

Energy Detection Spectrum Sensing in Cognitive Radio

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Abstract: -Wireless communications and the utilization of the radio frequency spectrum have witnessed a tremendous boom during the past few decades. The current static frequency allocation schemes are unable to accommodate the requirements of an increasing number of higher data rate devices. Cognitive radio (CR) with effective primary user detection has become a candidate for more efficient spectrum utilization systems based on opportunistic spectrum sharing. Spectrum sensing is one of the challenging task for cognitive radio. Energy detection is one of the popular spectrum sensing technique for cognitive radio.

In this paper, we analyze the performance of energy detection technique to detect primary user (PU). To evaluate the performance of the detection techniques, MATLAB software has been used for simulation. Simulations were carried out and graphs of probability of detection vs. the probability of false alarm were observed and analysed. The detection probability increases with respect to the increase in false alarm. Also significant reduction in probability of missed detection have been achieved with this sensing technique. The detection probability also varies with the SNR value. SNR has a great influence on the probability of detection. With an increase in SNR value, the probability of detection increases.

I. INTRODUCTION

Cognitive radio based on dynamic spectrum access, arises to be a tempting solution to the spectral congestion problem by introducing opportunistic usage of the frequency bands that are not heavily occupied by licensed users. With dynamic spectrum access, secondary (unlicensed) users can access spectrum owned by primary (licensed) users when it is temporally and/or geographically unused. This unused spectrum is termed as spectrum opportunity. The ability to reliably and autonomously identify unused frequency bands is envisaged as one of the main functionalities of cognitive radios.

II. MAIN FUNCTIONS OF CR

1. *Spectrum Sensing:* this is a fundamental function in CR to enable cognitive radio users (CRs) to detect the underutilized spectrum of primary systems and improve overall spectrum efficiency.
2. *Spectrum Management:* functions are required for CR to achieve users' communication needs by capturing

the best available spectrum; CR should decide on the best spectrum band and the channels within it to meet the QoS requirements over all available spectrum channels.

3. *Spectrum Mobility:* this is the process whereby cognitive radio users change their frequency of operation. Cognitive radio networks aim to use the spectrum dynamically by allocating the radio terminals to operate in the greatest available frequency channels.
4. *Spectrum Sharing:* this is one of the main challenges in open spectrum usage, providing efficient and fair dynamic spectrum allocation methods to distribute the unoccupied spectrum of primary users to the competitive secondary users.

Being the focus of this paper, **spectrum sensing** by far is the most important component for the establishment of cognitive radio. Spectrum sensing is the task of obtaining awareness about the spectrum usage and existence of primary users in a geographical area. This awareness can be obtained by using geolocation and database, by using beacons, or by local spectrum sensing at cognitive radios. In this paper, we focus on spectrum sensing performed by cognitive radios because of its broader application areas and lower infrastructure requirement.

III. CLASSIFICATION OF SPECTRUM SENSING

Spectrum sensing (SS) refers to detecting the spectrum holes (unused spectrum) and sharing it without harmful interference with other cognitive users. It is the task of obtaining spectrum occupancy information. The most efficient and simple approach to identify spectrum opportunity with low infrastructure requirement is to detect primary receiver within operative range of CR. Practically, however, it is not feasible as CR cannot locate PU receiver, and hence, spectrum sensing techniques usually rely on primary transmitter detection. Before looking into the details of spectrum sensing methods, we summarize the typical grouping of SS schemes in **Fig. 1** and highlight characteristic features of these sensing approaches in the following.

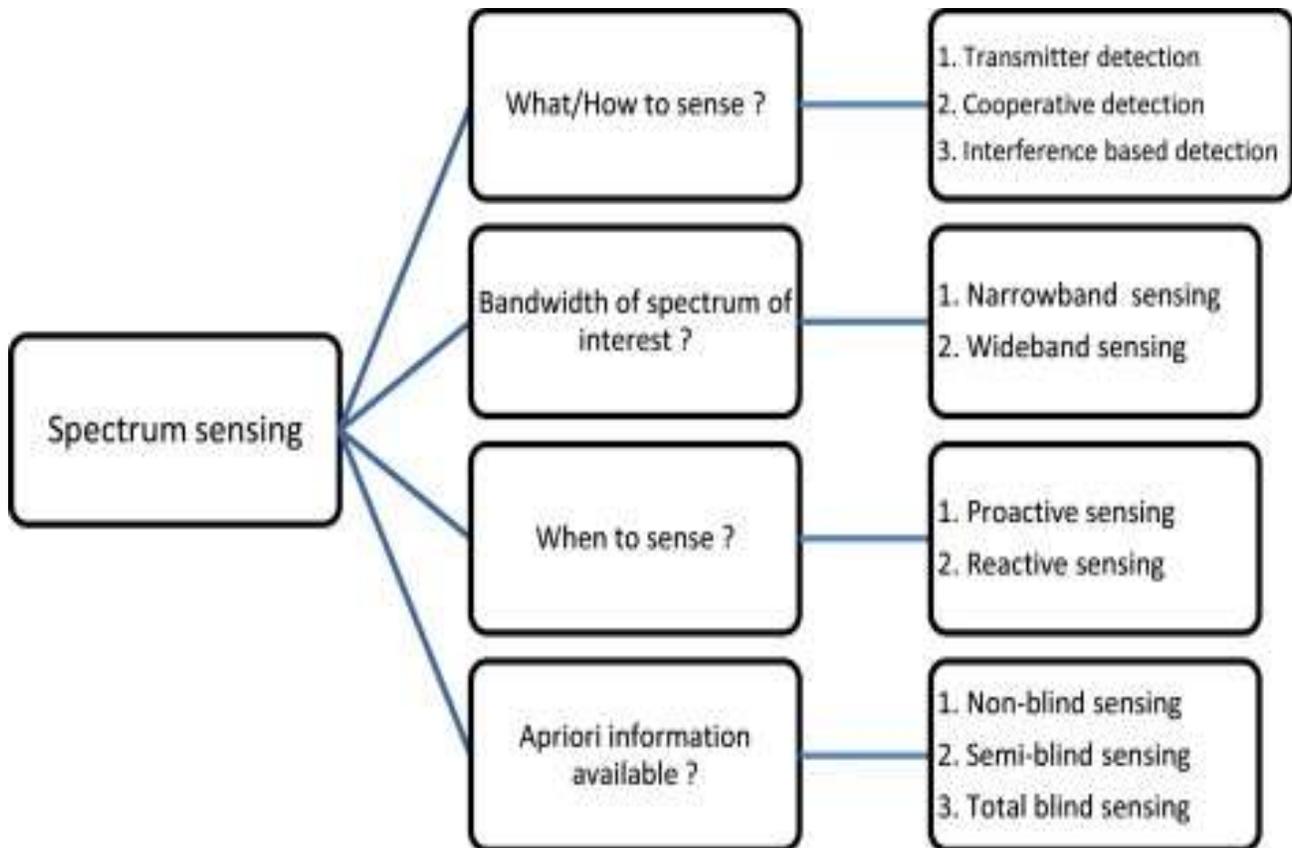


Fig.1 Classification of Spectrum Sensing Techniques [1]

