Toward an Efficient CRWSN Node Based on Stochastic Threshold Spectrum Sensing

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Abstract. The high demand for wireless sensor networks (WSNs) is growing in different applications. Most WSNs use the unlicensed band (ISM band) which leads to congestion in that band. On the other hand, without damaging the quality of service (QoS) of the network, minimizing the consumed energy is vital in sensor networks design. Cognitive radio-based wireless sensor networks (CRWSNs) afford some solutions to the problem of scarce unlicensed band spectrum. The spectrum sensing is the main function of the cognitive radio networks. In this paper, for maximizing the accuracy of sensing, as well as the energy efficiency of the network, proposed novel method by employing adaptive spectrum sensing. Spectrum sensing is performed by Secondary User (SU) to identify if the Primary User (PU) is idle, then for verifying that primary user is actually idle, sensing the spectrum again is done by secondary user in order to provide better protection for the primary user. Because of CRWSN has a constraint in energy, that adaptive interval of sensing could also, be modified to optimize the energy efficiency of the network according to the different activity of the PU. Simulation results were provided to validate the efficacy of the proposed algorithms to enhance both spectrum sensing performance and energy efficiency.

Keywords: Wireless sensor network · Cognitive radio-based wireless sensor network · Spectrum sensing · Sensing time · Energy efficiency · Sensing performance

1 Introduction

The challenge of spectrum shortage has become more significant due to the massive rise of wireless communication techniques. Owing to the restricted frequency deployment systems, the restricted available spectrum cannot satisfy the increasing demand for wireless communications [1]. Cognitive radio (CR) with an amoral attitude and flexible access to spectrum has come to pass to solve this problem. Based on a software-defined radio, cognitive radio is identified as an intellectual wireless communication platform that is conscious of its surroundings that is efficiently communicated with optimal use of the radio spectrum [2].

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In this paper, we consider new WSN technology with Cognitive Radio called Cognitive Radio Wireless Sensor Network (CRWSN). The CR technology enables sensor nodes to identify appropriately licensed bands by implementing spectrum sensing in CRWSNs, where the Secondary Users (SUs) can use spectrum gaps or white spaces opportunistically to increase bandwidth utilization while detecting the Primary Users (PUs) as idle. Because PUs should not be clashed with SUs, it is very essential for SU to track the movement of PUs accurately. The time of sensing is a key factor which can improve the performance of sensing. In general, longer scanning time will minimize sensing errors and provide the PU with better security. The optimum sensing time therefore leads to a balance between sensing performance and secondary throughput [3].

In this paper, we employ the sensing optimization results to enhance the efficiency of the CRWSN making it more robust to the noise fluctuations, since a stochastic method of threshold level determination helps in overcoming the noise fluctuations, otherwise the time optimization offers more sensing accuracy and leads to high energy efficiency.

The remainder of this paper is formulated as follows. Section 2 provides a literature review on spectrum sensing using the technique of energy detection, in addition to describing the threshold expression in noise uncertainty condition using a stochastic method. Section 3 illustrates how we could implement proposed stochastic threshold for the energy detection technique in the design phase of the proposed method, and formulates the energy-efficient optimization problem for optimum sensing time. Throughout Sect. 4, simulations are used to test the efficiency of the proposed scheme. Finally, Sect. 5 concludes the paper and discusses the future work.

2 Basic Concepts

2.1 Energy Detection Based Spectrum Sensing

The most popular spectrum sensing methods currently are the matched filter detection [4], energy detection [5, 6], cyclostationary detection [7] and eigenvalue-based detection [8]. Various comparisons between these approaches are widely covered in the literature, e.g. in [9], however, we can summarize the main differences between these techniques as follows. The eigenvalue-based method of detection does not require the information of the PU's signal properties, but the computation is complex. Cyclostationary method of detection is robust to the noise uncertainty and able to distinguish noise and PU which leads to high sensing accuracy, but it is complex. The matched filter detection method has the lowest time of execution and robust under low SNR conditions, but the PU signal information is needed and High computational complexity.

