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Simulation based Analysis of Non-Cooperative Spectrum Sensing Techniques in Cognitive Radio

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Abstract— *Increasing number of wireless applications and users has led to dearth of bandwidth for such applications. Static frequency allocation utilizes the spectrum inefficiently, fostering the requirement for dynamic spectrum allocation. One of such application of dynamic spectrum allocation is a Cognitive Radio. A Cognitive Radio senses and understands its radio environment, to recognize vacant spectrum and utilize it, hence leading to increased spectrum efficiency. In Cognitive radio networks, the secondary (unlicensed) user (SU) opportunistically exploits the radio spectrum, without causing intrusion to primary (licensed) user (PU). Therefore, Spectrum Sensing is a crucial step in a Cognitive Radio based systems. In this paper, we perform analysis of various Spectrum-Sensing techniques by performing simulations and plotting the curve between probabilities of detection (P_d) and signal to noise ratio (SNR). Based on the practical results, we conclude for the most suitable Spectrum Sensing technique in Cognitive Radio.*

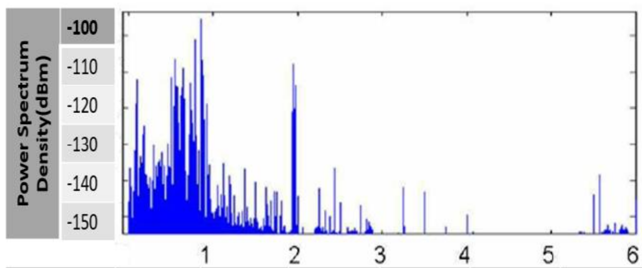
Keywords*— Cognitive Radio, Spectrum Sensing, Probability of detection.*

I. INTRODUCTION

The Federal Communication Commission (FCC) divides the radio spectrum into various frequency bands, and statically allocates them to various wireless applications [01]. The assigned frequency can only be exploited by the application licensed by the agency, and not by any other category of user. This leads to inefficient use of resources, because many applications do not need employment of large bandwidth, as shown in figure 1. Moreover, the evolution from voice-only communications to multimedia applications has increased the requirement of allotted radio spectrum. The aforementioned reasons have led to unwanted denial of services.

To solve the spectrum scarcity issue, the deployment of dynamic allotment based radio system has gained momentum. One such type of system is a Cognitive Radio system - A fascinating emerging technology promising the solution of the scarcity problem by strategic spectrum access. According to Federal Communication Commission, a Cognitive Radio is defined as: "Cognitive radio: A radio or system that senses its operational electromagnetic environment and dynamically and autonomously adjust its radio operating parameters to modify system operation, such as maximize throughput, mitigate interference, facilitate interoperability, access secondary markets.” [02] In order to adapt to the opportunistic spectrum environment, The CR networks necessitates the spectrum-aware operations, which forms the cognitive cycle [03]. As illustrated in figure 2, the cognitive cycle consists of Spectrum Sensing, Spectrum decision, Spectrum sharing and Spectrum mobility.

Spectrum Sensing: It is one the most crucial part of a Cognitive Radio. It allows the secondary users to learn about the transmission environment by detecting the users, using a plethora of various techniques. This data is used by SUs to make the decision of transmission on that frequency band[03].



Freq.(GHz)	0-1	1-2	2-3	3-4	4-5	5-6
Utilization(%)	54.4	35.1	7.6	0.25	0.128	4.6

Figure 1 Spectrum Utilization

a)*Spectrum decision:* It is the ability of a Cognitive Radio to select best available spectrum band to fulfil the Quality of Service requirements of the secondary user. This has to be done without causing interference to the primary user. Each CR performs Spectrum Sensing to sense the empty bands and then it accomplishes spectrum decision from the availability opportunistically. It mainly involves three functions: spectrum characterisation, spectrum selection and CR reconfiguration [03].

b)*Spectrum sharing [03]:* One of the crucial hurdles in a CR is self-organisation of network amongst other CR networks in surrounding environment. This is done while keeping in mind the trade-off between efficiency and interference with other CRs. It is done with help of adaptive algorithms that efficiently allocates transmission powers.

c)*Spectrum mobility:* It is the process by which a CR user changes its frequency of operation when the licensed user is detected on the operating band. The mobilisation is done while maintaining seamless communication requirements during transitions to a better spectrum or unused spectrum.

