HAWASSA UNIVERSITY

INSTITUTE OF TECHNOLOGY

FACULTY OF ELECTRICAL ENGINEERING

DEPARTMENT OF ELECTRICAL AND COMPUTER ENGINEERING

PERFORMANCE ANALYSIS OF DECISION THRESHOLDS ON DUAL-HOP CRNs BASED ON ENERGY DETECTIONS

BY

TSEGAYE AYELE ABERA

ADVISOR: MERHAWIT BERHANE (Ph.D.)

CO-ADVISOR: LULSEGAD TESFAYE (M.Sc.)

A THESIS

SUBMITTED TO THE DEPARTMENT OF ELECTRICAL AND COMPUTER ENGINEERING IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE DEGREE OF

MASTER OF SCIENCE

IN

COMMUNICATION ENGINEERING AND NETWORKING

HAWASSA, ETHIOPIA

MARCH 2022

ADVISORS' APPROVAL SHEET

SCHOOL OF GRADUATE STUDIES

HAWASSA UNIVERSITY

This is to formally to declare that the thesis entitled '' **Performance Analysis of Decision Thresholds on Dual-hop CRNs Based Energy Detections''** submitted in partial fulfillment of the obligations for the degree of Master's in Communication Engineering and Networking, the Graduate Program of the Department of Electrical and Computer Engineering. Consequently, put forward that the student has fulfilled the requirements and herby can submit the thesis to the department.

Merhawit Berhane (Ph.D.)	________________	1/09/2022
Name of Advisor	signature	date
Lulseged Tesfaye (M.Sc.)	________________	________________
Name of Co-Advisor	signature	date

HAWASSA UNIVERSITY

SCHOOL OF GRADUATE STUDIES

EXAMINERS' APPROVAL SHEET

As members of the board of examiners of the final master's degree, open defense. We certify that we have lead evaluated the thesis prepared by **Mr. Tsegaye Ayele** under the title **''Performance Analysis of Decision Thresholds on Dual-hop CRNs Based on Energy Detections''** and recommend that it be accepted as fulfilling the thesis requirement for the degree of M.Sc. in Communication Engineering and Networking.

Mr. Tamirat Yenealem	____________________	______________
Name of chairperson	signature	date
Mr. Shanko Chura	____________________	5/03/2022
Name of internal examiner	signature	date
Dr. Sultan Feisso	____________________	5/09/2022
Name of external examiner	signature	date
Merhawit Berhane (Ph.D.)	____________________	1/09/2022
Name of principal advisor	signature	date
Lulseged Tesfaye (M.Sc.)	____________________	__________
Name of Co-advisor	signature	date

Final approval and acceptance of the contingent upon the submission of the final copy of the thesis to the SG and DGC/SGC of the candidate department

Thesis approved by

____________________	____________________	____________________
SGS	signature	date

Declaration

I hereby declare that this M.Sc. thesis is my original work and has not been presented for a degree at Hawassa University and other institutions, and all sources of material used for this thesis have been duly acknowledged.

Tsegaye Ayele __________________ __________________

Name of student Signature Date

This MSc thesis has been submitted for examination with my approval as an advisor.

Merhawit Berhane (Ph.D.) __________________ 1/09/2022

Name of Advisor Signature Date

MARCH 2022

Abstract

Cognitive radio is a robust technology that helps to overcome spectrum underutilization. In recent generations, there has been an exponential growth in bandwidth usage and arising underutilization of radio spectrum resources, due to increasing the extent of radio spectrum demands. However, the spectrum detection and decision threshold techniques are a promised wireless communication technology dedicated to the efficient use of the free spectrum bands. The main challenges in cognitive radio network (CRN) are an inefficient use of licensed spectrum bands due to noise uncertainty, the selection of the most appropriate decision threshold technique based on fading environments. Therefore, investigations on minimizing interferences to obtain accurate information from the desired sensing region of licensed bands at the fusion center during the energy detection process.