The energy detector method, also known as radiometry or periodogram, is the most popular way of detecting spectrum due to its low complexity of implementation and rapid efficiency [10]. To formulate the spectrum sensing, a binary hypothesis is used. H0 and H1 denote the idle hypothesis and the busy PU states respectively, while pi and pb specify H0 and H1 probabilities, respectively. Therefore, $p_i + p_b = 1$.

In this paper, we consider the energy detection method to detect the PU operation. The SU compares the energy obtained to a predefined threshold, and if the energy obtained is greater than the limit, the PU will be considered busy; otherwise, the PU will be considered idle. The energy detector test statistics G(z) can be expressed as follows [3]:

$$G(z) = \frac{1}{\sigma_v^2} \sum_{n=1}^{N} |z(n)|^2, \tag{1}$$

where z(n) is the signal sampled and N is the samples number taken during the sensing process. If the PU is H_1, z(n) = f(n) + v(n), where the PU's signal is f(n), This is expected to be an independent and identically distributed (iid) random process with a mean of zero and a variance of σ_f^2, and v(n) is a white Gaussian noise with a mean of zero and a variance of σ_v^2. On the other side, if the PU is in H_0, z(n) = v(n). The test statistics follow the central and non-central distribution of chi-square with 2N degrees of freedom under hypothesis H_0 and H_1, respectively. The test statistic can be approximated as Gaussian because the central limit theorem can be applied when the value of N is high enough [2]. We can then describe the test statistics as follows:

$$G(z) \sim \begin{array}{ll} N(N, 2N) & H_0 \\ N(N(1+\gamma), 2N\left(1+\gamma)^2\right) & H_1 \end{array} \tag{2}$$

where the Signal to Noise Ratio (SNR) received from the PU is $\gamma = \sigma_f^2/\sigma_v^2$. On this basis, it is possible to define the probability of detection p_D and the probability of false alarm P_{FA} as follows:

$$p_D = p(H_1|H_1)p_D = Q\left(\frac{\lambda}{\sqrt{2N}(1+\gamma)} - \sqrt{\frac{N}{2}}\right) \tag{3}$$

$$p_{FA} = p(H_1|H_0) = Q\left(\frac{\lambda}{\sqrt{2N}} - \sqrt{\frac{N}{2}}\right) \tag{4}$$

where the threshold of sensing λ is in comparison with the power received. Specifically, the PU is considered active when the SU senses the PU and the energy obtained is greater than λ; otherwise the PU is considered idle. Q(·) is the Q function.

The number of samples N can be calculated as N = 2t W, where W is the PU signal bandwidth and t denotes the time of sensing [2]. Using (3), the threshold of sensing λ can be obtained as:

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

where $Q^{-1}(\cdot)$ is the inverse of the Q-function defined above. Substituting by λ in (4), the P_{FA} is obtained as:

$$p_{FA} = Q\left((1+\gamma)Q^{-1}(p_D) + \gamma\sqrt{\frac{N}{2}}\right), \tag{6}$$

P_D should be greater than or equal to a predefined threshold p_D^{th} to ensure essential protection for the PU in CRWSNs. Based on (6), since p_D is a fixed value, P_{FA} decreases as the sensing time increases. Moreover, as p_D decreases, the value of $Q^{-1}(p_D)$ increases and P_{FA} decreases as $Q^{-1}(p_D)$ increases. Therefore, P_D is set as p_D^{th} ($p_D = p_D^{th}$) to make sure that the available secondary throughput is maximum.

2.2 Noise Uncertainty Stochastic Approach

The fluctuations in noise are defined as random signals because we cannot accurately determine their values, that is, they are values of uncertainty. Let's denote the estimated variance in noise as [11]:

$$10\log\left(\hat{\sigma}_v^2\right) = \alpha + 10\log\left(\sigma_v^2\right) \tag{7}$$

where α flouts a uniform distribution in the [−UdB, UdB] interval, and at U = 0 there is no ambiguity about noise. The resulting estimated noise $\hat{\sigma}_v^2$ falls to $\left[(1/r)\sigma_v^2, r\sigma_v^2\right]$, and $r = 10^{(U/10)}$.

