2016 13th International Conference on Embedded Software and Systems

Optimizing Spectrum Sensing Time for Energy-Efficient CRSNs

Fanhua Kong
Dept. of Computer Science and Engineering
Kyung Hee University
Yongin 446-701, Korea
kongfanhua@khu.ac.kr

Zilong Jin
School of Computer and Software
Nanjing University of Information Science and Technology
Nanjing, China
zljin@nuist.edu.cn

Jinsung Cho, Seokhee Jeon, and Sungwon Lee
Dept. of Computer Science and Engineering
Kyung Hee University
Yongin 446-701, Korea
(chojs, jeon, drsungwon)@khu.ac.kr

***Abstract*—By cognitive radio technology, secondary users (SUs) can use licensed bands opportunistically without causing interferences to primary users (PUs). Spectrum sensing is performed by SUs to detect that PUs are present or not. Therefore, spectrum sensing is a key technology for cognitive radio (CR), and sensing time is a critical parameter for spectrum sensing performance. The longer sensing time can result in a higher sensing accuracy. However, it will lead to occupying data transmission period, and consuming higher energy in spectrum sensing. In this paper, a novel spectrum sensing scheme is proposed to guarantee both of the sensing accuracy and energy efficiency. In the proposed scheme, SU will dynamically decide to perform spectrum sensing one or two periods according to the sensing result of the current frame for guaranteeing the sensing accuracy. Furthermore, in order to guarantee the network energy efficiency, the spectrum sensing time is optimized through the mathematical model of the secondary network. Simulation results validate that the energy efficiency and miss detection probability of SU can be improved significantly by the proposed scheme.**

Keywords—cognitive radio sensor networks; sensing time; energy efficiency; miss detection probability; bisection method

I. INTRODUCTION

Due to the fixed spectrum allocation policy and the rapid deployment of wireless devices, the problem of spectrum scarcity is becoming more aggravating. In addition, the fact that most of licensed wireless spectrum bands are underutilized is also confirmed by Federal Communications Commission (FCC). In order to mitigate the problem of spectrum scarcity, cognitive radio (CR) technology is proposed to improve spectral efficiency [1]. The unlicensed secondary users (SUs) are allowed opportunistically to occupy the licensed bands by CR technology when licensed primary users (PUs) do not occupy them. Because CR technology can enable SUs share the licensed spectrums with PUs in collision-free way, CR technology has got a lot of attention and has been widely applied in various wireless networks to improve spectral efficiency [2-4].

In cognitive radio sensor networks (CRSNs), cognitive radio technology enables sensor nodes detect available licensed spectrum by spectrum sensing, and makes SUs opportunistically use the *spectrum hole* or *white space* to improve spectral efficiency when PU is detected to be absent. It is required that PUs should not be interfered by SUs. As a consequence, spectrum sensing is very important for SUs to accurately detect that PU is present or not. For spectrum sensing, sensing time is a key parameter which can yield a tradeoff between sensing performance and SU throughput. Concretely, sensing time is longer, sensing performance is better, and a better protection can be provided for PU. However, there will be less time left for data transmission, and it will degrade the SU throughput.

There are many works on sensing time optimization in cognitive radio networks (CRNs). In [5], a scheme for joint optimization of channel sensing time and channel sensing order is proposed. In the proposed objective function, the sensing errors are taken into consideration to penalize collisions with PU. The optimization problem is formulated to find optimal sensing time which can maximize the secondary throughput. Hao *et al*. [6] develop a novel adaptive spectrum sensing scheme to improve the average throughput reward. The variation of time-varying channels is considered in the proposed scheme. The spectrum sensing duration can be adjusted according to the previous sensing results and channel state information. In [7], a learning-based spectrum sensing time optimization scheme is proposed to maximize the average throughput of the cognitive radio system. By optimizing spectrum sensing time, the objective that maximizing the average throughput of a cognitive radio system is achieved. In order to find optimal value of channel sensing time, a neural network-based optimization approach is also proposed.

