ADDIS ABABA UNIVERSITY

SCHOOL OF GRADUATE STUDIES

FACULTY OF TECHNOLOGY

ELECTRICAL AND COMPUTER ENGINEERING DEPARTEMENT

PERFORMANCE EVALUATION ON TRANSMITTER DETECTION TECHNIQUES FOR COGNITIVE RADIO

By

Fikreselam Gared Mengistu

A Thesis Submitted to the School Of Graduate Studies of Addis Ababa University in Partial Fulfilment of the Requirements for the Degree of

Masters of Science

In

Electrical and Computer Engineering

October 2010

Addis Ababa, Ethiopia

ADDIS ABABA UNIVERSITY

SCHOOL OF GRADUATE STUDIES

FACULTY OF TECHNOLOGY

DEPARTEMENT OF ELECTRICAL AND COMPUTER ENGINEERING

PERFORMANCE EVALUATION ON TRANSMITTER DETECTION TECHNIQUES FOR COGNITIVE RADIO

By

Fikreselam Gared Mengistu

Advisor

Dr.-Ing. Mohammed Abdo

Tables of contents

Page No.

Abstract

Wireless communications and the utilization of the radio frequency spectrum have witnessed a tremendous boom during the past few decades. Given the limitations of the natural frequency spectrum, it becomes obvious that the current static frequency allocation schemes cannot accommodate the requirements of an increasing number of higher data rate devices.

Cognitive Radio has come after several studies indicating that most of the allocated radio spectrum is idle most of the time. As a result, spectrum regulation around the world is in progress to allow unlicensed access in a non-interfering way. Cognitive radio is a candidate technology for more efficient spectrum utilization systems based on opportunistic spectrum sharing. But to avoid interference, effective detection of primary users is a major issue of cognitive radio.

In this thesis work, various literature reviews on cognitive radio and detection theory by different authors which help to understand necessary theoretical background for thesis work have been made. Performance of energy detector, replica correlation detector and cooperative detector has been evaluated using different performance metrics and the performance of energy detector has been enhanced. To evaluate the performance of the detection techniques MATLAB software has been used for simulation.

The results of performance evaluation for the detectors have shown that the replica correlation detector (delivers P_m of less than 1%) is better than energy detector (delivers P_m of less than 10% but greater than 1%) under both AWGN and Rayleigh fading channel. But due to fading, single node detection is unreliable and results in a high probability of missed detection and lower probability of correct detection. Thus, Rayleigh fading degrades the performance of single node energy and replica correlation detectors. It has been shown that cooperative detection helps to reduce the fading effect of single node detection and it is concluded that cooperative spectrum detection outperforms single user energy detection and replica correlation detector. Thus, the OR fusion rule of cooperative detection delivers better performance. In this paper, noise uncertainty has been shown to introduce considerable amount of degradation in the detection performance of energy and replica correlation detectors. It has been also shown that cooperative detection helps to reduce the effect of noise uncertainty factor in the overall detection performance of cognitive radio.

Finally, this work proposes a new enhanced energy detector algorithm method. Its performance has been compared with standard squared law energy detector algorithm. The Simulation results indicate that the new energy detector algorithm method has better performance than square law energy detector. The enhanced energy detector delivers probability of detection 12% better than square law energy detector.

Keyword: **cognitive radio, hypothesis test and spectrum detector (energy, replica correlation and cooperative detector)**

Acknowledgements

Although there are many people I would like to acknowledge during my thesis work, I am forever indebted to my advisor Dr._Ing Mohammed Abdo, who has given me an invaluable opportunity to do my thesis on extremely interesting area and for his role in the development of my thesis. He has always motivated me to strive to do my best. Therefore his support, advice, and discussions have greatly helped me to successfully complete this thesis.

I would like to express my deepest gratitude to Dr._Ing Hailu Ayele for his invaluable comments. I wish to thanks also my family who have always been sources of encouragement throughout my life. Finally, my warmest thanks go to all my friends, especially to Abiy Bekele.

Fikreselam Gared

October 2010

List of Abbreviations

AWGN	Additive White Gaussian Noise
BWRC	Berkeley Wireless Research Center
BER	Bit Error Rate
BF	Base Function
CR	Cognitive Radio
CFAR	Constant False Alarm Rate
CROC	Complementary Receiver Operating Characteristics
CSD	Cooperative Spectrum Detection
FCC	Federal Communication Commission
FICORA	Finnish Communications Regulatory Authority
HDC	Hard Decision Combining
IEEE	Institution of Electrical and Electronics Engineering
IR	Impulse Radio
ITU	International Telecommunication Union
LOS	Line-Of-Sight
LRT	Likelihood Ratio Test
MAI	Multi-User Access Interference
ML	Maximum likelihood
NB	Narrow Band
NBI	Narrow Band Interference
NTIA	National Telecommunication Information Administration
PDF	Probability Density Function
PSD	Power Spectral Density

PU	Primary User
QoS	Quality of Service
RF	Radio Frequency
ROC	Receiver Operating Characteristics
RV	Random Variable
SDR	Software Defined Radio
SDR CRWG	Software Defined Radio Cognitive Radio Working Groups
SDR SIG	Software Defined Radio Special Interest Group Cognitive Radio
SNR	Signal to Noise Ratio
SU	secondary User
UHF	Ultra High Frequency
VT CRWG	Virginia Tech Radio Cognitive Radio Working Groups

List of Symbols

$p_{\alpha}(\alpha)$	Fading PDF
$\sigma_n{}^2$	Noise variance
$\sigma_s{}^2$	Signal variance
$\chi^2{}_{2TW}$	Central chi square distribution with 2TW degrees of freedom
$\chi^2{}_{2TW}\ (2\gamma)$	Non-central chi-squared distribution with 2TW degrees of freedom and non centrality parameters 2γ
$\epsilon_{2(\gamma^2+1)}$	Exponential distribution
$f_{\bar{\gamma}}(\gamma)$	PDF of instantaneous SNR
T_{dec}	Time between sensing decisions
T_{fd}	Time between failures in detection
δ_{NP}	Neyman-Pearson test
π_0	Priori probability of hypothesis Ho
π_1	Priori probability of hypothesis H1
Es	energy per symbol
h	Amplitude gain of a channel
H0	Hypothesis 0 corresponding to PU inactive (absent)
H1	Hypothesis 1 corresponding to PU active (present)
n(t)	Noise process
N0	One-sided noise power spectral density
Ns=n	Number of secondary users
p(y)	marginal probability mass function
Pd	Probability of detection of one SU

Pf	Probability of false alarm of one SU
Pm	Probability of miss detection of one SU
Qd	Probability of detection of cooperative detection
Qf	Probability of false alarm of cooperative detection
Qm	Probability of miss detection of cooperative detection
R (t)	Received signal process at the input of the detector
s(t)	Primary user signal
T	Observation time interval (second)
TW	Time Bandwidth product
W	bandwidth
Y	Decision statistics
α	fading amplitude
γ	Signal to Noise Ratio
δ (y)	decision function
$\Lambda(y)$	Likelihood ratio
$\mathcal{N}(\mu, \sigma^2)$	Gaussian distribution with mean μ and variance σ^2
λ	Decision Threshold
ρ	Parameter of noise uncertainty

List of figures

LIST OF TABLES

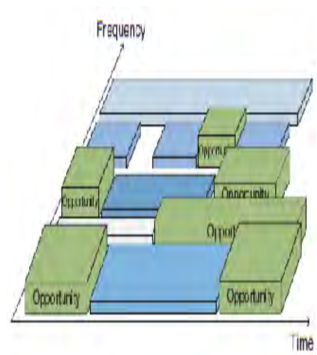
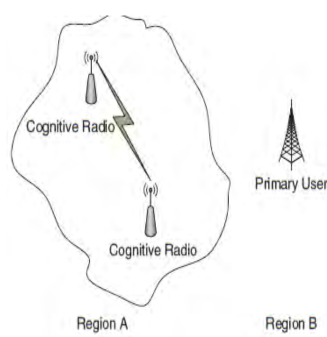
Chapter 1: INTRODUCTION

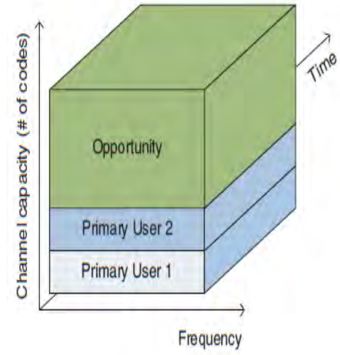
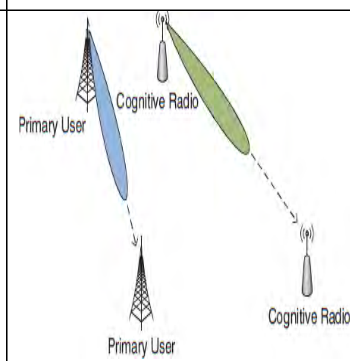
1.1. OVERVIEW

Communication is broadly classified as wired and wireless. It is commonly believed that there is a scarcity of spectrum availability at frequencies that can be economically used for wireless communications; this misconception has arisen from the intense competition for use of spectra at some bands of frequencies. At some other frequencies there is actually very little spectrum usage. This seems totally in contradiction to the concern of spectrum shortage, since in fact we have spectrum abundance, and the spectrum shortage is in part an artificial result of the regulatory and licensing process. Therefore, the spectrum usage is inconsistent with different regulatory agencies (e.g. Federal Communication Commission (FCC) in the United States) frequency chart that indicates there are multiple allocations over all of the frequency bands [1], [2]. It is this discrepancy between these agencies allocations and actual usage which indicates that a new approach to spectrum licensing is needed. What is clearly needed is an opportunistic usage of this licensed spectrum. An approach, which can meet these goals, is to develop a radio system that is able to reliably sense the spectral environment over a wide bandwidth, detect the presence or absence of primary users and use the spectrum only if communication does not interfere with any primary user. These radios are lower priority secondary users, which exploit cognitive radio (CR) techniques, to ensure non-interfering co-existence with the primary users. Regulatory domains are also realizing the need for new technologies in order to efficiently use available spectral resources. Recent studies by the FCC spectrum policy task force have reported vast temporal and geographic variations in the usage of allocated spectrum [2]. In order to utilize these 'white spaces', the FCC has issued a notice of proposed rule making advancing CR technology as a candidate to implement negotiated or opportunistic spectrum sharing [3]. A radio or system that senses and aware of its operational environment and can be trained to dynamically and autonomously adjust its radio operating parameters accordingly is called cognitive radio. Cognitive radio is a new concept of reusing licensed spectrum in an unlicensed manner. The unused resources are often referred to as spectrum holes or white spaces. These spectrum holes could be reused by cognitive radios in an opportunistic way, sometimes called secondary users.

The definition of opportunity determines the ways of measuring and exploiting the spectrum space. The conventional definition of the spectrum opportunity, which is often defined as "a band of frequencies that are not being used by the primary user of that band at a particular time in a particular geographic area", only exploits three dimensions of the spectrum space: frequency, time, and space. However, there are other dimensions that need to be explored further for spectrum opportunity. These dimensions are known as the code and angle dimension of the spectrum space. Table1 shows these dimensions with some description. There might be geographical positions where some frequency bands are allocated to a primary user system, but not currently used. These geographical spectrum holes could be employed by secondary users. There might also be certain time intervals for which the primary system does not use the licensed spectrum. These time domain spectrum holes could also potentially be employed by secondary users. The introduction of cognitive radios will inevitably create increased interference and thus degrade the quality of service of the primary system. The impact on the primary system, for example in terms of increased interference, must be kept at a minimal level. To keep the impact at an acceptable level, secondary users must sense the spectrum to detect whether it is available or not. To be effective, secondary users must be able to detect very weak primary user signals.

Table 1 multi-dimensional radio spectrum space and transmission opportunities

Dimension	**What needs to be sensed?**	**Comments**	**Illustrations**
Frequency	Opportunity in the frequency domain.	Availability in part of the frequency spectrum. The available spectrum is divided into narrower chunks of bands. Spectrum opportunity in this dimension means that all the bands are not used simultaneously at the same time, i.e. some bands might be available for opportunistic usage.	
Time	Opportunity of a specific band in time.	This involves the availability of a specific part of the spectrum in time. In other words, the band is not continuously used. There will be times where it will be available for opportunistic usage.	
Geographical Space	Location (latitude, longitude, and elevation) and distance of primary users.	The spectrum can be available in some parts of the geographical area while it is occupied in some other parts at a given time. This takes advantage of the propagation loss (path loss) in space. These measurements can be avoided by simply looking at the interference temperature. No interference means no primary user transmission in a local area. However, one needs to be careful because of hidden terminal problem.	

Code	The spreading code, time hopping (TH), or frequency hopping (FH) sequences used by the primary users. Also, the timing information is needed so that secondary users can synchronize their transmissions w.r.t. primary users. The synchronization estimation can be avoided with long and random code usage. However, partial interference in this case is unavoidable.	The spectrum over a wideband might be used at a given time through spread spectrum or frequency hopping. This does not mean that there is no availability over this band. Simultaneous transmission without interfering with primary users would be possible in code domain with an orthogonal code with respect to codes that primary users are using. This requires the opportunity in code domain, i.e. not only detecting the usage of the spectrum, but also determining the used codes, and possibly multipath parameters as well.	
Angle	Directions of primary users' beam (azimuth and elevation angle) and locations of primary users.	Along with the knowledge of the location/ position or direction of primary users, spectrum opportunities in angle dimension can be created. For example, if a primary user is transmitting in a specific direction, the secondary user can transmit in other directions without creating interference on the primary user.	

1.2. MOTIVATION

Inefficient spectrum allocation and the growing problem of spectrum scarcity have prompted an examination of how the radio frequency spectrum is utilized. Cognitive radio is a candidate technology for more efficient spectrum utilization systems based on opportunistic spectrum sharing. The main specific benefit of cognitive radio system is that it would allow systems to use their spectrum sensing capabilities to optimize their access of using the spectrum. From a regulator's perspective, dynamic spectrum access techniques using cognitive radio could minimize the burden of spectrum management even maximizing spectrum efficiency.

However, a common assumption regarding cognitive radios is that they are unlicensed spectrum users that should avoid interfering with existing primary sources. Therefore effective detection of primary users is a major issue of cognitive radio. Wireless communication systems must collect information about the radio spectrum in order to adapt their operation and behaviour to provide a better match to the prevailing conditions. Thus, spectrum detection is becoming increasingly important to future wireless communication systems for identifying underutilized spectrum.

Therefore this thesis work principally focuses on reducing interference between primary (legacy) user and secondary (cognitive) user by comparing the performance of spectrum detection techniques: with a view of identifying an effective method of usage detection.

1.3. OBJECTIVE

1.3.1 General objective

The general objective of this thesis work is to evaluate the performance of transmitter detection techniques for cognitive radio.

1.3.2 Specific objectives:

- To study the fundamental characteristics and behaviours of spectrum detection.
- To evaluate the performance of different signal detection (energy, replica correlation and cooperative detection) techniques using a set of performance metrics under AWGN and Rayleigh fading channel.
- To evaluate Receiver operating characteristics(ROC) of the detection techniques
- To evaluate complementary Receiver operating characteristics(CROC) of the detection techniques
- To evaluate the impact of noise uncertainty on the performance of detection
- To compare the performance of energy, replica and cooperative detection
- To enhance the performance of energy detection technique

1.4. METHODOLOGY

Various literature reviews on cognitive radio and spectrum detection by different authors which help to understand necessary theoretical background for thesis work have been made. Based on the limitation of cognitive radio, approximate performance metrics which help us to evaluate the performance of energy, replica correlation and cooperative detection have been selected. By analyzing the theoretical and mathematical description for the detection techniques system model, their performance is evaluated by using Matlab software. Finally, the performance of the energy detection technique has been enhanced.

1.5 THESIS CONTRIBUTION

The spectrum scarcity and spectrum underutilization problem has stimulated a number of exciting activities in the technical, economic and regulatory domains in searching for better spectrum management policies and techniques. The cognition capability of a CR can make opportunistic spectrum access possible which can be implemented by spectrum detection functionality. Therefore the main contributions of this paper are:

- We perform some detailed theoretical analysis on the performance of Primary user (PU) detection.
- We considered noise uncertainty factors for performance evaluation.
- We took replica correlation based cooperative detector under both OR and AND rule fusion scheme.
- We perform the enhancement of energy detection technique.

1.6 THESIS OUTLINE

The outline of this thesis is summarized as follows: chapter two is about cognitive radio technology which includes different definitions and concepts of cognitive radio which have been given by different researchers, benefits and limitation of cognitive radio and cognition cycle of cognitive radio. Chapter three is about general concepts of detection theory. Chapter four is devoted to spectrum detection algorithms (energy, replica correlation and cooperative detector) for cognitive radio and about enhanced energy detector. Chapter five is devoted to simulation results with discussions and the final chapter (chapter six) is conclusion and recommendation.

Chapter 2: COGNITIVE RADIO

2.1 INTRODUCTION

The radio frequency spectrum is a limited natural resource to enable wireless communication between transmitters and receivers. Licenses are usually required for operation on certain frequency bands. The use of radio spectrum in each country is nationally governed by the corresponding national regulatory agencies. In Finland, the decision-making body is the Finnish Communications Regulatory Authority (FICORA). In the United States (U.S.), the Federal Communications Commission (FCC) manages the non-federal use of spectrum while the National Telecommunications Information Administration (NTIA) governs the federal use. Traditional communication system design is based on allocating fixed amounts of resources to the user. But the users' increasing demand for new service with good quality is being restricted by the scarcity of spectrum bands because all important spectrum bands for wireless communication are already occupied by the traditional allocation system. This indicates that spectrum is one of the key natural resource. When talking about the frequency spectra, one usually refers to the wide range of signals being licensed and used for different sort of radio communication. The reason for these licenses is that if many people used the same frequencies for different applications these applications would cause heavy interference to each other. The actual spectra of physical radio communication are soon completely bought up. This can be seen by looking at Figure 2.1 [4].

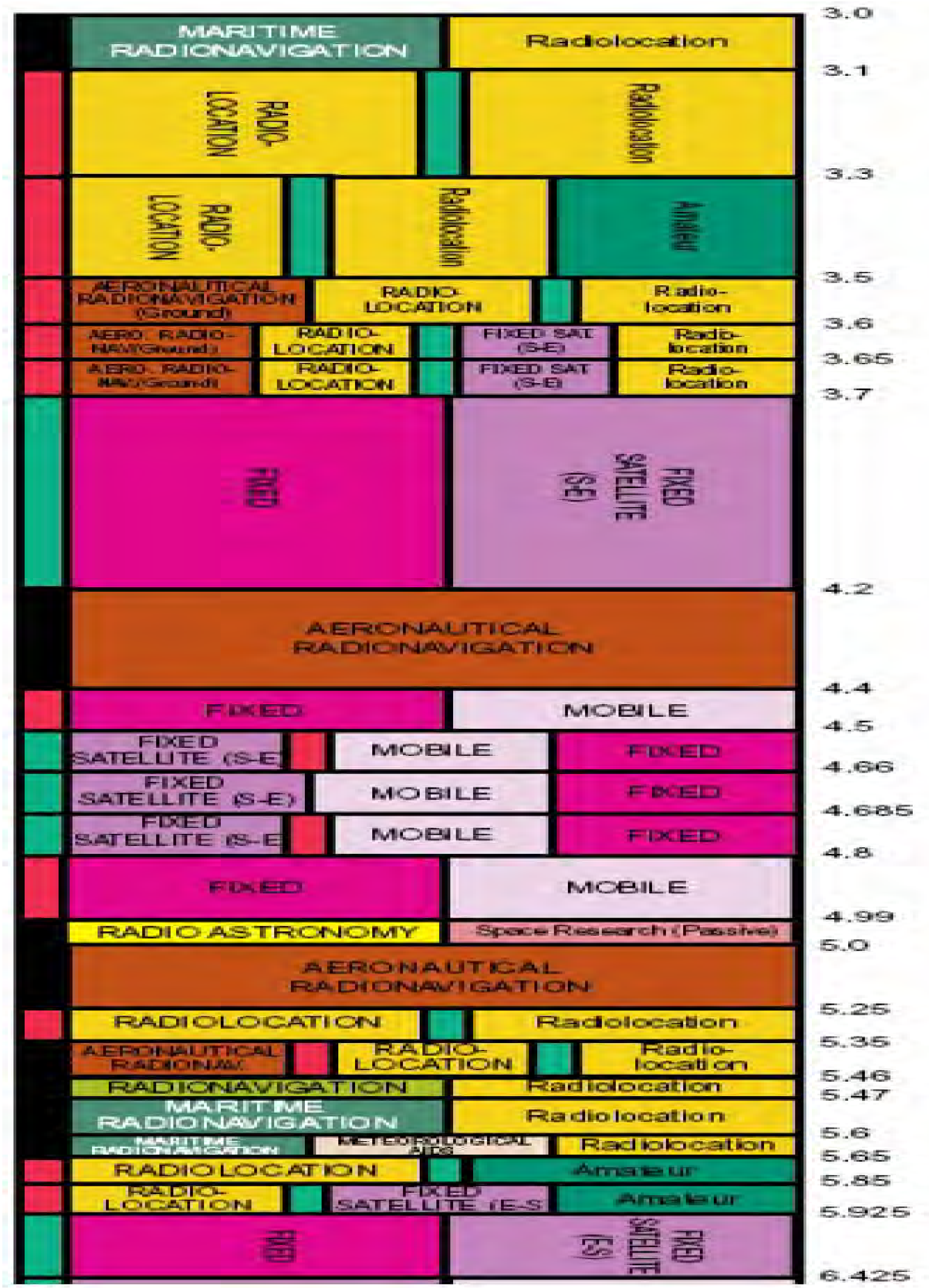


Figure 2.1 The FCC frequency allocation chart from 3-6GHz [4]

Moreover, the Ethiopian's telecommunication agency frequency allocation chart, Fig. 2.2, also indicates that most spectrum bands are allocated for different applications.

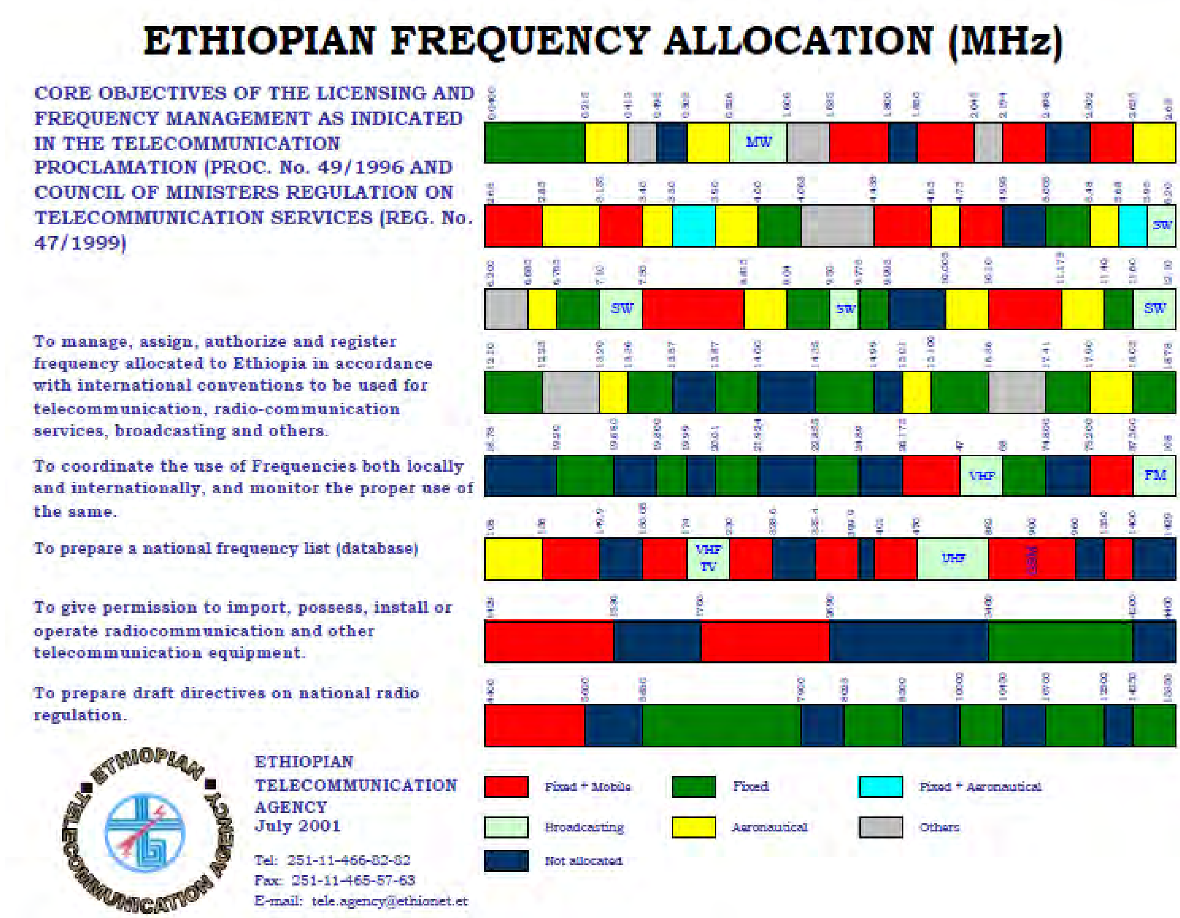


Figure 2.2: Frequency allocation chart of Ethiopia telecommunication agency.

Wireless technologies and wireless devices have proliferated dramatically over the past decade and thus increasing the demand for electromagnetic spectrum. Because of the current approach to spectrum access, spectrum supply has not kept up with spectrum demand leading to the appearance of scarcity in the electromagnetic spectrum. However, research performed by various entities such as the FCC indicates that this assumption is far from reality; there is available spectrum since most of the spectrum allocated sits underutilized [2].

Practical measurements have shown that although the spectra of available frequencies are more or less bought up, at specific locations, a majority of frequencies are not used at all [5]. This can easily be seen in Figure 2.3, which shows measurements made at Berkeley in urban area. From the chart we can see that most of the spectrum ranging from 3GHz to 6GHz is not utilized most of the time.

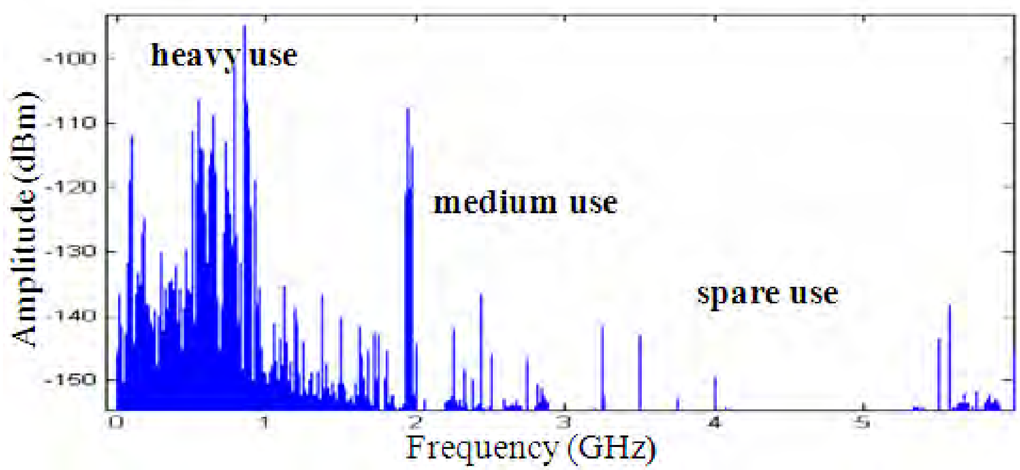


Figure 2.3 Spectrum utilization measurements taken at Berkeley Wireless Research Center (BWRC).

If we see the scanned portions of the radio spectrum power spectral density (PSD) measurement of the received 6GHz wideband signal at BWRC shown above, we would find that some frequency bands in the spectrum are largely unoccupied most of the time (spare use), Some other frequency bands are only partially occupied (medium use) and the remaining frequency bands are heavily used (heavy use).

As shown in Fig.2.3, actual spectrum measurements taken at Berkeley Wireless Research Center (BWRC) indicate low utilization of the allotted spectrum, especially in the 3-6 GHz frequency range [1] [6]. Figure 2.4 is the result of a number of different factors including overly conservative allocation of guard bands and the natural gaps in utilization that occur throughout the day due to variations in demand. As an example of variations in demand, Figure 2.5 shows a Matlab representation of spectrum measurements made in Germany at Karlsrhue in a more heavily used band. As the figure illustrates there is significant variation in spectrum underutilization in frequency, and though not depicted, there is also significant variation in terms of location. [7]

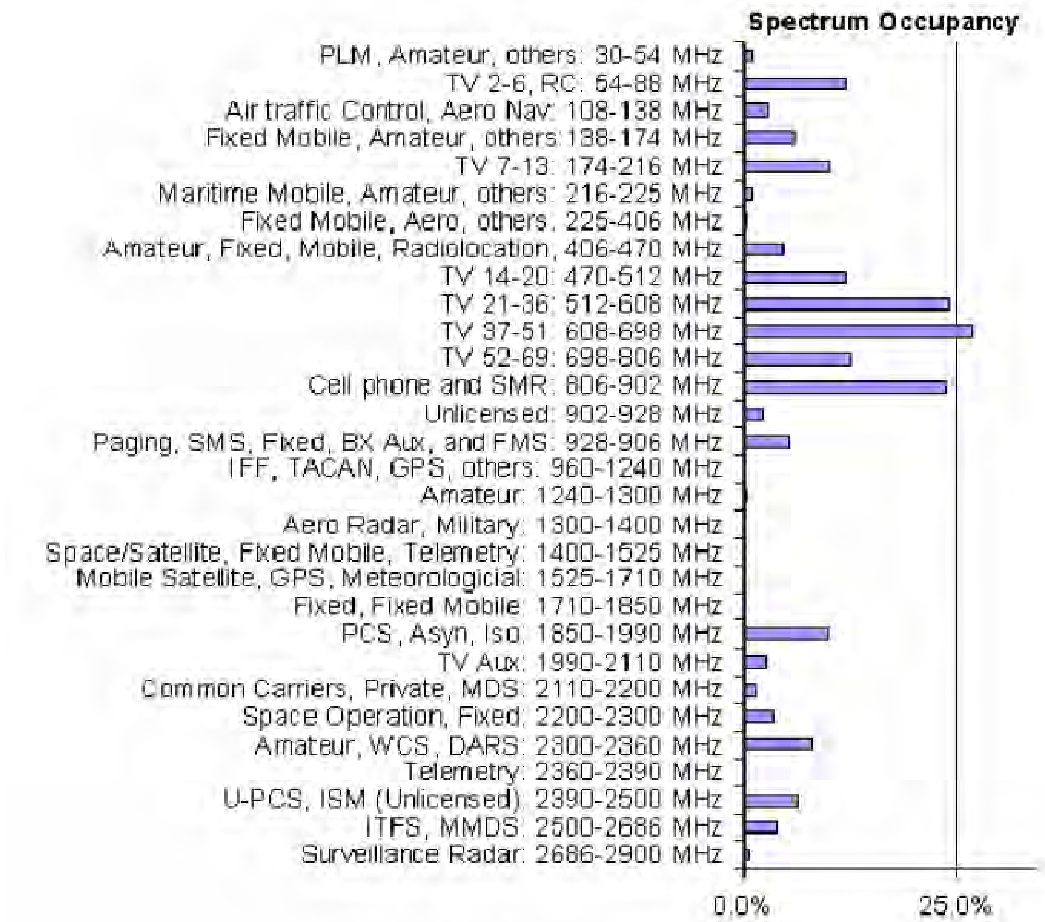


Figure 2.4: Spectrum availability by band

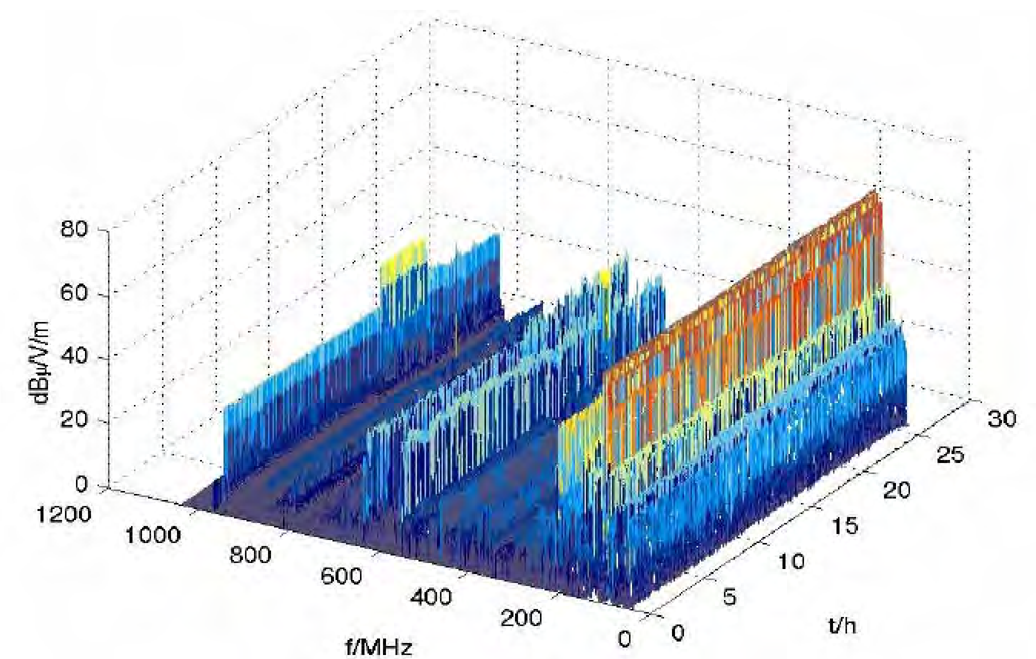


Figure 2.5: Matlab capture of channel measurements from Germany

So while the dramatically increasing demand for spectrum has fostered a perception that spectrum is scarce, the reality is that spectrum is abundant but poorly utilized. To improve spectrum utilization, opportunistic spectrum utilization has been proposed wherein devices occupy spectrum that has been left vacant. After observing the spectrum holes locations in time and frequency where spectrum is underutilized opportunistic devices could fill in these holes to support concurrent services.

