

Research Article

Improving Spectrum Sensing for Cognitive Radio Network Using the Energy Detection with Entropy Method

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Spectrum is one of the world's most highly regulated and limited natural resources. Cognitive Radio (CR) is a cutting-edge technology that aims to solve the future spectrum shortage issue in wireless communication systems. CR is one of the most widely used methods for maximizing the use of the wireless spectrum. Spectrum sensing is a critical step in discovering spectrum gaps in CR. Matching filter detection, energy detection (ED), cyclostationary detection, correlation coefficient detection, and wavelet detection are some of the frequency band sensing techniques. ED has received the most attention from many researchers because of its convenience and low computation complexity. However, noise instability, or the random and unavoidable variation of noise that exists in any communication link, greatly decreases the output of ED, especially whenever the signal-to-noise ratio (SNR) is poor. As a result, this research provides an exciting spectrum sensing option known as the energy detection with entropy method technique. In contrast to conventional ED, the proposed energy detection with entropy method offers better sensing performance in low SNR circumstances. According to simulation results, the proposed method has a significant performance improvement of about 18.58% when compared to CED at a given SNR of -18 dB.

1. Introduction

Wireless communication technologies are rapidly evolving in order to satisfy people's demands and requirements, which are changing dramatically. As wireless systems and technology advance, the demand for radio spectrum also grows in the same manner. The proliferation of wireless systems and networks has resulted in a scarcity of spectrum resources, which are limited and precious natural resources [1]. On the contrary, recent studies on current spectrum allocation show underutilization of the allocated spectrum by the licensed user at any specific location and time. Cognitive radio (CR) has been identified as a possible technology for addressing the issues of spectral scarcity and underutilization [2, 3]. CR has been regarded as an appropriate solution for resolving the imbalance or disparity between scarce spectrum and the underutilized spectrum.

Spectrum Sensing (SS) is regarded as the most critical component in the establishment of CR [4–6]. SS is the most fundamental and important process of CR to find the unused or vacant spectrum, which is called “spectrum holes.” Under a CR environment, the sensing of the spectrum is done in order to trace the unused spectrum segments from the target spectrum pool in order to use those segments in a fair and optimal manner such that there should be no unwanted interference to the licensed primary user.

Cognitive radio (CR) is a vital technology that allows for more efficient use of the finite and inefficiently utilized frequency bands in an opportunistic manner [7, 8]. CR is also described as a wireless communication system that intelligently learns and adapts to its surroundings. There are two kinds of bands: licensed and unlicensed. Licensed bands are those that can only be used by authorized parties or users, whereas unlicensed bands can be used by everyone

who wants to use them. According to those bands, there are two kinds of users in the CR Network (CRN) [9]. The users who have the privilege of using licensed bands at any time are known as primary users (PUs), whereas the users who have the privilege of using unlicensed bands are known as secondary users (SUs). Almost all of the time and in many parts of the world, licensed bands are not efficiently utilized by the PUs [1]. There are always gaps and possibilities in the spectrum. A spectrum hole occurs when a frequency band is unoccupied (or when a vacant band occurs in the frequency spectrum). CRN has four main tasks/functions, which are spectrum sensing (SS), spectrum mobility/handoff, spectrum management/decision, and spectrum sharing [10].

The main goal of CR is to resolve the bandwidth crises problem by utilizing the natural resources well such as transmitted energy, time, and frequency [11–13]. CR technology detects the available spectrum bands and identifies which bands are vacant and where. Detecting vacant bands is only possible by using SS techniques, which are useful in improving the spectral efficiency of a network. Unutilized spectrum bands can be considered as a spectrum from which spectrum band frequencies can be assigned to cognitive radio users (CRUs). Without collecting these spectrum bands into a common pool, CR users can use frequencies that have been discovered to be vacant directly. Moreover, cognitive radio (CR) methods can be utilized internally inside a licensed network to enhance spectrum utilization efficiency. In a CR network, the secondary users (SUs) periodically observe the spectrum radio and communicate opportunistically through the spectrum gaps, or white space. As indicated in Figure 1, there are three popular types of SS methods for identifying a PU licensed available spectrum [14].

Several spectrum sensing methods, such as energy detection (ED), match filter detection (MFD), and cyclostationary detection (CD), which are termed noncooperative detection or single-stage methods, are used to sense the spectrum for CR. ED is the simplest and easiest of these methods because it does not need information about the PU signal. It's simple to use and has a short sensing time [15–17]. The ED method involves searching for the frequency band of interest and performing tests to compare the received energy with a predefined threshold to determine whether the PU is active or not. Unfortunately, at low SNRs, the ED technique is not robust in detecting spectrum holes correctly. To overcome the challenges of the ED method, the energy detection method with entropy-based detection sensing is introduced in this research.

Transmitter-based detection is one of the major categories of SS techniques. It is also known as noncooperative SS techniques. Noncooperative detection refers to the sensing terminal does not cooperate with each others or the availability of one terminal only for sensing the spectrums. Therefore, is spectrum sensing decision is made based on the local measurements and observations of secondary users [18–20]. The detection model is purely based on the analysis of the received signal at the SUs receiver end. Transmitter based detection methods are commonly based on the assumption that the cognitive

device is unaware of the primary transmitter's location [20]. As a result, cognitive users have to rely on the detection of weak signals from the primary transmitter and use only local observations to carry out SS. A cognitive device is not fully aware of the spectrum occupancy in its vicinity (coverage area). Therefore, totally avoiding harmful interference with PUs is impossible. Furthermore, the transmitter-based detection is ineffective in preventing a hidden terminal problem [18, 20].