These above-mentioned schemes of spectrum sensing time optimization which are specific to CRNs cannot be directly applied in CRSNs, because they do not consider energy restriction. In CRSNs, wireless sensor devices have to suffer the energy constraint, because it is hard or even impossible to recharge or change the battery for sensor devices due to application environment. This makes energy consumption become the most important factor to consider when schemes are designed for CRSNs. In other words, in order to prolong the network lifetime, how to improve the network energy efficiency becomes the most crucial problem. However in

Correspondence should be addressed to Jinsung Cho; chojs@khu.ac.kr
This research was supported by Basic Science Research Program through National Research Foundation of Korea(NRF) funded by the Ministry of Education(NRF-2013R1A1A2059741).

978-1-5090-3727-8/16 $31.00 © 2016 IEEE
DOI 10.1109/ICESS.2016.11

terms of CRSNs, there are not many works specific to energy-efficient spectrum sensing with sensing time optimization.

In [8], a spectrum sensing method based on cognitive monitoring network is proposed. A network of sensors is deployed in the network coverage area to perform the cooperative spectrum sensing. SUs will use extremely short time to send query to monitoring sensors, and then receive the sensing result as the response. In this way, throughput can be maximized irrespective of the sensing duration. However, delay will be increased by the communication between SUs and monitoring sensors. Jiang *et al.* [9] investigate a joint energy efficient optimization method for spectrum sensing and nodes selection. In this work, a dynamic censored spectrum sensing scheme is employed. Each sensor node compares the received energy power with the censoring thresholds, and then decides when to stop sensing. In this way, the sensing time can be shortened and unnecessary energy consumption can be saved. However, if sensor node collects just one sample and stop sensing, the probability of sensing error will be high.

The performance of spectrum sensing can be evaluated by miss detection probability and false alarm probability. Miss detection occurs when SU does not detect PU under the fact that PU is actually present. False alarm is interpreted as that SU detects PU while PU is actually absent. Therefore, miss detection will result in the interference to PU, and false alarm will lead to lower SU throughput. A longer sensing time will bring a lower miss detection probability and a higher false alarm probability. It thus appears that a tradeoff between sensing performance and SU throughput must exist, and it is related to the length of sensing time. All of aforementioned works perform spectrum sensing one time and find optimal sensing time maximizing throughput. If the problems of sensing error occur, there is no chance to fix them. PU will be interfered, and more unnecessary energy and available spectrum opportunities will be wasted.

In this paper, we propose a novel spectrum sensing scheme which is specific to CRSNs. In order to improve network energy efficiency, a system model is established and the optimal sensing time is derived. According to the sensing result of the current frame, SU can dynamically decide to perform spectrum sensing one or two times. Because miss detection probability and false alarm probability do not coincide with each other, in this paper, we pay more attention to decrease miss detection probability and prefer to provide a better protection for PU. In the proposed scheme, SU just performs spectrum sensing one time if sensing result shows that PU is present. If sensing result shows that PU is absent, in order to provide a better protection for PU, SU will perform spectrum sensing again to confirm the absence of PU. If the sensing result still shows that PU is absent, SU will transmit data. Otherwise, SU will keep salient and wait for the next frame. The main merit of this method is that miss detection probability can be decreased in this way, and accordingly PU can get a better protection. Due to the lower miss detection probability, more invalid data transmission can be avoided, and unnecessary energy consumption will be saved. Furthermore, through a set of simulations, it is verified that the proposed scheme can improve the network energy efficiency and miss detection probability significantly.