Under the condition of noise uncertainty, signal power P_s should be larger than the entire noise power interval size to distinguish the presented signal situation from only noise fluctuation σ_v^2 [2], i.e.,

$$P_s > r\sigma_v^2 - (1/r)\sigma_v^2 = (r - 1/r)\sigma_v^2 \tag{8}$$

$$SNR = P_s/\sigma_v^2 > (r - 1/r) \tag{9}$$

Under both hypotheses, the mean of the test statistics is related to the noise variance. For practice, the estimated noise variance $\hat{\sigma}_v^2$ is used to calculate the noise variance instead of the noise variance σ_v^2. In simulations, noise uncertanity is considered to better satisfy the realistic implementation settings.

Two major problems in spectrum sensing are the noise uncertainty and quality degradation, e.g. the false alarm probability P_{FA} increases and the probability of detection P_D decreases. In addition, a fixed threshold energy detection algorithm provides degraded quality with noise uncertainty. This indicates that in the presence of noise uncertainty, the dynamic threshold would yield better performance [10].

3 System Model

In this paper, we consider a typical CRWSN consists of a single PU, and a secondary connection transmitter-receiver pair as shown in Fig. 1. In addition, other source and sink nodes are also exist for data transmission and the main spectrum access links are the PU link or the licensed band, and the SU link or the opportunistic spectrum.

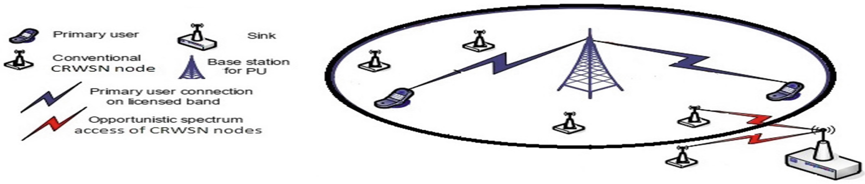

Fig. 1. Proposed system model.

3.1 The Proposed Threshold Expression

The Old Threshold Under Noise Uncertainty

The value of the threshold λ_0 can be determined as follows. In the case of hypothesis H0, which only corresponds to the presence of noise, we know that g [n] is (i.i.d.) Gaussian random variables with zero-mean and σ_v^2 variance. When the samples are large enough, using the Central Limit Theorem (CLT), the noise approaches Gaussian distribution (μ − v, σ_v^2), which can be determined from simulation. Then the λ_0 threshold value is [2, 6].

$$\lambda_0 = \mu_v + \sigma_v.Q^{-1}\left(1 - (1 - P_{FA})^{\frac{1}{N}}\right) \tag{10}$$

Stochastic Threshold

The probability of false alarm P_{FA}, will get increased in conventional signal threshold detection with U dB uncertainty if the actual noise σ_v^2 is greater than the expected noise variance $\widehat{\sigma}_v^2$. For an optimal trade-off between P_D and P_{FA}, the decision threshold λ could be selected. It is important to get the knowledge of noise intensity and signal strength to get the optimum threshold value of λ_S. Noise power can be estimated, but it is necessary to obtain signal power, transmission and propagation characteristics. The threshold is usually chosen in practice to fulfill a certain P_{FA}, which only requires knowledge of the noise power. Unless signal SNR is small, the situation is similar to hypothesis H_0, the detection probability P_D will be increased, e.g. the probability of detection in conventional signal threshold detection with uncertainty UdB. When the signal SNR decreases, the test statistics will be lower than the threshold more often if σ_v^2 is lower than $\widehat{\sigma}_v^2$, which is equal to the threshold increase. Then the detection probability will be increasing. The high and low threshold values can be set using the maximum, minimum noise uncertainty value respectively [12] as follows:

$$\lambda_H = \lambda_0 + U, \text{and } \lambda_L = \lambda_0 - U \tag{11}$$

There are three cases for signal decision according to Eq. (11): 1) If G(z) > λ_H, so signal is existing.

2) If G(z) < λ_L, then signal is missing. 3) If λ_L < G(z) < λ_H, there is no decision. In this scenario, the sensing will fail and the receiver will request a new spectrum sensing from the cognitive user [12].

