Optimizing Spectrum Sensing Time With Adaptive Sensing Interval for Energy-Efficient CRSNs

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***Abstract*— The cognitive radio (CR) technology allows secondary users (SUs) to occupy the licensed bands opportunistically without causing interferences to primary users (PUs). SUs perform spectrum sensing to detect whether PUs are busy or idle. Therefore, spectrum sensing directly affects the performance of the PU protection and the secondary throughput. The sensing time is a critical parameter for spectrum sensing performance, and the optimum sensing time is a tradeoff between the spectrum sensing performance and the secondary throughput. In this paper, a novel spectrum sensing scheme is proposed to maximize both sensing accuracy and network energy efficiency. In order to provide a better protection for the PU, another spectrum sensing is adaptively performed according to the first sensing result. In other words, SU will perform spectrum sensing again to confirm that the PU is indeed idle when the first sensing result indicates the PU is idle. Due to the energy constraint in CR sensor networks, this adaptive sensing interval can also be adjusted according to the varying activity of the PU to maximize the network energy efficiency. Finally, our simulation study validates that the proposed scheme improves both the spectrum sensing performance and the energy efficiency compared with other existing methods.**

***Index Terms*— Cognitive radio sensor networks, sensing time, sensing interval, energy efficiency, miss detection probability, bisection method.**

I. Introduction

DUE to the rapid growth of wireless communications, the spectrum scarcity problem is becoming more severe. The limited usable spectrum cannot meet the increasing demand of wireless communications because of the fixed spectrum allocation policy. Moreover, Federal Communications Commission (FCC) has confirmed that most licensed wireless spectrum bands are severely underutilized – the utilization of the licensed bands only ranges from 15% to 85% [1]. In order to mitigate the problem of spectrum scarcity, the Cognitive Radio (CR) technology has been proposed to improve the spectral efficiency [2]. The unlicensed Secondary Users (SUs) are allowed to occupy the licensed bands opportunistically using the CR technology when the licensed Primary Users (PUs) do not occupy them. Since the CR technology allows SUs to share the licensed bands with PUs in a collision-free manner, it has been widely applied in various wireless networks to improve spectral efficiency [3]–[5].

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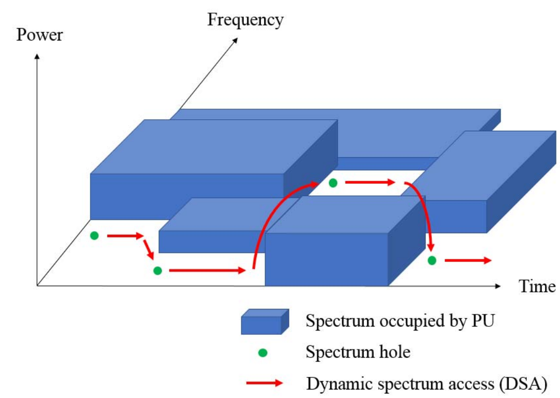

Fig. 1. Dynamic spectrum access.

In Cognitive Radio Sensor Networks (CRSNs), the CR technology enables sensor nodes to detect available licensed bands by performing spectrum sensing, and SUs can opportunistically use *spectrum holes* or *white spaces* to improve spectral efficiency when PUs are detected to be idle. This dynamic spectrum access is shown in Fig. 1. Since PUs should not be interfered by SUs, spectrum sensing is very important for SUs to accurately detect the presence of PUs. The performance of spectrum sensing depends on miss detection and false alarm probabilities. A *miss detection* occurs when the SU fails to detect the presence of the PU. A *false alarm* occurs when the SU falsely detects the presence of the PU. Therefore, a miss detection causes interference to the PU, while a false alarm leads to lower secondary throughput. The sensing time is a key parameter that can affect the sensing performance. More specifically, a longer sensing time will reduce the sensing errors and provide a better protection for the PU. However, less time will be left for data transmission and the secondary throughput will be reduced. Therefore, the optimal sensing time leads to a tradeoff between sensing performance and secondary throughput.

In CRSNs, energy consumption is the most crucial factor because wireless sensor devices are powered by batteries, which are hard or even impossible to recharge or change due to the application environment. Therefore, improving the network energy efficiency and prolong the network lifetime are the most important challenges.

Deepak *et al.* proposed a spectrum sensing method based on a cognitive monitoring network, where a network of sensors is deployed in the network coverage area to perform the cooperative spectrum sensing [6]. In their method, SUs take extremely short time to send a query to monitoring sensors, and then receive the sensing result. Therefore, the secondary throughput can be maximized irrespective of the sensing duration. However, there will be delay due to the communication between SUs and monitoring sensors. In addition, the monitoring sensors will still consume energy for spectrum sensing and the feedback of sensing results, but the authors do not consider this issue and simply focus on how to maximize the time for data transmission. Jiang *et al.* investigated a joint energy-efficient optimization method for spectrum sensing and nodes selection [7]. In this work, a dynamic censored spectrum sensing scheme is employed, where each sensor node compares the received power with a censoring threshold, and then decides when to stop sensing. This allows the sensing time to be shortened and the unnecessary energy consumption to be avoided. However, the probability of sensing error will be high if a sensor node collects just a few samples and stops sensing.

