = \frac{2(\eta \alpha_0 p_0 g_{\mathbf{r},k} - E_k^c)^+}{\alpha_k}, \quad k = 1, \cdots, K.$$
 (32)

Second, due to Proposition 3.2, we let $p_0 = P_{\text{peak}}$. Moreover, we assume that the equal power allocation (EPA) at the HRN in the WIT phase, the transmit power at the HRN for pair k is thus given by

$$p_k = \min\left\{\frac{2(P - \alpha_0 P_{\text{peak}})}{1 - \alpha_0}, P_{\text{peak}}\right\}, k = 1, \cdots, K.$$
 (33)

Third, due to the energy decay in the WPT phase, the transmit power of sources may be small, thus the performance of this considered dual-hop relaying system may depend on the rate of first hop under most cases. As a result, in this section, we only focus on maximizing the sum rate of the first hop. Therefore, we have the following problem:

$$\max_{\alpha \in \mathcal{D}} \qquad \sum_{k=1}^{K} \frac{\alpha_k}{2} \log_2 \left(1 + \frac{2A_k}{\alpha_k \sigma^2} \right) \tag{34}$$

where $A_k \triangleq (\eta \alpha_0 P_{\text{peak}} g_{\text{r},k} - E_k^c)^+ h_{1,k}$.

<u>Proposition 3.3</u>: The optimal solution of Problem (34) with given α_0 is given by

$$q_k = \frac{2}{(1 - \alpha_0)h_{1,k}} \sum_{k=1}^K A_k, \quad k = 1 \cdots, K, \quad (35)$$

$$\alpha_k = \frac{A_k}{\sum_{k=1}^{K} A_k} (1 - \alpha_0), \quad k = 1 \cdots, K.$$
 (36)

Proof: Please refer to Appendix B.

With given α_0 , we can obtain a set of $\{\alpha, p, q\}$ by (33), (35) and (36). Then, the optimal α_0 maximizing the sum-rate can be found by the one-dimensional search.

To summarize, the above suboptimal algorithm is given in Algorithm 2. The complexity of steps 3-5 is $\mathcal{O}(K)$. The complexity for searching α_0 is $\mathcal{O}(1/\epsilon)$. Therefore, the whole complexity of Algorithm 2 is $\mathcal{O}(K/\epsilon)$, which is linear in Kand much lower than that of the optimal algorithm in above subsection.

IV. RESOURCE ALLOCATION IN FDMA CASE

Problem (P2) is a mixed integer programming and thus is NP-hard and non-convex. However, it has been shown that the duality gap of the resource allocation problems in FDMA systems becomes zero when the number of SCs goes to large [27], [28]. This means that the optimal solution obtained in dual domain is equivalent to the optimal solution of the original non-convex problem due to the zero duality gap. Thus we solve Problem (P2) in dual domain.

At first, we introduce non-negative Lagrangian multipliers $\lambda = \{\lambda_{k,n}\} \succeq 0$ and $\beta = \{\beta_{k,n}\} \succeq 0$ corresponding to the two rates of the first and second hops in (14b), and $\nu = \{\nu_k\} \succeq 0$ associated with the energy causality constraint (10). Moreover, $\mu \ge 0$, $\xi \ge 0$ are introduced to associate with the total time constraint (7) and total energy constraint (9), respectively. Then the dual function of Problem (P2) can be defined as

$$g(\boldsymbol{\lambda}, \boldsymbol{\beta}, \boldsymbol{\nu}, \boldsymbol{\mu}, \boldsymbol{\xi}) \triangleq \max_{\{\boldsymbol{p}, \boldsymbol{q}, \boldsymbol{x}, \boldsymbol{\alpha}, \boldsymbol{R}\} \in \mathcal{D}} \mathcal{L}(\boldsymbol{p}, \boldsymbol{q}, \boldsymbol{x}, \boldsymbol{\alpha}, \boldsymbol{R}, \boldsymbol{\lambda}, \boldsymbol{\beta}, \boldsymbol{\nu}, \boldsymbol{\mu}, \boldsymbol{\xi}),$$
(37)

where D is the set of all primal variables $\{p, q, x, \alpha, R\}$ satisfying the constraints, and the Lagrangian of Problem (P2) is

$$\mathcal{L}(\boldsymbol{p}, \boldsymbol{q}, \boldsymbol{x}, \boldsymbol{\alpha}, \boldsymbol{R}, \boldsymbol{\lambda}, \boldsymbol{\beta}, \boldsymbol{\nu}, \boldsymbol{\mu}, \boldsymbol{\xi}) = \sum_{k=1}^{K} \sum_{n=1}^{N} x_{k,n} [R_{k,n} + \lambda_{k,n} (R_{1,k,n} - R_{k,n}) \\ + \beta_{k,n} (R_{2,k,n} - R_{k,n})] + \mu (1 - \alpha_0 - \alpha_1) \\ + \xi \left(P - \alpha_0 p_0 - \sum_{n=1}^{N} \sum_{k=1}^{K} \frac{\alpha_1}{2} p_{k,n} \right) \\ + \sum_{k=1}^{K} \nu_k \left(\eta \alpha_0 p_0 g_{\mathrm{r},k} - \sum_{n=1}^{N} \frac{\alpha_1}{2} q_{k,n} - E_k^c \right).$$
(38)

Computing the dual function $g(\lambda, \beta, \nu, \mu, \xi)$ requires to determine the optimal $\{p, q, x, \alpha, R\}$ for given dual variables $\{\lambda, \beta, \nu, \mu, \xi\}$. In the following we present the derivations in detail.