In this thesis work, performance analysis of decision thresholds on dual-hop CRN's based on energy detection (ED) to conquer the reviewed problems on kinds of literature. Thus, the comparatives of fixed and adaptive threshold techniques receiver operating characteristic (ROC) curve plots based on the effect of noise uncertainty (NU) parameters and different SNR Environments to obtain outperformed decision thresholds.

In addition, evaluating the effect of the number of signal samples size on detection probability during the ED process, the performance analysis of adaptive ED at different SNR environments based on ROC and complementary ROC curve plots. Moreover, in the evaluation of hard decision rules performance for adaptive thresholds of ED at fusion center (FC), the obtained ROC curve plots for ''Logic-OR'' fusion rule performs high false alarming probability with high detection probability than ''Logic-AND'' Rules. Based on discussion results, adaptive decision thresholds performed better than fixed thresholds at low SNR conditions, while the fixed decision thresholds relatively had better performance in high SNR environments. Furthermore, when the sample size increases the detection performance also increases proportionally at perceived SNR ranges. Lastly, the performance evaluations are executed using MATLAB R2018a software and an OFDM signal with Quadrature Phase Shift Keying (QPSK) scheme is advanced based on desired values of false alarming probability ($P_{FA} \leq 0.1$) and detection probability ($P_D \geq 0.9$) at different SNR and number of sample size (N) values.

Keywords: CRN, Energy Detection, Sample Sizes, Decision Thresholds, Fusion Rules, NU.

Acknowledgments

Firstly, I would like to thank GOD, for blessing me that this thesis can be done successfully. I would like to express my deep and sincere gratitude to my **advisor Merhawit Berhane (Ph.D.)** for her instructions, continuous encouragement, valuable discussion, and support throughout the whole process of this thesis. In addition, I am great thanks to my **co-advisor Lulseged Tesfaye (M.Sc.)** for his valuable discussion and support throughout the thesis work. A special thanks to the Electrical and Computer Engineering department for providing me with adequate computer laboratory infrastructure to carry out this thesis.

Lastly, I offer my regards and blessings to all of those who supported me in any respect during the completion of the thesis, particularly my dearest family and all my friends for their sincere supplication, feelings, and love throughout the whole master study and the work with this thesis.

Table of Contents

List of Tables

List of Figures

List of Abbreviations

Acronym	Description
5G	Fifth Generations
ADF	Adaptive-Decode-Forward.
AF	Amplify Forward.
AWGN	Additive White Gaussian Noise
BPF	Band Pass Filter
CRNs	Cognitive Radio Networks
CC	Cognitive Controller
CDF	Cumulative Distribution Function
CFD	Cyclo-stationary Feature Detection
CROC	Complementary Receiver operating characteristic
CSS	Cooperative Spectrum Sensing
CPU	Central Processing Unit
DAF	Decode-Amplify and Forward
DBs	Decibel’s
DF	Decode and Forward schemes
DFT	Direct Fourier Transform
DSA	Dynamic Spectrum Access
ED	Energy Detection
EMC	Electromagnetic Compatibility
EMI	Electromagnetic Interference
FFT	Fast Fourier Transform

FC	Fusion Center
FCC	The Federal Communications Commission
FDF	Fixed-Decode-Forward
GHz	Giga Hertz
IEEE	Institute of Electrical and Electronics Engineers
IID	Independent and Identically Distributed
ISI	Inter Symbol Interference
ITS	Intelligent transportation system
ISM	Industrial, Scientific and Medical
LOS	Line-of-Sight
MATLAB	Matrix Laboratory
Mbps	Megabits per second
MFD	Matched Feature Detection
MIMO	Multiple In-Multiple Out
NTIA	National Telecommunications and Information Administration
NU	Noise Uncertainty
OFDM	Orthogonal Frequency-Division Multiplexing
PU	Primary User
PD	Probability of Detection
PFA	Probability of False Alarm
PMD	Probability of Miss-Detections
QPSK	Quadrature-Phase Shift-Keying
QoS	Quality-of-Service