Based on the aforementioned discussion, this paper proposes a novel spectrum sensing scheme for CRSNs. Since miss detection probability and false alarm probability are unrelated, the proposed method focuses on reducing the miss detection probability to provide a better protection for the PU. This is achieved by having the SU dynamically decide whether or not to perform another spectrum sensing based on the result of the first spectrum sensing. More specifically, the SU performs spectrum sensing once and then remains silent if the sensing result indicates that the PU is busy. If the sensing result shows that the PU is idle, the SU will perform spectrum sensing again to confirm the idle state of the PU. If the second sensing result still shows that the PU is idle, the SU will transmit data; otherwise, the SU will remain silent. This reduces the possibility of interference caused by miss detections. In addition, the number of invalid data transmissions, and thus the amount of unnecessary energy consumption is reduced. The proposed method also considers the activity of the PU to improve the network energy efficiency. More specifically, if the PU is relatively active, the probability that it will remain busy during the next frame will be high. As a consequence, performing spectrum sensing for each and every frame is unnecessary, and the sensing interval, which is defined as the time interval during which the spectrum state will remain unchanged and thus no further spectrum sensing is needed [8], can be increased (i.e., more than one frame) to save energy for spectrum sensing. Therefore, the network energy efficiency can be improved further. On the other hand, if the PU is relatively inactive, the SU will perform spectrum sensing at the beginning of each frame. Therefore, the opportunities for data transmission can be improved by providing better protection for the PU. Finally, an optimization system model is developed to derive the optimal sensing time to maximize the network energy efficiency. Our simulation study validates that the proposed scheme can significantly improve the network energy efficiency and reduce miss detection probability.

The rest of the paper is organized as follows. Sec. II discusses the related work. In Sec. III, the system model of the proposed method is presented. In Sec. IV, an energy-efficient optimization problem is formulated to obtain the optimal sensing time. In Sec. V, the performance of the proposed scheme is evaluated using simulations. Finally, Sec. VI concludes the paper and discusses possible future work.

II. Related Work

Some recent works on sensing time optimization have been presented in [9]–[11]. Ewaisha *et al.* proposed a joint optimization of channel sensing time, energy detection threshold, and channel sensing order [9]. To formulate the objective function, the secondary throughput and the sensing errors are considered as the reward and the penalty for collisions with the PU, respectively. The secondary throughput is maximized by finding the optimal sensing time for the objective function. Hao *et al.* developed an adaptive spectrum sensing scheme to improve the average throughput and at the same time ensure protection for PUs [10]. The variation of time-varying channels is considered, and the probability of missed transmission opportunity can be adjusted to improve the average throughput. More specifically, their method reduces the missing transmission probability when the channel state good and allows for a high missing transmission probability when channel state is bad. Based on the previous sensing results and the channel state information, the current channel state is predicted and the sensing time, which affects the missing transmission probability, is adjusted accordingly. Shokri-Ghadikolaei *et al.* proposed a learning-based sensing time optimization scheme to maximize the average throughput [11]. The authors use a multilayer feedforward neural network to learn the actual behavior of the secondary link, and based on this, a Kennedy-Chua neural network is employed to find the optimal sensing time.

However, the above-mentioned proposals on sensing time optimization are specific to CRNs and they do not consider the energy consumption, which is the most important factor in CRSNs. Therefore, these schemes cannot be directly applied to CRSNs. In recent years, energy efficiency maximization through optimizing spectrum sensing time has also spurred great interest, and some related work have been proposed [12]–[16].

Zhong *et al.* formulated a joint optimization problem for energy-efficient cooperative spectrum sensing and transmission in a multi-channel CR system [12]. The energy efficiency is maximized by jointly optimizing the sensing time, the number of cooperative sensing SUs, and the transmission bandwidth. Awin *et al.* considered a joint optimal transmission power and sensing time for energy-efficient spectrum sensing [13]. The optimization problem is formulated with these two variables (i.e., transmission power and sensing time) with the goal of maximizing PU protection. This is achieved by applying an iterative algorithm to determine the optimal transmission power and sensing time that maximizes the energy efficiency of a CR system. Zhang *et al.* also investigated the power control and sensing time optimization problem in a cognitive small cell network [14]. The cross-tier interference mitigation, imperfect hybrid spectrum sensing, and energy efficiency are considered. The hybrid spectrum sensing that combines spectrum sharing access and opportunistic spectrum access is considered in the optimization problem. An iterative resource allocation algorithm is developed to achieve the optimal sensing time and power allocation, which in turn maximizes the energy efficiency. Luo *et al.* proposed a minimizing mean detection time scheme [15]. More specifically, based on the premise of meeting the basic requirements of a secondary network (i.e., the detection probability must not be smaller than a pre-defined threshold and the false alarm probability must not be larger than a pre-defined threshold), the sensing time is minimized and the remaining time left for data transmission is maximized. Li *et al.* proposed an energy-efficient technique for cooperative spectrum sensing [16]. All SUs perform cooperative spectrum sensing for one period. If the PU is detected to be idle, SUs will transmit data. The optimal sensing time is achieved by optimizing the network energy efficiency, which is defined as the ratio of the secondary throughput and the total energy consumption.

All the above-mentioned proposals only perform spectrum sensing once and then find the optimal sensing time to maximize the energy efficiency. However, if sensing errors occur, no attempt is made to correct them. The PU will be interfered by SUs' communication, and energy and available spectrum opportunities will be wasted. In addition, existing methods perform spectrum sensing at the beginning of each frame. However, this is unnecessary since the state of the PU always lasts for several time slots, i.e., frames. The fact that activity of the PU follows the Markov process has been verified in [17]. Therefore, performing spectrum sensing for each slot will waste energy if the activity of the PU is not considered.

The problem of sensing interval optimization has been studied in [8] and [18]. Xing *et al.* investigated a technique where the spectrum sensing interval is adjusted based on the network environment and requirements of SUs [8]. This is achieved by finding a balance between energy consumption and network throughput while considering the interference to the PU. Liu *et al.* investigated a method for optimizing the spectrum sensing interval [18], which is similar to the work in [8]. However, in contrast to the work in [8] where perfect sensing is assumed (i.e., no sensing errors can occur), the authors considered imperfect spectrum sensing (i.e., sensing errors can occur). The optimal spectrum sensing interval is obtained by trading off among the average energy consumption for spectrum sensing, the average secondary throughput, and the average interference to the PU. However, these methods only focus on the sensing interval and ignore the spectrum sensing time.