A. Optimizing $\{p, q, x, \alpha, R\}$ for Given $\{\lambda, \beta, \nu, \mu, \xi\}$

1) Maximizing Lagrangian over $\{R_{k,n}\}$: Similar to TDMA case, the part of dual function with respect to $\{R_{k,n}\}$ is given by

$$g_R(\boldsymbol{\lambda}, \boldsymbol{\beta}, \boldsymbol{\nu}, \boldsymbol{\mu}, \boldsymbol{\xi}) = \max_{\boldsymbol{R} \succeq 0} \sum_{k=1}^K \sum_{n=1}^N (1 - \lambda_{k,n} - \beta_{k,n}) x_{k,n} R_{k,n}.$$
(39)

To make sure that the dual function is bounded, we have $1 - \lambda_{k,n} - \beta_{k,n} \equiv 0$. In such case, $g_R(\lambda, \beta, \nu, \mu, \xi) \equiv 0$ and we obtain that $\beta_{k,n} = 1 - \lambda_{k,n}$. Note that $0 \leq \lambda_{k,n} \leq 1$ to make sure that $\beta_{k,n}$ is non-negative. By substituting the result above into (38), we have

$$\mathcal{L}(\boldsymbol{p}, \boldsymbol{q}, \boldsymbol{x}, \boldsymbol{\alpha}, \boldsymbol{\lambda}, \boldsymbol{\nu}, \boldsymbol{\mu}, \boldsymbol{\xi}) = \sum_{k=1}^{K} \sum_{n=1}^{N} x_{k,n} \left[\lambda_{k,n} R_{1,k,n} + (1 - \lambda_{k,n}) R_{2,k,n} \right] + \mu (1 - \alpha_0 - \alpha_1) + \xi \left(P - \alpha_0 p_0 - \sum_{n=1}^{N} \sum_{k=1}^{K} \frac{\alpha_1}{2} p_{k,n} \right)$$

$$+\sum_{k=1}^{K}\nu_{k}\left(\eta\alpha_{0}p_{0}g_{\mathbf{r},k}-\sum_{n=1}^{N}\frac{\alpha_{1}}{2}q_{k,n}-E_{k}^{c}\right).$$
 (40)

2) Maximizing Lagrangian over $\{p_{k,n}\}$, $\{q_{k,n}\}$, $\{x_{k,n}\}$ and α_1 : Observing the Lagrangian in (40), we can rewrite (40) as follows:

$$\mathcal{L}(\boldsymbol{p}, \boldsymbol{q}, \boldsymbol{x}, \boldsymbol{\alpha}, \boldsymbol{\lambda}, \boldsymbol{\nu}, \boldsymbol{\mu}, \boldsymbol{\xi})$$

$$= \sum_{n=1}^{N} \mathcal{L}_{n}(\boldsymbol{p}, \boldsymbol{q}, \boldsymbol{x}, \boldsymbol{\alpha}, \boldsymbol{\lambda}, \boldsymbol{\nu}, \boldsymbol{\xi}) + \mu(1 - \alpha_{0} - \alpha_{1})$$

$$+ \boldsymbol{\xi}(P - \alpha_{0}p_{0}) + \sum_{k=1}^{K} \nu_{k} \left(\eta \alpha_{0}p_{0}g_{\mathrm{r},k} - E_{k}^{c}\right), \qquad (41)$$

where

$$\mathcal{L}_{n}(\boldsymbol{p},\boldsymbol{q},\boldsymbol{x},\boldsymbol{\alpha},\boldsymbol{\lambda},\boldsymbol{\nu},\boldsymbol{\xi}) = \sum_{k=1}^{K} x_{k,n} \left[\lambda_{k,n} R_{1,k,n} + (1-\lambda_{k,n}) R_{2,k,n} \right] - \sum_{k=1}^{K} \frac{\alpha_{1}}{2} \left(\xi p_{k,n} + \nu_{k} q_{k,n} \right).$$
(42)

Maximizing \mathcal{L} over $\{p_{k,n}\}$ and $\{q_{k,n}\}$ is equivalent to maximizing each \mathcal{L}_n over $p_{k,n}$ and $q_{k,n}$, which is shown in the following. Each SC *n* should be allocated to at most one pair and we can apply exhaustive method for SC to obtain the optimal k^* . Particulary, assume that SC *n* is selected for pair *k*, then (42) is equivalent to

$$\mathcal{L}_{n}(p_{k,n}, q_{k,n}, \alpha_{1}, \lambda_{k,n}, \nu_{k}, \xi) = \lambda_{k,n} R_{1,k,n} + (1 - \lambda_{k,n}) R_{2,k,n} - \frac{\alpha_{1}}{2} \left(\xi p_{k,n} + \nu_{k} q_{k,n} \right).$$
(43)