In transmitter-based detection, each CR user behaves individually and assesses the spectrum occupancy depending on its own local observations [21]. Detecting a transmitted signal of licensed users in a CRN environment is difficult due to a number of uncertainties, including channel uncertainty, which refers to dynamic variation in channel fading and shadowing circumstances; aggregated interference uncertainty, which occurs when there are too many unauthorized users in the same CRN that interfere with one another; and lastly, the noise uncertainty, which can affect the performance of the receiver operating characteristics (ROC) curve and detection sensibility [21, 22]. In SS, the problem of hidden terminals is also seen as a major challenge [21, 22].

Cooperative spectrum sensing (CSS) provides a solution to the problem that arises in spectrum sensing due to noise uncertainty, receiver uncertainty, fading and shadowing [18]. Particularly, CSS is used to overcome the hidden terminal problems occurred for single node detection. As discussed earlier, there are three approaches to CSS; centralized, distributed (decentralized), and relay-assisted approaches [23]. Under the centralized CSS approach, each secondary user employs the single node detection techniques to perform the local spectrum sensing and then sends the decision result to the fusion center (FC). Lastly, the FC analyses the aggregated information and makes a decision based on certain judgment criteria to complete the spectrum process. SU sends their results to FC either by using hard decision combining (OR Rule, AND Rule, Majority rule) or soft decision combining (EGC, MRC, SLC) [23]. However, this study considers only transmitter-based detection since it is the basis for other types of spectrum sensing techniques (i.e., cooperative detection and relay-assisted technique).

The increasing demand for wireless services has put a lot of restrictions on how the available radio spectrum, which is a finite and valuable resource, can be used. Because of the recent rapid rise of wireless communications, the issue of spectrum utilization has become even more critical. In addition to this, a fixed spectrum allocation policy has resulted in spectrum underutilization, as a large amount of licensed spectrum is not adequately exploited. In order to overcome the problem of spectrum underutilization, cognitive radio (CR) has emerged as a viable solution for increasing the efficiency of available radio spectrum utilization. Spectrum sensing is an essential task for CR since it helps in the detection of the spectrum gaps (frequency bands that are underutilized). As mentioned in the background section, there are a variety of spectrum sensing techniques [18, 24–28]. Among those techniques, the energy detection (ED) method is the simplest and easiest one. But at

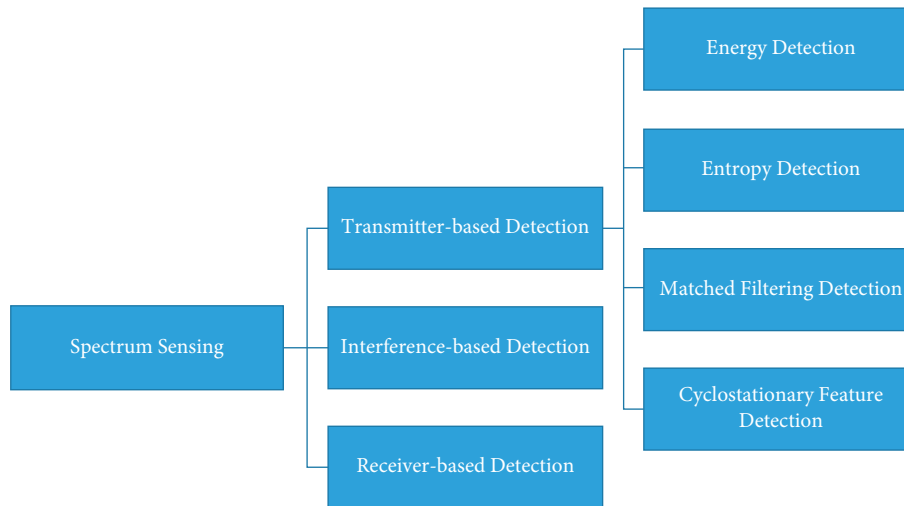


FIGURE 1: Spectrum sensing technique.

low SNR signals, the performance of energy detection spectrum sensing is degraded or reduced. So, in order to overcome the problem at low SNR, energy detection with the entropy method has been used in this research study. The main purpose of this study is to improve the spectrum sensing performance of ED at low SNR using energy detection with entropy methods.

This study focuses on implementing SS techniques for CRs. For implementation, the ED noncooperative SS method is adopted. Also, entropy is added to energy detection techniques to enhance SS performance for CRs. An analytical study of energy detectors with entropy has been done to enhance the performance of conventional techniques. The comparison between traditional energy and the proposed energy detection with entropy technique have been done using MATLAB simulations. Performance evaluations of the proposed technique at different sampling values are also done using MATLAB simulations. The comparison results show that the proposed method outperforms the conventional energy detection (CED) by a significant performance improvement. For instance, at a given SNR of -18 dB, the detection probability of the proposed technique is 0.4818, while the detection probability of CED is 0.4063. In other words, the proposed method has a significant performance improvement of about 18.58% when compared to CED.

2. Literature Review

In [6], analysis of the energy detection SS technique in CR is presented. The theoretical concept of different types of spectrum sensing techniques is discussed clearly with their mathematical formulas. In this study, the ED method is one of the SS techniques that is analysed in detail. An energy detection method is used to detect the unused portions of the spectrum and make them available for reuse. By using the energy detection method, we can identify and allocate gaps in the spectrum to secondary users. Also, the effects of fading, shadowing, and hidden terminal problems on detection performance are discussed. This study analyses

energy detection techniques well, but it fails to detect PU signals at low SNR levels. In [29], energy detection-based spectrum sensing in Rayleigh fading environments is discussed. The closed form mathematical equations for AWGN and Rayleigh channels, including detection probability and probability of false alarm in respect to the SNR, are derived. The results of simulations and theoretic calculations are compared. According to the comparison, this study confirmed that the probability of detecting a primary signal is lower in Rayleigh channels compared to the AWGN channels. The results of this study show that as the SNR value increases, so does the detection probability. Furthermore, it is evident that an increase in false alarm probability increases the detection performance.