Typically, spectrum sensing is classified into three main detection approaches. In a *non-cooperative primary transmitter detection* approach, CR makes a decision about the presence or absence of PU on its local observations of primary transmitter signal. In comparison, *cooperative detection* refers to transmitter detection based SS methods where multiple CRs cooperate in a centralized or decentralized manner to decide about the spectrum hole. Each cooperating node in cognitive radio oriented wireless network (**CROWN**) may apply any sensing method locally, and then share its raw/refined sensing information with other node(s), depending on a selected cooperation strategy. Both of these approaches fall under the category of *spectrum overlay* wherein SUs only transmit over the licensed spectrum when PUs are not using that band. The third detection approach, based on *spectrum underlay*, wherein, SUs are allowed to transmit concurrently with PUs under the stringent interference avoidance constraint was analyzed and declared to be non-implementable . [2]

Depending on the application at hand, CR can opt for either *narrowband* or *wideband* sensing. Thus, the focus of CR will

be on identifying narrowband hole or free wideband spectrum. To find spectrum opportunity, CR may adopt either a *proactive* (periodic) or *reactive* (on-demand) sensing strategy. Either of the two approaches may be employed in the absence or presence of cooperation among CRs. *A priori* information required for PU detection is another important criterion upon which different SS methods are classified. In this category, different transmitter detection based sensing techniques are categorized as *non-blind*, *semi-blind* or *total blind*. Non-blind schemes require primary signal signatures as well as noise power estimation to reliably detect PU. Semi-blind schemes are relaxed in the sense that they need only noise variance estimate to detect a spectrum hole. However, most practical sensing techniques are generally total blind, requiring no information on source signal or noise power to determine PU activity.

Fundamental to all these classifications is to detect presence or absence of PU signal. Here, we focus on transmitter detection sensing based on a non-cooperative and cooperative approach. **Fig.2** gives classification of transmitter detector spectrum sensing techniques.

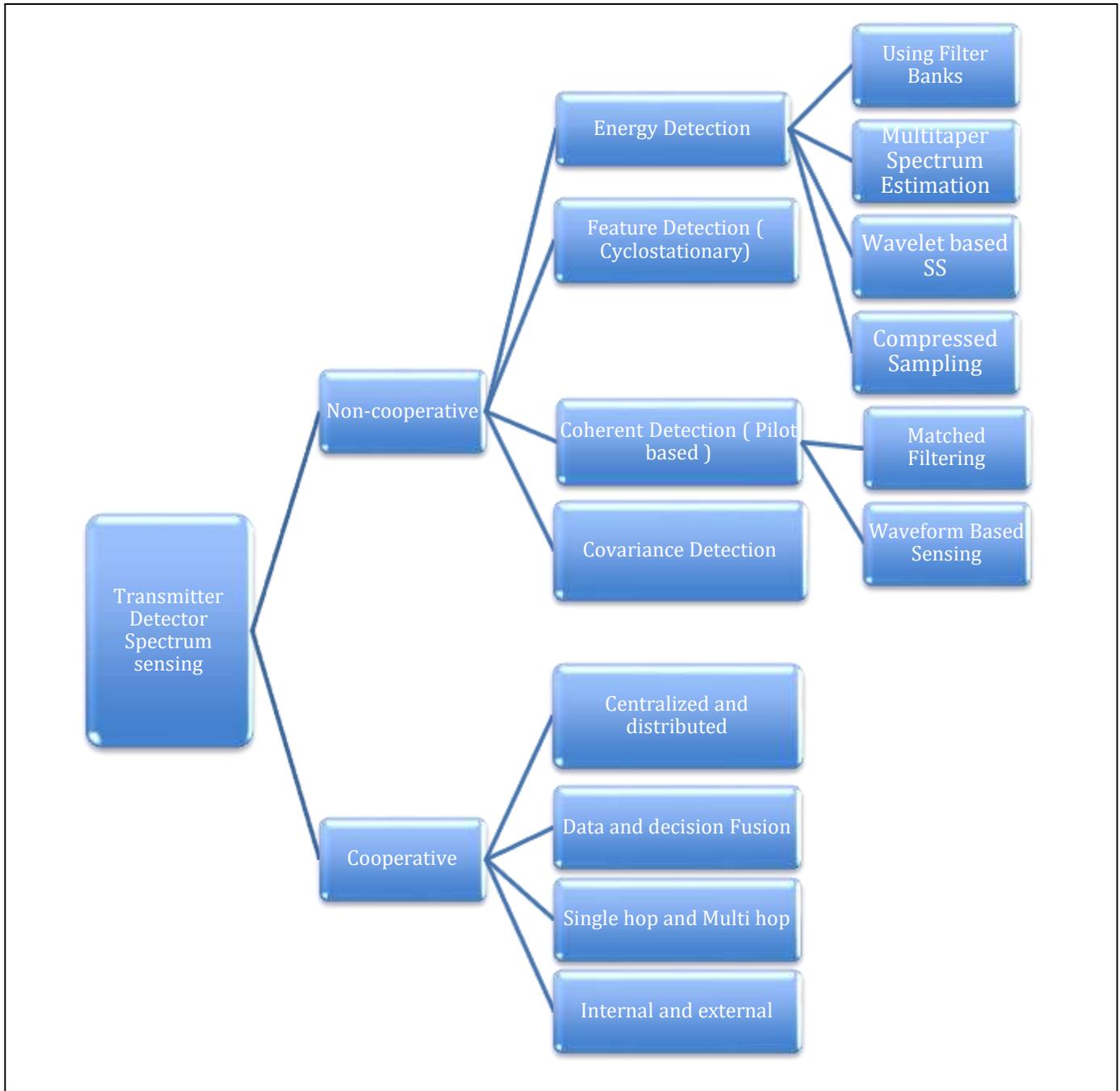


Fig.2 Classification of Transmitter Detector Spectrum Sensing

In this paper, we are going to analyze the performance of energy detection technique to detect primary user (PU). We will see energy detection block diagram followed by different equations and design parameters.

