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Research Article

Energy-Efficient Resource Allocation in Cognitive Wireless-Powered Hybrid Active-Passive Communications

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Integrating hybrid active-passive communications into cognitive radio can achieve a spectrum- and energy-efficiency information transmission, while the resource allocation has not been well studied particularly for the network with multiple secondary users (also termed as the Internet of Things (IoT) users). In this article, we formulate an optimization problem to maximize the energy efficiency of all the IoT nodes in a cognitive wireless-powered hybrid active-passive communication network by taking the interference from the IoT node to the primary link, the energy causality constraint, and the minimum throughput constraint per IoT node. By using the Dinkelbach method and introducing auxiliary variables, we devise an iterative algorithm to optimally solve the formulated problem. Computer simulations are provided to validate the quick convergence of the iterative algorithm and the advantages of the proposed scheme in terms of the energy efficiency.

1. Introduction

In the past decade, it has been witnessed that the Internet of Things (IoT) technology has wide applications in our daily lives particularly in the smart factory. To realize smart applications, a large number of tiny IoT nodes should be deployed to collect data from the environment and then send the collected data to the information fusion, resulting in a huge need for spectrum resource [1–3]. It is reported by the European Union that just eHealthCare IoT connectivity requires at least 5.2 GHz bandwidth if dedicated spectrum is allocated to each tiny IoT node [4]. However, most of the spectrum resources have been allocated, leading to the shortage of spectrum resources.

To relieve the conflict between the increasing demand for spectrum and the limited spectrum resources, cognitive radio (CR) has been proposed as an efficient solution for this problem by letting IoT nodes share the same spectrum resource as the primary user [5, 6]. In CR, the tiny IoT node is allowed to access the spectrum allocated to the primary user in the opportunistic or spectrum sharing manner, while ensuring the Quality of Servers (QoS) of the primary user. On the other hand, due to the cost and form factor constraints, the tiny IoT nodes are powered by the battery with a limited capacity that can be quickly drained by information transmissions, thus limiting the battery life of these tiny IoT nodes. Recall that the primary signal can function as the energy and information sources simultaneously. Wireless-powered transfer is introduced into CR, yielding a cognitive wireless-powered communication [7].

In previous studies on cognitive wireless-powered communication (see [7–11] and reference therein), it was considered that the IoT node firstly harvests energy from the primary signal and subsequently uses the harvested energy to transmit signal by accessing the spectrum of the primary user via active radios (AR). In AR, the IoT node needs to generate the carrier signal and modulate its information on the carrier signal. Such an approach requires power-consuming components, e.g., oscillator [12–14]. Accordingly, AR achieves a high transmission rate but at the cost of a high power consumption. Since the energy consumed by the IoT node is constrained by its harvested energy, the IoT node should allocate a large proportion of time period to harvest energy and leave a limited time for AR, which may lead to a low throughput [15–18]. Recently, passive communication has received much attention due to its low power consumption. The key idea of passive communications is allowing IoT node encoding information on the incident signal and reflecting the encoded signal to the receiver, thus removing the need of power-consuming components and realizing a low-power communication [12–14]. Due to this, the passive communication has been introduced into cognitive radio for addressing the above challenge [19]. However, the rate of the passive communication enabled IoT node is still low. Recall that both AR and passive communication have different tradeoffs between the communication rate and power consumption [15–18], which can be exploited to achieve efficient data transmissions for IoT nodes in cognitive wireless-powered communications. The above combination is referred as the cognitive wireless-powered hybrid active-passive communication in this paper.

In this conference paper [20], the authors considered that the cognitive wireless-powered hybrid active-passive communication operates in the overlay mode and maximized the IoT node's throughput by optimizing the tradeoff between passive communication and AR, subject to the constraint where the harvested energy of the IoT node is not less than that consumed by itself. Subsequently, this conference paper was extended into a journal paper [21], where the same problem was studied in both the overlay and underlay modes. In [22], the authors considered the cognitive wireless-powered hybrid active-passive communication with multiple IoT nodes, and the main contribution was to maximize the sum throughput of all the IoT nodes by jointly optimizing the energy harvesting time, the passive communication time, and the AR time for each IoT node. The authors in [23] proposed another wireless-powered cognitive hybrid active-passive communication network, where the power beacon is deployed for increasing the harvested energy of the IoT node and optimized the time for energy harvesting, passive communication, and AR of the IoT node. The above works [20–23] focused on the throughput maximization and did not optimize the backscatter coefficient. Such a gap was filled by [24]. Since the energy efficiency is of significance for wireless communications, the authors proposed to maximize the energy efficiency of the IoT node in an overlay-based cognitive wireless-powered hybrid active-passive communication, subject to the maximum tolerated interference to the primary link and the imperfect spectrum sensing constraints. The authors of [25] studied the multi-IoT nodes in cognitive wireless-powered hybrid active-passive communication and maximized the energy efficiency of all the IoT nodes, while considering the energy causality constraint and the minimum throughput constraint per IoT node. However, this work largely ignored the interference from the IoT node to the primary link; thus, the designed resource allocation may not work in practical cognitive wireless-powered hybrid active-passive communications and this should be fixed.

