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Joint Optimization of Spectrum Sensing and Transmit Power in Energy Harvesting-Based Cognitive Radio Networks

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ABSTRACT Proliferation of mass market applications and all forms of smart devices have driven the explosive growth of wireless sensor data traffic in recent years. In spite of notable advancements in wireless sensor technologies, energy scarcity due to a limited battery capacity still remains a critical impediment to consumer electronics applications. Thus, the energy harvesting (EH) technology, utilizing extra energy collected from radio frequency (RF) signals, is regarded as a promising solution for addressing the battery problem. This paper presents, analyzes, and discusses a joint sensing and power allocation scheme for cognitive radio in conjunction with EH, in which a secondary transmitter can harvest energy from RF signals transmitted by a primary transmitter during spectrum sensing. We formulate a non-convex optimization problem to find the optimal sensing time and power allocation for maximizing energy efficiency, while satisfying the constraints on the amount of harvested energy and interference at primary receivers. Using nonlinear fractional programming, the original problem can be reformulated into a tractable convex one, and an energy efficient resource allocation algorithm is devised while taking into account RF EH. Simulation results are used to verify the optimality of the proposed scheme, where the secondary network can accomplish maximum energy efficiency.

INDEX TERMS Energy efficiency, cognitive radio, energy harvesting, power control, optimization.

I. INTRODUCTION

The reliability and performance of wireless networks are significantly limited by the lifetime of wireless sensors. Various methods have been devised to address this problem, where the main challenge was improving the energy efficiency of wireless sensors [1]. As well as efforts to reduce energy consumption, energy harvesting (EH) from radio frequency (RF) signals has recently been considered as a prospective technique for solving the problem of energy shortage. This technique allows a wireless sensor to convert RF signals into energy that can be used for its own purposes, e.g., data processing and transmission [2].

Cognitive radio networks (CRNs) have also recently been proposed as efficient means of utilizing unused spectrum, thereby improving spectrum efficiency. In a CRN, unlicensed secondary networks (SNs) can opportunistically access the spectrum unoccupied by licensed primary networks (PNs), provided that the use of the spectrum by the SNs does not interrupt the operation of the PNs [3]–[10]. Accordingly, the search for a vacant spectrum is one of the most important tasks for CRNs, in which spectrum sensing based on energy detection is generally used [4], [7]. Although spectrum sensing and RF EH have different power sensitivity levels (e.g., -60 dBm for spectrum sensing [11] while -10 to -30 dBm for RF EH [12]), the sensitivity of RF EH is expected to be improved in the near future. Therefore, EH can be efficiently undertaken during the spectrum sensing, i.e., SNs have an opportunity to gather energy from the RF signals transmitted by PNs while determining the status of PNs during spectrum sensing.

In this context, EH in CRNs has recently been the subject of extensive investigation [13]–[19]. In [13], an optimal spectrum sensing policy was proposed for maximizing the expected total throughput of SNs under energy causality and collision constraints. The optimal transmit power and density of secondary transmitters (STs), which maximize the throughput of SNs, were found in [14]. Hoang *et al.* [15] derived an optimal channel access policy for SNs based on Markov Decision Process (MDP). In addition, the joint information and energy cooperation strategy between PNs and SNs was studied in [16] and [17]. Pratibha *et al.* [18] adapted homogeneous Poisson point processes to propose a decentralized channel-selection strategy for improving the throughput of SNs in multiband CRNs. Finally, in [19], the authors demonstrated the joint impact of sensing probability, access probability, and energy queue capacity on the achievable throughput of a multiuser CRN.

Nevertheless, previous studies on SNs in EH-based CRNs have mainly focused on the maximization of throughput of SNs only. However, the energy efficiency, which is the transmitted bits per unit of bandwidth and energy, can be a more significant metric for SNs in EH-based CRNs than the throughput because the amount of data to be transmitted in this environment is small in general and the lifetime of network is utmost important. Accordingly, it is necessary to take into account the maximization of energy efficiency for SNs in EH-based CRNs, which can be challenging since the characteristics of both EH and CR have to be jointly considered. It should be noted that previous works which consider energy efficiency in CRNs [10] cannot be directly applied to this environment due to the consideration of EH.

We herein propose a joint sensing and power allocation scheme that maximizes the energy efficiency of SNs in EH-based CRNs, where a ST is capable of harvesting energy from the RF signals transmitted by a primary transmitter (PT) during spectrum sensing. Our main contributions can be summarized as follows.

- We derive the optimal sensing time and power allocation for maximizing the energy efficiency of SNs in EH-based CRNs, whilst not violating the constraints imposed by PNs and EH, i.e., the maximum interference caused at a primary receiver (PR) and the minimum required harvested energy. Specifically, a practical model for CRNs is considered, in which imperfect spectrum sensing and the channel occupancy of PNs are taken into account. We expect our findings to point to the possibility of mitigating the energy shortage problem for wireless sensors in CRNs.
- By applying a nonlinear fractional programming, we translate a non-convex problem into a tractable convex one, and solve the problem using optimization techniques. Based on the optimal solution, we propose an iterative method for finding the optimal sensing time and power allocation policy jointly.
- Via simulations in various environments, we verify the optimality of the proposed scheme. We find that the energy efficiency of the proposed algorithm can be maintained at its maximum value, while that of a conventional scheme which only considers the maximization of throughput drops significantly as the maximum transmit power increases. These results give insights about the effects of sensing time and power allocation regarding the energy efficiency of SNs with an EH capability, which is the major contribution of our work.

The remainder of the paper is organized as follows. In Section II, we describe our system model and formulate the non-convex optimization problem to maximize the energy efficiency. In Section III, the optimization problem is solved using a nonlinear fractional programming, and an iterative way to find the optimal solution is proposed. Finally, numerical results are provided in Section IV, and Section V concludes the paper.