IV. ENERGY DETECTION

It is a non coherent and non cooperative detection method that detects the primary signal based on the sensed energy . Due to its simplicity and no requirement on a priori knowledge of

primary user signal, energy detection (ED) is the most popular sensing technique in cooperative sensing. [3-5]

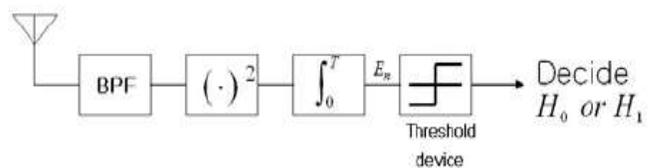


Fig.3 Energy detector block diagram[6]

The block diagram for the energy detection technique is shown in the **Figure 3**. It is composed of four main blocks [7,8]:

- 1) Band Pass Filter
- 2) Squaring Device
- 3) Integrator
- 4) Threshold device

In this method, signal is passed through band pass filter of the bandwidth W , then multiplied by itself (squaring device) and is integrated over time interval. The output from the integrator block is then compared to a predefined threshold. This comparison is used to discover the existence of absence of the primary user. The threshold value can set to be fixed or variable based on the channel conditions. The ED is said to be the Blind signal detector because it ignores the structure of the signal. It estimates the presence of the signal by comparing the energy received with a known threshold V_t derived from the statistics of the noise. Analytically, signal detection can be reduced to a simple identification problem, formalized as a Binary Hypothesis Testing Problem. [9]

4.1 Binary Hypothesis Testing Problem

Depending on the idle state or busy state of the primary user, with the presence of the noise, the signal detection at the secondary user can be modeled as a Binary Hypothesis Testing Problem, given as:

Hypothesis 0 (H_0): signal is absent

Hypothesis 1 (H_1): signal is present

If the received signal, y , is sampled, the n^{th} ($n = 1, 2, 3 \dots$) sample, $y(n)$ can be given as [10,11] :

$$y(n) = w(n) \dots \dots \dots H_0 \dots \dots \dots \text{..equation(1)}$$

$$y(n) = x(n) + w(n) \dots \dots \dots H_1 \dots \dots \dots \text{....equation(2)}$$

where $x(n)$ is the signal transmitted by the PU, $x(n) = h s(n)$ where h is channel gain and $w(n)$ is the noise sample which is assumed to be Gaussian random variable with mean zero ($E[w(n)] = 0$) and variance $2\sigma_w^2$ i.e. $w(n) \sim \mathcal{N}(0, 2\sigma_w^2)$.

Then a **decision rule** can be stated as:

$$H_0 \text{ if } \varepsilon < V_t \dots \dots \dots \text{....equation(3)}$$

$$H_1 \text{ if } \varepsilon > V_t \dots \dots \dots \text{....equation(4)}$$

where ε is the test statistic. Energy detection differentiates between the two hypotheses H_0 and H_1 by comparing ε with threshold voltage V_t as shown in *equation (3) and (4)*. Setting the right threshold value is of critical importance [12]. The key problem in this regard is illustrated in **Fig. 4**, which shows probability density functions of received signal with and without active PU.

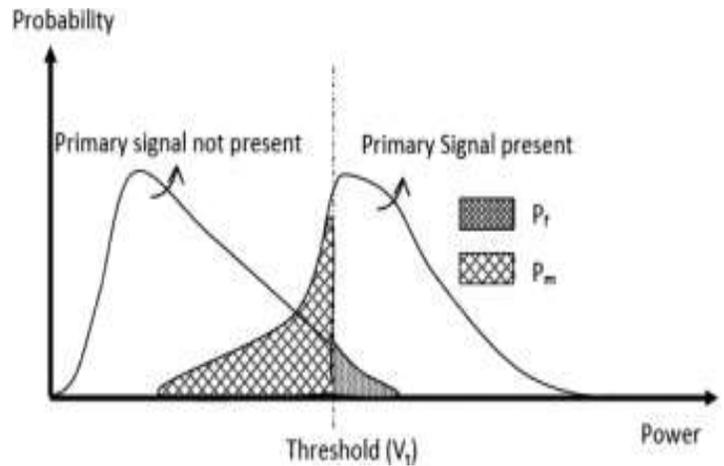


Fig. 4 Threshold setting in ED: trade off between missed detection and false alarm [1]

Hence if the selected V_t is too low, the false alarm probability ie.

$P_f = P_r (\varepsilon > V_t | H_0)$ increases, which results in low spectrum utilization. On the other hand, if V_t is kept unnecessarily high, the probability of missed detection $P_m = P_r (\varepsilon < V_t | H_1)$ is increased which may result in interference with an active PU. Hence, a careful trade off is considered while setting the threshold for ED [13].

4.2 Test Statistic

The output of the integrator (Fig. 3) is called **decision (test) statistic**. The test statistic is compared with the threshold to make the final decision on the presence/absence of the primary signal. However, the test statistic may not always be the integrator output, but a function that is monotonic with the integrator output [7].

The test statistic of the energy detector can be given as [14]:

$$\varepsilon = \frac{1}{2\sigma_w^2} \sum_{n=1}^N |y(n)|^2 \dots \dots \dots \text{....equation(5)}$$

where $2\sigma_w^2$ is the noise variance , N is sample number such that $N \approx 2TW$, where TW is the time-bandwidth product [15].