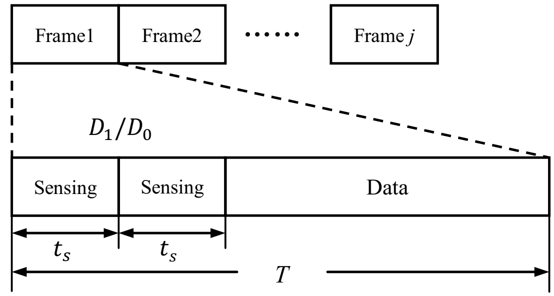

Fig. 1. Frame structure

The rest of the paper is organized as follows. In Section Ⅱ, system model is introduced. In Section Ⅲ, we present the problem formulation for sensing time optimization. In Section Ⅳ, the performance of proposed scheme is evaluated by a set of simulations. Finally, we conclude the paper and introduce the future work in Section Ⅴ.

II. System Model

In CRSNs, time is assumed to be divided into equal frame. Each frame contains two phases: sensing phase and data transmission phase. In the proposed scheme, individual spectrum sensing is supposed to be performed by a single SU. During the sensing phase, SU performs the spectrum sensing to detect PU. If PU is idle, SU will always have data to transmit during data transmission phase; otherwise, it will keep salient and wait for the next frame. In addition, it is worth noting that data transmission of SU is considered to be valid only when PU is actually absent.

As shown in Fig. 1, each frame time is T, and t_s denotes spectrum sensing time. D_0 and D_1 indicate sensing results which PU is absent and present, respectively. In the proposed scheme, the spectrum sensing time is related to the sensing result of the current frame. Concretely, SU firstly performs spectrum sensing for time t_s, if sensing result is D_1, SU will keep salient and wait for the next frame. If sensing result is D_0, in order to provide a better protection for PU, SU will perform spectrum sensing again for time t_s to confirm the absence of PU. If the sensing result of the second spectrum sensing is still D_0, SU will transmit data; otherwise, SU will keep salient. It is worth noting that if the sensing results of the first and second spectrum sensing are different, the second spectrum sensing result will be taken as the final result. Hence, according to the different sensing results of the first spectrum sensing, 6 cases can be listed as below.

Case 1: Under the fact that PU is present, the spectrum sensing result is D_1. In this case, SU correctly detects PU for the first spectrum sensing, so spectrum sensing is performed just one time.

Case 2: Under the fact that PU is present, the first sensing result is D_0, and the second sensing result is D_1. In this case, because the first spectrum sensing result is D_0, SU will perform spectrum sensing again to confirm the accuracy of the first spectrum sensing result. Even though miss detection occurs during the first spectrum sensing process, PU is successfully detected by the second spectrum sensing. In this way, PU can get a better protection.

Case 3: Under the fact that PU is present, both of the first and second spectrum sensing results are D_0. In other words, miss detection occurs during the first and the second spectrum sensing process. However, the probability of this case is very small, and it will be proved later.

Case 4: Under the fact that PU is absent, the spectrum sensing result is D_1. Because the sensing result is D_1, SU just performs spectrum sensing one time, even though false alarm occurs.

Case 5: Under the fact that PU is absent, both of the first and the second spectrum sensing results are D_0. In other words, SU successfully detects that PU is absent during the first and the second spectrum sensing process. The valid data is transmitted in this case.

Case 6: Under the fact that PU is absent, the first spectrum sensing result is D_0, and the second spectrum sensing result is D_1. Because the first spectrum sensing result is D_0, SU will perform spectrum sensing again. However, false alarm occurs during the second spectrum sensing process.

According to the above mentioned 6 cases, it is known that the valid throughput can be achieved by case 5. Case 3 will cause the problem of miss detection, while case 4 and 6 can lead to the problem of false alarm.

III. Formulation of Optimization Problem

In this section, the optimization model of the proposed scheme is established. The proposed scheme prefers to decrease the miss detection probability to provide a better protection for PU. Benefit from lower miss detection probability, more invalid data transmission is avoided. In this way, unnecessary energy consumption is saved, and then energy efficiency can be promoted.

A. Energy Detection Based Spectrum Sensing

In this paper, we use a binary hypothesis to formulate spectrum sensing. H_0 and H_1 denote the hypothesis of the absence and presence of PU. And p_0 and p_1 indicate probabilities of H_0 and H_1, respectively. Therefore, we can get $p_0 + p_1 = 1$.