III. System Model

This paper considers a simple CRSN comprised of a single PU and one secondary link with a transmitter-receiver pair.

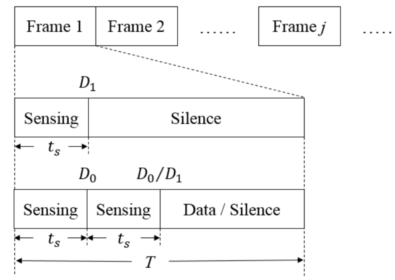

Fig. 2. Frame structure of spectrum sensing.

The time is divided into equal sized frames, where each frame consists two phases: the *sensing* phase and the *data transmission* phase. The spectrum sensing by the SU is assumed to be imperfect, and thus sensing errors (i.e., miss detection and false alarm) can occur. During the sensing phase, the SU performs spectrum sensing to detect the PU's activity. If the sensing result shows that the PU is idle, the SU always has data to transmit during the data transmission phase; otherwise, the SU will remain silent. In order to simplify the problem, the activity of the PU is assumed to follow a time framed structure. In other words, during one frame time, the spectrum is either occupied by the PU or vacant (i.e., the state of the PU does not change within a frame). Moreover, the activity of the PU is independent from one frame to another. It is also worth noting that the data transmission of the SU is considered to be valid only when the PU is actually absent.

Fig. 2 shows the frame structure for spectrum sensing, where T represents the frame time, t_s denotes the spectrum sensing time, and D_0 and D_1 indicate sensing results that the PU is idle and busy, respectively. In the proposed scheme, the SU dynamically performs the second spectrum sensing based on the first spectrum sensing result. More specifically, the SU performs spectrum sensing for time t_s, and then remains silent if the sensing result is D_1. If the sensing result is D_0, the SU will perform spectrum sensing again for time t_s to confirm the absence of the PU to provide better protection. If the second sensing result is still D_0, the SU will transmit data; otherwise, it will remain silent. Note that if the first and the second spectrum sensing results are different, the second spectrum sensing result will be taken as the final sensing decision.

The proposed scheme also considers the activity level of the PU. When the PU is relatively active and the final sensing result shows that the PU is busy, the sensing interval will be extended to multiple frames. This is because the probability that the PU will continue to be busy is higher than the probability that the PU will become idle in the next frame, and thus performing spectrum sensing at the beginning of each frame is unnecessary. Therefore, the energy required for spectrum sensing can be saved. When the PU is relatively inactive and the final sensing result shows that the PU is busy, the SU will perform spectrum sensing at the beginning of the next frame. This allows the SU to transmit data normally if the PU is idle during the next frame. In addition, if the final sensing result shows that the PU is idle, the SU will transmit data and perform spectrum sensing at the beginning

Fig. 3. Frame structure of sensing time and sensing interval.

of the next frame regardless whether the PU is relatively active or inactive. This leads to not only more opportunities for data transmission, but also the sensing error can be corrected during the spectrum sensing of the next frame.

Based on the first and the second spectrum sensing results, the six possible cases are listed below. Fig. 3 also shows the detailed frame structure of sensing time and sensing interval, where U_0 and U_1 denote the actual idle and busy states of the PU, respectively.

Case 1: The actual state of the PU is U_1, and the spectrum sensing result is D_1. In this case, the SU correctly detects the activity of the PU during the first spectrum sensing. Thus, the SU performs spectrum sensing only once, and then remains silent for n frames. Note that the current frame is included in the n frames. In other words, except for the current frame, the SU has to remain silent state for $n-1$ frames. When the PU is relatively inactive, i.e., $n = 1$, the spectrum sensing will be performed at the beginning of the next frame. On the other hand, n is greater than 1 when the PU is relatively active. The detailed calculation process of n will be presented in Sec. IV-B (see Eqs. (23), (24), and (25)).

Case 2: The actual state of the PU is U_1, but the first spectrum sensing result is D_0 and the second spectrum sensing result is D_1. In this case, since the first spectrum sensing result is D_0, the SU performs spectrum sensing again to confirm the correctness of the first sensing result. Even though a miss detection occurs during the first spectrum sensing, the PU's activity is successfully detected during the second spectrum sensing. This results in better protection. Since the final sensing result is D_1, the SU remains silent for n frames.

Case 3: The actual state of the PU is U_1, but both the first and the second spectrum sensing results are D_0. In other words, miss detection occurred during the first and the second spectrum sensing process. Since the data transmission of SUs is assumed to be valid only when the actual state of the PU is U_0, there is no valid secondary throughput in this case. Since the final sensing result is D_0, the SU performs spectrum sensing at the beginning of the next frame.

Case 4: The actual state of the PU is U_0, but the sensing result is D_1. In this case, a false alarm occurred. Since the sensing result is D_1, the SU performs spectrum sensing only once, and then remains silent for n frames.

Case 5: The actual state of the PU is U_0, and both the first and the second sensing results are D_0. In other words, the SU successfully detects the idle state of the PU during the first and the second spectrum sensing process. This will result in valid data transmission. The SU performs spectrum sensing at the beginning of the next frame.

Case 6: The actual state of the PU is U_0, but the first and the second spectrum sensing results are D_0 and D_1, respectively. In this case, a false alarm occurred during the second spectrum sensing process. Therefore, the SU remains silent for n frames.

Based on the above-mentioned six cases, Cases 1 and 2 successfully detected the activity of the PU. Case 3 caused the problem of miss detection, while Cases 4 and 6 led to the problem of false alarm. A valid throughput was achieved only for Case 5.