The **performance of energy detector** is characterized by using following metrics, which have been introduced based on the test statistic under the binary hypothesis:

- **False alarm probability (P_f):** the probability of deciding the signal is present while H_0 is true, i.e.

$$P_f = P_r (\varepsilon > V_t | H_0) \dots \dots \dots \text{....equation(6)}$$

where V_t is the detection threshold, and $P_r[\cdot]$ stands for an event probability. In the context of cognitive radio networks, a false alarm yields undetected

spectrum holes. So a large P_f contributes to poor spectrum usage by secondary users.

- **Missed-detection probability (P_{md}):** the probability of deciding the signal is absent while H_1 is true, i.e.,

$$P_{md} = P_r(\varepsilon < V_t | H_1) \quad \dots \text{equation(7)}$$

which is equivalent to identifying a spectrum hole where there is none. Consequently, large P_{md} introduces unexpected interference to primary users.

- **Detection probability (P_d):** the probability of deciding the signal is present when H_1 is true, i.e.,

$$P_d = P_r(\varepsilon > V_t | H_1) \quad \dots \text{equation(8)}$$

$$P_d = 1 - P_{md} \quad \dots \text{equation(9)}$$

Both reliability and efficiency are expected from the spectrum sensing technique built into the cognitive radio, i.e., a higher P_d (or lower P_{md}) and lower P_f are preferred.

The statistical properties of ε are necessary to characterize the performance of an energy detector. To get the statistical properties, signal and noise models are essential.

4.3 Signal Models

Based on the available knowledge of $s(n)$ the receiver can adopt an appropriate model, which helps to analyze the distribution of the test statistic under H_1 . For example, three different models, **S1**, **S2** and **S3**, are popularly used in the literature, and are given as follows:

S1: For given channel gain h , the signal to be detected, $y(n)$, can be assumed as Gaussian with mean $\mathbb{E}[y(n)] = \mathbb{E}[hs(n) + w(n)] = hs(n)$ and variance $2\sigma_w^2$. This case may be modeled as an unknown deterministic signal. For the signal transmitted over a flat band-limited Gaussian noise channel, a basic mathematical model of the test statistic of an energy detector is given in [7]. The receive SNR can then be given as:

$$\gamma_{s1} = \frac{|h|^2 \frac{1}{N} \sum_{n=1}^N |s(n)|^2}{2\sigma_w^2} \quad \dots \text{equation(10)}$$

S2: When the receiver has very limited knowledge of the transmitted signal (e.g., signal distribution), the signal sample may be considered as Gaussian random variable, i.e., $s(n) \sim \mathcal{N}(0, 2\sigma_s^2)$ and then

$y(n) \sim \mathcal{N}(0, 2(\sigma_w^2 + \sigma_s^2))$. The receiver SNR can then be given as:[9]

$$\gamma_{s2} = \frac{|h|^2 2\sigma_s^2}{2\sigma_w^2} \quad \dots \text{equation(11)}$$

S3: If the Gaussian assumption is removed from **S2** signal model, and signal sample is considered as random variable with mean zero and variance $2\sigma_s^2$, but with an unknown distribution, then $y(n)$ has mean zero and variance $2(\sigma_w^2 + \sigma_s^2)$. The receive SNR can also be given as: [9]

$$\gamma_{s3} = \frac{|h|^2 2\sigma_s^2}{2\sigma_w^2} \quad \dots \text{equation(12)}$$

For a sufficiently large number of samples, the signal variance can be written as:

$$2\sigma_s^2 \approx \frac{1}{N} \sum_{n=1}^N |s(n)|^2 \quad \dots \text{equation(13)}$$

and thus, all the receive SNRs given in equation (3.10 – 3.12) under different signal models have the same expression. In this case, the instantaneous SNR is denoted as γ .

4.4 Distribution of Test Statistics

The exact distributions of test statistics for different signal models are analyzed in the following under both hypotheses, H_0 and H_1 . By CLT approach- [9]

Under H_0

The false alarm probability can be given as:

$$P_f = Q\left(\frac{V_t - N(2\sigma_w^2)}{\sqrt{N}(2\sigma_w^2)}\right) \quad \dots \text{equation(14)}$$

where $Q(x) = \frac{1}{\sqrt{2\pi}} \int_x^\infty e^{-\frac{u^2}{2}} du$ is the Gaussian-Q function.

Under H_1

The detection probability, P_d can be derived for **S1** by:

$$P_{d,s1} \approx Q\left(\frac{V_t - N(2\sigma_w^2)(1 + \gamma)}{\sqrt{N(1 + 2\gamma)}(2\sigma_w^2)}\right) \quad \dots \text{equation(15)}$$

For **S2**,

$$P_{d,s2} \approx Q\left(\frac{V_t - N(2\sigma_w^2)(1 + \gamma)}{\sqrt{N}(1 + \gamma)(2\sigma_w^2)}\right) \quad \dots \text{equation(16)}$$

Note that $P_{d,s3}$ has the same expression as $P_{d,s1}$.

V. SPECTRUM SENSING STANDARDIZATION

Different TV broadcasters use chunk of the radio spectrum allowed for TV broadcasting (e.g., 54–806 MHz in US). White spaces (i.e., frequency slots unused by TV broadcasters) may include guard bands, free frequencies due to analog TV to digital TV switchover (e.g., 698–806 MHz in

US), and free TV bands created when traffic in digital TV is low and can be compressed into fewer TV bands. The US FCC allows to use white spaces by unlicensed users. Subsequently, following standardization efforts have materialized:

- ❖ The IEEE 802.22 standard for TV white spaces has been released with medium access control and physical layer specifications for WRAN.
- ❖ The ECMA 392 includes specification for personal/portable wireless devices operating in TV bands [16],
- ❖ The IEEE SCC41 develops supporting standards for radio and dynamic spectrum management [17].
- ❖ The IEEE 802.11af is for Wi-Fi on the TV white spaces using cognitive radio technology [18].

VI. DESIGN PARAMETERS

The main design parameters of the energy detector are the number of samples and threshold. Although the performance of the energy detector depends on SNR and noise variance as well, designers have very limited control over them because these parameters depend on the behavior of the wireless channel.