Contrary to fixed allocation system, adaptive design methodologies, on the other hand, typically identify the requirements of the user, and then allocate just enough resources, thus enabling more efficient utilization of system resources and consequently increasing capacity. Pushing the adaptive system design further by introducing advanced attributes such as multi-dimensional awareness, sensing, as well as learning from its experiences to reason, plan, and decide future actions to meet user needs leads to the cognitive radio concept. Therefore the idea of cognitive radio is to find means to use these gaps or holes in the frequency spectra and making use of the frequencies floating around unused.

2.2 DIFFERENT DEFINITIONS OF COGNITIVE RADIO

Different groups have given different definitions for cognitive radio. To better understand the definitions by the different groups, it is important to present them in brief as follows.

In the 1999 paper that first coined the term “cognitive radio”, Joseph Mitola III defines a cognitive radio as [3]:

“The term cognitive radio identifies the point at which wireless personal digital assistants and the related networks are sufficiently computationally intelligent about radio resources and related computer-to-computer communications to: detect user communications needs as a function of use context, and to provide radio resources and wireless services most appropriate to those needs.”

The other reputable author in the communication areas and a life fellow of IEEE, Simon Haykin, defines cognitive radio as [8]:

"An intelligent wireless communication system that is aware of its surrounding environment (i.e., outside world), and uses the methodology of understanding-by-building to learn from the environment and adapt its internal states to statistical variations in the incoming Radio frequency (RF) stimuli by making corresponding changes in certain operating parameters (e.g., transmit-power, carrier frequency, and modulation strategy) in real-time, with two primary objectives in mind:

- *highly reliable communications whenever and wherever needed;*
- *efficient utilization of the radio spectrum."*

Coming from a background where regulations focus on the operation of transmitters, the FCC has defined a cognitive radio as [9]:

"A cognitive radio goes one step further from software defined radio, and empowers the radio to alter its transmitter parameters based on interaction with the environment in which it operates."

Meanwhile, the other primary spectrum regulatory body in the US, the NTIA [10], adopted the following definition of cognitive radio that focuses on some of the applications of cognitive radio:

"A radio or system that senses its operational electromagnetic environment and can dynamically and autonomously adjust its radio operating parameters to modify system operation, such as maximize throughput, mitigate interference, facilitate interoperability, and access secondary markets."

While aiding the FCC in its efforts to define cognitive radio, IEEE USA offered the following definition [11]:

"A radio frequency transmitter/receiver that is designed to intelligently detect whether a particular segment of the radio spectrum is currently in use, and to jump into (and out of, as necessary) the temporarily-unused spectrum very rapidly, without interfering with the transmissions of other authorized users."

The broader IEEE tasked the IEEE 1900.1 group to define cognitive radio which has the following working definition [12]:

"A type of radio that can sense and autonomously reason about its environment and adapt accordingly. This radio could employ knowledge representation, automated reasoning and machine learning mechanisms in establishing, conducting, or terminating communication or networking functions with other radios. Cognitive radios can be trained to dynamically and autonomously adjust its operating parameters."

The Virginia Tech Cognitive Radio Working Group which has a large involvement in the development of the technology has adopted the following capability- focused definition of cognitive radio [13]:

"An adaptive radio that is capable of the following:

- *awareness of its environment and its own capabilities,*
- *goal driven autonomous operation,*
- *understanding or learning how its actions impact its goal,*
- *recalling and correlating past actions, environments, and performance."*

While it appears to be unlikely that there will be a harmonization of these definitions in the near future, an examination of the salient functionalities of these and other group definitions, as summarized in Table 2, reveals some commonalities among these definitions. First, all of these definitions assume that cognition will be implemented as a control process, presumably as part of a software defined radio. Second, all of the definitions at least imply some capability of autonomous operation.

Table 2: Cognitive Radio Definition Matrix.

Definer	Adapts (Intelligently)	Autonomous	Sensing its environment	Transmitter	Receiver	“Aware” Environment	Goal driven	Learn the Environment	Aware capabilities	Negotiate waveform	No interference
FCC	*	*	*	*							
Haykin	*	*	*	*	*	*	*	*			
IEEE 1900.1	*	*	*	*	*						
IEEE USA	*	*	*	*	*	*					*
ITU-R	*	*	*	*	*	*					
MITOLA	*	*	*	*	*	*	*	*	*	*	
NTIA	*	*	*	*	*	*	*				
SDRF CRWG	*	*	*	*	*		*				
SDRF SIG	*	*	*	*	*	*	*	*	*		
VT CRWG	*	*	*	*	*	*	*	*	*		

Even though there is no consensus on the formal definition of cognitive radio, the concept has evolved recently to include various meanings in several contexts. One of its main aspects is related to autonomously exploiting locally unused spectrum to provide new paths to the spectrum access. Other aspects include

- inter-operability across several networks
- adapting the system, transmission, and reception parameters without user intervention
- having the ability to understand and follow actions and choices of the users
- learning over time to become more responsive and to anticipate the user needs.

Cognitive radio concept proposes to furnish the radio systems with the abilities to measure and be aware of parameters related to the radio channel characteristics, availability of spectrum and power, interference and noise temperature, available networks, nodes, and infrastructures, as well as local policies and other operating restrictions. The primary advantage targeted with these features is to enable the cognitive systems to utilize the available spectrum in the most efficient way.

2.3 COGNITION CYCLE OF COGNITIVE RADIO

The differences in the definitions for cognitive radio can be largely attributed to differences in the expectations of the functionality that a cognitive radio will exhibit. In his dissertation [3], Joseph Mitola III considers the nine levels of increasing cognitive radio functionality shown in Table 3, ranging from a software radio to a complex self-aware radio.

Table 3: Levels of cognitive radio functionality

Level	Capability	Comments
0	Pre-Programmed	A software radio
1	Goal Driven	Chooses waveform according to goal. Requires environment awareness.
2	Context Awareness	Knowledge of what the user is trying to do
3	Radio Aware	Knowledge of radio and network components, environment models
4	Capable of planning	Analyze situation(level 2 and 3) to determine goals (QOS, power) follows prescribed plans
5	Conducts Negotiations	Settle on a plan with another radio
6	Learns Environment	Autonomously determines structure of environment
7	Adapts Plan	Generates new goals
8	Adapts Protocol	Proposes and negotiates new protocols

As a reference for how a cognitive radio could achieve these levels of functionality, [3] introduces the cognition cycle, shown in Fig.2.6, as a “top- level control loop for cognitive radio.” In the cognition cycle, a radio receives information about its operating environment (**Outside world**) through direct observation or through signalling. This information is then evaluated (**Orient**) to determine its importance. Based on this valuation, the radio determines its alternatives (**Plan**) and chooses an alternative (**Decide**) in a way that presumably would improve the valuation. Assuming a waveform change was deemed necessary, the radio then implements the alternative (**Act**) by adjusting its resources and performing the appropriate signalling. These changes are then reflected in the interference profile presented by the cognitive radio in the Outside world. As part of this process, the radio uses these observations and decisions to improve the operation of the radio (**Learn**), perhaps by creating new modelling states, generating new alternatives, or creating new valuations.

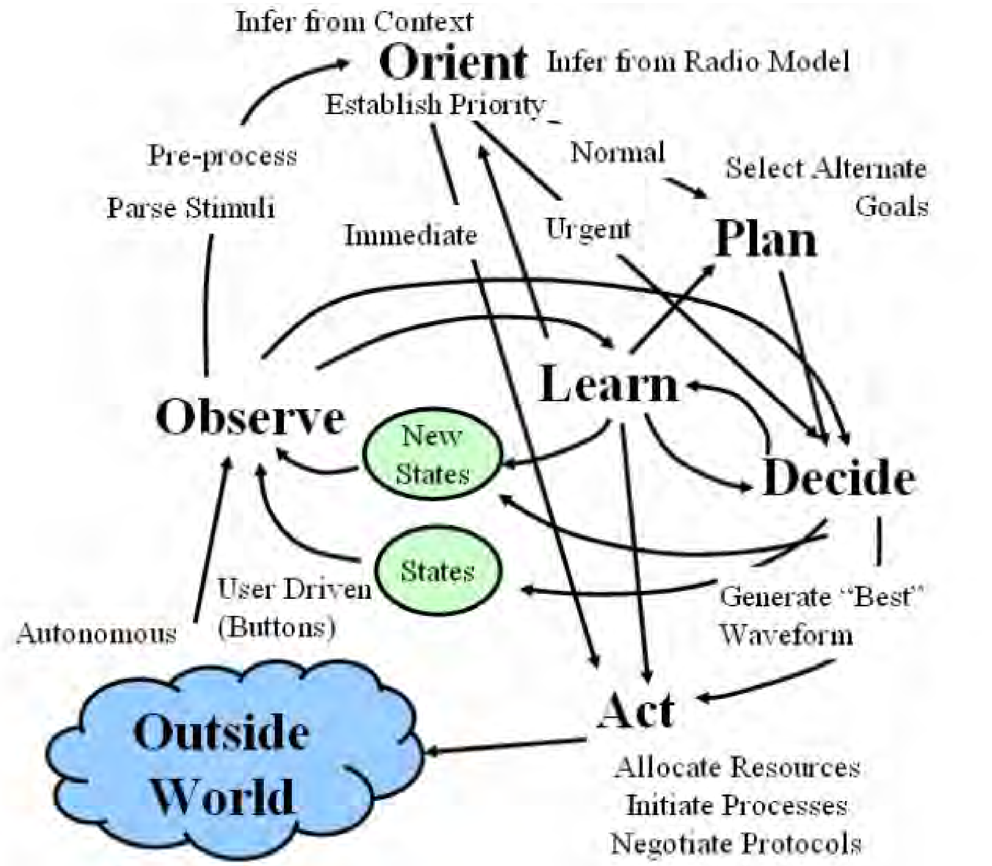


Figure 2.6: Cognition cycle, [13]

2.4 LIMITATIONS OF COGNITIVE RADIO

As there are significant advantages of CR, there are a number of key challenges. Ideally a CR should have no impact on other radio users, but in reality some impact is expected particularly on non-cognitive primary radio users. The autonomous adaptive nature of CR means that it could be difficult to predict and control the spectrum behaviour of individual radios: a concern for anyone who might suffer from CR interference.

A method may be required to audit and trace CR spectrum usage in legacy bands. The communications industry's greatest concern with CR is the hidden node problem. This situation arises when a CR is unable to detect all of the radios with which it might interfere, not because its own spectrum sensing is ineffective, but because some radios are hidden from it. The hidden node problem is a big challenge facing the widespread market deployment of spectrally aware CR. Figure 2.7 shows an example which demonstrates the hidden node problem: a CR is located far away from a transmitting contemporary user, but is very close to a receiving contemporary user. The receiving contemporary user is at the edge of its cell. Therefore as the figure shows there is a section where the carrier-to-interference ratio falls below the minimum required for reliable communications. CR will suffer from the same security issues as SDR such as malicious use, leading to unexpected or problematic behaviour of individual CRs or potentially entire networks.

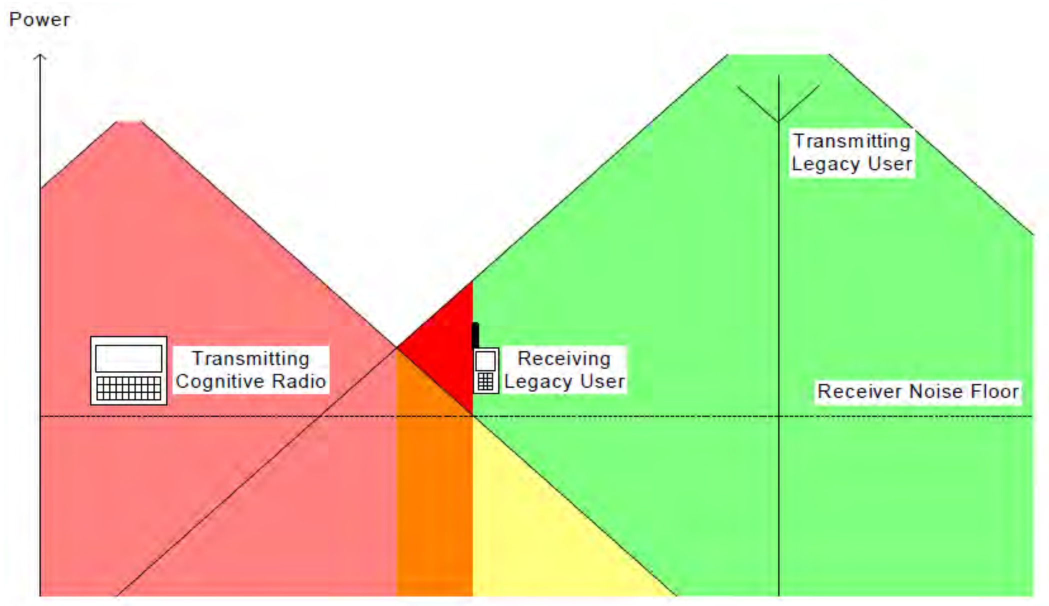


Figure 2.7: Hidden node problem

Chapter 3: DETECTION THEORY

3.1 INTRODUCTION

The field of signal detection is concerned with the analysis of received signals to determine the presence or absence of signals of interest, to classify the signals present, and to extract information either purposefully or inadvertently included in these signals. For example, in active radar, electromagnetic pulses or pulse trains are transmitted and the reflected signals are analyzed to determine the nature of air traffic (small airplanes, commercial airplanes, or hostile aircraft), to extract information such as distance, speed, and possibly to form an image that would allow the identification of the airplane type. Most signal detection problems can be cast in the framework of M-ary hypothesis testing, in which we have an observation (possibly a vector or function) on the basis of which we wish to decide among M possible statistical situations describing the observations. For example, in an ,M-ary communications receiver we observe an electrical waveform that consists of one of M possible signals corrupted by random channel or receiver noise, and we wish to decide which of the M possible signal is present. Obviously, for any given decision problem, there are a number of possible decision strategies or rules (like Bayes, minimax, Neyman-Pearson, etc) that could be applied.

SPACE OF POSSIBLE OBSERVATION AND TYPES OF ERROR

The structure of figure 3.1 is specified by a partition of the set of all possible observations into a set R and its complement R^C. The null hypothesis is rejected if the realized value of the observation falls in the rejection region. Similarly, hypothesis H1 is accepted if the realized value of the observation falls in the acceptance region. In testing hypothesis Ho versus H1, there are two types of errors that can be made .These errors are

Type I Error: This type of error is called false rejection. Decide H_1 is true, when actually Ho is true.

Type II Error: It is false acceptance. Decide Ho is true, when actually H_1 is true. This type of error causes miss detection.

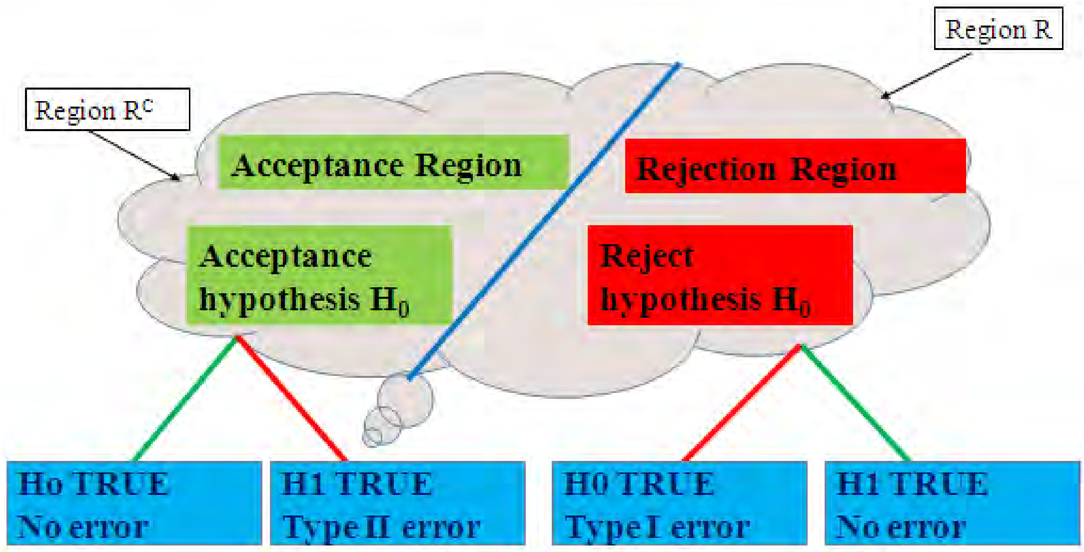


Figure 3.1 Structure of a decision rule for binary hypothesis testing

The trade off between probability of error type I and error type II is shown below in Fig.3.2. It shows a graph of two hypothetical probabilities versus power curve. The curve on the left is for the noise-alone trials, and the curve on the right is for the signal-plus-noise trials. The horizontal axis is labelled internal response and the vertical axis is labelled probability. Notice also that the curves overlap, that is, the internal response for a noise-alone trial may exceed the internal response for a signal-plus-noise trial. An example criterion is indicated by the vertical lines in Fig.3.2. The criterion line divides the graph into four sections that correspond to: hits, misses, false alarms, and correct rejections. On both hits and false alarms, the power is greater than the criterion. Hits correspond to signal-plus-noise trials when the power is greater than criterion, as indicated in the figure. False alarms correspond to noise-alone trials when power response is greater than criterion, as indicated in the figure. Similarly, on both misses and correct rejection, the power is less than the criterion. Miss corresponds to signal-plus-noise trials when the power is less than criterion, as indicated in the figure. Correct rejection corresponds to noise-alone trials when power response is less than criterion.

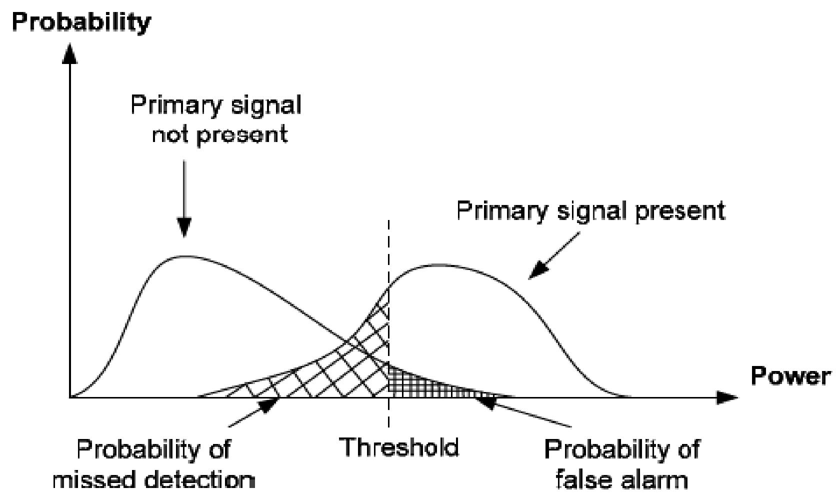


Figure 3.2 Trade off between probability of false alarm and miss detection

3.2 BAYESIAN BINARY HYPOTHESIS TESTING

The goal of binary hypothesis testing is to decide between two hypotheses H_0 and H_1 based on the observation of a random vector **Y**. We consider the cases where **Y** takes continuous or discrete values over a domain Y. In the continuous-valued case, Y = $\mathbb{R}^n$, and depending on whether H_0 or H_1 holds, **Y** admits the probability densities

$$H_0 : Y \sim f(y/H_0)$$

$$H_1 : Y \sim f(y/H_1). \tag{3.1}$$

In the discrete-valued case, **y** = {$\mathbf{y}_i$, i ε I} is a countable collection of discrete values **y***i* indexed by i ε I and depending on whether H_0 or H_1 holds, **Y** admits the probability mass distribution functions

$$H_0 : p(y/H_0) = p[Y = y/H_0]$$

$$H_1 : p(y/H_1) = p[Y = y/H_1]\ . \tag{3.2}$$

Then, given Y, we need to decide whether H_0 or H_1 is true. This is accomplished by selecting a decision function δ (Y) taking values in {0, 1}, where δ (y) = 1 if we decide that H_1 holds when Y = y, and δ (y) = 0 if we decide that H_0 holds when Y = y.

In effect, the decision function δ (y) partitions the observation domain Y into two disjoint sets y_0 and y_1 where

$$y_0: \{y: \delta(y) = 0\}$$

$$y_1: \{y: \delta(y) = 1\}. \tag{3.3}$$

Thus, there exist as many decision functions as there are disjoint partitions of Y. Among all decision functions, we seek to obtain decision rules which are "optimal" in some sense. This requires the formulation of an optimization problem whose solution, if it exists, will yield the desired optimal decision rule. The Bayesian formulation of the binary hypothesis testing problem is based on the philosophical viewpoint that all uncertainties are quantifiable, and that the costs and benefits of all outcomes can be measured. This means that the hypotheses H_0 and H_1 admit a priori probabilities

$$\pi_0: p[H_0] \;, \quad \pi_1: p[H_1] \;, \text{With } \pi_0 + \pi_1 = 1. \tag{3.4}$$

According to Bayes' rule, the a-posterior probabilities of the two hypotheses H_j with j = 0, 1 can be expressed as

$$p[H_j | Y = y] = \frac{f(y|H_j)\pi_j}{f(y)} . \tag{3.5}$$

So the Likelihood Ratio Test (LRT) reduces to the maximum a-posterior probability (MAP) decision rule

$$p[H_1 | y] \underset{H_0}{\overset{H_1}{\gtrless}} p[H_0 | y]. \tag{3.6}$$

When Y is discrete-valued, the a-posterior probabilities appearing in the MAP decision rule are given by

$$p[H_j | Y = y] = \frac{p(y|H_j)\pi_j}{p(y)} , \tag{3.7}$$

Where p(y) is the marginal probability mass function,

$$p(y) = \sum_{j=0}^{1} p(y|H_j)\pi_j. \quad (3.8)$$

Maximum Likelihood decision rule

In the absence of a-priori knowledge about the frequency of occurrence of each hypothesis and by assuming the two hypotheses are equally likely ($\pi_0 = \pi_1$), the LRT can be expressed as the maximum-likelihood (ML) decision rule for continuous-valued observations and discrete-valued observations are given respectively by

$$f[y|H_1] \underset{H_0}{\overset{H_1}{\gtrless}} f[y|H_0] \quad (3.9)$$

$$p[H_1|y] \underset{H_0}{\overset{H_1}{\gtrless}} p[H_0|y] \quad (3.10)$$

3.3: NEYMAN-PEARSON TESTING

In hypothesis testing, as in all other areas of statistical inference, there are two major schools of thought on designing good tests: Bayesian and classical. In the Bayesian setup, a prior probability $\pi_j = \Pr[H_j]$ of each hypothesis occurring is assumed known. In some applications, however, it may not be reasonable to assign a priori probability to a hypothesis. For example, what is the a priori probability of a supernova occurring in any particular region of the sky? What is the prior probability of being attacked by a ballistic missile? In such cases we need a decision rule that does not depend on making assumptions about the a priori probability of each hypothesis. Here the Neyman-Pearson criterion offers an alternative to the Bayesian framework. The Neyman-Pearson criterion is stated in terms of certain probabilities associated with a particular hypothesis test. The Neyman-Pearson criterion says that we should construct our decision rule to have maximum probability of detection while not allowing the probability of false alarm to exceed a certain value α.

3.3.1 Neyman-Pearson Criterion

In [14] Neyman and Pearson formulated the binary hypothesis testing problem pragmatically by selecting the test δ that maximizes $P_d(\delta)$ (or equivalently that minimizes $P_m(\delta)$) while ensuring that the probability of false alarm $P_f(\delta)$ is less than or equal to a number α. Let $D\alpha$ denote the domain

$$D\alpha = \{\delta : P_f \leq \alpha\} \tag{3.11}$$

Then the Neyman-Pearson test δ_{NP} solves the constrained optimization problem

$$\delta_{NP} = \underset{\delta \in D_\alpha}{\arg\max}\ P_d(\delta) \tag{3.12}$$

Theorem: Neyman-Pearson Lemma: initial statement

Consider the test

$$\begin{aligned} H_0 &: y \sim f_0(y) \\ H_1 &: y \sim f_1(y) \end{aligned} \tag{3.13}$$

where, $f_j(y)$ is a density. Define $\Lambda(y) = \frac{f_1(y)}{f_0(y)}$. The solution to the optimization for the hypotheses problem is given by

$$\begin{pmatrix} \Lambda(y) - \dfrac{f_1(y)}{f_0(y)} \geq \lambda & : H_1 \\ \Lambda(y) = \dfrac{f_1(y)}{f_0(y)} < \lambda & : H_0 \end{pmatrix} \tag{3.14}$$

Where threshold (λ) is such that

$$P_f = \int_{\forall y, \Lambda(y) > \lambda} f_0(y)\,dy = \alpha \tag{3.15}$$

The optimal test is unique up to a set of probability zero under H_0 and H_1. The optimal decision rule is called the likelihood ratio test. $\Lambda(y)$ is the likelihood ratio, and λ is a threshold. Observe that neither the likelihood ratio nor the threshold depends on the a priori probabilities Pr $[H_j]$. They depend only on the conditional densities f_i and the size constraint α.

<u>Sufficient Statistics and Monotonic Transformations</u>

For hypothesis testing involving multiple or vector-valued data, direct evaluation of the size Probability of false alarm (P_f) and power probability of detection (P_d) of a Neyman-Pearson decision rule would require integration over multi-dimensional, and potentially complicated decision regions. In many cases, however, this can be avoided by simplifying the Likelihood Ratio Test (LRT) to a test of the form

$$t \underset{H_0}{\overset{H_1}{\gtrless}} \lambda \tag{3.16}$$

Where the test statistic t = T (Y) is a sufficient statistic for the data. Such a simplified form is arrived at by modifying both sides of the LRT with monotonically increasing transformations, and by algebraic simplifications. Since the modifications do not change the decision rule, we may calculate P_f and P_d in terms of the sufficient statistic. For example, the false-alarm probability may be written by:

$$P_f = P_r[\mathrm{declare}\,H_1]$$

$$P_f = \int_{\forall t, t>\lambda} f_0(t)\,dt \tag{3.17}$$

Where f_0 (t) denotes the density of t under H_0. Since, t is typically of lower dimension than Y, evaluation of P_f and P_d can be greatly simplified. The key is being able to reduce the LRT to a threshold test involving a sufficient statistic for which we know the distribution.

Chapter4: SPECTRUM DETECTION FOR COGNITIVE RADIO

4.1 INTRODUCTION

Spectrum detection is the art of performing measurements on a part of the spectrum and forming a decision related to spectrum usage based upon the measured data. The recent rapid growth of wireless communications has made the problem of spectrum utilization ever more critical. On one hand, the increasing diversity (voice, short message, Web, and multimedia) and demand of high quality-of-service (QoS) applications have resulted in overcrowding of the allocated spectrum bands, leading to significantly reduced levels of user satisfaction. In recent years, the service providers are faced with a situation where they require a larger amount of spectrum to satisfy the increasing quality of service (QoS) requirements of the users. This has raised the interest in unlicensed spectrum access, and spectrum detection is seen as an important enabler for this. In a scenario in which there exist a licensed user (primary user), any unlicensed (secondary users) needs to ensure that the primary user is protected, i.e., that no secondary user is harmfully interfering any primary user operation. Spectrum detecting can be used to detect the presence or absence of a primary user.

The Institution of Electrical and Electronics Engineering (IEEE) has formed a working group (IEEE 802.22) to develop an air interface for opportunistic secondary access to the spectrum via the cognitive radio technology. The guiding philosophy of cognitive radio is to allow universal maximization of the spectrum utilization insofar as the unlicensed users do not cause degradation of service upon the original license holders. In practice, the unlicensed users, also called the cognitive users, need to monitor the spectrum activities continuously to find a suitable spectrum band for possible utilization and to avoid possible interference to the licensed users, also called the primary users. Since the primary users have the priority of service, the above spectrum sensing by cognitive users includes detection of possible collision when a primary user becomes active in the spectrum momentarily occupied by a cognitive user and relocation of the communication channels.

Spectrum sensing is based on a well known technique called signal detection. In a nutshell, signal detection can be described as a method for identifying the presence of a signal in a noisy environment. Analytically, signal detection can be reduced to a simple identification problem, formalized as a hypothesis test [15, 16, and 17], which can be described as shown in Fig.4.1.

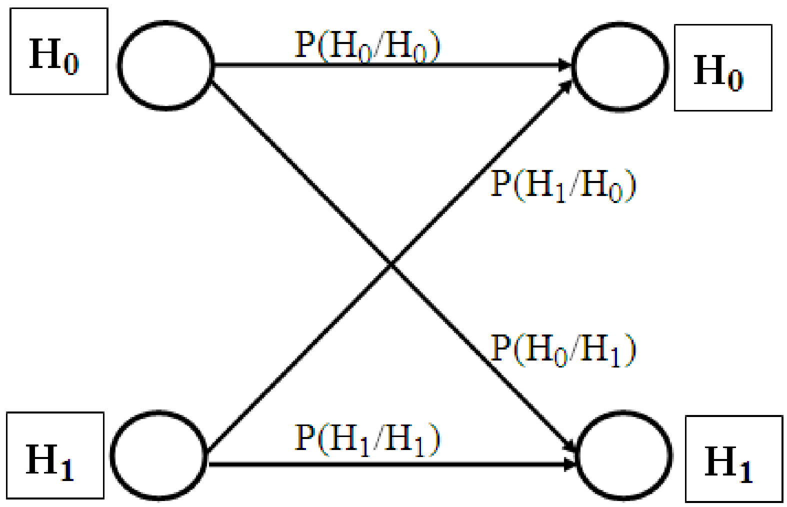


Figure 4.1 Hypothesis test and possible outcomes with their corresponding probabilities.

Spectrum sensing can be viewed as a binary hypothesis testing problem in which hypothesis H_0 indicates that the primary user (PU) is inactive whereas hypothesis H_1 indicates that a PU is active. If we denote the signal received at a secondary user (SU) by R (t), we can write

$$R(t) = \begin{cases} n(t) & : H_0 \\ h.\,s(t) + n(t) & : H_1 \end{cases} \qquad (4.1)$$

Where n (t) is a noise process, h is the amplitude gain of the channel, s (t) is the primary users (PU's) transmitted signal, H_0 is noise-only hypothesis and H_1 is the signal plus noise hypothesis. That means H_0 and H_1 are the sensed states for absence and presence of signal, respectively. Then, as seen in Fig.4.1, we can define four possible cases for the detected signal:

- Case1: declaring H_0 when H_0 is true $(H_0|H_0)$;
- Case2: declaring H_1 when H_1 is true $(H_1|H_1)$;
- Case3: declaring H_0 when H_1 is true $(H_0|H_1)$;
- Case4: declaring H_1 when H_0 is true $(H_1|H_0)$.