In this article, we consider a cognitive wireless-powered hybrid active-passive communication with multiple IoT nodes and propose to maximize the energy efficiency, while considering the maximum tolerated interference to the primary link, the energy causality constraint, and the minimum throughput constraint per IoT node. The formulated problem is optimally solved by our designed Dinkelbach-based iterative algorithm. Finally, the simulation results are provided to support our work.

2. System Model

As shown in Figure 1, we consider a cognitive wireless-powered hybrid active-passive communication network, which consists of a legacy transmitter (LT), a legacy receiver (LR), K IoT nodes, and an information gateway. All the devices are equipped with a single antenna. In order to harvest energy from the signals transmitted by the LT and encode and backscatter legacy signals for information transmission, it is assumed that both the radio frequency (RF) energy harvesting circuit and the backscatter circuit are equipped at each IoT node. Besides, the active transmission circuit is also equipped at each IoT node so that each IoT node can choose to transmit its own information via hybrid active-passive communications. Suppose that the perfect channel state information is known by the information gateway before the whole information transmission by the information exchange among the LT, the LR, IoT nodes, and the information gateway. Therefore, the information gateway can design the optimal resource allocation scheme based on all obtained channel state information and then transmit the designed scheme to IoT nodes so that each IoT node can operate by following the designed scheme. To obtain the performance bound, we assume perfect channel state information (CSI) and the details on how to obtain CSI can be referred to [26].

In the following part, we will clarify how to realize the legacy transmission and IoT nodes' transmissions in our considered network. Specifically, for the legacy transmission, the whole transmission block, denoted by T, can be divided into two periods according to whether the LT transmits the legacy signal or not. The two periods are the busy period and the idle period. Let β $(0 \leq \beta \leq 1)$ denote the channel busy ratio. At the busy period with the duration of βT, the LT transmits the legacy signal to the LR; i.e., the channel is in the busy period. Accordingly, the LR can receive the legacy signal and obtain the legacy information by decoding the received signal. At the same time, each IoT node can harvest energy from the legacy signal and backscatter the received signal to the information gateway. At the idle period with the duration of $(1-\beta)T$, the LT stops information transmission; i.e., the channel is in the idle period, while each IoT node can use its harvested energy to transmit its information to the information gateway.

Accordingly, for the IoT nodes' transmissions, the whole time block can also be divided into two phases, which are the backscatter communication phase and the active transmission phase. The backscatter communication phase is included in the busy period. In this phase, each IoT node take turns to perform backscatter communications so as to avoid the cochannel interference among different IoT nodes. Therefore, the backscatter communication phase can be further divided into K subphases. Let $\tau_k T$ with $\sum_{k=1}^{K}\tau_k T \leq \beta T$

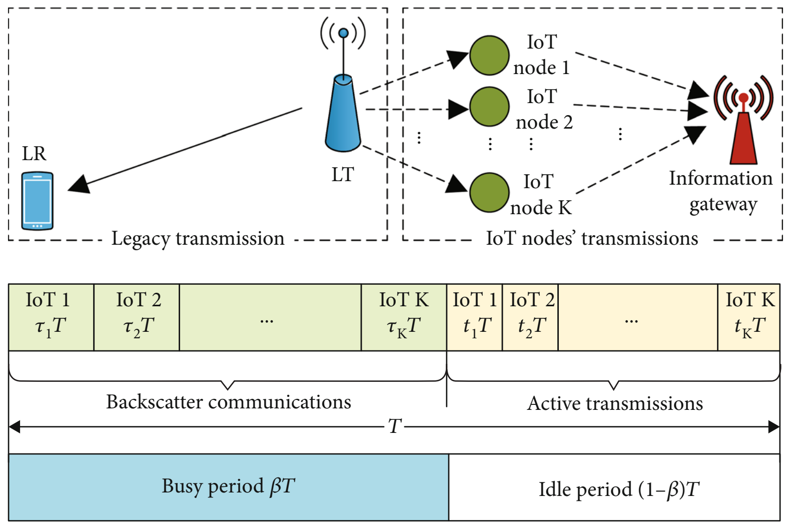

Figure 1: System model.

denote the duration of the kth subphase, where the kth IoT performs backscatter communication and the others keep harvesting energy in order to harvest energy as much as possible. The active transmission phase is included in the idle period. Likewise, in order to avoid the interference from other IoT nodes, the whole active transmission phase is also divided into K subphases. Let $t_k T$ with $\sum_{k=1}^{K} t_k T \le (1-\beta)T$ be the duration of the kth subphase in this phase, in which the kth IoT uses its harvested energy to transmit information and the others keep idle.