By differentiating (43) with respect to $p_{k,n}$ and $q_{k,n}$, and letting them to zero, the $p_{k,n}$ and $q_{k,n}$ maximizing \mathcal{L}_n are given by

$$p_{k,n} = \min\left\{ \left(\frac{1 - \lambda_{k,n}}{\xi N \ln 2} - \frac{\sigma^2}{h_{2,k,n}} \right)^+, P_{\text{peak}} \right\}, \quad (44)$$

$$q_{k,n} = \left(\frac{\lambda_{k,n}}{\nu_k N \ln 2} - \frac{\sigma^2}{h_{1,k,n}}\right)^+.$$
 (45)

After computing the power allocations $p_{k,n}$ and $q_{k,n}$ for WIT, we can obtain the SC allocation maximizing each \mathcal{L}_n as

$$x_{k,n} = \begin{cases} 1, & \text{if } k = \operatorname{argmax}_k \mathcal{L}_n, \\ 0, & \text{otherwise.} \end{cases}$$
(46)

With given $p_{k,n}$, $q_{k,n}$ and $x_{k,n}$, the Lagrangian (40) becomes a linear function of α_1 . From (40), to maximize \mathcal{L} , we have

$$\alpha_1 = \begin{cases} 1, & \text{if } \Psi > 0, \\ 0, & \text{otherwise.} \end{cases}$$
(47)

where Ψ is given by

$$\Psi = \sum_{k=1}^{K} \sum_{n=1}^{N} x_{k,n} \left[\lambda_{k,n} R_{1,k,n} + (1 - \lambda_{k,n}) R_{2,k,n} \right] - \frac{1}{2} \sum_{k=1}^{K} \sum_{n=1}^{N} x_{k,n} (\xi p_{k,n} - \nu_k q_{k,n}).$$
(48)

Here, $p_{k,n}$, $q_{k,n}$ and $x_{k,n}$ have been obtained by (44), (45) and (46), respectively.

Algorithm 3 Optimal Algorithm for Problem (P2)

1: initialize $\{\lambda, \nu, \mu, \xi\}$.

- 3: for each SC n do
- 4: Compute $\{p_{k,n}\}$ and $\{q_{k,n}\}$ according to (44) and (45), respectively.
- 5: Obtain the subcarrier allocation $\{x_{k,n}\}$ according to (46).
- 6: end for
- 7: Compute α_1, α_0, p_0 according to (47), (49) and (50), respectively.
- 8: Update $\{\lambda, \nu, \mu, \xi\}$ by the ellipsoid method using the subgradients defined in (51).
- 9: **until** $\{\lambda, \nu, \mu, \xi\}$ converge to a prescribed accuracy.
- 10: Set $p^* = p$, $q^* = q$ and $x^* = x$.
- 11: Obtain α^* by solving Problem (P2) with $p = p^*$, $q = q^*$ and $x = x^*$.

3) Maximizing Lagrangian over α_0 and p_0 : From (40), to maximize \mathcal{L} , we have

$$\alpha_0 = \begin{cases} 1, & \text{if } \sum_{k=1}^{K} \eta \nu_k g_{\mathrm{r},k} P_{\mathrm{peak}} - \xi P_{\mathrm{peak}} - \mu > 0, \\ 0, & \text{otherwise.} \end{cases}$$
(49)

$$p_0 = \begin{cases} P_{\text{peak}}, & \text{if } \sum_{k=1}^{K} \eta \nu_k g_{\mathbf{r},k} - \xi > 0, \\ 0, & \text{otherwise.} \end{cases}$$
(50)

B. Optimizing Dual Variables $\{\lambda, \nu, \mu, \xi\}$

Similar to TDMA case, the ellipsoid method can be employed to update $\{\lambda, \nu, \mu, \xi\}$ toward optimal $\{\lambda^*, \nu^*, \mu^*, \xi^*\}$ with global convergence [26], the subgradients required for which are

$$\Delta = \begin{bmatrix} \Delta \lambda_{k,n} = x_{k,n} (R_{1,k,n} - R_{2,k,n}), \forall k, n \\ \Delta \mu = 1 - \alpha_0 - \alpha_1 \\ \Delta \xi = P - \alpha_0 p_0 - \sum_{k=1}^{K} \sum_{n=1}^{N} \frac{\alpha_1}{2} p_{k,n} \\ \Delta \nu_k = \eta \alpha_0 p_0 g_{r,k} - \sum_{n=1}^{N} \frac{\alpha_1}{2} q_{k,n} - E_k^c, \forall k \end{bmatrix}$$
(51)

C. Discussions on Optimality and Complexity

It is worth noting that the optimal p^* , q^* and x^* are obtained at optimal $\{\lambda^*, \nu^*, \mu^*, \xi^*\}$. With given optimal p^* , q^* and x^* , Problem (P2) becomes a LP with α . The optimal α^* can be obtained by solving this LP.

To summarize, the algorithm for Problem (P2) is given by Algorithm 3. The complexity of steps 4-5 is $\mathcal{O}(KN)$. The complexity of steps 3-6 is $\mathcal{O}(KN^2)$. The ellipsoid method needs complexity of $\mathcal{O}(q)$, where q is the number of dual variables and q = KN + K + 2 in our case. The time complexity of the LP is $\mathcal{O}(K)$. Therefore, the whole complexity of Algorithm 3 is $\mathcal{O}(q^2KN^2 + K)$.

<u>Proposition</u> 4.1: In the case of the FDMA case with K source-destination pairs and $P_{\text{peak}} \to \infty$, the maximum sumrate obtained by solving Problem (P2) is given by $\alpha_0^* \to 0$ and $\alpha_1^* \to 1$.