6.1 Threshold

A pre-defined threshold ε is required to decide whether the target signal is absent or present. This threshold determines all performance metrics, P_d , P_f and P_{md} . Since it varies from 0 to 1, selection of operating threshold is important. The operating threshold thus can be determined based on the target value of the performance metric of interest. [9]

When the threshold increases (or decreases), both P_f and P_d decrease (or increase). For known N and σ_w , the common practice of setting the threshold is based on a constant false alarm probability P_f , e.g., $P_f \leq 0.1$. The selected threshold based on P_f can be given by using (3.14) as:

$$V_t = (Q^{-1}(P_f) + \sqrt{N})\sqrt{N}2\sigma_w^2 \quad \dots \text{equation}(17)$$

However, this threshold may not guarantee that the energy detector achieves the target detection probability (e.g., 0.9 specified in the IEEE 802.22 WRAN). Thus, threshold selection can be viewed as an optimization problem to balance the two conflicting objectives (i.e., maximize P_d while minimizing P_f).

6.2 Number of Samples

The number of samples (N) is also an important design parameter to achieve the requirements on detection and false alarm probabilities. For given false alarm probability P_f and detection probability P_d , the minimum number of samples required can be given as a function of SNR. By eliminating V_t from both P_f in (3.14) and P_d in (3.15) (here signal model **S1**

is used as an example), N can be given as: [9]

$$N = [Q^{-1}(P_f) - Q^{-1}(P_d)\sqrt{2\gamma + 1}]^2 \gamma^{-2}$$

....equation(18)

which is not a function of the threshold. Due to the monotonically decreasing property of function $Q^{-1}(\cdot)$, it can be seen that the signal can be detected even in very low SNR region by increasing N , when the noise power is perfectly known. Since $N \approx \tau f_s$ where τ is the sensing time and f_s is the sampling frequency, the sensing time increases as N increases. This is a main drawback in spectrum sensing at low SNR because of the limitation on the maximal allowable sensing time (e.g., the IEEE 802.22 specifies that the sensing time should be less than 2 s). Therefore, the selection of N is also an optimization problem.

VII. SIMULATION RESULTS

ROC plots for Energy Detector based spectrum sensing

P_{md} = Probability of missed detection

P_d = Probability of detection

P_f = Probability of false alarm

N = Number of samples

SNR = Signal to noise ratio

Detection probability (P_d), False alarm probability (P_f) and missed detection probability (P_{md}) are the key measurement metrics that are used to analyze the performance of spectrum sensing techniques. The performance of an spectrum sensing technique is illustrated by the receiver operating characteristics (ROC) curve which is a plot of P_d versus P_f (or) P_f versus P_m . The performance of energy detector is analyzed using ROC (Receiver operating characteristics) curves. Monte-Carlo method is used for simulation.

7.1. The plot of Probability of false alarm versus Probability of detection:

The plot of Probability of false alarm versus Probability of detection is illustrated in **Figure.5**. Probability of false alarm (P_f) is on X-axis and probability of detection (P_d) is on Y-axis. In the simulation, study input random bit stream is multiplied by 1 MHz sinusoidal carrier signal to get 1 MHz BPSK modulated signal, which is transmitted in AWGN channel. The detection performance can be performed by varying the probability of false alarm from 0.01,0.02.....1 and finding the probability of detection by using Monte Carlo simulation. Here the number of sample points taken is **N=1000** and **SNR = -12dB**.

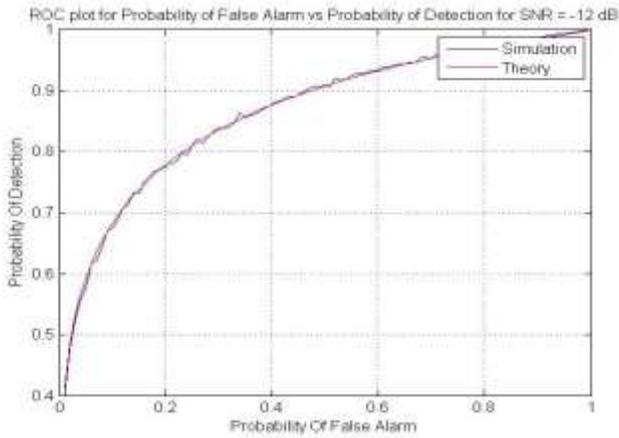


Fig.5 ROC curve for P_f vs P_d Energy detector based spectrum sensing at SNR= -12dB

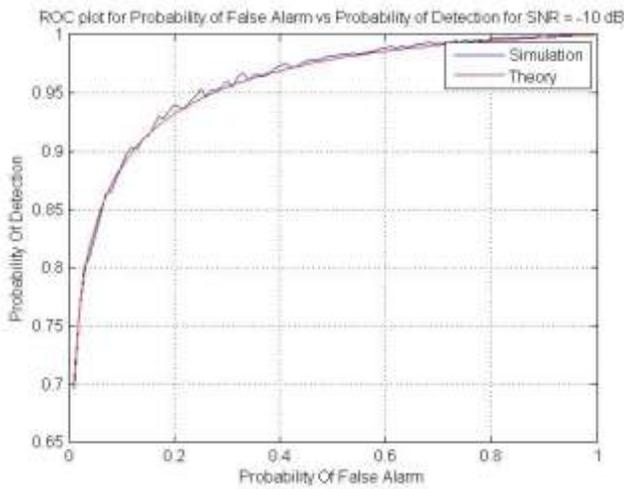


Fig. 6 (a) Plot between P_f and P_d at SNR= -10db

The experiment is repeated for different values of SNR ie. SNR= -10db, -5db, 0db, -20db and plotted in **fig. 6 (a), (b), (c) and (d)** respectively.