To overcome that problem of G(z) lies between λ_L and λ_H, the stochastic suggested threshold λ_S will investigate threshold various values between lower and higher thresholds and drawing their histogram to get some insights from it as follows. After building the histogram, threshold with most repeated value which has the greater histogram would be selected for use if the signal lies between λ_L and, then λ_S is defined as:

$$\lambda_S = Max_n\left(\sum_{i=1}^{k} \lambda_i\right) \tag{12}$$

where n is the complete observations number, i is a number of iterations and λ_i is a function of histogram which counts the number of observations falling between the threshold values (known as bins). Additionally, k is the bins entire number (k = $\frac{\lambda_H - \lambda_L}{h}$) and h is size of bin. Summation's largest value of the equivalent threshold value is selected and used as the stochastic threshold.

3.2 The Proposed Sensing Time Scheme

Following the frame structure in [3], equally dividing time to frames, that contains firstly phase for sensing, then second phase for transmitting data. It is believed that the inaccurate SU's spectrum sensing, causing errors in sensing (i.e., false alarm and miss detection). The SU conducts spectrum sensing during the sensing process to detect the behavior of the PU. If the result of sensing finds that the PU is idle, during the data transmission process the SU always has data to transmit, otherwise, the SU would remain silent. To simplify the problem, a time-framed structure is assumed to follow the operation of the PU. In other words, the spectrum is either occupied by the PU or vacant during one frame time.

Figure 2 displays the spectrum sensing frame structure where T represents frame time, t_s denotes time of spectrum sensing, D_0 and D_1 show sensing outcomes when the PU is idle and active, respectively. The SU conducts the second spectrum sensing dynamically in the proposed scheme based on the first test of spectrum sensing. In particular, for time t_s sensing spectrum is performed by SU, and then keeps quiet if the sensing output is D_1. If the sensing result is D_0, spectrum sensing will be performed by the SU for time t_s again to verify the absence of the PU for better protection. The SU will transmit data if the second sensing result is still D_0, Else it will keep quiet. Moreover, the final decision for sensing is obtained from 2nd sensing result, when the result of 2nd sensing is differing from the 1st sensing result.

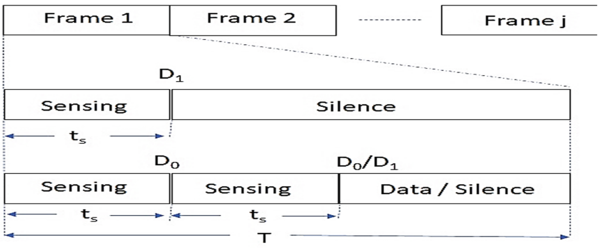

Fig. 2. Structure of spectrum sensing frame.

It is possible to save the energy needed for spectrum sensing at each frame start, when takes into account the primary activity level as sensing interval will be expanded to several frames if the primary user is active according to results of final sensing. As a result of improving the accuracy of spectrum sensing, the number of inaccurate data transmission is reduced, this is in turn increases network energy efficiency by avoiding excessive energy consumption due to incorrect data transmission. Six possible cases based on the results of the first and second spectrum sensing are shown in Fig. 3.

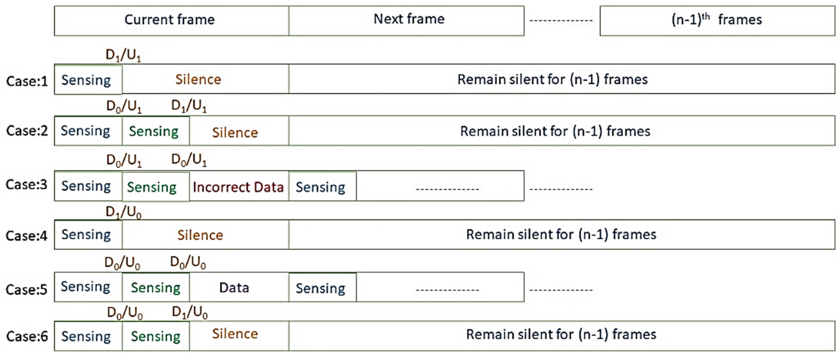

Fig. 3. Sensing time and sensing interval frame structure.