Proof: Clearly, we can easily obtain that $\alpha_0 > 0$; otherwise, no energy is harvested at the sources in the considered R-WPCN. Thus, $\alpha_1 < 1$. Denote $s_0 = \alpha_0 p_0$, $s_{k,n} = \alpha_1 p_{k,n}/2$ and $m_{k,n} = \alpha_1 q_{k,n}/2$ as energy variables. For ang given $s_0, s_{k,n}, m_{k,n}$ and $x_{k,n}$ satisfying the primary constraints (7), (8), (9), (10), the objective function of Problem (P2) is an increasing function of α_1 according to (14b). Thus, the sumrate is maximized when $\alpha_1^* \to 1$, which follows $\alpha_0^* \to 0$. The proof is thus completed.

By Proposition 4.1, the positive harvested energy at the sources is achieved under the assumption that the HRN is able to transmit an infinite power due to $\alpha_0 \rightarrow 0$. For a finite P_{peak} , a nonzero time ratio should be scheduled to the WPT phase to harvest sufficient energy for WIT. Similar to the TDMA case, when it comes to the more general case with $P_{\text{peak}} < \infty$, we have the following proposition,

<u>Proposition</u> 4.2: In the case of the FDMA case with K source-destination pairs and $P_{\text{peak}} < \infty$, the maximum sumrate is achieved by $p_0^* = P_{\text{peak}}$.

Proof: The proof is similar as the proof of Proposition 3.2, and thus is omitted here.

D. Suboptimal Algorithm

The main complexity of the above optimal algorithm is resulted from the ellipsoid method. In this section, we propose a suboptimal algorithm by assuming equal power allocation (EPA) over SCs, which can eliminate the dual updates, while the optimal α_0 is obtained by the one-dimensional search.

First, due to the energy decay in the WPT phase, the transmit power of sources may be small, thus the performance of this considered dual-hop relaying system may depend on the rate of first hop under most cases. As a result, we heuristically choose the pair having the maximum $h_{1,k,n}$ to occupy SC n, which is given by

$$x_{k,n} = \begin{cases} 1, & \text{if } k = k^* = \operatorname{argmax}_k h_{1,k,n}, \\ 0, & \text{otherwise.} \end{cases}$$
(52)

With given α_0 , we let $p_0 = P_{\text{peak}}$ according to Proposition 4.2. Then, from (9) and (10), the power allocation by assuming EPA can be given by

$$p_{k,n} = \begin{cases} \min\left\{ \left[\frac{2(P-\alpha_0 P_{\text{peak}})}{\alpha_1 N}\right]^+, P_{\text{peak}} \right\}, & \text{if } x_{k,n} = 1, \\ 0, & \text{otherwise.} \end{cases}$$
(53)

$$q_{k,n} = \begin{cases} \frac{2(\eta \alpha_0 P_{\text{peak}} g_{\text{r},k} - E_k^c)^+}{\alpha_1 M_k}, & \text{if } x_{k,n} = 1, \\ 0, & \text{otherwise.} \end{cases}$$
(54)

where M_k is the number of SCs assigned to source k, which can be determined via (52).

The above suboptimal algorithm is summarized in Algorithm 4. The complexity of steps 3-5 is $\mathcal{O}(KN)$. The complexity for searching α_0 is $\mathcal{O}(1/\epsilon)$, therefore the whole complexity of the algorithm is $\mathcal{O}(KN/\epsilon)$, which is much lower than that of Algorithm 3.

Algorithm 4 Subptimal Algorithm for Problem (P2)

- 1: Divide α_0 in [0,1] with fixed step ϵ .
- 2: for each $\alpha_0 P_{\text{peak}} \leq P$ do
- 3: Obtain the SC allocation $\{x_{k,n}\}$ by (52).
- 4: Compute the power allocations $\{p_{k,n}\}$ and $\{q_{k,n}\}$ according to (53) and (54), respectively.
- 5: Compute the sum-rate according to (13) for given α₀.
 6: end for
- 7: Choose the optimal α_0^* that has the maximum sum-rate.

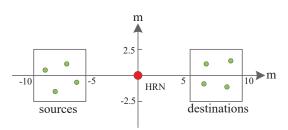


Fig. 3: The location of R-WPCN in the simulations.

V. NUMERICAL RESULTS

In this section, we provide extensive numerical results to evaluate the performance of the proposed algorithms. In the simulation setup, we assume that the total bandwidth is 10 MHz for both TDMA and FDMA cases and the noise spectral density is assumed to be -174 dBm/Hz. We set the energy conversion efficiency as $\eta = 0.8$ and the processing cost as $E_k^c = 1 \times 10^{-7}$ Joule at all sources. For all simulations, we set K = 4 pairs of sources-destinations unless otherwise noted. Moreover, we consider a two-dimensional plane of node location as shown in Fig. 3, where the source nodes and destination nodes are randomly but uniformly distributed in the corresponding square regions, and the HRN can move along with the x-axis from -5 m to 5 m. The HRN is assumed to locate at (0,0) unless otherwise noted. In this paper, the passloss exponent is 3 and we adopt Richan fading channel model for the small-scale fading, where the Richan factor is set to be 3.