IV. Formulation of Optimization Problem

This section develops the optimization model for the proposed scheme. The goal of the proposed scheme is to decrease the sensing errors to provide a better protection for the PU. The benefit of a higher spectrum sensing accuracy is that the number of invalid data transmissions can be decreased. This in turn avoids unnecessary energy consumption caused by invalid data transmissions, and thus the energy efficiency is improved. In addition, the PU activity level is considered by increasing the sensing interval as the activity of the PU increases. Because of the increased sensing interval, energy consumption for spectrum sensing can be reduced and the network energy efficiency can be further improved.

A. Energy Detection Based Spectrum Sensing

A binary hypothesis is used to formulate the spectrum sensing. H_0 and H_1 denote the hypothesis of the idle and the busy states of the PU, respectively. p_0 and p_1 indicate the probabilities of H_0 and H_1, respectively. Therefore, $p_0 + p_1 = 1$.

Currently, matched filter detection [19], [20], energy detection [21], [22], cyclostationary detection [23], [24], and eigenvalue-based detection [25], [26] are the most common spectrum sensing methods. The comparisons of these methods have also been performed in [27] and [28]. The matched filter detection method has the lowest execution time, but the information of the PU signal is necessary. The cyclostationary detection method is robust to the noise uncertainty, but it is complex and the knowledge of cyclic frequencies of the PU is required. The eigenvalue-based detection method does not require the information of the PU's signal properties, but the computation is complex. The energy detection method is sensitive to noise uncertainty and interference level, but it is very simple and does not need the priori knowledge of the PU. For this reason, it is the most widely used spectrum sensing method [29]–[31].

The proposed method also employs the energy detection method to detect the activity of the PU. The SU compares the received energy power with the predefined threshold. If the received energy power is higher than the threshold, the PU is considered busy; otherwise, the PU is considered to be idle. The test statistic for the energy detector $T(y)$ can be expressed as follows:

$$T(y) = \frac{1}{\sigma_u^2}\sum_{n=1}^{N}|y(n)|^2, \tag{1}$$

where $y(n)$ is the sampled signal and N is the number of samples performed during the sensing phase. When the state of the PU is H_1, $y(n) = s(n) + u(n)$, where $s(n)$ is the signal of the PU, which is assumed to be iid random process with a mean of zero and a variance of σ_s^2, and $u(n)$ is a white Gaussian noise with a mean of zero and a variance of σ_u^2. On the other hand, when the state of the PU is H_0, $y(n) = u(n)$. The test statistic follows the central and non-central chi-square distribution with $2N$ degrees of freedom under hypothesis H_0 and H_1, respectively [32]. The test statistic can be approximated as Gaussian because the central limit theorem can be applied to it when the value of N is large enough [33]. Then, the test statistic can be defined as follows:

$$T(y) \sim \begin{matrix} \mathcal{N}(N, 2N) & H_0 \\ \mathcal{N}(N(1+\gamma), 2N(1+\gamma)^2) & H_1, \end{matrix} \tag{2}$$

where $\gamma = \sigma_s^2/\sigma_u^2$ is the received Signal to Noise Ratio (SNR) from the PU. Based on this, the detection probability p_d and the false alarm probability p_f can be defined as follows:

$$p_d = p(H_1|H_1) \quad \text{and} \tag{3}$$
$$p_f = p(H_1|H_0). \tag{4}$$

Based on the statistics of $T(y)$, p_d and p_f can be rewritten as follows:

$$p_d = Q(\frac{\lambda}{\sqrt{2N}(1+\gamma)} - \sqrt{\frac{N}{2}}) \quad \text{and} \tag{5}$$

$$p_f = Q(\frac{\lambda}{\sqrt{2N}} - \sqrt{\frac{N}{2}}), \tag{6}$$

where λ is the sensing threshold, which is used to compared with the received energy power. More specifically, when the SU detects the PU and the received power is higher than λ, the PU is considered to be busy; otherwise, the PU is considered to be idle. $Q(\cdot)$ is the Q-function, which is given as

$$Q(x) = \frac{1}{\sqrt{2\pi}}\int_x^{\infty} exp(-\frac{t^2}{2})dt. \tag{7}$$

Eq. (7) shows that $Q(x)$ is a monotonically decreasing function. The number of samples N can be calculated using the following equation [32]:

$$N = 2tW, \tag{8}$$

where t denotes the sensing time and W is the bandwidth of the PU signal. The sensing threshold λ can be derived using Eq. (5) as below:

$$\lambda = \sqrt{2N}(1+\gamma)(Q^{-1}(p_d) + \sqrt{\frac{N}{2}}), \tag{9}$$

where $Q^{-1}(\cdot)$ denotes the inverse of the Q-function. By substituting λ into Eq. (6), p_f can be obtained as

$$p_f = Q((1+\gamma)Q^{-1}(p_d) + \gamma\sqrt{\frac{N}{2}}). \tag{10}$$

In order to guarantee essential protection for the PU in CRSNs, p_d should be greater than or equal to a predefined threshold p_d^{th}. According to Eq. (10), p_f decreases as sensing time increases when p_d is a fixed value. In addition, the value of $Q^{-1}(p_d)$ increases as p_d decreases, and p_f decreases as $Q^{-1}(p_d)$ increases. Therefore, for the purpose of maximizing the available secondary throughput, p_d is fixed as p_d^{th}, i.e., $p_d = p_d^{th}$.

Based on the six cases discussed in Sec. III, only Case 3 leads to the problem of miss detection. Hence, the probability that the SU cannot detect the presence of the PU, p_m^1, can be expressed as

$$p_m^1 = p_1(1-p_d)^2. \tag{11}$$

B. Optimization Problem Formulation

Fig. 3 showed that the SU can either transmit data or remain silent for up to n frames, and this is decided based on the different final sensing results. Therefore, the sensing interval varies depending on the different final sensing results and the activity level of the PU. In order to optimize the network energy efficiency, the proposed scheme focuses on the average secondary throughput and energy consumption per average frame time. In order to analyze the optimization problem and calculation process, in addition to the six cases summarized in Fig. 3, four new spectrum sensing cases based on all the possible two consecutive final sensing results are shown in Fig. 4 and discussed below:

Case 1: The two consecutive final sensing results are D_0 and D_1. In this case, the SU transmits data during the current frame after detecting that the PU is idle. During the next frame, the SU detects that the PU is busy, and then remains silent for n frames.