In [30], numerical analysis of histogram-based estimation techniques for entropy-based spectrum sensing is proposed. In this study, spectrum detection-based on Entropy had been proposed to sense primary transmission in a Cognitive Radio Network (CRN). To estimate entropy, the histogram method was used. The performance of the entropy-based detection with respect to several rules for calculating the number of bins in the histogram is evaluated. And, it demonstrated that the performance of detection is different for each of the aforesaid rules due to the probability distribution of the PU signal. The main focus of this study is only focused on the optimal determination of the number of bins. However, the current hot research topics in the area of CRs are improving the performance of spectrum sensing. The authors in [31] present their study on selective clustering energy detectors for cognitive radio networks—conceptual design and experimental assessment. This work presents a new ED that determines a dynamic threshold based on clustering and aggregating selected sequences of energy measurements obtained from a software-defined radio. In [2], spectrum sensing evaluation based on the entropy strategy applied to the Cognitive Radio network is presented. Bartlett periodogram is used to perform Entropy Estimation. A trade-off between variance and the spectral resolution for Bartlett periodogram is presented. This study tries to do spectrum sensing only by entropy detection using the

Bartlett periodogram. However, entropy detection using Bartlett periodogram has more computational complexity than two-stage SS using ED and entropy detection.

In [32], SWIPT cooperative spectrum sharing for a 6G-enabled cognitive IoT network is presented. In this study, two simultaneous wireless information and power transfer (SWIPT) cooperative spectrum sharing methods are proposed to improve the energy and spectrum efficiency of a 6G-enabled cognitive IoT network, in which Internet of Things (IoT) devices access the primary spectrum by serving as orthogonal frequency division multiplexing (OFDM) relays with the energy harvested from the received radio frequency (RF) signal.

The authors in [33] present their study on incentive mechanism-based cooperative spectrum sharing for OFDM cognitive IoT networks. In this study, we use contract theory to model the incentive mechanism in an OFDM-based cognitive IoT network under a practical scenario with incomplete information where UIDs act as the employer and employees, respectively.

3. System Model of Spectrum Sensing

Generally, spectrum sensing (SS) can be modelled as a binary hypothesis problem in the detection theory and can be given as

$$y(n) = \begin{cases} w(n): H_0, \\ s(n) + w(n): H_1, \end{cases} \quad (1)$$

where $n = 1, 2, 3, \dots, N$ is the sample number in the sampled signal that has been received, $y(n)$ is the sampled signal that has been received by secondary users, $w(n)$ is zero mean AWGN (additive white Gaussian noise) with variance σ_w^2 , $s(n)$ is the signal from PU with variance σ_s^2 and zero mean. H_0 and H_1 represents absence (null hypothesis) and presence (alternative hypothesis) of the PU, respectively [34].

The probability matrix for different scenarios and their possible outcomes is shown in Figure 2.

Figure 2 shows four alternative scenarios or cases for the detected signal:

- (i) Case 1: deciding H_0 when H_0 is active (H_0/H_0)
- (ii) Case 2: deciding H_1 when H_1 is active (H_1/H_1)
- (iii) Case 3: deciding H_0 when H_1 is active (H_0/H_1)
- (iv) Case 4: deciding H_1 when H_0 is active (H_1/H_0)

The probability of detection (P_d), missed detection probability (P_m), and probability of false alarm (P_f) are generally defined as

$$\begin{aligned} P_d &= p\left(\frac{H_1}{H_1}\right), \\ P_m &= 1 - P_d = p\left(\frac{H_0}{H_1}\right), \\ P_f &= p\left(\frac{H_1}{H_0}\right). \end{aligned} \quad (2)$$

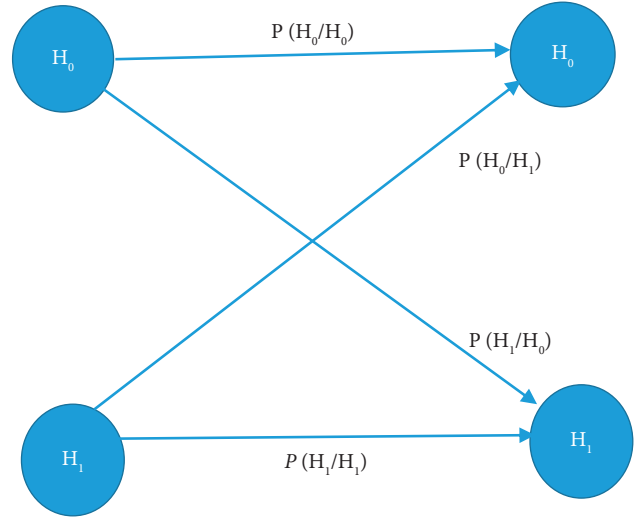


FIGURE 2: Hypothesis testing and probable outcomes, along with their probability.

Accordingly, detection probability is equal to the probability of deciding H_1 when H_1 is active and the missed detection probability is equal to the probability to deciding H_0 when H_1 is active. The false alarm probability is the probability of deciding H_1 when H_0 is active.