In the proposed scheme, energy detector is employed as the spectrum sensing method. The main advantage is that it is very simple to be implemented, and the priori knowledge of PU is needless. SU compares the received energy power with the predefined threshold. If the received energy power is bigger than the predefined threshold, PU is considered to be present. The test statistic of energy detector can be expressed as below:

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

where N is the number of sample times during the sensing time. $y(n) = u(n)$ when the state of PU is H_0, and $y(n) = s(n) + u(n)$ when the state of PU is H_1. The signal of PU, $s(n)$, is assumed to be iid random process with mean zero and variance σ_s^2. $u(n)$ is assumed to be a white Gaussian noise with mean zero and variance σ_u^2. 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. The test statistic can be approximated as Gaussian, because central limit theorem can be applied for it when the value of N is large.

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

where $\gamma = \frac{\sigma_s^2}{\sigma_u^2}$, it is denoted as the signal to noise ratio (SNR) received from PU. According to the definition of detection probability and false alarm probability, we can get followings:

$$p_d = p(H_1|H_1) \ , \tag{3}$$

$$p_f = p(H_1|H_0) \ . \tag{4}$$

And based on the statistics of $T(y)$, we can get:

$$p_d = Q\left(\frac{\lambda}{\sqrt{2N}(1+\gamma)} - \sqrt{\frac{N}{2}}\right), \tag{5}$$

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

where λ is the sensing threshold, it is used to be compared with the received energy power. $Q(\cdot)$ is Q function which is given as

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

Eq. (7) shows that $Q(\cdot)$ is a monotone decreasing function. The sample times N can be calculated by the following equation [10]:

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

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

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

where $Q^{-1}(\cdot)$ denotes the inverse function of Q function. By substituting the function of λ into Eq. (6), we can get:

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

In CRSNs, in order to satisfy the essential requirement of CRSNs, there should be a certain threshold of detection probability and false alarm probability for SUs. Concretely, the detection probability p_d should not be smaller than a predefined threshold p_d^{th}, i.e. $p_d \geq p_d^{th}$, and the false alarm probability of SU p_f should not be bigger than a predefined threshold p_f^{th}, i.e. $p_f \leq p_f^{th}$. According to Eq. (10), it is known that p_f will be decreased with increasing sensing time when p_d

is a fixed value. Because Q function is a monotone decreasing function, it is known that both of p_d and p_f will decrease with decreasing sensing time according to Eq. (5) and Eq. (6). Therefore, in order to maximize the throughput of SU, the detection probability p_d is fixed as the value of p_d^{th} in this paper, i.e. $p_d = p_d^{th}$.

In terms of miss detection probability, according to aforementioned 6 cases, it can be known that only case 3 leads to the problem of miss detection. Hence, the miss detection probability of proposed scheme p_m^1 can be expressed as below.

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

B. Optimization Model

In order to find the optimal sensing time which can maximize the energy efficiency of CRSN, the optimization model is established as below.

Based on the aforementioned 6 cases, it is known that the valid throughput can be achieved only by case 5. Then, the average throughput can be calculated as

$$\psi(t_s) = p_0\left(1-p_f\right)^2(T-2t_s)C\,, \tag{12}$$

where C is the SU's channel capacity without the interference caused by PUs. The function of C can be expressed by Eq. (13) according to the Shannon theory.

$$C = \log_2(1+\gamma_s)\,, \tag{13}$$

where γ_s denotes the SNR that SU transmits data without interference from PU. And according to 6 cases, the energy consumption functions can be formulated as below.