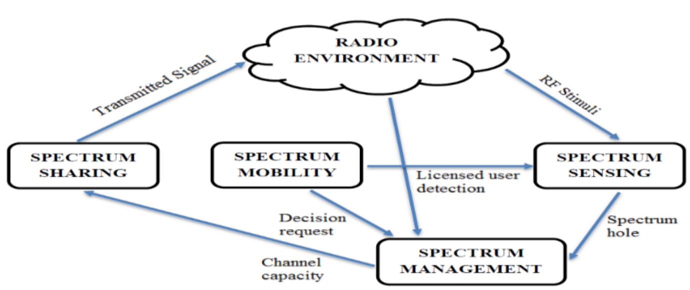


Figure 2 Cognitive Radio Cycle

Amongst the steps in the cycle, Spectrum Sensing is the deciding factor which governs the correct operation of a Cognitive radio, as improper detection of spectrum can mislead the secondary user, in turn causing interference to the licensed user. Studies reveals that efficiency of the Cognitive radio is frequently compromised by multipath fading, transmission channel, shadowing and receiver uncertainty [04]. This can lead to erroneous or delayed decision and hence inaccurate spectrum allocation. Therefore, proper, rapid and immediate Spectrum Sensing is advisable. In this article, we look into various Spectrum Sensing Techniques through simulations in MATLAB. The following section II will look into the classification of Spectrum Sensing Techniques. Furthermore, we will run simulations of the various Non-Cooperative Spectrum Sensing techniques in section III. Lastly, the section IV discusses and compares our observations and section V concludes the research paper.

II. CLASSIFICATIONS

Over the period of the last few years, there has been a great deal of progress in Spectrum Sensing methods for CR based systems. Amongst the assortment of the Spectrum Sensing Techniques, the principal classification is on the basis of Cooperative technique and Non-Cooperative technique[03]. In Non-Cooperative Spectrum Sensing, also known as local Sensing, each SU pursues sensing for its own purpose, disregarding the requirements and decisions of other SUs. As there are no dealings with the other SUs in the same frequency band, the decisions are taken locally. Though, this practice suffers from errors due to shadowing, fading interferences and noise uncertainty. Whereas, in Cooperative Spectrum Sensing techniques, the SUs relate and communicate with each other and come to a conclusion for sensing, while keeping in mind the requirements and objectives of other SUs in the same frequency band. Whilst, Cooperative Spectrum Sensing has the advantage of being more accurate, it suffers from major drawbacks of requirement of higher bandwidth due to presence of control channels and procurement of increased cost and time during implementation and execution, due to extensive infrastructure[03]. Hence, we perform analysis of Non-Cooperative Spectrum Sensing in this article.

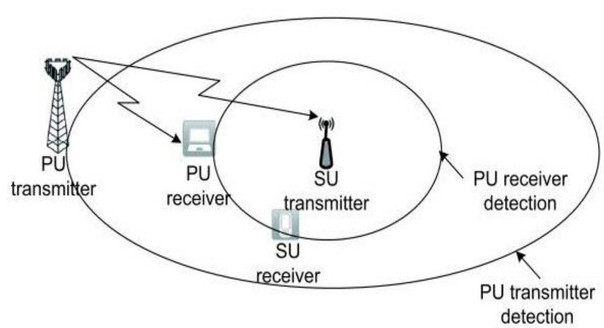


Figure 3 Spectrum Sensing Concept

A. *Spectrum Sensing model*

Spectrum Sensing enables the secondary user to detect the unused spectrum, which is vital for proper functioning of a cognitive radio. The working concept of Spectrum Sensing is as given in figure 3[06]. Therefore, to avoid the interference with primary user, secondary user has to conduct Spectrum Sensing. Generally, the radius of PU transmitter and receiver vary. In some cases, the radii of PU transmitter and receiver may differ, leading to false detection. Also, as it is difficult for secondary user to differentiate between PU signals from other pre-existing SUs, we treat them as one received signal, *s(t)*. So, received signal, *x(t)* at our SU, can be expressed as [06]

$$x(t) = \begin{cases} n(t) & ,H_0 \\ s(t) + n(t) & ,H_1 \end{cases} \quad (1)$$

Where, *n(t)* is the noise added due to channel. H_0 and H_1 represents the Hypothesis of the presence and absence of the Primary user. The intent of Spectrum Sensing is to determine which hypothesis is fulfilled, on the basis of received signal, *x(t)*. The detection performance is considered by Probability of detection, P_d and probability of false detection, P_f. P_d being the probability of decision H_1, while H_1 is true. And P_f indicates the probability, when conclusion of H_1 is reached during the condition of H_0.