Based on the six cases, the PU activity was successfully detected in Cases 1 and 2. Case 3 triggered miss detection problem, while Cases 4 and 6 contributed to false alarm problem. Only in case 5, a good result was achieved. From the discussed cases, case 3 only leads to the missed detection problem p_m^1 can be specified as:

$$p_m^1 = p_b(1 - p_D)^2 \tag{13}$$

while p_m^2 is identified as:

$$p_m^2 = p_b(1 - p_D) \tag{14}$$

Based on Fig. 3. When data is transmitted (i.e., Case 3 and Case 5), it must execute a spectrum sensing twice. As discussed above, when the primary user actual state is U_0 is valid only for data transmission. the invalid throughput probability as a result of miss detection P_{x1} and the valid throughput probability P_{x2} could be estimated by the following equations [3]:

$$p_{x1} = p_b(1 - p_D)^2 \tag{15}$$

$$p_{x2} = p_i(1 - p_{FA})^2 \tag{16}$$

Thus, the SU probability for data transmission can be determined using following expression as modeled in [3]

$$P_X = P_{X1} + P_{X2} \tag{17}$$

As shown in Fig. 3, the SU may be silence in two situations: 1) the SU perform the spectrum sensing once and the result is D_1 so it became silent n frames as case 1 and 4, 2) the SU perform the spectrum sensing once and the result is D_0 then perform the 2nd spectrum sensing and the result is D_1 so it became silent n frames as case 2 and 6. the probability of doing spectrum sensing once and twice is P_{y1} and P_{y2} and can expressed as

$$p_{y1} = p_b p_D + p_i p_{FA} \tag{18}$$

$$p_{y2} = p_b(1 - p_D)p_D + p_i(1 - p_{FA})p_{FA} \tag{19}$$

when D_1 is the sensing final result. Thus, P_v is the probability that sensing final result D_1, is given as follows:

$$p_y = p_{y1} + p_{y2} \tag{20}$$

when P_x and P_y are known, and assuming that we have two successive frames, the throughput can be discussed, it will be four situations for the secondary throughput: 1) through data then remains silent for n frames, 2) Remain silent for n frames then remain silent for n frames, 3) through data then through data, 4) Remain silent for n frames then through data. situations 1, 3, and 4 returns correct secondary throughput S_{T1}, S_{T3}, and S_{T4}, respectively, that equations are defined as follows [3]:

$$S_{T1} = S_{T4} = \frac{p_{x2} p_y (T - t_s) C}{n + 1} \tag{21}$$

$$S_{T3} = p_{x2}^2 (T - t_s) C + p_{x1} p_{x2} (T - t_s) C \tag{22}$$

where C denotes the channel capacity of the SU without PU interference that can be described according to Shannon theorem $(C = \log_2(1 + \gamma s))$, where γs indicates the SU transmitter received SNR. Furthermore, n gives the frames number that the SU stays silent. For S_{T3} the valid throughput for two frames(current and next frames) represented by the term $p_{x2}^2(T - t_s)C$, and the term $p_{x1}p_{x2}(T - t_s)C$, is the achieved throughput by one frame when the other frame senses a miss detection. The total average valid throughput per average frame S_T is:

$$S_T(ts) = S_{T1} + S_{T3} + S_{T4} \tag{23}$$

As n is the number of frames and it is set to positive integers, it's value can be modified depending on the PU activity. The values of p_i and p_b determines the value of n. as the PU busy the sensing interval increased, thus n depends essentially on the prob that PU busy state will continue. Assume that the PU current state is U_1, then the probability that it will stay occupied for n frames, $p_s(n)$, is determined by:

$$p_s(n) = p_b^{n-1}(1 - p_b), n \in \{1, 2, 3, \ldots\} \tag{24}$$

Then the probability of the PU being occupied for at most n frames Ps(n), can be described as:

$$P_s(n) = \sum_{i=1}^{n} p_s(i) \tag{25}$$

A threshold ψ is specified for Ps(n), which corresponds to $0 \leq \psi \leq 1$. The n values depending on ψ based on the equation as follows:

$$n = min\{n : P_s(n) \geq \psi\} \tag{26}$$

After the previous clarification for the two proposed schemes, stochastic threshold and sensing time, the proposed CRWSN node will use the two mentioned schemes as follows when turning on the CRWSN node it will discover the working environment to determine the appropriate value of stochastic threshold which will be used as an offline threshold for spectrum sensing operations will be performed either as a first sensing or second sensing, which will enhance the sensing performance.