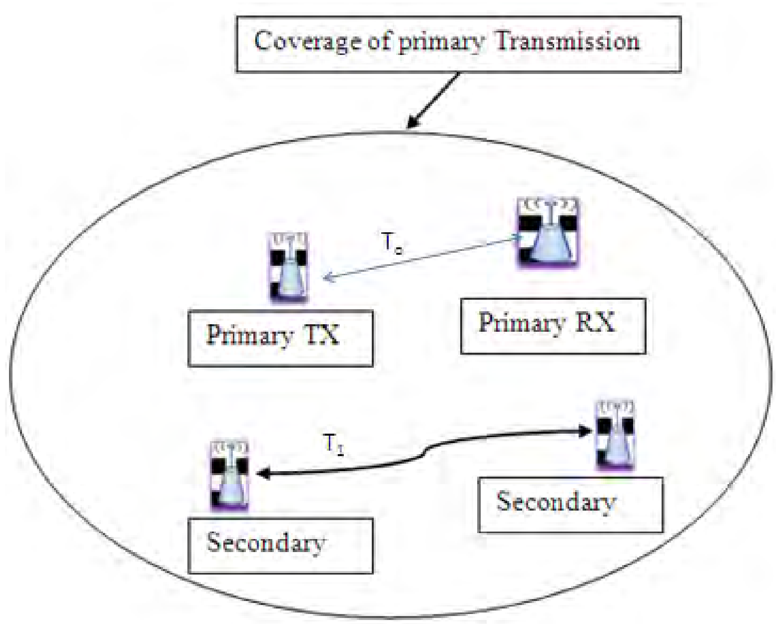
The performance of spectrum sensing can be characterized by the probability of false alarm ($P_f = P(H_1|H_0)$), probability of miss detection and the probability of detection ($P_d = P(H_1|H_1)$).

The term Pf is the probability that a secondary user decides the primary user is active when the PU is actually inactive. It reflects the level of missed access opportunity for the SU. The term P_d is the probability that a SU decides that the PU is active when the PU is actually active. The probability of miss detection ($P_m = 1 - P_d$) indicates the level of interference introduced to the PU (Primary users) by a SU (secondary users). Typically, Pm is restricted to be below an acceptable level to protect the PU. Among the above cases, case 2 is known as a correct detection, whereas cases 3 and 4 are known as a missed detection and a false alarm, respectively. Clearly, the aim of the signal detector is to achieve correct detection all of the time, but this can never be perfectly achieved in practice because of the statistical nature of the problem. Therefore, signal detectors are designed to operate within prescribed minimum error levels. Missed detections are the biggest issue for spectrum sensing, as it means possibly interfering with the primary system. Nevertheless, it is desirable to keep the false alarm rate as low as possible for spectrum sensing, so that the system can exploit all possible transmission opportunities.

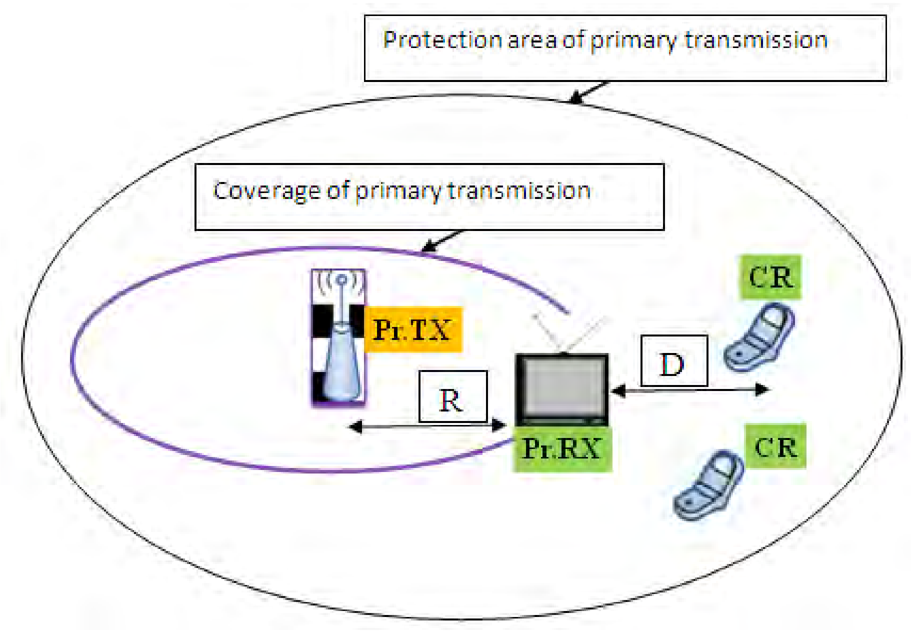
4.2 SPECTRUM HOLES AND SPECTRUM ANALYSIS

Cognitive radio is designed to identify and scavenge the spectrum holes in the licensed spectrum bands. A spectrum hole is defined as a licensed spectrum band that can be used by CR users without interfering with the primary or licensed users. Generally spectrum holes can be broadly divided into two categories: temporal spectrum holes and spatial spectrum holes, which are shown in Fig.4.2 (a) and (b), respectively. A temporal spectrum hole means that there is no primary transmission over the spectrum band of interest during the time of sensing (over a reasonable period); hence, this band can be utilized by CR users in the current time slot. For the temporal spectrum holes, as indicated in Fig.4.2 (a), the secondary users are located in the coverage area of the primary transmission. Consequently, it is relatively easy to detect the presence or absence of the primary user activity since CR users only need to have a similar detection sensitivity as regular primary receivers and, more importantly, identifying the presence of a primary signal is much easier than demodulating and decoding it. Therefore, spectrum sensing in this case does not pose an onerous demand on signal processing.

A spatial spectrum hole exists when the spectrum band of interest is occupied by the primary transmission only in a restricted area; hence, this band can be utilized by CR users well outside this area [18]. In contrast with the utilization of temporal spectrum holes, secondary users utilizing spatial spectrum holes work outside the coverage of the primary transmission, as indicated in Fig.4.2 (b). Since there are no primary receivers outside the coverage area, secondary communication over the licensed band is allowed if only the secondary transmitter does not interfere with the primary transmission and reception within the coverage area. To accomplish this, the secondary transmitter has to successfully detect the presence of the primary signal at any location where the secondary transmission may cause intolerable interference to the possible nearby primary receiver. Since the secondary users fall outside the coverage area of the primary transmission, detection of the primary signal in this case is a challenging task.



(a) Temporal spectrum holes



(b) Spatial spectrum holes

Figure 4.2 Spectrum holes for secondary communication.

To avoid intolerable interference with the primary transmission, any secondary transmitter with transmit power Ps must successfully detect the presence of primary signal when it is R plus D away from the primary transmitter. In other words, there exists a protection area for the primary transmission in which the presence of primary signal must be successfully detected by secondary transmitters to avoid interfering with the primary transmission. As indicated in Fig.4.2 (b), the protection area of primary transmission contains coverage of primary transmission and is larger than the primary transmission coverage. Since the secondary users are required to detect the presence of primary signal well outside the primary transmission coverage, the detection of spatial spectrum holes entails advanced spectrum sensing techniques.

<u>Spectrum analysis</u>

The available spectrum holes show different characteristics which vary over time and it is important to understand the characteristics of different spectrum bands. Spectrum analysis enables the characterization of different spectrum bands, which can be exploited to get the spectrum band appropriate to the user requirements.

In order to describe the dynamic nature of cognitive radio networks, each spectrum hole should be characterized considering not only the time-varying radio environment but also the primary user activity and the spectrum band information such as operating frequency and bandwidth. Hence, it is essential to define parameters such as interference level, channel error rate, path-loss, link layer delay, and holding time that can represent the quality of a particular spectrum band as follows:

- **Interference**: Some spectrum bands are more crowded compared to others. Hence, the spectrum band in use determines the interference characteristics of the channel. From the amount of the interference at the primary receiver, the permissible power of cognitive radio user can be derived, which is used for the estimation of the channel capacity.
- **Path loss**: The path loss increases as the operating frequency increases. Therefore, if the transmission power of cognitive radio user remains the same, then its transmission range decreases at higher frequencies. Similarly, if transmission power is increased to compensate for the increased path loss, then this results in higher interference to other users.
- **Wireless link errors**: Depending on the modulation scheme and the interference level of the spectrum band, the error rate of the channel changes.
- **Sensing Time:** Due to the primary importance of the legacy system, the secondary system must be designed to free the medium as soon as it senses that a legacy network has initiated a transmission. For efficient use of the spectrum, these secondary networks must also sense available spectrum as quickly as possible, in the least possible number of received samples. In general terms, spectrum sensing techniques work through a compromise between the number of samples and accuracy.
- **Holding time**: The activities of primary users can affect the channel quality in cognitive radio networks. Holding time refers to the expected time duration that the cognitive radio user can occupy a licensed band before getting interrupted. Obviously, the longer the holding time, the better the quality would be. Since frequent spectrum handoff can decrease the holding time, previous statistical patterns of handoff should be considered while designing Cognitive radio networks with large expected holding time.

From the primary user's point of view the critical performance measure is the time between the potential appearance of sources of harmful interference that correspond to failing in detecting the presence of primary user. The time between false alarms (i.e. time between detecting a target when there is no target) is critical, we can derive the time between failures in detection T_{fd} from the probability of detection P_d as:

$$T_{fd} = \frac{T_{dec}}{1-P_d} \tag{4.2}$$

where T_{dec} denotes the time between sensing decisions in periodic spectrum sensing. T_{dec} depends on the primary user's tolerance to harmful interference. In [19], a spectrum capacity estimation method has been proposed that considers the bandwidth and the permissible transmission power. Accordingly, the spectrum capacity, C, can be estimated as follows:

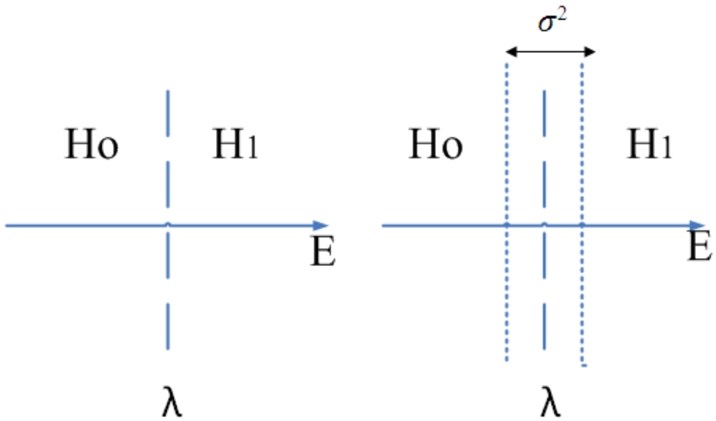
$$C = B\log\left(1 + \frac{S}{N-I}\right) \tag{4.3}$$

where 'B' is the bandwidth, 'S' is the received signal power, 'N' is e receiver noise power, and 'I' is the interference power received at receiver due to the primary transmitter.

4.3 ENERGY DETECTOR ALGORITHM

Energy detector is the most common way of spectrum detection because of its low computational and implementation complexities [20]. It is based on the principle that, at the reception, the energy of the signal to be detected is always higher than the energy of the noise. The energy detector is said to be a blind signal detector because it ignores the structure of the signal. The decision is made by comparing the decision statistics which corresponds to energy collected in the observation time, to an appropriate threshold [21, 22 and 23], that is traditionally selected from the statistics of the noise to satisfy the false alarm rate specification of the detector based on Constant False Alarm Rate (CFAR) principle.

The energy detector relies completely on the variance of the noise which is taken as a fixed value. This is generally not true in practice, where the noise floor varies and we will see the effect of noise uncertainty in section 4.3.2. Essentially this means that the energy detector will generate errors during those variations, especially when the signal to noise ratio (SNR) is very low, as seen in Fig.4.3(b), where we see an area of uncertainty surrounding the threshold in contrast with the case portrayed in Fig.4.3 (a) in which perfect noise knowledge is considered.

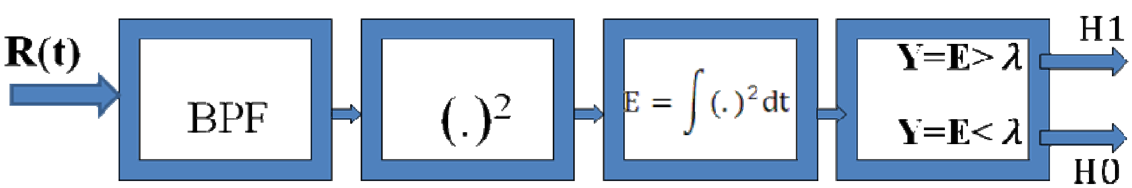


(a) Ideal energy detector scheme. (b) Detection uncertainty for the energy detector.

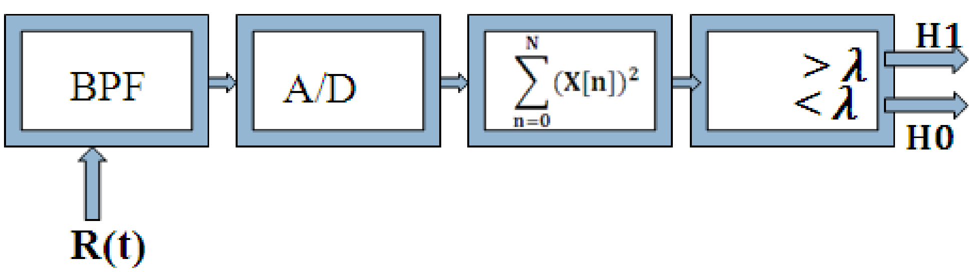
Figure 4.3: Ideal and actual energy detection schemes.

4.3.1 SYSTEM MODEL OF ENERGY DETECTION UNDER AWGN CHANNEL

The system model for energy detection which is used to identify the presence or absence of primary signal is shown below in Fig.4.4. From the given block diagram, in order to measure the energy of the received signal, the output signal of bandpass filter, used to limit the noise power and to normalize the noise variance, with bandwidth W is squared and integrated over the observation interval T. Finally, the output of the integrator, Y, is compared with a threshold, λ, to decide whether a licensed user is present or not [24].



(a) continuous form decision statistics



(b) discrete form decision statistics

Figure 4.4 block diagram of energy detector system model

The flow chart which is used to describe the block diagram shown in Fig.4.4 is shown below. The generated signal is passed through white Gaussian noise (AWGN) channel, according to the above block diagram the energy of signal plus noise will be calculated and finally the evaluated energy will be compared with the threshold value to decide on the presence or absence of the primary signal which passes through additive white Gaussian noise channel. We took the threshold value for the cost of probability of false alarm of less than or equal to 10% and different values of noise variance ranging from 0.5 to 1. At the comparator, if the energy is greater than the threshold value, it shows that the transmitted signal is present and it is not possible to use the cognitive radio as a secondary user with in the coverage area of the primary users. Whereas, if the energy is less than the predefined threshold value, the primary signal is not accessing its spectrum and it is time to use the cognitive radio in an opportunistic way until the presence of the primary signal is detected.

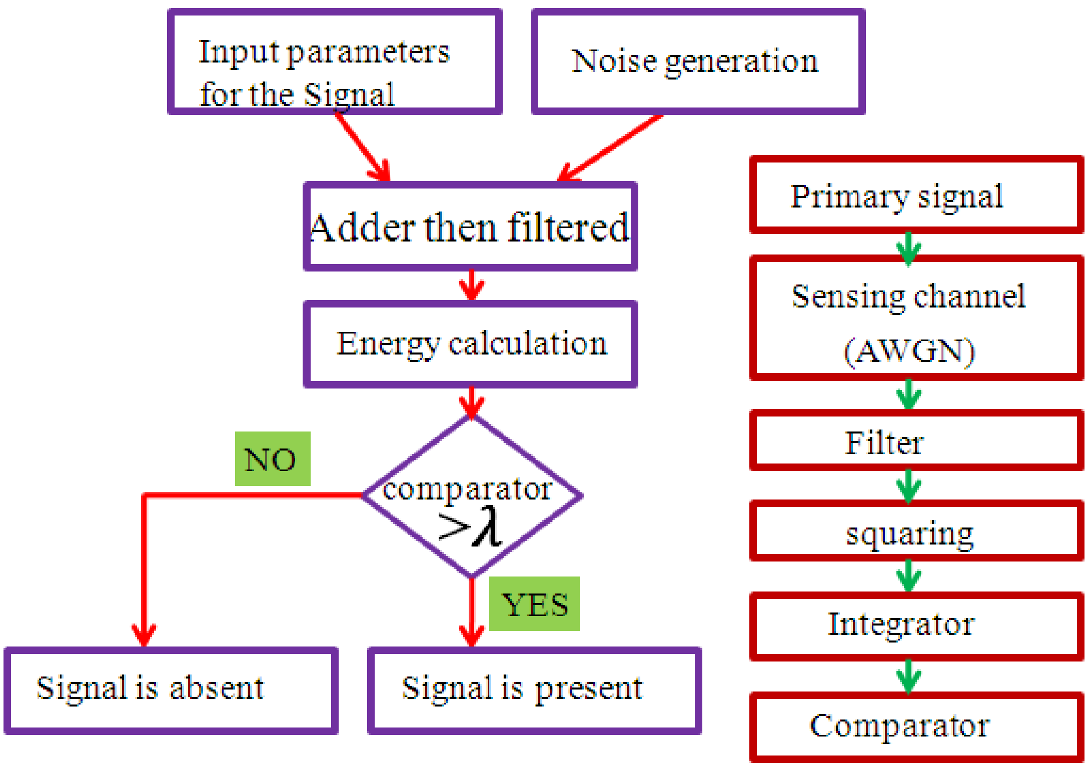


Figure 4.5: Flow chart for system model of energy detector

The energy detector decides between two hypotheses; H_1 which corresponds to signal plus noise, and H_0 which is the noise-only hypothesis. The hypothesis model for transmitter detection can be defined as:

$$R(t)=\begin{cases} n(t) & : H_0 \\ s(t)+n(t) & : H_1 \end{cases} \tag{4.4}$$

Here R(t) is the signal received by the secondary user, s(t) is the signal transmitted by the primary transmitter, n(t) is the noise introduced by AWGN. H_0 is the null hypothesis when there is no primary signal and H_1 indicates the presence of primary signal [25]. The decision statistics Y for zero mean Gaussian distributed noise only (H_0) follows central chi square distribution with 2TW (twice of time-bandwidth product) degrees of freedom. In the case that the primary signal is present (H_1) it follows a non-central chi-squared distribution with 2TW degrees of freedom and non centrality parameters 2γ .Where γ is the mean signal to noise ratio (SNR) in the linear scale .And the observation decision statistics ($Y=\sum_{n=0}^{N}(X[n])^2$,where x[n] is the output signal of the ADC) is given by [26]:

$$Y=\begin{cases} \chi^2{}_{2TW} & H_0 \\ \chi^2{}_{2TW}\,(2\gamma) & H_1 \end{cases} \tag{4.5}$$

The probability density function (PDF) of test statistic Y of equation4.5 can then be written as shown in equation 4.6 [26]:

$$f_y(y)=\begin{cases} \frac{1}{2^{TW}\Gamma(TW)}y^{TW-1}e^{-\frac{y}{2}}, & H_0 \\ \frac{1}{2}\left(\frac{y}{2\gamma}\right)^{\frac{TW-1}{2}}e^{-\frac{2\gamma+y}{2}}I_{TW-1}\left(\sqrt{2\gamma y}\right), & H_1 \end{cases} \tag{4.6}$$

Where $\Gamma(.)$ is gamma function and $I_x(.)$ is the x^{th}-order modified Bessel functions of the first kind. The probability of detection P_d and false alarm P_f are then given as follows [26].

$$P_d=P_r(Y>\ \lambda|H1)=Q_{(N=TW)}(\sqrt{2\gamma},\sqrt{\lambda}\ ) \tag{4.7}$$

$$P_f=P_r(Y>\ \lambda|Ho)=P_f=\frac{\Gamma(TW,\frac{\lambda}{2})}{\Gamma(TW)} \tag{4.8}$$

But with sufficiently large values of observation N, using central limit theorem, the distribution of the test statistic can be approximated as Gaussian. Hence the statistic is given by [26]

$$Y \sim \begin{cases} \mathcal{N}(\mu_0, {\sigma_0}^2) & : Ho \\ \mathcal{N}(\mu_1, {\sigma_1}^2) & : H1 \end{cases} \tag{4.9}$$

where, $\mathcal{N}(\mu, \sigma^2)$ is Gaussian distribution with mean μ and variance σ^2 and for the system model given above the mean and variance for both hypotheses H_0 and H_1 are given by:

$$\mu_0 = N{\sigma_n}^2, {\sigma_0}^2 = 2N\,{\sigma_n}^4 \tag{4.10}$$

$$\mu_1 = N({\sigma_s}^2 + {\sigma_n}^2), \ {\sigma_1}^2 = 2N\,({\sigma_s}^2 + {\sigma_n}^2)^2 \tag{4.11}$$

Then the probability of detection and false alarm for sufficient large value of N could be calculated by substituting equation 4.10 and 4.11 into equation 4.9 and given as:

$$P_d = Q\left(\frac{\lambda - N({\sigma_n}^2 + {\sigma_s}^2)}{\sqrt{2N({\sigma_n}^2 + {\sigma_s}^2)^2}}\right) = Q\left(\frac{\lambda - N(1+\gamma){\sigma_n}^2}{\sqrt{2N(1+2\gamma){\sigma_n}^4}}\right) \tag{4.12}$$

$$P_f = Q\left(\frac{\lambda - N{\sigma_n}^2}{\sqrt{2N{\sigma_n}^4}}\right) \tag{4.13}$$

If the number of samples used in sensing is not limited, an energy detector can meet any desired P_d and P_f simultaneously. But the minimum number of samples, which is a function of the signal to noise ratio $SNR=\frac{{\sigma_s}^2}{{\sigma_n}^2}$, is evaluated by [26]:

$$N = 2[(Q^{-1}(P_f) - Q^{-1}(P_d))SNR^{-1} - Q^{-1}(P_d)]^2 \tag{4.14}$$

That means, number of samples required for the detection that meets specified P_d and P_f, scales as O ($1/SNR^2$). If the probability of false alarm rate is predefined and proper threshold is selected, it is possible to evaluate the probability of detection P_d in terms of probability of false alarm and signal to noise ratio by the following equation:

$$P_d = Q\left(\frac{\left(1 + Q^{-1}(P_f)\right) - (1 + SNR) * \sqrt{\frac{N}{2}}}{(1 + SNR)}\right) \qquad (4.15)$$

4.3.2 NOISE UNCERTAINTY MODEL OF ENERGY DETECTOR UNDER AWGN CHANNEL

Although it is generally assumed for simplicity that the variance of the receiver noise is known, noise variance is never exactly known in the case of real systems even if the system is calibrated. There are several factors that contribute to the existence of noise uncertainty. For example, thermal noise due to change in temperature, change in amplifier gain due to change in temperature, calibration error etc. As noise uncertainty in the receiver in unavoidable, it is very important to analyze its effect on the detection performance.

Let us model the noise process w[n] to have any distribution W from a set of possible distributions w. This set is called the noise uncertainty set. Although the actual noise variance might vary over distributions set w, let us assume that there is a single nominal noise variance σ_n^2 associated with the noise uncertainty set w. As energy detector evaluates the detection performance based of the incoming signal, the distributional uncertainty of noise can be summarized in a single interval $\sigma_w^2 \varepsilon[(\frac{1}{\rho})\sigma_n^2, \rho\sigma_n^2]$ where σ_n^2 is the nominal noise power and ρ>1 is the parameter that quantifies the size of the noise uncertainty. The parameter is often considered in its dB equivalent as $10log_{10}(\rho)$. To understand the noise uncertainty for the detector the shaded area in the Fig.4.6 represents the uncertainty in the noise power. From the figure it is clear that if the test statistic falls within the shaded region, there is no way to distinguish between the two hypotheses. By including the noise uncertainty factor shown in Fig 4.6, probability of false alarm, threshold and probability of detection can be written as:

$$P_f - Q\left(\frac{\lambda - N\rho{\sigma_n}^2}{\sqrt{2N\rho^2{\sigma_n}^4}}\right) \qquad (4.16)$$

$$\lambda = \sqrt{N\rho^2 {\sigma_n}^4}\, Q^{-1}(P_{fa}) + N\rho {\sigma_n}^2 \qquad (4.17)$$

$$P_d = Q\left(\frac{\lambda - N(\frac{1}{\rho}{\sigma_n}^2 + {\sigma_s}^2)}{\sqrt{2N(\frac{1}{\rho}{\sigma_n}^2 + {\sigma_s}^2)^2}} \right) \qquad (4.18)$$

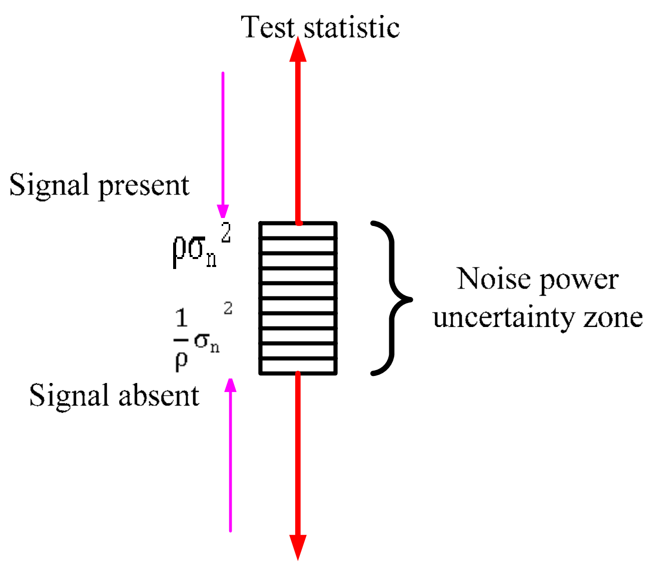


Figure 4.6 understanding noise uncertainty regions

Noise level uncertainty renders robust detection below certain SNR impossible [27, 28]. To constrain the resulting false alarm rate, the detection threshold has to be set based on the worst case noise level uncertainty. Consequently, if the signal power is below a certain level, the energy detector cannot distinguish the signal from a slightly larger noise power regardless of the detection time. This threshold is called the SNR wall in [28]. Consequently, the energy detector performance depends heavily on the accuracy and reliability of the noise level estimate. The noise uncertainty factor ρ can be expressed in terms of SNR wall as shown below:

$$SNR_{wall} = \frac{\rho^2 - 1}{\rho} \qquad (4.19)$$

4.4 ENERGY DETECTION UNDER RAYLEIGH FADING CHANNEL

Radio-wave propagation through wireless channels is a complicated phenomenon characterized by various effects, such as multipath and shadowing. A precise mathematical description of this phenomenon is either unknown or too complex for tractable communications systems analyses. However, considerable efforts have been devoted to the statistical modelling and characterization of these different effects. The result is a range of relatively simple and accurate statistical models for fading channels which depend on the particular propagation environment and the underlying communication scenario.

4.4.1 MODELING OF FLAT FADING CHANNELS

When fading affects systems, the received carrier amplitude is modulated by the fading amplitude α, where α is a Random Variable (RV) with mean-square value $\Omega = \overline{\alpha^2}$ and probability density function (PDF) $p_\alpha(\alpha)$, which is dependent on the nature of the radio propagation environment. After passing through the fading channel, the signal is perturbed at the receiver by additive white Gaussian noise (AWGN), which is typically assumed to be statistically independent of the fading amplitude α , and which is characterized by a one-sided power spectral density N_0 (W/Hz). Equivalently, the received instantaneous signal power is modulated by $\alpha 2$. Thus we define the instantaneous signal-to-noise power ratio per symbol by $\gamma = \alpha^2 Es/N_0$ and the average SNR per symbol by $\bar{\gamma} = \Omega\ Es/N_0$, where Es is the energy per symbol. Our performance evaluation of digital communications over fading channels will generally be a function of the average SNR per symbol $\bar{\gamma}$. In addition, the PDF of γ is obtained by introducing a change of variables in the expression for the fading PDF $p_\alpha(\alpha)$ of α, yielding [23]

$$p_\gamma(\gamma) = f_\gamma(\gamma) = \frac{p_\alpha\left(\sqrt{\Omega\gamma/\bar{\gamma}}\right)}{2\sqrt{\gamma\bar{\gamma}/\Omega}} \qquad (4.20)$$

Multipath fading is due to the constructive and destructive combination of randomly delayed, reflected, scattered, and diffracted signal components. This type of fading is relatively fast and is therefore responsible for the short-term signal variations. The Rayleigh distribution is frequently used to model multipath fading with no direct line-of-sight (LOS) path. In this case the channel fading amplitude is distributed according to:

$$p_{\alpha}(\alpha) = \frac{2\alpha}{\Omega}\exp\left(-\frac{\alpha^2}{\Omega}\right), \alpha \geq 0 \qquad (4.21)$$

And hence, the instantaneous SNR per symbol of the channel γ, is distributed according to an exponential distribution given by [23]

$$p_{\gamma}(\gamma) = f_{\gamma}(\gamma) = \frac{1}{\bar{\gamma}}\exp\left(-\frac{\gamma}{\bar{\gamma}}\right) \qquad (4.22)$$

From equation4.1, the energy of the signal for both the H_0 and H_1 cases, under the assumption that h is Rayleigh distributed is given by [24]:

$$Y = \begin{cases} {\chi^2}_{2(N+1)} & : Ho \\ e_{2(\gamma^2+1)} + {\chi^2}_{2N}(\lambda) & : H1 \end{cases} \qquad (4.23)$$

Where χ^2 is a chi-square distribution and $e_{2(d^2+1)}$ is the exponential distribution with parameter $\alpha = 2(\gamma^2 + 1)$ with probability density function $f(x,\alpha) = \alpha e^{-\alpha x}$and γ is the signal to noise ratio. It is clear to see that, under the hypothesis H_0, the statistics are the same as for the AWGN channel case (Pf is independent of the SNR). However, the H_1 case behaves differently and has the probability of detection as given by distributed [24]:

$$P_d = \int_0^{\infty} Q_{(N=TW)}\left(\sqrt{2\gamma}, \sqrt{\lambda}\,\right) f_{\gamma}(x)\,dx \qquad (4.24)$$

Then by substituting equation 4.7 and 4.22 in to equation 4.24 we can obtain the closed expression for probability of detection and shown below:

$$P_d = e^{-\frac{\lambda}{2}} \sum_{n=0}^{N-2} \frac{1}{n!}\left(\frac{\lambda}{2}\right)^n + \left(\frac{1+\bar{\gamma}}{\bar{\gamma}}\right)^{N-1} * \left(e^{-\frac{\lambda}{2(1+\gamma)}} - e^{-\frac{\lambda}{2}} \sum_{n=0}^{N-2} \frac{1}{n!}\left(\frac{\lambda * \bar{\gamma}}{2(1+\bar{\gamma})}\right)^n \right) \tag{4.25}$$

4.5 REPLICA CORRELATION DETECTOR ALGORITHM UNDER AWGN CHANNEL

A replica-correlation detector is performed based on the correlation between the received signal X(t) and the replica known primary signal s(t). The block diagram of system model for both continuous and discrete time case are shown in Fig.4.7 and Fig.4.8 respectively and its flow chart for the system is shown in Fig.4.9

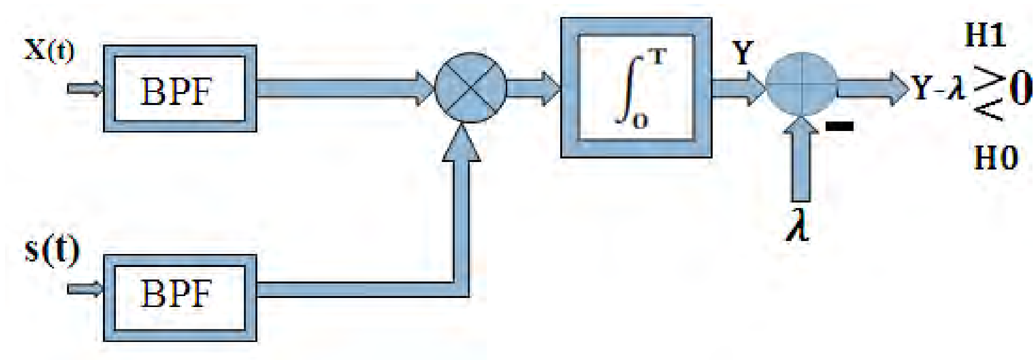


Figure 4.7 block diagram of replica correlation detector system for continuous time case

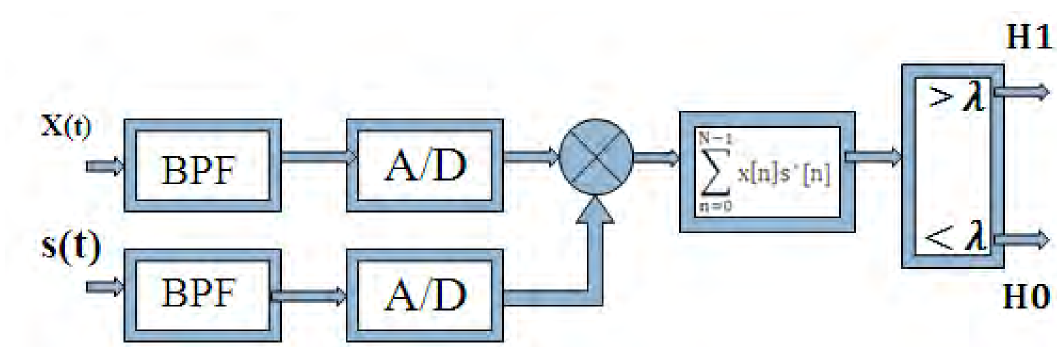


Figure 4.8 block diagram of Replica correlation detector system for discrete time case

