ADDIS ABABA UNIVERISTY

ADDIS ABABA INSTITUTE OF TECHNOLOGY (AAiT)
SCHOOL OF ELECTRICAL AND COMPUTER ENGINEERING

SNR Enhancement of Energy Detector Algorithm using Adaptive Wiener Filter in Cognitive Radio.

By

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Advisor

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I, undersigned and declare that this thesis is my original work, has not been presented for a degree in this or any other university, and all sources of materials used for the thesis have been fully acknowledged.

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ABSTRACT

The underutilization of existing radio spectrum and scarcity of available channel become a challenge for modern era communication system. Services such as high speed data communication requires more bandwidth and wide spectrum range. The rising demand in wireless services and applications bring channel constraint on the existing frequency spectrum allocation scheme. To mitigate such a problem the idea of cognitive radio technique came into picture. Cognitive radio can be defined as a radio system that can adaptively and dynamically allow user(s) to use the spectrum when the primary user is absent. The detection and decisions of the primary signal can be facilitated by spectrum sensing technique. Among those techniques, energy detector spectrum sensing is a transmitter based spectrum sensing technique which detects the presence of primary user in cognitive radio system. Detection of primary signal is made by comparing the received signal energy to that of pre-determined energy threshold value. However the performance indicator matrices show that the energy detector algorithm has poor performance when the received SNR value is too low.

This thesis work attempts to analyze and compare the performance of energy detector when adaptive Weiner filter is inserted on the front end of conventional energy detector. Based on the performances matrices value, evaluation of the systems (conventional and enhanced energy detector) response will be done. The performance matrices parameters include: Receiver operating curve (ROC), Complement Receiver Operating Curve (CROC), threshold value vs false alarm probability and Detection probability Vs SNR value. The results are presented for AWGN and Rayleigh flat fading channel model. Accordingly focus is made on how the conventional energy detector behaves when the adaptive Wiener filter is inserted on the front end.

Finally simulation results show that, insertion of adaptive Wiener filter in the front end of conventional energy detector has improved all the performance matrices considered in thesis work.

Keywords: **Cognitive radio, primary user, spectrum sensing, energy detector, performance matrices (receiver operating curve, complementary receiver operating curve, threshold value, false alarm and detection probability), adaptive Weiner filter.**

CONTENTS

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LIST OF ABREVATIONS

AWGN: Additive white Gaussian noise.

AP: Access Point.

ADC: Analog to Digital Converter.

AUC: Area under curve.

BS: Base Station.

BPF: Band Pass Filter.

CFAR: Constant False alarm Rate.

CR: Cognitive Radio.

CROC: Complementary Receiver Operative Cure.

DFT: Direct Fourier Transform.

EEG: Electroencephalogram.

ETA: Ethiopian telecommunication Agency

FCC: Federal Communication commission of USA.

FFT: Fast Fourier Transform.

FSA: Fixed Spectrum Allocation Scheme.

FIR: Finite Impulse Response.

GUESS: Gossiping Updates for Efficient Spectrum Sensing.

IIR: Infinite Impulse Response.

LLR: Likelihood Ratio.

MATLAB: Matrix laboratory.

OSA: Opportunistic Spectrum Access.

PDF: Probability density function.

PU: Primary User.

RF: Radio Frequency.

RLS: Recursive Least Square algorithm.

ROC: Receiver Operative Curve.

RX: Receiver.

SSC: Shared Spectrum Company.

SNR: Signal noise ratio.

SU: Secondary User.

SCF: Cyclic Spectral correlation function.

SIR: Signal Interference Ratio.

TRAI: Telecom Regulation Authority of India.

TX: Transmitter.

WLAN: Wireless Local Area Network.

LIST OF SYMBOLS

B :	Bandwidth of signal.
C_0:	Region Absence of primary users
C_1:	Confusions Area.
$C_{2:}$	Presence of primary user.
dB:	Decibel.
e(m):	Error signal.
E:	Energy of a signal.
E [X]:	Average energy of the signal x.
E [.]:	Expected value
f_0 :	Center frequency
f_c :	Center frequency.
h (k):	Channel gain at kth instant,
H_0 :	null hypothesis; the absences of PU signal.
H_1:	The presence of PU in the system.
$I_v(.)$:	Vth-order modified Bessel function of first kind
K	Boltzmann‟s constant.
L:	length of the sampled signal.\
N_0:	One side noise power spectral density
n(k):	System noise(AWGW)
$n_r(n)$:	Real component of noise.
$n_I(n)$:	Imaginary component of noise.
$P(f_c, B)$:	Interference power centered at f_c
P(H0|H0):	Probability of correct non detection.
$P(H_1\|H_1)$:	Probability of correct detection: = P_d

$P(H_0 \mid H_1)$:	Probability of missed detection: $=P_{md}$
$P(H_1 \mid H_0)$:	Probability of false alarm detection: $=P_{fa}$
r (t) :	Received signal.
R_x:	Autocorrelation of the signal.
R_{xy}:	Cross correlation between signal x and y.
s(k):	Represents the signal to be detected.
S:	Complex signal.
S_x:	Power spectral value of the signal x.
S (f, α):	Spectral correlation function.
T:	Period of the signal
T_1:	Interference temperature.
w:	Bandwidth of the signal
w(m)	Weiner filter coefficients.
x(k):	Represents the
x(t):	Output signal
x(m)	Input signal to Adaptive filter.
y (t):	Input signal
y(m):	Desired signal adaptive filter
α:	Cyclic frequency.
σ_2:	Noise variance.
λ :	Threshold value.
τ :	Delay time·
Λ:	Likely hood function
γ:	Non-centrality parameters.
(.):	Gamma function

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Chapter 1

Introduction

1.1. Background and Motivation

Technological advancement of wireless communication in this century brings a variety of wireless products/devices that can be used for a wide range of application. Devices in wireless environments operate on specified licensed spectrum range. The operational frequency range has to be designed and allocated properly. This spectrum assignment and management is done by governmental institution, Ethiopian Telecommunication agency (ETA) in Ethiopia, Federal Communication Commission (FCC) of USA, and Telecom Regulation Authority of India (TRAI). The type of scheme which uses such an assignment technique is called Fixed Spectrum Allocation Scheme (FSA).

The radio frequency bands which were allocated can be used in cellular network, FM radio, TV broadcasting service etc. Within the current spectrum regulatory frame work, all frequency bands are exclusively assigned to specific services and no violation from unlicensed user/s is allowed [1],[2].

Figure 1-1 illustrates how the radio spectrum is arranged based on the application services, and the frequency spectrum range. As the technology moves from voice telephony to higher data rate, the existing scheme (FSA) does not accommodate and satisfy the user demand. However, study at FCC shows that the spectrum usage is higher on certain area and lesser in other. This shows significant amount of the spectrum remains underutilized [3]. It also depicts the spectrum utilization efficiencies is highest for wireless service, particularly the assignment is so congested in cellular network (GSM) and FM radio bands , TV bands and fixed radio system [4] . It is well known that, the licensed user/s (user which has a privilege to use a channel any time) might not be operational and use the channel all the time in area where it operated. Data from the FCC shows that spectrum usage in the band below 3 GHz has utilization efficiencies of 15% to 85% [4].

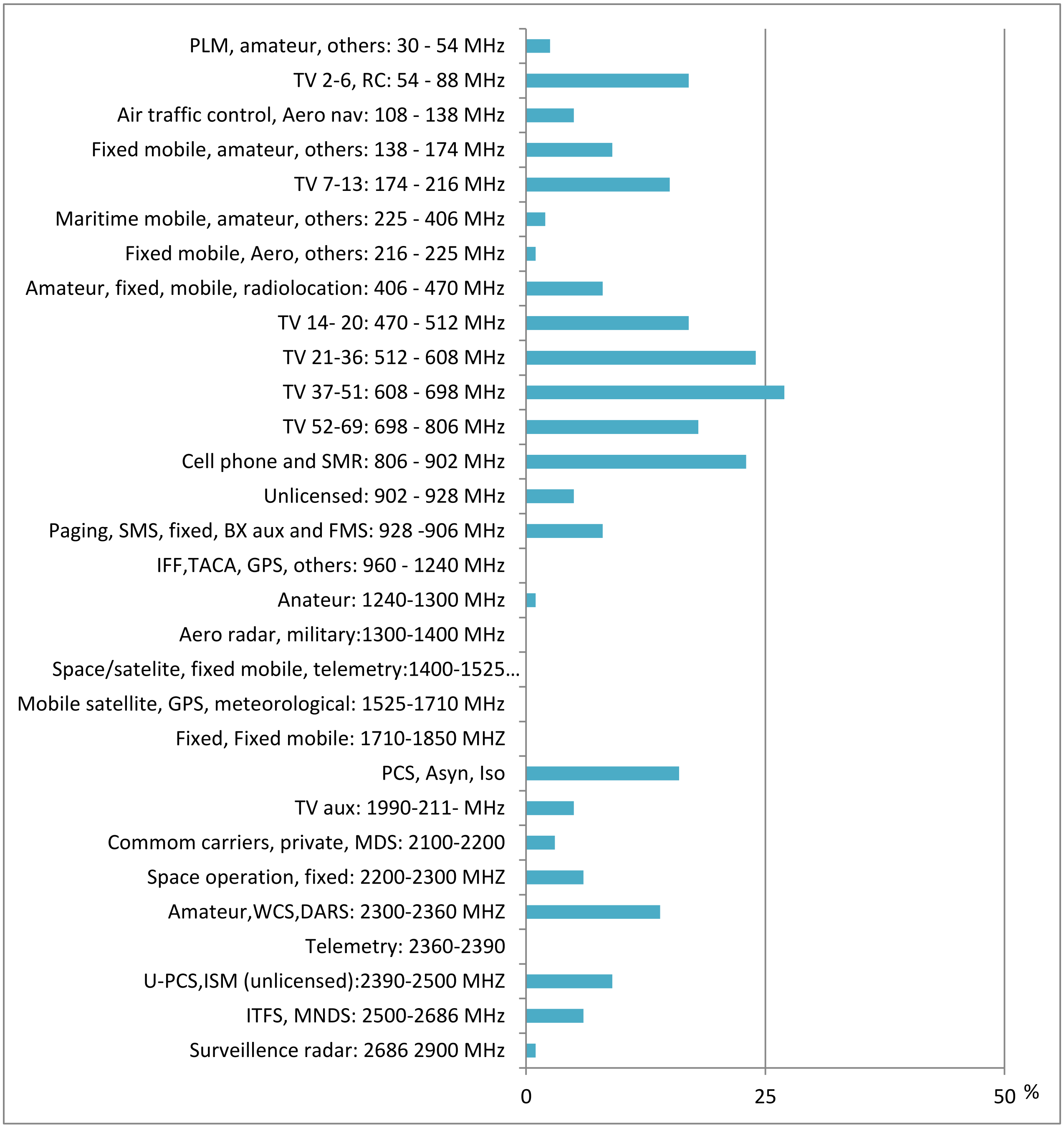

Figure 1-1: Spectrum Concentration [1].

Figure 1-2 shows the RF measurements survey conducted by Shared Spectrum Company (SSC). It illustrates how the license users use the frequency spectrum in seven geographical areas. It is observed that the average spectrum usage over these locations is only about 5.2%; and 94.8% of the spectrum remain vacant.

Hence the scarcity of radio frequency spectrum is not because of the lack of natural spectrum resource rather it is because of the of static spectrum allocation technique. Accordingly, the use of fixed spectrum allocation scheme in newly emerging technologies services and application creates serious channel congestion [6].

The RF experimental results also illustrate the fixed spectrum allocation scheme (FSA) is not well suited for new technological services and does not accommodate future services (high speed data rate service and like) [6].

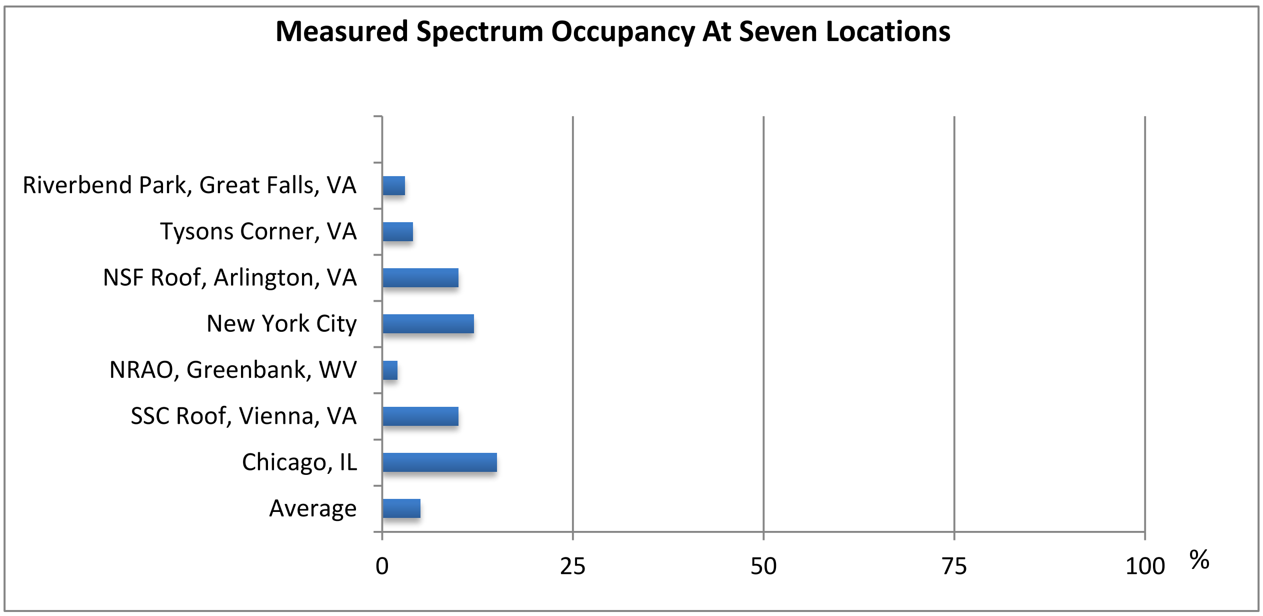

Figure 1-2: Spectrum occupancy measurement over some locations [6].

In this scenario the development of new bandwidth demanding wireless technologies would depend on the availability of radio spectrum or free channel. Adding new services to existing infrastructure mean less spectrum availability and it leads to channel scarcity and congestion. Thus the spectrum scarcity problem is getting worse due to the emergence of new wireless services and applications [5]. As it was discussed in the Figure1-2, the FCC indicates that the actual licensed spectrum is largely underutilized. It proved that, the fixed radio spectrum allocation (FSA) policy has served well in avoiding interference among the radio spectrum users and give an exclusive right to the licensed users to use certain portion of the spectrum. However it has created less efficiency in spectrum usages [4],[6]. Therefore, as the new service and application emerges in wireless technology, the fixed frequency allocation policy becomes the cause of radio spectrum scarcity. Thus the FCC recommends that efficiency of the spectrum can be improved by allowing the system to use the specified spectrum range along with the primary users. Such users with this feature are referred to as *Secondary users*. These users have privilege to use the available resources within minimal interference to the primary users [7].

Work has been done to mitigate the radio spectrum scarcity and spectrum underutilization problem. The radio technology that addresses this solution is called *cognitive radio (CR)*.
The idea of cognitive radio was first proposed by I. Mitola in 1999, he stated that "*radio etiquette (or protocol) is the set of RF bands, air interfaces, protocols, and spatial and temporal patterns that moderate the use of radio spectrum"* [8].

In 2005, Haykin also stated in his paper "C*ognitive radio is an intelligent wireless communication system which has the knowledge of its surrounding environment and uses the methodology of understanding, learning and adapting the internal states of variations of incoming radio frequency (RF). The corresponding changes of statistical variation include certain operating parameters (transmit power, carrier frequency, and modulation strategy) in real time, with two primary objectives in mind highly reliable communications whenever and wherever needed; and efficient utilization of the radio spectrum* [9]. "

Accordingly CR can be defined as a radio system that can adaptively and dynamically allow user(s) to use the spectrum in the opportunistic way. Or Cognitive Radio is: "*A radio system which dynamically and autonomously senses its operational electromagnetic environment.* The word *autonomously* means exploiting unused spectrum to provide new path to spectrum access *and adjust radio operating parameters such as maximizing system throughput, mitigate interference and facilitate access to secondary user* [10]." The CR technologies enable to identify and manage the vacant spectrum known as spectrum *holes* [3],[4],[9],[11]. Figure1-3 shows the spectrum holes in a region of space, when the primary user is absent.

In CR, system parameters are dynamically updated according to the RF signal energy. Figure 1-4 clearly shows that, the cognitive process is a closed loop structure where by the current radio environments parameter are sensed, analyzed and decision is made by the CR system to adapt the environment. Sensing of the radio parameters is based on the algorithm used in the system. Spectrum sensing and the channel estimation is the prior condition to implement CR system. The cycles in cognitive radio consists of:

- **Radio sensing and analysis**
    - Sensing and estimation of radio environment temperature.
    - Detection of spectrum holes.
- **Channel identification**
    - Estimation of channel state information.
    - Prediction of channel capacity that the transmitter uses
- **Transmit power control and dynamic control of spectrum**.