3.1. System Model of the Energy Detection Technique. An ED technique is employed in this study to enhance the sensing performance at low SNR, which is one of the SS detection techniques. The block diagram of the ED that is used to determine whether a primary user is present is depicted in Figure 3 [19]. To calculate the received signal energy, the signal that is passed through BPF (used to normalize noise variance and to minimize the power of the noise) of bandwidth W is first squared by using a square-law device and then summed (integrated for continuous signal) over the observation interval T . Finally, the summation's output (integration's output) is compared with a predefined threshold " λ ," to determine whether the licensed user is present.

The received signal's energy is compared to the detection threshold to determine if the PU is present or not in the energy detection system. Energy detection test statistics are as follows:

$$T(y) = \frac{1}{N} \sum_{n=1}^N |y(n)|^2. \quad (3)$$

Under the noise only condition (H_0) of zero mean Gaussian distribution, the test statistics decision of energy detection follows a central chi-square distribution with $2TW$ degrees of freedom. Note that TW represents the product of time bandwidth. On the contrary, under H_1 conditions, the test statistics decision follows a noncentral chi-square distribution with noncentrality parameters of 2γ and degrees of freedom of $2TW$. Here, γ represents the

linear scale of the mean SNR. As a result, the decision test statistics for energy detection under H_0 and H_1 hypothesis are given as follows [35, 36]:

$$Y = \begin{cases} \chi_{2TW}^2 & H_0 \\ \chi_{2TW}^2(2\gamma) & H_1 \end{cases}. \quad (4)$$

Then, the probability density function (PDF) of test statistics Y can be expressed as [35, 36]

$$f_Y(y) = \begin{cases} \frac{1}{2^{TW}\Gamma(TW)} y^{TW-1} e^{-(y/2)}, & H_0 \\ \frac{1}{2} \left(\frac{y}{2\gamma}\right)^{(TW-1/2)} e^{-(2\gamma+y)/2} I_{TW-1}(\sqrt{2\gamma y}), & H_1 \end{cases}, \quad (5)$$

where $\Gamma(\cdot)$ is the complete gamma function and $I_x(\cdot)$ is the x^{th} -order modified Bessel function of the first kind. The probability of false alarm and the probability of detection are, respectively, given as [35, 36]

$$P_f = P_r(Y > \lambda/H_0) = \frac{\Gamma(TW, (\lambda/2))}{\Gamma(TW)}, \quad (6)$$

$$P_d = P_r\left(Y > \left(\frac{\lambda}{H_1}\right)\right) = Q_{(N=TW)}(\sqrt{2\gamma}, \sqrt{\lambda}),$$

where $Q_{(N=TW)}(\cdot, \cdot)$ is the generalized Marcum Q-function.

Without coherent detection, the samples of the primary signal $S[n]$ can be described as a Gaussian process with variance σ_s^2 . As a result, $y[n]$ is a Gaussian process. The number of needed samples N in the low SNR region is high, as can be seen. The test statistics can be estimated as a Gaussian distribution using the central limit theorem [37]. The test statistics are given by [35]

$$Y = \begin{cases} N(\mu_0, \sigma_0^2): H_0 \\ N(\mu_1, \sigma_1^2): H_1 \end{cases}, \quad (7)$$

$$H_0: T \sim \text{Normal}(N\sigma_w^2, 2N\sigma_w^4), \quad (8)$$

$$H_1: T \sim \text{Normal}(N(\sigma_w^2 + \sigma_s^2), 2N(\sigma_w^2 + \sigma_s^2)^2), \quad (9)$$

where $\mathbb{N}(\mu, \sigma^2)$ is the Gaussian distribution with mean μ and variance σ^2 . The mean and variance for both hypothesis H_0 and H_1 are given, respectively, as [35, 36]

$$\begin{aligned} (\mu_0 = N\sigma_w^2; \sigma_0^2 = 2N\sigma_w^4), \\ (\mu_1 = N(\sigma_s^2 + \sigma_w^2); \sigma_1^2 = 2N(\sigma_s^2 + \sigma_w^2)^2). \end{aligned} \quad (10)$$

The detection probability (P_d) and false alarm probability (P_f) are two parameters used to evaluate the detection performance of any SS method. For the large values of N , P_d and P_f with the substitution of equation (10) can be expressed as [35, 36]

$$P_d = P\left(T > \frac{\lambda}{H_1}\right) = Q\left(\frac{\lambda - N(\sigma_w^2 + \sigma_s^2)}{\sqrt{2N(\sigma_w^2 + \sigma_s^2)^2}}\right), \quad (11)$$

$$P_f = P\left(T > \frac{\lambda}{H_0}\right) = Q\left(\frac{\lambda - N\sigma_w^2}{\sqrt{2N\sigma_w^4}}\right), \quad (12)$$

where

$$Q(x) = \frac{1}{\sqrt{2\pi}} \int_x^\infty \exp\left(-\frac{y^2}{2}\right) dy, \quad (13)$$

where $Q(x)$ is Q-function.

The detection threshold can be given as

$$\lambda = \sigma_w^2 [\sqrt{2N} Q^{-1}(P_f) + N]. \quad (14)$$

The minimum number of samples needed is dependent on the SNR and can be computed as [36]

$$N = 2[(Q^{-1}(P_f) - Q^{-1}(P_d))\text{SNR}^{-1} - Q^{-1}(P_d)]^2. \quad (15)$$

3.2. System Model for the Proposed Technique. In this study, we propose energy detection with an entropy methods technique to improve the spectrum sensing performance of the energy detector technique in low SNR situations. There are many types of entropy techniques, such as entropy of uniform distribution and entropy of Gaussian distribution. In this research, the entropy of a discrete Gaussian distribution is used since the energy measurements are a Gaussian distribution.