II. SYSTEM MODEL AND PROBLEM FORMULATION

As shown in Fig. 1, we consider EH-based CRNs with one primary and one secondary link. The instantaneous channel gains of the link between the ST and the secondary receiver (SR), the link between the PT and the SR, the link between the ST and the PR, and the link between the PT and the ST, are denoted by h_{ss}, h_{ps}, h_{sp}, and g_{ps}, respectively. We assume that the links experience a flat fading channel and the channel gains at the links are ergodic, stationary, and known at the SNs [3], [6]. In addition, the ST should acquire channel state information on h_{ss}, h_{ps}, h_{sp}, and g_{ps}, in order to perform power allocation. We also consider channel estimation error since it is impossible to obtain perfect channel state information at the ST in practice. Herein, the real channels and the estimated channels have the following relations: $h_{ss} = \hat{h}_{ss} + \varepsilon$, $h_{ps} = \hat{h}_{ps} + \varepsilon$, $h_{sp} = \hat{h}_{sp} + \varepsilon$, and $g_{ps} = \hat{g}_{ps} + \varepsilon$, respectively, where ε is the channel estimation error with zero-mean and variance σ_ε^2 [20]–[22].[1] The noise at the SR is assumed to be independent and identically distributed (i.i.d.) circularly symmetric complex Gaussian (CSCG) with zero mean and N_0 variance, i.e., $\mathcal{CN}(0, N_0)$.

In order to access the spectrum licensed to the PNs, the ST must determine the channel occupancy of the PT, i.e., whether it is idle or busy, using spectrum sensing. Herein, we assume that the energy detection[2] is used for the spectrum sensing [7]. Two hypotheses, $\mathcal{H}_0$ and $\mathcal{H}_1$, are considered, where $\mathcal{H}_0$ represents the case where the channel is idle while $\mathcal{H}_1$ represents the case where the channel is busy.

[1]The effect of the channel estimation error on the performances of system will be evaluated and discussed in Figs. 9 and 10.

[2] Although we only consider the energy detection for spectrum sensing, our proposed scheme can be applied to the case when the other types of spectrum sensing [23], e.g., soft combining, is considered by properly changing the value of $\mathcal{P}_f$ and $\mathcal{P}_d$. Moreover, our work can also be applied to the case when a Geolocation Database is used to determine which spectrum is idle [9], [24]. In this case, we can assume that the detection of PT is perfect, i.e., $\mathcal{P}_f = 0$ and $\mathcal{P}_d = 1$.

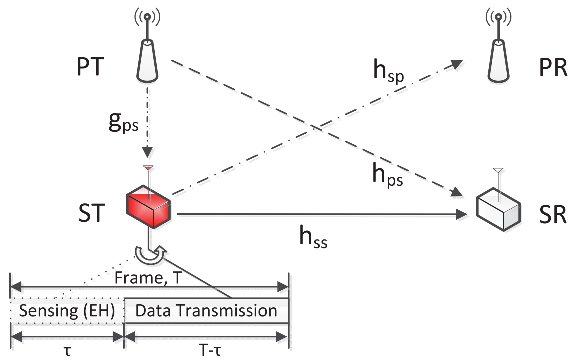

FIGURE 1. System model which depicts EH-based CRNs.

In the energy detection, the signal strength of channel is accumulated for N_{ED} channel samples, such that the test statistics for the energy detection, which we denote as $T_{ED}(y)$, can be written as follows.

$$T_{ED}(y) = \frac{1}{N_{ED}} \sum_{n=1}^{N_{ED}} |y(n)|^2, \tag{1}$$

where $y(n)$ is the received signal sample. The ST determines whether the channel is vacant or not based on $T_{ED}(y)$, i.e., the channel is assumed to be busy when $T_{ED}(y) \geq \epsilon$ and it is assumed to be idle otherwise, where ϵ is the detection threshold.

In spectrum sensing, there are two important performance metrics which are the probability that a ST falsely detects a presence of PT when no PT is present (false alarm probability, denoted by $\mathcal{P}_f$) and the probability that a ST properly detects an existence of active PT when one is present (detection probability, denoted by $\mathcal{P}_d$). Let τ, f_s, and γ be the sensing time, sampling frequency,[3] and received signal-to-noise ratio (SNR) from the PT at the ST, respectively. Then, $\mathcal{P}_d$ can be written as [4]

$$\begin{aligned}\mathcal{P}_d &= \Pr(T_{ED}(y) \geq \epsilon | \mathcal{H}_1) \\ &= \mathcal{Q}\left(\left(\frac{\epsilon}{N_0} - \gamma - 1\right)\sqrt{\frac{\tau f_s}{2\gamma + 1}}\right),\end{aligned} \tag{2}$$

where $\mathcal{Q}(\cdot)$ is the complementary distribution function of the standard Gaussian, i.e., $\mathcal{Q}(x) = \frac{1}{\sqrt{2\pi}} \int_x^{\infty} e^{-t^2/2} dt$. On the other hand, the false alarm probability, $\mathcal{P}_f$, can be obtained as

$$\begin{aligned}\mathcal{P}_f &= \Pr(T_{ED}(y) > \epsilon | \mathcal{H}_0) \\ &= \mathcal{Q}\left(\left(\frac{\epsilon}{N_0} - 1\right)\sqrt{\tau f_s}\right).\end{aligned} \tag{3}$$

Therefore, when the value of ϵ increases, both $\mathcal{P}_d$ and $\mathcal{P}_f$ decrease. In this paper, we assume that a target $\mathcal{P}_d$ is predefined and ϵ is adjusted in order to satisfy this target value. In this case, $\mathcal{P}_f$ can be rewritten as follows.

$$\mathcal{P}_f = \mathcal{Q}\left(\sqrt{2\gamma + 1}\mathcal{Q}^{-1}(\mathcal{P}_d) + \sqrt{\tau f_s}\gamma\right). \tag{4}$$

[3]In this paper, we assume that $N_{ED} = \tau f_s$ [4].

It should be noted that the cooperative spectrum sensing is not considered in our work because only one ST performs spectrum sensing.