Let P_s denote the transmit power of the LT and $s(n)$ be the nth symbol to be transmitted by the LT with normalized power. Then, the transmitted signal at the LT is given by $x(n) = \sqrt{P_s}s(n)$. Denote $c(n)$ as the nth transmitted symbol at the IoT node with $\mathbb{E}[|c(n)|^2] = 1$ and $\alpha_k \in (0, 1)$ as the normalized reflection coefficient at the kth IoT node, where a part of the received signal with ratio α_k is backscattered to the information gateway and the rest is flowed to the RF energy harvesting module. Then, the received signal at the LR in the kth subphase of the backscatter communication phase can be expressed as

$$y_{k,R} = f_0 x(n) + \sqrt{\varepsilon\alpha_k} f_k h_k c(n) x(n) + u_R(n), \quad (1)$$

where f_0 is the channel coefficient of the LT-LR link, $\varepsilon \in (0, 1)$ is the backscatter efficiency, h_k is the channel coefficient between the LT and the kth IoT node ($k \in \{1, 2, \cdots, K\}$), f_k denotes the channel coefficient between the kth IoT node and the LR, and $u_R(n)$ is the additive white Gaussian noise (AWGN) at the LR. Correspondingly, the signal-to-interference-plus-noise ratio (SINR) for decoding $s(n)$ at the LR is given by

$$\gamma_{k,R} = \frac{P_s |f_0|^2}{\varepsilon\alpha_k |f_k|^2 |h_k|^2 P_s + \sigma^2 W}, \quad (2)$$

where σ^2 denotes the power spectral density and W is the system bandwidth.

For the kth IoT node in the kth subphase of the backscatter communication phase, the received signal can be represented as

$$y_k(n) = g_0 x(n) + \sqrt{\varepsilon\alpha_k} g_k h_k c(n) x(n) + u_G(n), \quad (3)$$

where g_0 denotes the channel coefficient of the LT-the information gateway link, g_k is the channel coefficient of the kth IoT node-the information gateway link, and $u_G(n)$ is the AWGN at the information gateway.

Obviously, the backscatter communication suffers the interference from the LT's transmission, which leads to a poor performance, since the backscattered signal is much weaker than the legacy signal due to the double-fading effect in the backscattered signal. To address this issue and improve the performance of the backscatter communication, the successive interference cancellation (SIC) is employed to decode $c(n)$ at the information gateway. Specifically, the information gateway will decode $s(n)$ first and subtract it from the received signal before decoding $c(n)$. Thus, the SINR for decoding $s(n)$ is given by

$$\gamma_{1k} = \frac{P_s |g_0|^2}{\varepsilon\alpha_k |g_k|^2 |h_k|^2 P_s + W\sigma^2}. \quad (4)$$

When $s(n)$ is decoded successfully, i.e., $\gamma_{1k} \ge \gamma_{\min}$, where $\gamma_{\min}$ is the minimum required signal-to-noise ratio (SNR) to decode $s(n)$, the SNR for decoding $c(n)$ is given by

$$\gamma_{2k} = \frac{\varepsilon\alpha_k |g_k|^2 |h_k|^2 P_s}{W\sigma^2}. \quad (5)$$

Initialize the maximum iterations $I_{\max}$ and the maximum error tolerance ε;
Set the maximum energy efficiency $q = 0$ and iteration index $l = 0$;
repeat
  Solve $\mathbf{P}_4$ with a given q and obtain the optimal solution (τ^+, t^+, P^+);
  if $\sum_{k=1}^{K} C_k^{(2)+} - q(\sum_{k=1}^{K} P_{c,k}\tau_k^+ + \sum_{k=1}^{K} (y_k^+ + p_{c,k}t_k^+)) < \varepsilon$ **then**
    Flag = 1;
    Set $\tau^* = \tau^+$, $t^* = t^+$, $P^* = y^+/t^+$, $q^* = \sum_{k=1}^{K} C_k^{(2)+}/\sum_{k=1}^{K} P_{c,k}\tau_k^+ + \sum_{k=1}^{K} (y_k^+ + p_{c,k}t_k^+)$ and return;
  else
    Set $q = \sum_{k=1}^{K} C_k^{(2)+}/\sum_{k=1}^{K} P_{c,k}\tau_k^+ + \sum_{k=1}^{K} (y_k^+ + p_{c,k}t_k^+)$, $l = l + 1$;
    Flag = 0;
  end if
until Flag = 1 or $l = I_{\max}$

Algorithm 1: Dinkelbach-based iterative algorithm for $\mathbf{P}_2$.

According to (5), the achievable throughput of the kth IoT node via the backscatter communication can be computed as

$$C_k^b = W\tau_k T \log_2(1 + \gamma_{2k}) = W\tau_k T \log_2\left(1 + \frac{\varepsilon\alpha_k |g_k|^2 |h_k|^2 P_s}{W\sigma^2}\right). \quad (6)$$

Please note that $c(n)s(n)$ may not follow the Gaussian distribution. However, for analytical tractability, we assume that $c(n)s(n)$ follows the Gaussian distribution such that the throughput of the backscatter communication can be approximated by using Shannon capacity [14–17].