Fig. 4 demonstrates the sum-rate versus the total transmit power P in the TDMA case with $P_{\text{peak}} = 2P$. We introduce the following two benchmark schemes for the purpose of performance comparison. First, the equal energy allocation (EEA) scheme is considered, where the energy allocated for WPT at the HRN is fixed as $\alpha_0 P_{\text{peak}} = P/2$, while the optimal time allocation is still obtained as Algorithm 1. In addition, we consider the equal resource allocation (ERA) for WIT with given α_0 , where the equal time and power allocations for WIT are assumed and the optimal α_0^* is obtained as Algorithm 2. For all schemes, the sum-rate is observed to increase with the total transmit power P. Compared with EEA and ERA, we can see that the proposed optimal and suboptimal algorithms achieve better performance. And the suboptimal algorithm is observed to perform very closely to the optimal algorithm, which demonstrates the effectiveness of the proposed suboptimal resource allocations.

Fig. 5 illustrates the duality gaps versus the different num-

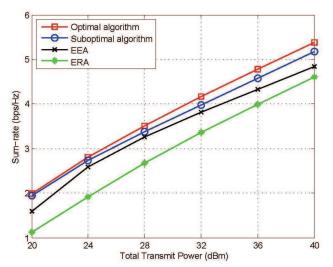


Fig. 4: Sum-rate versus total transmit power P in TDMA-based R-WPCN, where $P_{\rm peak}=2P.$

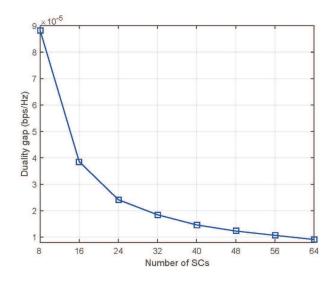


Fig. 5: Duality gap versus number of SCs, where P = 30 dBm, $P_{\text{peak}} = 2P$.

bers of SCs N. The duality gap is shown to decrease with the SCs number N. It can be observed that the duality gap is indeed approximately zero with 64 SCs, which verifies the effectiveness of the proposed dual-based algorithm of FDMA case.

Fig. 6 demonstrates the sum-rate versus the total transmit power P in the FDMA case. The peak power constraint P_{peak} is set to be 2P. For performance comparison, we consider the following three benchmarking schemes. The first one is subcarrier pairing scheme where the subcarrier allocation in the two hops can be different [29]. The second one is equal energy allocation (EEA) where the WPT energy is fixed as $\alpha_0 P_{\text{peak}} = P/2$, while the optimal power and SC allocations are still obtained as Algorithm 3. The last benchmark is that the subcarrier assignment is fixed (FSA) while the optimal time and power allocations are also jointly optimized as Algorithm 3. For all schemes, we can observe that the sum-rate is increasing with the total transmit power P and the proposed optimal scheme achieves considerable gain compared with the

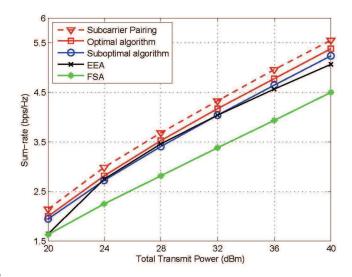


Fig. 6: Sum-rate versus total transmit power P in FDMA-based R-WPCN, where N = 64, $P_{\text{peak}} = 2P$.

other benchmark schemes. Compared with the optimal algorithm, it can be observed that the performance gain achieved by subcarrier pairing is limited but requires additional $\mathcal{O}(N^3)$ complexity by Hungarian algorithm. Besides, the suboptimal algorithm with low complexity also has good performance. Moreover, we can observe that the EEA scheme is only efficient under some particular system setup (24 < P < 32 dBm), while the suboptimal algorithm has a good performance over a wide range of transmit power compared with the EEA scheme, which demonstrates the superiority of the proposed suboptimal algorithm. The poor performance of FSA compared to the proposed schemes indicates that dynamic SC allocation provides significant improvement in terms of the sum-rate.



Fig. 7 illustrates system performance versus P_{peak} with the fixed total transmit power P = 30 dBm. First, it can be observed that the sum-rate increases with P_{peak} and reaches a plateau when $P_{\text{peak}} > 40$ dBm. This is because that the total available power P is fixed and thus the sum-rate must be bounded even if P_{peak} becomes sufficiently large. Second, for both schemes, we can see that the optimal α_0^* decreases with P_{peak} . This is because that less time for WPT is needed to obtain the harvested energy requirement with a larger P_{peak} . In addition, we can also observe that the energy for WPT increases with P_{peak} and then remains fixed for both schemes, where almost all the available energy is used for WPT. This is because that the optimal WPT energy is under the peak power constraint, which becomes infeasible when P_{peak} becomes sufficiently large.