$$E_1 = p_1 p_d E_s t_s\,, \tag{14a}$$

$$E_2 = 2p_1(1-p_d)p_d E_s t_s\,, \tag{14b}$$

$$E_3 = p_1(1-p_d)^2\left(2E_s t_s + E_t(T-2t_s)\right), \tag{14c}$$

$$E_4 = p_0 p_f E_s t_s\,, \tag{14d}$$

$$E_5 = p_0\left(1-p_f\right)^2\left(2E_s t_s + E_t(T-2t_s)\right), \tag{14e}$$

$$E_6 = 2p_0\left(1-p_f\right)p_f E_s t_s\,, \tag{14f}$$

$$\phi(t_s) = E_1 + E_2 + E_3 + E_4 + E_5 + E_6\,, \tag{14g}$$

where E_1, E_2, E_3, E_4, E_5, and E_6 represent the energy consumption of case 1, 2, 3, 4, 5, and 6, respectively. ϕ denotes the average of total energy consumption. E_s and E_t are the energy consumption of spectrum sensing and data transmission for the unit time, respectively. In this paper, energy efficiency is defined as the number of bits transmitted per unit of energy consumption [11]. So the function of energy efficiency can be expressed as

$$\eta(t_s) = \frac{\psi(t_s)}{\phi(t_s)}\,. \tag{15}$$

$$s.t.\ p_f \le p_f^{th}\,.$$

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

1: Input: a, b, ε
2: $c = (a+b)/2$
3: Calculate the derivative of $\eta(x)$, denoted as $\eta'(x)$
4: While $|a-b| \ge \varepsilon$, and $\eta'(x) \ne 0$
5: If $\eta'(a) * \eta'(c) < 0$
6: $b \leftarrow c$
7: Else
8: $a \leftarrow c$
9: End if
10: $c \leftarrow (a+b)/2$
11: End While
12: Output: a or b or c

Fig. 2 The pseudo-code of the bisection method

C. Bisection Method

In this paper, the bisection method is applied to find the optimal sensing time t_s. If function $y = f(x)$ is continuous during the interval $[a\,,b]$, and the condition that $f(a)\cdot f(b) < 0$ is also satisfied, the bisection method can be utilized to find the approximation of a point making $y = 0$. The bisection method is a root-finding method. Specifically, an interval is bisected, then a subinterval which the root lies in is selected to be bisected further, and this process will be performed repeatedly. At last, the approximation of root can be obtained when two endpoints of the interval are close enough. The pseudo-code description of the bisection method is given in Fig. 2.

In line 1 of the pseudo-code, we first determine the limit of error and lower and upper bounds of interval, which are denoted as ε, a and b, respectively. The limit of error ε should be a small value. Then we calculate the midpoint of interval c (line 2) and the derivative of objective function $\eta'(x)$ (line 3). In lines 5-10, we check whether the new lower and upper bounds of interval can satisfy $|a-b| \le \varepsilon$. If $|a-b| \le \varepsilon$ is satisfied, the solution can be approximated as a or b or c (line 12); otherwise, the procedure will start from line 5 again.

IV. Performance Evaluation

In this Section, the performance of proposed scheme is evaluated. The proposed scheme is compared with other two sensing time optimization schemes. Because the activity of PU is not fixed, PU can occupy the licensed band whenever PU wants. Consequently in the simulation, the activity of PU is taken into consideration. A set of simulations for the performance evaluation are implemented with MATLAB.

A. Simulation Parameters

In the simulation, we assume a CRSN which is consisted of one PU and ten secondary senor nodes randomly distributed in a circular region with radius 50m. To evaluate the performance of proposed scheme, the simulation parameters are set as below. According to IEEE 802.22 cognitive radio WRAN standard, $p_d^{th} = 0.9$, and $p_f^{th} = 0.1$ [12]. The length of frame $T = 0.2$s, $W = 6MHz$. The SNR received from PU $\gamma = -20dB$. The SNR that SU transmits data $\gamma_s = 20dB$, hence, the SU's