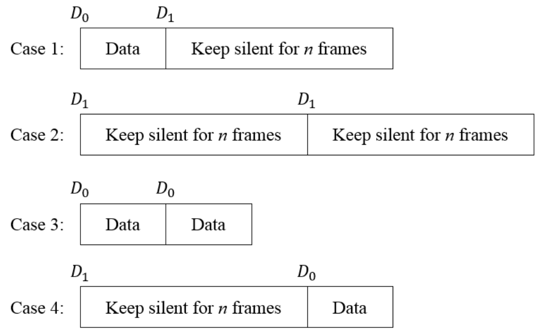

Fig. 4. Summary of spectrum sensing cases.

Case 2: The two consecutive final sensing results are both D_1. Since the PU was detected to be busy twice, the SU remains silent for n frames for two consecutive times.

Case 3: The two consecutive final sensing results are both D_0. Therefore, the SU transmits data in the current and the next frame after detecting that the PU is idle.

Case 4: The two consecutive final sensing results are D_1 and D_0. After detecting that the PU is busy, the SU remains silent for n frames. Then, since the next final sensing result indicates that the PU is idle, the SU transmits data.

Note that sensing errors (i.e., false alarm and miss detection) can occur in these four cases. That is, the data transmission will be invalid if a miss detection occurs, and the opportunities for data transmission will be wasted if a false alarm occurs.

According to Fig. 3, if a data transmission occurs (i.e., Case 3 and Case 5), spectrum sensing must be performed twice. As mentioned before, a data transmission is valid only when the actual state of the PU is U_0. Therefore, the probability of invalid throughput caused by miss detection Po_1 and the probability of valid throughput Po_2 can be calculated by the following equations:

$$Po_1 = p_1(1 - p_d)^2, \tag{12}$$

$$Po_2 = p_0(1 - p_f)^2. \tag{13}$$

Therefore, the probability that the SU transmits data can be calculated using

$$Po = Po_1 + Po_2. \tag{14}$$

The SU remains silent when the PU is busy or a false alarm occurs. Here, the silent situation is classified into the following two conditions based on the number of times spectrum sensing is performed: (1) the SU performs spectrum sensing just once and remains silent and (2) the SU performs spectrum sensing twice and remains silent. According to Fig. 3, when Cases 1 and 4 occur, spectrum sensing is performed only once. When Cases 2 and 6 occur, spectrum sensing is performed twice. These two conditions can be represented by the follow equations:

$$Pv_1 = p_1 p_d + p_0 p_f, \tag{15}$$

$$Pv_2 = p_1(1 - p_d)p_d + p_0(1 - p_f)p_f, \tag{16}$$

where Pv_1 and Pv_2 are the probabilities of performing spectrum sensing once and twice, respectively, when the final sensing result is D_1. Thus, the probability that the final sensing result is D_1, Pv, is given as follows:

$$Pv = Pv_1 + Pv_2, \tag{17}$$

When Po and Pv are known, the optimization model based on Fig. 4 can be established.

Cases 1, 3, and 4 in Fig. 4 yield valid secondary throughputs Tp_1, Tp_3, and Tp_4, respectively, which are defined by the following equations:

$$Tp_1 = \frac{Po_2 Pv(T - 2t_s)C}{n + 1}, \tag{18}$$

$$Tp_3 = Po_2^2(T - 2t_s)C + Po_1 Po_2(T - 2t_s)C, \tag{19}$$

$$Tp_4 = \frac{Po_2 Pv(T - 2t_s)C}{n + 1}, \tag{20}$$

where C is the SU's channel capacity without interference from the PU, which can be expressed as follows according to the Shannon theorem:

$$C = log_2(1 + \gamma_s), \tag{21}$$

where γ_s denotes the SNR received from the SU transmitter. In addition, n denotes the number of frames that the SU remains silent. For Tp_3, the term $Po_2^2(T - 2t_s)C$ represents the valid secondary throughput achieved by the two frames (i.e., the current and the next frames), and the term $Po_1 Po_2(T - 2t_s)C$ represents the valid secondary throughput achieved by one of the two frames when a miss detection occurs during the other frame. Therefore, the average total valid secondary throughput per average frame Tp is represented as

$$Tp(t_s) = Tp_1 + Tp_3 + Tp_4, \tag{22}$$

In this paper, n is set to a positive integer, which can be adjusted based on the activity of the PU. In another words, the value of n is dependent on the values of p_0 and p_1. Since the sensing interval is increased only when the PU is busy, the proposed method focuses on the probability that the busy state of the PU will continue. Suppose the current state of the PU is U_1, then the probability that it will continue to be busy for exactly n frames, $p_p(n)$, can be calculated by

$$p_p(n) = p_1^{n-1}(1 - p_1), n \in \{1, 2, 3, \ldots\}. \tag{23}$$

Therefore, the probability that the PU will be busy for at most n frames, $P_p(n)$, can be expressed as

$$P_p(n) = \sum_{i=1}^{n} p_p(i). \tag{24}$$

Here, a threshold θ is set for $P_p\ (n)$, which satisfies $0 \leq \theta \leq 1$. The value of n is a function of θ based on the following equation:

$$n = min\{n : P_p(n) \geq \theta\}. \tag{25}$$

Eq. (25) indicates that n increases as θ increases. Therefore, if θ is too large, the longer sensing interval n will result in less opportunities for data transmission, which in turn degrades the secondary throughput. If θ is too small, the shorter sensing interval will waste more energy for spectrum sensing when

$p_1 \geq p_0$. Moreover, this problem will become more servere when p_1 becomes much larger than p_0.

