A Novel Spectrum Sensing Scheme with Sensing Time Optimization for Energy-Efficient CRSNs

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Abstract The Cognitive Radio (CR) technology enables Secondary Users (SUs) to occupy licensed bands when Primary Users (PUs) are not occupy them. Spectrum sensing is a key technology for SUs to detect PUs, and the sensing time is a critical parameter for spectrum sensing performance. Optimum sensing time tradeoffs between the spectrum sensing performance and the secondary throughput. This paper proposes a novel spectrum sensing scheme that performs spectrum sensing for either one period or two periods based on the previous sensing result. Due to the energy constraint in Cognitive Radio Sensor Networks (CRSNs), the energy efficiency is maximized by optimizing spectrum sensing time. In order to seek the optimal sensing time, the objective function is proven to be a concave function and the Golden Section Search method is employed. Our simulation study verifies that the proposed scheme improves the network energy efficiency, especially when PUs are more active.

Keywords Cognitive radio sensor networks, sensing time, energy efficiency, golden section search method.

1 INTRODUCTION

Due to the fixed spectrum allocation policy and the rapid deployment of wireless devices, the problem of spectrum scarcity is becoming more severe. Nevertheless, Federal Communications Commission (FCC) has reported that most licensed wireless spectrum bands are underutilized [1]. Recently, Cognitive Radio (CR) technologies have been proposed to alleviate the spectrum scarcity problem [2]. CR has attracted a lot of attention because it allows unlicensed Secondary Users (SUs) to

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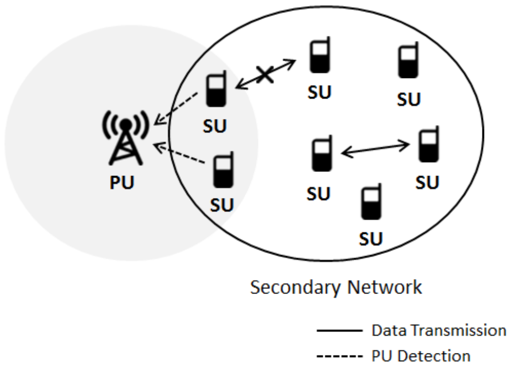

Fig. 1 Architecture of cognitive radio network

opportunistically access the licensed bands when licensed Primary Users (PUs) are not occupying them. Due to this benefit, CR technologies have been extensively applied in various wireless networks to improve spectral efficiency [3-5].

SUs utilizing CR technologies can find *spectrum holes* or *white spaces*, and share the licensed bands with PUs in a collision-free manner. Fig. 1 presents a simple Cognitive Radio Network (CRN), where the PU has higher priority for occupying the licensed bands. The shaded area indicates the communication range of the PU, and the solid and the dashed arrows represent the data transmission between SUs and the PU detection, respectively. When the SUs in the shaded area detect that the PU is busy, they cannot occupy the licensed band and communicate with other SUs. If the SUs detect that the PU is not busy, they can transmit data (using RTS/CTS or other methods to coordinate the communications among SUs). Fig. 1 shows a simple CRN with one PU and several SUs. However, if more than one PU exist, SUs must perform spectrum sensing on all the licensed bands they occupy. Thus, it is very important for SUs to accurately determine whether or not PUs are present. *Spectrum sensing* is the key technology used to detect PUs, and the amount of time spent sensing is a critical parameter for performance. The optimal sensing time trades off between the detection accuracy and the achieved secondary throughput. More specifically, a longer spectrum sensing time leads to better sensing accuracy, but less time remains for data transmission degrading the throughput of the secondary network.

For the optimum spectrum sensing time, miss detection and false alarm probabilities are the main performance metrics. A *miss detection* occurs when an SU fails to detect a PU that is present. A *false alarm* occurs when an SU detects a PU when it is actually absent. If a miss detection occurs, the communications by SUs will interfere with the PUs' communications. As a result, PUs can have better protection from interference if miss detection probability is lower. From the perspective of SUs, if the probability of false alarm is lower, opportunities for SUs to utilize spectrum holes for data transmission become higher and the secondary throughput will increase. A longer sensing time will lead to a lower miss detection probability (i.e., higher detection probability) but a higher false alarm probability (see Sec. 4.1).

Energy consumption is the most important factor in CRSNs. In CRSNs, low-cost, battery-powered sensor nodes are dispersed in a specific area to satisfy various applications, including environment monitoring, surveillance, health care, and battlefield control [6]. Due to the application environment, it is hard or impossible to change or recharge the batteries for the sensor nodes. Therefore, improving energy efficiency and prolonging the network lifetime become the crucial issue for the development of CRSNs.

Therefore, this paper proposes a novel spectrum sensing scheme to improve the energy efficiency of CRSNs. The proposed scheme takes into consideration the previous sensing result. If the sensing result of the current frame is the same as the sensing result of the previous frame, the SU simply performs a spectrum sensing once. Otherwise, the SU will perform another spectrum sensing for a second time to ensure the correctness of the first sensing result. There are two main advantages to the proposed method:

(a) If a PU is actually absent during both the previous and the current frames and a *false alarm* occurs during the first spectrum sensing of the current frame, then the probability that the sensing error can be corrected during the second spectrum sensing increases. As a result, the secondary throughput can be improved.

(b) If a PU is actually present during both the previous and the current frames and a *miss detection* occurs during the first spectrum sensing of the current frame, then the probability that the sensing error can be corrected during the second spectrum sensing increases. As a result, PU can obtain a better protection from interference and energy efficiency can be improved by reducing the number of invalid transmissions due to miss detection.

Our simulation study validates that the proposed scheme reduces sensing errors and improves network energy efficiency, especially when PUs are relatively active.

The rest of the paper is organized as follows. Sec. 2 discusses the related work. Sec. 3 presents the system model of the proposed method. In Sec. 4, an optimization problem is formulated to obtain the optimal sensing time. In Sec. 5, the performance of the proposed scheme is evaluated using simulations. Finally, Sec. 6 concludes the paper and discusses a possible future work.

