Energy-efficient Resource Allocation for Wirelessly Powered Backscatter Communications

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Abstract

In this letter, we consider a wireless-powered backscatter communication (WP-BackCom) network, where the transmitter first harvests energy from a dedicated energy RF source in the sleep state, and then backscatters information and harvests energy simultaneously through a reflection coefficient. Our goal is to maximize the achievable energy efficiency of the WP-BackCom network via jointly optimizing time allocation, reflection coefficient and transmit power of the dedicated energy RF source. The optimization problem is non-convex and challenging to solve. We develop an efficient Dinkelbach-based iterative algorithm to obtain the optimal resource allocation scheme. The study shows that for each iteration, the energy-efficient WP-BackCom network is equivalent to either the network in which the transmitter always operates in the active state, or the network in which the dedicated energy RF source adopts the maximum allowed power.

I. INTRODUCTION

INTERNET of Things (IoT) allows billions of low-power IoT devices to access wireless communications and communicate with each other so that people and things can be connected at anytime and anyplace. The limited lifetime of IoT devices is a fundamental problem for massively implementing IoT deployment. Driven by this, several advanced technologies, e.g., wireless-powered communication networks (WPCNs) [1] and backscatter communications [2], were proposed to address this problem. One particular promising solution is backscatter communications since it allows IoT devices to modulate and reflect the incident RF signals without active RF transmission components and to harvest energy for circuit

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This work was supported by the scholarship from China Scholarship Council, the Natural Science Foundation of China (61801382), the Science and Technology Innovation Team of Shaanxi Province for Broadband Wireless and Application (2017KCT-30-02), the US National Science Foundations grants under the grants NeTS-1423348 and the EARS-1547312.
operation. Hence backscatter communications consume much less energy than WPCN involving active RF transmission components [2].

In [3], the hardware of backscatter communication prototypes was designed by leveraging ambient WiFi signals, to realize backscatter and energy harvesting. In one of the theoretical analysis [4], the authors investigated the impacts of the time allocation and the reflection coefficient on wirelessly powered backscatter communication system, where dedicated RF energy sources were deployed to power backscatter users. The coexistence of harvest-then-transmit protocol and backscatter communication was also investigated in wireless-powered heterogeneous networks [5], where ambient RF signals and dedicated RF signals transmitted by a dedicated energy source are considered. In addition to [4], [5], where the main focus was on system-level backscatter communications, the authors of [6] studied the joint design of time allocation and reflection coefficient to maximize throughput in a typical backscatter communication scenario that consists of one RF energy source, one backscatter user, and one receiver. The outage probability was also derived in a similar scenario [7]. Backscatter communication has also been combined with other types of communication techniques, e.g., cognitive radio [8], [9], device-to-device [10], and relaying [11]. For example, the existing studies [8], [9] showed that, in a backscatter assisted cognitive radio network, the system spectral efficiency (SE) can be significantly improved by choosing appropriate backscatter communication parameters. Another example is the application of backscatter communications to relay networks [11], where the relay is equipped with a backscatter circuit to reflect the received information to the destination via RF signals from the dedicated energy source. It was shown that the combination can improve the system SE by using an advanced transmission scheme.

Although the aforementioned works [3]–[12] have laid a solid foundation for understanding backscatter communications from various perspectives, e.g., hardware design and SE, the energy efficiency (EE) of backscatter communication has not been studied yet. Motivated by this observation, in this letter, we focus on the design of energy-efficient resource allocation scheme in a wireless-powered backscatter
communication (WP-BackCom) network, where the transmitter modulates and reflects its information to
the receiver via RF signals from dedicated RF energy source, as well as harvests energy to power its
circuit. An efficient Dinkelbach-based iterative algorithm is developed to determine the energy-efficient
resource allocation scheme. Specifically, an optimization problem is firstly formulated to maximize the
EE by jointly optimizing the time allocation, the reflection coefficient and the transmit power of dedicated
energy source. Then the non-convex original optimization problem in fractional form is transformed into
an equivalent optimization problem in the subtractive form based on fractional programming. We further
show that the transformed problem can be cast into two convex EE maximization problems. In one problem
the transmitter always operates in the active state and in the other problem the dedicated energy RF source
adopts the maximum allowed power.