The radio sensing and the channel identification operation has been done by the receiver while the transmit power control is done by the transmitter. Based on the type of detection method used in the transmitter various techniques were employed to sense the presence of primary user (licensed user) in cognitive radio system. Broadly speaking, spectrum sensing can be categorized as follows [3],[10],[11],[13]:

- Primary Transmitter Detection.
    - Energy Based detection
    - Matched filter Based detection
    - Cyclostationary based detection
    - Covariance based detection
- Cooperative and Collaboration Detection.
    - Centerline server based detection
    - External detection
    - Distributive collaborative detection
- Interference based Detection

- Primary receiver signal based detection
- Interference temperature based detection

Among the listed spectrum sensing techniques, energy detection is one of the techniques used to sense the presence of the primary user in the system. It compares the Signal to Noise ratio of the signal with that of the adjusted energy threshold value. The threshold is set based on the value of probability of false alarm detection and correct decision. However performance indicator matrices show that, the energy detector algorithm has poor performance under low Signal to noise ratio (SNR). Various researchers found out that when the SNR value of the received signal is too low as compared to the threshold value, the detection performance of energy detector algorithm becomes poor [12],[13][14].

In view of the above, we propose a new outlook to enhance the signal detection using adaptive Wiener filter. The adaptive Wiener filter is designed and implemented at the front end of the conventional energy detector. The de-noised signal from the output of the filter is passed to conventional energy detector

The thesis base line channel model is AWGN. Likewise, the simulation of results of conventional and enhanced energy detector will also be examined when Rayleigh channel model is considered.

1.2.Problem Statement

In frequency spectrum allocation technique, the conditional knowledge of information on the presence or the absent of primary user in a channel is a must. If the system lacks this priory information, and the unlicensed user transmits information on the occupied channel, interference might occur in the system. Apart from this, as new services and applications are added to the system more bandwidth is required. However, the existing fixed spectrum allocation (FSA) scheme doesn‟t accommodate the newly emerged services and applications. Such problems can be mitigated by the idea of cognitive radio along with spectrum sensing technique [13]. Among the listed spectrum sensing listed, energy detector is one of the spectrum sensing algorithms with low computational complexity and infrastructure cost. Nevertheless the performance indicator matrices show that the energy detector has poor performance when the received SNR of the signal is too low [14]. This is due to the facts that, at low SNR, signal is so corrupted and the received energy is below the energy detector threshold value and the system will face difficulty in distinguishing noise from the signal. Thus in this work we inserted the adaptive Wiener filter in the front end of the conventional energy detector. Thus the simulation result of conventional and enhanced energy detector response will be compared and analyzed.

1.3.Motivation

The under usage and the scarcity of channel become a challenge for modern communication system. Services such as high speed data communication require more bandwidth. However the scheme we have for spectrum assignment is not well suited and appropriate for emerging new services. Accordingly the concept of cognitive radio (CR) come into picture [3],[4]. The CR technology is a solution to the spectral scarcity by offering spectral awareness and managements. Making the CR system more adaptive (Software and hardware based) the performance of the system can be improved. The CR system identifies and locates the availability of vacant spectrum holes or channel using spectrum sensing algorithm. Energy detector is one of the simplest and efficient (infrastructural cost) sensing technique used to detect the presence of primary user in a system. However the performance indicator matrices shows that, system performances of energy detector become too poor as the received signal SNR become too low as compared to the system threshold value. Various research papers have been presented to mitigate such a drawback. Generally, cognitive radio becomes an excellent solution to new technologies, application, and wireless service in near future [6],[11].

By employing this technology, spectrum sensing become a main challenge in the cognitive process, since it requires an advance technique in Digital Signal Process (DSP), knowledge of probability and stochastic and finally technique in signal detection and estimation. Due to these reasons, the Cognitive Radio specifically energy detector become an interesting research area.

1.4.Literature review

In the year of 1967 the concept of energy detector was developed by Urkowitz. He assumed that the signal to be analyzed should be deterministic and pass through a flat band limited power density spectrum of Gaussian noise with known mean and variance [16].

Applying sampling theorem, he found that, the signal to be analyzed can be approximated by the sum of squares of statistically independent random variables having zero mean and unity variance. The resulting sum has chi-square distribution and can be reduces to a simple identification problem of binary hypothesis model [16],[17].

This binary hypothesis model and spectrum sensing technique use to detect the presence of primary user in cognitive radio. Among the existing spectrum sensing technique, energy detector is a transmitter based detector type where a prior knowledge of the PU does not required. Furthermore the energy detector method has low computational and infrastructural cost. However performance indicator matrices showed that the response of energy detector at low SNR value is too poor. When the receiver receive low SNR signal as compared to the threshold signal, the CR system decides wrongly about the present or absent of primary signal [11]. To mitigate such problem various researchers had present their study these are:

In 2009 Lili Duan, Lei Zhangl,Yujun Chu and Shouyin Liu, presented the idea of double thresholds detection method in the conventional energy detector algorithm. In their research they outline that every cognitive radio users firstly obtain independently and only the users with reliable information send their local decision to the common receiver based on double threshold. When all cognitive users don"t send the local decision to a common receiver it will cause sensing error. If the system fails to sense then only cognitive user with the highest reputations is selected by the common receiver to sense the spectrum using conventional energy detector. In order to solve the failed sensing problem the researchers use two schemes which have two step local sensing and common receiver fusions. And simulation result suggested that the curves of their algorithm are almost similar with the response of the conventional algorithm and their scheme eliminate the failed sensing problem. However the exact values of the two point‟s threshold were not presented in their report [18].

In 2012 Xin Liu, Cheng Wen and Xuezhi Tan found the exact value of the double threshold. They proposed the double threshold and weighted cooperative detections mechanism which uses for each user to detect the PU independently. If the detected energy signal value falls outside the double threshold area, the CR system make a local 1 bit decision and sent it to the coordinator and fused by the OR logic. Otherwise the energy values falling between the double thresholds are combined with the optimum weight vector and the coordinator. The researchers found the exact mathematical formulas of threshold values λ_1 and λ_2 by dividing the region into C_0, C_1 and C_2 (where C_0, $C_1$and C_2 are the region of Absence of primary users; Confusions area and Presence of primary user respectively). Simulation results show that the detection probabilities of the proposed scheme are better than that of the single threshold cooperative detection [19].

Amira Ben Jamma and Monia Turki proposed the algebraic method to enhance the performance of energy detector algorithm. Their approach is based on the algebraic spike detection method used to detect spikes in Electroencephalography (EEG) signals. It is known that the presence of primary user can be displayed as spectrum amplitude in the form of spikes on the range of frequency we are interested. They use this method to classify occupied bands and vacant ones. They found that through the algebraic process a function highly correlated with the presence of spike on the spectrum. And they consider this function as smoothed version of the spectrum of the noisy input signal. Based on this idea they introduce an enhanced energy detector detection using algebraic approach. By combining the algebraic technique and bank of Finite Impulse Response (FIR) filters, simulation result show that performance the proposed scheme is much better than the conventional energy detector [20].

In 2012 Yiming Zhou, Zheng Zhou and Shibo Zhang proposed energy autocorrelation based detection technique as a solution to overcome shortcoming of conventional energy detector by taking the advantage of statistical characteristics of Gaussian white noise statistical value of energy and autocorrelation of samples. In their work two statistics structured based energy and auto correlation of samples are considered. Without the prior information on noise and signal the proposed scheme can leads to stable and accurate result. The simulation test result showed that the energy auto correlation based detection is much better than energy based detection. Furthermore, the energy autocorrelation based detection methods shows similar performance result when the SNR>-12dB. And it has also shown that the improving probability of detection is limited by increasing the number of signal samples [21].

Daniela Mercedes Martinez Plata and Angela Gabriel Andrade Reatiga in 2012 proposed a dynamic selection of detection threshold technique. In their work the process of threshold selection in energy detection is addressed by the Constant False alarm Rate (CFAR) method and selection is carried out considering present condition of noise level. They propose adjusting the detection threshold dynamically based on the noise level; present during detection process.

Therefore this thesis, we propose a new look to enhance the SNR of energy detector using adaptive wiener filter. The wiener filter is designed and implemented at the front end of the conventional energy detector. The filtered signal from the output of wiener filter passed to conventional energy detector and the result will be examined and compared to the conventional energy detector in under different environment (AWGN and Rayleigh) [22].

1.5. Methodology

Different manuscript, journals and online literatures have been reviewed on the principle, and application of each spectrum sensing detection technique in cognitive radio. Reviewing the materials help us to identify the problems and limitations of the available spectrum sensing technique. Accordingly this thesis work selected energy detector spectrum sensing technique for study purpose. Theoretical background of cognitive radio and performance matrices analyses are presented for different channel models. Finally the performance matrices are applied to evaluate and compare the simulation result of conventional and enhanced energy detector. Matlab 2014a software is the simulation platform used in this thesis work.

1.6.General Objective

The general objective of this thesis is to enhance the performance of energy detector at low SNR using adaptive Wiener filter.

1.6.1. Specific Objective

The specific objectives of this thesis are:

- To study and analyze the effect of adaptive wiener filter on the front end of energy detector for AWGN and Rayleigh channels models and compare the result with conventional energy detector response.

1.7.Thesis Outline

The outline of this thesis is organized as follows: Chapter two is about the theoretical background of cognitive radio: Spectrum Sensing Technique, Adaptive Wiener filter. Chapter three is about System Modeling, Performance Metrics, Energy Detector test statistics, and enhanced energy detector system. Chapter four is presents and discusses: simulation results. In this section the matlab simulation results are obtained for conventional and enhanced energy detector compared. Chapter five is about thesis conclusion and Recommendation for Future Work.

Chapter 2

Theoretical Background

This chapter discusses cognitive radio and different spectrum sensing algorithms. Furthermore research work in Spectrum Sensing (SS) algorithms will also discuss and finally both advantages and disadvantages of each spectrum sensing technique presented.

2.1.History of Cognitive Radio

The word "Cognition" is the processes of knowing, learning and understanding things around the surround. Thus cognitive radio can be defining as a technique of getting or acquainted with the surrounding radio environment parameters and manipulating these values according to users" needs and requirements [8].The principle of cognitive state that, the secondary user/s (SU) uses the free spectrum (empty frequencies) without creating interference to the licensed user or primary user (PU).

The CR system improves the spectrum utilization efficiencies and it allows user(s) to use the spectrum in the opportunistic way. In order to obtain benefit from the cognitive radio, the system needs to go through the following process:

- Determine which portions of the spectrum are available and detect the presence of licensed users. When the user operate in the licensed band (spectrum sensing).
- Select the best available channel (spectrum management).
- Coordinate access to this channel with other users (spectrum sharing).
- Vacate the channel when a licensed user is detected (spectrum mobility).

2.2.Spectrum Sensing Technique Method

As it was discussed in the above sections the CR brings the idea of communication systems where by the unlicensed users (secondary user) can exploit the unused portions of the licensed spectrum also called "spectrum holes". In such a way the system parameters (temperature of the

From equation 2-2 and figure2-1, the output can be represented by two logical states where by the absence of signal information and presence of signal respectively. The former state is the nullity condition of the system and called the null hypothesis H_0.

Where as in the second state, the transmitter transmit the sampled information signal x(k) and convolved with the channel response h(k) the output signal information is combined with the noise signal. And it is denoted as H_1**.** Moreover, Figure 2-1 is the logical representation state equation 2.1, and the four conditional probability state can be stated as [15], [16], [17].

- Case 1: Declaring H_0 When $H_0$is true $P(H_0|H_0)$: Is probability of correct non detection.
- Case 2 Declaring H_1 When $H_1$is true $P(H_1|H_1)$: Is probability of correct detection: = $P_{d.}$
- Case 3: Declaring H_0 When $H_1$is true $P(H_0|H_1)$: Is probability of missed detection: =$P_{md.}$
- Case 4: Declaring H_1 When $H_0$is true $P(H_1|H_0)$:Is Probability of false alarm detection: =$P_{fa.}$

The signal detector has two probabilistic outcomes which define the state of PU as the absent (equivalent to saying logical value 0) and present state logical value 1. These two states help us to decide whether PU signal is the present or not. However decision is not always favorable due to the stochastic nature of the environment. Therefore, to detect the primary signals the detector is designed to operate within a certain range of energy level/s called energy threshold values [16]. Sometimes decisions were made in favor of missed detection. This happened when secondary user interfere with primary system. The probability of detection give information about the present of the primary user is the spectrum. For optimal signal detection the probability of detection should be maximized.

Figure 2-2 depicts the classification of spectrum sensing technique in cognitive radio system [10]:

- Transmitter based detection/non cooperative detection.
- Interference based detection and
- Cooperative detection

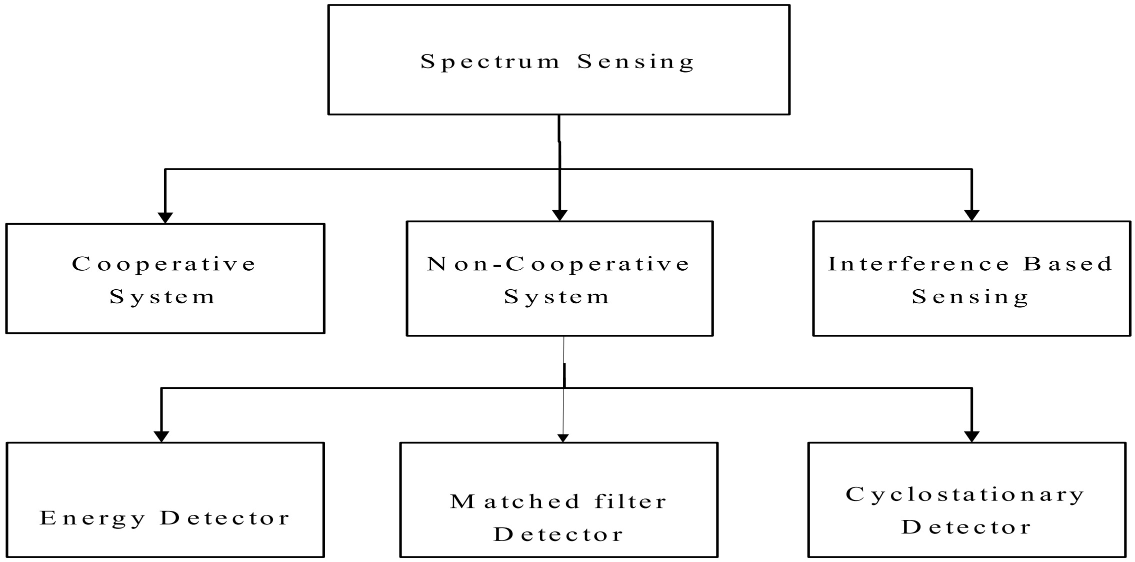

Figure 2-2: Classification of spectrum sensing technique [10]

2.2.1. Transmitter Detection

This approach is the simplest and the most common technique used to detect the presence of primary user over the range of frequencies of which operates [11]. It can be implemented with low infrastructure cost and minimum system requirements. However, this type of detection method lacks an intelligent knowledge about the presence of primary users. Therefore the detection of primary user is done on the basis of the received signal at the secondary user end. In order to know the presence of spectrum hole in the system, the secondary user (SU) measure the system energy (CR) level and decide whether primary user is present or not. Decision of present of PU is carried based on the binary hypothesis model [11], [13],[14].

Applying spectrum sensing in cognitive radio facilitates and improves the signal detection process. Based on the technique used in signal detection the transmitter detection technique includes [10].

- Energy detection,
- Matched filter and
- Cyclo stationary detection

2.2.1.1. Energy Detection

Energy detection (also called radiometry) is a non-coherent detection method that detects the presence of the primary signal based on the sensed energy level [19]. It uses the basic principle of signal detection method. The measured signal is always higher than that of the energy threshold value. To ensure whether the channel is idle or not, the energy detector uses the radio environment metric values such as frequency energy or received signal strength. This technique doesn‟t require a priori knowledge information of PU signals [10],[13]. If the prior knowledge of the PU signal is unknown, the energy detection technique becomes an optimum detecting method for any zero mean constellation signal [22]. Figure 2-3 depict the discrete version of energy detector.

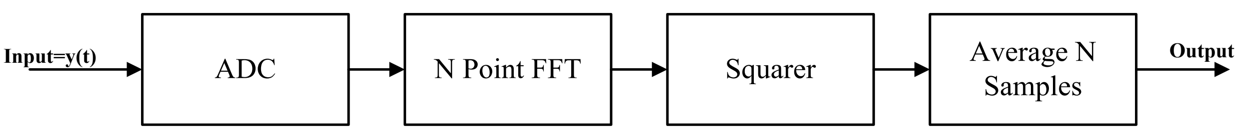

Figure 2-3: Block diagram of energy detector [10].

As it can be depicted in figure 2-3 the input signal ***y (t)*** is filtered with a band pass filter to select the bandwidth of interest. The output signal is then passed to the ADC block, squared and integrated over the observation interval time T. At the front end the output of the integrator is compared to a predetermined threshold to check the presence of PU signal. When the spectral signal is analyzed in frequency domain, the fast Fourier transforms (FFT) based method is used. Specifically, the received signal of **y *(t)*** sampled in a time window, and converted into digital signal as discrete version. This signal passed through an FFT device to get the power spectrum **$|Y\ (f)\ |^2$.** The peak of the power spectrum is then located. After windowing the peak of the spectrum, we get $|x\ (f)\ |^2$as an output. The signal energy is then collected in the frequency domain.

Even though the energy detection method is simplest spectrum sensing technique, it has the following drawback [24],[26],[27].

- It became difficult to differentiate the interference from the other secondary user when they share same channels.
- The threshold value is depending on the noise variance value if the noise power is too small, it creates an estimation error which leads to poor performance.
- At low SNR it is too difficult to measure the noise variance accurately hence performance of energy detector is become poor.
- The sensing time taken to achieve a given probability of detection is high.
- The detection performance is subject to the uncertainty of noise power.
- Energy detection method cannot be used to detect the spread spectrum signal.