The hypothesis model for transmitter detection can be defined as:

$$x(t) = \begin{cases} n(t) & : H_0 \\ s(t) + n(t) & : H_1 \end{cases} \tag{4.26}$$

Here x (t) is the signal received by the unlicensed user, s (t) is the signal transmitted by the licensed transmitter, n (t) is the noise introduced by AWGN. A decision value of replica-correlation detector for the presence of signal of both continuous and discrete case is given respectively by equation 4.27 and 4.28.

$$Y = \mathrm{Re}\left\{ \int_0^T x(t) S^*(t) dt \right\} > \lambda \tag{4.27}$$

$$Y = \mathrm{Re}\left\{ \sum_{n=0}^{N-1} x[n] S^*[n] \right\} > \lambda \tag{4.28}$$

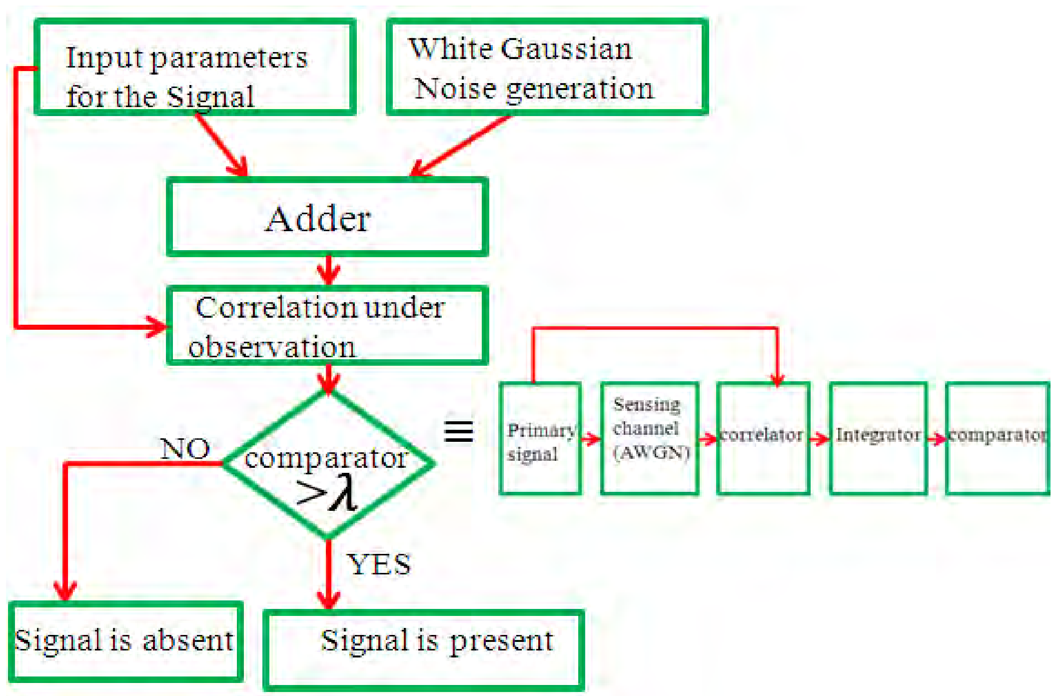


Figure 4.9: flow chart for system model of replica correlation detector

For simplicity of derivation; we assumed that the noise and the signal are independent. From these assumption the received signals or samples which are a linear combinations of the noise and transmitted signal, it can be considered as independent. As the result, $x(t)s(t)$ or $x[n]s[n]$ is a sequence of independent identically distributed (i.i.d) random variables with zero mean and variance of $\sigma_n{}^2\sigma_s{}^2$ for hypothesis H_0 and mean of $\sigma_s{}^2$and variance of $\sigma_s{}^2(1+\sigma_n{}^2+\sigma_s{}^2)$ for hypothesis H_1. Using central limit theorem to the decision static of the replica correlation detector Y for large sample index value N, the distribution of the test statistic can be approximated as Gaussian. Hence the statistic is given by

$$Y \sim \begin{cases} \mathcal{N}(0, N\sigma_n{}^2\sigma_s{}^2) & : Ho \\ \mathcal{N}(N\sigma_s{}^2, N\sigma_s{}^2(1+\sigma_n{}^2+\sigma_s{}^2)) & : H1 \end{cases} \qquad (4.29)$$

Then the probability of detection and false alarm for sufficient large value of N could be calculated by substituting the corresponding mean and variance for both hypotheses and given as:

$$P_d = Q\left(\frac{\lambda - N\sigma_s{}^2)}{\sqrt{N\sigma_s{}^2(1+\sigma_n{}^2+\sigma_s{}^2)}}\right) \qquad (4.30)$$

$$P_f = Q\left(\frac{\lambda}{\sqrt{N\sigma_n{}^2\sigma_s{}^2}}\right) \qquad (4.31)$$

4.5.1 EFFECT OF NOISE UNCERTAINITY ON REPLICA CORRELATION DETECTOR

By applying the concept described on noise uncertainty of energy detector we can also know the effect of noise uncertainty on the performance of replica correlation detector. Probability of detection, probability of false alarm and probability of miss detection are the basic parameters used to model the Receiver Operating Characteristics (ROC) and Complementary Receiver Operating Characteristics (CROC). These receiver characteristics are modelled as shown in Fig.4.10 and the three probabilities under the consideration of noise uncertainty are given by the following equations.

$$P_d = Q\left(\frac{\lambda - N\sigma_s^{\,2})}{\sqrt{N\sigma_s^{\,2}(1 + \frac{1}{\rho}\sigma_n^{\,2} + \sigma_s^{\,2})}}\right) \qquad (4.32)$$

$$P_f = Q\left(\frac{\lambda}{\sqrt{N\rho\sigma_n^{\,2}\sigma_s^{\,2}}}\right) \qquad (4.33)$$

$$P_m - 1 - Q\left(\frac{\lambda - N\sigma_s^{\,2})}{\sqrt{N\sigma_s^{\,2}(1 + \frac{1}{\rho}\sigma_n^{\,2} + \sigma_s^{\,2})}}\right) \qquad (4.34)$$

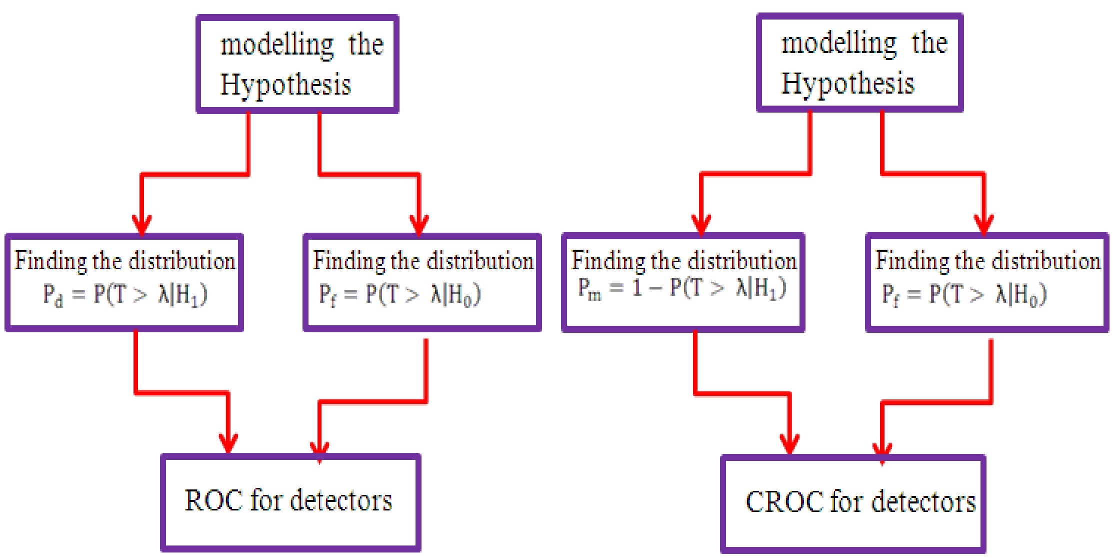


Figure 4.10: model of ROC and CROC

4.6 REPLICA CORRELATION DETECTOR UNDER RAYLEIGH FADING CHANNEL

Multipath fading is due to the constructive and destructive combination of randomly delayed, reflected, scattered, and diffracted signal components. This type of fading is relatively fast and is therefore responsible for the short-term signal variations. The Rayleigh distribution is frequently used to model multipath fading with no direct line-of-sight (NLOS) path. It is clear to see that, under the hypothesis H_0, the statistics are the same as for the AWGN channel case (since Pf is independent of the SNR). However, the H_1 case behaves differently and has the probability of detection under fading channel is evaluated by averaging the probability of detection under AWGN over the fading distribution:

$$P_d = \int_0^{\infty} P_{d(AWGN)}(\sqrt{2\gamma}, \sqrt{\lambda}\ ) f_{\gamma}(x) dx \qquad (4.35)$$

$$P_d = \int_0^{\infty} Q\left(\frac{\lambda - N\sigma_s^{\,2})}{\sqrt{N\sigma_s^{\,2}(1 + \sigma_n^{\,2} + \sigma_s^{\,2})}}\right) \frac{1}{\bar{\gamma}} \exp\left(-\frac{x}{\bar{\gamma}}\right) dx \qquad (4.36)$$

4.7 COOPERATIVE DETECTOR ALGORITHM

Among many other challenges one of the most important challenge for the implementation of CR network is the hidden node problem, when a CR is shadowed or in a deep fade [29]. Cooperative systems such as wireless sensor networks exploit the benefits of spatial diversity that geographically dispersed sensors provide. In the case of cooperative detection multiple CR's can collaborate with each other in order to make a global decision about the existence of the PU as shown in the scenario of Fig.4.11. Therefore cooperative detection refers to spectrum sensing methods where information from multiple secondary users is incorporated for primary user detection.

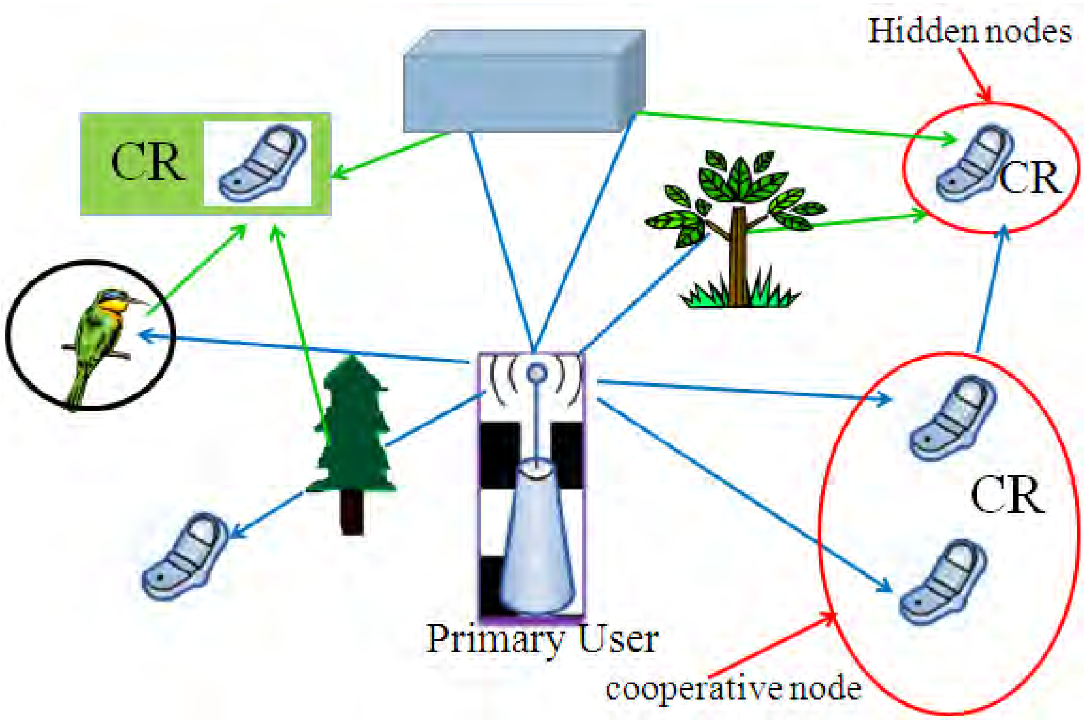
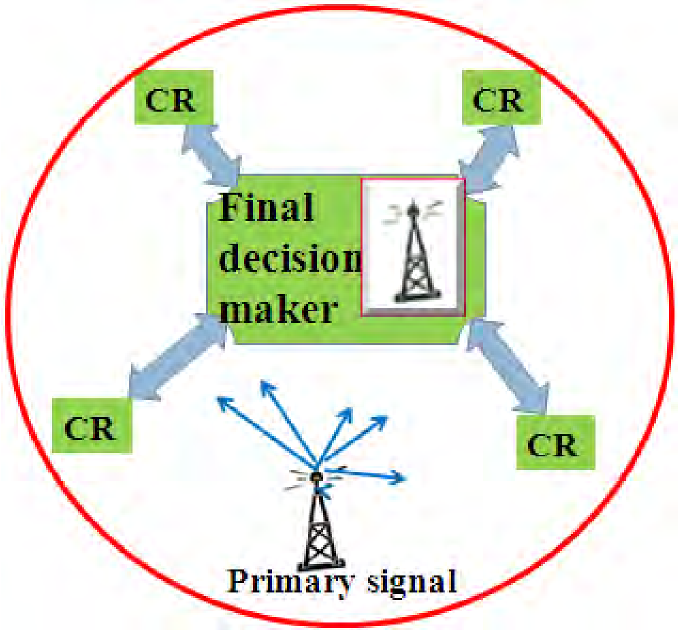


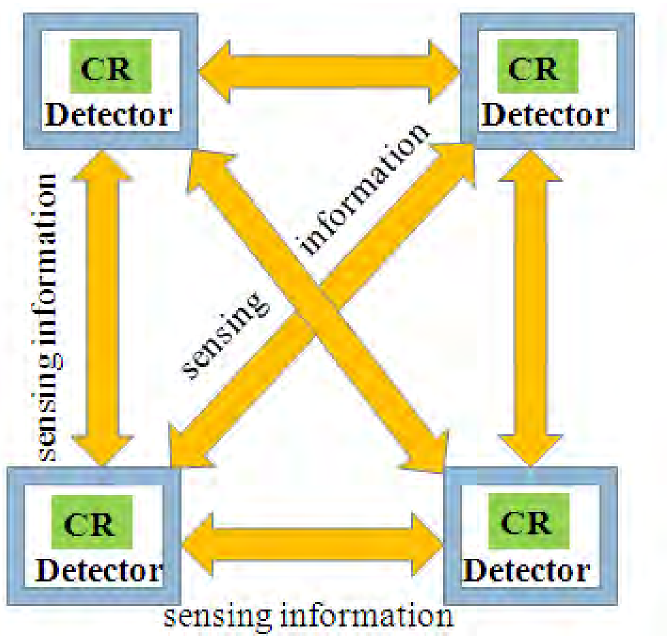
Figure 4.11 Scenario of cooperative signal detection for cognitive radio

Cooperative detection can be implemented either in a centralized or in a distributed manner [30, 31]. In centralized systems, the local sensors (cognitive radios) take local measurement to detect the primary user and forward their decision to a central processor that performs the final decision to accept or reject the hypothesis based on the decision reports. Contrary to centralized systems, in decentralized systems, cognitive nodes share sensing information among them selves but they make their own decisions as to which part of the spectrum they can use. Hence there is no need for a backbone infrastructure for the case of distributed detection. These two systems are shown in Fig.4.12.

In Cooperative spectrum detection (CSD), every SU performs its own spectrum sensing measurements and can also make a local decision on whether the PU is present or absent. All of the SUs forward their soft (local measurement) or hard (1-bit) decision to a common receiver, often called fusion centre or a band manager. Fusion centre may be centralised or distributed.



(a)



(b)

Figure 4.12 Fusion center of cooperative detection (a) centralized (b) distributed

Hard Decision Combining (HDC)

In HDC, fusion centre collects binary decisions from the individual SUs, identifies the available spectrum and then broadcast this information to the other SUs. The optimal decision fusion is based on Neyman-Pearson criterion by comparing Likelihood Ratio with the threshold vector as,

$$\frac{f(D/H_1)}{f(D/H_0)} \underset{H_0}{\overset{H_1}{\gtrless}} \lambda \qquad (4.37)$$

Where $D = [D_1, D_2, D_3, \dots D_{Ns}]$ denotes binary decisions from Ns secondary users (SUs) and $D_i \in \{0,1\}$, λ is the optimal threshold and $f(D/H_0)$and $f(D/H_1)$ represents the probability density functions of D under hypothesis H_0 and H_1, respectively. Mathematical analysis using Neyman-Pearson criterion is mathematically un-tractable especially if the local measurements are correlated and hence sub optimal solutions are always preferable [32]. There are many other ways to combine or fuse hard decisions based on counting rules; we have used OR and AND fusion rule. In AND all CRs should declare H_1 in order to make a global decision that PU is present while in OR rule, fusion centre declares H_1 if any of the received decision is H_1. At the fusion centre, all D_i's are fused together according to the following fusion rule [33]:

$$Y_c = \begin{Bmatrix} \sum_{i}^{Ns} D_i \geq k & : H_1 \\ \sum_{i}^{Ns} D_i \leq k & : H_0 \end{Bmatrix} \qquad (4.38)$$

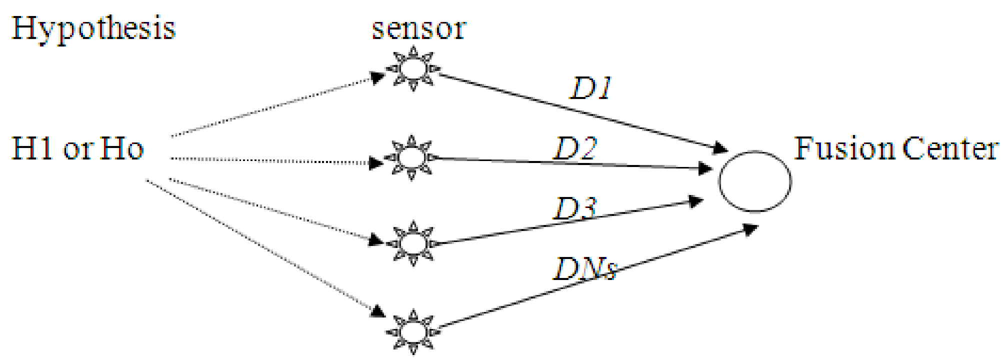


Figure4.13 Hard decision combination

That is, the band manager makes its decision by comparing a weighted sum of the individual hard decisions to a threshold, assigning a larger weight to more reliable measurements. In order to simplify the implementation, we assume that all users employ the same decision threshold. Then the average probabilities of detection and false-alarm for the k-out of-(n=Ns) rule are related to their single-user counterparts through,

$$Q_d = P_{dt} = 1 - \sum_{i=k}^{Ns} \binom{Ns}{i} P_d{}^i (1 - P_d)^{Ns-1} \qquad (4.39)$$

$$Q_f = P_{ft} = 1 \quad \sum_{i=k}^{Ns} \binom{Ns}{i} P_f{}^i (1 \quad P_f)^{Ns-1} \qquad (4.40)$$

Where, P_d and P_f are the individual probabilities of detection and false-alarm respectively and Ns=n is number of secondary users. If each user only sends one-bit decision ("1" for signal present) and no other information is available at the central processor, some commonly adopted decision fusion rules are described as follows [34].

(a) "Logical-OR (LO)" Rule (the case when k = 1): If one of the decisions is "1," the final decision is "1." Assuming that all decisions are independent, then the probability of detection and probability of false alarm of the final decision are given respectively by the following equations.

$$Q_d = P_{dt} = 1 - \prod_{i=1}^{Ns} (1 - P_d{}^i) \qquad (4.41)$$

$$Q_f = P_{dt} = 1 - \prod_{i=1}^{Ns} (1 - P_f{}^i) \qquad (4.42)$$

where P_d^i and P_f^i are the probability of detection and probability of false alarm for user i,respectively.

(b)"Logical-AND (LA)" Rule (the case when k = Ns): If and only if all decisions are "1," the final decision is "1." This logical rule is mostly applicable for the CR under the coverage area of all primary signals transmit better signal to noise ratio level. The probability of detection and probability of false alarm of the final decision are given by :

$$Q_d = P_{dt} = \prod_{i=1}^{Ns} P_d{}^i \qquad (4.43)$$

$$Q_f = P_{ft} = \prod_{i=1}^{Ns} P_f{}^i \tag{4.44}$$

where P_d^i and P_f^i are the probability of detection and probability of false alarm for user i,respectively.

4.7.1 COOPERATIVE DETECTOR ALGORITHM USING ENERGY DETECTOR

We did for both energy and replica correlation detector based cooperative detector algorithms. In this section we develop a mathematical expression for energy detector based cooperative detection when all secondary cognitive users use energy detection. The sytem model and flow chart for the system model we use are shown In Fig.4.14 and 4.15 .

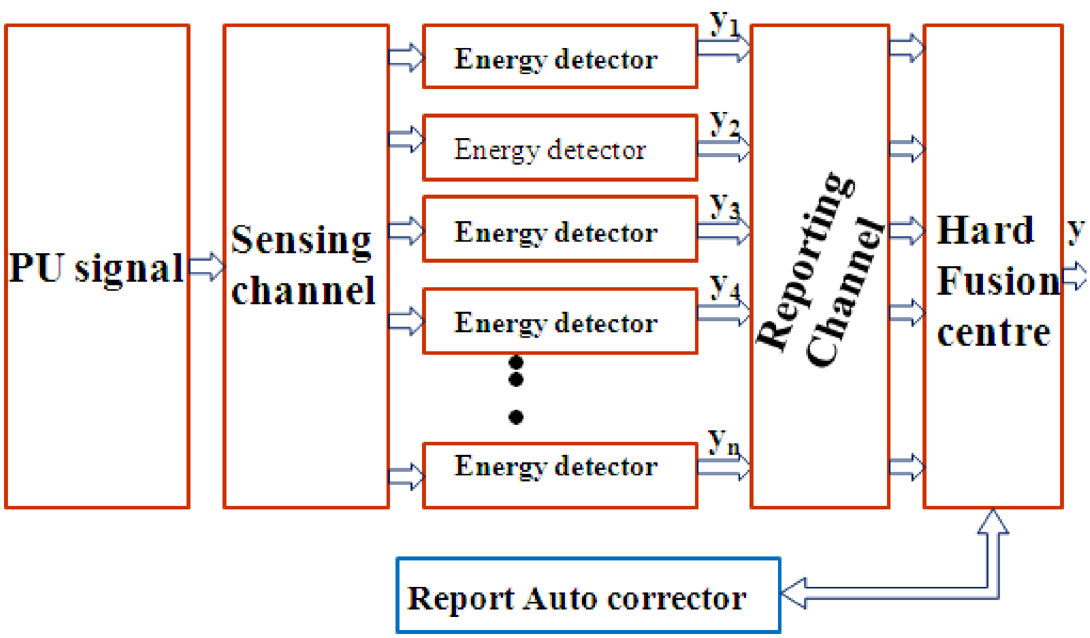


Figure 4.14 Sytem model for energy detector based cooperative detector algorithm

For the above system each secondary user uses energy detector algorithm to make local decision. The sensing (reporting) information from each energy detector are passed through reporting channel to the fusion ceter. At the fusion center hard decision fusion is used because of lower communication overhead over the reporting channels. If the server of the hard fusion center receives a local decision'0' due to imperfect reporting channel, it has a pre-knowledge that only detection'1' resul is reported so it auto-corrects the reported error using report autocorrector block.

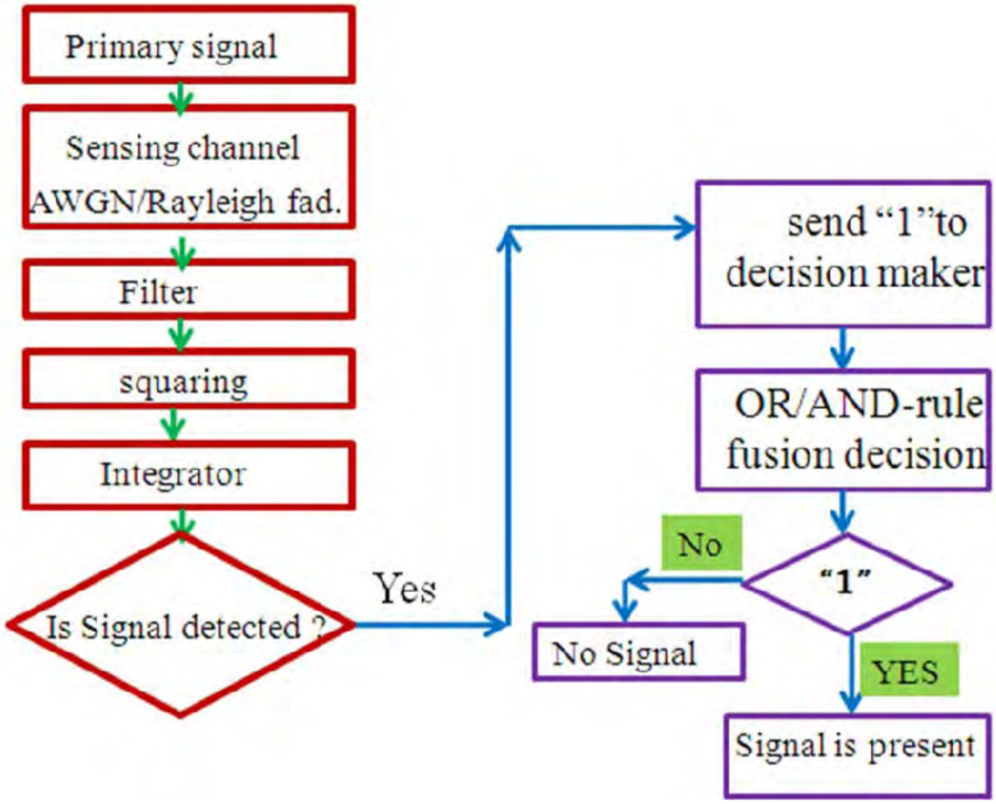


Figure 4.15 Flow chart of the system model for cooperative detection

As we can see from the above flow chart,Fig.4.15, the energy detection of each secondary user will send its decision result to its cooperative cognitive nodes, and then each cooperative node decide the presence or absence of the primary user by applying fusion rule for the received sensing information. By using the probability of detection and probability of false alarm expression of energy detector derived at the section of energy detector algorithm and the total probability of detection and probability of false alarm of cooperative detection, the mathematical expression for energy detection based cooperative detection for AWGN channel shown below (assuming each secondary nodes have equal probability of detection P_d and probability of false alarmP_f) are derived for OR-rule fusion center. These equations are derived from equation 4.29, 4.30, 4.31, 4.32, 4.33, 4.41 and 4.42.

$$Q_d = 1 - \left(1 - Q\left(\frac{\lambda - N({\sigma_n}^2 + {\sigma_s}^2)}{\sqrt{2N({\sigma_n}^2 + {\sigma_s}^2)^2}}\right)\right)^{Ns} \qquad (4.45)$$

$$Q_f = 1 - \left(1 - Q\left(\frac{\lambda - N\sigma_n{}^2}{\sqrt{2N\sigma_n{}^4}}\right)\right)^{Ns} \qquad (4.46)$$

And probability of detection and false alarm with noise uncertainty factor are given by:

$$Q_d = 1 - \left(1 - Q\left(\frac{\lambda - N(\frac{1}{\rho}\sigma_n{}^2 + \sigma_s{}^2)}{\sqrt{2N(\frac{1}{\rho}\sigma_n{}^2 + \sigma_s{}^2)^2}}\right)\right)^{Ns} \qquad (4.47)$$

$$Q_f = 1 - \left(1 - Q\left(\frac{\lambda - N\rho\sigma_n{}^2}{\sqrt{2N\rho^2\sigma_n{}^4}}\right)\right)^{Ns} \qquad (4.48)$$

When each cognitive radio of energy detector for cooperative detection is under fading channel, probability of false alarm is the same as the AWGN case but its probability of detection and probability of miss detection in terms of signal to noise ratio are derived from equation 4.35, 4.41 and 4.42 and gives equation 4.49 and 4.50.

$$Q_d = 1 - \left(1 - e^{-\frac{\lambda}{2}}\sum_{i=0}^{N-2}\frac{1}{i!}\left(\frac{\lambda}{2}\right)^i + \left(\frac{1+\bar{\gamma}}{\bar{\gamma}}\right)^{N-1} * \left(e^{-\frac{\lambda}{2(1+\gamma)}} - e^{-\frac{\lambda}{2}}\sum_{i=0}^{N-2}\frac{1}{i!}\left(\frac{\lambda * \bar{\gamma}}{2(1+\bar{\gamma})}\right)^i\right)\right)^{Ns} \qquad (4.49)$$

$$Q_m = \left(1 - e^{-\frac{\lambda}{2}} \sum_{i=0}^{N-2} \frac{1}{i!}\left(\frac{\lambda}{2}\right)^i + \left(\frac{1+\bar{\gamma}}{\bar{\gamma}}\right)^{N-1} * \left(e^{-\frac{\lambda}{2(1+\gamma)}} - e^{-\frac{\lambda}{2}} \sum_{i=0}^{N-2} \frac{1}{i!}\left(\frac{\lambda * \bar{\gamma}}{2(1+\bar{\gamma})}\right)^i\right)\right)^{Ns} \quad (4.50)$$

4.7.2 COOPERATIVE DETECTOR ALGORITHM USING REPLICA CORRELATION DETECTOR

When the secondary users performing their detection operation in a collaborative way, each secondary users can use replica correlation detection. That means the secondary user detector is performed on the correlation between the received signal and the replica known signal. Then multiple receivers process their observed data independently and send their decisions to a specific user, which then makes a final decision or each receivers can decide by the combination of its decision result and the information it got from other receiver. The model and flow diagram for the replica correlation based cooperative detector are similar with the energy based cooperative detector except its local detector of energy detector is replaced by replica correlation detector and shown in Fig 4.16 and 4.17. The only difference is each secondary detector is based on replica correlation detection algorithm. Thus, the performance parameters for replica correlation based cooperative detection are given by the following equations for both AWGN and Rayleigh fading channel. But our target for cooperative detection is under fading channel.

$$Q_d = 1 - \left(1 - Q\left(\frac{\lambda - N\sigma_s^{\,2}}{\sqrt{N\sigma_s^{\,2}(1 + \sigma_n^{\,2} + \sigma_s^{\,2})}}\right)\right)^{Ns} \quad (4.51)$$

$$Q_f = 1 - \left(1 - Q\left(\frac{\lambda}{\sqrt{N\sigma_n^{\,2}\sigma_s^{\,2}}}\right)\right)^{Ns} \quad (4.52)$$

Where, equation 4.51 and 4.52 are for OR-rule replica correlation based cooperative detection algorithm under AWGN.