II. SYSTEM MODEL AND WORKING FLOW

We consider a WP-BackCom network [5]–[7] consisting of one dedicated RF energy source, one
transmitter with backscatter circuits (termed as node A), and one receiver (termed as node B), as shown in
Fig. 1. The dedicated RF energy source and node B have stable energy sources. Node A is a battery-free
node and backscatter communication is employed to realize information transfer and harvest energy for
circuit operation. We assume that the harvested energy in each slot is temporarily stored in a capacitor of
node A, part of which will be used to power circuits and the rest will be fully discharged in the same slot
due to the very low storage time of the capacity [13]. In other words, there will be no energy stored in
node A at the end of each slot. An entire slot is less than the coherence interval, which is normalized to 1
without loss of generality. There are two states, sleep state $\tau_s$ and active state $\tau_a$, in one slot. Let $h_0$, $h_1$, $h_2$ denote the channel gains of the RF energy source–A link, the A–B link and the RF energy source–B
link, respectively. Each link is assumed to undergo independent identically distributed quasi-static fading
and to be reciprocal. Perfect CSI is assumed in order to investigate the performance bound.

For each slot, node A leverages the RF signals from the dedicated RF energy source $x(n)$ ($\mathbb{E}[|x(n)|^2] = 1$)
to realize information transmitting and energy harvesting for circuit operation. Node A firstly operates
in the sleep state to harvest energy from received RF signals and the harvested energy in this state is
calculated as $E_{\text{sleep}}^h = \eta P_0 h_0 \tau_s$, where $P_0$ and $\eta$ are the transmit power of the dedicated RF energy
source and the energy harvesting efficiency coefficient, respectively. Here we ignore the harvested energy
from the noise since both A and B are passive users and their received noise powers are much smaller
than the received signals $x(n)$ [5]–[9]. In the active state, part of the received RF signal, $\sqrt{\beta P h_0} x(n)$,
is employed as the vehicle for modulating and backscattering the information of node A and the rest,
the harvested energy in this state and the backscattered signals are written as $E^h_{\text{active}} = \eta (1 - \beta) P_0 \tau_a$ and $\hat{x}(n) = \sqrt{\beta P_0 \lambda} x(n) c(n)$, respectively, where $c(n)$ is node A’s signal satisfying $\mathbb{E} |c(n)|^2 = 1$ [9]. The received signal at node B is given by $\hat{x}(n) = \sqrt{h_1} \hat{x}(n) + \sqrt{h_2} x(n) + w(n)$, where $w(n)$ is the additive white Gaussian noise with variance $\sigma^2$ at the receiver. Following [6], [9], the received signal-to-noise ratio (SNR) can be written as $\gamma = \beta P_0 \frac{h_1}{\sigma^2} \lambda$ after applying successive interference cancellation (SIC). Accordingly, the throughput is $R = \tau_a \log_2 (1 + \beta P_0 \lambda)$, where $\lambda = \frac{h_0 h_1}{\sigma^2}$.

The total energy consumption of the network consists of two parts: the energy consumption in the dedicated energy RF source and the node B. Therefore, the total energy consumption of the whole system is written as $E^c_{\text{total}} = P_0 \tau_a + P_{sc} \tau_s + P_{rc} \tau_a + P_{sc} \tau_a + P_{rc} \tau_a$, where $\xi \in [0, 1]$ is the power amplifier efficiency; $P_{sc}$ and $P_{rc}$ are the constant circuit powers consumed by the dedicated RF energy source and the nodes B, respectively. Note that the constant circuit power of the node A, denoted by $P_{tc}$, does not be included in $E^c_{\text{total}}$ since the energy consumption of the node A is powered by the harvested energy, which has been included in the energy consumption of the RF source.