2.2.1.2. Matched Filter Detection

The matched filter detection is a linear filter design that is used to maximize the ratio of input output signal for the given input signal when the secondary users with the prior knowledge of primary user signal is present. It is an optimal detection method for the system when the known priory information of the primary user‟s. The operation of matched filter is equivalent to the operation of a correlation in which the unknown signal is convolved with the filter whose impulse response is a mirror and a time shift version of the reference signals [32].

The operation of matched filter detection is expressed as [32]:

$$Y[n] = \sum_{k=-\infty}^{k=\infty} h[n-k]x[k] \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots 2.3$$

Where x and h are the unknown signal and the impulse response of matched filter respectively. k is the delay in discrete time analysis. Y[n] is the convolution result of sample delay of h with that of unknown signal x. The output of the matched filter is compared with the threshold value **κ** and decision is made whether primary user is present in the system or not.

The detection process in matched filter will take less times as compared to other sensing technique, however for each primary user detection process, it needs a dedicate receiver and consume more power to execute the detection. Thus employing such system will increase the infrastructure cost [32].

2.2.1.3. Cyclostationary Detection

The cyclostationary detection uses the periodicity characteristics of primary signal to identify its presence or absent. The periodicity feature is commonly embedded in sinusoidal signal carriers, pulse train, spread code hopping sequence or cyclic prefixes of the primary user. This detection method use cyclic spectral correlation function (SCF) to detect the presence of primary signal in the system [33].The cyclostationary signals exhibits both the feature of periodic statistics and spectral correlation. The signal x (t) is said to be cyclostationary (in wide sense) if the mean E_X and the autocorrelation Rx (t, τ) of the signal exhibit periodic properties with time. Its periodicity can be expressed as:

$$R_x(t+\tau/2\,, t-\tau/2) = R_x(t+T_0+\tau/2\,, t+T_0-\tau/2\,) \ldots\ldots\ldots\ldots.\ldots..2.3$$

For some period T_0defined for $T_0 \neq 0$ and delay τ we have:

$$R_x(t+\tau/2, t-\tau/2) = E\{x(t+\tau/2)x(t-\tau/2)\} \ldots\ldots\ldots\ldots\ldots.\ldots\ldots\ldots...2.4$$

Where E [.] is the expectation value or the mean of the signal. Since R_x is a periodic function it is possible to express in Fourier series as [33]:

$$R_x(t+\tau/2, t-\tau/2) = \sum_{\alpha} R_x{}^{\alpha}(\tau)e^{j2\pi\alpha t} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots..\ldots.2.5$$

where α includes the sum of overall integer multiple of the reciprocal of the fundamental period T_0 and $R_x{}^{\alpha}$ is the cyclic auto correlation of the signal whose Fourier coefficient $R_x{}^{\alpha}(\tau)$ is given by [33]:

$$R_x{}^{\alpha}(\tau) = \frac{1}{T_0}\int_{\frac{-T_0}{2}}^{\frac{T_0}{2}} R_x\left(t+\frac{\tau}{2}, t-\frac{\tau}{2}\right) e^{-j2\pi\alpha t}dt \ \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots..2.6$$

Due to the periodicity nature the cyclostationary, the signal shows high correlation property between widely separated spectrum components. The spectral cyclic autocorrelation function in Eqn 2.6 has the Fourier transform [33]:

$$S_x(f) = \int_{-\infty}^{+\infty} R_x{}^{\alpha}(\tau) e^{-j2\pi f\tau} \, d\tau \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots 2.7$$

Given N samples of signal, the estimated spectral correlation function SCF $S_x{}^{\alpha}(f)$ is given by [34]

$$S_x{}^{\alpha}(f) = \frac{1}{N}\sum_{n=1}^{N} X_l\left(n, k + \frac{k_\alpha}{2}\right) X_L{}^{*}\left(n, f - \frac{k_\alpha}{2}\right) \ldots\ldots\ldots\ldots\ldots 2.8$$

$$\text{where} \qquad X_L(n,k) = \frac{1}{\sqrt{L}} \sum_{l=n-\frac{L}{2}}^{l=n+\frac{L}{2}-1} x(l) e^{\frac{-j2\pi kl}{L}} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots 2.9$$

Equation 2.8 is an L point DFT at n^{th} samples of the received signal and $K_\alpha = \alpha L/F_s$ is the index frequency bin corresponding to cyclic frequency α and the SCF of the received signal. It is correlated with known priory signal and compared to the threshold value to test the presence of primary signal in the system.

The block signal representation of cyclostationary detection system can be depicted in Figure 2-4

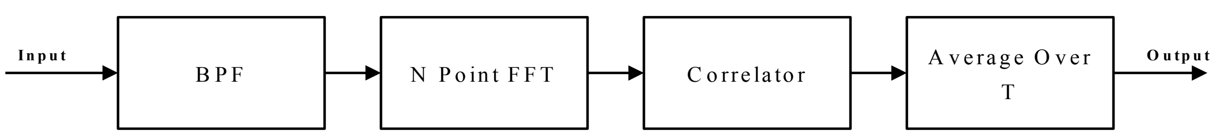

Figure 2-4: Block diagram of Cyclostationary detection [33]

Since the noise in system is random in nature and does not show any periodic nature, the spectral correlation cannot be found in any interference signal or stationary noise. If the PU signal shows strong cyclostationary properties, it can be detected at very low SNR values by exploiting the information (cyclostationary feature) embedded in the received signal.

Generally speaking the cyclostationary detection process can be summarized as:

- The cyclic autocorrelation function (CAF) of the observed signal x (t) calculated as $\{E\{x(t+\tau)x^*(t-\tau)e^{-j2\pi\alpha t}\}$ where E {.} denotes the statistical expectation operation and α is the cyclic frequency.
- The spectral correlation function (SCF) *S (f, α)* is obtained from the DFT of the CAF. The *SCF* is also called cyclic spectrum which is a two dimensional function in terms of frequency and cyclic frequencyα.
- The detection is completed by searching for the unique cyclic frequency corresponding to the peak in the SCF plane.

However the cyclostationary detection has the following drawback:

- Since the technique uses the spectral correlation, at high signal amplitude the spectral leakage is observed;
- The detection performance of the system become poor as the number of sample taken is too small because of poor estimate of the cyclic spectral density , and longer observation time is required,

2.3.Interference type Detection

The interference type detection is centric type detection technique where by the radiated power is regulated or controlled at the transmitter. When multiple transmitters transmit signal information on channel, the overall temperature effect in the system will be high. Thus this cumulative effect will result in interference.

The interference type detection can also be considered as temperature model and measure how the system is functioning at the particular modulation parameters and the extent at which the system with stand if an interference happened in the system. It is well known, the received signal power at the receiver is inversely proportional to the square of the distance. When the transmitted power level with respect to noise is less than receiver signal sensitivity, the information signal may reach to the noise floor and the receiver treat this signal as a noise. Thus

experience strong signal from the PU TX can cooperate and share the sensing result with other users, and the combined cooperative decision derived from the spatially collected observation scan improved the observation of individual CR user. Thus, the overall detection performance of the system can be improved [37]. The performance improvement of cooperative detection due to the spatial diversity is called cooperative gain. It can be vied as the parameters of the hardware. Although the cooperative gain can be achieved by cooperative ways but it is affected by the following factors:

- When CR users blocked by the obstacle are in spatially correlated shadowing, their observations also correlated.
- Cooperative sensing can experience cooperation overhead (extra sensing time, delay, energy,) as compared to the individual (non-cooperative) spectrum sensing case.

2.4.1. Centralized Cooperative Detection

As the name indicate, in this type of spectrum sensing the central unit /the fusion center or base station (BS) is used as a decision making node center collect sensing information signals from different cognitive devices or secondary users [38]. The collected information either broadcast to all SU or the BS controls the cognitive radio traffic system and makes decisions based on the information collected. This central point could be an Access point (AP) in wireless is network (WLAN). The purpose is to mitigate the fading effect of the channels and increase the detection performance of the system. Figure 2-7 described the centralized cooperative detection scenario in the figure we can see that the cognitive radio network is provided by a fusion center or the base station (BS) which can be used as a decision making in spectrum sensing mode. The k^{th} SU senses the channel for N consecutive time period and observe a complex baseband equivalent signal x_k ,$x_k \in \mathbb{C}^N$(k=1,2,3…K).

Table 2-1: Summary of Spectrum Sensing Algorithm

Transmitter Based Energy Detection.		
Spectrum Sensing Algorithm	Advantages	Disadvantages.
Energy detection	• Does not require a prior info • Low computational cost.	• Poor performance under low SNR.
Cyclostationary features	• Valid in low SNR region. • Robust against interference.	• Require the partial prior info • High computational cost.
Matched filtering	• Optimal performance. • Low computational cost.	• Require the prior knowledge of the primary user information
Cooperative and Collaboration Detection.		
Centralized based detector	• Fusion center or central processor controls the network and collects information from all the sense nodes or radios within the network. • More accurate spectrum sensing over the area where the CRs are located. • Improve sensing performance in the fading, shadowing and noise uncertainty	• Require back bone infrastructure. • Fading impact in sensing channel and hidden node problem. • Complexity in decision fusion
Distributed based Detector	• It does not depend on a Fusion Center to make decision. • Nodes share the sensed information to each other. • Does not require any back bone infrastructure. • Less complexity with reduced overhead protocol.	• The CR user don"t have any kind of cooperation, each CR user will independently detect the channel, • Since detection of holes is done independently without informing other User interference might happen
Interference based Detection.		
Interference temperature based detection	• The radiated power in the interference of the system is regulated at the transmitter. • SU utilize the channel if the signal level of the primary user is below the interference temperature limit.	• Higher interference yields a lower SIR which means that capacity is reduced for particular signal bandwidth. • Difficulty in determining specific receiver interference temperature levels for the various communication

2.5.Adaptive Weiner Filter

Wiener filters are a class of optimum linear filters which involve linear estimation of a desired signal sequence from another related sequence. In the statistical approach to the solution of the linear filtering problem, it is assumed that the availability of certain statistical parameters (e.g. mean and correlation functions) of the useful signal and unwanted additive noise. The insertion of filter blocks in circuit is to minimize the effect of noise at the output signal. The approach is to minimize the mean square value of the error signal that is defined as the difference between some desired response and the actual filter output. The Weiner filter can either be finite impulse response (FIR) or infinite impulse response (IIR) type filters when the input signal is stationary, the resulting solution is commonly known as the Weiner filter. To implement the adaptive Wiener filter, we use the recursive least square algorithm (RLS) [41],[42]. It is a time update version of the Wiener filter.

For Stationary signal the RLS converge to the same optimum filter coefficients as that of Wiener filter [41],[42].In recursive least square technique the adaptation starts with some initial filter state and successive samples of the input signals are used to adapt the filter coefficients.

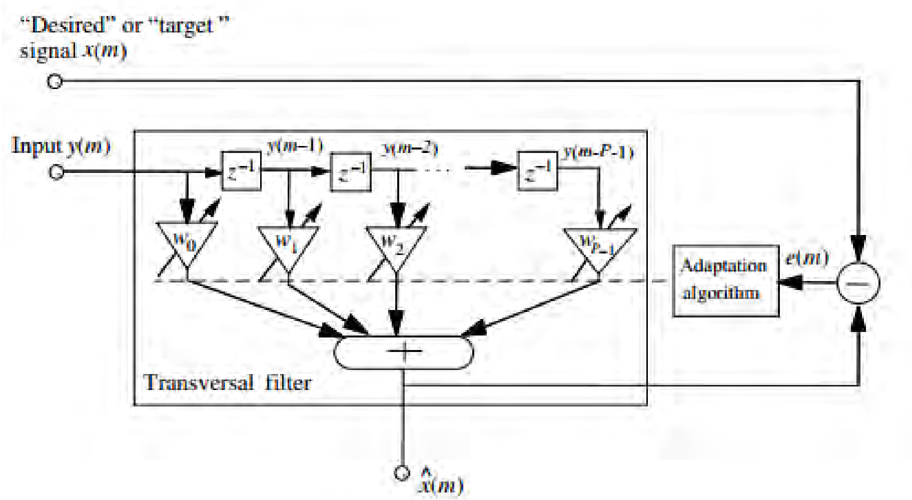

Figure 2-9: Illustration of the configuration of an adaptive filter [41].

Figure 2-9 illustrates the configuration of an adaptive filter where y(m),x(m) and w(m)=[w_0(m),w_1(m),…….w_{p-1}(m)] denote the filter input, the desired signal and the filter coefficients vector respectively.

The filter output can be expressed as [41]

$$\hat{x}(m) = W^T(m)y(m) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots .. \ldots .2.11$$

Where $\hat{x}(m)$ is an estimate of the desired signal $x(m)$ the filter error signal x (m) is defined as [41]

$$e(m) = x(m) - \hat{x}(m) = x(m) - w^T(m)y(m) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots .2.12$$

The adaptation process is based on the minimization of mean square error in equation (2.12). It becomes optimum when

$$E[e^2(m)] = E\{[x(m) - w^T y(m)]\}^2$$

$$= E[x^2(m)] - 2w^T(m)E[y(m)x(m)] + w^T(m)E[y(m)y^T(m)]w(m)$$

$$= r_{xx}(0) - 2w^T(m)r_{yx}(m) + w^T(m)R_{yy}(m)w(m) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots .2.13$$

The Wiener filter is obtained by minimizing the mean square error of equation 2.13 with respect to the filter coefficients. In the case of stationary signals the result of filter coefficients becomes: [41]

$$w = R^{-1}{}_{yy} R_{yx} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots . \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots .. ..2.14$$

Where R_{yy} is the autocorrelation matrix of the input signal and R_{yx} is the cross correlation vector between the input and the desired signals. To formulate the recursive time update for the adaptive formulation from equation 2.14 for a block of N samples vectors the correlation matrix is given as: [41]

$$R_{yy} = Y^T Y = \sum_{m=0}^{N-1} y(m)y^T(m) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots . \ldots\ldots\ldots .2.15$$

Where $y(m) = [y(m), \ldots\ldots\ldots\ldots\ldots ; y(m-P)]^T$ and the sum of vector product in equation 2.15 can be expressed in recursive fashions as follows.

$$R_{yy}(m) = R_{yy}(m-1) + y(m)y^{T}(m) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots 2.16$$

Now lets us introduce the time variations of the signal statistics of the adaptation factor be λ then the autocorrelation estimation in equation 2.16 is an exponential decaying windowed given by[41]:

$$\mathrm{R_{yy}}(m) = \lambda \mathrm{R}_{\boldsymbol{yy}}(m-1) + \mathrm{y(m)y^{T}(m)} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots 2.17$$

The adaptation factor λ is in the range of $0 < \lambda < 1$ similarly, the cross correlation vector is given by

$$\mathrm{R_{yx}} = \sum_{\boldsymbol{m=0}}^{\boldsymbol{N-1}} \mathrm{y(m)x(m)} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots 2.18$$

The sum of the product in Eqn 2.18 can be calculated in recursively form as:

$$\mathrm{R_{yx}(m)} = \mathrm{R_{yx}}(m-1) + \boldsymbol{y}(m)x(m) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots 2.19$$

Equation 2.19 can be made recursive using exponential decaying factor

$$\mathrm{R_{yx}(m)} = \lambda \mathrm{R_{yx}}(m-1) + \boldsymbol{y}(m)x(m) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots 2.20$$

The solution of Least Square (LS) in equation 2.20, give us the recursive time update for the inverse matrix form [41]:

$$\mathrm{R_{yy}}^{-1}(\mathrm{m}) = \mathrm{R_{yy}}^{-1}(\mathrm{m}-1) + \mathrm{update} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots 2.21$$

The above analyses present the mathematical relation between the input and desired signal and it quantified by cross correlation, auto correlation, adaption factor and wiener coefficients.

When channel is either in idle or busy state, the detection of primary user in cognitive radio system can be modeled using binary hypothesis test. It is recalled that:

Hypothesis 0 (H_0): the primary signal is absent.

Hypothesis 1 (H_1): the primary signal is present

The complex input signal **S** has real component S_r and imaginary component S_i can be represent by $\boldsymbol{S} = \boldsymbol{S_r} + \boldsymbol{j}\,\boldsymbol{S_i}$ then n^{th} sampled output signal **y** at (n=1,2,3,…..) is given by[43]:

$$y(k) = \begin{cases} n(k), \quad 0 \le k \le N-1 \ \text{idle state} \\ S(k) + n(k) \ \ 0 \le k \le N-1 \ \text{busy state} \end{cases} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots 3.1$$

Both s(n) and n(t) are the complex signal and noise respectively , can be written as:

$$n(k) = n_r(k) + jn_i(k) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots 3.2$$

$$s(k) = s_r(k) + js_i(k) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots 3.3$$

In realistic term equation.3.1 can be re write as

$$H_1 : y(k) = \begin{cases} n(k), & 1 \le k \le no - 1 \\ s(k) + n(k) & no \le k \le N \end{cases} \ldots\ldots\ldots\ldots\ldots\ldots\ldots 3.4$$

Where N is the number of samples, equation 3.4 is a realistic and logical representation of a signal defines in equation 3.1.