The proposed technique is the same as the energy detection technique except after energy measurement or test statistics, it applies an entropy method as shown in Figure 3.

Since the test statistics, decision of energy detection for noise only (H_0) Gaussian distribution with zero mean follows the distribution of central chi-square with $2TW$ degrees of freedom. Note that TW represents the product of time bandwidth. On the contrary, H_1 follows a noncentral chi-square distribution with noncentrality parameters of 2γ and degrees of freedom of $2TW$. Here γ represents the linear scale of the mean SNR. As the number of samples N increases, the test statistics can be estimated as a Gaussian distribution.

$$H_0: T \sim \text{Normal}(\mu_0, \sigma_0^2), \quad (16)$$

$$H_1: T \sim \text{Normal}(\mu_1, \sigma_1^2),$$

where $\text{Normal}(\mu, \sigma^2)$ denotes a Gaussian distribution with variance σ^2 and mean μ . For both hypotheses, the mean and variance are as follows:

$$\begin{aligned} (\mu_0 = N\sigma_w^2, \sigma_0^2 = 2N\sigma_w^4), \\ (\mu_1 = N(\sigma_w^2 + \sigma_s^2), \sigma_1^2 = 2N(\sigma_w^2 + \sigma_s^2)^2). \end{aligned} \quad (17)$$

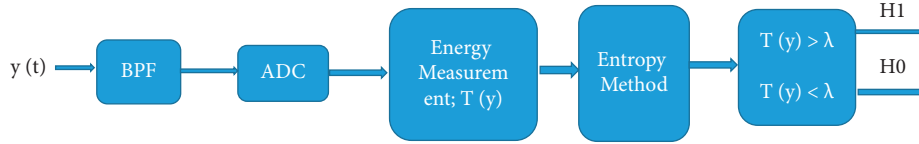


FIGURE 3: Block diagrams of the proposed technique of the energy detector with entropy.

With these substitution the P_d and P_f can be expressed by equations (11) and (12), respectively.

Since the test statistics of energy detection is Gaussian distribution as the number of samples increases, the proposed technique applies a Gaussian entropy method on to it.

The probability density function $p(x)$ of Gaussian random variables is given as follows:

$$p(x) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{(x-\mu)^2}{2\sigma^2}\right), \quad (18)$$

where σ and μ denotes the standard deviation and mean of the Gaussian random variable respectively. For this research lets us consider $\mu = 0$ and $\sigma = 0.5$ for simplicity.

Entropy can be defined as a measure of the average information content per symbol. In data communication, the term entropy refers to the relative degree of randomness.

Entropy of the PDF $p(x)$ of continuous random variable is given as follows:

$$H(x) = - \int_{-\infty}^{\infty} p(x) \log_2^{(p(x))} dx. \quad (19)$$

But, since this research uses a digital implementation, the integration of entropy is replaced by summation as follows:

$$H(x) = - \sum_{x=-\infty}^{\infty} p(x) \log_2^{(p(x))}, \quad (20)$$

where $p(x)$ denotes a Gaussian random variable's probability density function.

4. Results and Discussion

Under this section, the results of SS simulations achieved using employing both the CED as well as the proposed techniques are presented and also discussion analyses on the results obtained from both techniques are presented. The following important performance metrics are used to analyze the performance of CED as well as the suggested technique: detection probability, false alarm probability, probability of missed detection, and SNR. For this research study, the performance of conventional and proposed techniques over an additive white Gaussian noise (AWGN) channel is evaluated using the MATLAB simulation tool. The parameters that are used for simulation in this research are listed in Table 1.

4.1. Results of the Conventional Energy Detector (CED).

Under this subsection, two cases are considered in the implementation: the simulation cases and theoretical cases. The theoretical case illustrates the ROC curve depending on

TABLE 1: Parameters used for simulation.

Simulation parameters	Type and values
Cognitive users	Single user
Types of primary signal	Random
Detection type	Energy detection (ED)
SNR values of transmitted signal	-20 dB up to 0 dB
Probability of false alarm	0.1 to 1
Number of samples	1000, 1500 and 2000
Channel	AWGN
Mean and variance	0 and 1 for AWGN

the theoretical calculation, whereas the simulated scenario shows the ROC curves based on the actual sensing information. So, under this subsection, the comparison between theoretical and simulated energy detector techniques is discussed. In this research study, the conventional energy detector refers to the ED without an entropy method.

The performance of conventional energy detection through the AWGN channel is simulated under this section. The following simulation results are discussed for conventional energy detection techniques:

- (i) Probability of detection versus signal-to-noise ratio
- (ii) Probability of detection versus probability of false alarm

4.2. Probability of Detection versus SNR for the Energy Detection Technique. The SNR range in this simulation is from -20 dB to 0 dB, and the false alarm probability is also considered as a constant that has a value of 0.2. In addition, 1,000 received signal samples and 10,000 simulations of Monte-Carlo are taken into account. The value of SNR increases over its range with step increments of 1 dB. Figure 4 depicts the SNR versus P_d when the false alarm probability is set to 0.2.

Also, Figure 4 depicts the relationship between theoretical and simulation results of energy detection techniques; as shown in the figure, there is a strong correlation between them. The results of both simulation and theoretical show the same trend as observed in the plot. The result indicates that the performance of ED at low values of SNR deteriorates. At a below -18 dB SNR value, the performance of ED is too low, i.e., it cannot differentiate between the signal of PU and noise. As the SNR value increases, the probability of detection also becomes increase sharply up to -7 dB. After -7 dB, CED attains the maximal detection probability, i.e., the energy detection technique can distinguish PU signal in the spectrum from noise is shown in Table 2.