For energy harvesting, a more practical nonlinear energy harvesting model [26] is considered here to be more practical. Please note that our proposed Algorithm 1 can be used for any nonlinear energy harvesting model. Then, the harvested energy at the kth IoT node in this subphase is given by

$$E_k^b = \frac{E_{\max}\left(1 - \exp\left(-a(1-\alpha_k)P_s|h_k|^2\right)\right)}{1 + \exp\left(-a(1-\alpha_k)P_s|h_k|^2 + ab\right)}\tau_k T, \quad (7)$$

where $E_{\max}$ denotes the maximum harvestable power when the circuit is saturated and a and b represent the fixed parameters determined by the resistance, capacitance, and diode turn-on voltage. Let $P_{c,k}$ be the circuit power consumption of the kth IoT node when backscattering. Then, the constraint $E_k^b \geq \tau_k T P_{c,k}$ should be satisfied so that the harvested energy is enough for the circuit operation and the kth IoT node can backscatter signals to the information gateway. We note that the IoT node can also harvest energy from the signal transmitted by other IoT nodes, but it is too much smaller compared with that of LT. Thus, in this work, we assume that each IoT node only harvests energy from the signals from the PT.

Note that the harvested energy of the kth IoT node for the other subphases is used to support its active transmission in the active transmission phase. Thus, the total harvested energy for the active transmission can be calculated as

$$E_k^a = \frac{E_{\max}\left(1 - \exp\left(-aP_s|h_k|^2\right)\right)}{1 + \exp\left(-aP_s|h_k|^2 + ab\right)}(\beta - \tau_k)T. \quad (8)$$

For the kth IoT node in the kth subphase of the active transmission phase, its achievable throughput is given by

$$C_k^a = W t_k T \log_2\left(1 + \frac{P_k|g_k|^2}{W\sigma^2}\right), \quad (9)$$

where P_k is the transmit power of the kth IoT node during the active transmission phase.

3. Energy-Efficient Resource Allocation

In this section, with the practical nonlinear energy harvesting model considered, we aim to maximize the energy efficiency of all the IoT nodes in the investigated network by jointly optimizing the backscattering time $[\tau_1,\cdots,\tau_K]$ and reflection coefficients $[\alpha_1,\cdots,\alpha_K]$ of all IoT nodes in the backscatter communication phase and the transmit power $[P_1,\cdots,P_K]$ and time $[t_1,\cdots,t_K]$ of all IoT nodes in the active transmission phase, subject to the energy causality constraint, the minimum SNR requirements, etc.

3.1. Problem Formulation. The goal of this work is to maximize the energy efficiency of all the IoT nodes, which is defined as the ratio of the total achievable throughput of all the IoT nodes, denoted by C_{sum}, to all the IoT nodes' energy consumption, namely, E_{sum}. In the following part, we aim to determine the expressions of C_{sum} and E_{sum}. Based on (6) and (9), we can determine the expression of C_{sum} as

$$\begin{aligned} C_{\text{sum}} &= \sum_{k=1}^{K}\left(C_k^b + C_k^a\right) \\ &= \sum_{k=1}^{K}\left(W\tau_k T\log_2\left(1 + \frac{\varepsilon\alpha_k|g_k|^2|h_k|^2P_s}{W\sigma^2}\right)\right. \\ &\quad \left. + W t_k T\log_2\left(1 + \frac{P_k|g_k|^2}{W\sigma^2}\right)\right). \end{aligned} \quad (10)$$

As for the total energy consumption of all the IoT nodes, E_{sum} consists of the energy consumed in the backscatter communication phase and the energy consumption in the active transmission phase. Let $p_{c,k}$ denote the constant circuit power consumption at the kth IoT node in the active transmission phase. Then, E_{sum} can be computed as

$$E_{\text{sum}} = \sum_{k=1}^{K} P_{c,k}\tau_k T + \sum_{k=1}^{K}\left(P_k + p_{c,k}\right)t_k T. \tag{11}$$

Therefore, the energy efficiency maximization problem can be formulated as

$$\begin{aligned}
\mathbf{P}_1:\quad & \max_{(\boldsymbol{\tau},\mathbf{t},\boldsymbol{\alpha},\mathbf{P})} \frac{C_{\text{sum}}}{E_{\text{sum}}}\\
\text{s.t.}:\quad & \text{C1}: \sum_{k=1}^{K}\tau_k T \le \beta T,\ \sum_{k=1}^{K} t_k T \le (1-\beta)T\\
& \text{C2}: \gamma_{1k} \ge \gamma_{\min},\quad k\in\{1,\cdots,K\}\\
& \text{C3}: \gamma_{k,R} \ge \gamma_{\min},\quad k\in\{1,\cdots,K\}\\
& \text{C4}: E_k^b \ge \tau_k T P_{c,k},\quad k\in\{1,\cdots,K\}\\
& \text{C5}: \left(P_k + p_{c,k}\right)t_k T \le E_k^a,\quad k\in\{1,\cdots,K\}\\
& \text{C6}: \sum_{k=1}^{K}\left(C_k^b + C_k^a\right) \ge C_{\min}\\
& \text{C7}: 0 \le \alpha_k \le 1,\quad k\in\{1,\cdots,K\}\\
& \text{C8}: \tau_k \ge 0, t_k \ge 0, P_k > 0,\quad k\in\{1,\cdots,K\},
\end{aligned} \tag{12}$$

where $\boldsymbol{\tau} = [\tau_1,\cdots,\tau_K]$, $\mathbf{t} = [t_1,\cdots,t_K]$, $\boldsymbol{\alpha} = [\alpha_1,\cdots,\alpha_K]$, $\mathbf{P} = [P_1,\cdots,P_K]$, and $C_{\min}$ is the total minimum required throughput for all IoT nodes.