RF	Radio Frequency
ROC	Receiver Operating characteristics
SDR	Software Defined Radio
SNR	Signal-to-Noise Ratio
SU	Secondary User
V2R	Vehicle-to-roadside
VANET	Vehicle-to-roadside Vehicular unplanned network
Wi-MAX	Worldwide Interoperability for Microwave Access
WRAN	Wireless Regional Area Network

Chapter 1
Introduction

1.1 Background

Wireless communication is a method of transmitting information from one point to another without any connection like, wires, cables, or any physical connection medium, generally, in a communication system information is transmitted from transmitter to receiver that placed over a limited distance.

In [1], Radio communications have grown very great in amount since the early development in the late 19th and early 20th century and now have affected people's lives in every corner of the globe. As a having a great value, the radio spectrum must be carefully managed to mitigate spectrum pollution, maximize utilization, and decreases interference. In different countries, wireless systems i.e. commercial or government-operated (licensed) spectrum allocated by the regulatory agencies. In the US, the two main policymakers who oversee spectrum use – the NTIA (National Telecommunications and Information Administration) and the FCC (the federal communications commission) – have divided the usable radio spectrum (0-300 GHz) frequency bands, which are allocated to radio services for examples, fixed, radio navigation, mobile telephony, TV broadcasting, and various satellite services. [1] The radio spectrum allocated for different radio transmissions and applications shown in figure. 1.1.

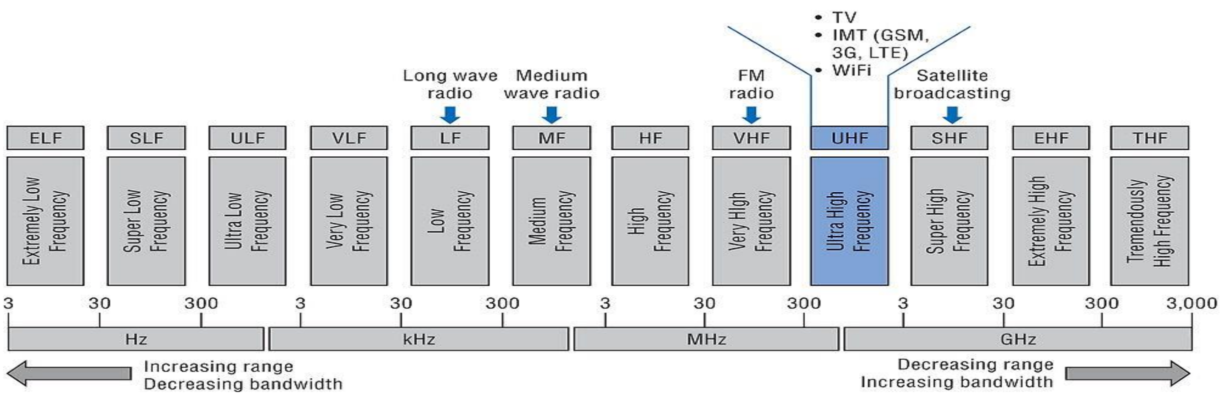

Figure 1- 1: Radio spectrum allocated for wireless communications

Because the increasing demand for wireless, communications has increased the demand for radio spectrum. Therefore, some of the new broadband communication technologies were introduced to utilize the radio spectrum effectively [2].

- **Multiple-Input Multiple-Output (MIMO)**

MIMO is a wireless technology, in which the radio trans-receiver has multiple antennas for digital data communications. The IEEE802.11n (i.e. Wi-Fi) uses MIMO to achieve the maximum data rate up to 600Mbps at 2.4 GHz [1, 2]. Therefore, cognitive radio systems that allow higher data throughput without additional bandwidth or power increase and which includes large-scale antenna arrays are capable of shrinking the cell size and minimizing the transmit power for channel training.