2 RELATED WORK

Some recent work on sensing time optimization for CRNs have been presented in [7-12]. Ewaisha *et al*. investigated a joint optimization of sensing time, decision threshold, and channel sensing order [7]. They derived a reward function that includes a negative term to penalize collisions with PUs, and the secondary throughput is maximized by finding the optimal solution for the reward function. In this work, the channels are sensed in order and if it is sensed to be idle, the capacity of this channel will be compared with the next idle channel. Then, the channel with the highest capacity is selected for data transmission. However, the state of channel occupancy is not considered when the channel sensing order is obtained. If the channel with the highest capacity is frequently occupied by the PU, more time and energy will be wasted to search for the optimal channel for data transmission. Hao *et al.* developed an adaptive spectrum sensing scheme to maximize the average throughput [8]. Their work considered time-varying channels, and adjusted the missing transmission probability to improve the average throughput. More specifically, they reduce the missing transmission probability when the channel is good and allow a high missing transmission probability when the channel is bad. Based on the previous sensing results and the channel state information, the current channel state is predicted and the sensing time is adjusted accordingly. This work assumes that the channel state information can only be obtained when the spectrum sensing is over and the sensing result indicates the channel is idle. This way, if the channel is rarely occupied by the PU, much time and energy will be needed to predict the current channel state before each spectrum sensing and data transmission. Shokri-Ghadikolaei *et al.* proposed a learning-based sensing time optimization scheme to maximize the average throughput [9]. More specifically, a multilayer feedforward neural network is utilized for learning the actual behavior of the secondary link, and based on this, a Kennedy-Chua neural network is employed to find the optimal sensing time. This work assumes that an SU senses several channels in order until a transmission opportunity is found. However, the authors only focus on sensing time optimization and the optimization of channel sensing order is ignored. An inappropriate channel sensing order will also result in more time and energy consumption to search the channel for data transmission. Sun *et al.* investigated the tradeoff between sensing accuracy and secondary throughput for cooperative spectrum sensing based on soft decision [10]. They analyzed the impact different system parameters have on the optimal sensing time, and showed that they can lead to different results. Liu *et al.* investigated a joint optimization of the sensing time and the number of cooperative users, which maximized CRN throughput subject to the constraints of both false alarm and miss detection probabilities [11]. Yin *et al.* proposed a joint sensing-time adaption and data transmission scheme to improve spectrum utilization and throughput [12]. Their method bundles two adjacent sensing periods to form a sensing block. At first, an SU performs a partial spectrum sensing, and if it does not detect a PU, it transmits data; otherwise, the SU performs a full spectrum sensing. However, the aforementioned techniques are specific to CRNs and they do not take into consideration energy restriction for CRSNs. Therefore, these technologies cannot be directly applied to CRSNs.

Zhong *et al*. investigated a joint optimal energy-efficient cooperative spectrum sensing and transmission in a multi-channel CR system [13]. The network energy efficiency is maximized by jointly optimizing the sensing time, the number of cooperative sensing SUs, and the transmission bandwidth. However, the authors optimize the number of cooperative sensing SUs using the exhaustive search method, and then investigate the optimum sensing time, transmission bandwidth and power. If the network consists of hundreds of SUs, the computational complexity will be high. Luo *et al*. proposed a scheme that minimizes the mean sensing time with the goal 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 [14]. Their scheme minimizes the spectrum sensing time, and thus maximizes the time remaining for data transmission. They show that the minimum average sensing time can be attained when the false alarm probability reaches its threshold. However, even though the maximum time is left for data transmission, the probability of sensing errors becomes high due to the low detection probability and the high false alarm probability. This will cause more interference to the PU and lose more opportunities for data transmission.

In terms of CRSNs, Deepak *et al.* proposed a method based on cognitive monitoring network, where a separate network of sensors is deployed to perform cooperative spectrum sensing within a network coverage area [15]. Thus, instead of performing spectrum sensing, SUs spend a short amount of time to send query to and then receive sensing results from monitoring sensors. This allows the secondary throughput to be maximized irrespective of the sensing duration. However, the delay due the communication between SUs and monitoring sensors will increase. In addition, monitoring sensors will expend energy for spectrum sensing. Jiang *et al*. investigated an energy-efficient optimization method for spectrum sensing and node selection [16]. 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 way, the sensing time can be reduced and unnecessary sensing energy consumption can be avoided. However, if a sensor node collects just a few samples and then stops spectrum sensing, the probability of sensing error will increase.

Awin *et al*. investigated a joint optimal transmission power and sensing time for energy-efficient spectrum sensing [17]. The optimization problem is formulated as a function of two variables (i.e., transmission power and sensing time) subjected to PU protection constraints. An iterative algorithm is applied 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 for energy efficient cognitive small cell network [18]. The cross-tier interference mitigation, imperfect hybrid spectrum sensing, and energy efficiency are considered. A 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. Li *et al*. proposed an energy-efficient technique for cooperative spectrum sensing [19]. In their method, all SUs perform cooperative spectrum sensing for one period. If the sensing result shows that the PU is absent, SUs will transmit data. The optimal sensing time is attained by optimizing the ratio of the secondary throughput and the total energy consumption. However, the work in [17], [18], and [19] perform spectrum sensing just once and then find the optimal sensing time that maximizes the network energy efficiency. If miss detections and false alarms occur, there is no opportunity to correct these sensing errors. This will cause interference and the available spectrum opportunities will be wasted. In our proposed scheme, spectrum sensing will be performed again when the sensing results of the current and previous frames are different. This allows the sensing errors have a certain probability to be corrected.

3 SYSTEM MODEL

This paper considers a CRSN consisting of a single PU and multiple SUs communicating on a licensed band, which is subdivided into several non-overlapping sub-bands. Moreover, an SU is assigned to a sub-band to sense whether it is occupied by the PU. Time is divided into equal sized frames, where each frame consists of two phases: the *sensing* phase and the *data transmission* phase. Each SU performs spectrum sensing during the sensing phase to detect the PU. Each SU will transmit data if the PU is detected to be idle or absent; otherwise, it will keep silent and wait for the next frame. Furthermore, each

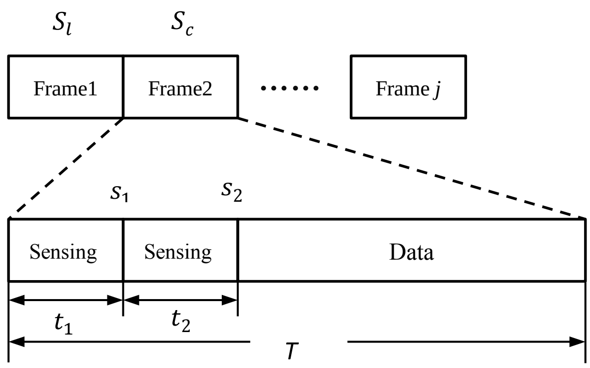

Fig. 2 Frame structure

SU is assumed to always have data to transmit if the sensing result shows that the PU is absent. If the sensing results of the current and previous frames are the same, an SU simply performs spectrum sensing only once for the current frame. If the sensing result of the current frame is different from the sensing result of the previous frame, an SU will perform another spectrum sensing to ensure the accuracy of the first sensing result. Note that if the first and the second sensing results of the current frame are different, the second sensing result will be taken as the final sensing decision, even if it is wrong. This can occur because the spectrum sensing is not perfect, and thus an SU may not be able to ascertain the actual states of the PU. The spectrum sensing accuracy is related to the miss detection and false alarm probabilities. Therefore, in order to simplify the proposed scheme, the sensing result of the previous frame is considered as the correct state (i.e., the actual state of the PU), even though it may be wrong.