Fig. 8 examines the effect of the relay position on the energy for WPT and the sum-rate, where the total transmit power is set to be 30 dBm and the HRN moves along with the x-axis from d = -5 m to d = 5 m. First, we can observe that the energy allocated for WPT is increasing with d for both cases. This may be because that the channel gains for WPT become worse with a longer distance from sources to HRN, which

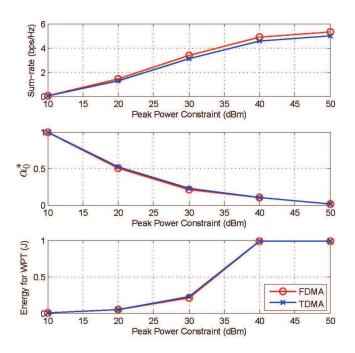


Fig. 7: System performance versus peak power constraint $P_{\rm peak},$ where N=64 and $P=30~\rm dBm.$

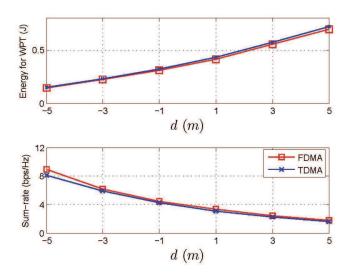


Fig. 8: Optimal energy for WPT and sum-rate versus the distance d_1 , where N = 64, P = 30 dBm and $P_{\text{peak}} = 2P$.

requires more energy at the HRN allocated to WPT. Besides, the sum-rate for both schemes is observed to decrease with d, which is different from the traditional relaying systems. On the one hand, due to the doubly distance-dependent signal attenuation for both WPT and the first hop of WIT, the rate of the first hop cannot be improved though the WPT energy becomes larger. On the other hand, since the energy for WIT is decreasing with d due to the larger WPT energy, the rate of the second hop is also bottlenecked. As a result, the HRN should be located in proximity to the sources.

Fig. 9 depicts the sum-rate and the optimal energy for WPT versus the number of pairs K with P = 30 dBm. First, it can be observed that the FDMA scheme achieves higher

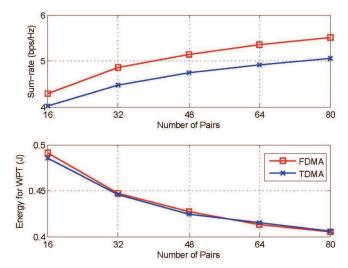


Fig. 9: Sum-rate and optimal energy for WPT versus the number of pairs, where N = 64, P = 30 dBm and $P_{\text{peak}} = 2P$.

sum-rate compared to the TDMA scheme. Besides, we can see that the sum-rate for both schemes increases with the number of pairs and the rate tends to be saturated due to the limited bandwidth and transmission power of the system. In addition, it can be observed that the energy for WPT decreases with the increasing number of pairs, this may be because that more pairs can harvest energy from the same energy signals broadcasted by the HRN, which results in a higher energy efficiency.

VI. CONCLUSIONS

This paper studied a new R-WPCN based on TDMA and FDMA for multiple source-destination pairs with the help of a HRN which acts as both roles of an energy transmitter and an information forwarder. By considering the "chargethen-forward" protocol at the HRN, we studied the sum-rate maximization problem for both TDMA and FDMA cases. For the TDMA case, we proposed a global optimal solution, while for the FDMA case, we designed an asymptotically optimal solution. To tradeoff the performance and complexity, the suboptimal algorithms for both cases were also proposed. Extensive simulations showed that our proposed algorithms significantly outperform the conventional schemes.

The following directions can be considered for possible future works. First, the HRN is equipped with large-scale antenna array (or massive MIMO). Specifically, massive MIMO can generate concentrated energy beams to power wireless nodes and thus deal with the challenge of long-distance WPT. Second, multiple HRNs with full-duplex could be considered to improve spectral efficiency, where distributed coordinated beamforming at the HRNs for both WPT and WIT will be interesting. Third, it may also consider that the direct link exists between the sources and destinations. In this case the resource allocation schemes will be largely different. Last, it will be interesting to extend our work to the multiple frames, where sources can accumulate energy and then transmit information over different frames, and the HRN can dynamically allocate its resources over different frames.

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APPENDIX A PROOF OF PROPOSITION 3.2

It can be proved by contradiction as follows: We denote the optimal solution of Problem (P1') as $\{\alpha_k^*\}_{k=0}^K$, $\{s_k^*\}_{k=0}^K$ and $\{m_k^*\}_{k=1}^K$. Suppose that $s_0^* < \alpha_0^* P_{\text{peak}}$, i.e., $p_0^* < P_{\text{peak}}$. Then, we consider the following solution s_0^* and $\{\tilde{\alpha}_k\}_{k=0}^K$, where $s_0^* = \tilde{\alpha}_0 P_{\text{peak}}$, i.e., $\tilde{p}_0 = P_{\text{peak}}$. Since $p_0^* < \tilde{p}_0$, we have $\alpha_0^* > \tilde{\alpha}_0$ with the same optimal s_0^* . From (15b) and (15g), we can obtain that $\tilde{\alpha}_k \ge \alpha_k^*$ for $k = 1, \cdots, K$. Moreover, according to constraint (15d), as the objective function of Problem (P1') is an increasing function of $\{\alpha_k\}_{k=1}^K$ with given s_k^* and m_k^* , the case $\{\tilde{\alpha}_k\}_{k=0}^K$ achieves higher sum-rate than the case $\{\alpha_k^*\}_{k=0}^K$. Thus, this contradicts with the assumption that the $\{\alpha_k^*\}_{k=0}^K$ is the optimal solution. Therefore, the optimal solution must be given by $\{\tilde{\alpha}_k\}_{k=0}^K$ and $\tilde{p}_0 = s_0^*/\tilde{\alpha}_0 = P_{\text{peak}}$, which completes the proof.