As we are now accustomed to the hypotheses of a PU, we will look into the classification of Non-cooperative Sspectrum Sensing techniques as shown in figure 4[07].

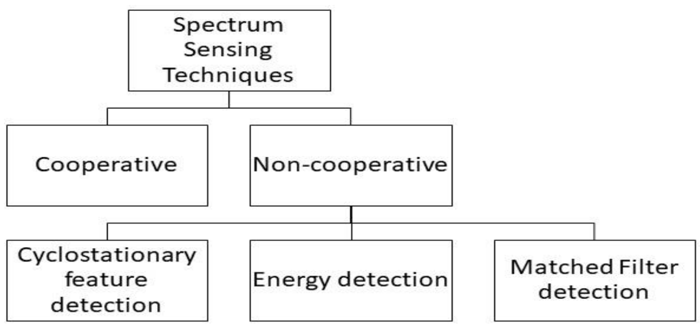


Figure 4 Spectrum Sensing Techniques

1) *Match Filter Detection*

When the transmitted signal is known, it is the simplest and most optimum detection technique. It correlates received signal with the known PU signal, which in turn maximizes the SNR [07]. The schematic diagram of Matched Filter Detection technique is given in figure 5.

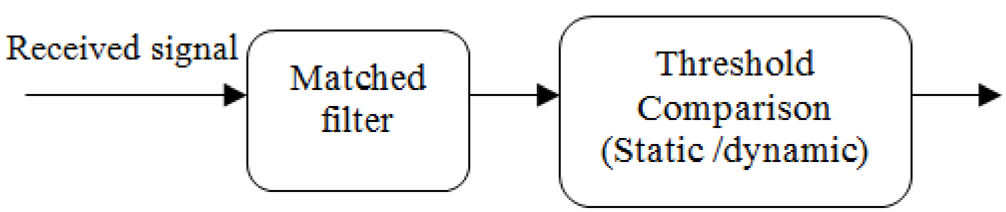


Figure 5 Matched Filter Detection

It has the advantage of faster achievement of a certain probability of detection in a shorter time. Whereas, it requires the reproduction of transmitted signal at receiver, which increases the power consumption, making it impractical for wider deployment in Cognitive radio [07].

2) *Energy detection*

It is the most commonly implemented Spectrum Sensing Technique in a Cognitive radio. In this technique, the signal is detected by juxtaposing the average energy of received signal with a predefined threshold (Γ_{ED}) value. If the threshold is found lesser than the received signal energy, the Primary user is considered present, or else the primary user is deemed absent. It is most suitable when there is negligible information available about the primary user signal. The energy detection technique block diagram is as given in figure 6.

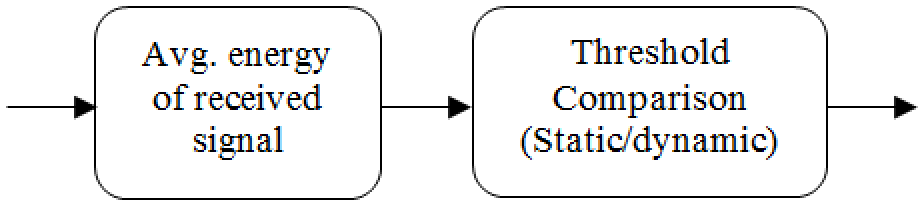


Figure 6 Energy Detection

The system given above, calculates the energy of received signal (T_{ED}) by averaging the squared values of FFT of given N samples. It can be mathematically denoted as [08]

$$T_{ED} = \frac{1}{N} \sum_{n=1}^{N} \{x_n\}^2 \qquad (2)$$

Where, N is the number of samples and x_n is the n^{th}sample of the received signal. This energy is compared with a predetermined threshold (Γ_{ED}), calculated as [08]

$$\Gamma_{ED} = \frac{Q^{-1}(P_f)}{\sqrt{N}} + 1 \qquad (3)$$

The above threshold is kept same for all discussed Non-Cooperative Spectrum Sensing techniques elaborated in this article. In Energy Detection, the decision is taken based on following:

If, $T_{ED} > \Gamma_{ED}$ Primary user is present.