Fig. 2 shows the frame structure of the proposed scheme. The fame length is T and t_1 and t_2 represent the first and the second spectrum sensing period, respectively. As mentioned before, if the first and the second sensing results of the current frame are different, the second sensing result will be taken as the final sensing decision. Since the longer sensing time can lead to a better sensing performance, the condition $t_2 \geq t_1$ is imposed to increase the accuracy of the second sensing result. In addition, S_l and S_c represent the actual state of PU for the previous and the current frame, respectively, and s_1 and s_2 denote the first and the second sensing results of the current frame, respectively. The variables $S_l, S_c,$ s_1, and s_2 are assigned 0 and 1 to represent the absence and presence of a PU, respectively, and thus have the following meanings:

S_l=0 or 1: PU was idle or busy in the previous frame.

S_c=0 or 1: PU is idle or busy in the current frame.

s_1=0 or 1: The first sensing result of the current frame indicating that PU is idle or busy.

s_2=0 or 1: The second sensing result of the current frame indicating that PU is idle or busy.

Based on S_l, S_c, s_1, and s_2, there are 12 possible cases considered by the proposed scheme:

Case 1 (S_l=0, S_c=0, s_1=0): The PU is idle during both the previous and the current frames, and the SU detects that the PU is idle during t_1. Since the sensing result (s_1=0) is the same as the previous frame (S_l=0), the SU will perform spectrum sensing only once, and then transmit data during the time period $T - t_1$.

Case 2 (S_l=0, S_c=0, s_1=1, s_2=0): The PU is idle during both the previous and the current frames, but a false alarm occurs and the SU detects that the PU is busy during t_1. Since the first sensing result (s_1=1) is different from the previous frame (S_l=0), the SU will perform spectrum sensing again during t_2. The second sensing result (s_2=0) is taken as the final sensing result. Since the final sensing result shows that the PU is idle, the SU will transmit data during the time period $T - t_1 - t_2$. Even though a false alarm occurred during t_1, this error can be corrected during t_2 and, as a consequence, higher secondary throughput will be achieved.

Case 3 (S_l=0, S_c=0, s_1=1, s_2=1): A false alarm occurs during both t_1 and t_2. The SU will keep silent and wait for the next frame, and thus there is no secondary throughput.

Case 4 (S_l=1, S_c=0, s_1=0, s_2=1): The first sensing result (s_1=0) is different from the final sensing result of the previous frame (S_l=1), thus the SU will perform spectrum sensing again during t_2. However, a false alarm occurs during t_2. Therefore, the SU will keep silent and wait for the next frame, and thus there is no secondary throughput.

Case 5 (S_l=1, S_c=0, s_1=0, s_2=0): The SU performs spectrum sensing during t_1 and t_2, and both sensing results indicate that the PU is absent. The data will be successfully transmitted.

Case 6 (S_l=1, S_c=0, s_1=1): A false alarm occurs during t_1. Nonetheless, the first sensing result (s_1=1) is the same as the previous frame (S_l=1), thus the SU will not perform spectrum sensing again. The SU will keep silent and wait for the next frame, and thus there is no secondary throughput.

Case 7 (S_l=1, S_c=1, s_1=0, s_2=1): A miss detection occurs during t_1 and the first sensing result (s_1=0) is different from the previous frame (S_l=1), but the PU is detected during t_2. As a consequence, a better protection is provided against miss detection and more energy will be saved.

Case 8 (S_l=1, S_c=1, s_1=0, s_2=0): A miss detection occurs during t_1 and t_2. Since the SU failed to detect the PU, it will transmit data. However, the data transmission will fail and there will be no secondary throughput.

Cases	State				Outcome		
	S_l	S_c	s_1	s_2	FA	MD	TP
1	0	0	0	N/A	N	N	Y
2	0	0	1	0	N	N	Y
3	0	0	1	1	Y	N	N
4	1	0	0	1	Y	N	N
5	1	0	0	0	N	N	Y
6	1	0	1	N/A	Y	N	N
7	1	1	0	1	N	N	N
8	1	1	0	0	N	Y	N
9	1	1	1	N/A	N	N	N
10	0	1	0	N/A	N	Y	N
11	0	1	1	0	N	Y	N
12	0	1	1	1	N	N	N

Table 1 Summary of spectrum sensing cases

Case 9 (S_l=1, S_c=1, s_1=1): The SU successfully detects the PU, and it will remain silent and wait for the next frame.

Case 10 (S_l=0, S_c=1, s_1=0): A miss detection occurs during t_1 and the sensing result (s_1=0) is the same as the previous frame (S_l=0), thus spectrum sensing will be performed only once. Since data transmission is successful only when the PU is actually absent, there will be no secondary throughput.

Case 11 (S_l=0, S_c=1, s_1=1, s_2=0): The SU detects the PU during t_1. Since the sensing result (s_1=1) is different from the sensing result of the previous frame (S_l=0), the SU performs spectrum sensing again, and a miss detection occurs during t_2. Therefore, the data transmission will fail and there will be no secondary throughput.

Case 12 (S_l=0, S_c=1, s_1=1, s_2=1): The SU successfully detects the PU during t_1 and t_2, and thus it will remain silent and wait for the next frame.

Based on the aforementioned cases, the valid secondary throughput can be achieved only for cases 1, 2 and 5, while cases 3, 4 and 6 will lead to false alarm. Cases 7, 9 and 12 can successfully detect the PU, while cases 8, 10, and 11 will cause miss detection. The summary of 12 cases is presented in Table 1, which also includes for each case whether or not false alarm (FA), miss detection (MD), and valid throughput (TP) occur.

4 PROBLEM FORMULATION

This section analyzes how sensing time affects the sensing accuracy and the secondary throughput

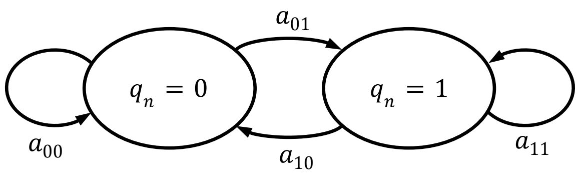

Fig. 3 Markov model for spectrum occupancy of PUs

by developing an analytical model. The main objective of the analysis is to find an optimal sensing time that maximizes network energy efficiency as well as yields good sensing accuracy.

4.1 Energy Detector Based Spectrum Sensing

Our analysis uses a binary hypothesis to formulate the spectrum sensing. Let H_0 and H_1 denote the hypothesis of the idle and busy states of a PU, respectively. The probabilities of H_0 and H_1 are denoted as p_0 and p_1, respectively, and $p_0 + p_1 = 1$. In the proposed scheme, the PU's spectrum occupancy is assumed to follow a Markov chain model shown in Fig. 3. The existence of a Markov chain for the spectrum occupancy by PUs has been validated in [20]. The state space of the Markov process is X=$\{H_0, H_1\}$, where $H_0 = 0$ and $H_1 = 1$. As shown in Fig. 3, q_n which denotes the actual state of PU can be 0 or 1 (i.e., H_0 or H_1). The state transition probability matrix A is defined as A=$\{a_{ij}\}$, $a_{ij} = P(q_{n+1} = j|q_n = i)$ for $i, j \in X$, where q_n and q_{n+1} denote the actual states of PU in n^{th} and $(n+1)^{st}$frame, respectively. More specifically, a_{00} and a_{11} denote the probabilities that the state of PU maintains H_0 and H_1 from the current frame to the next frame, respectively. a_{01} and a_{10} denote the probabilities that the state of PU becomes H_1 from H_0 and H_0 from H_1 in the next frame, respectively. In addition, $a_{00} = a_{10} = p_0$ and $a_{01} = a_{11} = p_1$ are assumed. Moreover, the busy and idle periods of PU are assumed to be longer than the frame length. As a consequence, the probability that the state of PU changes more than once in a frame is negligible.