As seen from Fig.1, each frame of the CRN consists of a sensing slot with a time duration τ, and a data transmission slot with a time duration $T - \tau$ [7]. During the sensing slot, the ST does not transmit data and performs spectrum sensing i.e., quiet period [7], in order to determine the status of the PT, along with energy harvesting. In our system model, the concept of interference temperature [5] is taken into account such that when the channel is detected to be idle, the ST transmits data with high power P_0; otherwise when the channel is detected to be busy, the ST transmits data with low power P_1. Given that the status of the PT can be confused by the ST due to sensing error, four different cases of spectral efficiency for SNs are possible. Let r_{ij} be the spectral efficiency of the SNs, where the first subscript index i indicates the actual status of the PT ('0' for idle and '1' for active) and the second subscript index j describes the status of the PT perceived by the ST ('0' for absent and '1' for present). Then, r_{ij} can be summarized as follows.

$$\begin{aligned}r_{00} &= \log_2\left(1 + \frac{\hat{h}_{ss}P_0}{N_0}\right), \\ r_{01} &= \log_2\left(1 + \frac{\hat{h}_{ss}P_1}{N_0}\right), \\ r_{10} &= \log_2\left(1 + \frac{\hat{h}_{ss}P_0}{\hat{h}_{ps}P_p + N_0}\right), \\ r_{11} &= \log_2\left(1 + \frac{\hat{h}_{ss}P_1}{\hat{h}_{ps}P_p + N_0}\right).\end{aligned} \tag{5}$$

Here, P_p is the transmit power of the PT which is assumed to be constant. Moreover, we assume that the ST always has data to transmit.

The average spectral efficiency of the SNs can then be expressed as

$$\begin{aligned}R(\tau, P_0, P_1) = \mathbb{E}\Bigg\{\frac{T-\tau}{T}\Big[&\mathcal{P}(\mathcal{H}_0)(1-\mathcal{P}_f)r_{00} + \mathcal{P}(\mathcal{H}_0)\mathcal{P}_f r_{01} \\ &+ \mathcal{P}(\mathcal{H}_1)(1-\mathcal{P}_d)r_{10} + \mathcal{P}(\mathcal{H}_1)\mathcal{P}_d r_{11}\Big]\Bigg\}.\end{aligned} \tag{6}$$

Here, $\mathcal{P}(\mathcal{H}_0)$ is the probability that the channel is idle while $\mathcal{P}(\mathcal{H}_1)$ is the probability that the channel is occupied.

Next, we define a net energy dissipation at the ST.[4] At first, the expected amount of harvested energy at the ST during τ should satisfy the minimum required energy (E_m) constraint, which can be formulated as

$$P_H = \mathbb{E}\left\{\frac{\tau}{T}\mathcal{P}(\mathcal{H}_1)P_p\eta\hat{g}_{ps}\right\} \geq E_m, \tag{7}$$

[4]In this paper, we used the unit of Joule-per-second for energy consumption. Therefore, the terms "power" and "energy" can be used interchangeable.

where η is the energy conversion efficiency from the received RF signals into harvested energy by the ST.

Next, the average transmit power constraint at the ST during the data transmission phase should be considered as follows.

$$P_T = \mathbb{E}\left\{\frac{T-\tau}{T}\left[P_0\mathcal{P}(\mathcal{H}_0)(1-\mathcal{P}_f)+P_1\mathcal{P}(\mathcal{H}_0)\mathcal{P}_f + P_0\mathcal{P}(\mathcal{H}_1)(1-\mathcal{P}_d)+P_1\mathcal{P}(\mathcal{H}_1)\mathcal{P}_d\right]\right\} \leq P_{av}, \quad (8)$$

where P_{av} is an allowable maximum average transmit power. By using (7) and (8), the net energy balance at the ST can be summarized as

$$P(\tau, P_0, P_1) = P_C + P_T - P_H, \quad (9)$$

where P_C is the power consumed in the circuit.

The energy efficiency of the ST, which is represented by $C_E = \frac{R(\tau,P_0,P_1)}{P(\tau,P_0,P_1)}$, is considered as the major performance metric of our proposed scheme, such that τ, P_0 and P_1 are adjusted to maximize C_E. It should be noted that the energy efficiency reflects the transmitted bits per unit of bandwidth and energy (bits/Hz/joule); in other words, it shows how efficiently the ST uses energy for transferring bits, and is thus a more appropriate metric for energy-limited sensor networks than the spectral efficiency [21], [22], [25], [26].

Our consideration of CRNs implies that the interference caused by the ST to the PR must be regulated in order to guarantee the quality of service (QoS) of the PNs. Specifically, the average interference at the PR, i.e., I_S, should satisfy the following inequality.

$$I_S = \mathbb{E}\left\{\frac{T-\tau}{T}\left[\hat{h}_{sp}P_0\mathcal{P}(\mathcal{H}_1)(1-\mathcal{P}_d)+\hat{h}_{sp}P_1\mathcal{P}(\mathcal{H}_1)\mathcal{P}_d\right]\right\} \leq I_m, \quad (10)$$

where I_m is the maximum tolerable interference by the PR. Note that $\frac{T-\tau}{T}$ is multiplied because the ST does not transmit when spectrum sensing is performing.

Finally, we formulate the optimization problem to find the optimal sensing time and power allocation, i.e., τ, P_0, and P_1, that maximizes the energy efficiency of the SNs, as follows.

$$\max_{\tau,P_0,P_1} \frac{R(\tau, P_0, P_1)}{P(\tau, P_0, P_1)}$$
$$\text{s.t. } (7),\ (8),\ (10),\ P_0 \geq 0,\ P_1 \geq 0,\ 0 \leq \tau \leq T. \quad (11)$$

III. OPTIMAL SENSING TIME AND POWER ALLOCATION

Unfortunately, it is difficult to solve the optimization problem (11) because its objective function is not convex with respect to (w.r.t.) the sensing time τ. In order to resolve this problem, we seek an optimal transmit power for a fixed value of τ. The optimal sensing time τ^* can then be found using a one-dimensional exhaustive search[5] over the interval $(0, T)$.