3.2.Energy detector test statistics

Figure 3-1(a) and Figure 3-1(b) shown the output of the analog/ digital integrator is called the test statistics of the system. The purpose of this test statistics is to compare the threshold value with that of the received signal SNR value and decide the presence/absence of primary signal in CR system [44]. When Nyman-Person Criterion applied one binary hypothesis model the probability density function of the given signal **y** can be expressed as log likelihood function and compared with the threshold value η as: $\mathcal{H}$ is $f_y|\mathcal{H}(x) : \mathcal{H}(x) \in \{\mathcal{H}_0, \mathcal{H}_1\}$

Then the log likelihood function Λ_{LR} is given by [17] [43]:

$$\Lambda_{LR} = log\left(\frac{P(y|H_1)}{P(y|H_0)}\right) \underset{H_0}{\overset{H_1}{\gtrless}} \eta \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots 3.4$$

Based on the above test statistics, the performance of energy detector is defined using the following metrics:

- False alarm probability (P_f): the probability of deciding the signal is present while H_0 is true, i.e., Pf = Pr[$\Lambda > \lambda | H_0$] where λ is the detection threshold, and Pr[.] stands for an event probability[44]. 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}= Pr[$\Lambda < \lambda | H_1$], 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= Pr[$\Lambda > \lambda | H_1$] and thus, Pd = 1 - P_{md}.

LLR characterize the statistical characteristic properties of the performance of an energy detector. To get the statistical properties, signal and noise models are essential. And the noise components, $n_r(n)$and $n_i(n)$, are zero mean Gaussian,

3.3.Performance metric measurement

The performance of the spectrum sensing technique can be quantified by the performance metric values. These values determine the correctness of the presence of the spectrum hole or channel in the system [44]. The following parameters are used to check the performance of energy detector:

- Probability of detection.
- Probability of false alarm.
- Probability of miss detection.
- The receiver operating characteristics curve (ROC).
- The Complementary receiver operating characteristics curve (CROC).
- Sensing gain of the receiver and
- Total error rate.

For the sake of simplicity this thesis uses the first five performance metrics. The performance matrices ROC curve measures the sensitivity of the detector and can be used in binary hypothesis system. Currently the application of this curve has become much popular. Over the past years in the fields of signal detection and estimation the overall detection capabilities of the detector is represented by the graphical plot of probability of detection (P_d)or probability of miss detection (P_{md}) versus probability of miss detection (P_f) as the threshold varies. Generally speaking the ROC curve can be given as the function of false alarm probability: Pd = f(Pf) and it shows the tradeoff between detection probability and false alarm rate for an optimum threshold [43].

A receiver operating curve (ROC) is a technique for visualizing, organizing and selecting classifiers (true positive, false positive) based on their performance. The graph has been used to evaluate the performance of the system. The ROC curve is widely applicable in signal detection and estimation for radar system. It depicts the tradeoff between probability of detection (true positive) and false alarm probability (false positive). Graphically it is represented by a two dimensional plot where the detection probability and false alarm probability plotted on the Y and X axis respectively. The classifiers can be discrete and mapped as a single point on ROC space. Specifically points on the ROC curve can be coordinate as a pair of points A(0,0),B(0,1),C(1,1)and D(1,0) can be depict in figure 3-2.

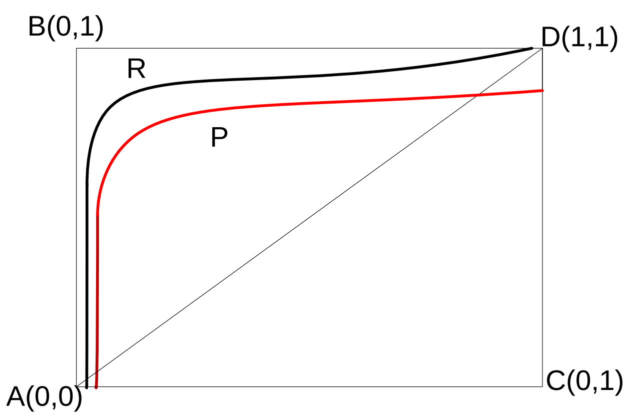

Figure 3-2: Receiver Operating Curve area for curve R and P[47]

The comparison of classifier can be done by reducing the ROC performance to a single scalar value representation. A common method is to calculate the area under ROC curve called Area under curve (AUC). Since the AUC is the portion of the area of unit square its value always between 0 and 1. The square in figure 3-2 has a maximum area equal to 1 m^2, comparing the area of under curve P (the red line color) to that of Curve R (the black line color), it is observed that the area of the curve R has higher value than that curve P. Thus that ROC curve, who‟s AUC higher as compared to other ROC curve, will have an improved performance than other. Likewise, for the CROC analysis those CROC curve who‟s AUC has least as compared to other CROC AUC will perform higher than other [47].

3.4.Derivations of P_d and P_f for Different Channel Models.

Let‟s consider the low pass representation of band pass noise signal **n**(t) as [31]:

$$\mathrm{n(t) = n_i(t)cos2\pi ft - n_q(t)sin2\pi ft} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots 3.5$$

Where n (t) is a band pass complex noise signal having a power spectral density N_0, bandwidth BW, in phase $n_i(t)$ and quadrature component $n_q(t)$ of, noise. The energy of the noise for period of T is given as [31]:

$$E = \int_0^T n(t)^2\, dt \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots 3.6$$

Equation 3.6 can be approximated as:

$$E = \int_0^T n(t)^2\, dt = \frac{1}{2}\int_0^T [n_i(t)^2 + n_q(t)^2\,]dt \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots 3.7$$

Since n_i and n_q are low pass representation of a noise signal then, from sampling theorem the low pass noise signal representation of the noise signal [31]

$$n_i = \int_{-\infty}^{+\infty} c_{jk}\mathrm{sinc}\left(\mathrm{Bwt} - j\right) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots 3.8$$

Where $\text{sinc}x = \frac{\sin\pi x}{x}$ and $c_{jk} = n_i\left(\frac{k}{B}\right)$ are Gaussian random variables with zero mean and variance and from the result of trigonometric integration we have [31]

$$\int_{-\infty}^{\infty} \text{sinc}(B_w t - j)\,\text{sinc}(B_w t - m)dt = \begin{cases} \frac{1}{B_w} & j = m \\ 0 & j \neq m \end{cases} \quad \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots.\dots\dots..3.9$$

Substituting equation 3.8 and 3.9 in equation 3.6 we found

$$\int_{-\infty}^{\infty} n_i(t)^2 dt = \frac{1}{B_w}\sum_{j=-\infty}^{\infty} {c_{ij}}^2 \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots.3.10$$

Since the signal has a period T we consider the signal from the interval [0, T] in equation 3.10 the phase and the quadrature component of the noise can be re write as [16]:

$$\int_{0}^{T} n_i(t)^2 dt = \frac{1}{B_w}\sum_{j=1}^{BT} {c_{ij}}^2 \text{ And } \int_{0}^{T} n_q(t)^2 dt = \frac{1}{B_w}\sum_{j=1}^{BT} {c_{qj}}^2 \dots\dots\dots\dots.3.11$$

Let $\frac{\mathbf{C_{ij}}}{\sqrt{\mathbf{2BN}}} = \mathbf{d_{ij}}$ and also $\frac{\mathbf{C_{qj}}}{\sqrt{\mathbf{2BN}}} = \mathbf{d_{qj}}$, Rearranging the values $\mathbf{C_{ij}}$ **and** $\mathbf{C_{qj}}$ and substitute these into equation 3.11 we obtain

$$E = \int_{0}^{T} n(t)^2 dt = \left[\sum_{j=1}^{BT} {d_{ij}}^2 + \sum_{j=1}^{BT} {d_{qj}}^2\right].N_0 \dots\dots\dots\dots\dots\dots\dots\dots\dots.3.12$$

Dividing the left side and the right side by N_o we obtain:

$$\frac{E}{N_o} = \frac{1}{N_o}\int_{0}^{T} n(t)^2 dt = \left[\sum_{j=1}^{BT} {d_{ij}}^2 + \sum_{j=1}^{BT} {d_{qj}}^2\right] \dots\dots\dots\dots\dots\dots\dots\dots\dots.3.13$$

$$\frac{E}{N_o} = \sum_{j=1}^{BT} {d_{ij}}^2 + \sum_{j=1}^{BT} {d_{qj}}^2 \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots.3.14$$

Equation 3.12 is the energy of the signal over the time period T on interval [0, T].The output of this filter is then squared and integrated over a time interval of period T yield a test statistic value under null hypothesis. Equation 3.13 is the SNR value of the received signal energy. Under null hypothesis H_0:$x(t) = n(t)$ only the noise is present in system then test statistics will be:

$$y = \sum_{j=1}^{B_w T}\left[{d_{ij}}^2 + {d_{qj}}^2\right] \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots.\dots\dots\dots.3.15$$

From equation 3.15 it is observed that $\sum_{j=1}^{BT} {d_{ij}}^2$ *and* $\sum_{j=1}^{BT} {d_{qj}}^2$ are the distribution of the received noise signal at the detector node which is a chi-square distribution having $2B_wT$ freedom and similarly H_1: $y(t) = x(t) + n(t)$ hypothesis, the received signal is the sum of the desired signal and the noise.(since the correlation between the signal and noise is zero) equation 3.15 of the test statistics Y become [43]:

$$\int_0^T y(t)^2\, dt = \left[\sum_{j=1}^{B_wT} \left(d_{ij}{}^2 + b_{ji}{}^2\right)^2 + \sum_{j=1}^{B_wT} \left(d_{qj}{}^2 + b_{qj}{}^2\right)^2\right] . N_0 \ldots\ldots.\ldots\ldots\ldots .3.16$$

Dividing both sides by N_0 and denoting the result Y we have:

$$Y = \frac{1}{N_0}\int_0^T y(t)^2\, dt = \left[\sum_{j=1}^{B_wT} \left(d_{ij}{}^2 + b_{ji}{}^2\right)^2 + \sum_{j=1}^{B_wT} \left(d_{qj}{}^2 + b_{qj}{}^2\right)^2\right] \ldots\ldots\ldots\ldots\ldots\ldots 3.17$$

The test statistics in equation 3.17 under the condition H_1 is non-central Chi-square distribution with $2B_wT$ freedom. The non-central chi-square distribution offers a statistical test value that uses to determine how far the estimation is from the null hypothesis. d, is the time bandwidth product at the node and γ is the non-centrality parameters equal to the signal noise ratio γ can be written write as: $\gamma = \frac{E_S}{N} = \frac{E_S}{2N_0}$.Therefore the decision statistics under hypothesis H_0 and H_1 are $Y \sim X_{2d}{}^2(\gamma)$ and$Y \sim X_{2d}{}^2(2\gamma)$ respectively. The above results in a concise format become:

$$Y \sim \begin{cases} X_{2d}{}^2, \ldots\ldots\ldots\ldots H_0 \\ X_{2d}{}^2(2\gamma), \ldots\ldots\ldots\ldots\ H_1 \end{cases} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots ...3.18$$

Therefore the probability density function (PDF) of Eqn 3.18 of the chi-square becomes [16][31]

$$f_Y(y) = \begin{cases} \frac{1,}{2^d\Gamma(d)} y^{d-1} e^{\frac{-y}{2}} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots H_0 \\ \frac{1}{2}\left(\frac{y}{\gamma}\right) \frac{d-1}{2} e^{\frac{-(2\gamma+y)}{2}} I_{d-1}(\sqrt{2\gamma y} \ldots\ldots\ldots\ldots . H_1 \end{cases} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots 3.19$$

And the $\Gamma(.)$ is the modified gamma function defined as $\Gamma(x, a) = \int_a^\infty e^{-t}\, t^{-(x-1)} dt$ and $I_v(.)$ is the vth-order modified Bessel function of first kind. Using the above equations we can derive the probability and false alarm detection for different channel models specifically AWGN and Raleigh channel. Hence the detection probability of AWGN can be found for energy detector when the noise with constant spectral density and also AWGN can be considered as a non-fading channel [17], [24].

We know that P_d is the probability that H_1 is selected when the primary signal is present and P_{fa} is probability of false alarm when H_0 selected. We also assume that the threshold value of $\kappa$is selected hence the exact closed form expressions of Pd and P_{fa} can be defined as [17]

$$P_d = P(Y > \kappa | H_1) \ldots\ldots 3.20$$

$$P_{fa} = P(Y > \kappa | H_0) \ldots\ldots 3.21$$

Then from their PDF, it is possible to express P_{fa} as:[16]

$$P_{fa} = \int_{\kappa}^{\infty} f_Y(y) dy \ldots\ldots 3.22$$

Inserting the value of $\mathbf{f_Y}$ from Eqn 3.19 into Eqn 3.22:

$$P_{fa} = \int_{\kappa}^{\infty} \frac{1,}{2^d \Gamma(d)} y^{d-1} e^{\frac{-y}{2}} dy = \frac{1,}{2^d \Gamma(d)} \int_{\kappa}^{\infty} \frac{y^{d-1}}{2} e^{\frac{-y}{2}} dy \ldots\ldots 3.23$$

$$P_{fa} = \frac{1,}{2^d \Gamma(d)} \int_{\kappa}^{\infty} \frac{y^{d-1}}{2} e^{\frac{-y}{2}} dy \ldots\ldots 3.24$$

Letting $t = \frac{y}{2}$ and changing the lower and upper limit equation 3.24 becomes

$$P_{fa} = \frac{1,}{2^d \Gamma(d)} \int_{2t}^{\infty} t^{d-1} e^{-t} dy \ldots\ldots 3.25$$

3.4.1. Detection and False alarm probabilities over AWGN Channel

The approximate expression for P_d over AWGN channels in closed form expressions for both P_d and P_f the probability of detection and false alarm can be generally computed by:

$$p_{d} = P_r(Y > \lambda | H_1) \ldots\ldots 3.26$$

$$p_{f} = P_f(Y > \lambda | H_0) \ldots\ldots 3.27$$

Where λ is the decision threshold using equation 3.25 the P_f yields [16],[24], [46]:

$$P_f = \frac{\Gamma\left(\mathrm{d}, \frac{\lambda}{2}\right)}{\Gamma(\mathrm{d})} \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots . \ldots \ldots . . . . 3.28$$

$\Gamma(.)$Is the modified gamma function and d is the time bandwidth, from equation3.28. Obviously the detection probability P_d is the complement of miss detection P_{md} mathematically it can be put as:

$$P\mathrm{d} = 1 - P\mathrm{md} \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots . \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots . . . . . 3.29$$

$$P_d = Q_d\left(\sqrt{2\gamma}, \sqrt{\lambda}\right) \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots . 3.30$$

Where Q_b (a,b) is the generalized Marcum Q-function [17]

3.4.2. Detection and false alarm probabilities for Rayleigh channel

The detection and the false alarm probabilities of the Rayleigh channel can be derived from integrating its PDF on certain interval. If the signal amplitude follows Rayleigh distribution with respect to signal SNR γ and average SNR $\tilde{\gamma}$ then the PDF of the Rayleigh channel is given as:

$$\mathrm{f}(\gamma) = \frac{1}{\gamma} \exp\left(-\frac{\gamma}{\tilde{\gamma}}\right), \quad \gamma \geq 0 \ldots \ldots \ldots \ldots \ldots \ldots . . \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots . . \ldots . . 3.31$$

The average P_d can be evaluated using equation 3.30 letting and changing the variable $x = \sqrt{2\gamma}$ result in [24],[44],[46]

$$P_{dav} = e^{-\frac{\lambda}{2}} \sum_{n=0}^{u-2} \frac{1}{n!}\left(\frac{\lambda}{2}\right)^n + \left(\frac{1+\gamma}{\tilde{\gamma}}\right)^{u-1}\left[e^{-\frac{\lambda}{2(1+\gamma)}} - e^{-\frac{\lambda}{2}} \sum_{n=0}^{u-2} \frac{1}{n!} \frac{\lambda\gamma}{2(1+\tilde{\gamma})}\right] \ldots \ldots \ldots \ldots . \ldots \ldots \ldots 3.32$$

3.5. The Adaptive Weiner Filter energy detector

This thesis present the introduction of adaptive wiener filters at the front end of the energy detector. As the signal noise ratio become too low as that of threshold value, the performance of the system will be poor. Therefore in this work the insertion of adaptive wiener filter enhances response of the system by filtering the noise components. The implementation of the model is can be depicted using the following block and flow diagram.