Since probability of false alarm under AWGN and Fading channel is the same, we can consider the same result for fading channel as the case of AWGN. But for the case of probability of detection the obtained equation is shown in equation 4.53.

$$Q_d = 1-\left(1-\int_0^{\infty} Q\left(\frac{\lambda-N\sigma_s{}^2)}{\sqrt{N\sigma_s{}^2(1+\sigma_n{}^2+\sigma_s{}^2)}}\right)\frac{1}{\bar{\gamma}}\exp\left(-\frac{x}{\bar{\gamma}}\right)dx\right)^{Ns} \quad (4.53)$$

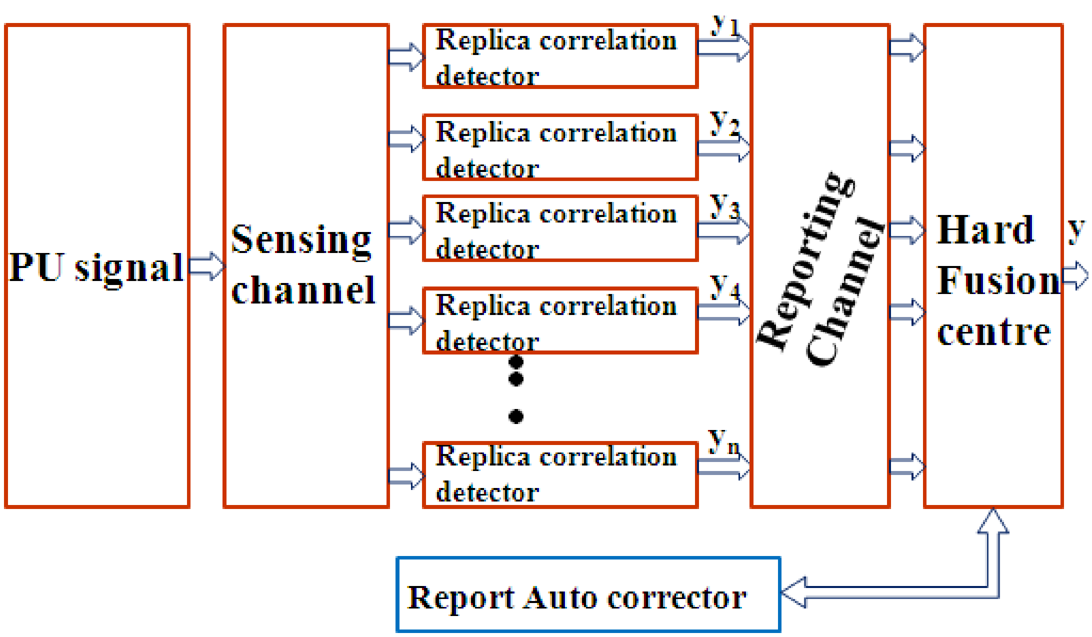


Figure 4.16 Sytem model for Replica correlation based cooperative detector algorithm

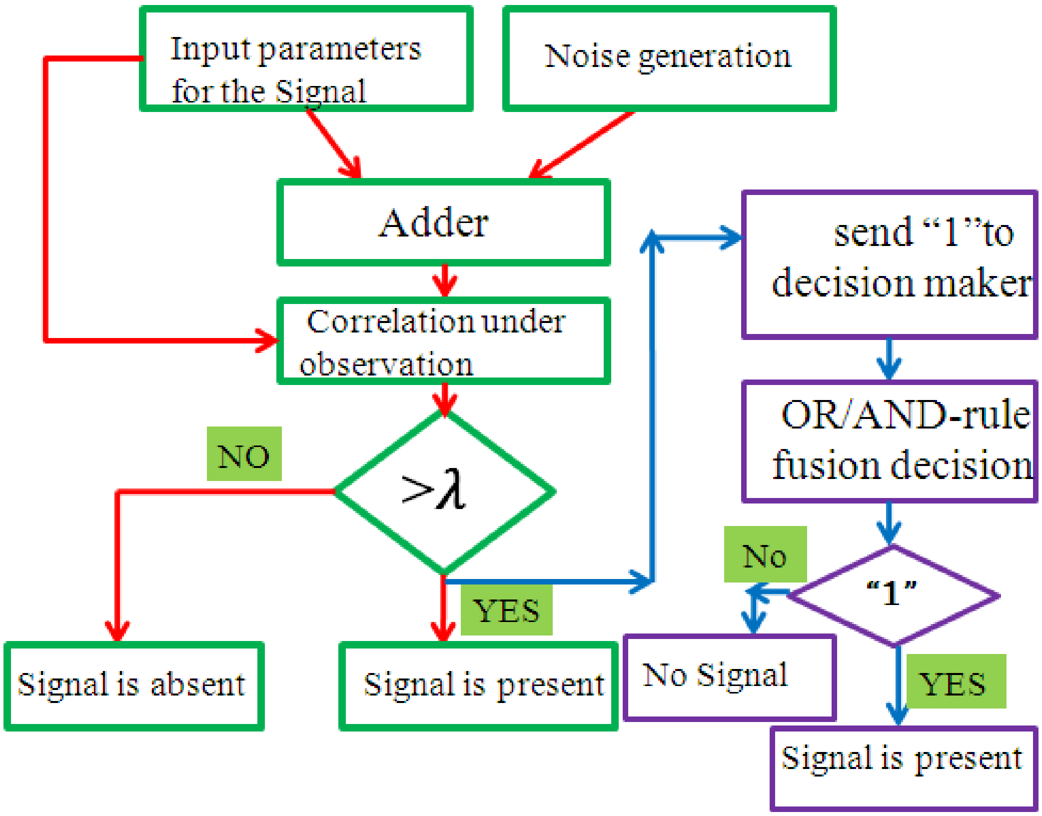


Figure 4.17 Flow chart of the system model for cooperative detection

4.8 ENHANCED ENERGY DETECTOR

The decision statistic in normal square law energy detection involves a noise-square term that may raise the noise floor. As a result, a conventional energy detector integrating over the entire symbol period unwittingly captures the noise-only portion of the received waveform, which causes an extra noise floor. Because the noise floor increases linearly with bandwidth-time product [35], conventional energy detection is less effective to detect wide band signals. To alleviate this problem, a cross-correlation detector that correlates R (t) with a shifted copy of the signal is adopted. The block diagram for cross correlation energy detection system is shown below.

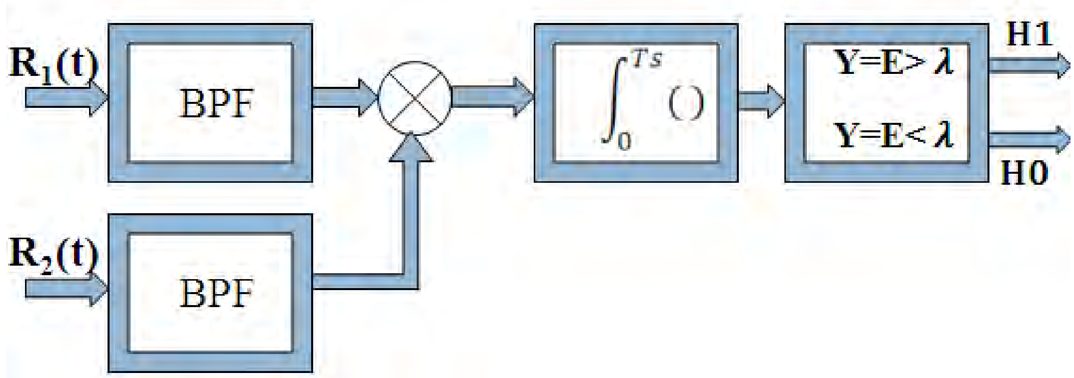


Figure 4.18 block diagram of enhanced energy detection

In signal processing, the correlation function of a random signal describes the general dependence of the values of the samples at one time on the values of the samples at another time. For continuous function, we can estimate the cross-correlation for a given interval, 0 to Ts (which is less than channel coherence time) seconds, of the sample function. And the detection statistic of the enhanced energy detection is given by:

$$\mathrm{Y} = \int_0^{T_s} R_1(t) R_2(t)\, dt \tag{4.54}$$

Where R_1 (t) = s (t) + n (t) and R_2 (t) =s (t + Ts) + n (t + Ts).That means two observed signal at a time difference or shift of Ts are correlated. Therefore the detection statistic for the enhanced detector can be defined as:

$$Y = \left\{ \begin{array}{ll} \int_0^{T_s} \mathrm{n(t)}n(t + T_s)dt & : \mathrm{H_0} \\ \int_0^{T_s} \big(\mathrm{s(t) + n(t)}\big)\ \big(\mathrm{s(t} + T_s) + \mathrm{n(t}+T_s)\big) & : \mathrm{H_1} \end{array} \right\} \tag{4.55}$$

The noise-square term in square law energy detector is replaced by the product of two non-overlapping segments of noise term. Notice that Y has a noise-noise term n (t)n(t + Ts) inside the integral, which decreases the noise floor due to the independence between shifted noise terms, thus resulting in better detection quality.

Now to facilitate receiver analysis, the pdf is approximated for sufficiently large values of N=TW. Therefore using central limit theorem, the distribution of the test statistic can be approximated as Gaussian. Hence the statistic is given by

$$Y \sim \begin{cases} \mathcal{N}(\mu_0, \sigma_0{}^2) & : Ho \\ \mathcal{N}(\mu_1, \sigma_1{}^2) & : H1 \end{cases} \tag{4.56}$$

Where:

$$\begin{cases} \mu_0 = 0 \\ \sigma_0{}^2 = T_s W \sigma_n{}^2 \\ \mu_1 = T_s W \sigma_s{}^2 = N\sigma_s{}^2 \\ \sigma_1{}^2 = N(\sigma_n{}^2+\sigma_s{}^2)^2 = T_s W(\sigma_n{}^2+\sigma_s{}^2)^2 \end{cases} \tag{4.57}$$

From equation 4.9, 4.10 and 4.57, one can see variances of enhanced energy detector are half of those in traditional square law energy detector. Based on the approximate pdf, we now derive the optimal decision threshold λ. The figure of merit is the probability of detection P_d given a fixed probability of false alarms P_f. For Gaussian pdf, the probability of false alarms can be expressed as

$$P_f = Q\left(\frac{\lambda-\mu_0}{\sigma_0}\right) \tag{4.58}$$

Where, Q ( ) is the complementary error function. The optimal threshold is thus given by

$$\lambda = \sigma_0 Q^{-1}(P_f) + \mu_0 \tag{4.59}$$

Given P_f, the probability of detection is given by

$$P_d = 1 - Q\left(\frac{\mu_1-\lambda}{\sigma_1}\right) = 1 - Q\left(\frac{\mu_1 - \sigma_0 Q^{-1}(P_f)+\mu_0}{\sigma_1}\right) \tag{4.60}$$

The optimal threshold for maximum likelihood (ML) demodulation of the detector is given by [36]:

$$\lambda^* = \frac{(\mu_0\sigma_1{}^2-\mu_1\sigma_0{}^2)-\sigma_0\sigma_1\sqrt{(\mu_1-\mu_0)^2+2(\sigma_1{}^2-\sigma_0{}^2)\ln\left(\frac{\sigma_1}{\sigma_0}\right)}}{\sigma_1{}^2-\sigma_0{}^2} \tag{4.61}$$

Chapter5:SIMULATION RESULTS & DISCUSSIONS

In this chapter the simulation results of the thesis work are presented. Simulation results and discussions on the performances of energy, replica correlation and cooperative detectors under both AWGN and Rayleigh fading channels are provided. Finally simulation results and discussions for enhanced energy detector are presented. All the simulations are carried out under the consideration of required probability of detection of 90%, probability of false alarm of 10% and probability of miss detection of 10% with in the band width of 6MHz. Some of the simulation parameters used for performance evaluation is shown in table 4.

Table 4 simulation parameters for spectrum detector performance evaluation

No.	Simulation parameters	Types and value	Remark
1	Interference signal	AWGN	No other interfering signal(assumption)
2	Detector	Energy, replica correlation and cooperative	Neyman-Pearson and LRT are considered
3	Bandwidth (W)	6MHz	
4	signal	BPSK	
5	Center frequency	4GHz	
6	Channel	AWGN and Rayleigh	
7	Noise variance ($\sigma_n{}^2$)	Variable (0.5 to 1)	Known and approximated
8	Noise uncertainty (ρ)	Varies from 0 to 5dB	
9	Number of observations(N)	Variable (10-100)	
10	Sensing time	1-5ms and 1.67 -16.67μs	
11	Number of secondary nodes(Ns=n)	1-10	
12	Average SNR($\bar{\gamma}$)	The same for all detection -6dB.-8dB,-10dB,2dB,5dB	Assumption
13	Detection index(d)	0-4	For replica correlation detection

14	Probability of detection	≥ 90%	Required for detection performance comparisons
15	Probability of false alarm	≤10%	Required for detection performance comparisons
16	Probability of miss detection	<10%	Required for detection performance comparisons

5.1 SIMULATION RESULTS AND DISCUSSION FOR ENERGY DETECTOR

To evaluate the performance of energy detector algorithm, different performance metrics (like: probability of detection, probability of false alarm, Probability of miss detection, sensing time, Receiver Operating characteristics and Complementary Receiver Operating characteristics) are taken into account.

The simulation results shown in Fig.5.1 and Fig.5.2 present the probability of detection and miss detection under AWGN channel versus threshold for the received signal to noise ratio (SNR) values of -8dB, -5dB , -1dB, 0dB, 1dB and 5dB. The threshold values are defined based on the noise variance and probability of false alarm using Constant False Alarm Rate (CFAR).

As one can see from the simulations, probability of detection is inversely proportional to the threshold whereas probability of miss detection is directly proportional to the threshold. For minimum value of threshold, it is possible to achieve better detection performance. But the performance of the energy detector deteriorates when the received signal to noise ratio decreases and the results also verifies this concept. As results show the performance of the detector for the SNR value of 5dB is better than the rest with signal to noise values of less than 5dB.

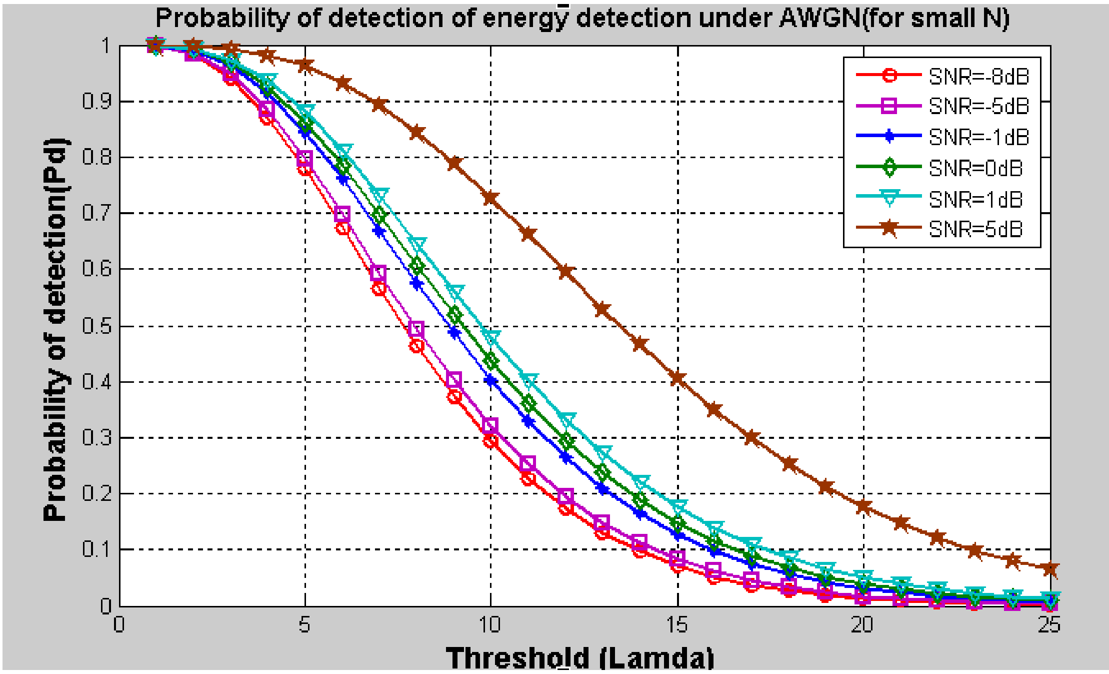


Figure 5.1: probability of detection for energy detection under AWGN for various SNR (SNR=-8dB, -5dB, -1dB, 0dB, 1dB and 5dB)

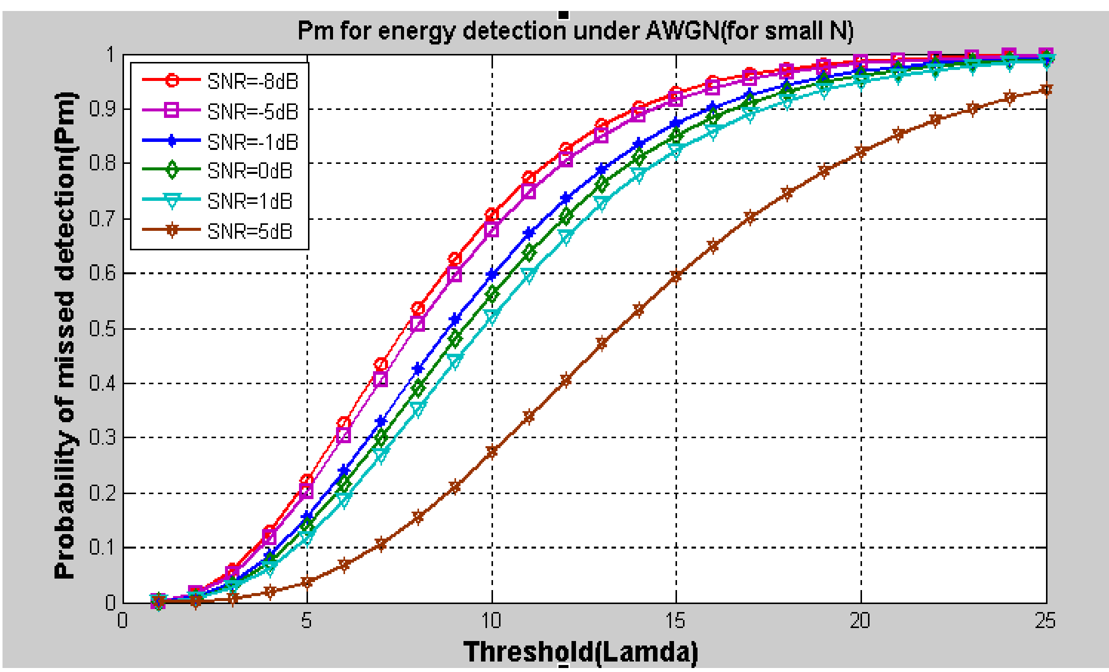


Figure 5.2 probability of miss detection versus threshold for energy detector under AWGN for various SNR (SNR=-8dB, -5dB, -1dB, 0dB, 1dB and 5dB)

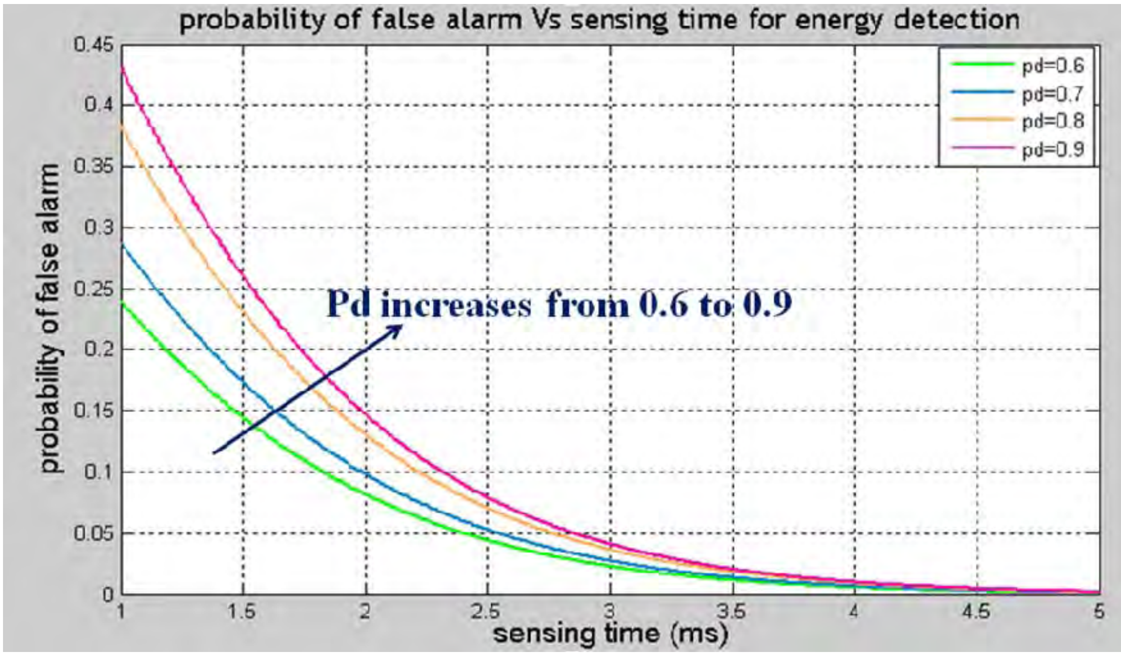


Figure 5.3: probability of false alarm versus sensing time for various values of probability of detection (Pd=0.6, 0.7, 0.8 and 0.9)

As the result of Fig. 5.3 indicates the probability of false alarm is plotted for each probability of detection. To get better performance of detector with minimum values of probability of false alarm, the detector needs large sensing time. For example, to have probability of false alarm (Pf=0.1) and probability of detection (Pd=0.7), the detector needs sensing time of 2ms. But for Pd=0.9, it needs sensing time of almost 2.3ms. In general, Fig 5.3indicates that to obtain better performance in probability of detection under fixed acceptable probability of false alarm, 10%, the detector needs higher sensing time.

Similarly Fig 5.4 shows that, probability of false alarm versus sensing time at a fixed satisfactory level of probability of detection. Here the threshold values are varied based on the values of probability of false alarm. It shows to get better performance of higher probability of detection (let 90 %,) for a fixed value of probability of false alarm, higher sensing time is required. The results of both Fig 5.3 and 5.4 are obtained for signal to noise ratio of -8dB. In general, longer sensing time means less time for actual transmission. This might reduce the overall throughput of the system.

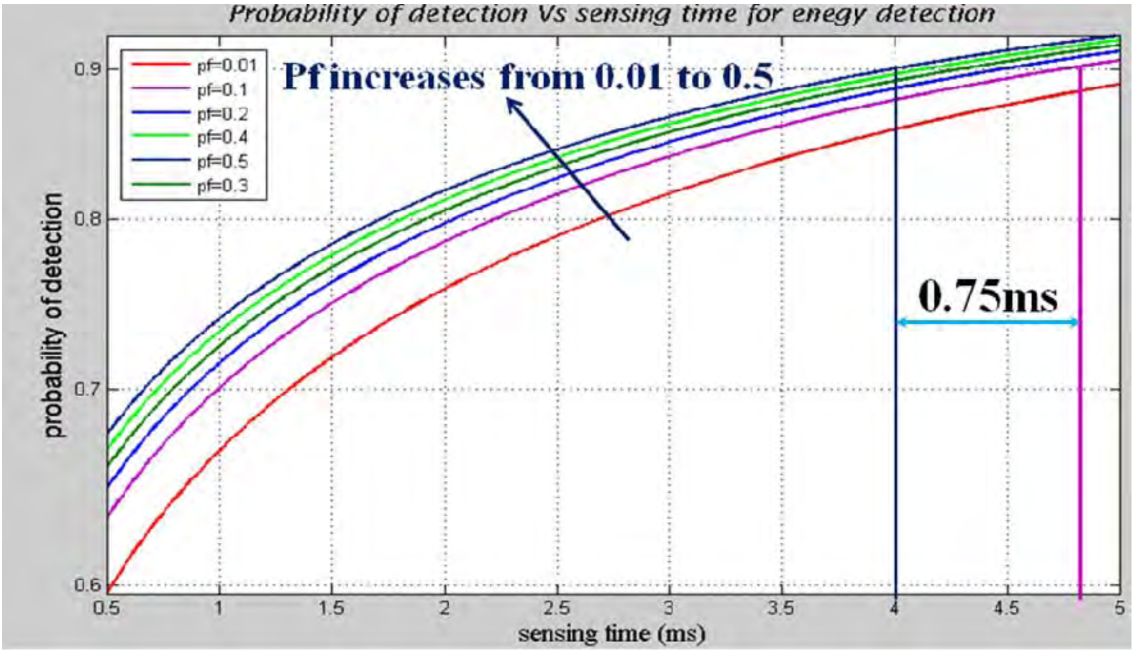


Figure 5.4: probability of detection versus sensing time for various values of probability of false alarm (Pf= 0.01, 0.1, 0.2, 0.3, 0.4, and 0.5)

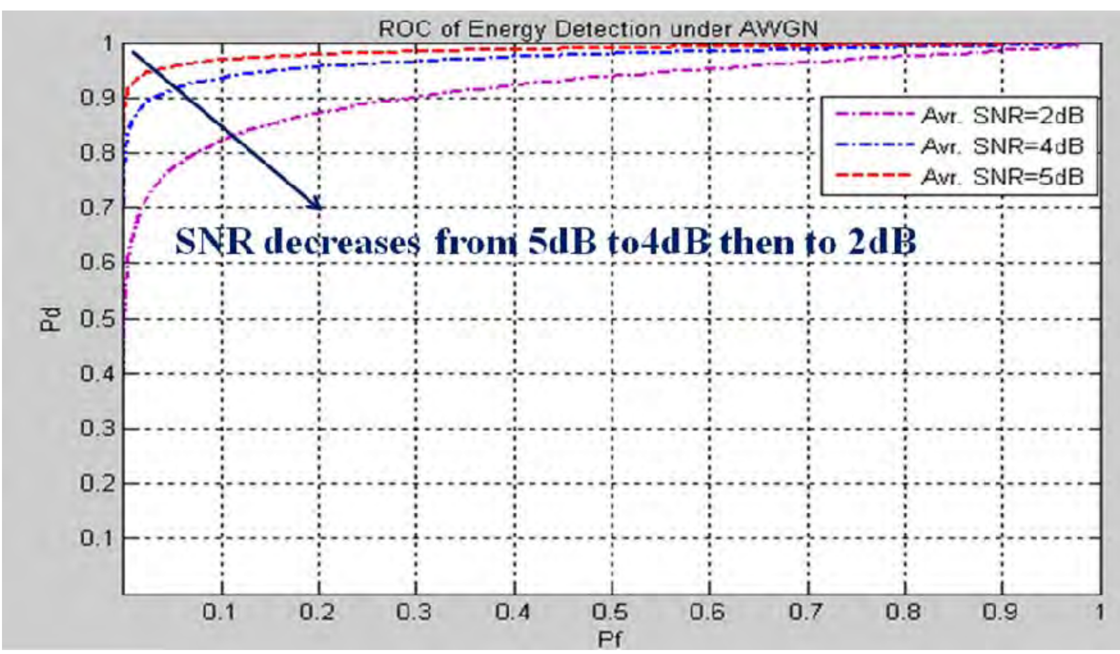


Figure 5.5: ROC of energy detector under AWGN for SNR of 2dB, 4dB and 5dB

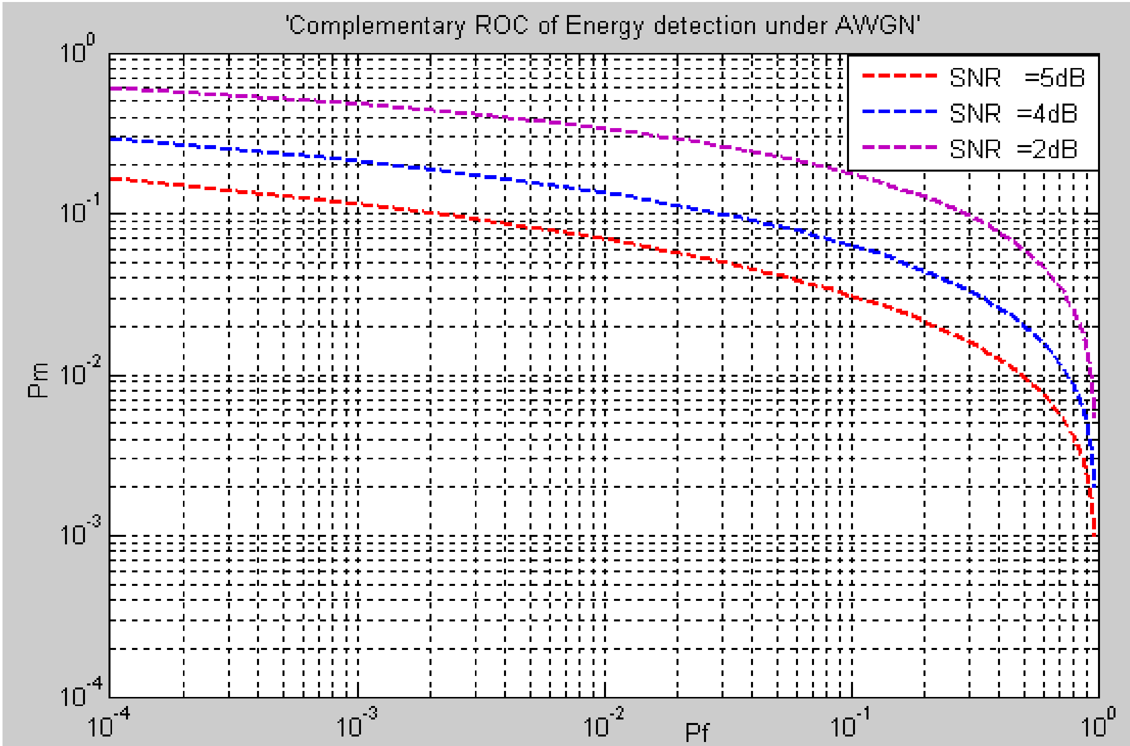


Figure 5.6: CROC for energy detector under AWGN for SNR of 2dB, 4dB and 5dB

Fig.5.5 and 5.6 show, the results for the performance metrics of receiver operating characteristics (plot of probability of detection versus probability of false alarm) and complementary receiver operating characteristics (plot of probability of miss detection versus probability of false alarm) of energy detector for small number of samples under AWGN respectively. As the signal to noise ratio increases probability of detection is better and probability of miss detection is minimum at a fixed point of probability of false alarm.

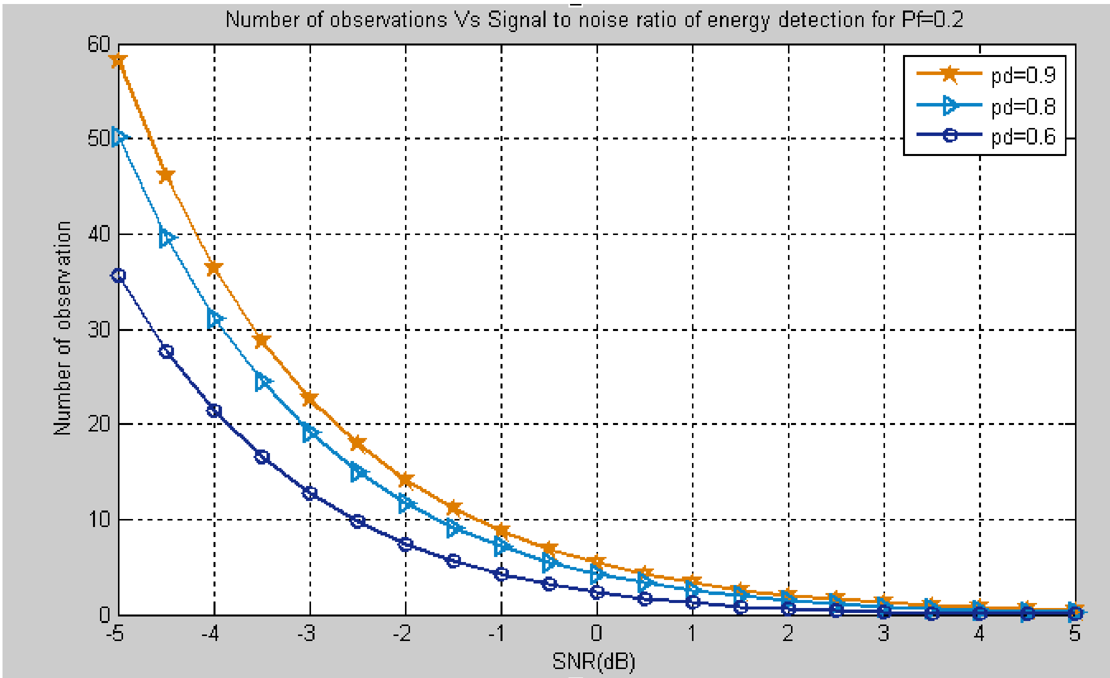


Figure 5.7: Number of samples versus signal to noise ratio of energy detector for different probability of detection (Pd=0.6, 0.8 and 0.9)

As can be seen from the simulation result of Fig.5.7, number of samples required for detection is inversely proportional to the SNR and the detector needs large observation to have better performance in probability of detection for lower signal to noise ratios. In other words if the signal to noise ratio level of received signal is higher, the detector requires smaller number of observations or samples. The simulation is carried out for the probability of false alarm of 10% which is acceptable to the primary users.

5.2 SIMULATION RESULTS AND DISCUSSIONS FOR ENERGY AND REPLICA CORRELATION DETECTOR UNDER AWGN AND RAYLEIGH FADING CHANNELS

In this section simulation results for the performance evaluation of energy and replica correlation detector algorithm under AWGN and Rayleigh fading channels are presented. All the performance evaluations are carried out for the simulation parameters shown in the Table 4.

Fig.5.8 and 5.9 are produced out to show the probability of detection and miss detection of both energy and replica correlation detector algorithm under AWGN for SNR=-10dB. As can be shown from the simulation results, replica correlation detector got better performance in probability of detection and probability of miss detection. This is because of the known signal is correlated with the received signal at the receiver in the case of replica correlation detector.