In order to maximize the secondary throughput and at the same time provide some desired level of protection to PU, t_1 needs to be minimized. Moreover, if a false alarm or a miss detection occurs, the second spectrum sensing time t_2 provides an opportunity to correct the sensing errors with a certain probability to improve performance. Therefore, t_1 can be expressed in terms of detection probability, p_d, and false alarm probability, p_f , as follows:

$$min\ t_1 \quad s.t.\ p_d \geq p_d^{th}, p_f \leq p_f^{th}, \tag{1}$$

where p_d^{th} and p_f^{th} represent the respective predefined thresholds that guarantee the necessary protection against interference and secondary throughput for PUs.

Due to the energy constraint in CRSNs, the value of t_2 can be calculated by maximizing the network energy efficiency. The proposed method utilizes an energy detector for spectrum sensing, which is widely used due to its simplicity and requires no prior knowledge of PUs [21-23]. The test statistic of an energy detector $T(y)$ can be calculated as follows:

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

where N is the number of samples performed during the sensing phase and $y(n)$ is the sampled signal. When the state of PU is H_0, then $y(n) = u(n)$, where $u(n)$ is the noise, which is a Gaussian iid random process with mean of zero and variance of σ_u^2. On the other hand, when the state of PU is H_1, $y(n) = s(n) + u(n)$, where $s(n)$ is the signal of PU, which is an iid random process with mean of zero and variance of σ_s^2 . The test statistic follows the central and non-central chi-square distribution with $2N$ degrees of freedom under the hypotheses H_0 and H_1, respectively [24]. The test statistic can be approximated as a Gaussian random process because the central limit theorem can be utilized when the value of N is sufficiently large [25], and thus $T(y)$ is given by

$$T(y) \sim \begin{matrix} \mathcal{N}(N, 2N) & H_0 \\ \mathcal{N}(N(1+\gamma), 2N(1+\gamma)^2) & H_1 \end{matrix}, \tag{3}$$

where $\gamma = \frac{\sigma_s^2}{\sigma_u^2}$ is the received Signal to Noise Ratio (SNR) from PU for PU detection. The detection probability p_d and the false alarm probability p_f can be expressed by

$$p_d = p(H_1|H_1), \tag{4}$$

$$p_f = p(H_1|H_0). \tag{5}$$

The miss detection is defined as when SU does not detect the presence of PU when PU is actually present. Therefore, the miss detection probability p_m can be expressed as $p_1(1 - p_d)$. Based on the test statistics of $T(y)$, the detection probability $p_d = p(T(y) > \lambda|H_1)$ and the false alarm probability $p_f = p(T(y) > \lambda|H_0)$ can be evaluated in terms of Q-function as [12, 26]:

$$p_d = Q\left(\frac{\lambda}{\sqrt{2N}(1+\gamma)} - \sqrt{\frac{N}{2}}\right), \tag{6}$$

$$p_f = Q\left(\frac{\lambda}{\sqrt{2N}} - \sqrt{\frac{N}{2}}\right), \tag{7}$$

where λ is the sensing threshold. If the received power is higher than λ, PU is considered to be busy; otherwise, PU is considered to be idle. $Q(\cdot)$ is the Q-function given as

$$Q(x) = \frac{1}{\sqrt{2\pi}} \int_x^{\infty} exp\left(-\frac{u^2}{2}\right) du. \tag{8}$$

The number of samples *N* can be represented by the following equation [24]:

$$N = 2tW, \tag{9}$$

where t is the sensing time and W is the bandwidth of the PU signal. Since $Q(x)$ is a monotonically decreasing function, both p_d and p_f will increase as sensing time increases. The sensing threshold λ can be calculated using Eq. (6) as shown below:

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

Substituting Eqs. (9) and (10) into Eq. (7) leads to the following equation for p_f:

$$p_f = Q\left((1+\gamma)Q^{-1}(p_d) + \gamma\sqrt{tW}\right). \tag{11}$$

According to Eq. (11), p_f decreases as p_d decreases. Since the objective is to maximize the secondary throughput and at the same time provide protection for PU from interference, the detection probability during t_1, p_d^1, is set equal to p_d^{th}. As mentioned earlier, t_1 can be calculated based on Eq. (1) subject to the constraint $p_f \leq p_f^{th}$. Thus, when p_f for t_1 equals to p_f^{th}, t_1 is minimized. Therefore, solving Eq. (11) for t with p_f set to p_f^{th} and p_d set to p_d^{th} leads to the following equation for t_1:

$$t_1 = \frac{\left(\left(Q^{-1}(p_f^{th}) - (1+\gamma)Q^{-1}(p_d^{th})\right)/\gamma\right)^2}{W}. \tag{12}$$

As mentioned earlier, t_2 can be calculated by maximizing the network energy efficiency. In the following subsection, an analytical model is developed to seek the optimal value of t_2. In the proposed scheme, the detection probability for t_2, p_d^2, is also fixed at p_d^{th}. As previously mentioned, t_2 should not be smaller than t_1. Since Q in Eq. (11) is a decreasing function, p_f decreases as sensing time t increases, i.e., $p_f^2 \leq p_f^1$, where p_f^1 and p_f^2 denote the false alarm probabilities of t_1 and t_2, respectively. Thus, the sensing accuracy of t_2 is better. This is the reason why the sensing result of t_2 is taken as the final sensing result if it is different from the sensing result of t_1.

4.2 Problem formulation

Among the 12 possible cases discussed in Sec. 3, the ones that provide valid secondary throughput are cases 1, 2 and 5, which are denoted as R_1, R_2, and R_5, respectively, and are represented as follows:

$$R_1 = p_0^2(1-p_f^1)(T-t_1)C, \tag{13a}$$

$$R_2 = p_0^2 p_f^1(1-p_f^2)(T-t_1-t_2)C, \tag{13b}$$

$$R_5 = p_1 p_0 \left(1 - p_f^1\right)\left(1 - p_f^2\right)(T - t_1 - t_2)C, \tag{13c}$$

where C denotes the channel capacity under the hypothesis H_0. According to Shannon theory, C can be calculated by

$$C = \log_2(1 + \gamma_s). \tag{14}$$

where γ_s is the SNR received from the SU transmitter.