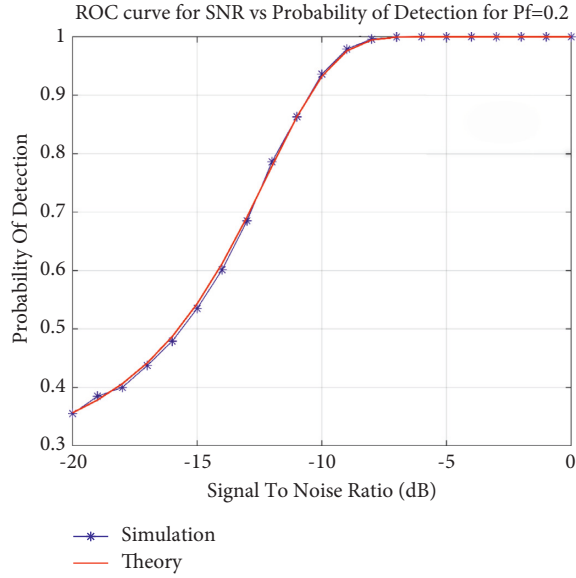


FIGURE 4: SNR vs. P_d ($p_f = 0.2$).

TABLE 2: Simulation result of SNR vs. P_d for CED (without entropy).

SNR vs. P_d for the conventional energy detector (without entropy)										
SNR in dB	-19	-17	-15	-13	-11	-9	-7	-5	-3	-1
P_d	0.3784	0.4385	0.5365	0.6855	0.8631	0.9793	0.9998	1	1	1

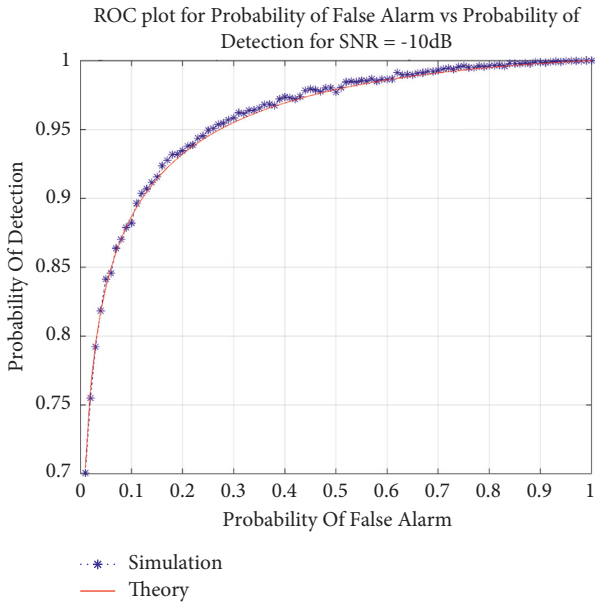


FIGURE 5: P_f vs. P_d at SNR = -10 dB.

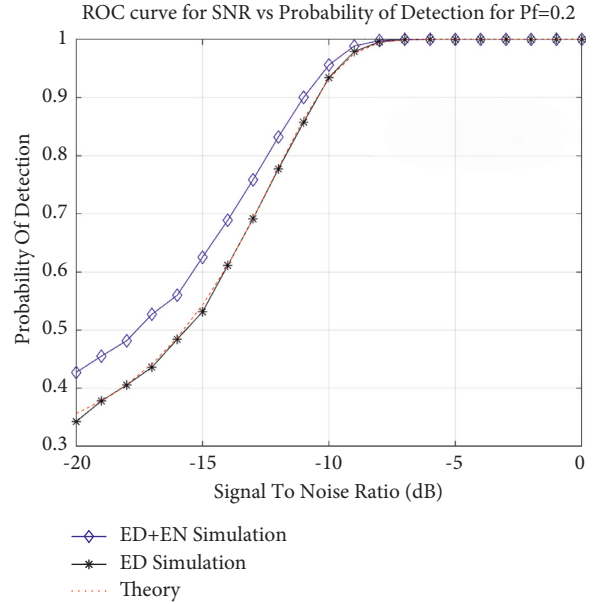


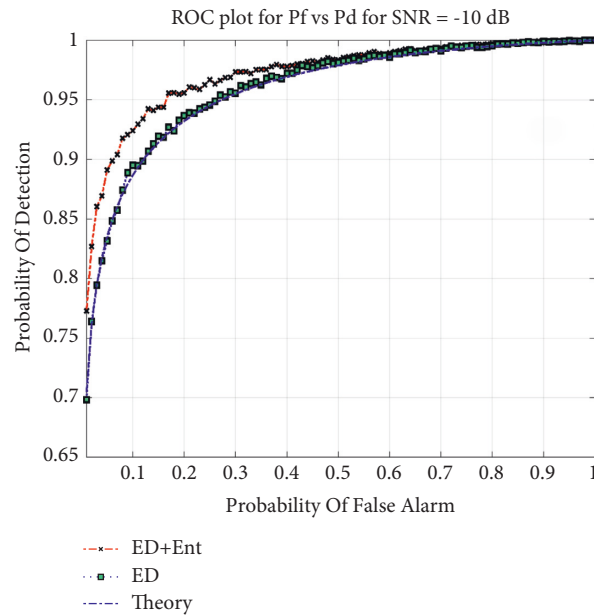
FIGURE 6: SNR vs. P_d (at $p_f = 0.2$).

4.3. Probability of Detection (P_d) versus Probability of False Alarm (P_f). Figure 5 depicts the simulation result of the ROC curve for a conventional energy detector under the AWGN channel. The ROC plot illustrates the relationship between detection probability and false alarm probability at an SNR value of -10 dB. An increase in the probability of

of false-alarm increases the probability of detection. A high false alarm probability leads to a poor spectrum. Hence, the false alarm probability should be as minimal as possible for accurate results and also to protect the primary user signal from interfering with secondary users.