### III. Energy-efficient Resource Allocation

#### A. Problem Formulation

In this subsection, we formulate an optimization problem to maximize the achievable EE by optimizing the time for sleep and active states, reflection coefficient and transmit power of the RF energy source. The EE $q$ is defined as the ratio of achievable throughput to total energy consumption [14], given as $q = \frac{\tau_a \log_2 (1 + \beta P_0 \lambda)}{\tau_a (\tau_a + \tau_s) + P_{rc} \tau_a + P_{sc} (\tau_a + \tau_s)}.$ Thus, the optimization problem can be written as

$$ P_1 : \max_{P_0, \tau_a, \tau_s, \beta} q,$$

s.t. $C1 : 0 < \beta \leq 1$, $C2 : 0 < \tau_a + \tau_s \leq 1,$

$$ C3 : 0 < P_0 \leq P_{\text{max}}, \quad C4 : \tau_a > 0, \tau_s \geq 0,$$

$$ C5 : P_{tc} \tau_a \leq E^h_{\text{sleep}} + E^h_{\text{active}}.$$

In $P_1$, $C2$ constrains the maximum time for the sum of sleep and active states. $C3$ constrains the maximum transmit power of the RF energy source. $C3$ constrains the maximum transmit power of the RF energy source. $C5$ guarantees that the total energy consumed by node A does not exceed the total harvested energy [6]. Note that $P_1$ is a non-convex problem due to the non-convex objective function and the non-convex constraint $C5$. In general, there is no standard algorithm to solve non-convex optimization problems efficiently. Nevertheless, we propose an iterative algorithm to obtain the optimal solution in what follows.
B. Solution

The problem $P_1$ is a non-linear fractional programming problem and hence this can be solved by developing an efficient Dinkelbach-based iterative algorithm. To this end, Lemma 1 is provided to transfer $P_1$ to a tractable problem.

**Lemma 1.** The optimal solution of $P_1$ can be obtained if and only if the following equality holds.

$$
\max_{P_0, \tau_s, \tau_a, \beta} \log_2 (1 + \beta P_0 \lambda) - q \left( \left( \frac{P_0}{\zeta} + P_{sc} \right) \left( 1 + \frac{\tau_s}{\tau_a} \right) + P_{rc} \right) = 0
$$

where $\beta^*$ denotes the optimal solution corresponding to the optimization variables. This Lemma can be proven readily from the generalized fractional programming theory [14].

Based on Lemma 1, the original problem (1) can be solved by solving the following problem $P_2$.

$$
P_2 : \max_{P_0, \tau_s, \tau_a, \beta} \log_2 (1 + \beta P_0 \lambda) - q \left( \left( \frac{P_0^*}{\zeta} + P_{sc} \right) \left( 1 + \frac{\tau_s^*}{\tau_a} \right) + P_{rc} \right)
$$

s.t. $C1 – C5$.

(2)

Even though the problem is more tractable, there are coupling relationships among different optimization variables, e.g., the coupling between $\beta$ and $P_0$, as well as the coupling among $P_0$, $\tau_s$, and $\tau_a$ in the objective function. Accordingly, the problem $P_2$ is still non-convex. In order to solve it, we first present the following Proposition.

**Proposition 1.** For any given system parameters and optimization variables, the optimal reflection coefficient $\beta^*$ of $P_2$ is calculated as $\beta^* = \max \left\{ 0, \min \left\{ 1 + \frac{\tau_s}{\tau_a} - \frac{P_{tc}}{\eta P_0 h_0}, 1 \right\} \right\}$.

**Proof.** Obviously, the objective function of $P_2$ increases with the increase of $\beta$. On the other hand, through some simple mathematical calculations, the constraint C5 is equivalent to the following inequality, which is $\beta \leq 1 + \frac{\tau_s}{\tau_a} - \frac{P_{tc}}{\eta P_0 h_0}$. Combing with C1, the Proposition 1 can be proven.

**Remark 1.** The proposed Proposition 1 serves two purposes. Firstly, we provide a closed-form expression for the optimal reflection coefficient and hence obtain the optimal reflection coefficient using this expression instead of other iterative algorithms. The second purpose is to obtain insightful understandings on the optimal reflection coefficient. For example, when $0 \leq 1 + \frac{\tau_s}{\tau_a} - \frac{P_{tc}}{\eta P_0 h_0} < 1$ holds, the optimal reflection coefficient increases with the increase of $\tau_s$, and more power of (or even all the) received signals in the active state will be used to backscatter, indicating that a higher EE could be achieved; when $1 + \frac{\tau_s}{\tau_a} - \frac{P_{tc}}{\eta P_0 h_0} \geq 1$ is satisfied, i.e., the harvested energy during sleep state is sufficient to cover the
energy consumed by circuits, the transmitter backscatters all the received signals during the active state and assigns more time for the active state and less time for the sleep state for EE maximization.