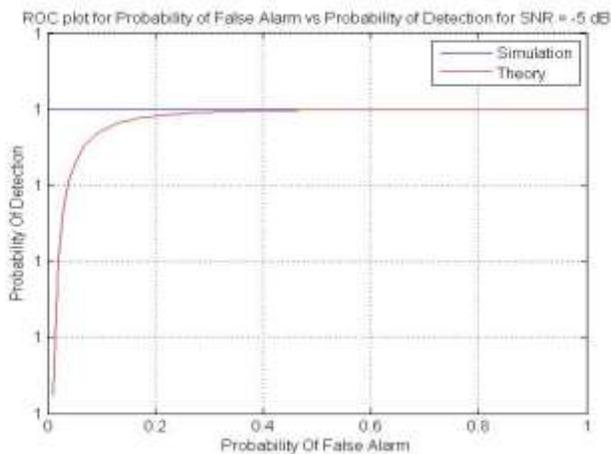


Fig. 6 (b) Plot between P_f and P_d at SNR= -5db

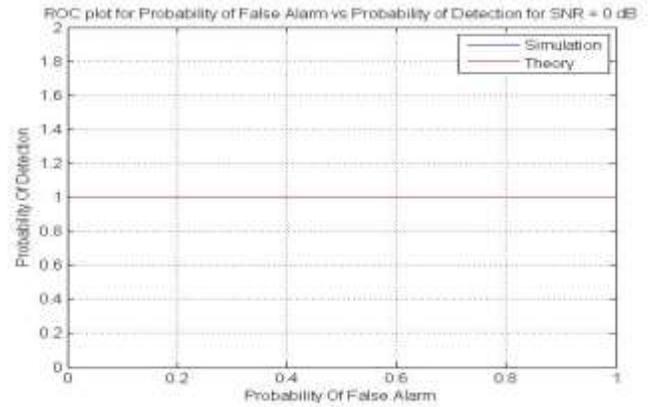


Fig. 6 (c) Plot between P_f and P_d at SNR= 0db

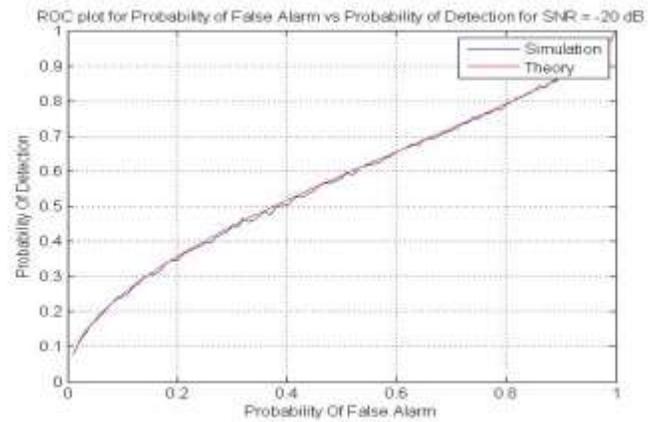


Fig. 6 (d) Plot between P_f and P_d at SNR= -20db

It can be interpreted from Fig.6 (a), (b), (c) and (d) that the performance of energy detector improves with increase in SNR and degrades with the decrease in SNR for the increase in probability of false alarm respectively. This is quantified in Table 1.

Probability of False Alarm (P_f)	Probability of Detection (P_d) (SNR= -12dB)	Probability of Detection (P_d) (SNR= -10dB)	Improvement in times
0.01	0.4	0.7	0.75
0.2	0.78	0.93	0.1923
0.4	0.87	0.97	0.115
0.6	0.94	0.98	0.425
0.8	0.97	0.99	0.0206
1.0	1.0	1.0	0

Table 1: Improvement in Probability of detection with increase in Signal to Noise Ratio in Energy Detection Method for AWGN Channel.

RESULT: Table 1 shows that 2 dB increase in Signal to Noise Ratio; increases the probability of detection (at SNR=-10dB) up to 0.75 times as compared to probability of detection (at SNR=-12dB) for AWGN Channel.

7.2. The plot of Probability of false alarm versus Probability of missed detection: The plot of P_f vs P_{md} is illustrated in **Figure.4.3**. P_f is on X-axis and P_{md} is on Y-axis. In the simulation, study input random bit stream is multiplied by 1 MHz sinusoidal carrier signal to get 1 MHz BPSK modulated signal, which is transmitted in AWGN channel. The detection performance can be performed by varying the probability of false alarm from 0.01, 0.02.....1 and finding the probability of missed detection by using Monte Carlo simulation. Here the number of sample points taken is $L=1000$ and $SNR = -12dB$.

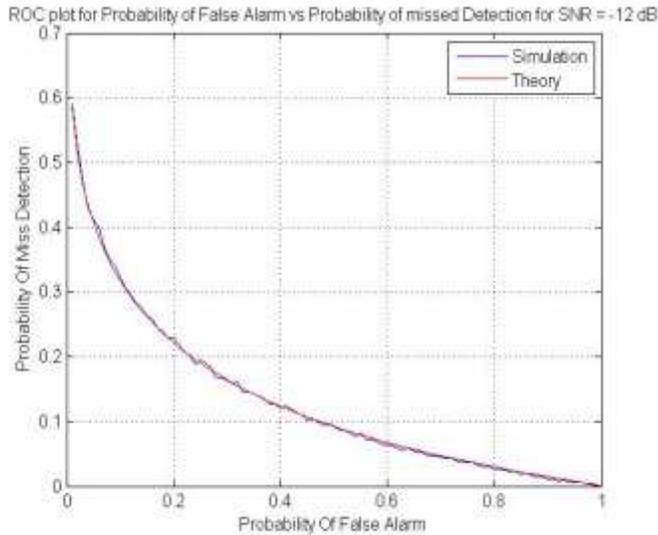


Fig.7 ROC curve for P_f vs P_{md} Energy detector based spectrum sensing at SNR= -12dB

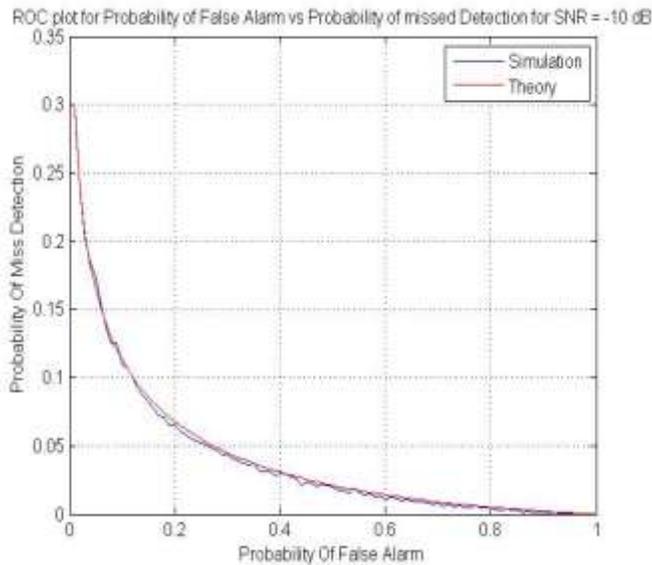


Fig. 8 (a) Plot between P_f and P_{md} at SNR= -10db

The experiment is repeated for different values of SNR ie. SNR= -10db, -5db, 0db, -20db and plotted in **fig. 8 (a), (b), (c) and (d)** respectively.