- **Cooperative MIMO Communications.**

Todays, the major problems in wireless communications are efficient use of bandwidth, reliable and higher data speeds. In additions, it is difficult to obtain reliable and accurate data at the receiver end due to interference, fading and others hidden terminals. Therefore, the important role of MIMO antennas, different copies of the same data transmitted by using multiple antennas play an important role for the efficient use of bandwidth, and reliable data transmission. Because of antenna size and wireless communication devices hardware complexity, difficult to use MIMO antennas on each mobile ends. So, using virtual MIMO systems, through cooperative communications, due to a single mobile antenna can use as a MIMO system [2]. Therefore, in a cooperative communication network, in Virtual MIMO scenario each node assists and cooperate with each other in order to achieve the diversified transmission through a virtual MIMO system [3]. Furthermore, cooperative networks used for reliable transmission and data rate by exploiting spatial diversity in a multi-user environment using cooperative techniques: -

- Relaying that facilitates the signal transmission between the source and the destination utilizing less power.
- The cooperative MIMO, which forms a distributed antenna system employing antennas of different users, is effective for poor line-of-sight propagation and for cell-edge users

and Multi-cell MIMO, the cooperation among base stations established via high-capacity wired backhaul links.

1.2 Statement of the Problem

The exponential growth of wireless communications has led to spectrum scarcity. Although cognitive radio has been developed to solve the spectrum scarcity and spectrum under-utilization issues. As an intelligent wireless communication system, cognitive radio is aware of the radio frequency environment and it selects the communication parameters (such as carrier frequency, modulation type, bandwidth, and transmission power) accordingly to optimize the spectrum usage and adapt its transmission environments. However, spectrum sensing in cognitive radio may suffer from the hidden terminal problem and very difficult task, as the various primary users will be employing different modulation schemes, data rates, and transmission powers in the presence of variable propagation environments and interference generated by the secondary users. The main challenges that require a great deal of investigation include: - The occurrence of spectrum scarcity and spectrum under-utilization due to: - the exponential growth of current wireless communication network technologies and the lack of trends in the adoption of adequate decision thresholds and spectrum sensing techniques based on their essential features, the performance of the energy detector is highly affected by noise variances in the wireless communication environments and the noise uncertainty (NU) problem includes the irregularity of noise power at the secondary user side due to a lack of prior knowledge of ED features during its operation. Moreover, the increasing wireless channel noise variances at low SNR environments highly affect the performance of decision thresholds of ED during its operations and the PU's information accuracy and reliabilities are great demands in CRN operations. However, during detection operation of wireless communication channels is highly affected due to the existence of distributional uncertainty of noise power.

1.3 Objective of the Research

1.3.1 General Objectives

The main objective of this thesis is a performance analysis of decision thresholds on dual-hop cognitive radio networks based on the Energy detection technique.

1.3.2 Specific Objectives

The specific objectives of this thesis work include:

- ❖ To analyze and compare the ROC curves for both decision threshold techniques: adaptive and fixed threshold techniques based on ED at different SNR environments.
- ❖ To analyze the effect of the number of signal samples and SNR on detection probability with varying Probability of false alarming (P_{FA}).
- ❖ The comparative analysis of decision thresholds performance with known and without NU factors.
- ❖ To analyze the performance of adaptive threshold techniques for energy detections based on consideration of different noise uncertainty parameters with a specific signal-to-noise ratio (SNR) and the number of signal sample sizes (N).
- ❖ To evaluate and compare the performance of hard decision fusion rules for adaptive thresholds of Energy detection at the fusion center.

1.4 Scope of the Research

These research work intentions on the performance analysis of decision thresholds on dual-hop cognitive radio networks based on Energy detection technique for efficient utilization of free spectrum bands on cognitive radio network users.