$T_{ED} < \Gamma_{ED}$ Primary user is absent.

While, Energy Detection has advantages of not requiring Primary user information, low computation time and less complexity, it suffers from poor performance at low SNR values.

3) Cyclostationary Feature Detection

An alternative to Energy Detection technique for low SNR systems is Cyclostationary Feature Detection. It exploits the fact that the transmitted signal is coupled with sine wave carriers, pulse trains, repeating spreading, hopping sequences or cyclic prefixes, which results in inherent periodicity [07]. These signals are categorized as Cyclostationary as their mean and autocorrelation exhibit periodicity. Whereas, noise does not have such behavior. So, the Cyclostationary features are discerned from the received signal, by applying Spectral correlation function to it. The Spectral correlation function is given as [06]

$$\Re_x{}^{(\beta)}(\tau) = E[x(t)x^*(\mathrm{t} - \tau)e^{-2\Pi\beta t}] \qquad (4)$$

Here, $E[\dot{.}]$ is expectation operator, * denotes the complex

conjugate and β represents the cyclic frequency. The Cyclostationary Feature Detection block diagram can be observed as figure 7.

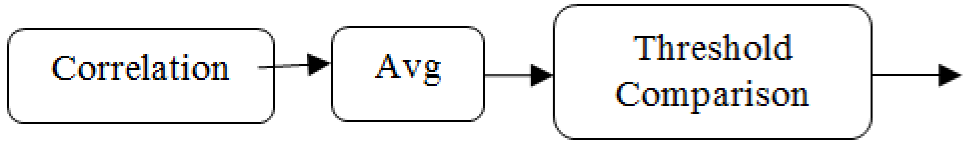


Figure 7 Cyclostationary Feature Detection

Cyclostationary techniques provide better detection performance at low SNR. Furthermore, as they have the ability to differentiate noise and signal, they are less susceptible to noise uncertainty and thus have lower probability of false detection. However, Cyclostationary techniques requires large sensing time and complexity with higher samples.

III. SIMULATIONS

Generalized model using Orthogonal Frequency Division Multiplexing (OFDM) with Quadrature phase shift keying (QPSK) modulated signal to simulate Non-Cooperative Spectrum Sensing techniques have been implemented in this paper. The hypothetical imitation of the system is as given in figure 8. This is achieved by passing the QPSK modulated signal through a serial to parallel converter and then performing Inverse Fast Fourier Transform (IFFT) on it. This is signal is now again converted into a bit stream by processing it through a parallel to serial converter. Now, cyclic prefix is added to the signal to remove the Inter-Symbol Interference (ISI), according to the category of the system implemented. The signal generated at transmitter block, is transmitted along a noise channel. In our case, we have implemented Rayleigh channel, as it is a more accurate representation of a noise channel at an infield communication system. At the receiver block, we perform the inverse process of the transmitter by removing cyclic prefixes and then applying Fast Fourier Transform (FFT) to a pre-converted parallel data. After applying FFT, we again convert the parallel data to serial data and apply the preferred Non-Cooperative Spectrum Sensing Technique on the signal. The applied Non-Cooperative Technique calculates the necessary quantity and threshold to make a decision on presence of Primary user in a Cognitive Radio.