[5]The exhaustive search is easy to perform because the optimal P_0 and P_1 are given in a closed-form expression, as shown later.

Therefore, in the following we focus on deriving the optimal values of P_0 and P_1 when τ is fixed.

Even though τ is fixed, the problem of finding the optimal values of P_0 and P_1 is still non-convex because the objective function is in fractional form. To transform the problem into a tractable form, we translate an original objective function into a subtractive form by adapting a nonlinear fractional programming [27], such as $f(\tau, P_0, P_1) = R(\tau, P_0, P_1) - qP(\tau, P_0, P_1)$. The transformation of the objective function can be summarized in the following lemma 1.

Lemma 1: We can obtain the solutions (P_0^+, P_1^+) and the corresponding q^+ by solving a subtractive objective function and updating q iteratively, given the following two facts.

(i) The maximum energy efficiency $q^+ = \frac{R(\tau,P_0^+,P_1^+)}{P(\tau,P_0^+,P_1^+)}$ is achieved if and only if the following condition is satisfied.

$$\begin{aligned} F(q^+) &= \max_{P_0,P_1} R(\tau, P_0, P_1) - q^+P(\tau, P_0, P_1) \\ &= R(\tau, P_0^+, P_1^+) - q^+P(\tau, P_0^+, P_1^+) \\ &= 0. \end{aligned} \quad (12)$$

(ii) The function $F(q) \geq 0$ is a monotonically decreasing function of q.

Proof: Please refer to [21], [27], and [25] for the proof. ■

Then, based on Lemma 1, the original problem (11) can be rewritten as follows.

$$\max_{P_0,P_1} R(\tau, P_0, P_1) - qP(\tau, P_0, P_1)$$
$$\text{s.t. } (7),\ (8),\ (10),\ P_0 \geq 0,\ P_1 \geq 0. \quad (13)$$

Note that the optimization problem (13) is convex w.r.t. P_0 and P_1, such that we can find the optimal power allocation using convex optimization techniques.

In order to find the optimal solution, we first derive the Lagrangian function of (13), $\mathcal{L}(P_0, P_1, \lambda, \beta, \mu)$, as shown below.

$$\mathcal{L}(P_0, P_1, \lambda, \beta, \mu) = R(\tau, P_0, P_1) - qP(\tau, P_0, P_1) + \lambda(P_H - E_m) + \beta(P_{av} - P_T) + \mu(I_m - I_S). \quad (14)$$

Then, the dual problem of (13) can be given by

$$\min_{\lambda,\beta,\mu,\geq 0} g(\lambda, \beta, \mu), \quad (15)$$

where the dual function, $g(\lambda, \beta, \mu)$, is represented by

$$g(\lambda, \beta, \mu) = \max_{P_0,P_1 \geq 0} \mathcal{L}(P_0, P_1, \lambda, \beta, \mu). \quad (16)$$

By taking the derivative of (14) w.r.t. P_0 and P_1, respectively, the values of P_0 and P_1 that maximize $\mathcal{L}(P_0, P_1, \lambda, \beta, \mu)$ can be calculated from the Karush-Kuhn-Tucker conditions, as shown in (17) and (18), as shown at the bottom of the next page. where $v_0 = \mathcal{P}(\mathcal{H}_0)(1 - \mathcal{P}_f)$, $w_0 = \mathcal{P}(\mathcal{H}_1)(1 - \mathcal{P}_d)$, $X_0 = (\log 2)\Big[(q + \beta)(v_0 + w_0) + \mu\hat{h}_{sp}w_0\Big]$, and $[y]^+ = \max(0, y)$. where $v_1 = \mathcal{P}(\mathcal{H}_0)\mathcal{P}_f$, $w_1 = \mathcal{P}(\mathcal{H}_1)\mathcal{P}_d$, and $X_1 = (\log 2)\Big[(q + \beta)(v_1 + w_1) + \mu\hat{h}_{sp}w_1\Big]$.

Algorithm 1 Optimal Sensing Time and Power Allocation

1: **for** τ=1:T
2: Initialize P_0 and P_1 as $\frac{P_{av}}{2}$, and q, β, μ as 0.5, 0.1, 0.
3: **repeat**
4: Set $q = R(\tau, P_0, P_1)\,/P(\tau, P_0, P_1)$
5: **repeat**
6: Update P_0 and P_1 according to (17) and (18)
7: Update β and μ
8: **until** Convergence of P_0 and P_1
9: Update $R(\tau, P_0, P_1)$ and $P(\tau, P_0, P_1)$
10: **until** $|R(\tau, P_0, P_1) - qP(\tau, P_0, P_1)| < \delta$
11: Return $P^+_{0,(\tau)} = P_0$, $P^+_{1,(\tau)} = P_1$, $q^+_{(\tau)} = q$
12: **end for**
13: $\tau^* = \arg\max_{\tau} q^+_{(\tau)}$, $P^*_0 = P^+_{0,(\tau^*)}$, $P^*_1 = P^+_{1,(\tau^*)}$, $q^* = q^+_{(\tau^*)}$

After calculating the transmit power, the dual variables including λ, β, and μ related to the corresponding constraints, i.e., (7), (8), and (10), can be updated via a gradient method to solve (15). Then, the transmit power can be recalculated based on the updated dual variables, and the optimal transmit power can be found using this iterative process.

In summary, the overall procedures of the proposed algorithm are described in Algorithm 1. From the initial values of the transmit power and the dual variables, q is set to $\frac{R(\tau,P_0,P_1)}{P(\tau,P_0,P_1)}$. Next, P_0 and P_1 are calculated according to (17) and (18), and the dual variables, i.e., λ, β, and μ, are updated iteratively until the inner loop (from line 5 to line 8) converges. For the converged values, $R(\tau, P_0, P_1)$ and $P(\tau, P_0, P_1)$ are updated, and the convergence of the outer loop (from line 3 to line 10) is checked. If the condition, $|R(\tau, P_0, P_1) - qP(\tau, P_0, P_1)| < \delta$, is satisfied, the algorithm stops and P^+_0 and P^+_1 are returned. For $\tau = 1 : T$, P^+_0 and P^+_1 are found and the resulting energy efficiencies are compared, enabling the optimal values to be found.