According to Cases 1, 2, 3, and 4 shown in Fig. 4, the corresponding energy consumptions Ea, Eb, Ec, and Ed, respectively, can be formulated. For Case 1, the energy consumption required for the SU to perform spectrum sensing once and twice, Ea_1 and Ea_2, respectively, to obtain the second final sensing result are formulated as

$$Ea_1 = \frac{PoPv_1(2E_st_s + E_t(T - 2t_s) + E_st_s)}{n+1}, \quad (26)$$

$$Ea_2 = \frac{PoPv_2(2E_st_s + E_t(T - 2t_s) + 2E_st_s)}{n+1}, \quad (27)$$

where E_s and E_t are the energy consumption of spectrum sensing and data transmission for a unit time, respectively. Therefore, the energy consumption for Case 1, Ea, can be calculated using

$$Ea = Ea_1 + Ea_2. \quad (28)$$

For Case 2, the energy consumptions required to perform spectrum sensing twice for 0, 1, and 2 times, Eb_1, Eb_2, and Eb_3, respectively, to obtain two final sensing results are formulated as

$$Eb_1 = \frac{Pv_1Pv_1(E_st_s + E_st_s)}{2n}, \quad (29)$$

$$Eb_2 = \frac{2Pv_1Pv_2(E_st_s + 2E_st_s)}{2n}, \quad (30)$$

$$Eb_3 = \frac{Pv_2Pv_2(2E_st_s + 2E_st_s)}{2n}. \quad (31)$$

Therefore, the energy consumption for Case 2, Eb, can be calculated by the following equation:

$$Eb = Eb_1 + Eb_2 + Eb_3. \quad (32)$$

As mentioned before, if a data transmission occurs, spectrum sensing must be performed twice during a single frame time. Therefore, in Case 3, the SU performs spectrum sensing twice and then transmits data. The energy consumption for Case 3, Ec, can be calculated by

$$Ec = Po^2(2E_st_s + E_t(T - 2t_s)). \quad (33)$$

Case 4 is the same as Case 1, where the energy consumptions required when the SU performs spectrum sensing once and twice, Ed_1 and Ed_2, respectively, to obtain the first final sensing result are as follows:

$$Ed_1 = \frac{PoPv_1(2E_st_s + E_t(T - 2t_s) + E_st_s)}{n+1}, \quad (34)$$

$$Ed_2 = \frac{PoPv_2(2E_st_s + E_t(T - 2t_s) + 2E_st_s)}{n+1}. \quad (35)$$

Therefore, the energy consumption for Case 4, Ed, can be calculated by

$$Ed = Ed_1 + Ed_2. \quad (36)$$

Finally, the total average energy consumption ϕ is given by

$$\phi(t_s) = Ea + Eb + Ec + Ed. \quad (37)$$

In this paper, energy efficiency is defined as the number of bits transmitted per unit of energy consumption [34]. Therefore, the energy efficiency function η can be expressed as

$$\eta(t_s) = \frac{Tp(t_s)}{\phi(t_s)}. \quad (38)$$

In the above objective function, sensing time t_s is the only unknown variable when the value of θ is given. Therefore, the energy efficiency can be maximized by finding the optimal sensing time t_s.

C. Bisection Method

In this paper, the bisection method is applied to find the optimal sensing time t_s. If the function $y = f(x)$ is continuous during the interval $[a, b]$ and the condition $f(a) \cdot f(b) < 0$ is satisfied, the bisection method can be utilized to solve the equation $f(x) = 0$ for the variable x. The bisection method is a root-finding method, where an interval is bisected then a subinterval that the root lies in is selected to be bisected further, and this process is repeated. Finally, the approximation of the root is obtained when the two endpoints of an interval are close enough.

The pseudo-code description of the bisection method is presented in Algorithm 1. In line 1, the lower and upper bounds of interval and the limit of error are given, which are denoted as a, b and ϵ, respectively. Note that the limit of error ϵ should be a small value. Then, the midpoint of interval c (line 2) and the derivative of the objective function $\eta\prime(x)$ (line 3) are calculated. In lines 4-9, a check is made to determine whether the condition $|a - b| \leq \epsilon$ is satisfied. If $|a - b| \leq \epsilon$ is satisfied, the solution can be approximated as a or b or c (line 10); otherwise, the procedure starts again from line 4.

Algorithm 1: The Pseudo-Code of the Bisection Method

1: **procedure** BISECTION_METHOD(a, b, ϵ)
2:     $c = \frac{(a+b)}{2}$
3:     Calculate the derivative of $\eta(x)$, denoted as $\eta\prime(x)$
4:     **while** $|a - b| \geq \epsilon$, and $\eta\prime(x) \neq 0$ **do**
5:         **if** $\eta\prime(a) * \eta\prime(c) < 0$ **then**
6:             $b \leftarrow c$
7:         **else**
8:             $a \leftarrow c$
9:         $c \leftarrow \frac{(a+b)}{2}$
10:     **return** a or b or c

V. Performance Evaluation

This section discusses the performance evaluation of the proposed scheme using MATLAB. The proposed scheme is compared with other two sensing time optimization schemes presented in [15] and [16].