Based on Proposition 1, $P_2$ is rewritten as

$$
P_3 : \max_{P_0, \tau_s, \tau_a} \log_2 \left( k + P_0 \lambda \left( 1 + \frac{\tau_s}{\tau_a} \right) \right)$$

$$
- q \left( \left( \frac{P_0}{\xi} + P_{se} \right) \left( 1 + \frac{\tau_s}{\tau_a} \right) + P_{rc} \right)$$

s.t. \ C2 – C4, C6 : 0 < 1 + \frac{\tau_s}{\tau_a} - \frac{P_{tc}}{\eta P_0 h_0} \leq 1, \tag{3}

where $k = 1 - \frac{\lambda P_{tc}}{\eta h_0}$, and C6 is derived from C1 and Proposition 1. Observe that the problem $P_3$ has less optimization variables and more tractable compared with the original problem $P_2$. However, the problem $P_3$ is still non-convex due to the existence of coupling in the objection function and the constraint C6. To cope with it, we introduce three auxiliary variables: $\tau = \tau_s + \tau_a$; $z = P_0 \left( 1 + \frac{\tau_s}{\tau_a} \right)$ and $t = 1 + \frac{\tau_s}{\tau_a}$. Based on these three auxiliary variables, the problem $P_3$ is equivalent to the following problem, given by

$$
P_4 : \max_{z, \tau, t} \log_2 \left( k + \lambda z \right) - q \left( \frac{z}{\xi} + P_{se} t + P_{rc} \right)$$

s.t. \ C7 : 0 < \tau \leq 1, \ C8 : 0 < z \leq P_{max} t, \ C9 : t \geq 1, \ C10 : 0 < t \left( 1 - P_{tc}/\eta z h_0 \right) \leq 1, \tag{4}

where the constraints C9 and C10 are derived from the constraints C4 and C6, respectively.

The problem $P_4$ is still non-convex due to the non-convex constraint C10, while we note that the objective function increases with the decrease of $t$ and the feasible region of $t$ is $\max \{1, z/P_{max} \} \leq t \leq \frac{1}{1 - P_{tc}/\eta z h_0}$. Based on this observation, we show that the problem $P_4$ is equivalent to the following two optimization problems $P_5$ and $P_6$.

$$
P_5 : \max_{z, \tau} \log_2 \left( k + \lambda z \right) - q \left( \frac{z}{\xi} + P_{se} + P_{rc} \right)$$

s.t. \ C7, C11 : 0 < z \leq P_{max}, \ C12 : \eta z h_0 - P_{tc} > 0. \tag{5}

$$
P_6 : \max_{z, \tau} \log_2 \left( k + \lambda z \right) - q \left( \frac{z}{\xi} + \frac{P_{se}}{P_{max}} + P_{rc} \right)$$

s.t. \ C7 : 0 < \tau \leq 1, \ C13 : P_{max} < z, \ C14 : \frac{P_{se}}{\eta h_0} \leq z \leq P_{max} + \frac{P_{se}}{\eta h_0}. \tag{6}

$P_5$ and $P_6$ are formulated based on $\frac{z}{P_{max}} \leq 1$ and $\frac{z}{P_{max}} > 1$, respectively. Obviously, the objective function of $P_5$ (or $P_6$) is a concave function and all the constraints are in linear format. Thus, the problem $P_5$ (or $P_6$) is convex and can be solved by CVX tool.