A. CASE FOR PERFECT SENSING

In the case of perfect sensing where $\mathcal{P}_d = 1$ and $\mathcal{P}_f = 0$, the allocated power can be simplified as (19) and (20).[6]

$$\tilde{P_0} = \left[\frac{1}{\log 2(q+\beta)} - \frac{N_0}{\hat{h}_{ss}}\right]^+. \tag{19}$$

[6]Note that (19) and (20) are derived only to find meaningful insights, and (17) and (18) should be used in our algorithm. On the other hand, (19) and (20) can be used when a Geolocation Database is used to determine which spectrum is idle [9], [24].

$$\tilde{P_1} = \left[\frac{1}{\log 2(q+\beta+\mu\hat{h}_{sp})} - \frac{\hat{h}_{ps}P_p + N_0}{\hat{h}_{ss}}\right]^+. \tag{20}$$

Although it is difficult to find any meaningful insight from (17) and (18) due to their complicated forms, the optimal power allocations for the perfect sensing case, i.e., (19) and (20), provide us with important information on the effects of energy efficiency, estimated data channel ($\hat{h}_{ss}$), and estimated interference channel ($\hat{h}_{sp}$) on the power allocation strategy. In particular, both transmit power, i.e., $\tilde{P_0}$ and $\tilde{P_1}$, increase when the direct channel for data transmission is good, because the SNs can increase the spectral efficiency still further. In addition, the average transmit power constraint is satisfied by controlling β, and the power is allocated to maximize the energy efficiency in consideration of q. In particular, the ST decreases $\tilde{P_1}$ by adjusting μ if the estimated interference channel gain ($\hat{h}_{sp}$) is large, in order to reduce the interference that it causes to the PR.

B. CASE FOR INTERWEAVE SPECTRUM SHARING

In the concept of interweave spectrum sharing [7], [9], the ST accesses the spectrum only when the channel is sensed to be idle, and otherwise, the ST ceases its transmission. However, due to the inaccurate spectrum sensing, i.e., missed detection [7], the ST might access the channel when it is actually occupied by the PU. As a result, the average spectral efficiency of the SNs, (6), can be reduced to

$$\bar{R}(\tau, P_0) = \mathbb{E}\left\{\frac{T-\tau}{T}\left[\mathcal{P}(\mathcal{H}_0)(1-\mathcal{P}_f)r_{00} + \mathcal{P}(\mathcal{H}_1)(1-\mathcal{P}_d)r_{10}\right]\right\}. \tag{21}$$

Correspondingly, the average transmit power constraint is simplified as follows.

$$\begin{aligned}\bar{P}_T(\tau, P_0) &= \mathbb{E}\left\{\frac{T-\tau}{T}\left[P_0\mathcal{P}(\mathcal{H}_0)(1-\mathcal{P}_f) + P_0\mathcal{P}(\mathcal{H}_1)(1-\mathcal{P}_d)\right]\right\} \\ &\le P_{av}.\end{aligned} \tag{22}$$

In addition, the average interference constraint at the PR is represented by

$$\bar{I_S} = \mathbb{E}\left\{\frac{T-\tau}{T}\left[\hat{h}_{sp}P_0\mathcal{P}(\mathcal{H}_1)(1-\mathcal{P}_d)\right]\right\} \le I_m. \tag{23}$$

Finally, we can formulate the optimization problem that maximizes the energy efficiency of SNs for interweave spec-

$$P_0 = \left[\frac{1}{2}\left\{\frac{v_0+w_o}{X_0} - \frac{\hat{h}_{ps}P_p+2N_0}{\hat{h}_{ss}} + \sqrt{\left(\frac{v_0+w_o}{X_0} - \frac{\hat{h}_{ps}P_p}{\hat{h}_{ss}}\right)^2 + \frac{4v_0\hat{h}_{ps}P_p}{X_0\hat{h}_{ss}}}\right\}\right]^+, \tag{17}$$

$$P_1 = \left[\frac{1}{2}\left\{\frac{v_1+w_1}{X_1} - \frac{\hat{h}_{ps}P_p+2N_0}{\hat{h}_{ss}} + \sqrt{\left(\frac{v_1+w_1}{X_1} - \frac{\hat{h}_{ps}P_p}{\hat{h}_{ss}}\right)^2 + \frac{4v_1\hat{h}_{ps}P_p}{X_1\hat{h}_{ss}}}\right\}\right]^+, \tag{18}$$

trum sharing, as follows.

$$\max_{\tau, P_0} \frac{\bar{R}(\tau, P_0)}{\bar{P}(\tau, P_0)}$$
$$\text{s.t. } (7),\ (22),\ (23),\ P_0 \geq 0,\ 0 \leq \tau \leq T. \quad (24)$$

Here, $\bar{P}(\tau, P_0) = P_C + \bar{P}_T - P_H$. In (24), the constraints (7), (22), and (23) correspond to the minimum required energy to be harvested, the maximum of the average transmit power of SNs, and the interference caused to the PR, respectively.

It should be noted that the optimization problem in (24) is almost the same with the optimization problem in (11) such that the similar approaches for finding solutions in the interference temperature case can be used to derive the optimal value of P_0. In fact, the optimal value of P_0 for (24) is identical to (17). Accordingly in the interweave CRNs, the ST transmits data with P_0 in (17) when the channel is idle, otherwise, it ceases its transmission by letting $P_1 = 0$.