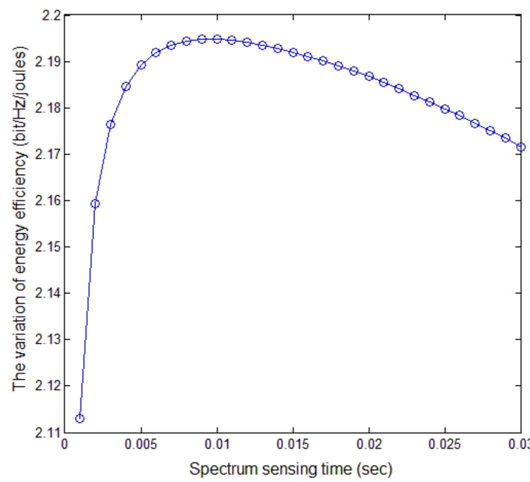

Fig. 3 The variation of energy efficiency with increasing spectrum sensing time

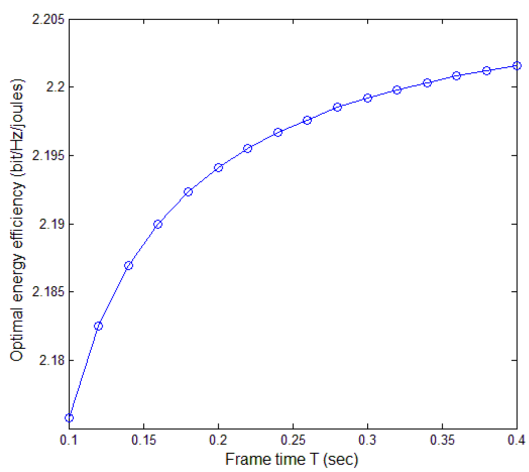

Fig. 4 The variation of optimal energy efficiency with increasing frame time

channel capacity $C = \log_2(1+\gamma_s) = 6.6582\ bits/sec/Hz$. E_s and E_t are assumed to be 0.1W and 3W, respectively.

B. Simulation Results

Fig. 3 shows the energy efficiency variation of SU with the increasing sensing time when $p_0 = 0.7$ is given. From Fig. 3, we can get that the energy efficiency of SU will increase with the increasing sensing time at first. And then after the optimal point, it decreases again. The reason is that false alarm probability is decreased with increasing sensing time, and this implies that more opportunities of *spectrum hole* can be utilized by SU, and more throughputs can be achieved. However, due to the fixed frame time *T*, data transmission time will be decreased with the increasing sensing time. It will affect the throughput of SU when sensing time is large. That is why energy efficiency of SU is decreased again. Fig. 3 also

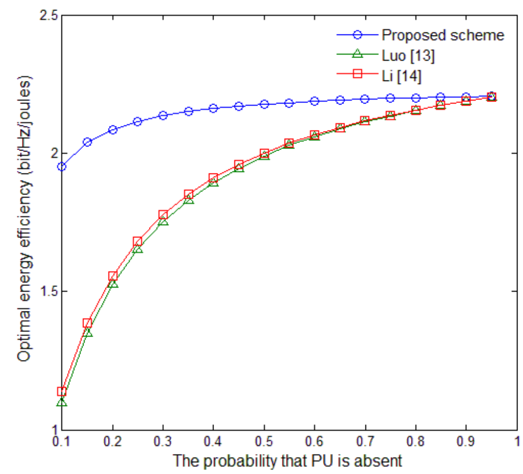

Fig. 5 Comparison of optimal energy efficiency

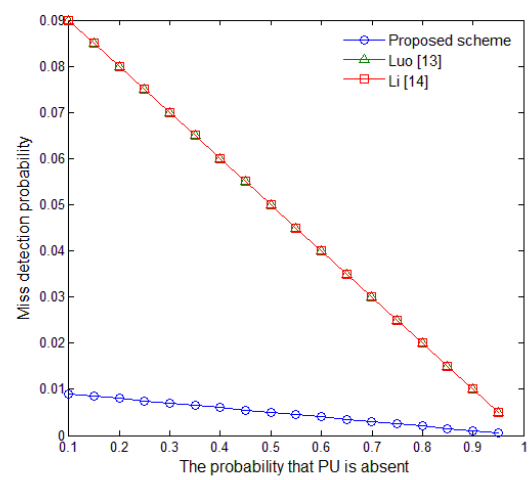

Fig. 6 Comparison of miss detection probability

confirms that the optimal sensing time which can maximize the energy efficiency of the secondary network exactly exists. It is worth noting that false alarm probability p_f is bigger than p_f^{th} when sensing time is very short. In the next simulations, the value of optimal sensing time will be obtained subjecting to $p_f \leq p_f^{th}$.