1.5 Thesis Contributions

In the telecom industry, due to the rapidly increasing demands of wireless communication technologies and increasing network coverages, spectrum scarcity is a critical problem. For this reason, evaluating the performance of cognitive radio networks based on their spectrum sensing technique and final decision threshold is a solution. This thesis work contributes and addresses supportive information includes:

- ❖ Determining the efficient decision threshold technique based on an energy detection (ED) spectrum-sensing algorithm with a high probability of detection at low SNR environments on dual-hop cognitive radio networks.
- ❖ Providing a deep consideration of the adaptive threshold of ED techniques on dual-hop CRNs, to get the intended sensing performance over Rayleigh fading environments.
- ❖ To increase the probability of detection accuracy and reliability, determining fuzzy combined logic sensing approach over a specified range of SNR levels during energy detection operations.

1.6 Thesis Outline

This thesis work organized into five chapters:

Chapter 1: The first chapter deals with the general introduction of the study including a background of the study, statement of the problem, objectives, methodology, Motivations, and scope of the research.

Chapter 2: The second chapter discusses the cognitive radio network basic concepts and functions of the cognitive radio networks. In addition, it describes the spectrum-sensing methods concept based on primary users (PUs) and secondary users (SUs) details.

Chapter 3: The third chapter discusses about the proposed system model and cognitive relaying protocols for CR systems, the common wireless communication models, fading channels, path loss, SNR, noise uncertainty, decision thresholds and energy detection process during operations.

Chapter 4: The fourth chapter deals with results and discussions.

Chapter 5: Finally, chapter five presents a conclusion that summarizes the major points of the Research and recommendations forwarded for further research works.

Chapter 2

Overview of Cognitive Radio Networks

2.1 Introduction

Cognitive radio is the latest technique, which can address the spectrum scarcity problem in many efficient ways. Due to the expansive growth in the usage of wireless communication systems around the world, there is a great demand for spectrum resources. Therefore, initiating the secondary spectrum use on an opportunistic basis makes wireless communication systems flexible; it can also provide future support for the growth in traffic and can enhance the demand in the traffic. Spectrum sensing enables cognitive radio systems to detect unused portions of the radio spectrum and then use them while avoiding interferences to the primary users.

What has motivated cognitive radio technology, an emerging novel concept in wireless access, is spectral usage experiments done by FCC and show that at any given time and location, much of the licensed (pre-allocated) spectrum is idle because licensed users (termed primary users) rarely utilize all the assigned frequency bands at all-time [14, 15]**.** Such unutilized bands called spectrum holes that is resulting in spectral inefficiency. Therefore, poor spectrum management rather than a true scarcity of usable frequency cause spectrum scarcity [15].

The spectrum is a valuable electromagnetic resource that controlled by government in order to manage complex issues. Presently, spectrums allocated to service providers by adopting the policy of fixed allocation in which transmission power is regulated and different frequency bands assigned for different services and applications. There has been tremendous growth of wireless users and applications over the last decade. Due to these, new applications require more spectrum allocation, but it is difficult to find the new spectrum as most of the spectrum bands are allocated by a policy of fixed allocation of spectrum utilization report provided by Federal Communications Commission (FCC) that varies between 80% - 90%) and is a function of space and time [15]. Thus, the persistent increase in demand of spectrum can't be fulfilled until a new scheme not found to control the limited spectrum. This new scheme is the dynamic spectrum access (DSA) in which secondary users (SUs) can use the idle licensed channels opportunistically known as spectrum hole or white space with only constraint of minimum interference to primary users (PUs) or licensed users. If the spectrum utilized on a time or frequency basis, the spectrum opportunities appear in the form of holes as shown in figure 2.1. In the time domain, it is the period of time during which the PU is not transmitting and in the frequency domain, it is the frequency band in which SU can use the frequency band for its transmission allotted to PU with no or minimum interference [15]. The technology that will make the dynamic spectrum allocation (DSA) reality is cognitive radio (CR). CR is a smart device having the capability to sense the entire spectrum in order to find the idle channels and utilize these idle channels opportunistically for communication as and when required. The opportunistic usage of these idle channels can increase the utilization of the precious spectrum. CR can enable the SUs to utilize licensed channels of PUs either on a negotiated or opportunistic basis. It can provide a basis for efficient wireless communication between users wherein nodes have the capability to alter any of its transmission or reception parameters in order to adapt to a continuously changing environment. [14, 15]. Therefore, CR is referring to a radio that can change its transmission parameters based on interaction with the operational fading environment and provided with the ability to its users includes [15]:

- ❖ Selection of the best vacant channel.
- ❖ Firmly decide the presence and absence of the licensed bands
- ❖ Coordinate access to the channels with others based on decisions
- ❖ Leave the channel when the licensed band detected.

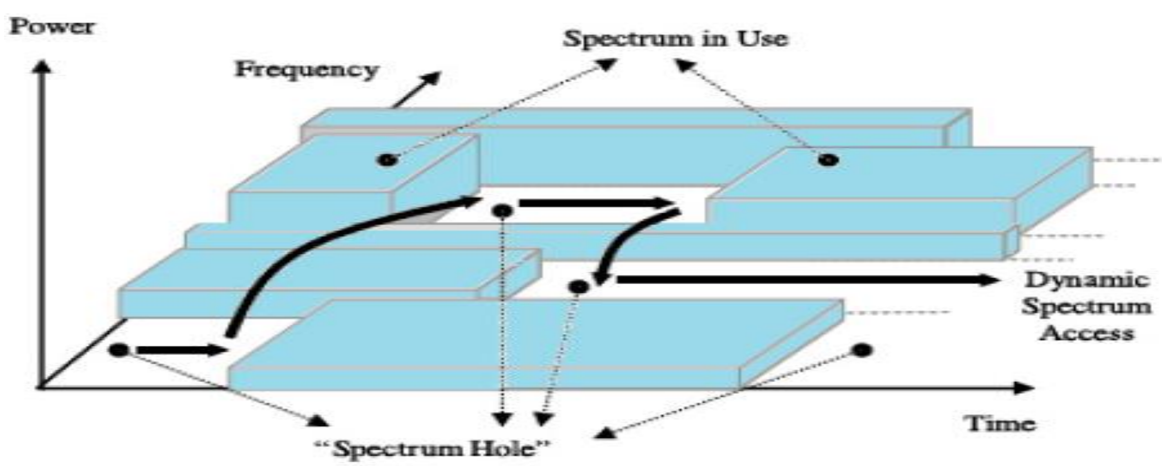

Figure 2- 1: Fundamental working principle of a CR system in [15].

2.2 Fundamentals of Cognitive Radio Networks

Cognitive radio is a form of wireless communication where a transceiver can intelligently detect the channels for communication which are in use, and which are not in use and move into unused channels while avoiding occupied ones [16]. This optimizes the use of available radio-frequency spectrum while interference minimized to other users. This is a paradigm for wireless communication where transmission or reception parameters of network or node changed for communication avoiding interference with licensed or unlicensed users.

A spectrum hole shown in the figure 2-1 is generally a concept of spectrum as non-interfering, considered as multi-dimensional areas within frequency, time, and space. For secondary radio systems, the main challenge is to be able to be sensing spectrum, when they are within such frequency bands [17].

2.3 Characteristics of the Cognitive Radio Networks

There are two main characteristics of cognitive radio networks in [16, 17].

- **Cognitive capability:** Cognitive Capability defines the ability to capture or sense the information from its radio environment of the radio technology. Joseph Mitola first explained the cognitive capability in term of the cognitive cycle "a cognitive radio continually observes the environment, orients itself, creates plans, decides, and then acts"
- **Re-configurability:**
  It refers to a radio capability to change the functions, and enables the cognitive radio programmed dynamically in accordance with radio environment (frequency, transmission, power, modulation scheme, communication protocol). In additions, in [16], the parameters included several re-configurability in cognitive radio systems: -
  - **Operating Frequency**: According to ability of CR to change its operating frequency. Based on the radio environment information, the most suitable operating frequency can be determined, and the communication can be dynamically officiated on this suitable operating frequency.