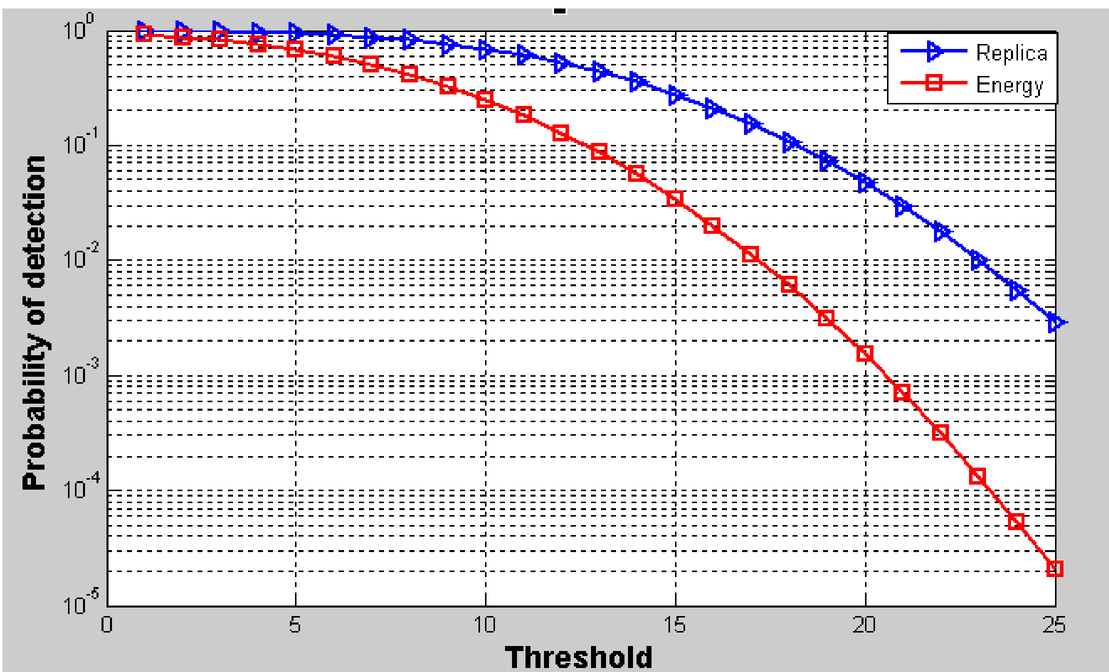


Figure 5.8: Probability of detection of energy and replica correlation detector under AWGN

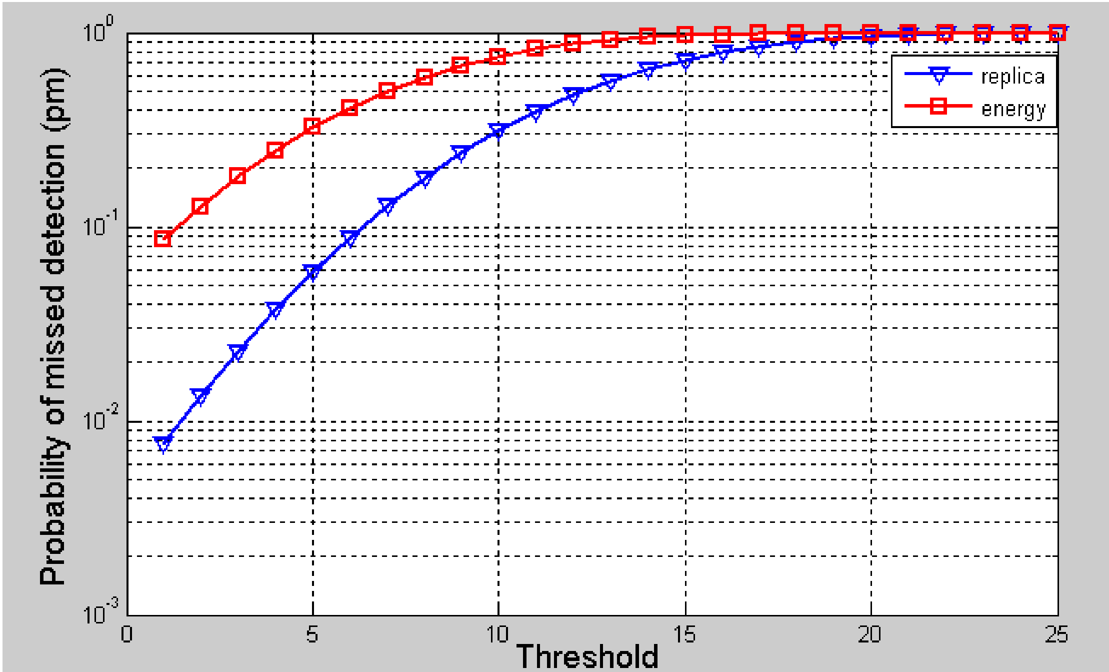


Figure 5.9: probability of miss detection of energy and replica correlation detector under AWGN

The probability of detection is a critical performance measure for spectrum detection. In particular, the introduction of cognitive radio techniques into the future spectrum regulatory framework requires taking the primary user system's view point if the systems are to be deployed on the same spectrum bands. Then it is critical how often the primary user of the spectrum tolerates failures in detection by the cognitive radio system, i.e. sources of potential interference to the primary user. For this we predict that the time between failures in detection also becomes the crucial parameter. The time between failures in detection sets the requirements for the performance of spectrum sensing techniques in terms of probability of detection. This is because the time between failures in detection depends on the probability of detection that should be made very high.

Therefore the simulation of Fig. 5.10 is produced to show time between failures in detection versus probability of detection for both energy and replica correlation detector. As one can see the result, when we got better performance in the probability of detection the time between failures in detection will drop and the replica correlation detector algorithm gives better performance.

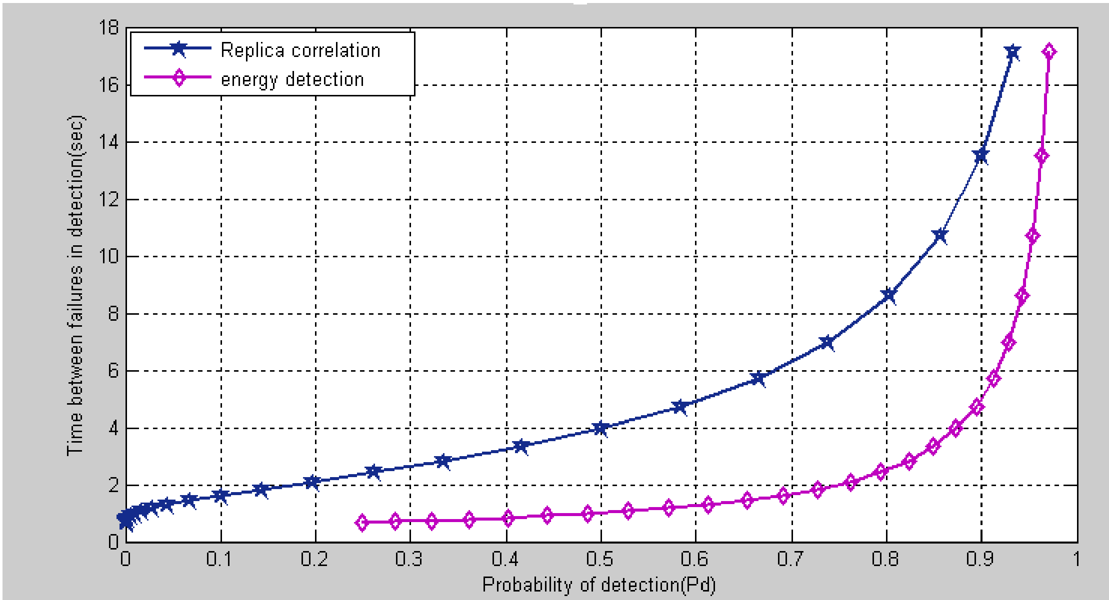


Figure 5.10: Time between failures in detection versus probability of detection of energy and replica correlation detector

The performance results of energy and replica correlation detector algorithm using probability of detection (Pd) and probability of miss detection (Pm) under both AWGN and Rayleigh fading channel for SNR=5dB are presented in Fig 5.11 and 5.12.

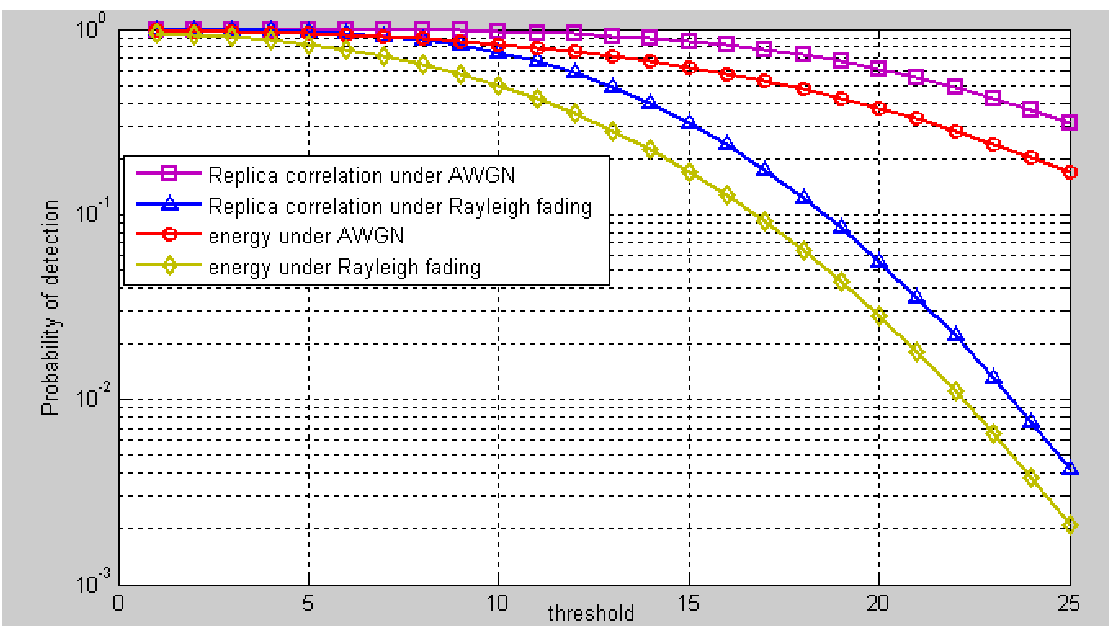


Figure 5.11: Performance of energy and replica correlation detector using probability of detection under both AWGN and Rayleigh fading channel (SNR=5dB)

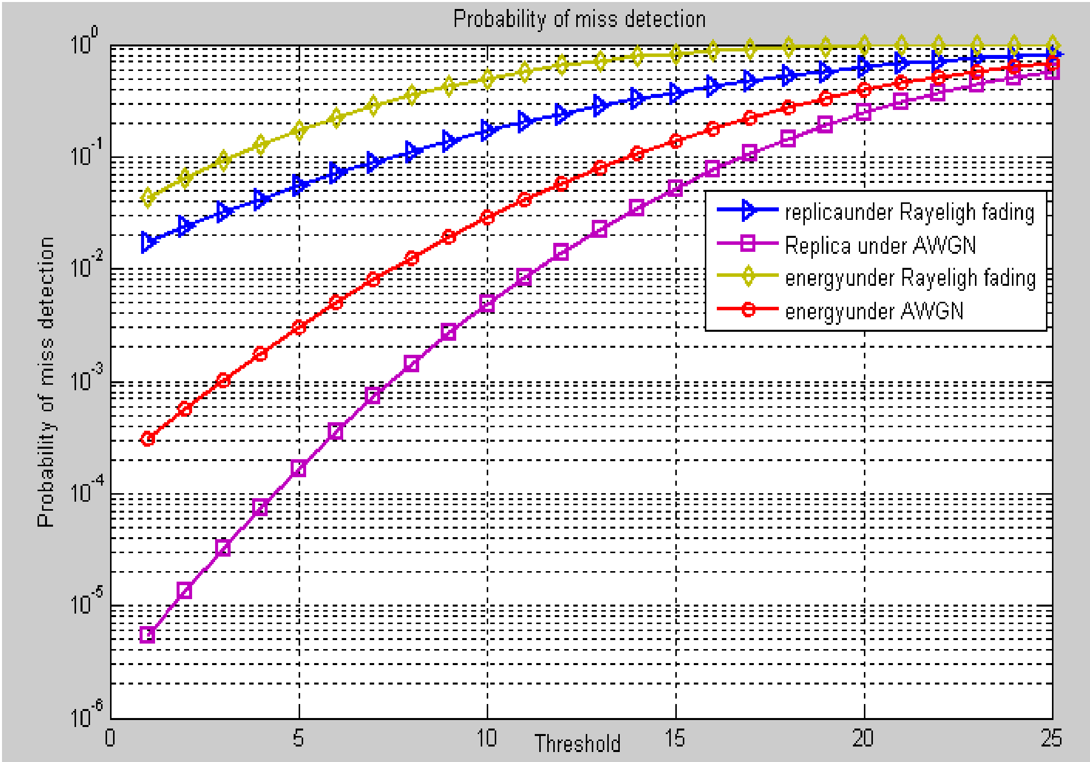


Figure 5.12: Performance of energy and replica correlation detector using probability of miss detection under both AWGN and Rayleigh fading channel (SNR=5dB)

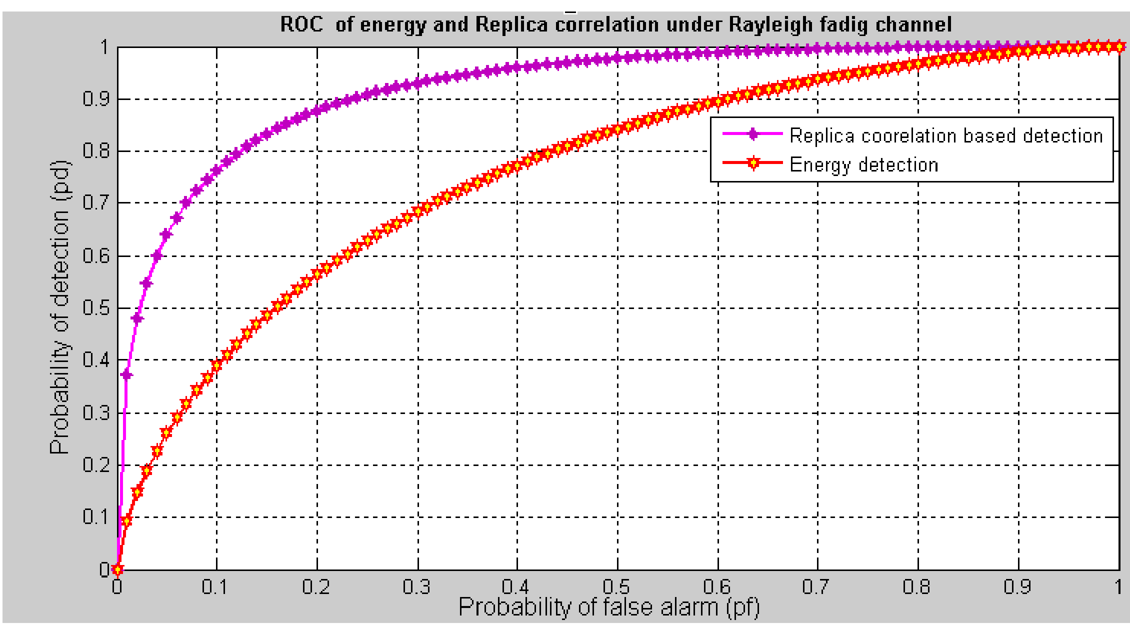


Figure 5.13 Simulation result of Receiver Operating Characteristics (ROC) of single node energy and replica correlation based detection under Rayleigh fading channel for SNR=2dB.

The plot in Fig. 5.13 shows the simulation result of receiver operating characteristics (ROC) of energy and replica correlation detector under Rayleigh fading channel for SNR of 2dB. As one can see from the result, the performance of the detectors at acceptable probability of false alarm (Pf= 0.1) is low. Especially energy detector is highly affected by the Rayleigh fading channel. In general, in an environment with Rayleigh fading single node detection are not sufficiently reliable for dynamic spectrum utilization. That means the sensing performance in Rayleigh fading channel is significantly lower compared to the AWGN channel.

5.3 SIMULATION RESULTS AND DISCUSSIONS FOR COOPERATIVE DETECTOR UNDER AWGN AND RAYLEIGH FADING CHANNEL

In this section, simulation results for energy detector based cooperative detection and replica correlation based cooperative detection algorithm are presented.

Before evaluating the performance of the detectors using various metrics, first the simulation result for the probability of detection of general cooperative detector algorithm with respect to probability of detection of single node for both "OR" and "AND" rules are presented in Fig.5.14. At some fixed value of single node probability of detection, probability of cooperative detection with more nodes of "OR "rule is better than single node and multiple nodes with "AND" rule.

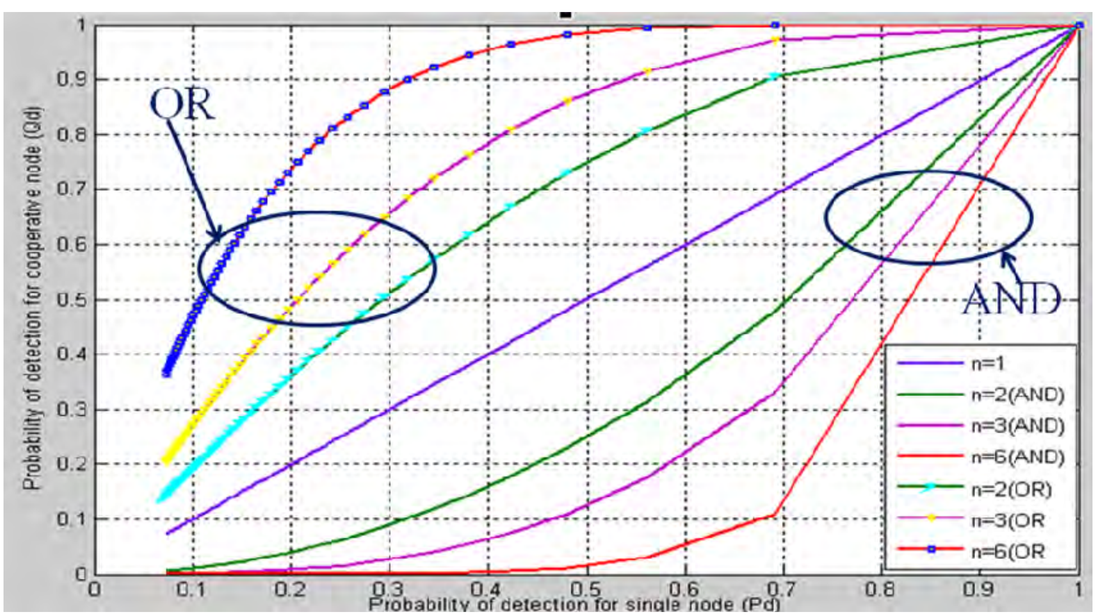


Figure 5.14: Probability of cooperative detection versus probability of single node detection for "OR" and "AND" Fusion

In the low SNR regime, the energy detector is highly vulnerable to fading and fluctuations in the level of the noise power. What if, instead of employing the energy detector at one location, we could do the same thing in other locations as well? It is expected that among several secondary receivers, even though some will suffer from fading, some will be able to correctly detect the medium. These concepts are verified by simulation results that compare the probability of detection, probability of miss alarm, receiver operating characteristics and complementary receiver operating characteristics of energy detector and cooperative detector algorithm.

The simulations for Fig 5.15, 5.16 and 5.17 are carried out for SNR value of -10dB for energy based cooperative detector algorithm under Rayleigh fading channel. The number of secondary nodes used for cooperation are Ns=n=2, 3, 4 and 10. These results are done by using both OR and AND- rule fusion scheme. As can been seen from the simulation results, the cooperative detector delivers better performance even at low signal to noise ratio level and the OR rule fusion scheme delivers better performance. Whereas, Fig.5.18 shows simulation result of probability of detection versus threshold for replica correlation based cooperative detector (Ns=2) under Rayleigh fading channel for the SNR level of -10 dB.

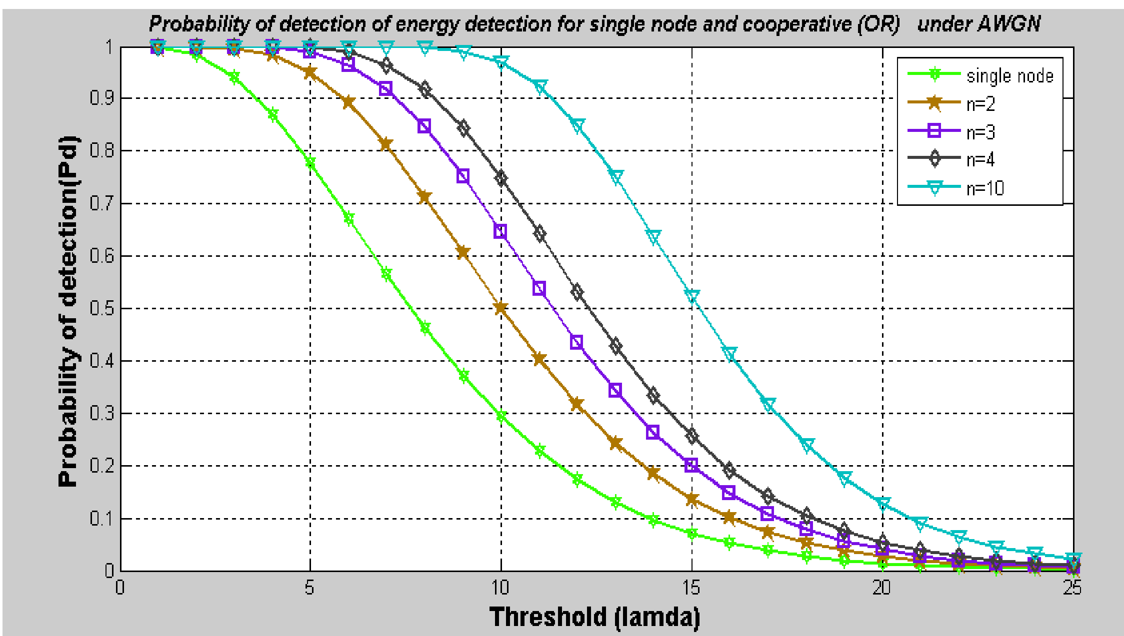


Figure 5.15: performance of energy and its cooperative detection for different number of secondary users (nodes) using “OR” rule fusion scheme

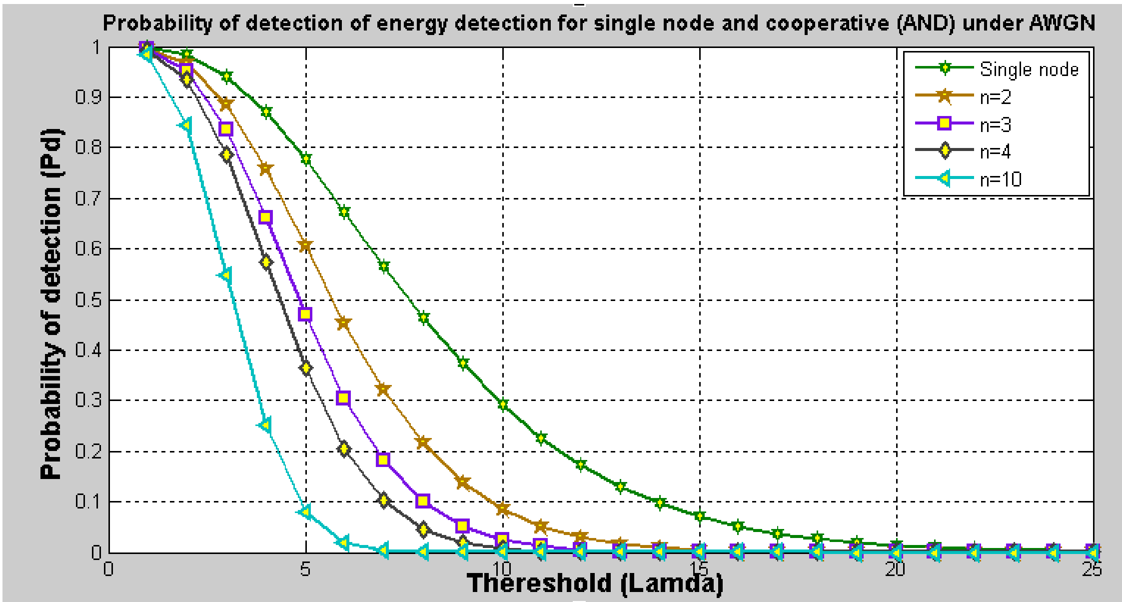


Figure 5.16 performances of energy and its cooperative detection for different number of secondary users (Ns=n=1, 2, 3, 4 and 10) using “AND” rule fusion scheme

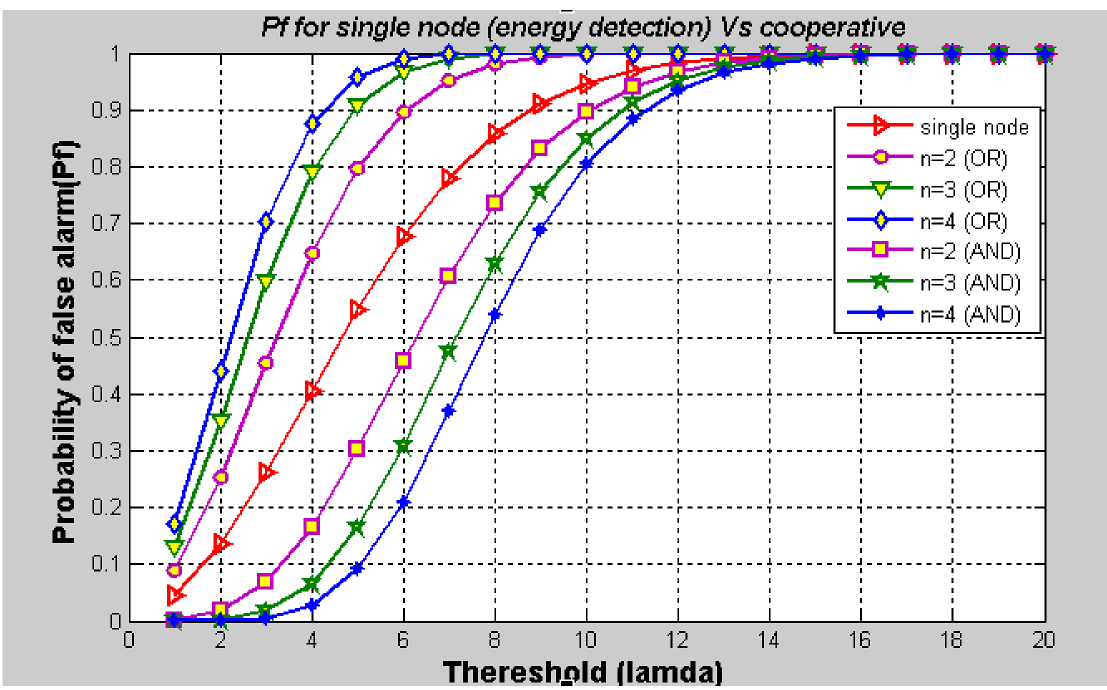


Figure 5.17 performance of energy and its cooperative detection for different number of secondary users (Ns=n=1, 2, 3 and 4) for both “OR” and “AND” rule fusion scheme

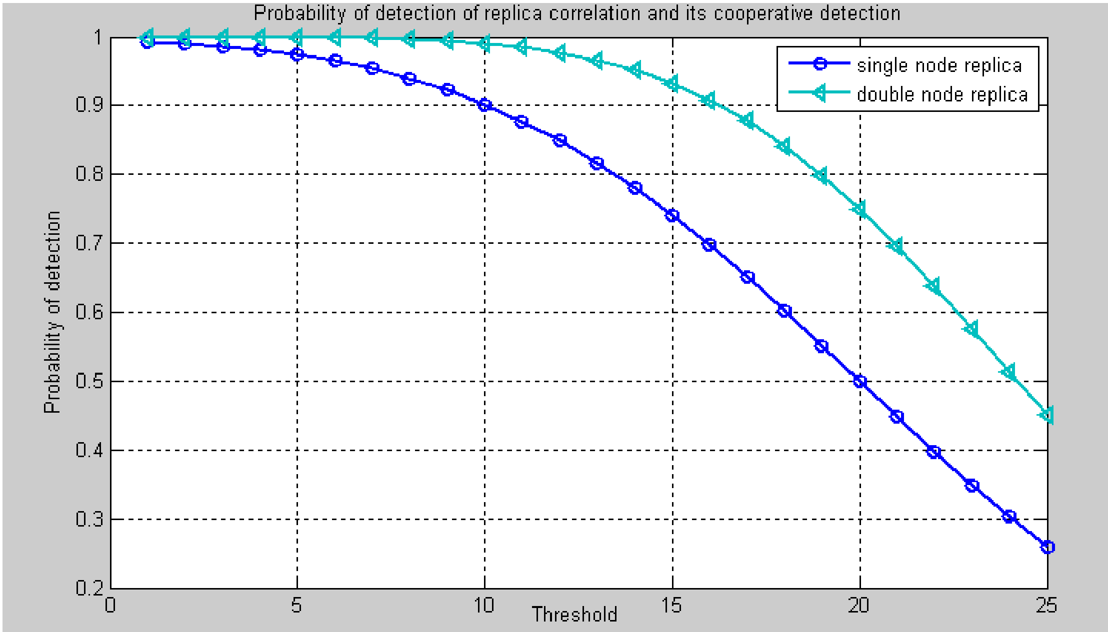


Figure 5.18: probability of detection of replica correlation and its cooperative under fading channel (SNR=-10dB)

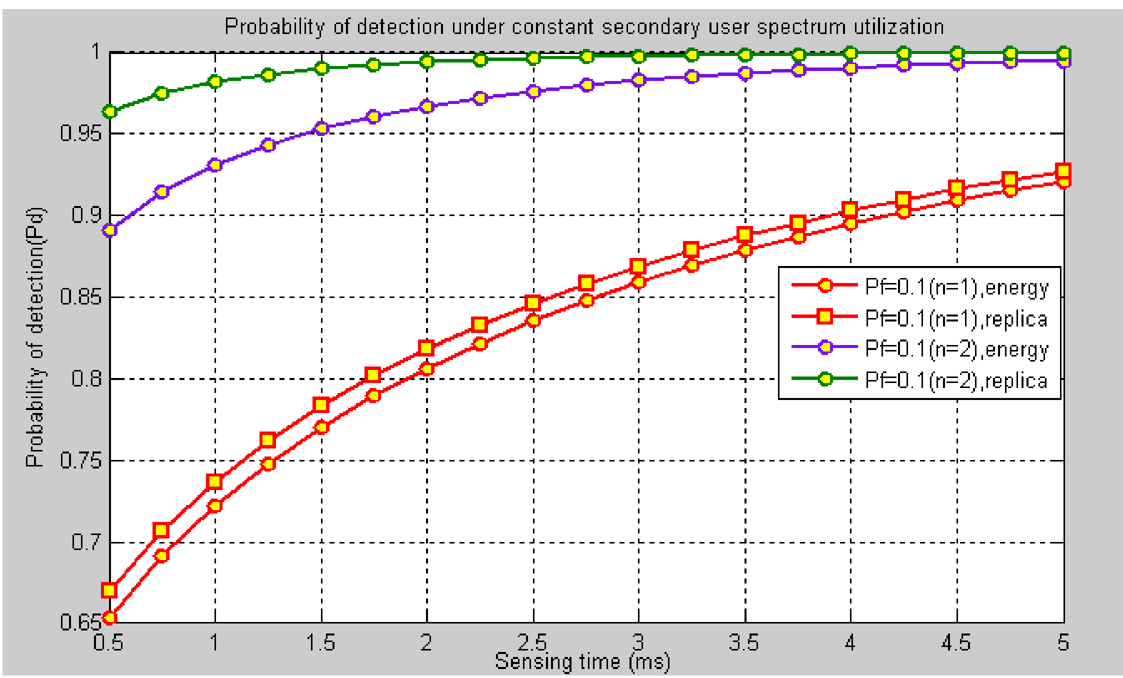


Figure 5.19 Plot of probability of detection versus sensing time for the three detector algorithms ("OR" rule fusion scheme, Ns=2).