In $\mathbf{P}_1$, constraint C2 is the necessary condition for effective backscatter transmission to ensure that the SIC can be performed successfully at the information gateway. Constraint C3 is to ensure that the LR can decode $s(n)$ successfully under the IoT nodes' interferences. Constraints C4 and C5 are the energy causality constraints, which ensure that the energy consumption of each IoT node in the backscatter communication and active transmission phases cannot be larger than its harvested energy. Constraint C6 ensures the total minimum throughput requirement for all IoT nodes.

It is obvious that problem $\mathbf{P}_1$ is a nonconvex fractional optimization problem and is very challenging to solve since the coupling relationships among different optimization variables, i.e., P_k and t_k, τ_k, and α_k, exist in both the objective function and the constraints, leading to a nonconvex objective function and several nonconvex constraints, e.g., C4, C5, and C6.

3.2. Solution to $\mathbf{P}_1$. In order to address $\mathbf{P}_1$, Proposition 1 is provided to obtain the optimal reflection coefficients as follows.

Proposition 1. *For any given system parameters and optimization variables, the optimal reflection coefficient for the kth IoT node is given by* $\alpha_k^* = \alpha_{\max}^k$, $k\in\{1,\cdots,K\}$, *where* $\alpha_{\max}^k$ *is given by* $\alpha_{\max}^k = \min\left((P_s|g_0|^2 - \gamma_{\min} W\sigma^2)/(\varepsilon|g_k|^2|h_k|^2 P_s\gamma_{\min}), (P_s|f_0|^2 - \gamma_{\min}\sigma^2 W)/(\varepsilon|f_k|^2|h_k|^2 P_s\gamma_{\min}), 1-(1/aP_s|h_k|^2)\ln\left((E_{\max} + P_{c,k}e^{ab})/(E_{\max} - P_{c,k})\right)\right)$.

Proof. When $\boldsymbol{\tau}$, $\mathbf{t}$, and $\mathbf{P}$ are given, it is obvious that the objective function of $\mathbf{P}_1$ increases with the increasing of α_k. On the other hand, by combining constraints C2, C3, and C4, the upper bound for α_k, denoted by $\alpha_{\max}^k$, is obtained. Thus, in order to achieve the maximum energy efficiency of all the IoT nodes, we have $\alpha_k^* = \alpha_{\max}^k$, $k\in\{1,\cdots,K\}$.

The proof is completed. □

Substituting $\alpha_k^* = \alpha_{\max}^k$, $k\in\{1,\cdots,K\}$ in to $\mathbf{P}_1$, the optimization problem $\mathbf{P}_1$ can be revised as

$$\begin{aligned}
\mathbf{P}_2:\quad & \max_{(\boldsymbol{\tau},\mathbf{t},\mathbf{P})} \frac{\sum_{k=1}^{K} C_k^{(1)}}{\sum_{k=1}^{K} P_{c,k}\tau_k T + \sum_{k=1}^{K}\left(P_k + p_{c,k}\right)t_k T}\\
\text{s.t.}:\quad & \text{C1}; \text{C8};\\
& \text{C5}-1: \left(P_k + p_{c,k}\right)t_k \le B_k(\beta - \tau_k),\quad k\in\{1,\cdots,K\}\\
& \text{C6}-1: \sum_{k=1}^{K} C_k^{(1)} \ge C_{\min},
\end{aligned} \tag{13}$$

where $C_k^{(1)} = W\tau_k T\log_2(1 + A_k\alpha_{\max}^k) + Wt_k T\log_2(1 + (P_k|g_k|^2/W\sigma^2))$, $A_k = \varepsilon|g_k|^2|h_k|^2 P_s/W\sigma^2$, and $B_k = (E_{\max}(1 - \exp(-aP_s|h_k|^2)))/[1 + \exp(-aP_s|h_k|^2 + ab)]$.

In order to tackle the nonconvex fractional objective function in $\mathbf{P}_2$, the Dinkelbach method is used to obtain the optimal solutions. In particular, let q^* and $*$ denote the maximum energy efficiency and the optimal solutions for the optimization variables of $\mathbf{P}_2$. Based on the generalized fractional programming theory [27], the maximum energy efficiency q^* is obtained if and only if the following equation holds:

$$\begin{aligned}
&\max_{(\boldsymbol{\tau},\mathbf{t},\mathbf{P})} \sum_{k=1}^{K} C_k^{(1)} - q^*\left(\sum_{k=1}^{K} P_{c,k}\tau_k T + \sum_{k=1}^{K}\left(P_k + p_{c,k}\right)t_k T\right)\\
&\quad = \sum_{k=1}^{K} C_k^{(1)*} - q^*\left(\sum_{k=1}^{K} P_{c,k}\tau_k^* T + \sum_{k=1}^{K}\left(P_k^* + p_{c,k}\right)t_k^* T\right)\\
&\quad = 0,
\end{aligned} \tag{14}$$

where $C_k^{(1)*} = W\tau_k^* T\log_2(1 + A_k\alpha_{\max}^k) + Wt_k^* T\log_2(1 + (P_k^*|g_k|^2/W\sigma^2))$.