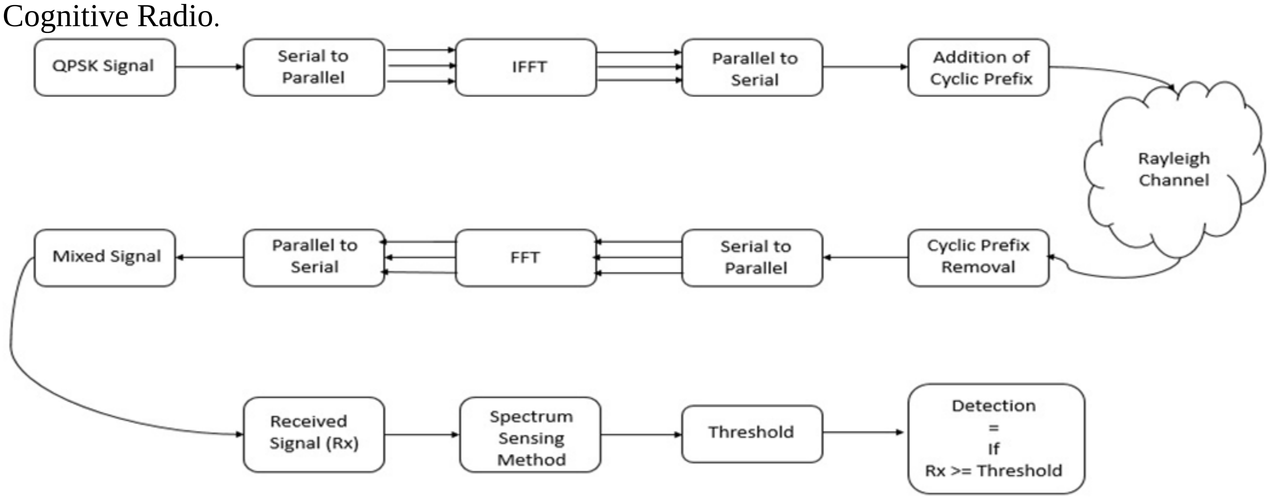


Figure 8 System Model

By reviewing the guidelines of a Long Term Evolution (LTE) network by 3gpp[11], we have kept the FFT size as 2048, according to our requirement of 20 MHz channel bandwidth and sampling frequency of 30.72 MHz [09]. According the same specifications, the number of data sub-carriers taken as 1200.

A. *Single threshold Non-Cooperative Spectrum Sensing Techniques*

Initially, by picking the number of samples (N) as 200, Probability of false detection (P_f) as 0.01 and 1000 Monte-carlo simulations, we have plotted the graph of P_d vs *SNR* for Matched Filter Detection, Energy Detection and Cyclostationary Feature Detection with the theoretical P_d vs *SNR* curve through MATLAB.

TABLE 1
SIMULATIONS PARAMETERS FOR FIGURE 9

Parameters	Value
Modulation	QPSK
Multiplexing	OFDM
FFT size	2048
Number of sub carrier channels	1200
Number of bits per OFDM symbol	600
Channel	Rayleigh
Monte Carlo simulations	1000
Number of samples	200
P_f	0.01
Threshold mechanism	Single Thresholding

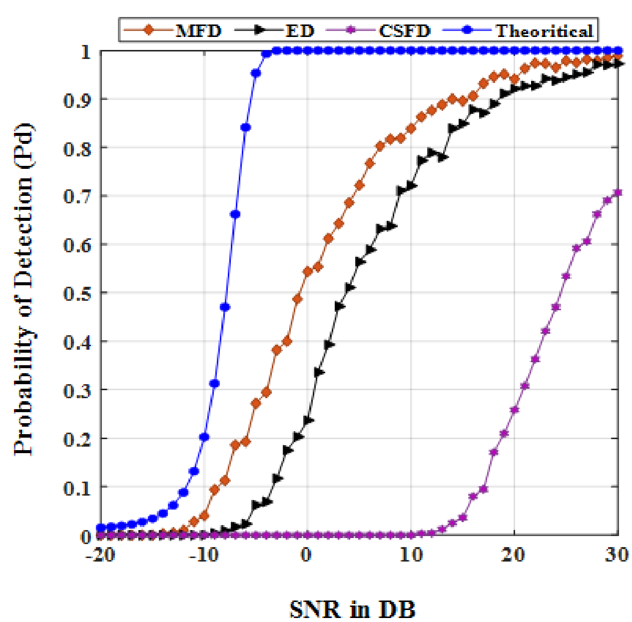


Figure 9 Simulation result for Single threshold.