A. Simulation Parameters

The simulation environment is a simple CRSN, which consists of a single PU and one secondary link with a transmitter-receiver sensor node pair that is randomly allocated within the communication range of the PU. The licensed band occupied

TABLE I
SIMULATION PARAMETERS

Parameters	Value
p_d^{th}	0.9
T	0.2 s
W	6 MHz
γ	-20 dB
γ_s	20 dB
C	6.6582 bits/sec/Hz
E_s	0.1 W
E_t	3 W
θ	0.5

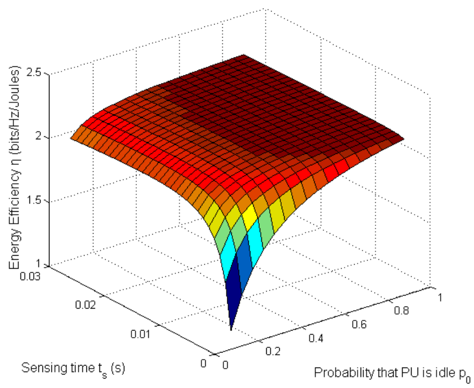

Fig. 5. The variation of energy efficiency as function of sensing time and p_0.

by the PU is assigned to the SUs. The parameters used for the simulation study are shown in Table I. According to the IEEE 802.22 cognitive radio WRAN standard, p_d^{th} is set to 0.9 [35]. The frame time T is 0.2 s and W is 6 MHz. The SNR received from the PU γ is -20 dB. The SNR received from the SU transmitter γ_s is 20 dB, so the SU's channel capacity C is $log_2(1+\gamma_s)$ = 6.6582 bits/sec/Hz. The energy consumed by spectrum sensing (E_s) and data transmission (E_t) for unit time are assumed to be 0.1 W and 3 W, respectively, which are set to the same values as in [16]. To achieve both secondary throughput and energy efficiency, θ is set to 0.5. In other words, the sensing interval is set to n that satisfies Eq. (25) when θ is given as 0.5. The level of the PU activity is defined as the probability that the PU is idle p_0, where $0 < p_0 < 1$.

B. Simulation Results

Fig. 5 shows the energy efficiency as a function of the sensing time t_s and the idle probability of the PU p_0. As can be seen, for the fixed value of p_0, the energy efficiency at first increases as the sensing time increases. Then, after the optimal sensing time, the energy efficiency decreases again as the sensing time increases. Fig. 6 is the Fig. 5 when p_0 is fixed as 0.5. Therefore, for different values of p_0, there is always an optimal spectrum sensing time that maximizes the energy efficiency. The reason for this can be more clearly seen in Fig. 6 and Fig. 7.

Fig. 6 shows the energy efficiency as a function of the sensing time when p_0 is fixed at 0.5. Note that p_0 can be fixed to any value within the interval (0, 1). The energy

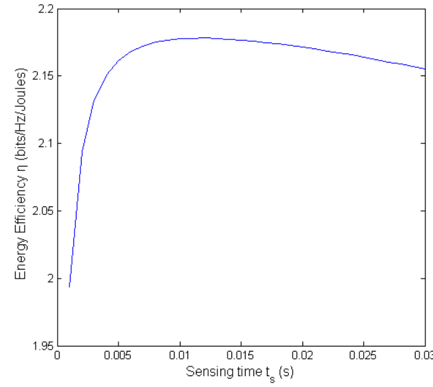

Fig. 6. The energy efficiency as a function of spectrum sensing time when $p_0 = 0.5$.

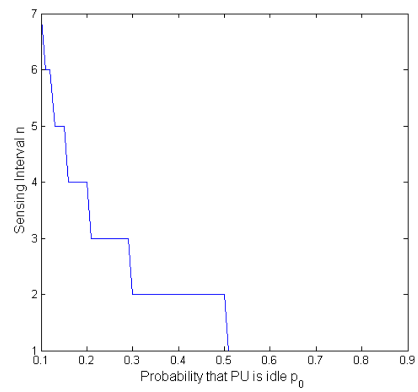

Fig. 7. The sensing interval as a function of p_0.

efficiency at first increases as the sensing time increases. The energy efficiency peaks at 2.18 bits/Hz/J when the optimal sensing time t_s is 0.012 s. After the optimal sensing time, the energy efficiency decreases again as the sensing time increases. The reason for this is that the false alarm probability decreases as the sensing time increases. This implies that there are more opportunities to utilize spectrum holes, and thus higher secondary throughput can be achieved. However, due to the fixed frame time T, the remaining time left for data transmission decreases as the sensing time increases. This directly affects the secondary throughput, especially when the sensing time becomes large. This is the reason why the energy efficiency decreases again after the optimal sensing time. Fig. 6 also shows that the bisection method can be utilized to find the optimal sensing time since the energy efficiency function continuous and the derivative of energy efficiency is larger than 0 before sensing time reaches the optimal value, and the derivative of energy efficiency function is smaller than 0 after the sensing time becomes bigger than optimal value.

Fig. 7 shows the sensing interval n as a function of p_0 when the threshold θ is fixed at 0.5 and the sensing result is D_1. As can be seen, the sensing interval n decreases as p_0 increases. When p_0 is larger than 0.5, the sensing interval n is always 1. In other words, the SU performs spectrum sensing at the beginning of each frame when p_0 > 0.5. The sensing interval n decreases as p_0 increases, and

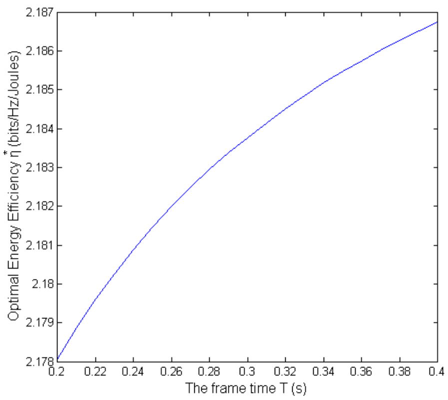

Fig. 8. The optimal energy efficiency as a function of frame time.