Remark 2. If $\frac{z}{P_{max}} \leq 1$ holds, we have $t^* = 1$ and $\tau_s^* = 0$, indicating that the harvested energy during the active state is sufficient to power the circuit and that node A always operates in the active state. In
energy source adopts the maximum allowed power. Moreover, we obtain that 'then-active' is a desirable working mode for node A; (ii) the maximum EE could be achieved when the

\[ P \] problems,

by using Lagrange duality method, where 

\( P \) with the increase (decrease) of 

addition, we derive the closed-form expressions for \( z^* \) and \( P_0^* \) based on Lagrange duality method and

\[ z^* = P_0^* t^*, \quad z^* = P_0^* = \frac{\ln 2}{u_1 + q/\xi} - \frac{k}{\lambda}, \] where \( u_1 \geq 0 \) is a Lagrange multiplier.

**Remark 3.** If \( \frac{z}{P_{\text{max}}} > 1 \) is satisfied, we have \( t^* = \frac{z^*}{P_{\text{max}}}, \) \( \tau_s^* > 0 \) and \( 0 < \tau_a^* < 1 \). Combing with \( z^* = P_0^* t^* \), it is not difficult to find that \( P_0^* = P_{\text{max}} \). There are two insights: (i) \( \tau_s^* > 0 \) and \( 0 < \tau_a^* < 1 \) mean that ‘sleep-then-active’ is a desirable working mode for node A; (ii) the maximum EE could be achieved when the energy source adopts the maximum allowed power. Moreover, we obtain that \( t^* = 1 + \frac{\tau_s^*}{\tau_a^*} = 1 + \frac{\ln 2}{q P_{\text{max}}/\xi + u_2 P_{\text{max}} - q P_{\text{rc}} - k/\lambda} \) by using Lagrange duality method, where \( u_2 \geq 0 \) is a Lagrange multiplier. It can be found that \( t^* \) increases with the increase (decrease) of \( P_{\text{sc}} (P_{\text{max}}) \). This finding and \( t^* = 1 + \frac{\tau_s^*}{\tau_a^*} \) reveal the relationships among \( \tau_s^*/\tau_a^* \), \( P_{\text{sc}} \) and \( P_{\text{max}} \) (or \( P_0^* \)).

**Remark 4.** It can be drawn from remarks 2 and 3 that the problem \( P_2 \) is equivalent to two optimization problems, \( P_5 \) and \( P_6 \), for two simplified sub-systems, which can be obtained by relaxing one constraint, e.g. \( \tau_s^* = 0 \) or \( P_0^* = P_{\text{max}} \).

Based on \( P_2-P_6 \), we summarize the Dinkelbach-based iterative algorithm for solving \( P_1 \) in Algorithm

Algorithm 1 Dinkelbach-based Iterative Algorithm
1: Set the maximum iterations \( L_{\text{max}} \), the maximum error tolerance \( \epsilon \), the maximum EE \( q = 0 \) and iteration index \( l = 0 \).
2: repeat
3: Solve \( P_5 \) and \( P_6 \) with a given \( q \), and obtain the optimal solutions \( (P_{01}^+, z_{1}^+, \tau_{1}^+) \) and \( (P_{02}^+, z_{2}^+, \tau_{2}^+) \);
4: if \( f_1 (z_{1}^+, \tau_{1}^+) > f_2 (z_{2}^+, \tau_{2}^+) \) then
5: \( (P_{01}^+, z^+, \tau^+) = (P_{01}^+, z_{1}^+, \tau_{1}^+) \)
6: else
7: \( (P_{01}^+, z^+, \tau^+) = (P_{02}^+, z_{2}^+, \tau_{2}^+) \)
8: end if
9: if \( \log_2 (k + \lambda z^+) \frac{q z^+}{\xi} - q P_{\text{sc}} \tau^+ - q P_{\text{rc}} < \epsilon \) then
10: Set Flag = 1, \( P_0^* = P_{01}^+, \) \( z^* = z^+, \) \( \tau^* = \tau^+ \) and return
11: else
12: Set Flag = 0, \( q = \frac{\log_2 (k + \lambda z^+)}{z^+} \) and \( l = l + 1 \)
13: end if
14: until Flag = 1 or \( k = L_{\text{max}} \)
15: Obtain the optimal solution for (1) as follows: \( P_{01}^*, \tau_a^* = \frac{P_{01}^* \tau_s^*}{\tau_a^*}, \tau_s^* = \tau^* - \tau_a^*, \beta^* = 1 + \frac{\tau_s^*}{\tau_a^*} - \frac{P_{01}^*}{\eta P_{01}^* h_0} \).
Fig. 2. The convergence of Algorithm 1.