Fig. 4 shows the variation of optimal energy efficiency with increasing frame time *T*, when p_0 is fixed as 0.7. It can be seen that the network energy efficiency of proposed scheme increases with the increasing frame time *T*. In other words, the performance of proposed scheme is better when the frame time *T* is longer. The reason is that the problem of miss detection can cause a greater negative impact on energy efficiency when the frame time *T* is longer. However the miss detection probability can be decreased significantly by our proposed scheme according to Eq. (11), hence, the performance of energy efficiency can be improved when the frame time T becomes longer.

In order to evaluate the performance of proposed scheme, the proposed scheme is also compared with other two schemes [13, 14]. Fig. 5 shows the comparison of the optimal energy efficiency with the increasing value of p_0. Luo *et al.* [13] propose a minimizing mean detection time scheme. On the premise of meeting the constraint of detection probability and false alarm probability, sensing time is minimized and maximum remaining time can be left for data transmission. It is worth noting that in order to compare these three schemes, the same simulation environment is assumed. The detection probability is fixed as 0.9 for these three schemes in the simulations of this paper. Hence, it can be known that when the false alarm probability reaches its constraint, the minimum average detection time in the scheme of [13] can be attained. To the best of our knowledge, most energy-efficient spectrum sensing techniques with sensing time optimization are specific to cooperative spectrum sensing. Therefore, in order to compare network energy efficiency with our proposed scheme, the number of cooperative spectrum sensing nodes in [14] is set as 1 for comparison simulations. In [14], SUs perform spectrum sensing one time, and optimal sensing time is achieved by optimizing the energy efficiency of CRSNs. According to Fig. 5, we can get that the optimal energy efficiency of proposed scheme is always higher than other two schemes, i.e. Luo [13] and Li [14], no matter what the value of p_0 is. In addition, it can be seen that the proposed scheme has a better performance if the value of p_0 becomes smaller. The reason will be explained by Fig. 6.

Fig. 6 compares the miss detection probability of proposed scheme with other two schemes in [13] and [14]. It can be seen that the miss detection probability of proposed scheme is always lower than other two schemes. Because SU just performs spectrum sensing one time in Luo [13] and Li [14], and the detection probabilities are set as the same as 0.9, Luo [13] and Li [14] have the same miss detection probability.

$$p_m^2 = p_1(1 - p_d)\,, \tag{16}$$

where p_m^2 means the miss detection probability of schemes in [13] and [14]. According to Eq. (11), we can get that p_m^1 is $(1 - p_d)$ times of p_m^2. In this paper, because p_d is fixed as 0.9, compared with other two schemes, the miss detection probability is decreased by ten times with our proposed scheme. Especially when the value of p_0 becomes smaller, the difference between p_m^1 and p_m^2 is larger. Even though we spend more time to detect PU when sensing result is D_0, due to the lower miss detection probability, PU can be protected better. More invalid data transmission can be avoided, and more unnecessary energy consumption can be saved. In this way, the network energy efficiency can be promoted, and the long-term network lifetime can be prolonged. That is why the energy efficiency of proposed scheme is higher than Luo [13] and Li [14] in Fig. 5.

V. CONCLUSION AND FUTURE WORK

In this paper, we proposed a novel spectrum sensing scheme for CRSNs, and the network energy efficiency is maximized by the optimization of sensing time. According to the sensing result of the current frame, SU can dynamically decide to perform spectrum sensing one or two times. In order to provide a better protection for PU, SU will detect PU again to confirm the absence of PU when sensing result shows that PU is absent. An optimization model is also built in this paper. In order to find the optimal sensing time, the bisection method is utilized. Finally, a set of simulations validate that the proposed scheme has a lower miss detection probability and a better performance in terms of energy efficiency. In the future work, the effect of sensing period on spectrum sensing will be considered for further study.