APPENDIX B Proof of Proposition 3.3

We can easily prove that Problem (34) is convex with given α_0 , which can be optimally solved by the Lagrangian dual method. The Lagrangian of Problem (34) is given by

$$\mathcal{L}(\boldsymbol{\alpha}, \lambda) = \sum_{k=1}^{K} \frac{\alpha_k}{2} \log_2 \left(1 + \frac{2A_k}{\alpha_k \sigma^2} \right) + \lambda (1 - \sum_{k=0}^{K} \alpha_k),$$

where $\lambda \geq 0$ denotes the Lagrangian multiplier associated with the constraint (1). Since the problem is convex, we can find its optimal solution by using Karush-Kuhn-Tucker (KKT) conditions. With given α_0 , let us denote the primary and dual optimality values of Problem (34) as $\{\alpha_k^*\}_{k=1}^K$ and λ^* . By differentiating $\mathcal{L}(\alpha, \lambda)$ with respect to α_k and using KKT stationary conditions, we obtain

$$\frac{1}{2}\log_2(1+2x_k) - \frac{1}{2\ln 2} + \frac{1}{2\ln 2(1+2x_k)} = \lambda^*, \quad (55)$$

where $x_k = \frac{A_k}{\alpha_k^* \sigma^2}, k = 1, \dots, K$. To make (55) more clearly, we denote $y_k = \frac{1}{1+2x_k}$, then (55) is equivalent to

$$\log_2 y_k = \frac{\ln y_k}{\ln 2} = \frac{y_k}{\ln 2} - \frac{1}{\ln 2} - 2\lambda^*.$$
 (56)

Thus, we have $-y_k - \delta = -\ln y_k = \ln \frac{1}{y_k}$, where $\delta = -1 - 2\ln 2\lambda^*$. Then, it is easy for us to get that $e^{-y_k - \delta} = \frac{1}{y_k}$, which is equivalent to $-y_k e^{-y_k} = -e^{\delta}$. As a result, the solution of (56) is given by $y_k = -W(-e^{\delta})$. Finally, due to $y_k = \frac{1}{1+2x_k}$ and $x_k = \frac{A_k}{\alpha_k^* \sigma^2}$, we can obtain that the solution of $\frac{\partial \mathcal{L}_k}{\partial \alpha_k} = 0$ is given by

$$\alpha_k^* = \frac{-2A_k W(-e^{\delta})}{\sigma^2 (1 + W(-e^{\delta}))}, \quad \forall k = 1, \cdots, K.$$
 (57)

From (57), we can find that $\alpha_k^*, k = 1, \dots, K$ is proportional to A_k . Moreover, it can be easily verified that

 $\sum_{k=1}^{k=K} \alpha_k^* = 1 - \alpha_0 \text{ must hold for Problem (34) with given } \alpha_0.$ Thus the optimal $\{\alpha_k^*\}_{k=1}^K$ with given α_0 is thus given by

$$\alpha_k^* = \frac{A_k}{\sum_{k=1}^K A_k} (1 - \alpha_0), \quad \forall k = 1 \cdots, K.$$
 (58)

By plugging (58) into (32), then the optimal $\{q_k^*\}_{k=1}^K$ with given α_0 is given by

$$q_k^* = \frac{2}{(1 - \alpha_0)h_{1,k}} \sum_{k=1}^K A_k, \quad \forall k = 1 \cdots, K.$$
 (59)

The proof is thus completed.