The theoretical probability of detection(P_d) is given by [13]

$$P_d = Q^{-1}\left(\frac{(\Gamma-(SNR+1))*\sqrt{N}}{\sqrt{(2*SNR)+1}}\right) \qquad (5)$$

Therefore, we get graph as shown in figure 9. Now, we vary the value of *N* to 20 and again plot the figure 10

TABLE 2
SIMULATIONS PARAMETERS FOR FIGURE 10

Parameters	Value
Modulation	QPSK
Multiplexing	OFDM
FFT size	2048
Number of sub carrier channels	1200
Number of bits per OFDM symbol	600
Channel	Rayleigh
Monte Carlo simulations	1000
Number of samples	20
P_f	0.01
Threshold mechanism	Single Thresholding

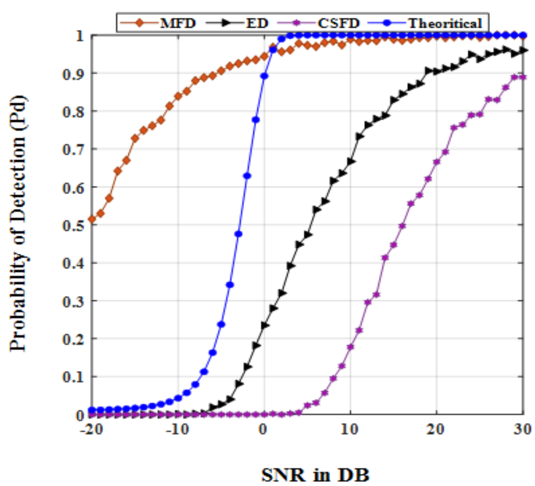


Figure 10 Simulation results (number of samples to 20)

Furthermore, by keeping number of samples (*N)* as 200 and considering the value of P_f as 0.1, we plot the figure 11. Lastly, we vary the value of monte-carlo simulations to 200 from 1000, to observe its effect obtained in figure 12.

TABLE 3
SIMULATIONS PARAMETERS FOR FIGURE 11

Parameters	Value
Modulation	QPSK
Multiplexing	OFDM
FFT size	2048
Number of sub carrier channels	1200
Number of bits per OFDM symbol	600
Channel	Rayleigh
Monte Carlo simulations	1000
Number of samples	200
P_f	0.1
Threshold mechanism	Single Thresholding

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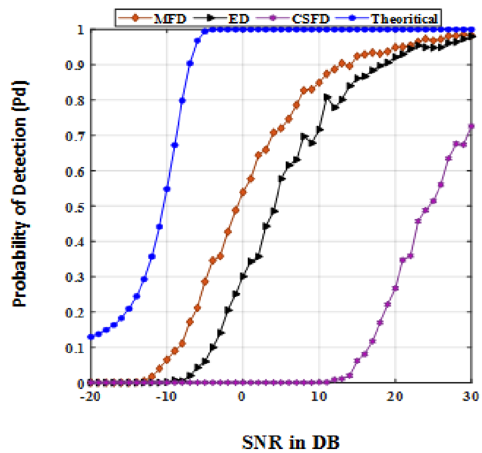

Figure 11 results false detection

Simulation (Probability of to 0.1)

TABLE 4
SIMULATIONS PARAMETERS FOR FIGURE 12

Parameters	Value
Modulation	QPSK
Multiplexing	OFDM
FFT size	2048
Number of sub carrier channels	1200
Number of bits per OFDM symbol	600
Channel	Rayleigh
Monte Carlo simulations	200
Number of samples	200
P_f	0.01
Threshold mechanism	Single Thresholding

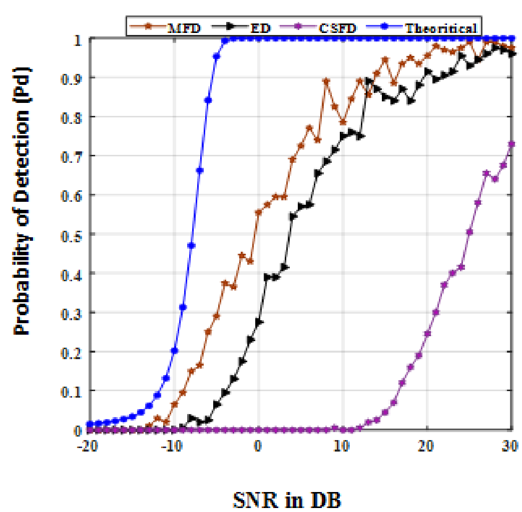

Figure 12 Simulation results (number of monte-carlo simulations 200)