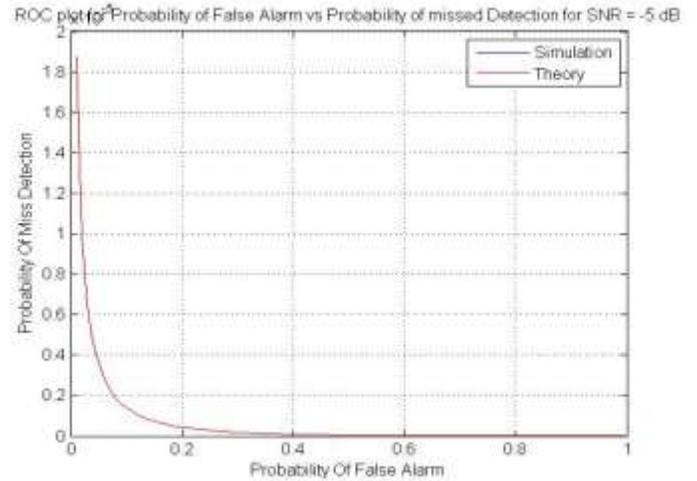


Fig. 8 (b) Plot between P_f and P_{md} at SNR= -5db

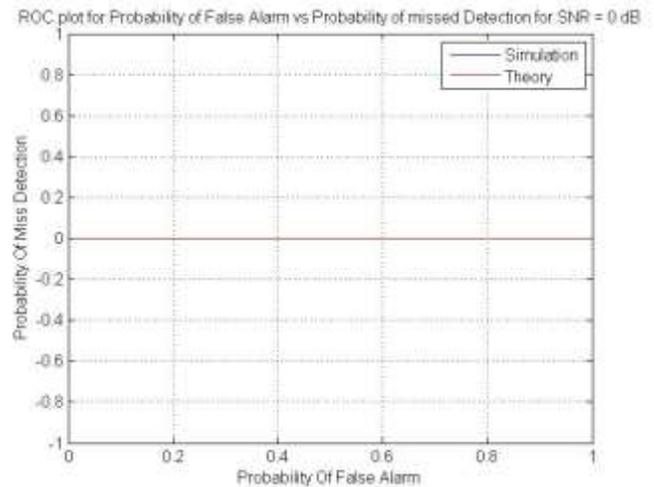


Fig. 8 (c) Plot between P_f and P_{md} at SNR= 0db

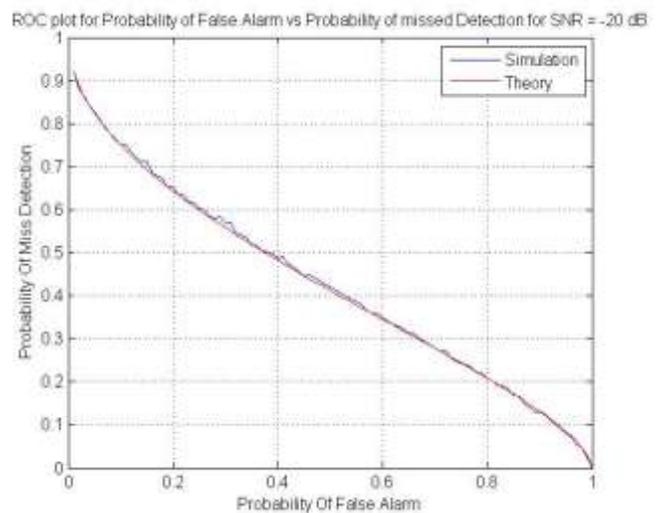


Fig. 8 (d) Plot between P_f and P_{md} at SNR= -20db

It can be interpreted from Figure.8 (a), (b), (c) and (d) that the performance of energy detector improves with increase in SNR and degrades with the decrease in SNR for the increase in probability of false alarm respectively. Since $P_{md} = 1 - P_d$, hence as P_d increases, P_{md} decreases. So when SNR increases, P_d increases and P_{md} decreases. This is quantified in Table 2.

Probability of False Alarm (P_f)	Probability of Missed Detection (P_{md}) (SNR= -12dB)	Probability of Missed Detection (P_{md}) (SNR= -10dB)	Improvement in times
0.01	0.6	0.3	0.5
0.2	0.22	0.07	0.68
0.4	0.13	0.03	0.77
0.6	0.06	0.02	0.67
0.8	0.03	0.01	0.67
1.0	0	0	0

Table 2: Improvement in Probability of missed detection with increase in Signal to Noise Ratio in Energy Detection Method for AWGN Channel.

RESULT: Table 2 shows that 2 dB increase in Signal to Noise Ratio; decreases the probability of missed detection (at SNR= -10dB) up to 77 times as compared to probability of detection (at SNR= -12dB) for AWGN Channel.

7.3. The plot of Probability of detection (P_d) versus Signal to Noise Ratio (SNR): The plot of Probability of detection (P_d) and Signal to Noise Ratio (SNR) is illustrated in Figure.9. Signal to Noise Ratio (SNR) is on X-axis and probability of detection (P_d) is on Y-axis. The detection performance can be performed by varying the SNR from -20dB, -19dB,.....0dB and finding the probability of detection by using Monte Carlo simulation. Here $P_f = 0.2$ and no. of samples $N=1000$.