IV. SIMULATION RESULTS AND DISCUSSION

In this section, the performance of the proposed algorithm is evaluated in EH-based CRNs with a single primary link and a single secondary link. In the simulation, the transmit power of PU-Tx, P_p, is 43 dBm while the transmit power of SU-Tx is varied. The duration of one frame is 10 ms and the channel gains in each link are assumed to be exponentially distributed random variables with a unit mean. Here, we assume that $\mathbb{E}[h_{sp}] = \mathbb{E}[h_{ps}]$. In addition, the probability that the channel becomes idle, i.e., $\mathcal{P}(\mathcal{H}_0)$, is assumed to be 0.7, and the target probability of energy detection, $\mathcal{P}_d$, is set to 0.9 [7]. Moreover, the noise variance is 0 dBm [6] and the maximum allowable interference to PU, I_m, is assumed to be -3 dBm [7].[7] For energy harvesting, an energy conversion efficiency, i.e., η, is assumed to be 0.25 [28], and $E_m = -20$ dBm [2], [26]. Furthermore, the P_C is assumed to be 40 dBm [25], [29] and $f_s = 10$ MHz. Finally, we set the channel estimation error as $\sigma_\varepsilon^2 = 0.1$ [20]–[22]. The simulation parameters are summarized in Table I.

We compared the performance of the following algorithms:

- ES (Exhaustive Search): The optimal sensing duration and power allocation are found by solving the optimization problem (11) using an exhaustive search.
- RA-EE (Resource Allocation for Energy Efficiency): The sensing duration and power allocation are found using our proposed scheme as shown in Algorithm 1.
- RA-RM (Resource Allocation for Rate Maximization): The sensing duration and power allocation that maximize the spectral efficiency of the SNs are found.

It should be noted that ES requires significantly more computations than our proposed scheme does. Although we do not include the results, we have found that the number of computations is reduced by 1/10 using RA-EE compared to ES. To be more specific, the average simulation time of ES for one iteration was measured as 284.9404 seconds while that of RA-EE was measured as 26.5961 seconds.

In Fig. 2, we show the energy efficiency, C_E, found by the proposed scheme, against the sensing time, τ, for varying γ and P_{av}. The optimal sensing time and corresponding energy efficiency, found by exhaustive search, are also depicted. The results show that the optimal sensing time and C_E coincide with those of our proposed scheme even when the channel estimation error exists, revealing its optimality and robustness to the channel estimation error. We also observe that the graph starts at $\tau = 0.7$ ms when γ is 0 dB, because the constraint on the harvested energy is not satisfied when τ is less than 0.7 ms, i.e., the optimization problem is infeasible. Moreover, the energy efficiency is high when P_{av} is high, i.e., $P_{av} = 30$ dBm, because the ST can transmit data at a higher power. In addition, for the same τ, the energy efficiency increases as γ increases because more energy can be harvested. It should be noted that although the energy efficiency is negatively affected due to the interference constraint (10) when γ is large, the positive effect from harvesting more energy overcomes this negative effect. Finally, we can find that small τ is chosen because the capacity is a logarithmic function of the transmit power such that short transmission period with high transmit power is not beneficial in the view of energy efficiency.

In Figs. 3-5, the energy efficiency (C_E), spectral efficiency (R), total consumed power (P), and transmit power

TABLE 1. Simulation Parameters.

Parameters	Values
Time frame duration	$T = 10$ ms
Transmit power of PU	$P_p = 43$ dBm
Channel idle probability	$\mathcal{P}(\mathcal{H}_0) = 0.7$ [7]
Noise variance	$N_0 = 0$ dBm [6]
Circuit power consumption	$P_C = 40$ dBm [25], [30]
Energy conversion efficiency	$\eta = 0.25$ [29]
Required harvested energy	$E_m = -20$ dBm [2], [26]
Allowable interference power	$I_m = -3$ dBm [7]
Sampling frequency	$f_s = 10$ MHz
Target detection probability	$\mathcal{P}_d = 0.9$ [7]
Channel estimation error	$\sigma_\varepsilon = 0.1$ [20]

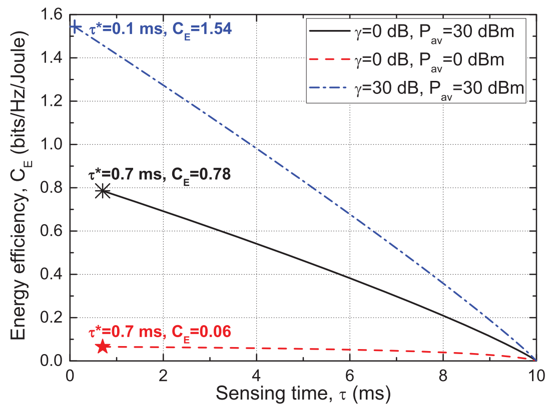

FIGURE 2. Energy efficiency versus sensing time τ.

[7] I_m is calculated assuming that the sensing threshold of CRN is -107 dBm when the noise variance is -104 dBm [7].

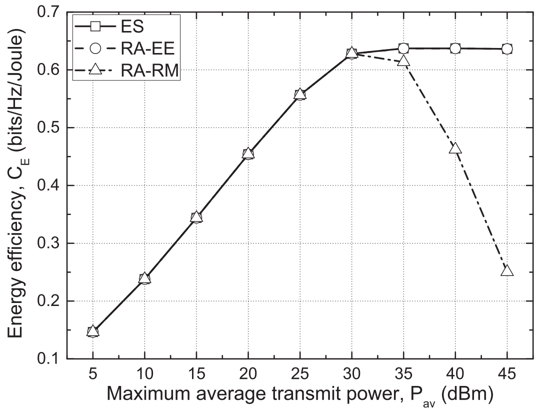

FIGURE 3. Energy efficiency versus P_{av}.

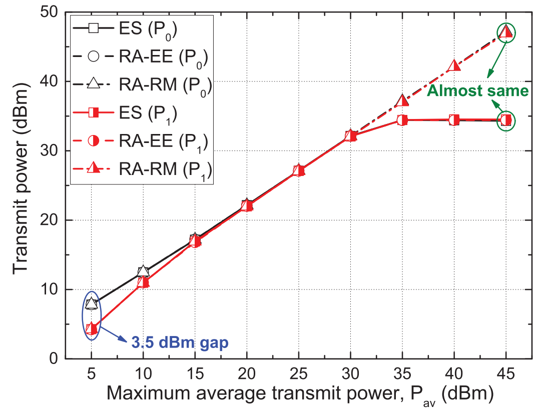

FIGURE 5. Transmit power versus P_{av}.