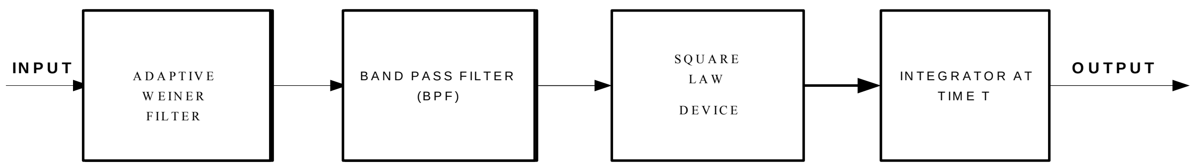

Figure 3-3: Enhanced energy detector spectrum sensing block diagram

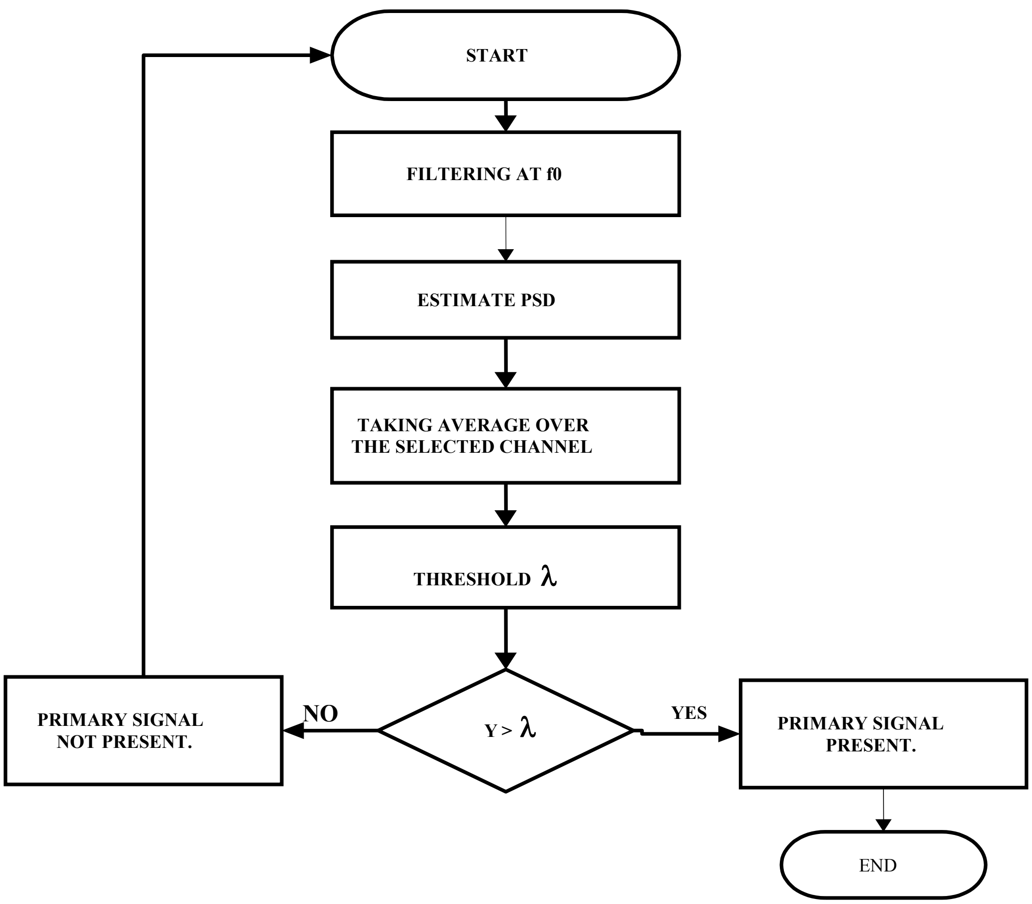

Figure 3-4: Flow diagram of Conventional Energy detector Spectrum [27]

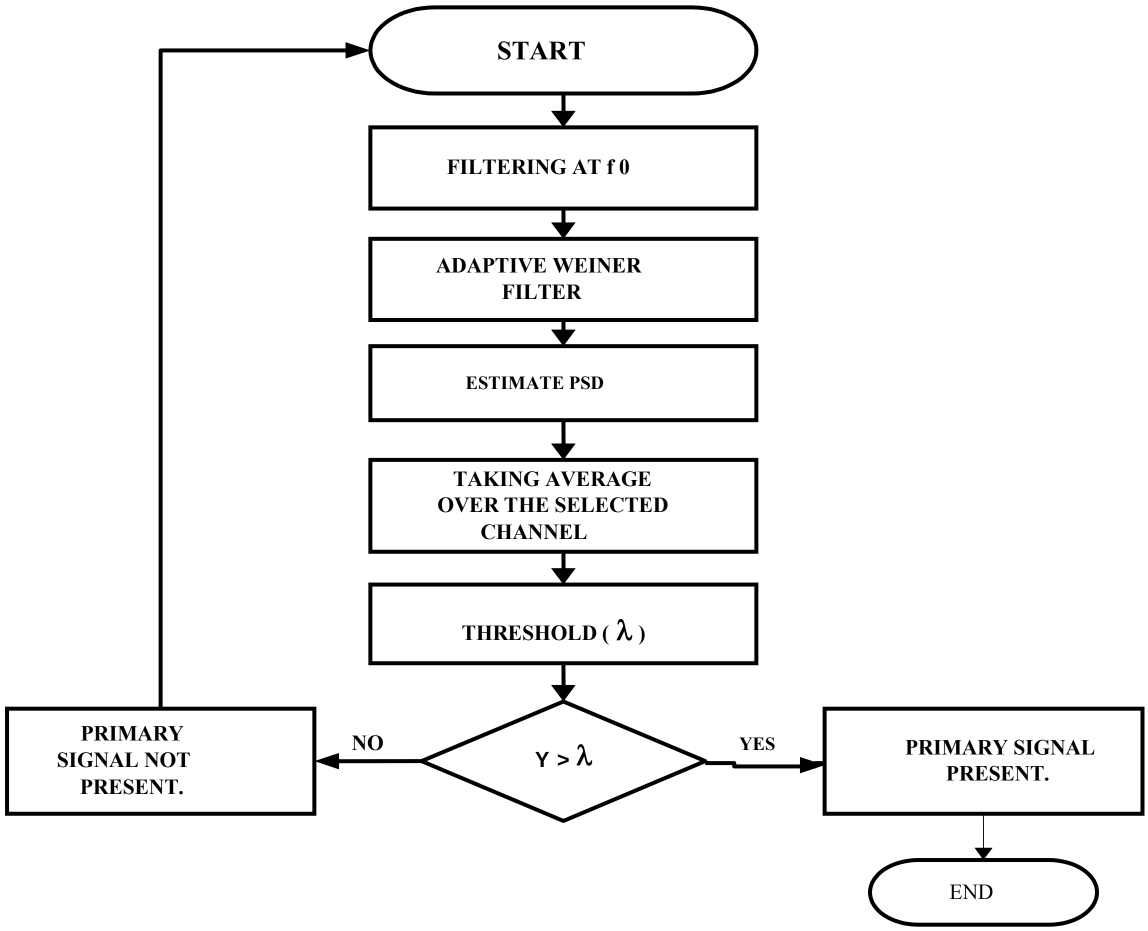

Figure 3-5 Thesis model energy detector spectrum sensing flow diagram in CR

By adaptive filter we mean that Wiener coefficients are updated recursively until they reach an optimum values. The Recursive Least Algorithm (RLS) filter is an adaptive formulation of Wiener filter. For stationary signals the RLS algorithm converges to the same solution as Wiener filter. Thus Recursive Least Square algorithm becomes the optimum solution of Wiener filter. Accordingly the enhanced block and logically representation of the energy detector is shown in figure 3.5.One of the challenges in filtering and detection of signal with low SNR is the problem of SNR wall. It is the phenomena where by the signal SNR value becomes below the detection threshold, in this scenario the signal detection, estimation and retrieval become too difficult. It occurs when the two test statistics begin overlap each other under the two binary hypotheses.

Chapter 4

Simulation Results and Discussions

In the previous chapter, the system model and the mathematical analysis for different channel models were discussed. Based on the mathematical result, MATLAB simulation was done for AWGN and Rayleigh channel models.

4.1.Simulation results and discussions parameters of energy detector.

The simulation parameters used in this thesis work are listed in table 4-1.

Table 4-1: Simulation Parameters

Simulation parameters	Type and values
Cognitive user	Single user
Transmitted Signal	BSK,QPSK
Detector Type	Energy Detector
Propagation channel model	Flat Mode channel
Initial update =lambda	0.99
Number of Monte Carlo simulation	100000
FIR Filter Order	32
Transmitted Signal SNR values	-5dB , 5 dB
Modulation Index	4
Probability of false alarm	0.01
Number of samples	10, 1000
Simulation Platform	RMatlab2014a
Mean and Variance (noise)	0,1
Channel	AWGN and Rayleigh

4.1.1. Simulation results and discussions of conventional and enhanced energy detector for AWGN channel

This section assesses the performance of conventional and enhanced energy detector algorithm based on the performance matrices which were outlined in the section 3.3.

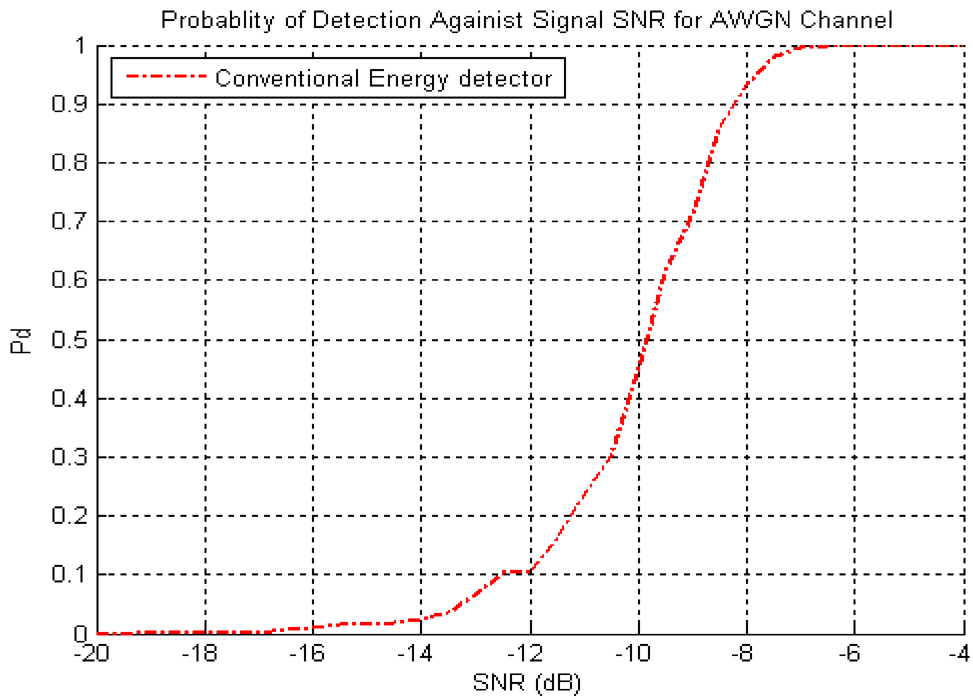

Figure 4-1: Conventional Probability of detection Vs Signal SNR.

Figure 4-1 is the conventional energy detector response based on the parameters listed on the table 4-1. The plot generated when 100 sampled signals are transmitted, with modulation index and type equal to 4 and QPSK respectively. Setting the value of false alarm probability equal to 0.01 figure 4-1 plot the relation between the detection probabilities Vs signal SNR values for AWGN channel under normal circumstances (without the introduction of adaptive Weiner filter).These values of detection probability for different value SNR values are generated and it shown in table 4.2. As the SNR value increase from -20dB to -4dB with step increment of 0.5dB, so does the detection probability. Though the detection values at lower SNR is too low, specifically for SNR values below -12dB, it reached around 0.44 of detection probability when the signal SNR is equal to -10dB. Finally for SNR values greater than -8dB, it attain maximum detection value equal to 1. Based on the value of detection values in table 4.2, values in SNR can possibly arranged in three regions (R):

R1:{-20≤ SNR ≤ -12.5dB}, R2:{-12dB≤ SNR ≤ -9.5dB} and R3:{-9dB≤ SNR ≤ -4dB}

In the region R1 the detection values observed in this region are too low, specifically the distance between the final and initial detection value is 0.084.

R2 is the region where moderate value detection is observed with respect to R1. In this case the plot start to move upward and the observed detection value is higher as compared to R1 region. Finally R3 is the region where the detection is become high and attains its maximum value.

Table 4-2: Simulation Result of Pd Vs SNR for Conventional Energy detector

Pd Vs SNR for Energy detector (WITHOUT FILTER)									
Sample #	1	2	3	4	5	6	7	8	
SNR(dB)	-20	-19.5	-19	-18.5	-18	-17.5	-17	-16.5	
P_d	0.004	0.002	0.003	0.003	0.002	0.007	0.003	0.006	
Sample #	9	10	11	12	13	14	15	16	
SNR(dB)	-16	-15.5	-15	-14.5	-14	-13.5	-13	-12.5	
P_d	0.007	0.01	0.009	0.009	0.022	0.043	0.056	0.088	
Sample #	17	18	19	20	21	22	23	24	
SNR(dB)	-12	-11.5	-11	-10.5	-10	-9.5	-9	-8.5	
P_d	0.115	0.158	0.237	0.356	0.44	0.581	0.74	0.834	
Sample #	25	26	27	28	29	30	31	32	33
SNR(dB)	-8	-7.5	-7	-6.5	-6	-5.5	-5	-4.5	-4
P_d	0.938	0.974	0.995	1	1	1	1	1	1

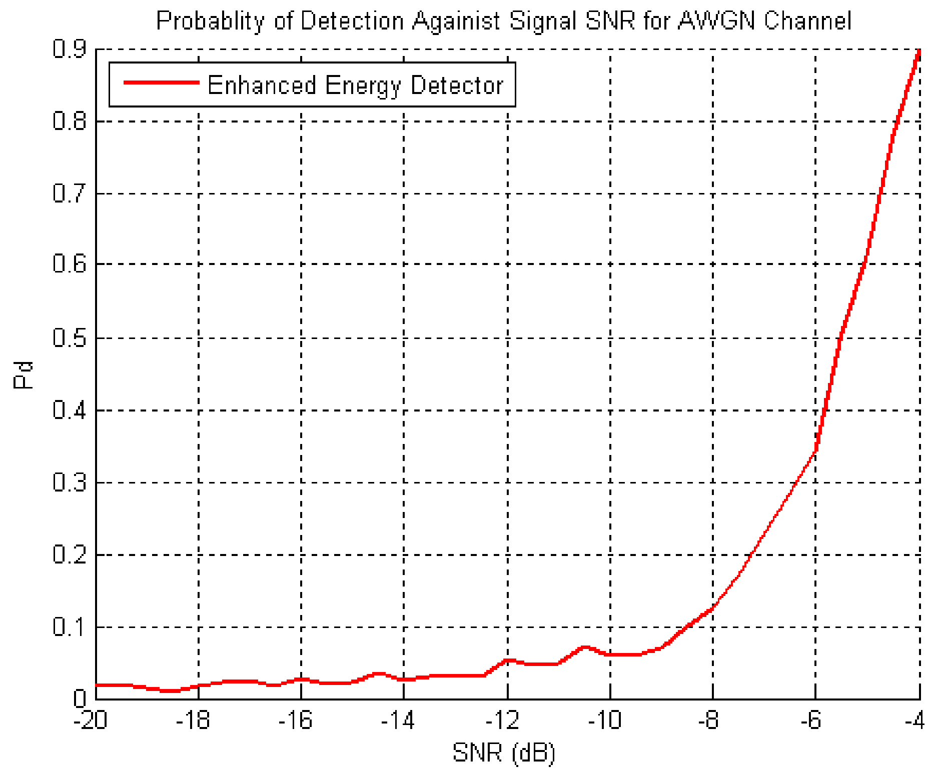

Figure 4.1.1-2: Enhanced Probability of detection Vs Signal SNR.

Figure 4-2 is the enhanced simulation plot when adaptive Weiner filter is inserted on the front end of energy detector. It generated the value of detection probability for corresponding SNR values .Similarly 100 sampled signals are transmitted, with modulation index and type equal to 4 and QPSK respectively. And also the adaptive Weiner filter has a filter order of 32 with initial recursive update value equal to 0.99. Setting the value of false alarm probability equal to 0.01 the enhanced system response generated the detection values in table 4-3. Likewise result in table 4.3, values in SNR can possibly arrange in three regions (R):

R1:{-20≤ SNR ≤ -12.5dB}, R2:{-12dB≤ SNR ≤ -9.5dB} and R3:{-9dB≤ SNR ≤ -4dB}

Comparing the detection probability values in table 4-2 with that of table 4-3, it is observed that table 4-3 showed the detection probabilities in region R1, has higher value that of table 4.2.

Thus the insertion of adaptive Wiener filter in the front end of energy detector improved the performance of the system at low value of SNR specifically in the region R1:{-20≤ SNR ≤ -12.5dB}.

Table 4-3 Simulation result Pd Vs SNR for Enhanced Energy detector (With Insertion of Adaptive Weiner Filter)

Pd Vs SNR for Energy detector (With Insertion of Adaptive Weiner Filter)									
Sample #	1	2	3	4	5	6	7	8	
SNR(dB)	-20	-19.5	-19	-18.5	-18	-17.5	-17	-16.5	
Pd	0.017	0.016	0.016	0.021	0.027	0.023	0.019	0.017	
Sample #	9	10	11	12	13	14	15	16	
SNR(dB)	-16	-15.5	-15	-14.5	-14	-13.5	-13	-12.5	
Pd	0.019	0.017	0.019	0.022	0.017	0.037	0.034	0.029	
Sample #	17	18	19	20	21	22	23	24	
SNR(dB)	-12	-11.5	-11	-10.5	-10	-9.5	-9	-8.5	
Pd	0.035	0.036	0.044	0.042	0.044	0.082	0.099	0.111	
Sample #	25	26	27	28	29	30	31	32	33
SNR(dB)	-8	-7.5	-7	-6.5	-6	-5.5	-5	-4.5	-4
Pd	0.127	0.161	0.212	0.266	0.35	0.468	0.628	0.743	0.881

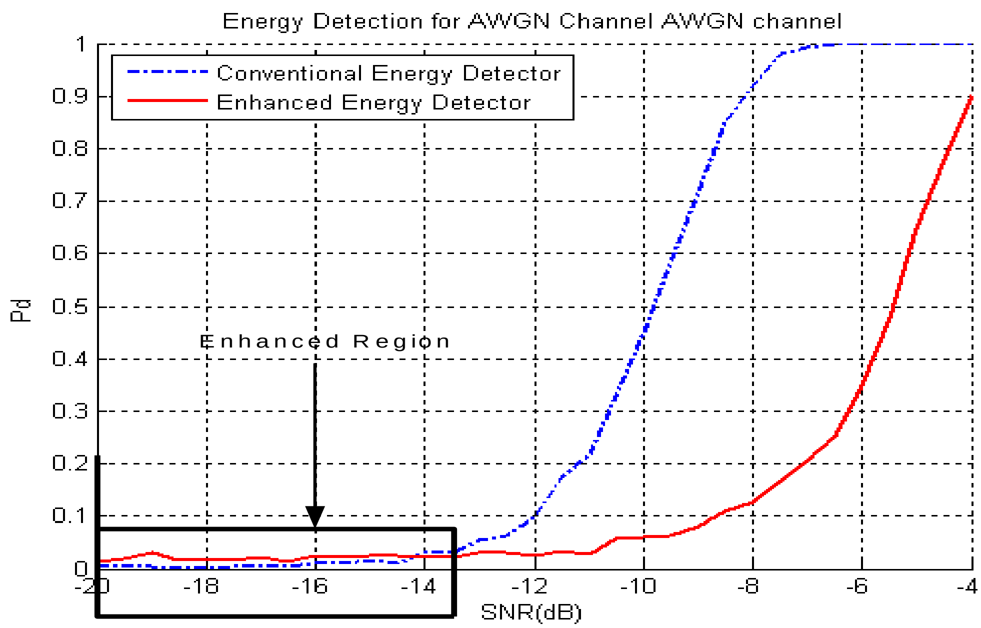

Figure 4-3: Conventional and enhanced energy detector Probability of detection Vs Signal SNR.