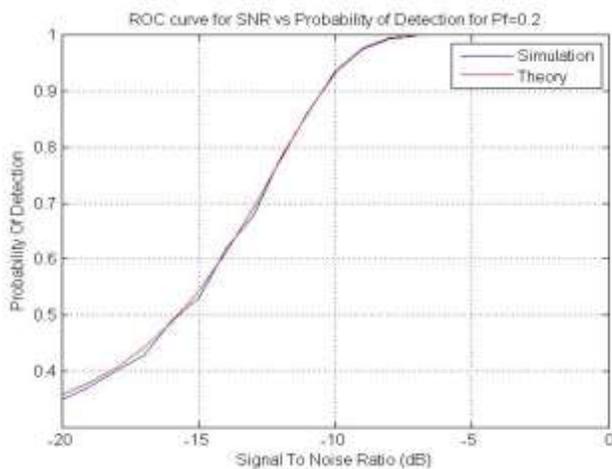


Fig.9 Plot for P_d vs SNR Energy detector based spectrum sensing at $N= 1000$

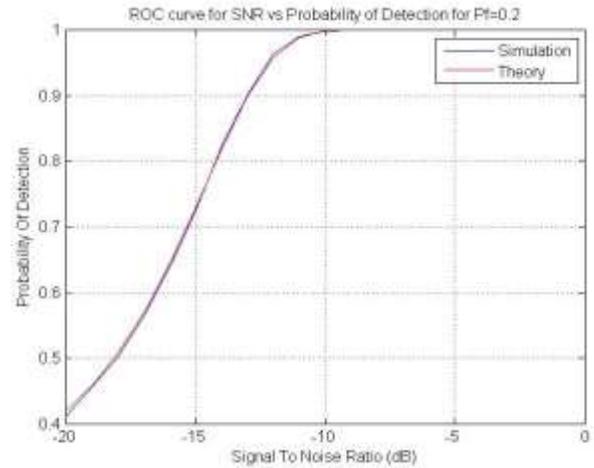


Fig.10 (a) Plot for P_d vs SNR at $N= 3000$

The experiment is repeated for different number of sample points ie. $N= 3000, 5000$ and 7000 and plotted in fig. 10 (a), (b) and (c) respectively.

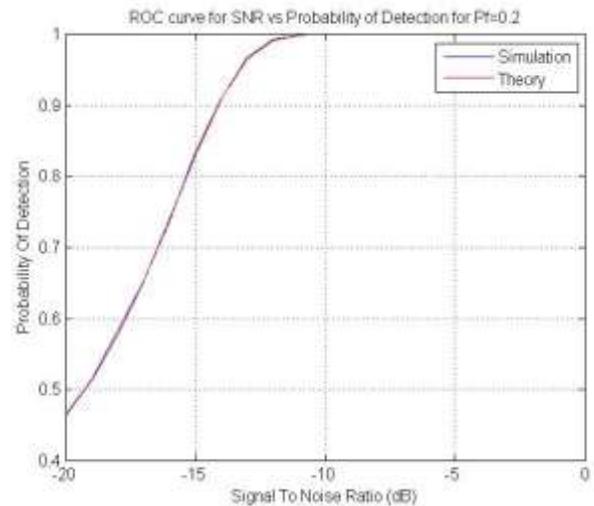


Fig.10 (b) Plot for P_d vs SNR at $N= 5000$

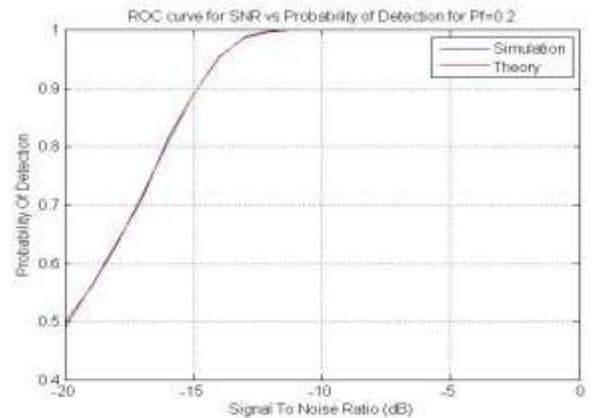


Fig.10 (c) Plot for P_d vs SNR at $N= 7000$

It can be interpreted from Fig.10 (a), (b) and (c) that the performance of energy detector improves with increase in the number of sample points. That is P_d increases with the increase in N for same values of SNR at fixed P_f . This effect is shown in **Table 3**.

Signal to Noise Ratio (SNR in dB)	Probability of Detection (P_d) (N= 1000)	Probability of Detection (P_d) (N=3000)	Probability of Detection (P_d) (N=5000)	Probability of Detection (P_d) (N=7000)
-20	0.3	0.42	0.47	0.5
-18	0.4	0.5	0.57	0.62
-15	0.55	0.72	0.84	0.89
-12	0.8	0.97	0.97	1
-10	0.95	1	1	1
-7	1	1	1	1

Table 3: Improvement in Probability of Detection with increase in number of samples in Energy Detection Method for AWGN Channel.

RESULT: **Table 3** shows that **increase** in the number of samples, increases the detection probability. For example, P_d increases from 0.55 to 0.89 when N is increased from 1000 to 7000. At SNR= -7dB, we get $P_d=1$.

VIII. CONCLUSION AND FUTURE SCOPE

Conclusion:

Spectrum is a very valuable resource in wireless communication systems, and it has been a focal point for research and development efforts over the last several decades. Cognitive radio, which is one of the efforts to utilize the available spectrum more efficiently through opportunistic spectrum usage, has become an exciting and promising concept. In this paper, we examined various aspects of cognitive radio and identified spectrum sensing as the prerequisite requirement for the deployment of cognitive radio oriented wireless networks.

In this thesis, studies have been carried out on spectrum sensing based on energy detection in Cognitive Radio Networks. Simulations were carried out and graphs of probability of detection vs. the probability of false alarm were observed and analysed. The detection probability increases with respect to the increase in false alarm. Significant reduction in probability of missed detection have been achieved with this sensing technique as evidenced from the simulation results. The detection probability also varies with the SNR value. SNR has a great influence on the probability of detection. With an increase in SNR value, the probability of detection increases and we get SNR= -7dB, where we get a detection probability of 1. Hence, we almost obtain the final result on energy detection according to our expectation.

Future scope:

- ❖ With the proposed Energy detector, we need to implement this concept in co-operative spectrum sensing for better performance.
- ❖ Hybrid Spectrum Sensing techniques like any two combinations of spectrum sensing techniques such as Energy detector and Matched detector (or) Cyclostationary detector, with Improved Double threshold Energy detection in both Co-operative, non-cooperative sensing needed for better detection performance.
- ❖ It is well-known that energy detector's performance is susceptible to uncertainty in noise power under such cases alternate detection schemes such as Cyclic feature detection, Wavelet based detection and Filter bank multicarrier approach or power control scheme may be employed.

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