REFERENCES

- R. Zhang and C. K. Ho, "MIMO broadcasting for simultaneous wireless information and power transfer," *IEEE Transactions on Wireless Communications*, vol. 12, no. 5, pp. 1989–2001, May 2013.
- [2] I. Krikidis, S. Timotheou, S. Nikolaou, G. Zheng, D. W. K. Ng, and R. Schober, "Simultaneous wireless information and power transfer in modern communication systems," *IEEE Communications Magazine*, vol. 52, no. 11, pp. 104–110, November 2014.
- [3] L. Liu, R. Zhang, and K. C. Chua, "Wireless information transfer with opportunistic energy harvesting," *IEEE Transactions on Wireless Communications*, vol. 12, no. 1, pp. 288–300, January 2013.
- [4] Z. Ding, I. Krikidis, B. Sharif, and H. V. Poor, "Wireless information and power transfer in cooperative networks with spatially random relays," *IEEE Transactions on Wireless Communications*, vol. 13, no. 8, pp. 4440–4453, August 2014.
- [5] Y. Liu, "Wireless information and power transfer for multirelay-assisted cooperative communication," *IEEE Communications Letters*, vol. 20, no. 4, pp. 784–787, April 2016.
- [6] Z. Zhou, M. Peng, Z. Zhao, W. Wang, and R. S. Blum, "Wirelesspowered cooperative communications: Power-splitting relaying with energy accumulation," *IEEE Journal on Selected Areas in Communications*, vol. 34, no. 4, pp. 969–982, April 2016.
- [7] A. A. Nasir, X. Zhou, S. Durrani, and R. A. Kennedy, "Wireless-powered relays in cooperative communications: Time-switching relaying protocols and throughput analysis," *IEEE Transactions on Communications*, vol. 63, no. 5, pp. 1607–1622, May 2015.
- [8] D. W. K. Ng, E. S. Lo, and R. Schober, "Wireless information and power transfer: Energy efficiency optimization in OFDMA systems," *IEEE Transactions on Wireless Communications*, vol. 12, no. 12, pp. 6352–6370, December 2013.
- [9] M. Zhang, Y. Liu, and R. Zhang, "Artificial noise aided secrecy information and power transfer in OFDMA systems," *IEEE Transactions* on Wireless Communications, vol. 15, no. 4, pp. 3085–3096, April 2016.
- [10] X. Zhou, R. Zhang, and C. K. Ho, "Wireless information and power transfer in multiuser OFDM systems," *IEEE Transactions on Wireless Communications*, vol. 13, no. 4, pp. 2282–2294, April 2014.
- [11] M. Liu and Y. Liu, "Power allocation for secure SWIPT systems with wireless-powered cooperative jamming," *IEEE Communications Letters*, vol. 21, no. 6, pp. 1353–1356, June 2017.
- [12] S. Wang, M. Xia, and Y. C. Wu, "Multipair two-way relay network with harvest-then-transmit users: Resolving pairwise uplink-downlink coupling," *IEEE Journal of Selected Topics in Signal Processing*, vol. 10, no. 8, pp. 1506–1521, December 2016.
- [13] S. Bi, C. K. Ho, and R. Zhang, "Wireless powered communication: opportunities and challenges," *IEEE Communications Magazine*, vol. 53, no. 4, pp. 117–125, April 2015.
- [14] K. Huang and V. K. N. Lau, "Enabling wireless power transfer in cellular networks: Architecture, modeling and deployment," *IEEE Transactions* on Wireless Communications, vol. 13, no. 2, pp. 902–912, February 2014.
- [15] H. Ju and R. Zhang, "Throughput maximization in wireless powered communication networks," *IEEE Transactions on Wireless Communications*, vol. 13, no. 1, pp. 418–428, January 2014.
- [16] H. Chen, Y. Li, J. L. Rebelatto, B. F. Uchoa-Filho, and B. Vucetic, "Harvest-then-cooperate: Wireless-powered cooperative communications," *IEEE Transactions on Signal Processing*, vol. 63, no. 7, pp. 1700–1711, April 2015.
- [17] H. Ju and R. Zhang, "User cooperation in wireless powered communication networks," in 2014 IEEE Global Communications Conference, December 2014, pp. 1430–1435.

- [18] Y. Zeng and R. Zhang, "Full-duplex wireless-powered relay with selfenergy recycling," *IEEE Wireless Communications Letters*, vol. 4, no. 2, pp. 201–204, April 2015.
- [19] H. Chen, X. Zhou, Y. Li, P. Wang, and B. Vucetic, "Wireless-powered cooperative communications via a hybrid relay," in 2014 IEEE Information Theory Workshop (ITW 2014), November 2014, pp. 666–670.
- [20] N. Zlatanov, D. W. K. Ng, and R. Schober, "Capacity of the two-hop relay channel with wireless energy transfer from relay to source and energy transmission cost," *IEEE Transactions on Wireless Communications*, vol. 16, no. 1, pp. 647–662, January 2017.
- [21] A. A. Nasir, H. D. Tuan, T. Q. Duong, and H. V. Poor, "Secure and energy-efficient beamforming for simultaneous information and energy transfer," *IEEE Transactions on Wireless Communications*, vol. 16, no. 11, pp. 7523–7537, November 2017.
- [22] Z. Sheng, H. D. Tuan, T. Q. Duong, and H. V. Poor, "Joint power allocation and beamforming for energy-efficient two-way multi-relay communications," *IEEE Transactions on Wireless Communications*, vol. 16, no. 10, pp. 6660–6671, October 2017.
- [23] H. H. M. Tam, H. D. Tuan, A. A. Nasir, T. Q. Duong, and H. V. Poor, "MIMO energy harvesting in full-duplex multi-user networks," *IEEE Transactions on Wireless Communications*, vol. 16, no. 5, pp. 3282–3297, May 2017.
- [24] A. A. Nasir, H. D. Tuan, T. Q. Duong, and H. V. Poor, "Secrecy rate beamforming for multicell networks with information and energy harvesting," *IEEE Transactions on Signal Processing*, vol. 65, no. 3, pp. 677–689, February 2017.
- [25] Y. Liu, J. Mo, and M. Tao, "QoS-aware transmission policies for OFDM bidirectional decode-and-forward relaying," *IEEE Transactions* on Wireless Communications, vol. 12, no. 5, pp. 2206–2216, May 2013.
- [26] S. Boyd and L. Vandenberghe, *Convex Optimization*. Cambidge University Press, 2004.
- [27] K. Seong, M. Mohseni, and J. M. Cioffi, "Optimal resource allocation for OFDMA downlink systems," in 2006 IEEE International Symposium on Information Theory, July 2006, pp. 1394–1398.
- [28] W. Yu and R. Lui, "Dual methods for nonconvex spectrum optimization of multicarrier systems," *IEEE Transactions on Communications*, vol. 54, no. 7, pp. 1310–1322, July 2006.
- [29] W. Dang, M. Tao, H. Mu, and J. Huang, "Subcarrier-pair based resource allocation for cooperative multi-relay OFDM systems," *IEEE Transactions on Wireless Communications*, vol. 9, no. 5, pp. 1640–1649, May 2010.