The total average secondary throughput R_{total} is then given by

$$R_{total} = R_1 + R_2 + R_5. \tag{15}$$

Based on the above discussion, the energy consumption for the 12 cases, E_{1-12}, and the total average energy consumption, E_{total}, can be expressed as follows:

$$E_1 = p_0^2\left(1 - p_f^1\right)(t_1 E_s + (T - t_1)E_t), \tag{16a}$$

$$E_2 = p_0^2 p_f^1\left(1 - p_f^2\right)\left((t_1 + t_2)E_s + (T - t_1 - t_2)E_t\right), \tag{16b}$$

$$E_3 = p_0^2 p_f^1 p_f^2 (t_1 + t_2)E_s, \tag{16c}$$

$$E_4 = p_1 p_0 p_f^2\left(1 - p_f^1\right)(t_1 + t_2)E_s, \tag{16d}$$

$$E_5 = p_1 p_0\left(1 - p_f^1\right)\left(1 - p_f^2\right)\left((t_1 + t_2)E_s + (T - t_1 - t_2)E_t\right), \tag{16e}$$

$$E_6 = p_1 p_0 p_f^1 t_1 E_s, \tag{16f}$$

$$E_7 = p_1^2 p_d^1 (1 - p_d^2)(t_1 + t_2)E_s, \tag{16g}$$

$$E_8 = p_1^2 (1 - p_d^1)(1 - p_d^2)\left((t_1 + t_2)E_s + (T - t_1 - t_2)E_t\right), \tag{16h}$$

$$E_9 = p_1^2 p_d^1 t_1 E_s, \tag{16i}$$

$$E_{10} = p_0 p_1 (1 - p_d^1)(t_1 E_s + (T - t_1)E_t), \tag{16j}$$

$$E_{11} = p_0 p_1 p_d^1 (1 - p_d^2)\left((t_1 + t_2)E_s + (T - t_1 - t_2)E_t\right), \tag{16k}$$

$$E_{12} = p_0 p_1 p_d^1 p_d^2 (t_1 + t_2)E_s, \tag{16l}$$

$$E_{total} = E_1 + E_2 + E_3 + E_4 + E_5 + E_6 + E_7 + E_8 + E_9 + E_{10} + E_{11} + E_{12}, \tag{16m}$$

where E_s and E_t are the energy consumed by spectrum sensing and data transmission for unit time, respectively.

In this paper, energy efficiency is defined as the number of bits transmitted per unit of energy consumption [27]. Therefore, the objective function of energy efficiency η can be expressed as:

$$\eta = \frac{R_{total}}{E_{total}}. \tag{17}$$

In Eq. (17), t_2 is the only unknown variable. The value of t_2 that maximizes the function η is the optimal sensing time. As mentioned before, the second sensing result will be taken as the final sensing decision when the first and the second sensing results of the current frame are different. Therefore, the condition $t_2 \geq t_1$ is assumed to increase the accuracy of the second sensing result. Moreover, since the frame time is set as T, t_2 must satisfy the constraint $t_1 \leq t_2 \leq T$. In addition, since both p_d^1 and p_d^2 are fixed at p_d^{th}, p_f^2 must also satisfy the constraint $p_f^2 \leq p_f^{th}$ to guarantee the requirement of secondary throughput for CRSNs when the optimal value of t_2 is calculated. Therefore, the maximization problem can be formulated as follows:

$$max\ \eta\,(t_2)\ \ s.t.\ t_1 \leq t_2 \leq T,\ p_f^2 \leq p_f^{th}. \tag{18}$$

4.3 Golden Section Search method

In order to determine the optimal value of t_2, the Golden Section Search method is applied to find the extremum (minimum or maximum) of a unimodal function. This subsection proves that the objective function $\eta(t_2)$ is a concave function, and the Golden Section Search method can be used to find the optimal value of t_2 that maximizes the energy efficiency.

Based on Eq. (15), the second derivative of R_{total} can be calculated as follows:

$$R''_{total} = R''_1 + R''_2 + R''_5, \tag{19}$$

where R''_1, R''_2, and R''_5 are the second derivatives of R_1, R_2, and R_5 in terms of t_2, respectively. According to Eq. (13a), (13b), and (13c), R''_1, R''_2, and R''_5 can be expressed as follows:

$$R''_1 = 0, \tag{20a}$$

$$R''_2 = -p_0^2 p_f^1 C(T - t_1) p_f^{2''} + 2p_0^2 p_f^1 C p_f^{2'} + p_0^2 p_f^1 C t_2 p_f^{2''}, \tag{20b}$$

$$R''_5 = -p_1 p_0 C\left(1 - p_f^1\right)(T - t_1) p_f^{2''} + 2p_1 p_0 C\left(1 - p_f^1\right) p_f^{2'} + p_1 p_0 C\left(1 - p_f^1\right) t_2 p_f^{2''}, \tag{20c}$$

where $p_f^{2'}$ and $p_f^{2''}$ are the first and second derivatives of p_f^2 in terms of t_2, respectively. According to Eq. (11), it can be obtained that $p_f^{2'} < 0$ and $p_f^{2''} > 0$. In addition, because $T - t_1 \geq t_2$, $R''_2 < 0$ and $R''_5 < 0$. Therefore, the relation $R''_{total} = R''_1 + R''_2 + R''_5 < 0$ can be obtained, and thus R_{total} is a concave function.

Then, the second derivative of E_{total} can be calculated in the same manner as given below:

$$E''_{total} = E''_1 + E''_2 + E''_3 + E''_4 + E''_5 + E''_6 + E''_7 + E''_8 + E''_9 + E''_{10} + E''_{11} + E''_{12}, \tag{21}$$

where E''_{1-12} denote the second derivatives of E_{1-12} in terms of t_2, respectively. According to the functions of E_{1-12}, E''_{1-12} can be expressed as follows:

$$E''_1 = 0, \tag{22a}$$

$$E''_2 = -p_0^2 p_f^1 (TE_t - t_1 E_t + t_1 E_s) p_f^{2''} - 2p_0^2 p_f^1 (E_s - E_t) p_f^{2'} - p_0^2 p_f^1 (E_s - E_t) t_2 p_f^{2''}, \tag{22b}$$

$$E_3'' = p_0^2 p_f^1 E_s t_1 p_f^{2''} + 2p_0^2 p_f^1 E_s p_f^{2'} + p_0^2 p_f^1 E_s t_2 p_f^{2''}, \quad (22c)$$

$$E_4'' = p_1 p_0 E_s t_1 \left(1 - p_f^1\right) p_f^{2''} + 2p_1 p_0 E_s \left(1 - p_f^1\right) p_f^{2'} + p_1 p_0 E_s \left(1 - p_f^1\right) t_2 p_f^{2''}, \quad (22d)$$

$$E_5'' = -p_1 p_0 \left(1 - p_f^1\right)(TE_t - t_1 E_t + t_1 E_s) p_f^{2''} - 2p_1 p_0 \left(1 - p_f^1\right)(E_s - E_t) p_f^{2'} \quad (22e)$$