B. Adaptive Double threshold based Non-cooperative Spectrum Sensing techniques

Single thresholding in Spectrum Sensing techniques can cause intrusion to the Primary user [10] as noise uncertainty is ignored. To subdue this phenomenon, we implement and simulate an Adaptive double-threshold based algorithm. Here, instead of performing Spectrum Sensing by calculating single threshold, we calculate two thresholds by [10],

$$\Gamma_1 = \left(\sqrt{\frac{2}{N}}Q^{-1}(P_f) + 1\right) * \frac{1}{\rho} \tag{6}$$

$$\Gamma_2 = \left(\sqrt{\frac{2}{N}}Q^{-1}(P_f) + 1\right) * \rho \tag{7}$$

Where, ρ is noise uncertainty of the channel, Γ_1 and Γ_2 are the computed thresholds for the Adaptive dual thresholding-based system. In practical systems, we cannot have the data about the noise power and hence uncertainty may occur due to interference in the channel. (6) & (7) overcomes the effect of noise uncertainty, and hence improves the overall performance of Non-Cooperative Spectrum Sensing in a Cognitive Radio.

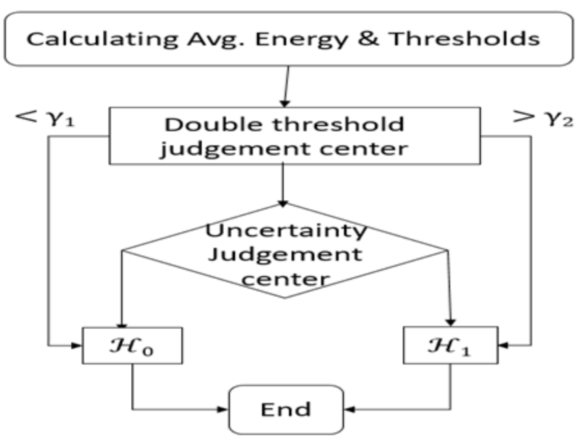

Figure 13 Adaptive Double-thresholding mechanism

The algorithm illustrated in figure 13 is utilizes the concepts given in [10], to enact the task of Non-Cooperative Spectrum Sensing.

We simulate this by recreating the algorithm and plotting the p_d vs *snr* plot in matlab, by considering number of samples, *n* as 200, false alarm probability, p_f as 0.01, noise uncertainty, ρ as 0.2 db and monte-carlo simulations as 1000. Hence, the graph as shown in figure 14 is achieved.

TABLE 5
SIMULATIONS PARAMETERS FOR FIGURE 14

Parameters	Value

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Modulation	QPSK
Multiplexing	OFDM
FFT size	2048
Number of sub carrier channels	1200
Number of bits per OFDM symbol	600
Channel	Rayleigh
Monte Carlo simulations	1000
Number of samples	200
P_f	0.01
Threshold mechanism	Adaptive Double
Noise uncertainty	0.2 dB

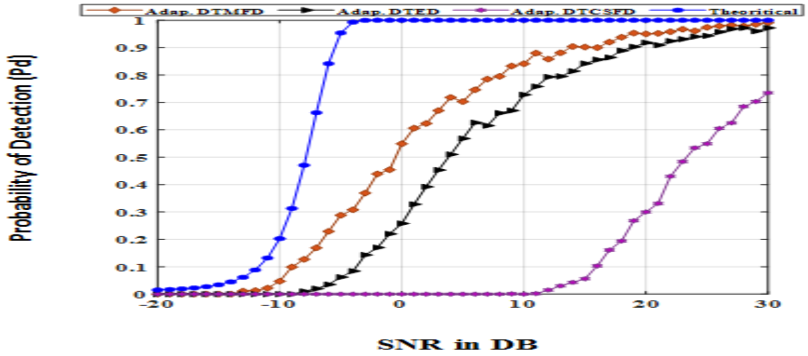

Figure 14 Simulation results of Adaptive Double threshold with Noise uncertainty=0.2 dB)

In realistic conditions, the value of ρ can vary from 0.2 dB to the worst of 3 dB Hence, by keeping the parameters same as previous case and varying the value of ρ to 3 dB and we plot the figure 15.