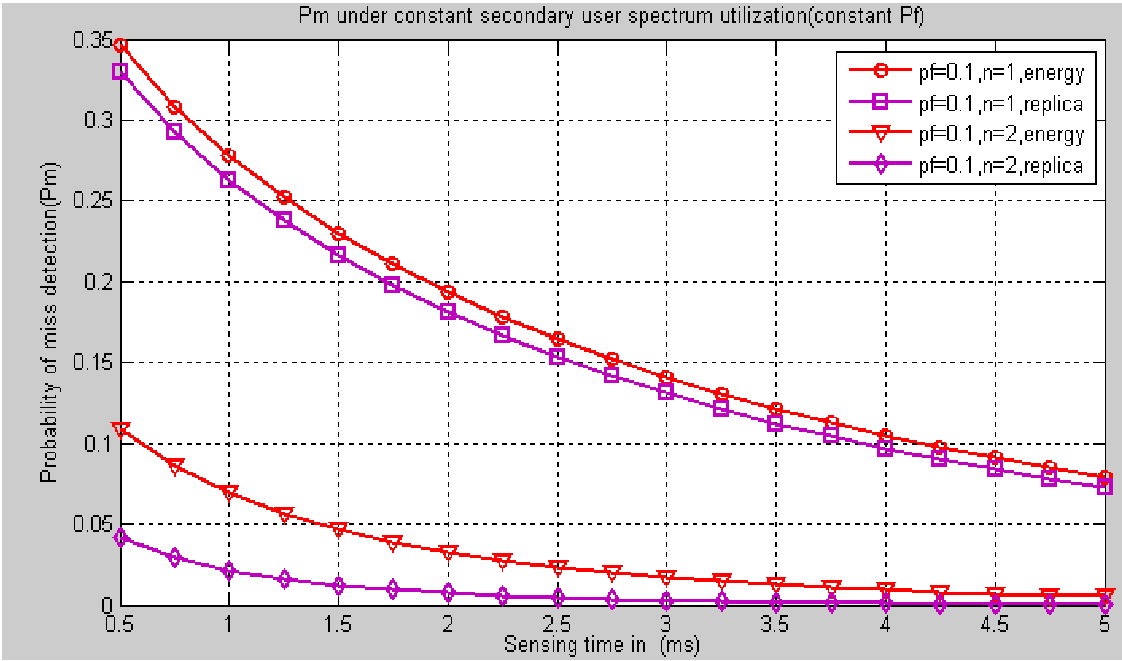


Figure 5.20: Plot of probability of miss detection versus sensing time for the three detector algorithms ("OR" rule fusion scheme, Ns=2)

Classical detection theory suggests that degradation in probability of detection or receiver operating characteristics can be countered by increasing the sensing time. But it is possible to achieve better performance using cooperative detection without increasing the sensing time and this concept is verified by results of Fig.5.19 and Fig 5.20. The simulation of Fig.5.19 and 5.20 are carried out for acceptable probability of false alarm, which is 10% , signal to noise ratio of -10dB and number of secondary nodes used for collaboration are two (Ns=n=2) for both energy and replica correlation based cooperative detector algorithms.

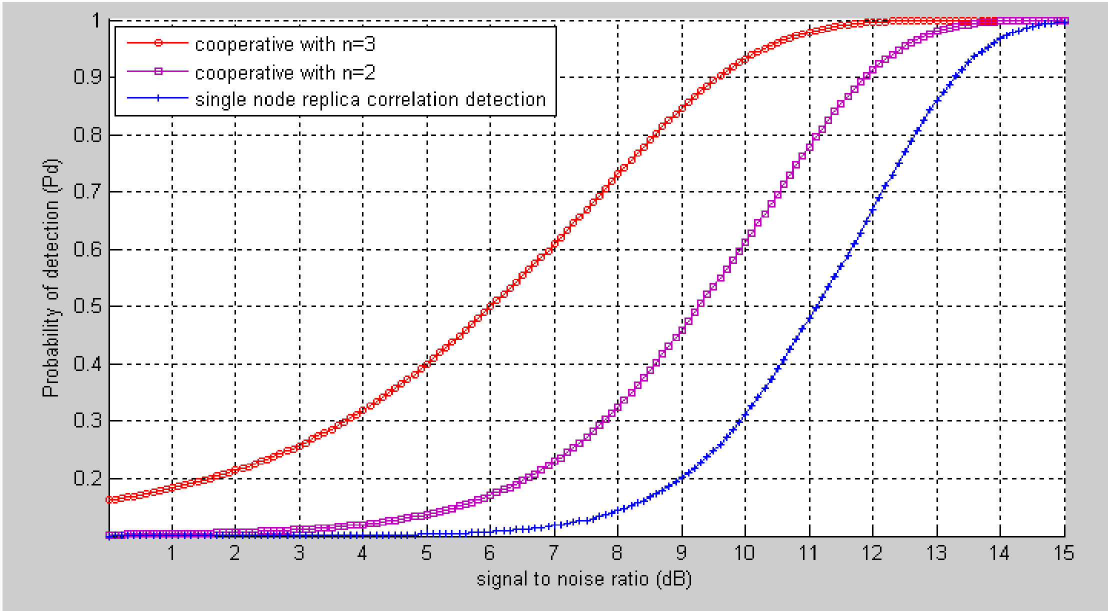


Figure 5.21 plot of Pd versus SNR for replica correlation and its cooperative detector (Rayleigh fading)

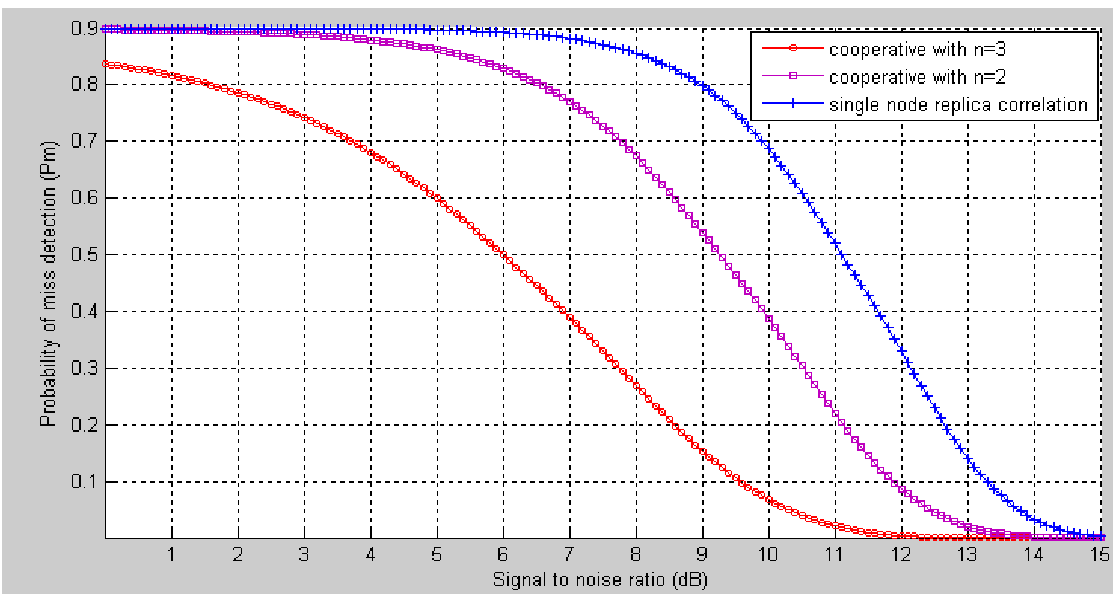


Figure 5.22 plot of Pm versus SNR for replica correlation and its cooperative detection (Rayleigh fading)

The above two results show probability of detection and miss detection versus SNR levels for single node replica correlation, two and three nodes replica correlation based cooperative detector under Rayleigh fading channel. As one can see the results, even if the performance of single node deteriorates for lower SNR value, collaboration of secondary users improves detection performance of the detector.

The performance by depicting the complementary receiver operating characteristic (CROC) for SNR of -6dB are simulated and shown in Fig.5.23, 5.24 and 5.25 for all types of detectors.

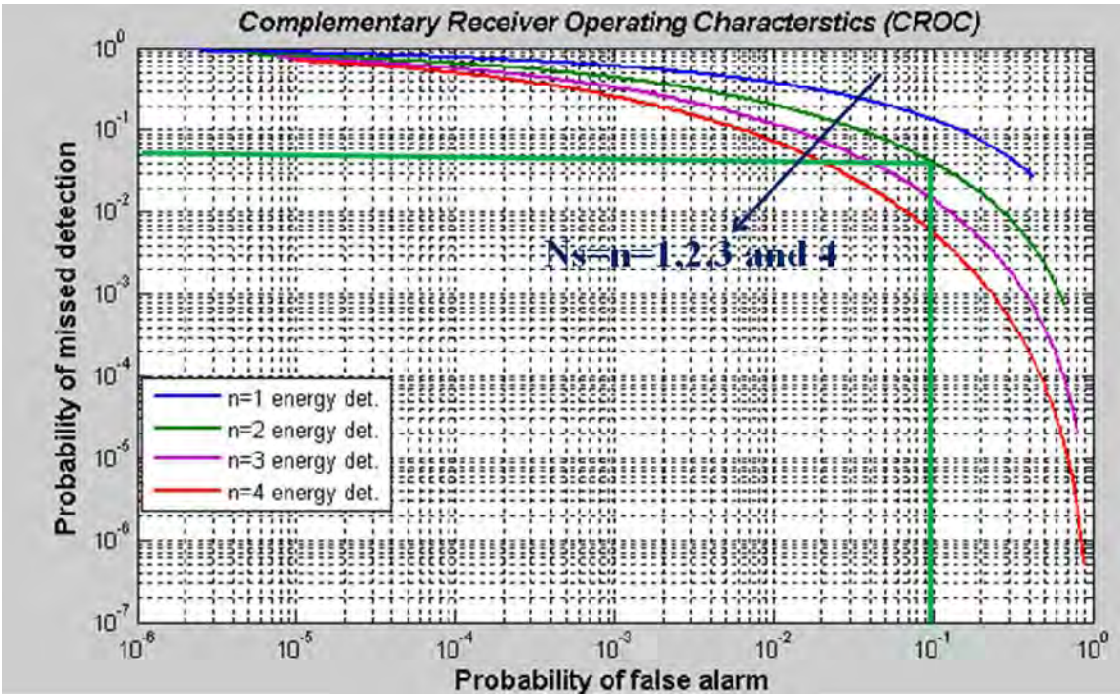


Figure 5.23 Plot of complementary receiver operating characteristics (CROC) of energy detector and its cooperative detector for an average SNR of -6dB (under fading)

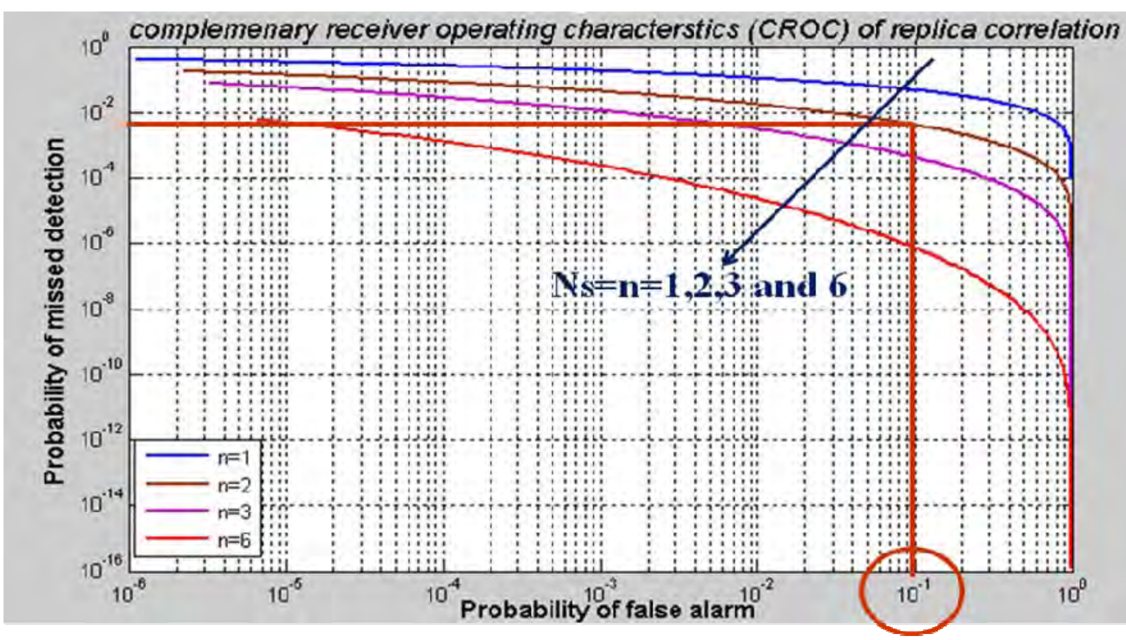


Figure 5.24 Plot of complementary receiver operating characteristics (CROC) of replica correlation detector and its cooperative detector for an average SNR of -6dB (under fading)

Fig.5.23 shows the complementary receiver operating characterises for energy and its cooperative detector and Fig.5.24 shows the CROC of replica correlation detector under Rayleigh fading channel.

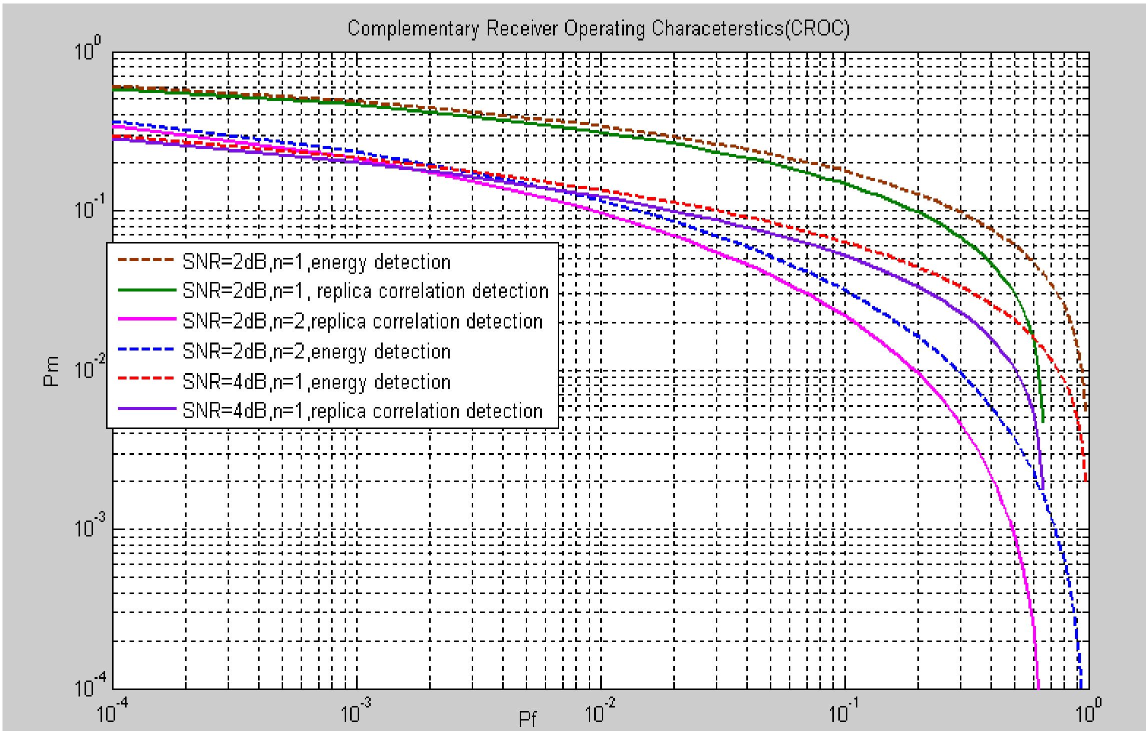


Figure 5.25: Complementary ROC performance comparison detector algorithms (Ns=n=1, 2 and SNR=2dB and 4dB).

From the above result (Fig.5.25), at p_f= 0.1 the P_m of double nodes replica correlation based cooperative detector is lower than double nodes energy detector based cooperative detector. This shows that the replica correlation based cooperative detection gives better performance. Because getting minimum probability of miss detection results better probability of detection.

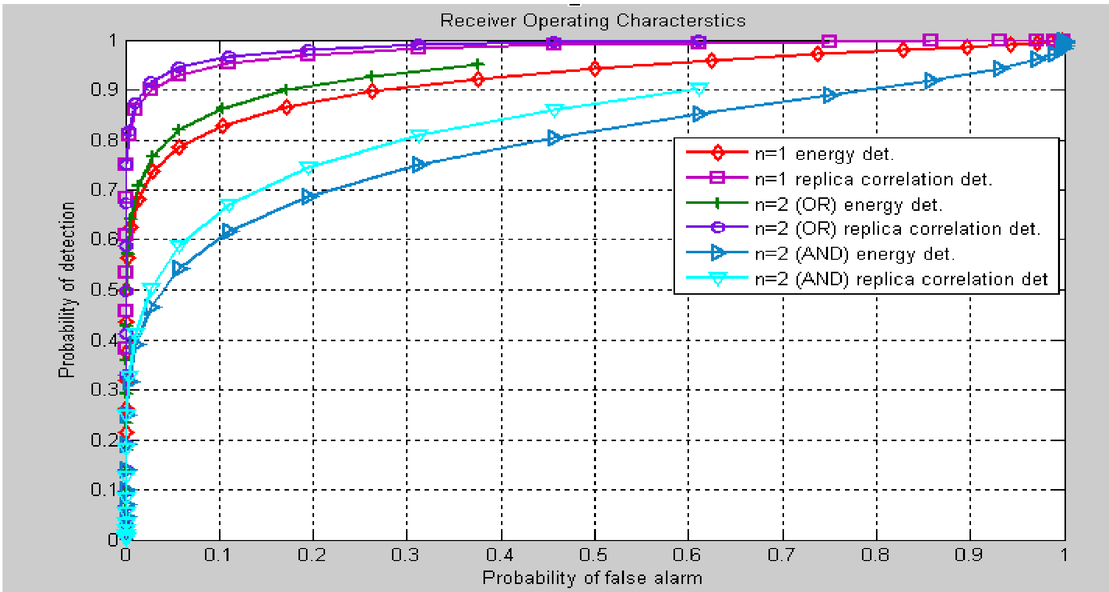


Figure 5.26: ROC performance of energy and replica correlation detection using OR and AND decision rules (SNR=-12dB)

In general, as can be seen from the simulation results for the performance of the cooperative detector under Rayleigh fading, the cooperative sensing (Ns>1) does increase the detection rate compared to its single user counter part and the performance enhancement largely depends on the number of cooperative users. Next we will see the performance of cooperative detector under AWGN.

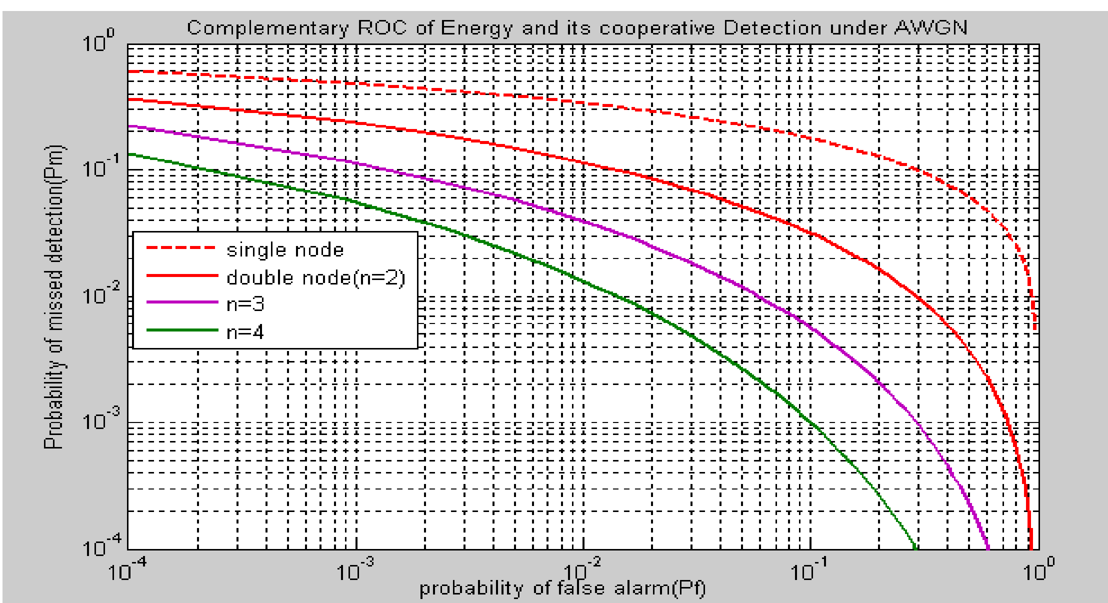


Figure 5.27 plot for Complementary ROC of energy detection algorithm and its cooperative detectors under AWGN channel (Ns=1, 2, 3 and 4, SNR=-10dB)

To quantify the different combinations of the probability of miss detection (Pm) and the probability of false alarm (Pf), we use a sliding threshold. The threshold is slid between the smallest and largest values of the output of the detector with a small step size and thus all combinations of Pm and Pf can be captured. The above result shows the complementary ROC curve that compares the detection performance of energy and its cooperative detection algorithm under AWGN. Therefore as the result indicates for the same probability of false alarm four secondary nodes cooperative detection gives small amount of probability of miss detection and this implies it delivers better probability of detection. For instance, for probability of false alarm=10^{-1}, Pm of single node energy detection is equal to $10^{-0.7}$ whereas Pm of three nodes cooperative detection is equal to 10^{-3} (which is smaller than the former Pm value).

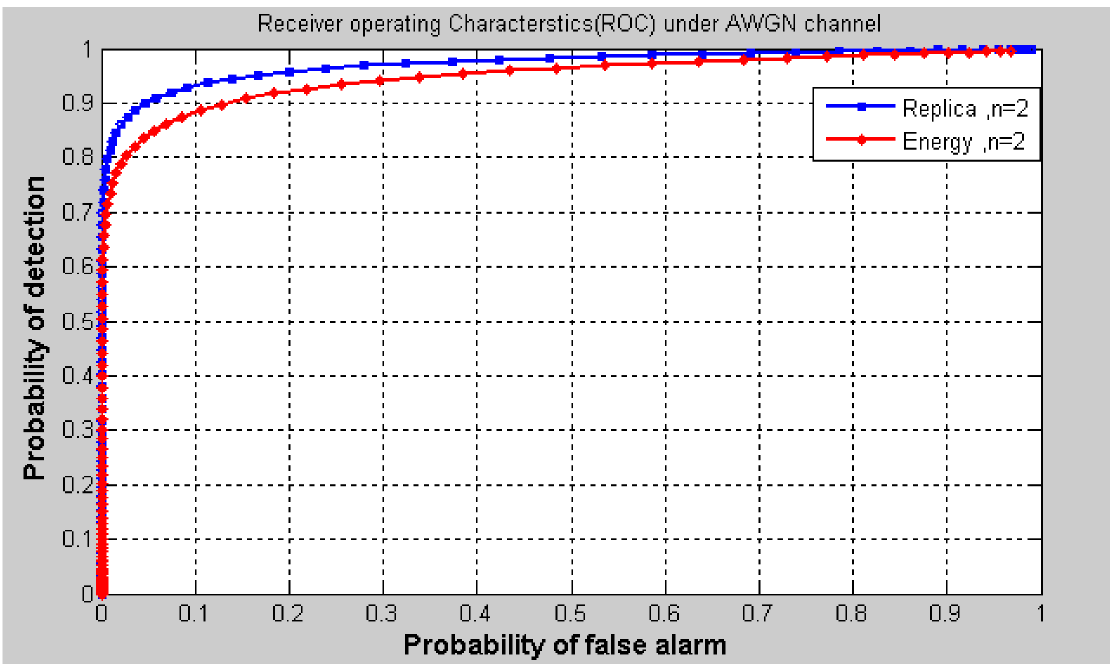


Figure 5.28 ROC of energy and replica correlation under AWGN for two sensing nodes

Performance of the energy detection and replica correlation detector are shown by Receiver Operating Characteristic (ROC) curves, which is a plot of the true positive rate(Probability of detection) versus the false positive rates (probability of false alarm) for two number of secondary nodes. As the plot indicates the performance of replica correlation is better than the energy detector.

5.4. SIMULATION RESULTS AND DISCUSSIONS OF DETECTORS UNDER NOISE UNCERTAINTY FACTOR

In simulating the previous results we assumed that the additive noise is white and Gaussian with zero mean and with known variance. However, the noise term is an aggregation of various sources including, not only thermal noise at the receiver and underlying circuits, but also interference due to nearby unintended emissions, weak signals from far away transmitters etc. Second, we assumed that noise variance is precisely known to the receiver, so that the threshold can be set accordingly. However, this is not possible as noise could vary over time. Therefore to show this effect we considered the noise uncertainty factor and the simulation results for the detection techniques with the consideration of noise uncertainty are shown below.

Clearly detector can be made to believe that the signal is present even when the signal is actually absent. On the flip side, it thinks that the signal is absent even when it is actually present. Thus, the following simulations clearly illustrate uncertainty in the noise to render the detector performance. Therefore to get correct detection parameter it is better to consider noise uncertainty factor. As one can see from Fig.5.29 and Fig.5.30, the complementary receiver operating characteristics for both energy and replica correlation detector gives some additional probability of miss detection at specific probability of false alarm for the detector with out the consideration of noise uncertainty factor.

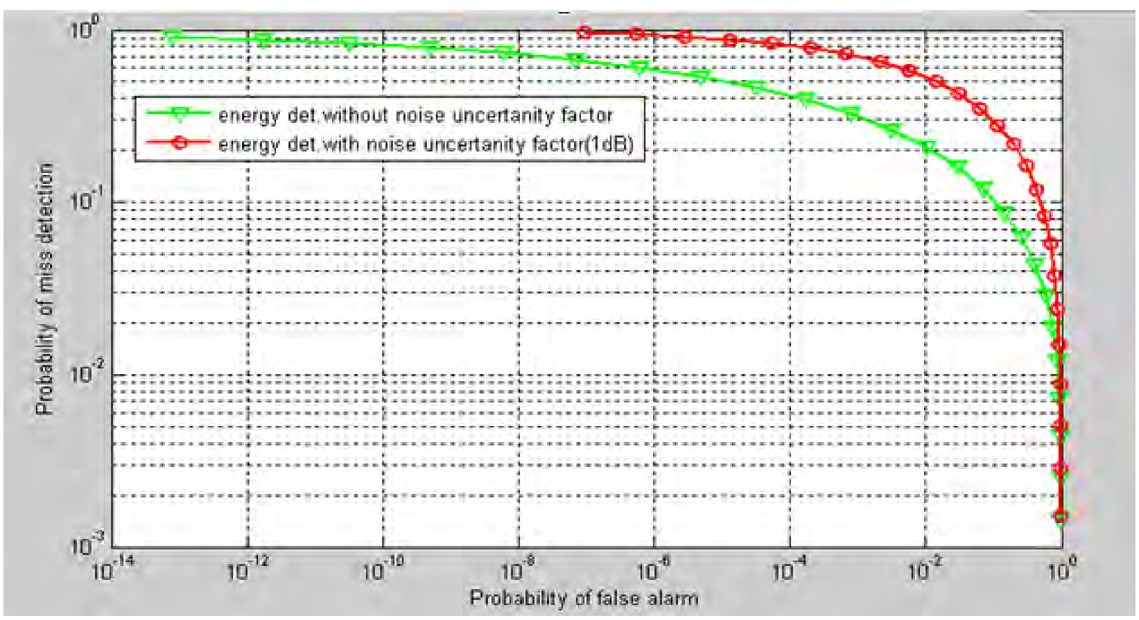


Figure 5.29: plot of complementary receiver operating characteristics energy detector under consideration of noise uncertainty factor (Rho=1dB)

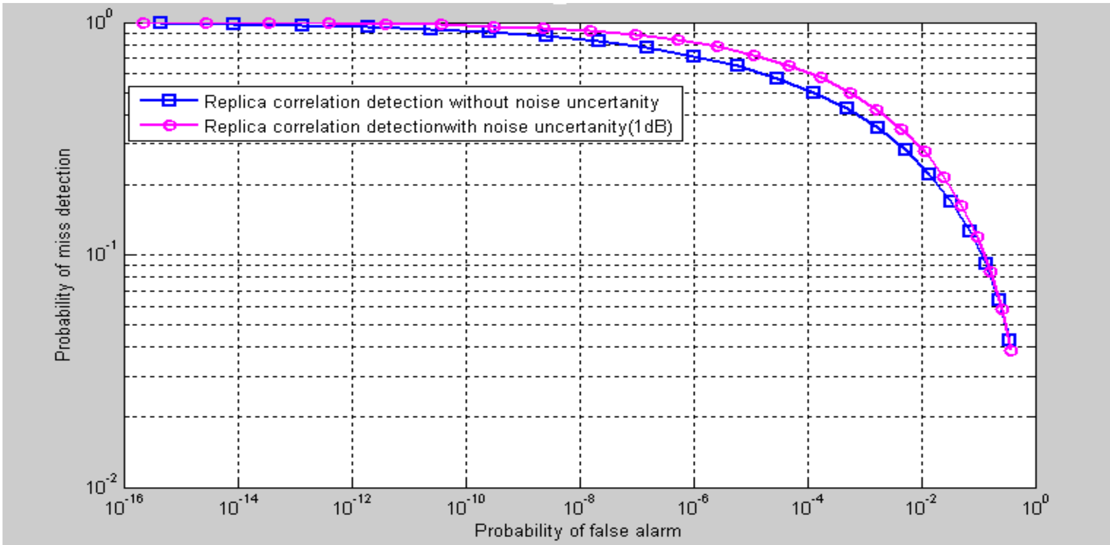


Figure 5.30 plot of complementary receiver operating characteristics replica correlation detector under consideration of noise uncertainty factor (Rho=1dB)

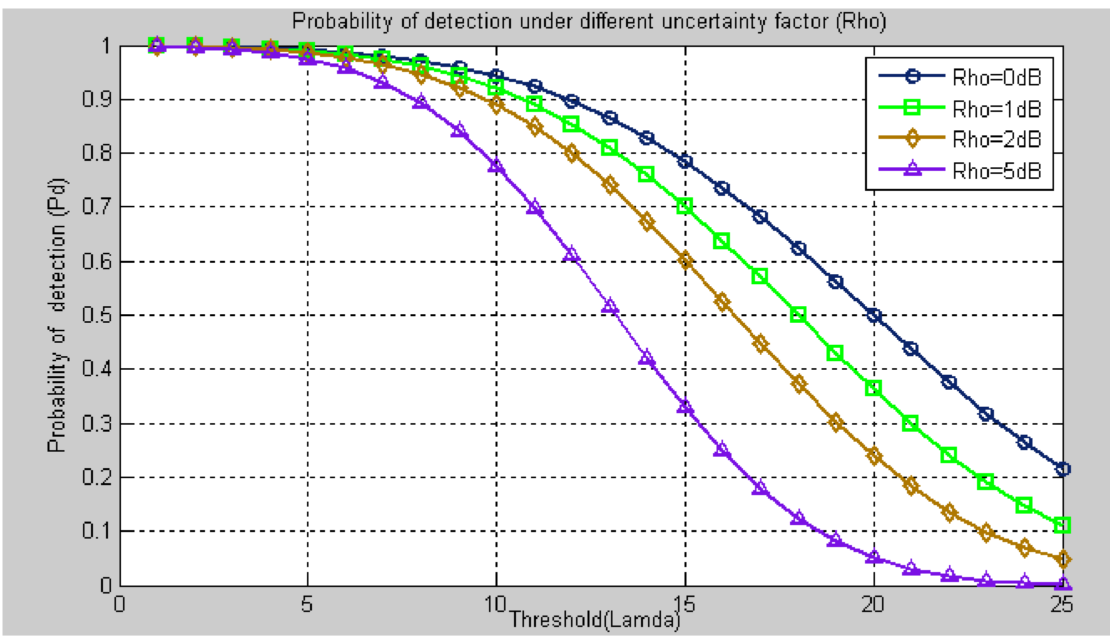


Figure 5.31: Probability of detection of energy detector under various noise uncertainty factors (Rho=0dB, 1dB, 2dB and 5dB)

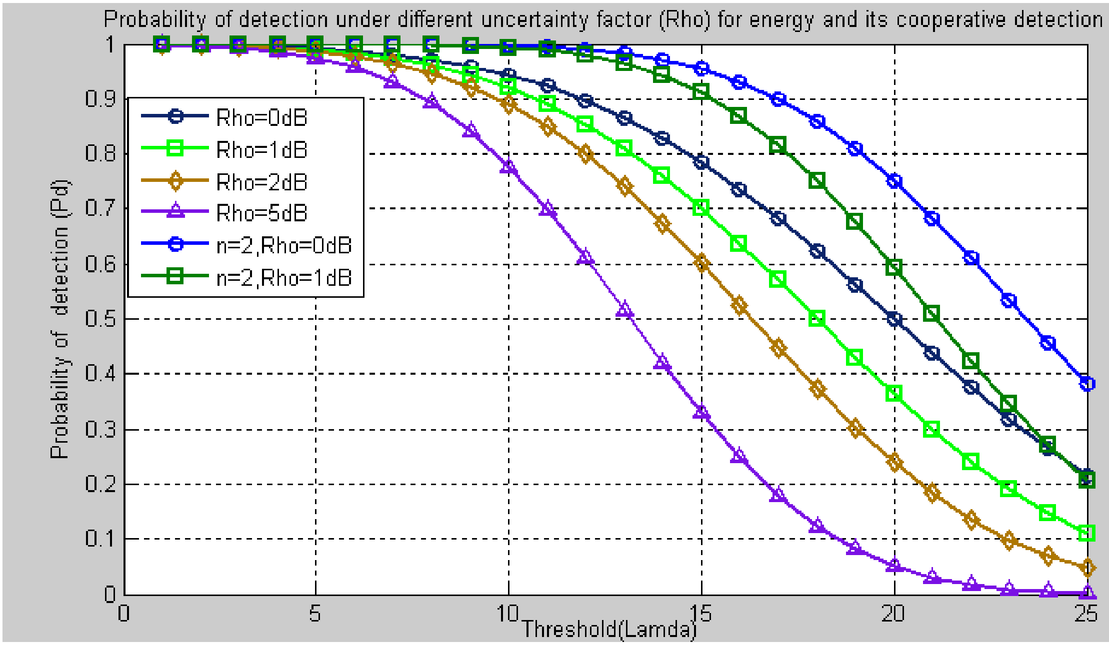


Figure 5.32: Probability of detection of energy detector and its cooperative detection with noise uncertainty factor of Rho=0 and 1dB.