$$-p_1 p_0 \left(1 - p_f^1\right)(E_s - E_t) t_2 p_f^{2''},$$

$$E_6'' = 0, \quad (22f)$$

$$E_7'' = 0, \quad (22g)$$

$$E_8'' = 0, \quad (22h)$$

$$E_9'' = 0, \quad (22i)$$

$$E_{10}'' = 0, \quad (22j)$$

$$E_{11}'' = 0, \quad (22k)$$

$$E_{12}'' = 0. \quad (22l)$$

Since $E_1'' = E_6'' = E_7'' = E_8'' = E_9'' = E_{10}'' = E_{11}'' = E_{12}'' = 0$, focusing on E_2'', E_3'', E_4'', and E_5'' leads to the following equations:

$$E_2'' + E_3'' = -p_0^2 p_f^1 E_t (T - t_1) p_f^{2''} + 2p_0^2 p_f^1 E_t p_f^{2'} + p_0^2 p_f^1 E_t t_2 p_f^{2''}, \quad (23)$$

$$E_4'' + E_5'' = -p_1 p_0 E_t \left(1 - p_f^1\right)(T - t_1) p_f^{2''} + 2p_1 p_0 E_t \left(1 - p_f^1\right) p_f^{2'} + p_1 p_0 E_t \left(1 - p_f^1\right) t_2 p_f^{2''}. \quad (24)$$

Since $E_2'' + E_3'' < 0$ and $E_4'' + E_5'' < 0$, $E_{total}'' < 0$ and as a result E_{total} is also a concave function. In addition, $\frac{R_{total}''}{E_{total}''} = \frac{C}{E_t}$, where $\frac{C}{E_t}$ is a fixed positive number larger than 1 according to the predefined values in Table 2. This means R_{total} and E_{total} increase or decrease simultaneously, and the variation rate of R_{total} is $\frac{C}{E_t}$ times of the variation rate of E_{total}.

Based on Eq. (17), the following equation can be obtained for $\eta(t)$:

$$\eta(t) = \frac{R_{total}(t)}{E_{total}(t)}, \quad (25)$$

$$\eta(t + \Delta t) = \frac{R_{total}(t + \Delta t)}{E_{total}(t + \Delta t)}, \quad (26)$$

where Δt denotes the increased time. Therefore, the difference of $\eta(t + \Delta t)$ and $\eta(t)$ can be expressed as

$$\eta(t + \Delta t) - \eta(t) = \frac{R_{total}(t + \Delta t)}{E_{total}(t + \Delta t)} - \frac{R_{total}(t)}{E_{total}(t)}. \quad (27)$$

When both sides of Eq. (27) are multiplied by $\frac{E_{total}(t+\Delta t)}{R_{total}(t)}$, the following can be obtained.

$$\frac{E_{total}(t + \Delta t)}{R_{total}(t)} \big(\eta(t + \Delta t) - \eta(t)\big) = \frac{R_{total}(t + \Delta t)}{R_{total}(t)} - \frac{E_{total}(t + \Delta t)}{E_{total}(t)}. \quad (28)$$

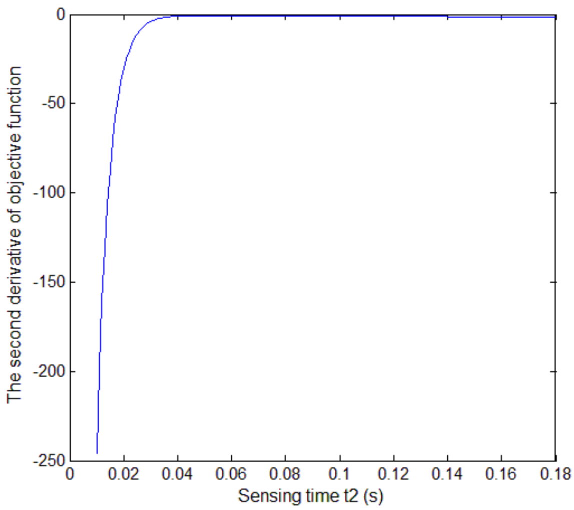

Fig. 4 The second derivative of objective function η as a function of sensing time t_2

As mentioned before, we have known that the variation rate of R_{total} is $\frac{C}{E_t}$ times of the variation rate of E_{total}, and $\frac{E_{total}(t+\Delta t)}{R_{total}(t)}$ is positive. When R_{total} and E_{total} increase, $\frac{R_{total}(t+\Delta t)}{R_{total}(t)}$ becomes larger than $\frac{E_{total}(t+\Delta t)}{E_{total}(t)}$ and thus $\eta(t+\Delta t)-\eta(t)>0$. When R_{total} and E_{total} decrease, $\frac{R_{total}(t+\Delta t)}{R_{total}(t)}$ becomes smaller than $\frac{E_{total}(t+\Delta t)}{E_{total}(t)}$ and thus $\eta(t+\Delta t)-\eta(t)<0$. In other words, $\eta(t)$ increases when R_{total} and E_{total} increase and $\eta(t)$ decreases when R_{total} and E_{total} decrease. Therefore, $\eta(t)$ is also a concave function, and the optimal value of t_2 that maximizes the energy efficiency must exist.

In addition, MATLAB was also utilized to show that $\eta(t)$ is a concave function.

Criteria: A function $f(x)$: $U \subset R \rightarrow R$ is concave if and only if its second derivative $f''(x) \leq 0$.

Proof: The second derivative of $\eta(t)$ is calculated using MATLAB with $p_0 = 0.7$ and the parameters presented in Table 2. The result is presented in Fig. 4, which shows that the second derivative of $\eta(t_2)$ is always less than 0, and as a consequence, $\eta(t_2)$ is a concave function. Moreover, Fig. 4 shows that the range of t_2 is between 0.01 and 0.18.

The Golden Section Search method can be applied if a function $f(x)$ is continuous and unimodal within the interval $[a,b]$. The golden ratio can be used to determine location of two interior points within the interval $[a,b]$, and one of the interior points can be re-used in the next iteration. Thus, the approximation of extremum can be achieved by successively narrowing the interval in which the extremum lies on. In general, the Golden Section Search method is used to find the minimum. Thus, $-\eta(t_2)$ is minimized (which means the energy efficiency of the SU is maximized) to find the optimal value of t_2.

The pseudo-code for the Golden Section Search method used in this paper is presented in Algorithm 1. In line 1, the lower and upper bounds of interval a and b and the error limit ε are provided as input. Note that ε should be a small value. λ is the golden ratio (λ= 1.6180...). Then, the interior points a_1 and a_2 within the interval [a,b], and the corresponding values of $-\eta(a_1)$ and $-\eta(a_2)$ are calculated (line 3-4). In lines 5-9, a check is made to determine whether the new lower and upper bounds of the interval satisfy the condition $|a-b| \leq \varepsilon$. If the condition is satisfied, the optimal sensing time t_2^* can be approximated as $1/2\,(a+b)$ (line 10); otherwise, the procedure repeats from line 5.