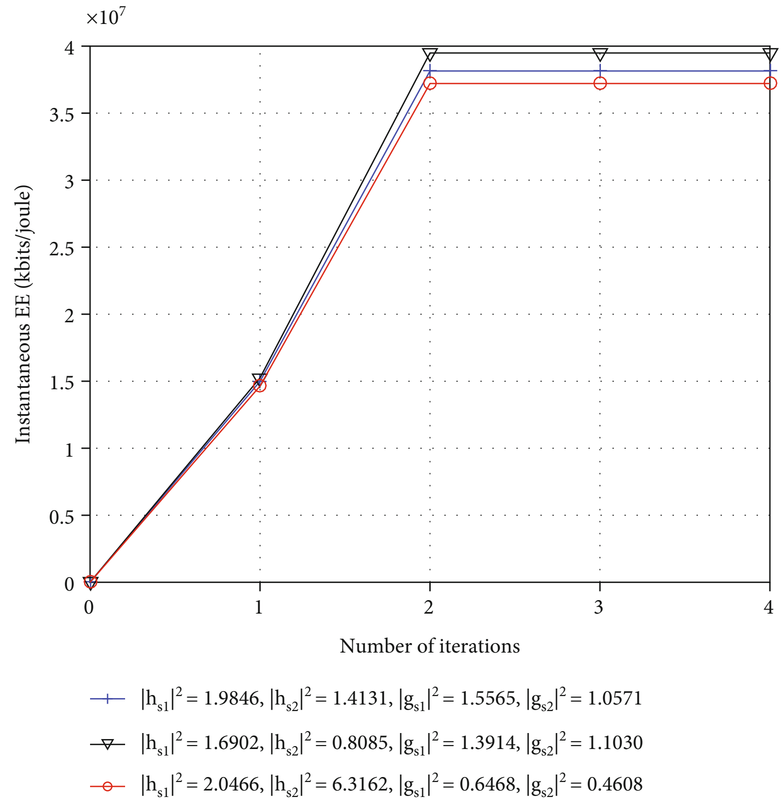

Figure 2: The convergence of the proposed algorithm.

Accordingly, problem $\mathbf{P}_2$ can be transformed by solving the following problem $\mathbf{P}_3$ with a given parameter q, given by

$$\begin{aligned} \mathbf{P}_3: \quad & \max_{(\boldsymbol{\tau},\mathbf{t},\mathbf{P})} \sum_{k=1}^{K} C_k^{(1)} - q\left(\sum_{k=1}^{K} P_{c,k}\tau_k T + \sum_{k=1}^{K}\left(P_k + p_{c,k}\right)t_k T\right) \\ \text{s.t.}: \quad & \text{C1, C5} - 1, \text{C6} - 1, \text{C8}, \end{aligned} \tag{15}$$

where q will be updated in each iteration.

As for $\mathbf{P}_3$, it is more tractable than $\mathbf{P}_2$, but it is still a nonconvex problem due to the coupling relationship between P_k and t_k. To address this problem, we introduce a series of auxiliary variables, denoted by y_k, into $\mathbf{P}_3$.

By letting $y_k = P_k t_k, \forall k$, $\mathbf{P}_3$ can be transformed as

$$\begin{aligned} \mathbf{P}_4: \quad & \max_{(\boldsymbol{\tau},\mathbf{t},\mathbf{y})} \sum_{k=1}^{K} C_k^{(2)} - q\left(\sum_{k=1}^{K} P_{c,k}\tau_k T + \sum_{k=1}^{K}\left(y_k + p_{c,k}t_k\right)T\right) \\ \text{s.t.}: \quad & \text{C1, C8} - 1: \tau_k \geq 0, t_k \geq 0, y_k > 0, \quad k \in \{1,\cdots,K\} \\ & \text{C5} - 2: y_k + p_{c,k}t_k \leq B_k(\beta - \tau_k), \quad k \in \{1,\cdots,K\} \\ & \text{C6} - 2: \sum_{k=1}^{K} C_k^{(2)} \geq C_{\min}, \end{aligned} \tag{16}$$

where $y = [y_1, \cdots, y_K]$ and $C_k^{(2)} = W\tau_k T \log_2(1 + A_k \alpha_{\max}^k) + Wt_k T \log_2(1 + (y_k |g_k|^2 / t_k W\sigma^2))$.

It is easy to prove that $\mathbf{P}_4$ is a convex problem and can be efficiently solved by many existing convex tools, i.e., the Lagrange duality method and the interior-point method. In the following part, the Lagrange duality method is used to obtain the optimal solutions to $\mathbf{P}_4$. Let P_k^+ denote the optimal transmit power of the kth IoT node during the active transmission phase, and it can be determined by Proposition 2.