4 Performance Evaluation

This section investigates the proposed scheme's performance evaluation using MATLAB. A comparison of proposed scheme with two other schemes for optimizing sensing time, adaptive sensing threshold discussed in [13] and hybrid threshold discussed in [14].

4.1 Simulation Parameters

The simulation scenario is a basic CRWSN, consisting of a single PU and a secondary link with a randomly assigned transmitter-receiver sensor node pair within the PU's communication range. The band that was licensed occupied by the PU is assigned to the SUs. Other simulation *parameters* as, $P_D^1 = 0.9$, $\mathrm{W} = 6\,\mathrm{MHZ}$, $\mathrm{T} = 0.2\,\mathrm{s}$, $\psi = 0.5$, $\gamma_s = -20\,\mathrm{dB}$, $\gamma = 20\mathrm{dB}$, and $C = 6.6582$ bits/sec/Hz.

4.2 Simulation Results

Figure 4-a illustrates the false alarm probability and the probability of missed detection of the old expression of threshold for different SNR at U = 0 dB and U = 1 dB noise uncertainty, it found that the missed detection prob is increased in case of U = 1 dB rather than U = 0 case which indicates that the sensing result using old threshold are effected by noise uncertainty, also the prob of false alarm is increased.

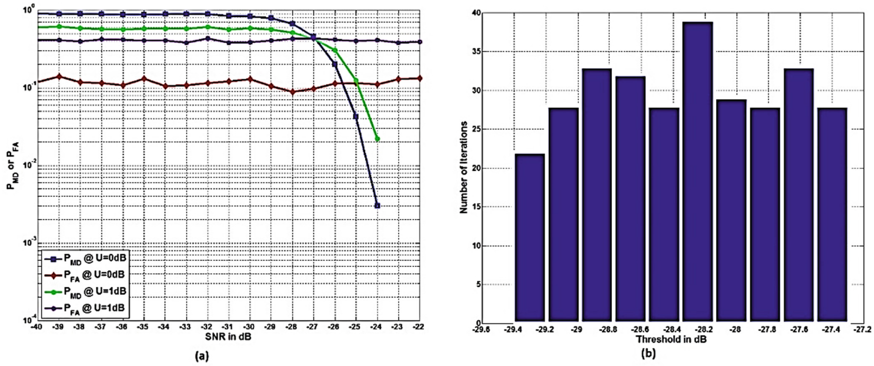

Fig. 4. a) For different SNR, missed detection prob. and false alarm prob. of the old threshold at U = 0 dB and U = 1 dB noise uncertainty respectively. b) Histogram for Stochastic-threshold in dB at environment of noise uncertainty.

Figure 4-b shows the histogram of the number of trials against the threshold levels in dB at ambient noise uncertainty. The value has the highest number of iterations occurs at a stochastic threshold equals −28.2 dB, so it has been selected.

In Fig. 5-a, plot of the Stochastic and double thresholds probabilities of false alarm and missed detection versus SNR for noise uncertainty of 1 dB, which shows the two schemes double threshold and stochastic threshold approximately have the same performance taking in consideration the advantage of stochastic in case of ambiguity when the received signal level in the middle between the higher and lower threshold.