Figure 4-3 depicts the conventional and enhanced energy detector simulation plot together. Thus the insertion of adaptive Weiner filter on the front end of conventional energy detector improvised the detection performance values at low values of SNR and specifically in the region R1

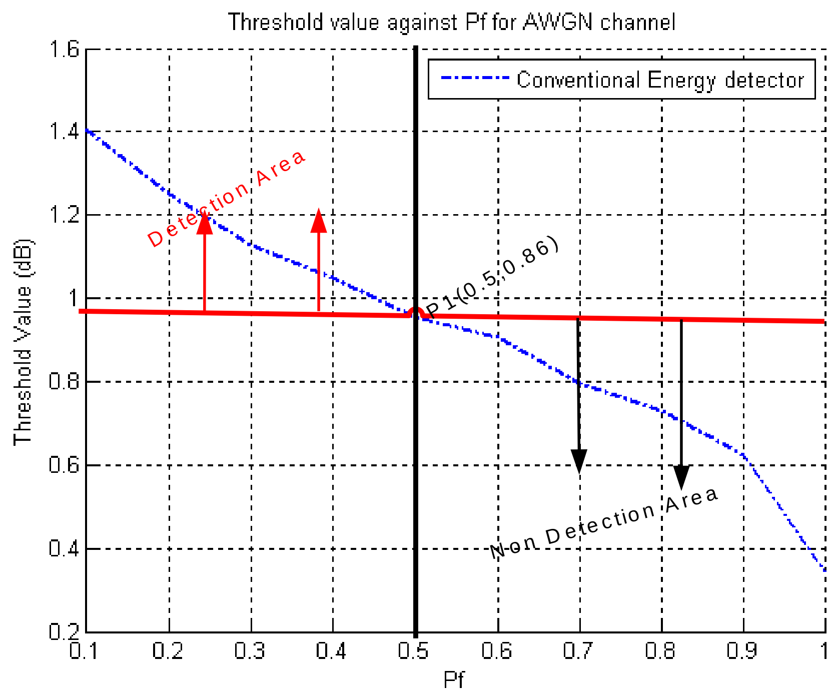

Figure 4-4: Conventional Energy detector Threshold Vs False alarm for AWGN.

Figure 4-4 depicts the relation between false alarm probabilities Vs the system threshold values when 10 sample signals with SNR value of 5dB is transmitted. Figure 4-4 shows as the value of P_f increased toward 1 the corresponding threshold values decrease toward 0.2. Specifically when the P_f value is set to be 0.5, the corresponding threshold value is around 0.86. This point can be marked as P1 (0.5, 0.86) on the graph. The point P1 is an intersection point for the red and black line drawn. The two intersected lines divide the whole region into four sections, but our interest area is the most upper left (detection area section) and most lower right section (Non Detection area). Setting the system parameters at point P1, received signal whose SNR is less than 0.86 dB, it falls within non detection area. Thus energy detector system decides there exist a vacant channel and primary user is absence. On contrary to this, if the received signal is greater than 0.86dB it falls within detection area. Hence the energy detector decides there exist primary user in a channel.

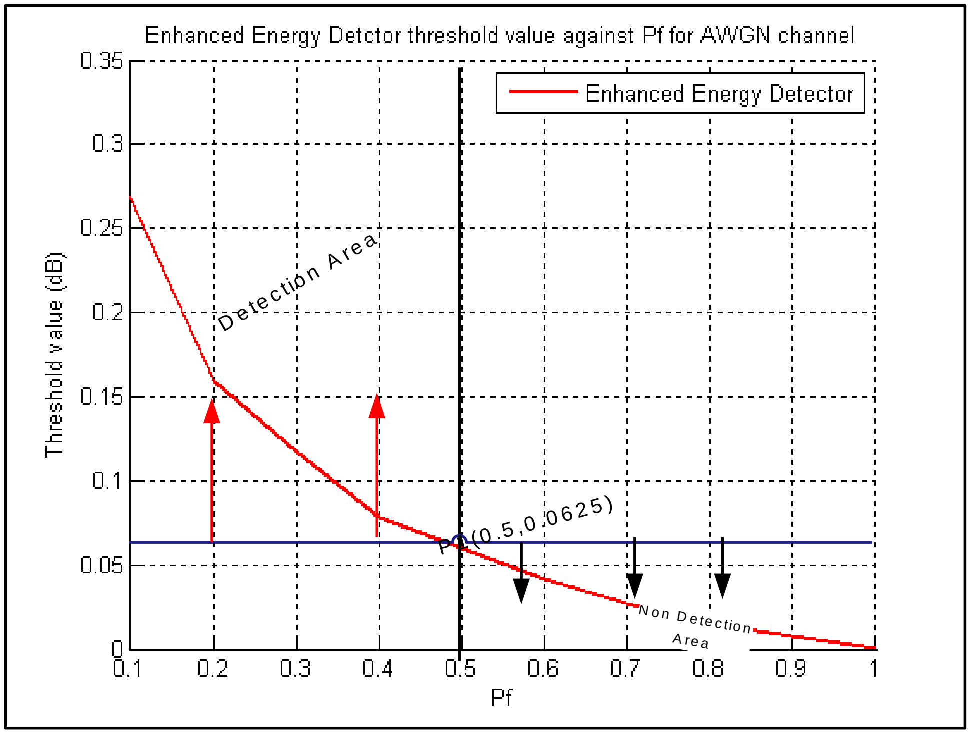

Figure 4-5: Enhanced Energy Detector Threshold Vs False alarm for AWGN.

Figure 4-5 depict the relation between false alarm probabilities Vs the system threshold values when the enhanced energy detector sensed 10 sample signal of 5dB SNR filter order 32.Similarly Figure 4-5 shows as the value of Pf increased toward 1the corresponding threshold values decrease toward 0.Specifically if P_f value is set to 0.5, the corresponding threshold value is around 0.0625.This point is marked as P2 (0.5, 0.0625) on the graph. The point P2 is an intersection point of the red and black line. It divide the whole region into four section but our area of interest is the upper left section(detection area section) and lower right section (Non Detection area).Setting the system parameters at point P2, signal whose SNR is less than 0.0625dB, the decisions fall in non detection area. Thus energy detector decides there exist a vacant channel and primary user is absence. On contrary, if the received signal is greater than 0.0625dB the decision is falls within detection area. Hence the enhanced energy detector decides there exist primary user in a channel. Moreover, area detection in enhanced energy detector is the higher than that of detection area in conventional case.

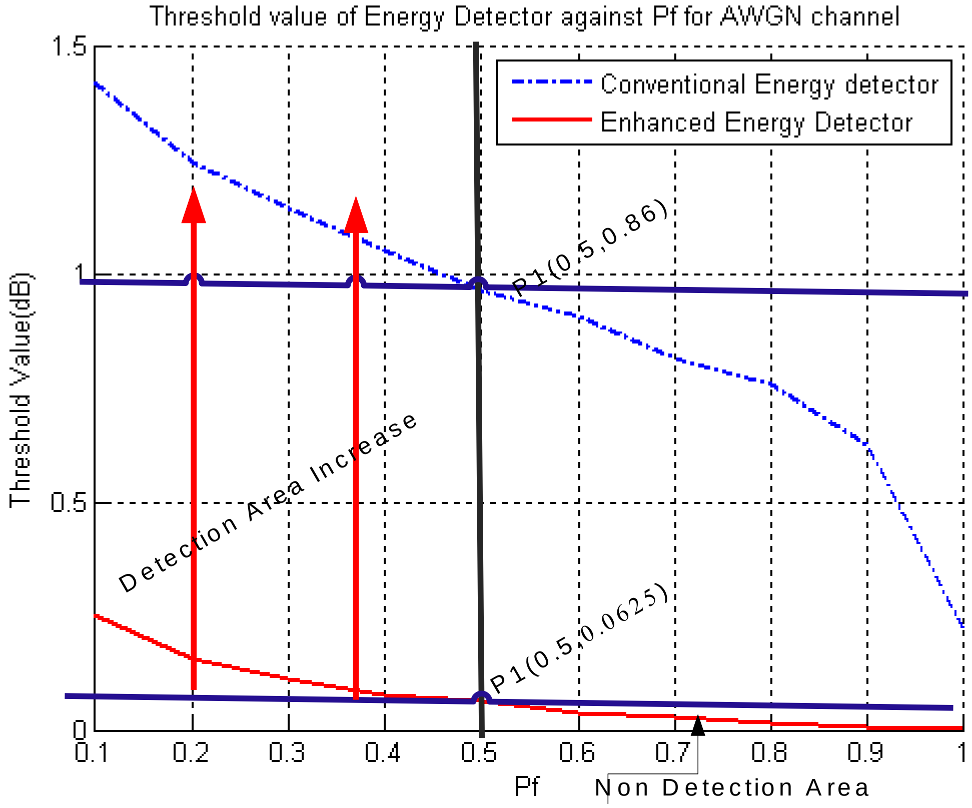

Figure 4-6: Conventional and Enhanced energy detector Threshold Vs False alarm probability for AWGN.

Figure 4-6 shows the simulation plot for both conventional and enhanced energy detector together. The detection area obtained from enhanced system is higher than that of corresponding conventional detection area. Thus the introductions of adaptive Weiner filter on the front end of energy detector increase the detection area of the system.

sample values Sample_1 and Sample_2 from table 4.4 and 4.5 for the same value of false alarm probability:

Sample_1: Conventional Energy detector

Pf	0.0025	0.0049	0.0081	0.0121
Pd_Simu	0.942434	0.951381	0.957675	0.962455
Pd_Approxm	0.894764	0.926457	0.945921	0.958905

Sample_2: Enhanced energy detector table

Pf	0.0025	0.0049	0.0081	0.0121
Pd_Simu	0.997188	0.998481	0.999091	0.99942
Pd_Approxm	0.996067	0.996934	0.997496	0.997896

Comparing the Samples_1 values to that of Sample_2 for same value of Pf value, it is observed that the detection probability (Pd_simu and Pd_Approx) values in Sample_2 is higher than that of values in Sample_1.In other word the area under curve obtained by curve made by Sample_2 is higher than that of curve made by sample 1.Thus figure 4-8 is an improved version of figure 4-7. Thus the insertion of adaptive Weiner filter on the front end of the energy detector increased the operational area of receiver operating curve. Therefore the system improved the detection probability of primary signal.

Table 4-4: ROC Matlab Simulation result of Conventional Energy Detector.

Matlab Simulation result of Conventional Energy detector ROC										
Pf	0.0001	0.0009	0.0025	0.0049	0.0081	0.0121	0.0169	0.0225	0.0289	0.0361
Pd_Simu	0.892247	0.927771	0.942434	0.951381	0.957675	0.962455	0.966262	0.969398	0.972044	0.974318
Pd_Approxm	0.669985	0.834907	0.894764	0.926457	0.945921	0.958905	0.968043	0.974721	0.97974	0.983594

Matlab Simulation result of Conventional Energy detector ROC										
Pf	0.0441	0.0529	0.0625	0.0729	0.0841	0.0961	0.1089	0.1225	0.1369	0.1521
Pd_Simu	0.976302	0.978054	0.979616	0.98102	0.982292	0.98345	0.984511	0.985488	0.986391	0.987228
Pd_Approxm	0.986604	0.988989	0.9909	0.992446	0.993707	0.994743	0.995598	0.996307	0.996899	0.997394

Matlab Simulation result of Conventional Energy detector ROC										
Pf	0.1681	0.1849	0.2025	0.2209	0.2401	0.2601	0.2809	0.3025	0.3249	0.3481
Pd_Simu	0.988008	0.988736	0.989418	0.990058	0.99066	0.991229	0.991766	0.992274	0.992757	0.993215
Pd_Approxm	0.997809	0.998158	0.998452	0.9987	0.99891	0.999088	0.999238	0.999365	0.999472	0.999563

Matlab Simulation result of Conventional Energy detector ROC										
Pf	0.3721	0.3969	0.4225	0.4489	0.4761	0.5041	0.5329	0.5625	0.5929	0.6241
Pd_Simu	0.993652	0.994068	0.99446	0.994845	0.995209	0.995559	0.995894	0.996217	0.99652	0.99682
Pd_Approxm	0.999639	0.999704	0.99975	0.999804	0.999842	0.999873	0.9999	0.999921	0.999939	0.999954

Matlab Simulation result of Conventional Energy detector ROC										
Pf	0.6561	0.6889	0.7225	0.7569	0.7921	0.8281	0.8649	0.9025	0.9409	0.9801
Pd_Simu	0.997121	0.99740	0.997679	0.99794	0.998212	0.998474	0.998737	0.999004	0.999289	0.999627
Pd_Approxm	0.999965	0.99997	0.999982	0.99998	0.999992	0.999995	0.999997	0.999999	1	1

Table 4-5: ROC Matlab Simulation result of Enhanced Energy Detector

Matlab Simulation result of Enhanced Energy detector ROC										
Pf	0.0001	0.0009	0.0025	0.0049	0.0081	0.0121	0.0169	0.0225	0.0289	0.0361
Pd_Simu	0.975559	0.993696	0.997188	0.998481	0.999091	0.99942	0.999613	0.999733	0.999811	0.999864
Pd_Approxm	0.989851	0.994483	0.996067	0.996934	0.997496	0.997896	0.998197	0.998433	0.998623	0.99878

Matlab Simulation result of Enhanced Energy detector ROC										
Pf	0.0441	0.0529	0.0625	0.0729	0.0841	0.0961	0.1089	0.1225	0.1369	0.1521
Pd_Simu	0.9999	0.999926	0.999945	0.999958	0.999968	0.999976	0.999981	0.999985	0.999989	0.999991
Pd_Approxm	0.998912	0.999024	0.99912	0.999204	0.999278	0.999343	0.999401	0.999453	0.9995	0.999542

Matlab Simulation result of Enhanced Energy detector ROC										
Pf	0.1681	0.1849	0.2025	0.2209	0.2401	0.2601	0.2809	0.3025	0.3249	0.3481
Pd_Simu	0.999993	0.999995	0.999996	0.999997	0.999998	0.999998	0.999998	0.999999	0.999999	0.999999
Pd_Approxm	0.999581	0.999615	0.999647	0.999676	0.999703	0.999727	0.99975	0.999771	0.99979	0.999808

Matlab Simulation result of Enhanced Energy detector ROC										
Pf	0.3721	0.3969	0.4225	0.4489	0.4761	0.5041	0.5329	0.5625	0.5929	0.6241
Pd_Simu	0.999999	1	1	1	1	1	1	1	1	1
Pd_Approxm	0.999824	0.99984	0.999854	0.999868	0.99988	0.999892	0.999903	0.999913	0.999922	0.9999

Matlab Simulation result of Enhanced Energy detector ROC										
Pf	0.6561	0.6889	0.7225	0.7569	0.7921	0.8281	0.8649	0.9025	0.9409	0.9801
Pd_Simu	1	1	1	1	1	1	1	1	1	1
Pd_Approxm	0.999939	0.99994	0.999954	0.999961	0.999968	0.999974	0.99998	0.999985	0.99999	0.9999

Sample_3: Conventional Energy Detector

Pf	0.0025	0.0049	0.0081	0.0121
Pm_Simu	0.105236	0.073543	0.054079	0.041095
Pm_Approxm	0.057566	0.048619	0.042325	0.037545

Sample_4: Enhanced Energy Detector

Pf	0.0025	0.0049	0.0081	0.0121
Pm_Simu	0.002812	0.001519	0.000909	0.00058
Pm_Approxm	0.003933	0.003066	0.002504	0.002104

It is observed that for same value of false alarm probability, the values of Pm_Simu and Pm_Approxm in Sample_ 4, is too small as compared to the corresponding values of Pm_Simu and Pm_Approxm in Sample_ 3. This shows that the insertion of adaptive Weiner filter lowered the miss detection values of the conventional energy. Hence the adaptive Weiner filter in the front end of energy detector has improved the system performance of energy detector by minimize the area under CROC curve.

Table 4-6: CROC Matlab Simulation result of Conventional Energy Detector.