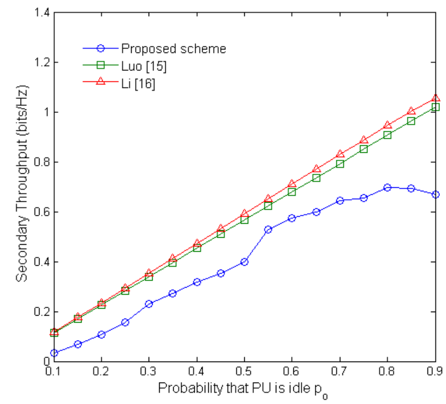

Fig. 10. Comparison of secondary throughput.

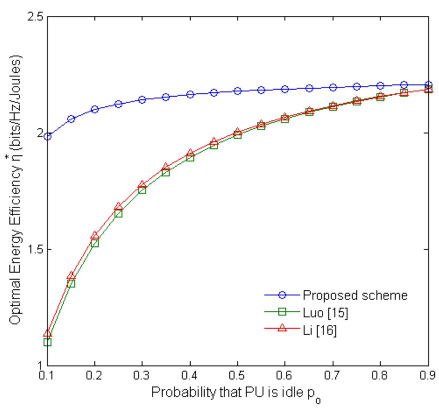

Fig. 9. Comparison of optimal energy efficiency.

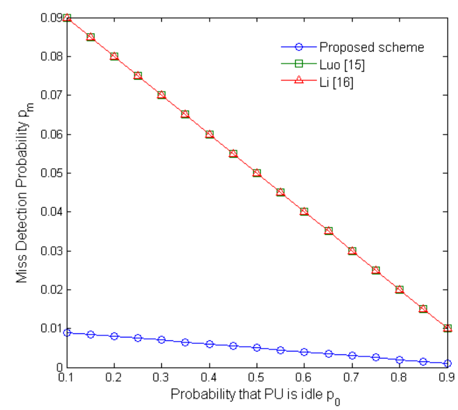

Fig. 11. Comparison of miss detection probability.

thus the SU performs spectrum sensing more frequently and there are more available opportunities to exploit spectrum holes to improve the secondary throughput. On the other hand, the sensing interval increases as p_0 decreases, and thus energy consumption for spectrum sensing is reduced to improve the energy efficiency. Guaranteeing both the energy efficiency and the secondary throughput is the reason why θ is set to 0.5. In fact, the threshold θ depends mainly on the preference between energy efficiency and secondary throughput.

Based on Eq. (38), Fig. 8 shows the optimal energy efficiency as a function of the frame time T when p_0 is fixed at 0.5. As can be seen, the network energy efficiency increases as T increases. In other words, the performance of the proposed scheme improves when T becomes longer. The reason for this is that the problem of miss detection can have a greater negative impact on energy efficiency when T becomes longer. If a miss detection occurs, the PU will be interfered for a longer time and more energy will be wasted for invalid data transmission as T increases. However, the miss detection probability can be decreased significantly by our proposed scheme according to Eq. (11). Therefore, the energy efficiency can be improved when T becomes longer.

Fig. 9 compares the optimal energy efficiency $\eta(t_s)^*$ of the proposed scheme with other two schemes proposed in [15] and [16] as a function of p_0 (where p_0 is in the interval [0.1, 0.9]) with the frame length T fixed at 0.2 s. As can be seen, the proposed scheme outperforms the other two schemes, particularly when $p_1 > p_0$. The reason for this can be explained by Fig. 10 and Fig. 11.

Fig. 10 compares the secondary throughput of these three schemes as a function of p_0 for T fixed at 0.2 s. As can be seen, the secondary throughput of the proposed scheme is lower than the ones proposed in [15] and [16]. This is because when the sensing result shows that the PU is idle, the SU will perform spectrum sensing again to guarantee the first sensing result. This reduces the remaining time left for data transmission. In addition, the sensing interval will become longer when the PU becomes more active and sensing results show the PU is busy. This reduces the energy consumption for spectrum sensing; however, the opportunities for data transmission is also lost when the SU remains silent for n frames. These are two main reasons why the secondary throughput of the proposed scheme is lower than other two schemes.

Fig. 11 compares the miss detection probability p_m^1 of the proposed scheme with the ones proposed in [15] and [16]. As can be seen, the miss detection probability of the proposed scheme is always lower than other two schemes. Since the SU performs spectrum sensing only once in [15] and [16], these two methods have the same miss detection probability p_m^2, which is given as

$$p_m^2 = p_1(1 - p_d). \tag{39}$$

According to Eq. (11) and Eq. (39), it can be seen that the ratio between p_m^1 and p_m^2 is $1 - p_d$. Since p_d is set to the same value as the other two schemes (i.e., 0.9), the miss detection probability decreases by a factor 10 with our proposed scheme. In particular, the difference between p_m^1 and p_m^2 becomes larger as p_0 becomes smaller. Even though more time is spent detecting the PU when the sensing result is D_0 and the secondary throughput for average frame is lower, the PU can be better protected due to the lower miss detection probability. Therefore, the number of invalid data transmissions can be decreased, and in turn energy consumption can be reduced. This improves the network energy efficiency and prolongs the network lifetime. Therefore, the network can be utilized more within the prolonged lifetime to offset the lost secondary throughput.

VI. Conclusion and Future Work

This paper proposed a novel spectrum sensing scheme for CRSNs, where the SU adaptively performs spectrum sensing for either one or two periods based on the first sensing result. This allows the SU to perform the spectrum sensing again to confirm that the PU is indeed idle when the first sensing result indicates the PU is idle, which leads to a better protection for the PU. In addition, the proposed method considers the activity level of the PU. Based on the different activity level of the PU, the sensing interval can be adjusted to further improve the energy efficiency. Finally, an optimization model is established, and the network energy efficiency is maximized by optimizing the spectrum sensing time using the bisection method. Our simulation study validates that the proposed scheme results in better spectrum sensing performance and higher energy efficiency. As a future work, a better method to optimize the sensing interval will be investigated using OpenBTS, which supports the Universal Software Radio Peripheral (USRP) [36].

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