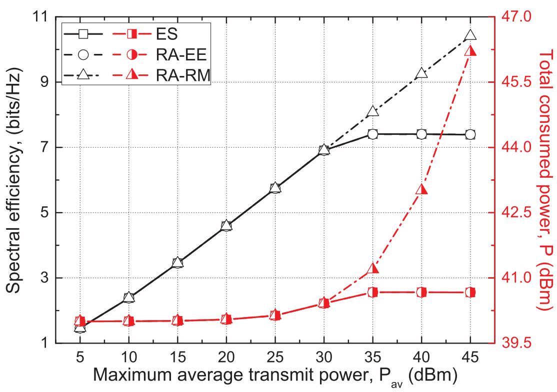

FIGURE 4. Spectral efficiency and total consumed power versus P_{av}.

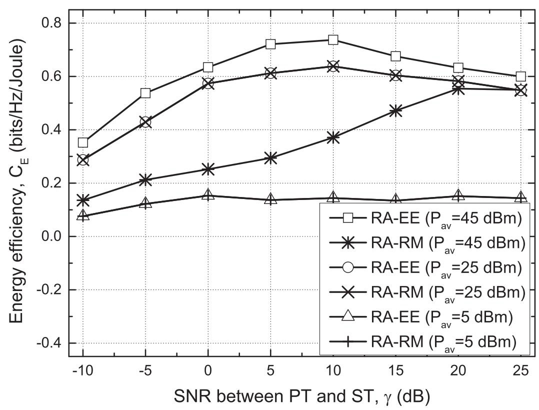

FIGURE 6. Energy efficiency versus γ by varying P_{av}.

(P_0 and P_1) of the ES, RA-EE and RA-RM schemes are shown for various values of maximum allowable transmit power, P_{av}. In the simulations, γ is set to 0 dB. First, we observe that the simulation results of RA-EE, which is based on Algorithm 1, coincide with those of ES, i.e., our proposed scheme in Algorithm 1 achieves optimal performance. As shown in Fig. 3, the C_E of RA-EE increases as P_{av} increases when $P_{av} \leq 30$ dBm, but it converges to its optimal value when $P_{av} > 30$ dBm. This indicates that extra transmit power beyond the optimal value causes a loss of energy efficiency. On the other hand, the C_E of RA-RM decreases abruptly when $P_{av} > 30$ dBm, because RA-RM only considers the maximization of the spectral efficiency. When $P_{av} = 45$ dBm, the energy efficiency of RA-EE is 2.6 times larger than that of RA-RM.

From Fig. 4, we find that the spectral efficiency of RA-RM is higher than that of the other two schemes while the total consumed power also increases rapidly when $P_{av} > 30$ dBm. For example, when $P_{av} = 45$ dBm, the spectral efficiency of RA-RM is 40 % higher than that of other two schemes while the total consumed power of RA-RM is 3.5 times higher than that of other two schemes. On the other hand, both the spectral efficiency and total consumed power are maintained for both ES and RA-EE, which results in the preservation of energy efficiency. In other words, the transmit power is not increased for ES and RA-EE in order to improve energy efficiency, even though P_{av} is increased. Finally, from Fig. 5, we find that P_0 and P_1 are almost the same when P_{av} is sufficiently large, i.e., $P_{av} > 15$ dBm, because the effect of interference from the PT is minor. However, more power is allocated to P_0 than P_1 as P_{av} decreases, since the interference from the PT plays a significant role. This indicates that it is better to use more power in cases of lower interference, i.e., P_0.

In Fig. 6, we show the energy efficiency, C_E, by varying γ and P_{av}. Given that our previous results justify the fact that the energy efficiency of ES and RA-EE are the same, we only show the results for RA-EE and RA-RM. As can be seen from the results, the energy efficiency of RA-EE increases as P_{av} increases, e.g., the energy efficiency increases 3.8 times maximally. It is due to the fact that the ST with high P_{av} has more capability to adjust its transmit power. We can also find that the energy efficiency of RA-EE decreases when γ is either low or high. To be more specific, when γ is high, the interference constraint of PN deteriorates the energy efficiency, on the other hand when γ is low, the harvesting of energy from PN deteriorates the energy efficiency, i.e., ST allocates more time for energy harvesting and time for data transmission diminishes. It should be noted that the energy

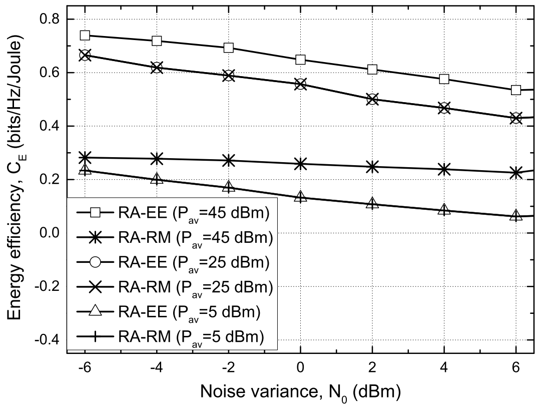

FIGURE 7. **Energy efficiency versus noise variance, N_0, by varying P_{av}.**

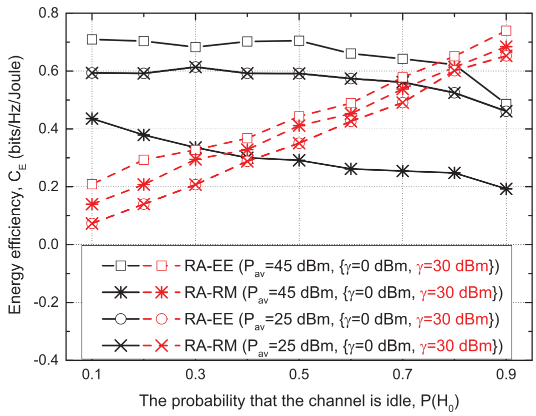

FIGURE 8. **Energy efficiency versus $\mathcal{P}(\mathcal{H}_0)$ by varying P_{av}.**

efficiency of RA-RM coincides[8] with that of RA-EE when $P_{av} = 25$ dBm and 5 dBm, however, it becomes different from that of RA-EE when $P_{av} = 45$ dBm. Specifically, in this case, the energy efficiency of RA-RM decreases as γ decreases, because the ST is likely to transmit with higher power compared with RA-EE to increase its data rate which results in the decrease of energy efficiency.