TABLE 3: SNR vs. P_d for both the conventional and proposed technique.

SNR vs. P_d for the energy detector with the entropy method										
SNR in dB	-19	-17	-15	-13	-11	-9	-7	-5	-3	-1
Pd_ED	0.3726	0.431	0.5326	0.6891	0.8596	0.9779	0.9994	1	1	1
Pd_ED_EN	0.4566	0.5208	0.6178	0.7588	0.903	0.9851	0.9998	1	1	1

FIGURE 7: P_f vs. P_d at SNR = -10 dB.TABLE 4: P_f vs. P_d for the energy detector with the entropy method at SNR = -10 dB and $L = 1000$.

P_f vs. P_d for the energy detector with the entropy method at SNR = -10 dB and $L = 1000$										
P_f	0.02	0.04	0.06	0.08	0.1	0.12	0.14	0.16	0.18	
Pd_ED	0.7621	0.809	0.846	0.865	0.8878	0.9035	0.9103	0.9201	0.9278	
Pd_ED_EN	0.8298	0.871	0.8936	0.9134	0.9245	0.9398	0.9415	0.9482	0.95	

4.4. Results of the Energy Detector with the Entropy Method Technique. In this section, the results and performance of energy detection with entropy methods are evaluated and analysed. Also, the comparisons between energy detection without entropy and with the entropy method are discussed. Like in conventional energy detection, the performance of the proposed technique for spectrum sensing is evaluated by key performance metrics that are discussed under this part.

Figure 6 shows SNR versus detection probability for theoretical ED, simulated ED, and proposed ED with the entropy method at the value of $P_f = 0.2$. The blue color with a diamond represents the proposed energy detection with the entropy method technique, and the black color with an asterisk represents conventional energy detection, whereas the red one represents the theoretical value of energy detection. As observed in Figure 6, the proposed technique has

better performance than the conventional detector at low SNR. At below -7 dB of SNR, the proposed technique has better performance than both theoretical and simulated values of conventional energy detectors. However, after -7 dB, all plot curves attain their maximum value of probability of detection, which is shown in Table 3. So, energy detection with the entropy method can distinguish primary user signal from noise better than traditional energy detection since it has good detection probability at low SNR (i.e., below -15 dB).

Figure 7 shows the ROC plot for P_f versus P_d at SNR values of -10 dB. In below simulation results, the red color with a cross represents the proposed energy detection with the entropy method technique; the blue color with a circle represents the conventional energy detection; the blue color with a dashed line represents the theoretical results of conventional energy detection. The ROC curve shows that as

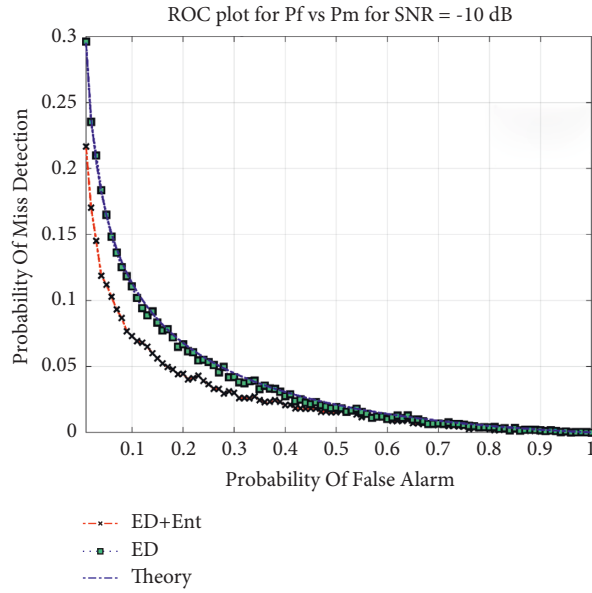


FIGURE 8: P_f vs. P_m at SNR = -10 dB.

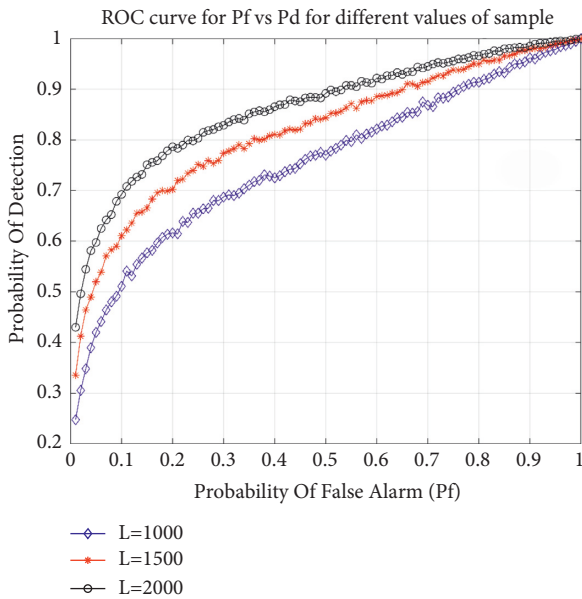


FIGURE 9: P_f vs. P_d at different sample values.

the false-alarm probability rises, the detection probability rises as well. The proposed technique has a greater probability of detection than conventional techniques, as shown in Table 4. The detection probability reaches its maximum value, $P_d = 1$, whenever the false alarm probability is larger than 0.8, as seen in the graph. It is clear from the figure that the proposed method performs better in terms of detection. For instance, at a given probability of false alarm of 0.1, the detection performance of the proposed technique is 0.9241, while the detection probability of CED is 0.8951. In other words, the proposed technique achieves the desired probability of detection with 0.17 probability of false alarm, while

the CED achieves it with 0.28. As a result, it is possible to deduce that the proposed method has better detection performance than CED, since it requires a lower probability of false alarm to obtain the desired probability of detection.