Proposition 2. *In the cognitive wireless-powered hybrid active-passive communication network, the optimal transmit power P_k^+ of the kth IoT node during the active transmission phase for maximizing the energy efficiency of all the IoT nodes is given by*

$$P_k^+ = \left[\frac{T(1+\lambda)}{(qT + \mu_k)\ln 2} - \frac{1}{D_k}\right]^+, \tag{17}$$

where $D_k = |g_k|^2 / W\sigma^2$ and $\mu_k \geq 0$ and $\lambda \geq 0$ are the dual variables corresponding to C5 − 2 and C6 − 2, respectively.

Proof. See the appendix. □

Substituting P_k^+ into $\mathbf{P}_4$, we observe that $\mathbf{P}_4$ is a linear programming problem with respect to t_k and τ_k. Thus, standard linear optimization tools, i.e., the simplex method, can be employed to obtain the optimal solutions efficiently. It is

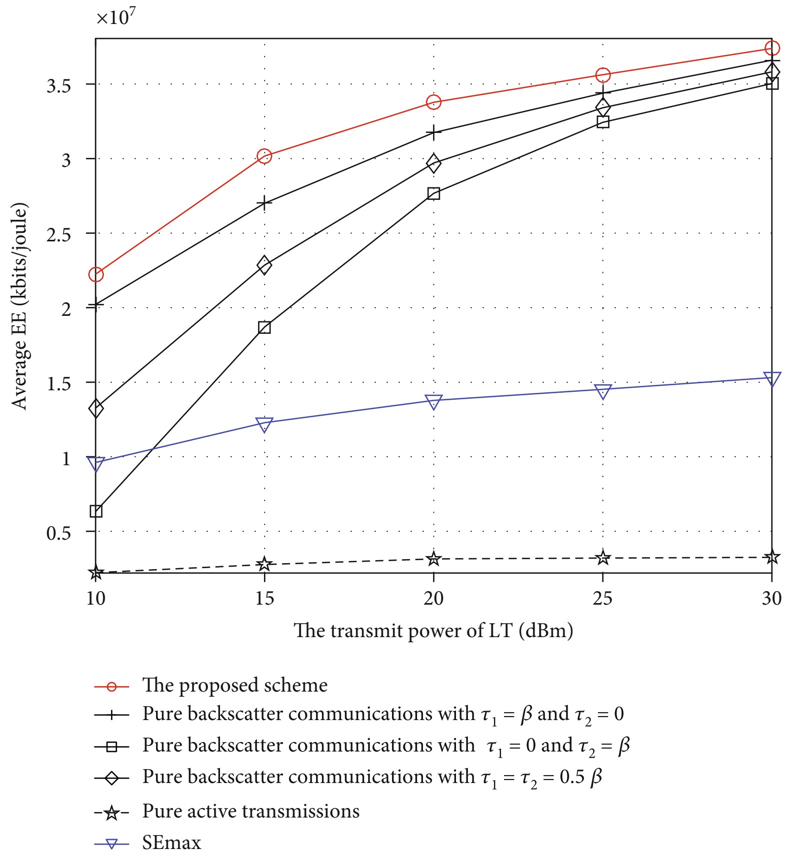

FIGURE 3: Average energy efficiency versus the transmit power of LT.

worth noting that $\alpha_{\max}^k$ may be less than 0. In such case, the IoT node cannot backscatter signals to the information gateway since the harvested energy is not enough for the circuit operation and $C_k^b = 0$. In order to achieve the maximum energy efficiency, we have $\tau_k^* = 0$.

3.3. Iterative Algorithm. In this subsection, a Dinkelbach-based iterative algorithm is proposed to obtain the optimal solutions to $\mathbf{P}_2$. The detailed process of the proposed algorithm is shown in Algorithm 1. Specifically, in each iteration, $\mathbf{P}_4$ with a given q should be optimally solved to obtain the optimal solution, denoted by (τ^+, t^+, P^+). Let ε denote the error tolerance. If the stop condition $\sum_{k=1}^K C_k^{(2)+} - q(\sum_{k=1}^K P_{c,k} \tau_k^+ T + \sum_{k=1}^K (y_k^+ + p_{c,k} t_k^+) T) < \varepsilon$ holds, then we have $\tau^* = \tau^+$, $t^* = t^+$, and $P^* = P^+$. Otherwise, q is updated as $q = \sum_{k=1}^K C_k^{(2)+} / (\sum_{k=1}^K P_{c,k} \tau_k^+ T + \sum_{k=1}^K (y_k^+ + p_{c,k} t_k^+) T)$. Then, repeat the above steps until the stop condition is satisfied.

4. Simulations

In this section, we verify the performance of the cognitive wireless-powered hybrid active-passive communication under the proposed scheme. Let d_1 denote the distance between the LT and the information gateway. d_{0k} and d_{k1} are denoted as the distances of the LT-the kth IoT node link and the kth IoT node-the information gateway link, respectively. In the following part, we present the basic parameter settings. We set $K = 2$, the path loss exponent $\varsigma = 3$, $P_s = 30$ dBm, $W = 10$ kHz, $\beta = 0.7$, $T = 1$ s, $\gamma_{\min} = 0$ dB, $\sigma^2 = -150$ dBm/Hz, $P_{c,1} = P_{c,2} = 10\,\mu$W, $p_{c,1} = p_{c,2} = 50\,\mu$W, $\varepsilon = 0.8$, $C_{\min} = 50$ kbps, $E_{\max} = 240\,\mu$W, $a = 5000$, and $b = 0.0002$. The distances are set as $d_{01} = d_1 = 5$ meters, $d_{02} = 8$ meters, and $d_{11} = d_{12} = 1$ meter.