REFERENCES

[1] J. Mitola, and G. Q. Maguire, "Cognitive Radio: Making Software Radios More Personal," *IEEE Personal Communications*, vol. 6, no. 4, pp. 13-18, 1999.

[2] M. Askari, Y. S. Kavian, H. Kaabi, and H. F. Rashvand, "A Channel Assignment Algorithm for Cognitive Radio Wireless Sensor Networks," in *Proc. Wireless Sensor Systems (WSS)*, 2012.

[3] R. Saifan, A. E. Kamal, and Y. Guan, "Spectrum Decision for Efficient Routing in Cognitive Radio Network," in *Proc. Mobile Adhoc and Sensor Systems*, 2012.

[4] H. M. Almasaeid, T. H. Jawadwala, and A. E. Kamal, "On-Demand Multicast Routing in Cognitive Radio Mesh Networks," in *Proc. Global Telecommunications Conference*, 2010.

[5] A. Ewaisha, A. Sultan, and T. ElBatt, "Optimization of Channel Sensing Time and Order for Cognitive Radios," in *Proc. Wireless Communications and Networking Conference (WCNC)*, pp. 1414-1419, 2011.

[6] H. He, G. Y. Li, and S. Li, "Adaptive Spectrum Sensing for Time-Varying Channels in Cognitive Radios," *IEEE Wireless Communications letters*, vol. 2, no. 2, pp. 1-4, 2013.

[7] H. Shokri-Ghadikolaei, Y. Abdi, and M. Nasiri-Kenari, "Learning-Based Spectrum Sensing Time Optimization in Cognitive Radio Systems," in *Proc. Telecommunications (IST)*, pp. 249-254, 2012.

[8] G. C. Deepak, and K. Navaie, "On the Sensing Time and Achievable Throughput in Sensor-Enabled Cognitive Radio Networks," in *Proc. Wireless Communication Systems (ISWCS)*, pp. 1-5, 2013.

[9] J. Fu, Z. Yibing, L. Yi, L. Shuo, and P. Jun, "The Energy Efficiency Optimization based on Dynamic Spectrum Sensing and Nodes Scheduling in Cognitive Radio Sensor Networks," in *Proc. Control and Decision Conference (CCDC)*, pp. 4371-4378, 2015.

[10] H. Urkowitz, "Energy Detection of Unknown Deterministic Signals," *Proceedings of the IEEE*, vol. 55, no. 4, pp. 523-531, 1967.

[11] Y. Pei, Y. C. Liang, K. C. Teh, and K. H. Li, "Energy-Efficient Design of Sequential Channel Sensing in Cognitive Radio Networks: Optimal Sensing Strategy, Power Allocation, and Sensing Order," *IEEE Journal on Selected Areas in Communications*, vol. 29, no. 8, pp. 1648-1659, Sep. 2011.

[12] C. R. Stevenson, G. Chouinard, Z. Lei, W. Hu, S. J. Shellhammer, and W. Caldwell, "IEEE 802.22: The First Cognitive Radio Wireless Regional Area Network Standard," *IEEE Communications Magazine*, vol. 47, no. 1, pp. 130-138, 2009.

[13] L. Luo, and S. Roy, "Efficient Spectrum Sensing for Cognitive Radio Networks via Joint Optimization of Sensing Threshold and Duration," *IEEE Transactions on Communications*, vol. 60, no. 10, pp. 2851-2860, Oct. 2012.

[14] X. Li, J. Cao, Q. Ji, and Y. Hei, "Energy Efficient Techniques with Sensing Time Optimization in Cognitive Radio Networks," in *Proc. IEEE Wireless Communications and Networking Conference (WCNC)*, pp. 25-28, 2013.