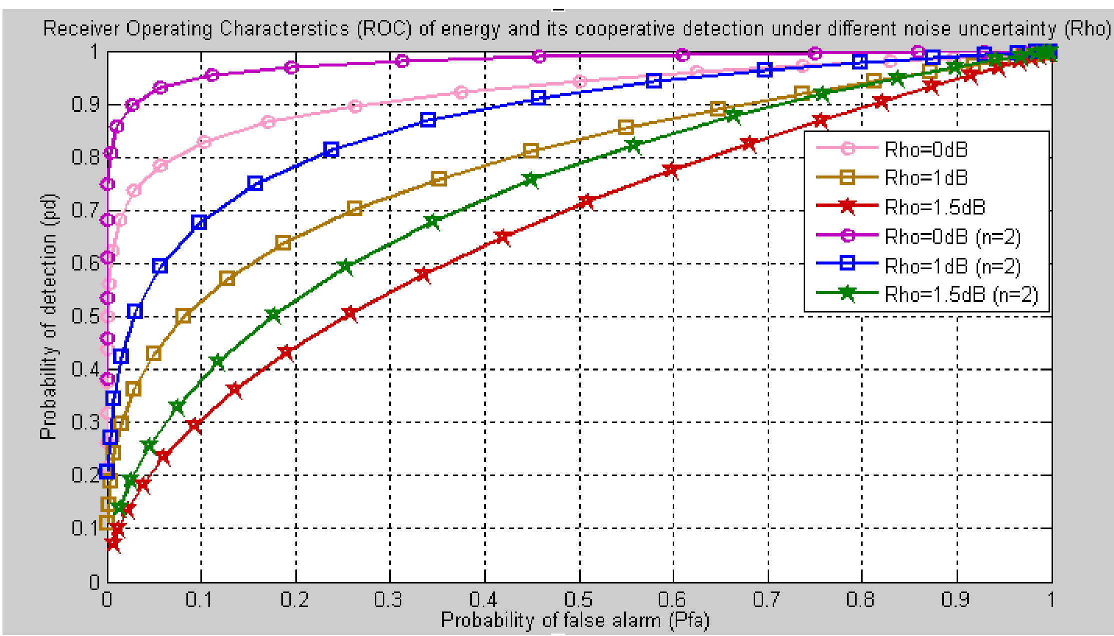


Figure 5.33: ROC of energy detector and its cooperative detector with noise uncertainty factor

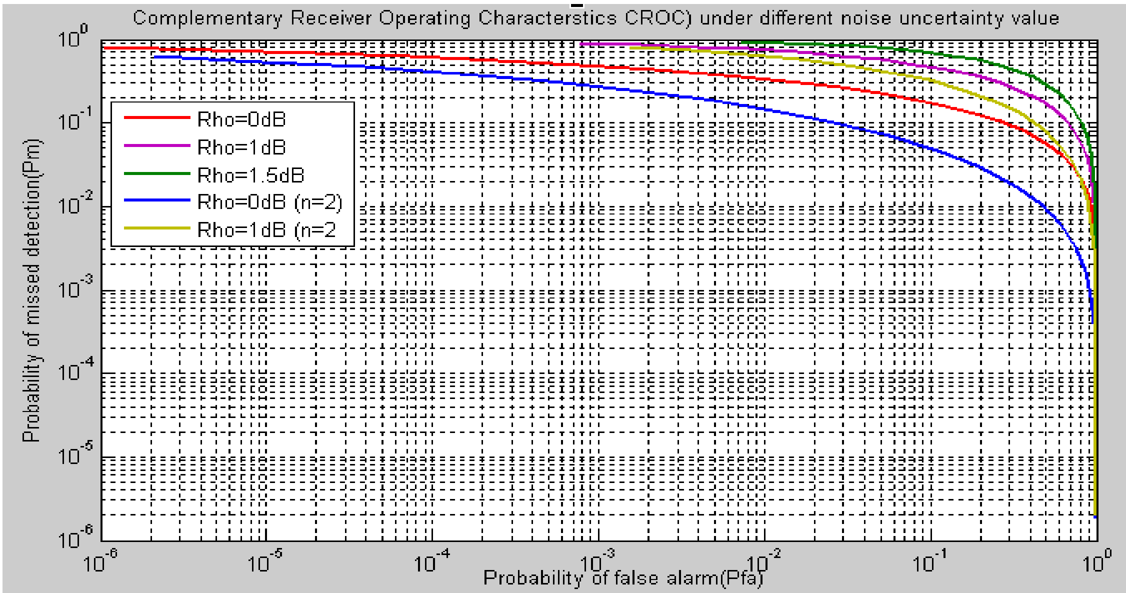


Figure 5.34: Complementary ROC performance comparison between energy its cooperative detection for different noise uncertainty factor (ρ=Rho=0dB,1dB and 1.5dB).

The above results show the effect of noise uncertainty on the performance of detectors. For instance the Rho = 0dB, the result shows without consideration of noise uncertainty. But as the value of noise uncertainty factor increases, the performance degrades. It can be seen clearly seen from the results that cooperative detection improves the performance of single node detection. Fig.5.35 shows the receiver operating characteristics for the three detector algorithms under the consideration of noise uncertainty factor 1dB.

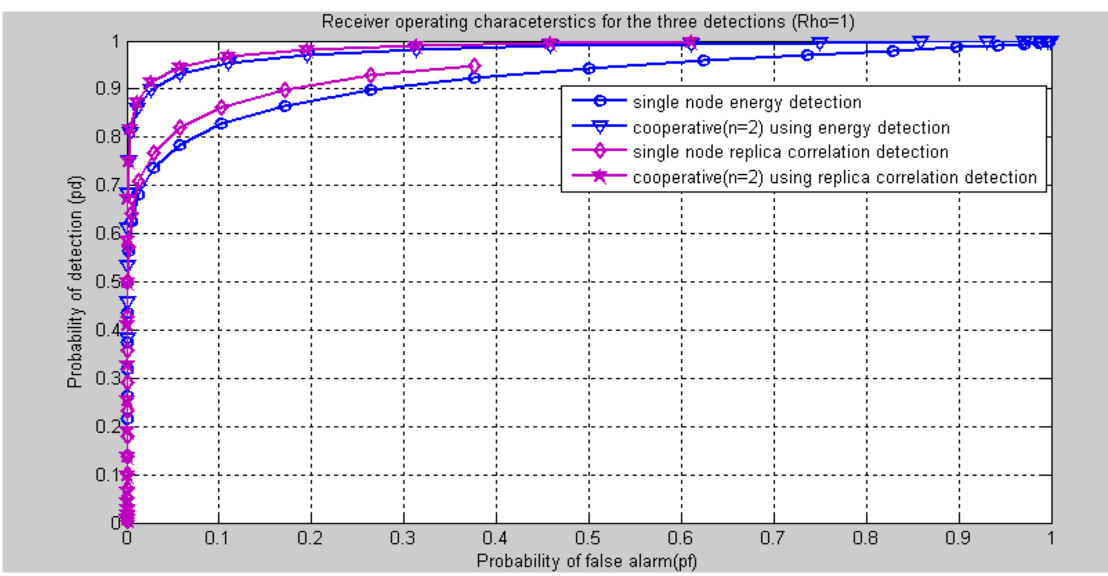


Figure 5.35: ROC performance comparison between energy, replica correlation and cooperative detector for noise uncertainty factor of 1dB.

5.5. SIMULATION RESULTS FOR ENHANCED DETECTION

The following simulations carried out to show the performance enhancement for the energy detector algorithm by using cross correlation of time shifted signal observations. The simulations are carried out for both AWGN and Rayleigh fading channel using SNR of 2dB.

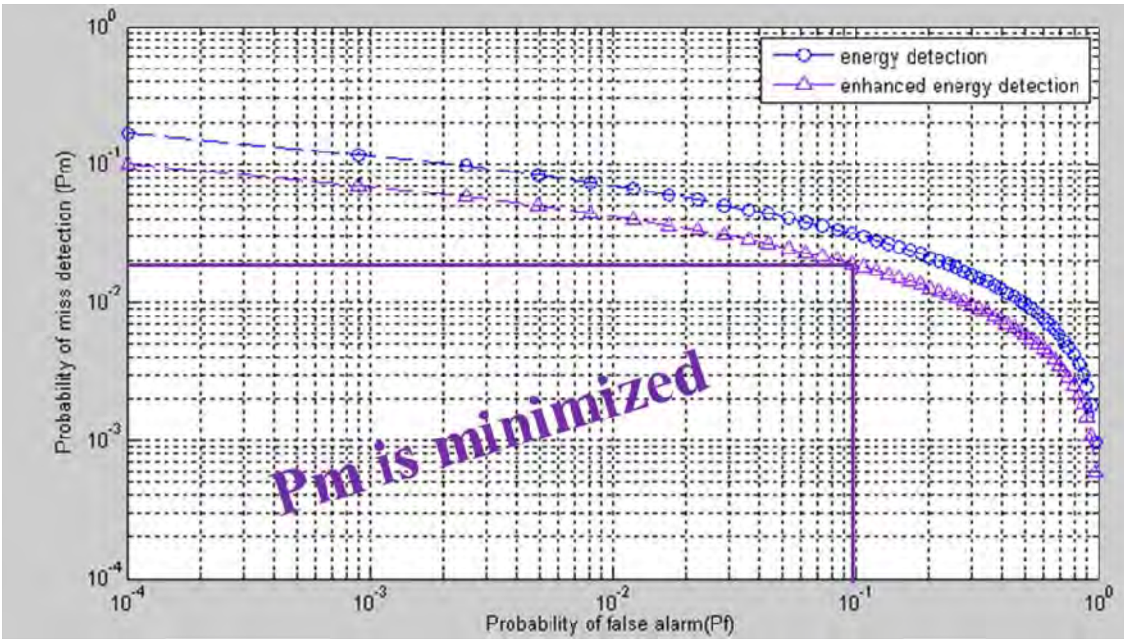


Figure 5.36: CROC performance of energy and enhanced energy detector Under AWGN

As we can see from the above simulation, the cross correlation based energy detector has improved the performance of energy detector. That means it is possible to got minimum probability of miss detection which results better performance by delivering greater probability of detection.

The simulations shown in Fig.5.37 and Fig.5.38 are simulated under Rayleigh fading channel. Both receiver operating characteristics and complementary receiver operating characteristics show the performance of energy detector is enhanced.

The noise-square term in square law energy detector is replaced by the product of two non-overlapping segments of noise term for the enhanced algorithm. Notice that the decision statistics of enhanced energy detector has a noise-noise term $n(t)n(t + Ts)$ inside the integral of equation 4.55, which causes little increase in the noise floor due to the independence between shifted noise terms, thus resulting in better detection quality.

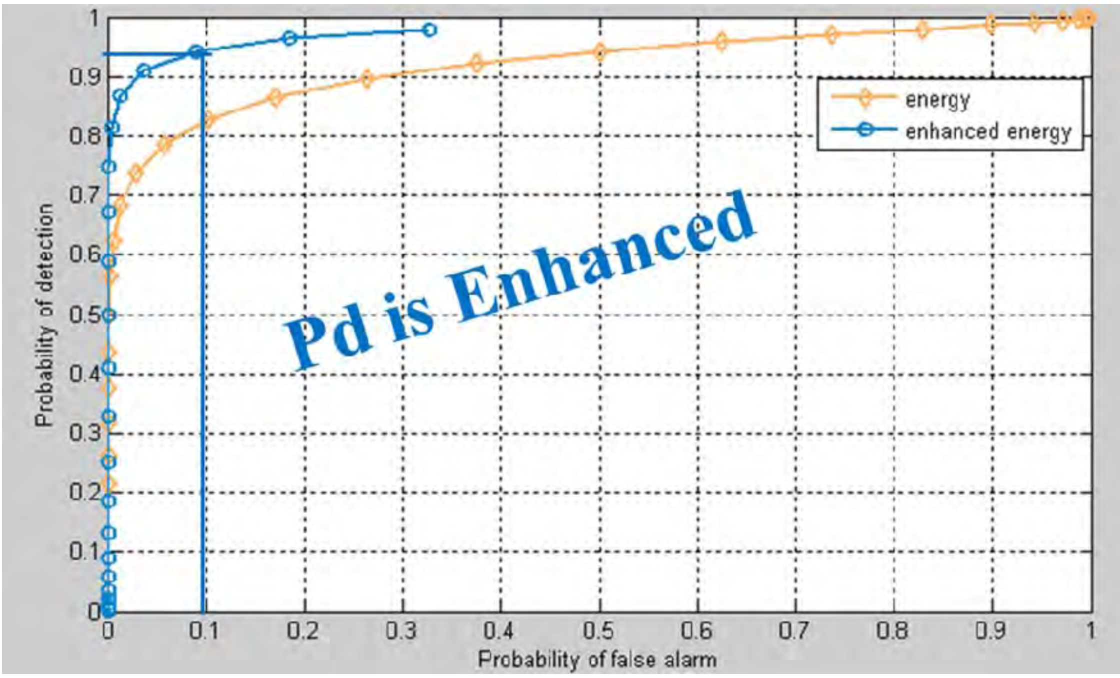


Figure 5.37: ROC performance of energy and enhanced energy detection Under Rayleigh fading channel.

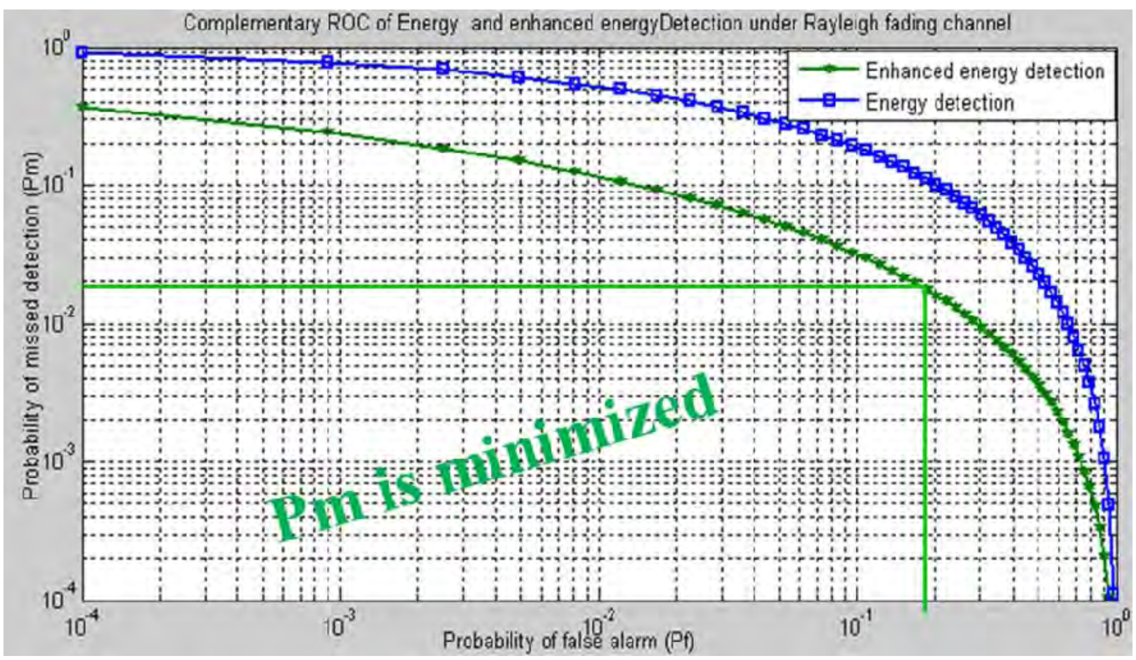


Figure 5.38: CROC performance of energy and enhanced energy detection Under Rayleigh fading channel

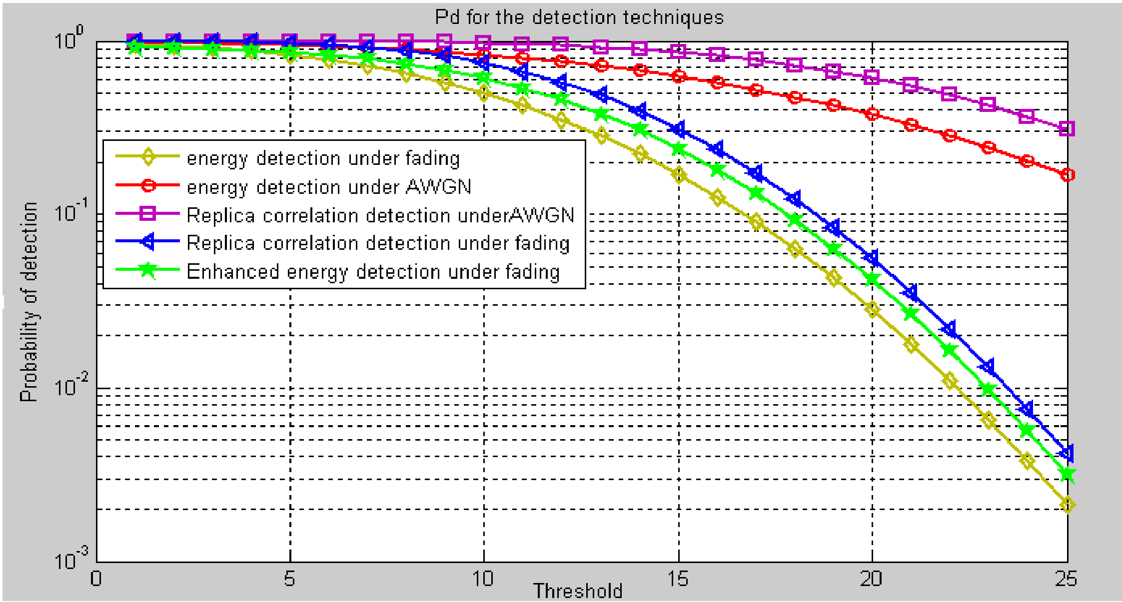


Figure 5.39: Probability of detection versus threshold for the detectors under AWGN and Rayleigh fading channels (SNR=-10dB)

The above figure indicates the simulation results for energy, replica correlation and enhanced energy detector under both AWGN and Rayleigh fading channels. As one can see the enhanced energy detector has better probability of detection than traditional energy detector.

Fig.5.40 indicates probability of miss detection of energy and enhanced energy detector under AWGN for probability of false alarm of 1%.

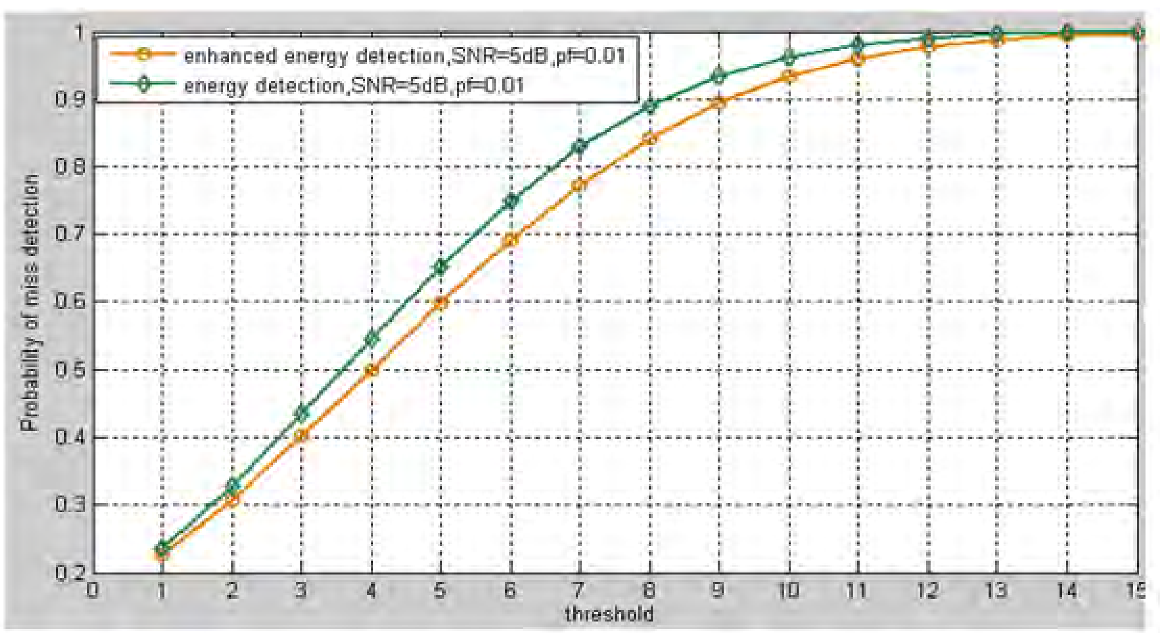


Figure 5.40: Probability of miss detection versus threshold for the detectors under AWGN (SNR=5dB and P_f=1%)

Table 5 summary of results for the detector algorithms

N0.	**Energy detector Algorithm**	**Replica correlation detector Algorithm**	**Cooperative detector Algorithm**
1	Low in complexity	Low in complexity	♣ higher in complexity ♣ higher cost ♣ higher power consumption
2	Its probability of detection is less than the other two detection techniques under both AWGN and Rayleigh fading channel	It has better probability of detection than energy detector, especially under Rayleigh fading channel.	Higher spectrum efficiency and it is the best option for faded environment
3	More susceptible for noise uncertainty	Less susceptible for noise uncertainty	Reduces the effect of noise uncertainty
4	Lower performance with in fixed sensing time	Better performance with in fixed sensing time than energy detector	Better sensing accuracy (OR-rule fusion scheme delivers better performance)
5	No need of prior-information of the primary signal	Needs prior-information of the signal	No need of prior-information for energy detector based cooperative detector.
6	No need of reporting overhead	No need of reporting overhead	Needs reporting overhead
7	Delivers poor receiver operating characteristics performance for lower signal to noise ratio level	Delivers medium receiver operating characteristics performance for lower signal to noise ratio level	Delivers better receiver operating characteristics performance even at low signal to noise ratio level

CHAPTER 6: CONCLUSION AND RECOMMENDATION

6.1 CONCLUSION

In this thesis we have discussed about a radio or system that senses and is aware of its operational environment and can be trained to dynamically and autonomously adjust its radio operating parameters accordingly. This radio is known as cognitive radio. However, a common assumption regarding cognitive radios is that they are unlicensed spectrum users that should avoid interference with the licensed primary users. Effective detection of primary users is the major issue of cognitive radio was to use the existing traditionally allocated spectrum in an opportunistic way. Thus, one of the important elements of the cognitive radio is detecting the available spectrum opportunities. In general, we have discussed about cognitive radio and the issues in spectrum detection performance of detector algorithms under both AWGN and Rayleigh fading channel in order to minimize interference between primary users and cognitive users. The detection algorithms we have taken for performance evaluations are energy detector, replica correlation detector and cooperative detector algorithms. Different results that are used to evaluate the performance of the detectors have shown and in accordance to the obtained results the following conclusion are drawn from this thesis work.

- Energy detector drops its performance for lower signal to noise ratio value and this performance are shown by probability of detection, miss detection and receiver operating characteristics. But to reduce the chance of interference with the primary users, an increase in probability of detection is needed and this are performed by increasing number of samples, increasing sensing time and by incorporating more secondary users. Energy detector is low in complexity than other detectors
- The lowest signal to noise ratio that a detection algorithm is able to detect with reliability of probability of false alarm and probability of detection for a given primary user signal, sensing time is an important metric to characterise spectrum

sensing performance. We have seen that replica correlation detector needs a sensing time lower than energy detector.

- Due to fading, single node detection is unreliable and results in a high probability of missed detection than AWGN channel. Thus Rayleigh fading degrades the performance of single node energy and replica correlation detectors. The result shows cooperative detection is the best option for spectrum detection in fading environments and it is concluded that cooperative spectrum detection outperform single user energy detector and replica correlation detector but introduces additional communications overhead of decision fusion. The OR rule fusion scheme of cooperative detection delivers better performance
- In this paper, noise uncertainty has been shown to introduce considerable amount of degradation in the detection performance of energy and replica correlation. It has been shown that cooperative detection helps to reduce the effect of noise uncertainty factor in the overall detection performance of cognitive radio.
- Efficient detection of the available spectrum opportunities is an important element of cognitive radio. This thesis proposed a new enhanced energy detection algorithm method and its performance was compared with standard squared law energy detection algorithm. Simulation results indicate that the enhanced energy detection method has better performance than traditional energy detection algorithm.

6.2 RECOMMENDATION FOR FUTURE WORK

Cognitive radio technology has opened numerous areas for future work which could be done to better understand the performance of primary user detection using cognitive radio. Some of the areas are as follows:

- This thesis work is limited to performance evaluation on detection techniques under Rayleigh fading channel, Therefore performance evaluation under different Nakagami-m and Rician fading channel should be investigated.
- Performing Likelihood ratio test in a fading environment using channel estimation and different threshold value for the case of cooperative detection should be studied.
- Detection performance evaluation using variable threshold values for individual nodes of cooperative cognitive radio could be another research area.
- Cross correlation based weighted energy detection could be investigated

REFERENCES

[1] D.Cabric, S.M.Mishra, D.Willkom, Rbroderson, A.Wolisz “CORVUS: a cognitive radio approach for usage of virtual unlicensed spectrum” July 29, 2007.

[2] Federal communications commission,”spectrum policy task force report” et docket no.02-135,’Nov, 2002

[3] J. Mitola, III,“Cognitive Radio: An Integrated Agent Architecture for software Defined Radio” PHD dissertation Royal Institute of Technology, Stockholm, Sweden, May 2008.

[4] Media Access Project, “Ex Parte Comments of Prometheus Radio Project, Consumer Federation of America, Public Knowledge, Champaign-Urbana Community Wireless Project, Benton Foundation, Electronic Frontier Foundation, New America Foundation, The Dandin Group, Wireless Tech Radio, and NYCWireless”, Ex Parte Comments on ET Docket No. 03-237, June 18, 2004. Website:

http://www.newamerica.net/files/archive/Doc_File_1876_1.pdf

[5] R. W. Brodersen, A. Wolisz, D. Cabric, S. M. Mishra, and D. Willkomm, Corvus: “A cognitive radio approach for usage of virtual unlicensed spectrum," 2004.

[6] M. McHenry , “NSF Spectrum Occupancy Measurements Project Summary”, Aug. 15, 2005.

[7] F. Jondral, “SPECTRUM POOLING - An Efficient Strategy for Radio Resource Sharing,” Blacksburg (VA), June 8, 2004.

[8] S. Haykin, Life fellow of IEEE, “Cognitive Radio: Brain-Empowered Wireless Communications,” IEEE Journal on Selected Areas in Communications, vol. 23, No 2, February 2005.

[9] FCC report and order,ET Docket No. 03-108 “ Facilitating opportunities for Flexible, Efficient, and Reliable spectrum use Employing cognitive radio Technologies”, March 11, 2005.

[10] Comments of the National Telecommunications and Information Administration on FCC ET Docket No. 03-108: “Facilitating Opportunities for Flexible, Efficient, And Reliable Spectrum Use Employing Cognitive Radio Technologies,” February 15, 2005.

[11] IEEEUSA “Improving Spectrum Usage through Cognitive Radio Technology,” IEEE USA Position, Nov 13, 2003,

[12] IEEE 1900.1Draft Document, “Standard Definitions and Concepts for Spectrum Management and Advanced Radio System Technologies,” June 2, 2006.

[13] James O’ Daniell,” Analysis and Design of cognitive radio Networks and Distributed radio resource Management Algorithms”, PHD dissertation, September 6, 2006.

[14] J. Neyman and E. Pearson, “On the problem of the most efficient tests of statistical hypotheses,” Phil. Trans. Royal Soc. London, vol. A 231, pp. 289–337, Feb. 1933.

[15] HL. Vantrees, “Detection, Estimation and Modulation Theory”. Wiley, vol. 1, 1968.

[16] V. Poor, “An Introduction to Signal Detection and Estimation.“Springer, 1994.

[17] H. Urkowitz. “Energy detection of unknown deterministic signals.” Proceedings of the IEEE, 55:523–531, 1967.

[18] G. D. Zhao, J. Ma, Y. G. Li, T. Wu, Y. H. Kwon, A. Soong, and C. Y. Yang, “Spatial spectrum holes for cognitive radio with directional transmission,” in Proc. IEEE Globecom’08, New Orleans, Louisiana, Nov. 2008.

[19] B. Wild, K. Ramchandran,”Detecting primary receivers for cognitive radio applications,” in: Proc. IEEE DySPAN 2005, November 2005, pp. 124–130.

[20] A. Sahai, N. Hoven, R. Tandra, “Some fundamental limits in cognitive radio, Allerton Conf. on Commun., Control and Computing, “ October 2004.

[21] H. Urkowitz, “Energy detection of unknown deterministic signals”. Proceedings of the IEEE, 55:523–531, 1967.

[22] V. I. Kostylev, “Energy detection of a signal with random amplitude”,2002.

[23] Marvin K. Simon and Mohamed-Slim Alouini,” Digital communication over fading channel”, second edition, pp. 20-22,2005

[24] F. F. Digham, M. S. Alouini, and M. K. Simon” On the energy detection of unknown signals over fading channels” 2003.

[25] A. Ghasemi, E.S. Sousa, “Collaborative spectrum sensing for opportunistic access in fading environment,” Proc. IEEE DySPAN 2005, pp. 131–136, 2005.

[26] F. Digham, M. Alouini, M. Simon, “On the energy detection of unknown signals over fading channels,” Proc. IEEE ICC 2005, vol. 5, pp. 3575–3579, 2003

[27] A. Sonnenschein and P. M. Fishman, “Radiometric detection of spread-spectrum signals in noise of uncertain power,” IEEE Transactions on Aerospace and Electronic Systems, vol. 28, no. 3, pp. 654–660, Jul. 1992.

[28] R. Tandra and A. Sahai, “SNR walls for signal detection,” IEEE Journal of Selected Topics in Signal Processing, vol. 2, no. 1, pp. 4–17, Feb. 2008.

[29] S. Mishra, A. Sahai, and R. Brodersen, “Cooperative Sensing among Cognitive Radios,” in IEEE International Conference on Communications, ICC’06, vol. 4, pp. 1658–1663, June 2006.

[30] G. Ganesan, Y.G. Li,” Cooperative spectrum sensing in cognitive radio networks,” in: Proc. IEEE DySPAN 2005, pp. 137–143, November 2005.

[31]J. Zhao, H. Zheng, G.-H. Yang,"Distributed coordination in dynamic spectrum allocation networks," in: Proc. IEEE DySPAN 2005, November 2005, pp. 259–268.

[32] C. da Silva, B. Choi, and K. Kim, "Distributed spectrum sensing for cognitive radio systems," in Information Theory and Applications Workshop, pp. 120–123 February, 2007

[33] A. Ghasemi and E. S. Sousa, "Opportunistic Spectrum Access in Fading Channels through Collaborative Sensing," IEEE Journal of Communications, vol. 2, no. 2, pp. 71–81, March 2007.

[34] E. Peh and Y.-C. Liang, "Optimization for cooperative sensing in cognitive radio networks," in Proceedings of the IEEE Wireless Communications and Networking Conference (WCNC '07), pp. 27–32, Hong Kong, March 2007

[35] S. Paquelet, L.-M. Aubert, "An energy adaptive demodulation for high data rates with impulse radio," Proc. IEEE Radio and Wireless Conf., pp. 323-326, Sept. 2004

[36] Zhi Tian and Brian M. Sadler "weighted energy detection of ultra-wideband signals" in proceeding of the IEEE, June 2005