Matlab Simulation result of Conventional energy detector CROC										
Pf	0.0001	0.0009	0.0025	0.0049	0.0081	0.0121	0.0169	0.0225	0.0289	0.0361
Pm_ Simu	0.330015	0.165093	0.105236	0.073543	0.054079	0.041095	0.031957	0.025279	0.02026	0.016406
Pm_Approxm	0.107753	0.072229	0.057566	0.048619	0.042325	0.037545	0.033738	0.030602	0.027956	0.025682

Matlab Simulation result of Conventional energy detector CROC										
Pf	0.0441	0.0529	0.0625	0.0729	0.0841	0.0961	0.1089	0.1225	0.1369	0.1521
Pm_ Simu	0.013396	0.011011	0.0091	0.007554	0.006293	0.005257	0.004402	0.003693	0.003101	0.002606
Pm_Approxm	0.023698	0.021946	0.020384	0.01898	0.017708	0.01655	0.015489	0.014512	0.013609	0.012772

Matlab Simulation result of Conventional energy detector CROC										
Pf	0.1681	0.1849	0.2025	0.2209	0.2401	0.2601	0.2809	0.3025	0.3249	0.3481
Pm_ Simu	0.002191	0.001842	0.001548	0.0013	0.00109	0.000912	0.000762	0.000635	0.000528	0.000437
Pm_Approxm	0.011992	0.011264	0.010582	0.009942	0.00934	0.008771	0.008234	0.007726	0.007243	0.006785

Matlab Simulation result of Conventional energy detector CROC										
Pf	0.3721	0.3969	0.4225	0.4489	0.4761	0.5041	0.5329	0.5625	0.5929	0.6241
Pm_ Simu	0.000361	0.000296	0.000242	0.000196	0.000158	0.000127	0.0001	7.87E-05	6.09E-05	4.65E-05
Pm_Approxm	0.006348	0.005932	0.005535	0.005155	0.004791	0.004441	0.004106	0.003783	0.003472	0.003171

Matlab Simulation result of Conventional energy detector CROC										
Pf	0.6561	0.6889	0.7225	0.7569	0.7921	0.8281	0.8649	0.9025	0.9409	0.9801
Pm_ Simu	3.48E-05	2.55E-05	1.82E-05	1.25E-05	8.23E-06	5.08E-06	2.86E-06	1.38E-06	4.90E-07	6.70E-08
Pm_Approxm	0.002879	0.002597	0.002321	0.002052	0.001788	0.001526	0.001263	0.000996	0.000711	0.000373

Table 4-7: CROC Matlab Simulation result of Enhanced Energy Detector

Matlab Simulation result of Enhanced energy detector CROC										
Pf	0.0001	0.0009	0.0025	0.0049	0.0081	0.0121	0.0169	0.0225	0.0289	0.0361
Pm_ Simu	0.024441	0.006304	0.002812	0.001519	0.000909	0.00058	0.000387	0.000267	0.000189	0.000136
Pm_Approxm	0.010149	0.005517	0.003933	0.003066	0.002504	0.002104	0.001803	0.001567	0.001377	0.00122

Matlab Simulation result of Enhanced energy detector CROC										
Pf	0.0441	0.0529	0.0625	0.0729	0.0841	0.0961	0.1089	0.1225	0.1369	0.1521
Pm_ Simu	9.98E-05	7.40E-05	5.55E-05	4.19E-05	3.19E-05	2.45E-05	1.88E-05	1.45E-05	1.13E-05	8.75E-06
Pm_Approxm	0.001088	0.000976	0.00088	0.000796	0.000722	0.000657	0.000599	0.000547	0.0005	0.000458

Matlab Simulation result of Enhanced energy detector CROC										
Pf	0.1681	0.1849	0.2025	0.2209	0.2401	0.2601	0.2809	0.3025	0.3249	0.3481
Pm_ Simu	6.80E-06	5.30E-06	4.12E-06	3.21E-06	2.50E-06	1.94E-06	1.50E-06	1.16E-06	8.97E-07	6.89E-07
Pm_Approxm	0.000419	0.000385	0.000353	0.000324	0.000297	0.000273	0.00025	0.000229	0.00021	0.000192

Matlab Simulation result of Enhanced energy detector CROC										
Pf	0.3721	0.3969	0.4225	0.4489	0.4761	0.5041	0.5329	0.5625	0.5929	0.6241
Pm_ Simu	5.26E-07	4.00E-07	3.02E-07	2.26E-07	1.68E-07	1.23E-07	8.96E-08	6.42E-08	4.52E-08	3.12E-08
Pm_Approxm	0.000176	0.00016	0.000146	0.000132	0.00012	0.000108	9.75E-05	8.73E-05	7.79E-05	6.90E-05

Matlab Simulation result of Enhanced energy detector CROC

Pf	0.6561	0.6889	0.7225	0.7569	0.7921	0.8281	0.8649	0.9025	0.9409	0.9801
Pm_ Simu	2.11E-08	1.38E-08	8.75E-09	5.29E-09	3.01E-09	1.58E-09	7.29E-10	2.76E-10	7.00E-11	5.07E-12
Pm_Approxm	6.07E-05	5.29E-05	4.56E-05	3.87E-05	3.23E-05	2.62E-05	2.04E-05	1.50E-05	9.68E-06	4.20E-06

4.1.2. Simulation and discussion result of conventional and enhanced energy detector for Rayleigh channel.

Based on the simulation parameters stated on table 4-1, this section discusses plot result of energy detector spectrum sensing when flat fading Rayleigh channel model considered.

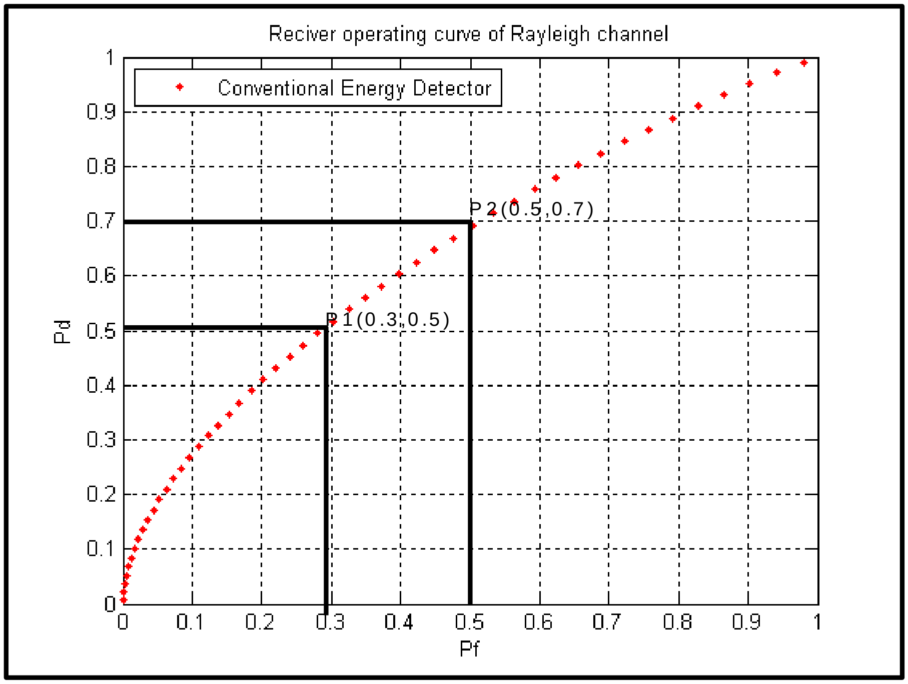

Figure 4-11: ROC Curve for energy detector in Rayleigh Channel model.

Figure 4-11 depicts the simulation result of ROC curve of Rayleigh channel model. The plot shows the relation between the false alarm values with that of the corresponding detection probabilities value when the signal received SNR is -5dB. As the signal SNR value is increased, the simulated plot will move upward and achieve the maximum value of area under curve (AUC). Considering points curve P1 (03, 0.5) and P2 (0.5, 0.7) when the energy detector Pf value is set to be 0.3, the system detection probability value is 0.5, which is 50% of detection probability. Again when the energy detector Pf value is set to be 0.5 the system detection value is around 0.7.

Figure 4-12 is an enhanced ROC curve of energy detector under flat fading Rayleigh channel model. The simulation is done when the received signal SNR is -5dB and order of filter is 32. Similarly points on the plot are mapped as P3 (0.3, 0.58) and P4 (0.5, 0.75). Comparing points P1and P3 on figure 4-11 to corresponding points P3 and P4 on figure 4-12 the value of probability detection on figure 4-12 is higher than that of values on figure 4-11. Thus the value of area under curve (AUC) in figure 4-12 is greater than area of curve obtained by figure 4-11. Specifically in enhanced case 58 % of detection probability is achieved when the Pf value is around 0.3. Whereas, in conventional case, at Pf value of 0.3, the detection value is around 50%.Similarly at Pf value of 0.5, the detection probability is around 0.75. Therefore the insertion of adaptive Wiener filter increases the area curve of (ROC) energy detector system.

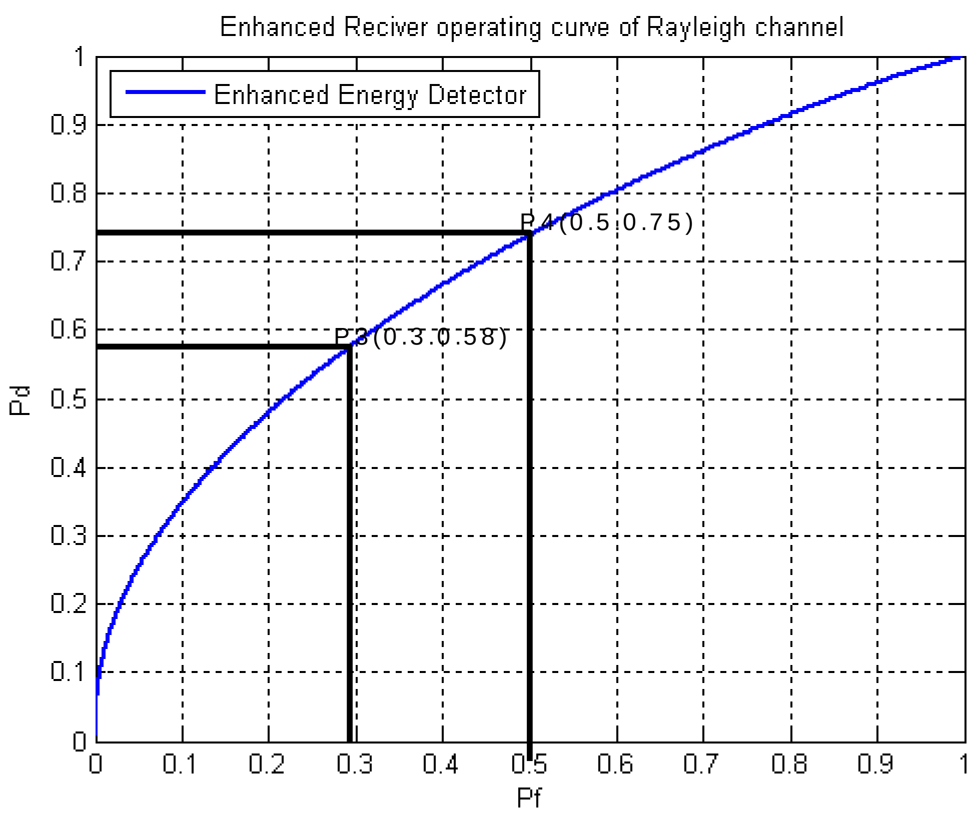

Figure 4-12: Enhanced ROC curve for energy detector in Rayleigh Channel model.

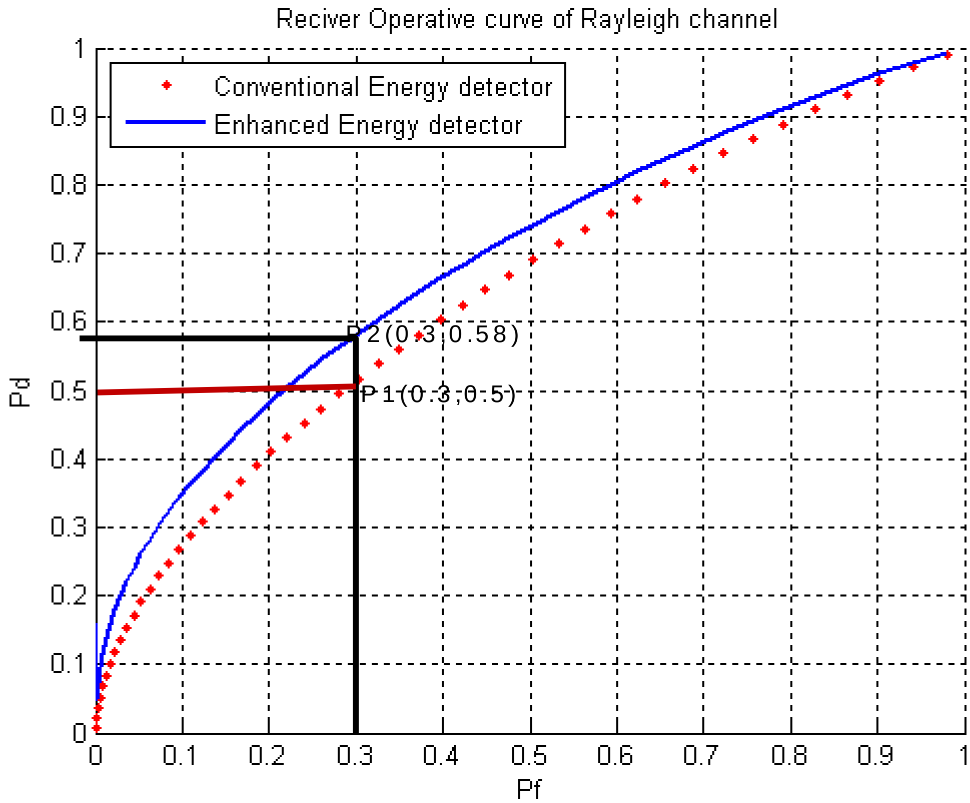

Figure 4-13: Conventional and Enhanced ROC curve for energy detector in Rayleigh Channel model.

Figure 4-13 shows the simulation plots of conventional and enhanced energy detector system when Rayleigh channel model is considered. The area under curve obtained from enhanced system (which is curve in blue) is higher than that of corresponding area under curve of conventional detection area. Thus the introductions of adaptive Weiner filter on the front end of energy detector enlarge the detection area of the system and improved the performance of the system by increase the system sensitivity.

Figure 4-14 and 4-15 depict the simulation result of the conventional and enhanced response complement receiver operating curve of (CROC) of energy detector. It tabulates the graph between probabilities of false alarm with that of miss detection. Based on the detection value, miss detection Pm=1-Pd. The CROC curve is plotted for both conventional and enhanced energy detector system. System whose area under curve is minimum will have an improved performance than other. Moreover, negating the simulation analysis and discussions of ROC, will result CROC. The signal SNR and the order of Weiner filter considered in this simulation are -5dB and 32 respectively. And also the channel model considered in this simulation is flat fading Raleigh channel.

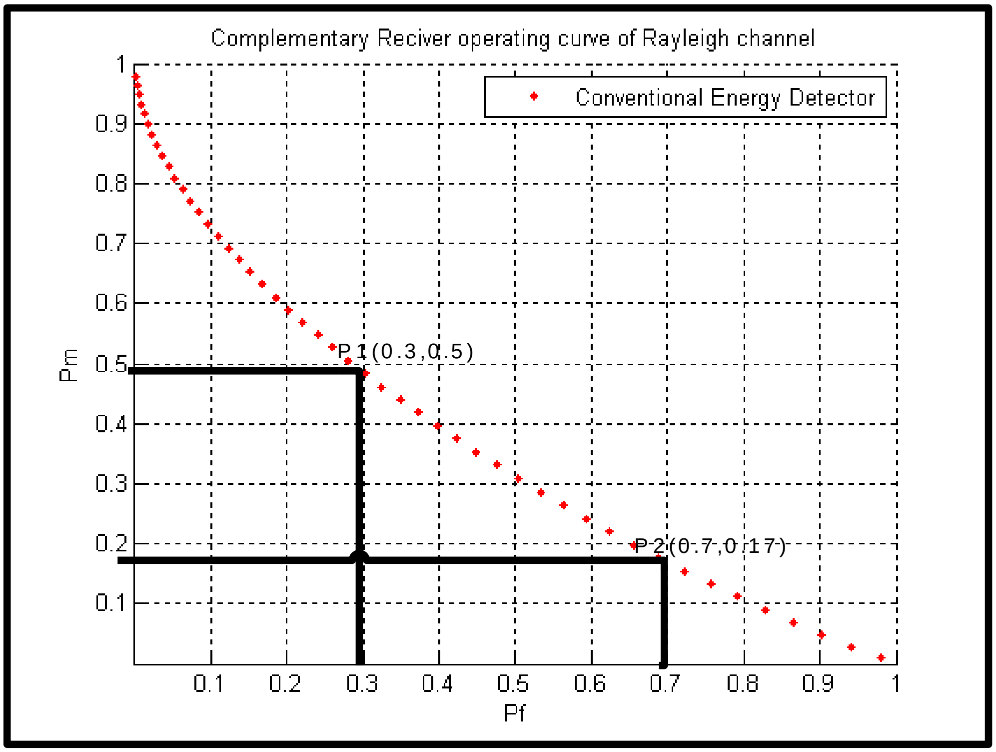

Figure 4-14: CROC curve for conventional energy detector in Rayleigh Channel model.