Fig. 3. An illustration of Remark 4.

Fig. 4. EE versus the maximum allowed power.

1, where $f_1(\cdot), f_2(\cdot), (P_{01}^+, z_1^+, \tau_1^+) \text{ and } (P_{02}^+, z_2^+, \tau_2^+)$ denote the objective function of $P_5$, the objective function of $P_6$, the optimal solution of $P_5$ and the optimal solution of $P_6$ in each iteration, respectively. In the proposed Algorithm 1, we solve $P_5$ and $P_6$ instead of $P_4$ with a given $q$ in each iteration and obtain the optimal solution, denoted by $(P_0^+, z^+, \tau^+)$, by comparing $f_1(z_1^+, \tau_1^+)$ with $f_2(z_2^+, \tau_2^+)$. For an error tolerance $\epsilon$, the solution to $P_4$ is determined when $\log_2(k + \lambda z^+) - \frac{qz^+}{\xi} - q \frac{P_{sc}}{\xi} \tau^+ - q \frac{P_{rc}}{\xi} < \epsilon$ or $l = L_{\text{max}}$ is satisfied.

IV. SIMULATION RESULTS

This section presents the numerical results to validate our proposed algorithm and investigate the achievable EE in our considered network. We adopt the distance-dependent path loss model $h_i = |g_i|^2 d_i^{-3}$, where $g_i \sim \mathcal{CN}(0, 1)$ is the channel coefficient. We set the other parameters as follows: $d_0 = 10$ m, $d_1 = 15$ m, $\xi = 0.9$, $P_{sc} = 100$ mW, $P_{tc} = 1$ mW, $P_{rc} = 10$ mW, $\sigma^2 = -100$ dBm, and $\eta = 0.6$.

Fig. 2 depicts the EE of the proposed Algorithm 1 versus the number of iterations under different channel coefficients. It can be seen that Algorithm 1 converges to the optimal EE after only two iterations. A concrete example to verify Remark 4 is presented in Fig. 3, where $|g_0|^2$ and $|g_1|^2$ are set to unit value and the step of the maximum allowed power of the dedicated RF energy source $P_{\text{max}}$ is 5 dBm. It is shown that the energy-efficient WP-BackCom network operates as expected in both modes, namely the mode where the dedicated energy RF source adopts the maximum allowed power or the mode where the transmitter always operates in the active state. Besides, our study shows that the considered network switches from mode 1 to mode 2 as $P_{\text{max}}$ increases.

In Fig. 4, we plot the average EE versus the maximum allowed power $P_{\text{max}}$ for four schemes, given by (i) optimal EE proposed in this letter; (ii) optimal SE to maximize the throughput [6]; (iii) optimal
EE with $P_0 = P_{\text{max}}$ or $\tau_s = 0$, as in (6) or (5). The average EE of in each of these four schemes is obtained through 500 Monte-Carlo simulations. It can be seen that our proposed scheme always achieves the highest EE among four schemes. In particular, as $P_{\text{max}}$ increases, one can see that the average EE of the optimal EE scheme first sharply increases and then remains unchanged while the average EE of the optimal SE scheme and optimal EE with $P_0 = P_{\text{max}}$ first increase and then strictly decrease due to its greedy usage of power. In addition, for the optimal EE with $\tau_s = 0$, one can also see that the average EE increases with the increase of $P_{\text{max}}$ due to the long efficient transmission time.

V. Conclusions

In this letter, we have proposed an energy-efficient resource allocation scheme with a Dinkelbach-based iterative algorithm to obtain the optimal time allocation, the optimal reflection coefficient and the optimal transmit power of the dedicated RF energy source in a WP-BackCom network. We have verified the fast convergence of the proposed iterative algorithm. It has also been shown that, for each iteration, the energy-efficient WP-BackCom network can function either as the network in which the transmitter always operates in the active state, or the network in which the dedicated energy RF source adopts the maximum allowed power.

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