Algorithm 1 The pseudo-code of the golden section search method

1: **procedure** GOLDEN_SEARCH_METHOD ($a,\ b,\ \varepsilon$)
2: $\lambda = 0.618$
3: $a_1 = b - \lambda(b-a),\ y_1 = -\eta(a_1)$
4: $a_2 = a + \lambda(b-a),\ y_2 = -\eta(a_2)$
5: **while** $|a-b| \geq \varepsilon$ **do**
6: **if** $y_1 > y_2$ **then**
7: $a = a_1,\ a_1 = a_2,\ a_2 = a + \lambda(b-a)$
8: **else**
9: $b = a_2,\ a_2 = a_1,\ a_1 = b - \lambda(b-a)$
10: **return** $t_2^* = \frac{1}{2}(a+b)$

5 PERFORMANCE EVALUATION

This section presents the performance evaluation of the proposed scheme using MATLAB. The performance of the proposed scheme is also compared with two other schemes proposed in [14] and [19]. In addition, our simulation study considers varying levels of PU activity, which is in contrast to most prior work that simply perform simulations using a fixed level of PU activity.

5.1 Simulation parameters

The simulation environment is a CRSN with one PU and ten SUs that are allocated randomly within the communication range of the PU. The licensed band occupied by the PU is subdivided into ten

Parameters	Value
p_d^{th}	0.9
p_f^{th}	0.1
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*

Table 2 Simulation Parameters

non-overlapping sub-bands, which are assigned to the ten SUs. The parameters used in our simulations are shown in Table 2. The values of p_d^{th} and p_f^{th} are set according to the IEEE 802.22 cognitive radio Wireless Regional Area Network (WRAN) standard [28]. The frame length T and the bandwidth of a sub-band W are set as 0.2 s and 6 MHz, respectively. Since γ_s is 20 dB, each SU has a channel capacity (C) of $\log_2(1+\gamma_s)$= 6.6582 bits/sec/Hz. The level of PU activity is defined as the probability that PU is absent p_0, where $0 < p_0 < 1$. Finally, the energy consumed by spectrum sensing (E_s) and data transmission (E_t) for unit time are set to the same values as in [19].

5.2 Simulation results

Fig. 5 shows the energy efficiency η of the proposed scheme as a function of sensing time t_2 when $p_0 = 0.7$. Note that p_0 is fixed at 0.7 to show the variation of the energy efficiency as a function of t_2. The simulation results with varying p_0 will be shown in Figs. 7~9. In Eq. (12), since p_d^{th} = 0.9, p_f^{th}= 0.1, W = 6 MHz, and γ= -20 dB, the sensing period t_1 is the only unknown variable and can be calculated as 0.011 s. As can be seen, the energy efficiency at first increases as t_2 increases, and then after the optimal point, it decreases again. The main reason for this is that p_d^2 is also fixed at p_d^{th}, and therefore p_f^2 decreases as t_2 increases according to Eq. (11). During t_2, the probabilities of correcting false alarm and miss detection that occurred during t_1 are $1-p_f^2$ and p_d^{th}, respectively, which improve energy efficiency. However, the time remaining for data transmission decreases as t_2 increases, which degrades network throughput. Therefore, after the optimal point for t_2, the energy efficiency decreases again, even though the sensing performance of t_2 improves. Fig. 5 confirms that the objective function $\eta(t_2)$ is a concave function, and its optimal value that maximizes the network energy efficiency actually exists. Note that the false alarm probability p_f^2 is greater than p_f^{th} when the sensing period is very short.

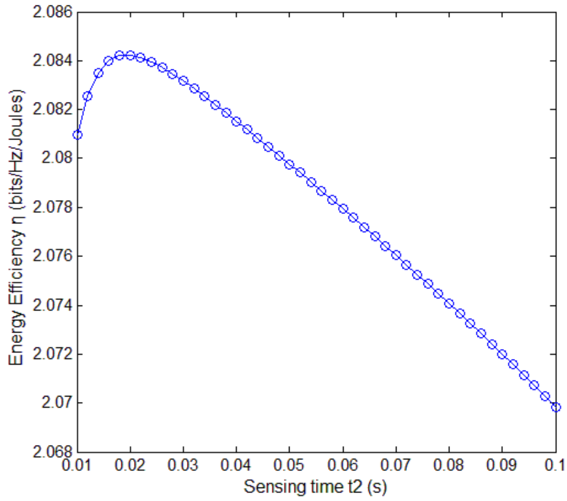

Fig. 5 Energy efficiency η as a function of sensing time t_2 with $p_0 = 0.7$

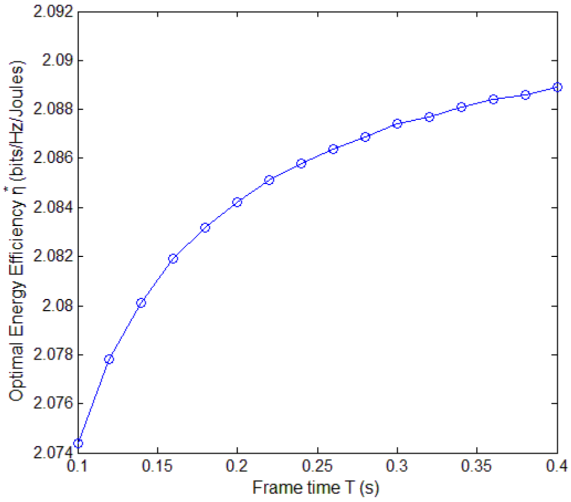

Fig. 6 The optimal energy efficiency η^* as a function of frame time *T* with $p_0 = 0.7$

In the next set of simulations, the optimal sensing period for t_2 will be obtained subjected to the requirement $p_f^2 \leq p_f^{th}$. Actually, because $t_2 \geq t_1$, the constraint $p_f^2 \leq p_f^{th}$ must be satisfied.

Fig. 6 shows the optimal energy efficiency η^* of the proposed scheme as a function of frame time *T* when p_0 is fixed as 0.7. As can be seen, the optimal network energy efficiency of the proposed scheme increases with *T*. The reason is that in general miss detection and false alarm have a greater negative impact on energy efficiency when *T* is longer. For example, if a miss detection occurs, the PU will be interfered by SUs' communications for a longer time as *T* increases. If a false alarm occurs, the opportunities for SUs to achieve secondary throughput decreases as *T* increases. However, these sensing errors can be corrected to some extent by the proposed scheme. Hence, energy efficiency can be

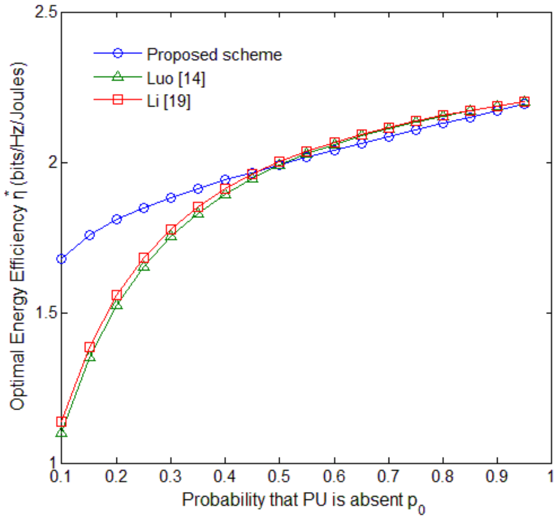

Fig. 7 Comparison of the optimal energy efficiency as a function of p_0 and T=0.2 s