Figure 4-14 shows there exist an inverse relationship between the value of Pm and Pf. As the value of Pf move toward 1 on the right side, the value Pm is decrease toward 0.Similarly if the Pf value of the detector is set to be 0.3, the corresponding miss detection value will be around 0.5 (equivalent 50% miss detection) yet again setting Pm value of 0.7 the system miss detection performance will be around 17% P2 (0.7, 0.17). Thus the performance conventional energy detector increases when the value of false alarm probability is move toward 1. `

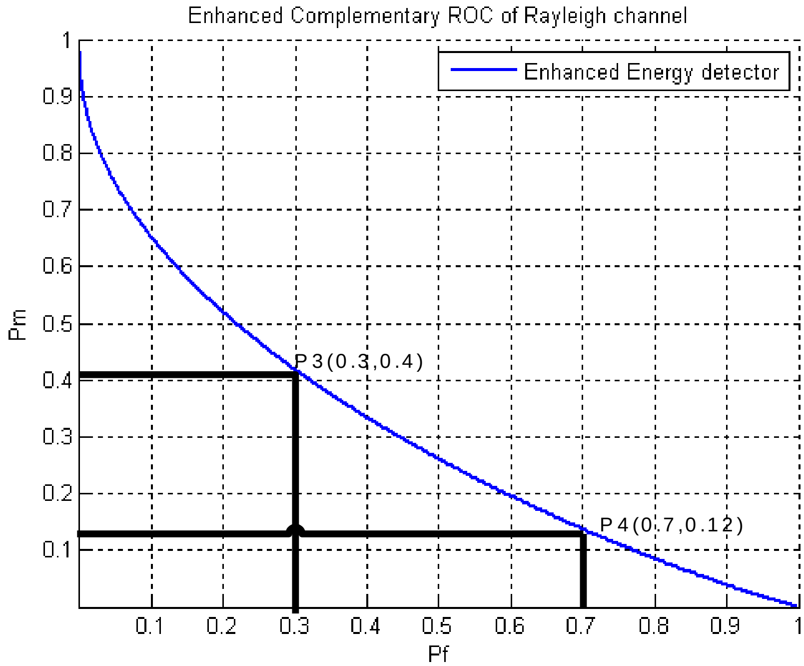

Figure 4-15: Enhanced CROC curve for energy detector in Rayleigh Channel model.

Figure4-15 is an enhanced version of CROC curve of figure 4-14. Analogous to previous discussion, values of Pf and Pm are mapped as points on graph. From the simulation result, as the value false alarm probability increase towards 1, the miss detection value of energy detector decrease to 0.If we set miss detection value at 0.3, the miss detection value will be 0.4 (value is equivalent 40%) where as ,for same value of Pf the corresponding Pm value in conventional energy detector was 50%. It implies the adaptive Weiner filter reduce the miss detection value by 10% .Similarly for Pf value of 0.7 the miss detection value for conventional energy detector is 0.17 (17%) and 0.12(12%) for enhanced energy detector. This shows that the insertion of adaptive filter reduce the miss detection probability value by 5% when the Pf is 0.7.Thus under constant false alarm probability value the insertion of adaptive Wiener filter in the front end of energy detector enhanced the performance of CROC by reducing the miss detection value.

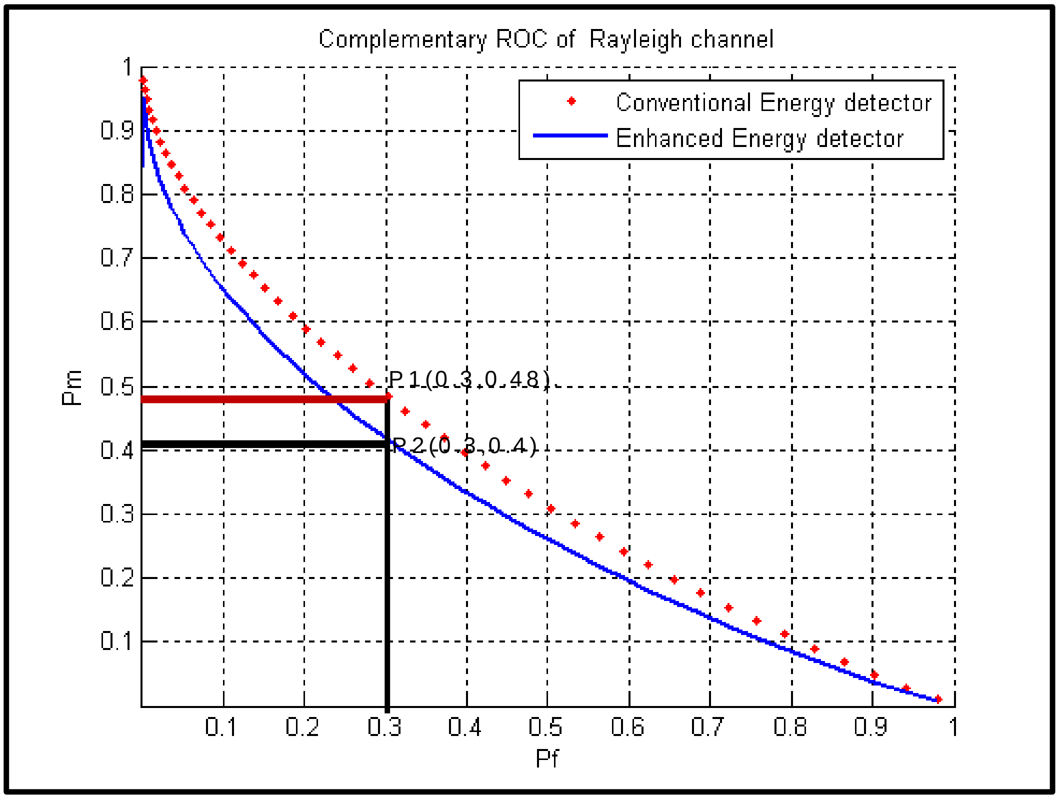

Figure 4-16: Conventional and Enhanced CROC curve of energy detector in Rayleigh Channel.

Figure 4-16 shows the CROC simulation plots of conventional and enhanced energy detector system when Rayleigh channel model is considered. The area under curve obtained from enhanced system (which is curve in blue) is lower than that of corresponding area under curve of conventional detection area (curve in dot red). Thus the introductions of adaptive Weiner filter on the front end of energy detector decrease the value of the area under curve of the system consequently the system detection performance of primary user is increase.

Chapter 5

Conclusion and Recommendation for Future Work

5.1.Conclusion

The underutilization of the existing spectrum and the scarcity of available channel has become a challenge for modern era communication system. Cognitive radio is a promising technology which mitigates the spectrum scarcity problem by providing a means to use a spectrum holes or vacant space. Considering opportunity provided by cognitive radios, the use of spectrum sensing method appears an important method to achieve satisfactory results in terms of efficient use of available spectrum and limited interference with the licensed primary users.

In this thesis, we investigated the response of Adaptive Weiner filter when the filter is inserted on the front end of energy detector. The mathematical formulas for detection and miss detection for AWGN and Rayleigh fading channel models were presented. Based on these, various simulations plot were presented for AWGN and Rayleigh fading channel.
The results are simulated using MatlabR2014a versions. Based on the simulation result the following conclusion can be drawn:

- The insertion of adaptive Weiner filter (RLS filter) on the front end of energy detector has improved all the performance matrices indicator considered in this thesis.

- At low value of signal SNR the performance of energy detector has improved when the adaptive wiener filter is inserted at the front end.

In the view of the above it can be concluded that objective of the thesis work is achieved.

5.2.Recommendation and Future work

Energy detection algorithm in cognitive radio is the most common method in detecting the presence of PU in the system and also a simple technique in cooperative sensing. In this thesis we enhanced the performance of energy detector when the received signal SNR is low. In this process the following problems are identified for future work:

- The simulation result was limited to AWGN and Rayleigh channels model, response of Nakagami and Rician fading channel should also be investigated.
- Since both (RLS and LS) algorithms converge to the same solution as that of Wiener filter, the effect of LS algorithm as a substitution to RLS could be investigated.
- Filter such as Butterworth and IIR adaptive filters response could also be investigated.

6. Reference

[1] Shahzad.A, "Comparative Analysis od Primary Transmiter Detction Based Spectrum Sensing Technique in Cognitive Radio Systems," *Australian Jornal Of Basic and Applied Science,* vol. 4, no. 9, pp. 4522-4531, 2010.

[2] E.Axell,G.Leus,E.G.Larsson, "Poor Spectrum Sensing for Cognitive Radio Sytem State of the art and Recent Advanced," IEEE Signal Processing Magazine, vol. 291, no. 3, pp. 101-116, 2012.

[3] Tevifik Yucek,Hu Seyin Arslan, "A Survey of Spectrum Sensing Algorithim for Cognitive Radio Application," *IEEE Communications Survey &Tutorial,* vol. 11, no. 1, pp. 116-130, Firist Quarter 2009.

[4] F. Communication, "Spectrum Policy Task Force," REP.ET Docket, pp. 2-135, 2002.

[5] K.G.Vinod, "Cluster Based PowerSpectrum Sensing Under Reduced Bandwidth Using Location Information," *AEUE-International Journal Of Electronics and Communications,* vol. 66, no. 8, pp. 619-624, 212.

[6] M. A. McHenry, P. A. Tenhula, D. McCloskey, D. A. Roberson, C. S.Hood, "Chicago Spectrum Occupancy Measurements & Analysis and Long Term Studies Proposal," *Proceeding of the Firist International Workshop on Technology and Police for Accesing Spectrum,* pp. 1-5, 2006.

[7] I. F. Akyildiz, L. Won-Yeol, C. V. Mehmet,M. Shantidev, "Next Generation Dynamic Spectrum Acess Cognitive Radio Wirless Network," *A Survey Computer Networks,* vol. 50, no. 2, pp. 2127-2159, 2006.

[8] Joseph.I.Mitola, "Cognitive Radio An Integrated Agent Architecture for Software Defined Radio," *PHD Thesis,Royal Institute of Technology Stockholm,* 2000.

[9] Simon Haykin, David J. Thomson, Jeffrey H. Reed, "Spectrum Sensing for Cognitive Radio," *IEEE Proceeding,* vol. 97, no. 5, pp. 849-877, 2009.

[10] Mohamood A. Abdulasattar, Zahir A.Hussien, "Energy Detection Technique for Spectrum Sensining in Cognitive Radio : A Survey," *International Journal Of Computer Networks & Communication(IJCNC),* vol. 4, no. 5, 2012.

[11] Nisha Yadav, Uman Rathi, "Spectrum Sensing Technique: Research, Challange and Limitation," *JECT,* vol. 2, no. 4, 2011.

[12] Hong jian Sun, Arumugam Nallanathan, Cheng-Xiang Wang, Yunfei Chen, "WideBAnd Spectrum Sensing for Cognitive Radio Network ASurvey," *IEEE Wirless Communication,* 2013.

[13] Erik Axell, Geert Leus,Erik G. Larsso, "Overview of Spectrum Sensing for Cognitive Radio," in *IAPR Workshop on Cognitive Information Processing*, 2010.

[14] Oyibo, A. Michael, James D. Gadze, Prince Anokye , "A performance Study of Energy Detecttion Based Spectrum Sensing for Cognitive Radio," 2011.

[15] R. Umar,A.U.H. Sheikh., "A Comparative Study of Spectrum Awareness Technique for Cognitive Radio Oriented Wirless Networks," pp. 1-23, 2012.

[16] H.Urkoitz, "Energy Detection of Unknown Deterministic Signals," *Proceedings Of IEE,* vol. 55, no. 4, pp. 523-531, 1967.

[17] Murray R Spiegel ,John J. Schiller, R. Alu Srinivasan, Probability and Statistics 2nd edition ., Schaum's Outline Series.

[18] Duan, Lei Zhangl,Yujun Chu,Shouyin Liu, "Double Thresholds Detection Method in Conventional Energy Detector Algorithim," *Wireless Communication and Mobile Computing,* 2009.

[19] Xin Liu,Chengwen ,Xuezhi Tan, "Double Threshold Cooperative Detection For Cognitive radio Based on Weighing," *Wireless Communication and Mobile Computing ,* pp. 1231-1243, 2014.

[20] M. Amira Ben Jamma, "Enhanced Energy Detector Via Algebraic Approach For Spectrum Sensing In Cognitive Radio Networks," pp. 1-5, 2013.

[21] Yiming Zhou ,Zheng Zhou ,Shibo Zhang, " An Improved Spectrum Sensing Method Energy Autocorrelation Based Detection Technology," *Circuit System Signal Processing,* pp. 273-282, 2013.

[22] Daniela Mercedes Martinez plata ,Angela Gabriel Andrade Reatiga, "A Dynamic Selection of Detection Threshold in Energy Detector Spectrum Sensing Technique.," vol. 35, pp. 135-143, 2012.

[23] C. Scott, " The Neyman Pearson Criterion," *Open Stax CNX module,* vol. 1m, no. 11548.

[24] Omar Altrad ,Sami Muhidat, "A New Mathematical Analysis of the Probability of Detection in Cognitive Radio over Fading Channels," *EURASIP Journal on wireless communication and Networking,* vol. 159, 2013.

[25] L.S. Cardoso, M. Debbah, S. Lasaulce, K. Mari,J. Palicot, "Spectrum Sensing in Cognitive Radio Networks," *Cognitive Radio Networks Architecture Protocols and standards,* 2009.

[26] H. Wang,G Noh D. Kim,S. Kim, D. Hong, "Advanced Sensing Techniques of Energy Detection in Cognitive Radios.," *Journal of Communication Networks,* vol. 12, no. 1, pp. 19-29, 2010.

[27] Prof.AbhijeetA.Chincholkar, Ms.Chaitali H.Thakare Yavatmal, "Matlab implementation of Spectrum Sensing Methods in Cognitive Radio," *Global Journal of Engineering Science and Research Management Chin holkar,* vol. 1, no. 2, pp. 2349-4506, 2014.

[28] Anirudh M. Rao, B. R. Karthikeyan, Dipayan Mazumdar, Govind R. Kadambi, "Energy Detection technique for Spectrum Sensing In Cognitive Radio," 2010.

[29] R. Sindhubargavi, M. YuvasrriSindhu , R. Saravanan, "Spectrum Sensing Using Energy Detection Technique for Cognitive Radio Networks using PCA Technique," *Indian Journal of Science and Technology,* vol. 7, no. 45, pp. 45-50, 2014.

[30] Saman Atapattu, Chintha Tellambura, Hai Jiang, "Energy Detection Based Cooperative Spectrum Sensing in Cognitive Radio Networks," *IEEE Transaction on Wireless Communication,* vol. 10, no. 4, 2011.

[31] J. G. Proakis, Digital communication, 4th ed., Mc Graw hill Publish, 2008.

[32] Pradeep Kumar Vermal, Mr. Sachin Taluja, Prof. Rajeshwar Lal Dua, "Performance Analysis of Energy Detection, Matched filter detection & Cyclo stationary feature detection Spectrum Sensing Techniques," *Intrnational Journal of Computational Energy Research,* vol. 2, no. 5, 2011.

[33] W. Gardner ,C. Spooner, , " Advantages of Cyclic-feature Detectors and Signal Performance interception," *IEEE Transactions on Communications,* vol. 40, no. 1, pp. 149-159, 1992.

[34] H. P. Zhi Quan, Shuguang Cui,A. Sayed,, "Collaborative Wideband Sensing for Cognitive Radios," *IEEE Signal Processing Magazine,* vol. 25, no. 6, pp. 60-73, 2008.

[35] Prathmesh Ghanekar, Pallavi Dhole, NileshPatil, "A Survey: Interference based Detection Spectrum Sensing in Cognitive Radio.," *International Journal of advanced Electric and Electronic Enginnering,* vol. 3, pp. 31-36, 2014.

[36] Khaled Ben Letaief, Wei Zhang, , "Cooperative Communications Cognitive Radio Networks," *Proceedings of the IEEE,* vol. 97, no. 5, pp. 878-893, 2009.

[37] B. F. L. B. Ian F. Akyildiz, "Cooperative Spectrum Sensing in Cognitive Radio Networks: A survey," *Physical Communication ,* vol. 4, p. 4062, 2011.

[38] M. M. A. B. Nima Noorshams, "Centralized And Decentralized Cooperative Spectrum Sensing In Cognitive Radio networks:A Novel Approach," *Signal Processing Advance in Wirless Communication IEEE,* 2010.

[39] Ashutosh Singh, Varsha Saxenaakzhse , "Different Spectrum Sensing Techniques Used in non Cooperative System.," *International Journal of Engineering and Innovative technology (IJEIT),* vol. 1, no. 2, pp. 2277-3754, 2012.

[40] F. Richard Yu, Helen Tang, Minyi Huang, Peter Mason, Zhiqiang Li, "Distributed Cooperative Spectrum Sensing in Mobile Ad Hoc Networks with Cognitive Radios," *Cornell Univeristy Liberary,* 2011.

[41] S. V.Vasegh, Advanced Signal Processing and Noise Reduction., 2nd ed., John Wiley & sons L.td.

[42] Alexander D.Poularikas, Zayed M.Ramadan, Adaptive filtering primer with MATLAB., 2nd ed.

[43] Saman Atapattu , Chintha Tellambura , Hai Jiang , Energy Detection for Spectrum Sensing in Cognitive Radio., Springer edition.

[44] F. F. Digham, "On the Energy Detection of Unknown Signals over Fading Channels," *IEEE Transaction on Communication,* vol. 55, no. 1, 2007.

[45] Omkar S. Vaidya, Vijaya M. Kulkarni , "Analysis of Energy Detection based Spectrum Sensing over Wireless Fading Channels in Cognitive Radio Network," *International Journal of Emerging Technology and Advanced Engineering Website: ,* vol. 3, no. 3, pp. 2250-2459, 2013.

[46] Fadel F. Digham, Mohamed Slim Alouini, Marvin K. Simon., "Energy Detection of Unknown Signals Over Fading Channels," *IEEE Transactions on Communications.,* vol. 55, no. 1, pp. 21-24, 2007.

[47] T. Fawecett, "An Introduction to ROC Analysis," *Pattern Recogntion Letters,* vol. 27, pp. 861-874, 2005.