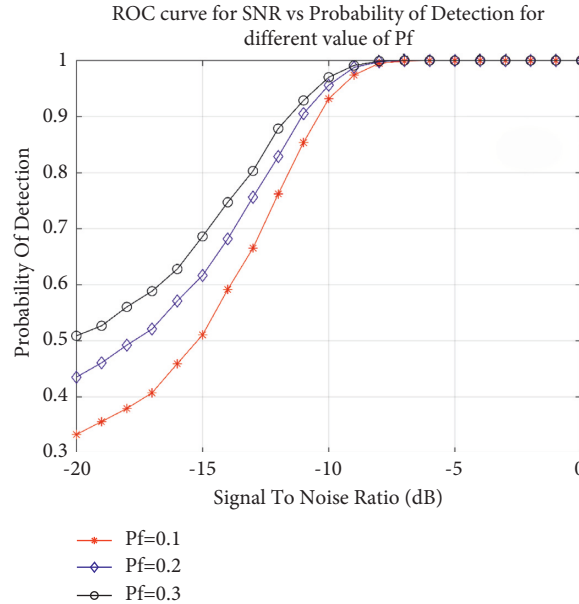
Figure 8 shows the CROC curve for P_f vs P_m at an SNR value of -10 dB. Like in the ROC curve for P_f vs P_d , the red color with a cross represents the proposed energy detection with the entropy method technique, and the blue color with a circle represents the conventional energy detection, whereas the blue color with a dashed line represents theoretical results of conventional ED. The proposed technique has a lower miss-detection probability than the conventional ED technique. As false alarm probability rises, the probability of miss-detection is decreased. Decreasing of miss-detection probability indicates an increase in detection. As miss-detection probability increases, the interference of PU and SU also increases, which is not preferable in spectrum sensing.

Figure 9 shows the ROC curve between P_d and P_f at different sampling values. As observed in the ROC curve, the detection probability increases as the sample number increases. However, an increase in the sampling number increases the computational complexity and sensing time. In this study, we tried to simulate the proposed technique on $L = 1000$, $L = 1500$, and $L = 2000$, where L is the number of samples, as illustrated in Table 5.

Figure 10 shows the plot curve for P_d vs. SNR at various P_f values. At a particular SNR value, as the false alarm probability increases, so does the probability of detection. As depicted in the graph, the probability of detection attains its maximum value after an -8 dB SNR value. In this simulation, the red color with an asterisk represents a p_f value of 0.1 and the blue color with a diamond represents a p_f value at 0.2, whereas the black color with a circle represents a p_f value at 0.3, as shown in Table 6.

TABLE 5: P_f vs. P_d for the energy detector with the entropy method at different sample values.

P_f vs. P_d for the energy detector with the entropy method at different sample values									
P_f	0.02	0.04	0.06	0.08	0.1	0.12	0.14	0.16	0.18
Pd_ED_EN At $L = 1000$	0.3188	0.3875	0.4442	0.4863	0.5109	0.547	0.5619	0.5862	0.6045
Pd_ED_EN At $L = 1500$	0.4108	0.4959	0.5345	0.5948	0.6138	0.6438	0.6586	0.6822	0.692
Pd_ED_EN At $L = 2000$	0.4954	0.5792	0.6249	0.6568	0.6961	0.7223	0.7378	0.7575	0.7638

FIGURE 10: SNR vs. P_d at various P_f values.TABLE 6: SNR vs. P_d for the energy detector with the entropy method at different P_f values.

SNR vs. P_d for the energy detector with the entropy method at different P_f values										
SNR in dB	-19	-17	-15	-13	-11	-9	-7	-5	-3	-1
Pd_ED_EN At $P_f = 0.1$	0.3461	0.408	0.5073	0.6632	0.8555	0.9752	0.9996	1	1	1
Pd_ED_EN At $P_f = 0$	0.4511	0.5178	0.6163	0.7552	0.9081	0.9878	1	1	1	1
Pd_ED_EN At $P_f = 0.3$	0.5336	0.5939	0.6887	0.8136	0.9329	0.9916	1	1	1	1

5. Conclusions and Future Study

In this study, the mathematical formulas for false alarm probability, probability of detection, and miss-detection probability under the AWGN channel model were presented. Numerous simulation plots for AWGN channels were presented based on them. The simulation results have shown that the proposed ED with the entropy method has enhanced performance for spectrum sensing compared to the CED at low SNR situations. The comparison results show that the proposed method outperforms the conventional energy detection (CED) by a significant performance improvement. For instance, at a given SNR of -18 dB, the detection probability of the proposed technique is 0.4818, while the detection probability of CED is 0.4063. In other words, the proposed method has a significant performance improvement of about 18.58% when compared to CED.

In this research, we assumed that the input signal to the SU was a randomly generated signal. In the future, the input signal can be evaluated using different types of digital modulation methods, such as BPSK, QPSK, M-ary and QAM. Only the AWGN channel model is used to evaluate the proposed methods. In the future, the proposed method can be tested using different channel models, such as Rayleigh, Nakagami, and Rician fading channels. Moreover, the proposed method should be performed either using double threshold or dynamic threshold rather than using predetermined threshold. Finally, the cooperative detection techniques for proposed methods should be performed.

Data Availability

Data are included within the article.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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