Figure 5-b demonstrates the probability of missed detection against SNR using the old, double and stochastic threshold respectively for noise uncertainty U = 0 dB and U = 1 dB. Additionally, missed detection prob Pm = 0.1 was obtained according to the 802.22 standard maximum acceptable value of PFA = 0.1, at 8.2 ms sensing duration

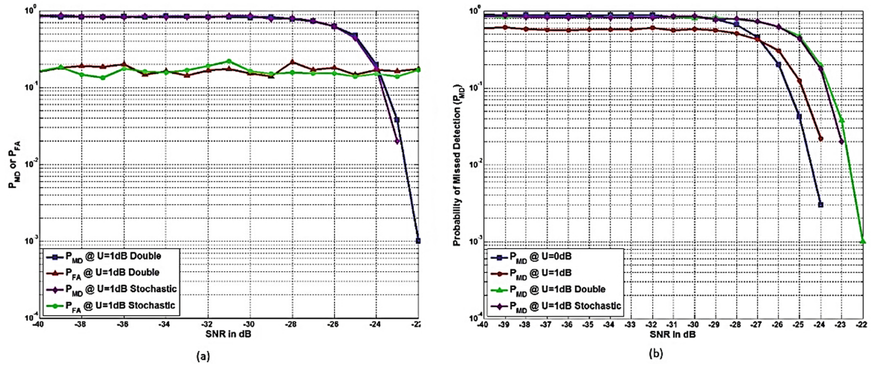

Fig. 5. a) For different SNR, probabilities of false alarm and missed detection of the stochastic and double thresholds at U = 1 dB noise uncertainty. b) For different SNR, Missed detection probability for the old threshold at U = 0 dB and U = 1 dB noise uncertainty, and the double and stochastic threshold under U = 1 dB noise uncertainty.

for original threshold at SNR = 25.5 dB at U = 0 dB and obtained at 25 dB SNR at U = 1 dB at P_{FA} = 0.4 which was not accepted by the standard, for the U = 1 dB, if target PFA = 0.1 is obtained at 22.6 dB SNR for the stochastic threshold and 22.5 dB SNR for the double threshold. The noise uncertainty U is 0 dB. If accurate information of noise exists, the old threshold exceeds the stochastic and double by 3 dB as illustrated in Fig. 5-a. Furthermore, if the expected noise uncertainty U = 1 dB, the efficiency of the original threshold is worse than the results of the stochastic and double threshold with respect to the situation $P_{FA} = 0.1$. Moreover, stochastic threshold performance outperforms by 0.1 dB, the double threshold as seen in Fig. 5-b.

To cover various levels of noise uncertainty that occur at different operation environments, we conduct a study to compute the corresponding stochastic threshold values. Figure 6-a concludes the results achieved from this study, where the increase in the noise uncertainty reduces the stochastic threshold. The prior knowledge of these values in the initialization phase will help the node to save time in the next operation phases.

Figure 6-b illustrates the sensing duration n as a function of pi when the threshold ψ is 0.5 and the output of the sensing is D1. As could be seen, as pi increases, the sensing duration n reduces. If pi is greater than 0.5, the interval of sensing n is often 1. In different words, at start of each frame, the SU executes spectrum sensing at pi > 0.5. The scanning interval n shrinks as pi increases, hence the SU executes more frequent spectrum sensing and there are additional chances for spectrum holes to be utilized so secondary throughput is enhanced. Moreover, as pi decreases, the sensing duration increases, thereby reducing spectrum sensing energy consumption to boost energy efficiency. In fact, the threshold ψ is highly dependent on the choice between energy efficiency and secondary throughput.

Figure 7-a shows the comparison of these three schemes in the secondary throughput for fixed T = 0.2 s as a function of pi. As is obvious, the proposed scheme's secondary throughput is lower than those suggested in [13] and [14]. This is

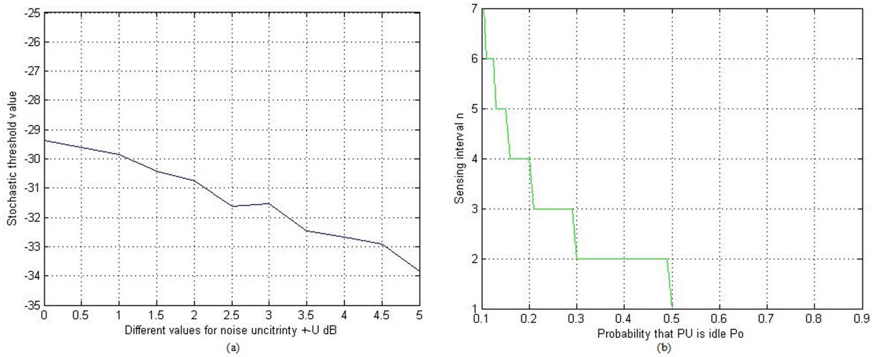

Fig. 6. a) Stochastics threshold values for different noise uncertainty. b) The interval of sensing as a function of *p*i.