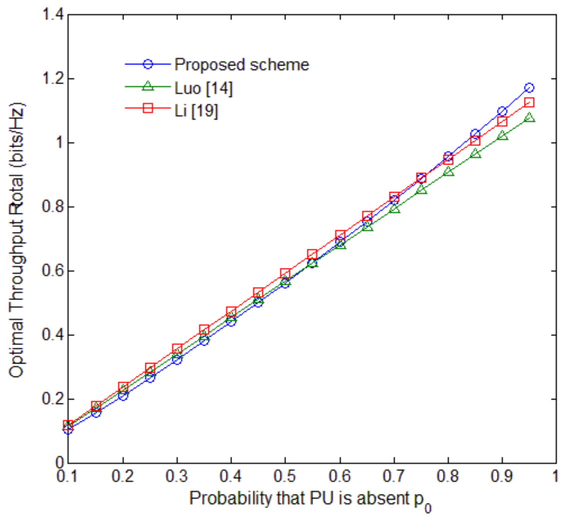

Fig. 8 Comparison of the optimal secondary throughput as a function of p_0 and T=0.2 s

improved when T becomes longer.

Fig. 7 compares the optimal energy efficiency η^* of the proposed scheme against the methods proposed in [14] and [19] as a function of p_0 (where p_0 is in the interval [0.1, 0.95]) with the frame length T fixed at 0.2 s. As can be seen, the proposed scheme is much better than the other two schemes when PUs are more active. More specifically, when p_0 = 0.1, the energy efficiency of the proposed scheme is 52% and 47% higher than the methods proposed in [14] and [19], respectively. As p_0 increases, the energy efficiency of the proposed scheme becomes slightly lower than the ones proposed

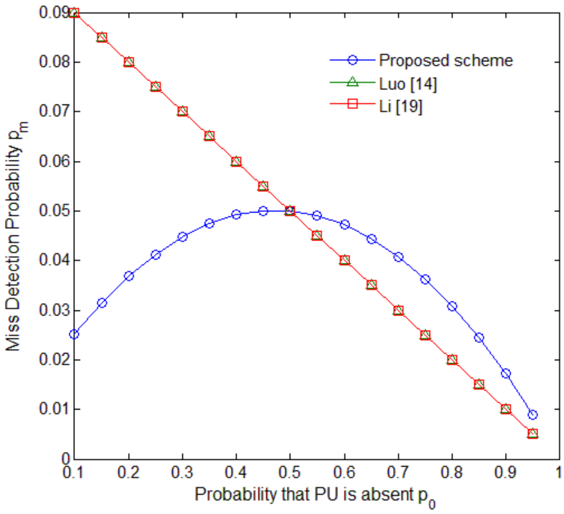

Fig. 9 Comparison of the miss detection probability as a function of p_0 and *T*=0.2 s

in [14] and [19]. When p_0 = 0.7, the energy efficiency of the proposed scheme is only 1.3% and 1.5% lower than the ones proposed in [14] and [19], respectively. Furthermore, the energy efficiency of the proposed scheme is almost the same with the ones in [14] and [19] when the value of p_0 becomes 0.95. These results clearly show that our proposed scheme is better when the varying PU activity is considered. The reason for this can be explained by Fig. 8 and Fig. 9.

Fig. 8 shows that the secondary throughput results of these three schemes as a function of p_0 for *T* fixed at 0.2 s. In the proposed scheme, even though the SUs may spend more time performing the second spectrum sensing, the network throughput can be improved when false alarms can be corrected. This is the reason why the throughput results of these three schemes are almost the same.

Fig. 9 compares the miss detection probability p_m of the three schemes as a function of p_0 for *T* fixed at 0.2 s. Note that the methods proposed in [14] and [19] have the same miss detection probability, denoted as p_m^2, as given below:

$$p_m^2 = p_1(1 - p_d), \tag{29}$$

Fig. 9 shows that the miss detection probability of the proposed scheme is much lower than the ones proposed in [14] and [19] when $p_0 < 0.5$. In particular, when $p_0 = 0.1$, the miss detection probabilities of the methods in [14] and [19] are 257% higher than our proposed scheme. However, when $p_0 \geq 0.5$, the miss detection probability of the proposed scheme is slightly higher. When $p_0 = 0.7$, the miss detection probability of the proposed scheme is 36% higher than the other two schemes. Among the 12 cases, the cases 8, 10, and 11 can lead to miss detection. Therefore, the mathematical model for miss detection probability of the proposed method p_m^1 can be formulated as follows:

$$p_m^1 = p_1^2(1-p_d)^2 + p_0p_1(1-p_d) + p_0p_1p_d(1-p_d), \quad (30)$$

where the first, second, and third terms represent the probabilities of the cases 8, 10, and 11, respectively. Therefore, the difference between p_m^1 and p_m^2 can be calculated as

$$p_m^1 - p_m^2 = p_1p_d(1-p_d)(p_0-p_1). \quad (31)$$

Since Fig. 8 shows that all of these three schemes have similar secondary throughputs, the energy consumption is the only factor that influence the energy efficiency. When $p_0 > 0.5$, the miss detection probability of the proposed scheme is a slightly higher than the ones in [14] and [19], thus the energy consumed by invalid data transmission will be higher. When $p_0 < 0.5$, the miss detection probability of the proposed scheme is much lower than the ones in [14] and [19]. Therefore, even though the proposed scheme spends more time to perform the second spectrum sensing when the first sensing result shows that the state of the PU has changed, there is a certain probability to that the miss detection can be corrected and thus provide better protection. This reduces the amount of invalid data transmissions performed by SUs, and decreases unnecessary energy consumption. This improves the network energy efficiency and prolongs the network lifetime.

6 CONCLUSION AND FUTURE WORK

This paper proposed a novel spectrum sensing scheme for CRSNs. Based on the sensing result of the current frame, SU can dynamically decide to perform spectrum sensing for another period. The second spectrum sensing is performed to ensure the accuracy of the current sensing result if it is different from the previous sensing result. The first spectrum sensing period for the current frame can be calculated based on the detection probability and false alarm probability that satisfy the essential requirements of CRSNs. The second spectrum sensing period is optimized by optimizing network energy efficiency. In order to find the optimal second spectrum period, the Golden Section Search method is employed. Finally, our simulation study showed that the proposed scheme is more energy efficient than existing methods. As a future work, we plan to further improve the network energy efficiency by optimizing the frame length, and the multicast of multichannel multiradio system combined with CR technology will also be considered as the future research direction [29].

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