In Fig. 7, we show the energy efficiency, C_E, as a function of N_0 for different values of P_{av}. As can be seen from the results, the energy efficiency decreases as N_0 increases for all cases, because the achievable spectral efficiency decreases, which agrees with our expectation. Moreover, we can observe that the energy efficiency of RA-RM coincides with that of RA-EE when $P_{av} = 25$ dBm and 5 dBm same with Fig. 6.

In Fig. 8, we show the energy efficiency, C_E, by varying the channel idle probability, $\mathcal{P}(\mathcal{H}_0)$, and P_{av}. First, we can find that the energy efficiency of RA-EE is larger than that of RA-RM when P_{av} is 45 dBm due to the excessive transmit power of RA-RM, which can be conjectured from Fig. 3. We can also find that the energy efficiency of all schemes decreases as $\mathcal{P}(\mathcal{H}_0)$ increases when P_{av} is high and γ is low, which is somewhat counter-intuitive. It is due to the fact that when $\mathcal{P}(\mathcal{H}_0)$ is large, the amount of harvested energy is lower,

[8]In this case, the ST cannot transmit with high power due to the interference constraint of PN which prevent the excessive transmit power use of RA-RM.

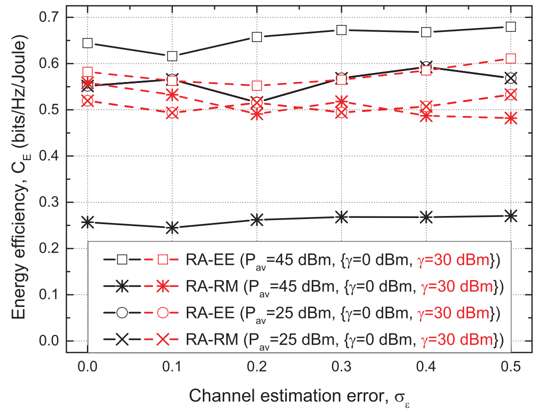

FIGURE 9. **Energy efficiency versus channel estimation error by varying P_{av}.**

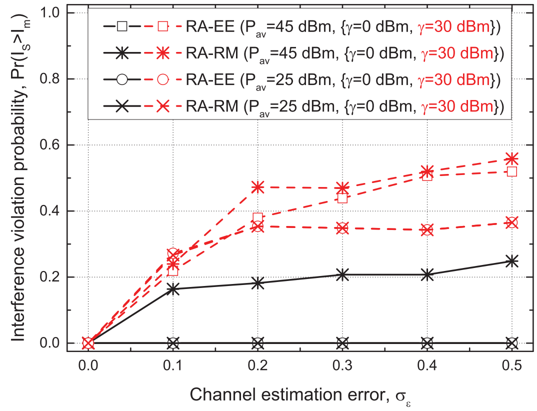

FIGURE 10. **Interference violation probability versus channel estimation error by varying P_{av}.**

which results in the increase of τ in order to satisfy the constraint on the harvested energy, P_H. Accordingly, the energy efficiency becomes lower due to the shorter period for data transmission. Moreover, the effect of interference from PT is minor such that the achievable data rate of ST is almost the same with or without the existence of PU. However, when γ is large, the ST can collect enough energy using short sensing period (which is the positive effect of high γ), but the interference from PT to SR as well as the interference from ST to PR are also enormous (which is the negative effect of high γ) at small $\mathcal{P}(\mathcal{H}_0)$. In this situation, the negative effect is more dominant to determine the energy efficiency in the appearance of PT, as a result, the energy efficiency of all schemes increases as $\mathcal{P}(\mathcal{H}_0)$ increases.

In Figs. 9 and 10, we show the energy efficiency, C_E, and the interference constraint violation probability, $\Pr(I_S > I_m)$, by varying the channel estimation error, σ_ε, and P_{av}. As we can see from the results, the energy efficiency of all schemes does not change greatly as σ_ε varies. However, an channel estimation error causes the inaccurate adjustment of the transmit power, which can result in the violation the allowable interference for PR. As a result, the interference violation probability increases as σ_ε increases. When $\gamma = 0$ dBm, the interference violation probability is zero when $P_{av} \leq$ 25 dBm for both schemes because the transmit power of ST is sufficiently small and the channel gain between ST and PR is sufficiently low such that the interference constraint of PR is not violated. However, when $\gamma = 30$ dBm, the channel gain between ST and PR is sufficiently large such that the interference violation probability is larger than zero even when $P_{av} \leq 25$ dBm. In addition, we can find that the interference violation probability of RA-RM is higher than that of RA-EE because RA-RM uses higher transmit power compared with RA-EE.

V. CONCLUSIONS

We investigated the EH of SNs from RF signals transmitted by PNs, in order to improve the energy efficiency of CRNs. In particular, we proposed an optimal sensing time and power allocation strategy for maximizing energy efficiency by taking into account the realistic constraints caused by energy harvesting in CRNs. The formulated problem was solved using optimization techniques, e.g., a nonlinear fractional programming, and an iterative method was used to find the optimal sensing time and power allocation. Finally, we revealed the optimality of our proposed scheme using simulations. Even though it might not be yet possible to harvest enough energy from RF signals to support the stable operation of wireless networks, we suggest that our results provide some insight for the development of a prospective technique for using self-powered CRNs. An interesting extension of this work might be the generalization of system model in which multiple STs and SRs coexist in the multichannel environment.

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