because the SU must execute the sensing again to guarantee the initial result of sensing when it indicates that the PU is idle. It minimizes the available data transmission time. Moreover, the interval of sensing becomes extended when the Primary user activity becomes more and the outcomes of sensing display that the primary user is active. This decreases spectrum sensing consuming for energy; however, when the SU stays silent for n frames, the chances for data transmission are also wasted. These are the two key reasons why the suggested scheme's secondary throughput is lower than the other two schemes.

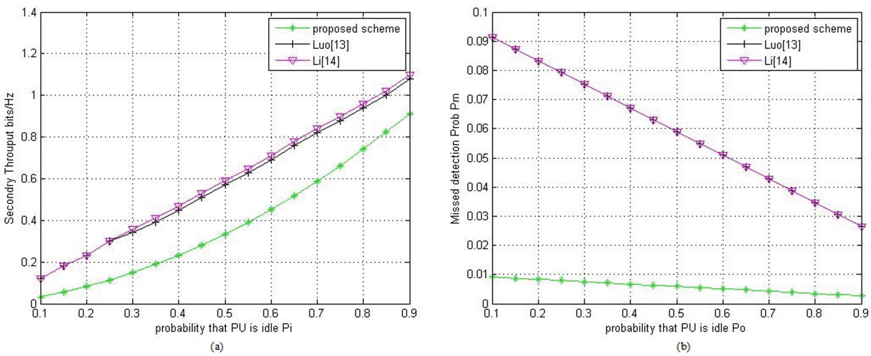

Fig. 7. a) Secondary throughput comparison. b) Miss detection probability comparison.

Figure 7-b compares the probability of miss detection p_m^1 of the planned scheme with the existing ones in [13] and [14]. The suggested scheme's probability of miss detection is often smaller than two other schemes. Because the SU just executes spectrum sensing once in [13] and [14], the probability of such two approaches is just like p_m^2, according to Eq. (14), it can be seen that the ratio between pm^1 and p_m^2 is $1 - p_D$. Since p_D is put on the value itself as just the two other techniques (i.e., 0.9),

with our suggested model the probability of miss detection reduces by a factor 10. In particular, as p_i becomes smaller, the difference among both p_m^1 and p_m^2 has become significantly larger. Even though when the result of the sensing is D_0 spending more time for detecting the primary user and for the average frame the secondary throughput is lower, the primary user has more protection because of the lower probability of miss detection, Therefore, the decrease in the incorrect data transmissions number will cause reduction in energy consumption which increases the energy efficiency of the network and extends the lifespan of the network. Therefore, within the extended lifetime, the network can be used more to substitute the wasted secondary throughput.

5 Conclusion and Future Work

This paper presents a creative model for CRWSN node, which determines the proposed stochastic threshold in the first run of the node that helps to overcome the noise uncertainty in the sensing environment, which shows an enhancement in sensing result. Then executes sensing on the basis of results of the first sensing for either one or two intervals. This helps the CRWSN as a secondary user to conduct again the spectrum sensing to verify that the primary user is in fact silent when the results of first sensing shows that the primary user is silent. Furthermore, the proposed solution respects the PU's level of activity. The interval of sensing may be varied to further enhance the energy efficiency depending on the different primary user activity levels.

Moreover, simulation analysis validates that higher energy efficiency and better performance of spectrum sensing occur from the proposed scheme. Simulation analysis shows that the stochastic proposed threshold at noise uncertainty existence of 1 dB exceeds the double threshold at $P_{FA} = 0.1$ and time of sensing 8.2 ms by more than 0.1 dB. As a future work, we can try the proposed CRWSN node model in cooperative sensing situation and study its effect on the cooperative sensing performance.

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