TABLE 8
SIMULATIONS PARAMETERS FOR FIGURE 15

Parameters	Value
Modulation	QPSK
Multiplexing	OFDM
FFT size	2048
Number of sub carrier channels	1200
Number of bits per OFDM symbol	600
Channel	Rayleigh
Monte Carlo simulations	1000
Number of samples	200
P_f	0.01
Threshold mechanism	Adaptive Double
Noise uncertainty	3 dB

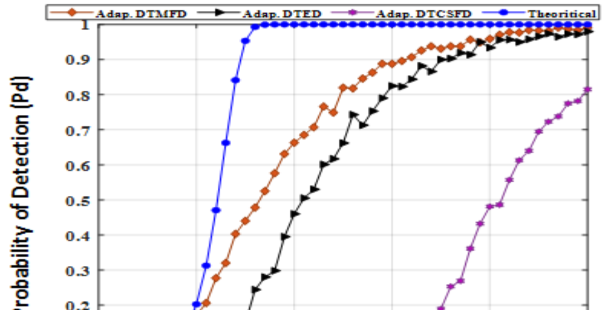

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Figure 15 Simulation results of Adaptive Double-thresholding (noise uncertainty=3 dB)

IV. DISCUSSIONS AND COMPARISON

From the simulation results, we observe that the Matched Filter Detection gives the best possible Non-Cooperative Spectrum Sensing, for all possible combinations of simulation parameters, as its P_d vs *SNR* curve is nearest to the theoretical curve. Its sensing capacity is followed by Energy Detection and at last by Cyclostationary Feature Detection method. On reducing the number of samples, the system becomes more confident to detect the presence of the PU signal. This can be visible in figure 10. Moreover, increasing the probability of false detection from 0.01 to 0.1, the P_d vs *SNR* plot adds complexity and requires more processing time as well as reduces threshold value, which directly affects the performance of the sensing technique, hence giving a higher probability of detection for lesser value of signal to noise ratio.

However, this effect is nullified for higher values of *SNR*. Since, the threshold is inversely proportional to the number of samples, premature detection in case of Matched Filter Detection is observed in figure 10. Hence, this leads to higher value of P_d at lower value of *SNR*. Lastly, on reducing the monte-carlo simulations, we observe that the graph becomes choppier, as compared to the higher value of monte-carlo simulations.

Finally, the Adaptive double thresholding-based Spectrum Sensing techniques, which overcomes the effect of noise uncertainty by spreading the thresholds difference as increase in the noise uncertainty, and find them better than single threshold based Non-Cooperative Spectrum Sensing techniques. Furthermore, we spot that the Matched Filter Detection is still the best amongst all Non-Cooperative Spectrum Sensing techniques if the Primary user signal information is available to the receiver, which is not possible in the practical case.

V. CONCLUSION

Spectrum is a very valued resource in wireless communication systems, and methods of its efficient utilization has been a leading point for research and development. Cognitive Radio is one such attempt trying to employ the available spectrum more efficiently through opportunistic spectrum usage. Spectrum Sensing is the key to proper implementation of a Cognitive Radio system. As Cooperative Spectrum Sensing requires extensive infrastructure and is complicated to implement, Non-Cooperative Spectrum Sensing Techniques are preferred. Several Spectrum Sensing methods are studied and simulated to find the optimum Non-Cooperative Spectrum Sensing technique. Cyclostationary Feature Detection yields the least value of probability of detection at a given *SNR*, while being more complex and time consuming. However, if receiver knows partial information of the transmitted signal, it can perform healthy Spectrum Sensing for environments having lower signal to noise ratio. The complexity, the sensing time and the energy required of the Cyclostationary Feature Detection increases with increase in the number of samples. Matched Filter Detection returns the nearest value of probability of detection to the expected curve, as compared to other Non-Cooperative Spectrum Sensing techniques, making it the best performing Non-Cooperative Spectrum Sensing technique. Nevertheless, it requires the complete information about the PU signal at the receiver to perform Spectrum Sensing, which is not practical in a communication system. Energy Detection cannot distinguish noise and the signal at low SNR value. However, it gives performance intermediate of Matched Filter Detection and Cyclostationary Feature Detection, while not requiring information of PU signal. It is also faster, least complex and easy to implement among all discussed Non-Cooperative Spectrum Sensing Techniques. The number of samples, Value of False alarm probability and Noise uncertainty plays a major role in identifying the Spectrum holes, and Energy Detection is least affected by them. Hence, Energy Detection can be considered the most suitable Non-Cooperative Spectrum Sensing Technique.

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