Figure 2 shows the convergence of the proposed algorithm, where $|h_{sk}|^2$ and $|g_{sk}|^2$ denote the small fadings of the LT-the kth IoT node link and the kth IoT node-the information gateway link, respectively. It can be seen that with any given channel settings, the proposed algorithm can always converge to the optimal energy efficiency after only two iterations, which indicates that our proposed algorithm is computationally efficient and has a fast convergent rate.

Figure 3 shows the average energy efficiency of all the IoT nodes versus the transmit power of the LT P_s. In order to demonstrate the superiority of the proposed scheme, we compare the energy efficiency under the proposed scheme with that under three other schemes, which are the pure backscatter communications with $t_k = 0$ (denoted as pure backscatter communications), the pure active transmissions with $\tau_k = 0$ (denoted as pure active transmissions), and the throughput maximization (denoted as SEmax), respectively. As for the pure backscatter communications, we consider three ways for allocating the backscatter time which are (1)

$\tau_1 = \beta$ and $\tau_2 = 0$; (2) $\tau_2 = \beta$ and $\tau_1 = 0$; and (3) $\tau_1 = \tau_2 = 0.5\beta$. For the pure active transmissions, the transmit time and power for each IoT node are optimized to maximize the energy efficiency of all the IoT nodes under the same constraints as $\mathbf{P}_1$. As for the throughput maximization, this scheme is optimized to maximize the total achievable throughput of all the IoT nodes under the same constraints as $\mathbf{P}_1$.

From this figure, we can see that the average energy efficiency of all the IoT nodes under all the schemes will increase with the increasing of P_s. The reasons are as follows. With a larger P_s, the received legacy signal at each IoT node is stronger and the harvested energy of each IoT node increases, bringing a higher throughput achieved by all the IoT nodes. Since the total throughput grows faster than the growth of the total energy consumption, all the curves show an upward trend. By comparisons, it can be observed that the proposed scheme always achieves the best performance in terms of the energy efficiency of all the IoT nodes among these schemes. This is because the proposed scheme provides more flexibility to utilize the resource efficiently to achieve the maximum energy efficiency. More interestingly, we observe that the energy efficiency under the pure active transmissions is lowest compared with the other schemes. This is because compared to the pure backscatter communications, the pure active transmissions need more energy to achieve the same throughput.

5. Conclusions

In this work, we have investigated the energy efficiency maximization for a cognitive wireless-powered hybrid active-passive communication network, where multiple IoT nodes transmit information to the information gateway via the backscatter communications and the active transmissions. Specifically, an optimization problem was formulated to maximize the energy efficiency of all the IoT nodes by jointly optimizing the backscatter time and reflection coefficients, the transmit time, and power of all the IoT nodes, subject to the energy causality constraint, the minimum SNR requirements, etc. The formulated problem was a highly nonconvex fractional optimization problem. In order to solve it, we proposed an iterative algorithm to obtain the optimal solutions. Simulation results have verified the fast convergence of the proposed algorithm and demonstrated the superiority of our proposed scheme in terms of the energy efficiency of all the IoT nodes.

Appendix

The Lagrangian function of $\mathbf{P}_4$ is given by

$$\begin{aligned}\mathscr{L} = {} & \sum_{k=1}^{K} C_k^{(2)} - q\left(\sum_{k=1}^{K} P_{c,k}\tau_k T + \sum_{k=1}^{K}\left(y_k + p_{c,k}t_k\right)T\right) \\ & + \sum_{k=1}^{K}\mu_k\left[B_k(\beta-\tau_k) - y_k - p_{c,k}t_k\right] + \lambda\left(\sum_{k=1}^{K} C_k^{(2)} - C_{\min}\right) \\ & + \nu\left(\beta - \sum_{k=1}^{K}\tau_k\right) + \rho\left(1-\beta-\sum_{k=1}^{K} t_k\right),\end{aligned} \tag{A.1}$$

where μ_k, λ, υ, and ρ are nonnegative Lagrangian multipliers. Then, the first-order derivative of the Lagrangian with respect to y_k can be given by

$$\frac{\partial \mathscr{L}}{\partial y_k} = \frac{(1+\lambda)TD_k t_k}{(t_k + D_k y_k)\ln 2} - qT - \mu_k, \tag{A.2}$$

where $D_k = |g_k|^2/W\sigma^2$. By letting $\partial\mathscr{L}/\partial y_k = 0$, we have

$$P_k^+ = \frac{y_k^o}{t_k^o} = \left[\frac{T(1+\lambda)}{(qT+\mu_k)\ln 2} - \frac{1}{D_k}\right]^+. \tag{A.3}$$

Therefore, Proposition 2 is obtained.

Data Availability

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

Conflicts of Interest

We declare that we do not have any commercial or associative interest that represents a conflict of interest in connection with the work submitted.

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