- **Modulation:** According to channel conditions and user requirements, the modulation scheme of CR should be adaptive.
- **Transmission Power:** Power constraints are control the transmission power reconfiguration by enabling dynamic configuration for transmission power within the permissible power limit. If higher power operation is not necessary, the CR reduces the transmitter power to a lower level to decrease the interference and allow more users to share the spectrum.
- **Communication Technology:** Among different communication systems, cognitive radio used to enable interoperability. The transmission parameters of a cognitive radio reconfigured during the transmissions. According to the spectrum characteristics these parameters reconfigured such that the cognitive radio switched to a different spectrum band, the parameters of the transmitter and receiver are networks require higher capacity to meet these applications requirements**.**

2.4 Functions of Cognitive Radio Networks

In [16], The whole functioning of cognitive radio networks explained through cognitive radio cycles. Therefore, four major functions of cognitive radio operations in a closed loop cycle described in the figure 2-2.

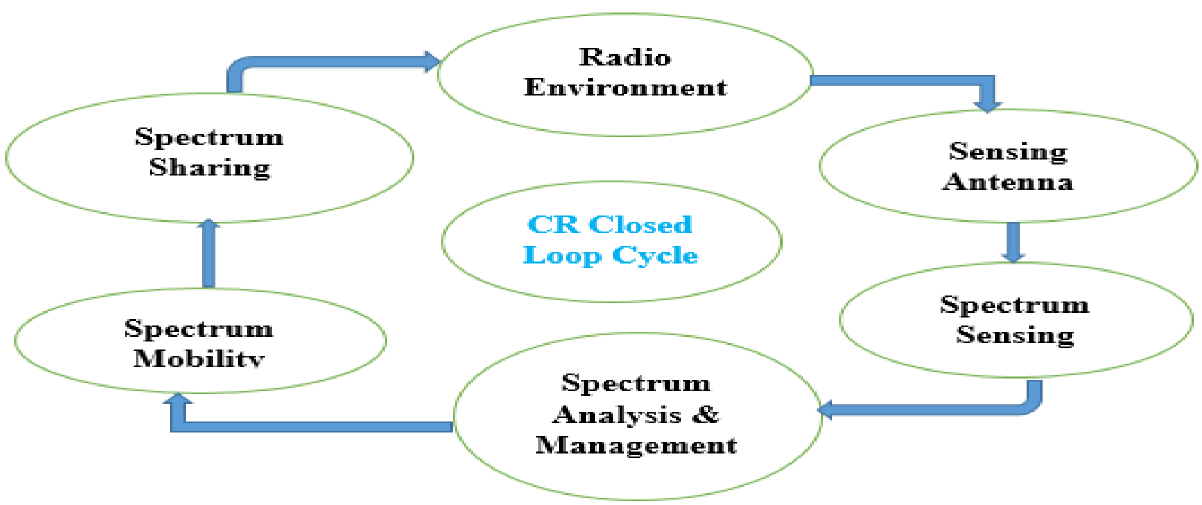

Figure 2- 2: Block diagram of the basic Cognitive Radio Cycle.

- **Spectrum Sensing**: The first step of spectrum sensing is that it determines the presence of primary user on a band. The cognitive radio is able to share the result of its detection with other cognitive radios after sensing the spectrum [16]. The goal of spectrum sensing is to find out the spectrum status and activity by periodically sensing the target frequency band.
- **Spectrum management:** Provides the fair spectrum scheduling method among coexisting users. The available white space or channel is immediately selected by cognitive radio if once found. This property of cognitive radio described as spectrum management. Spectrum sensing, spectrum analysis, and spectrum decision fall in spectrum management. Spectrum analysis makes possible the characterization of different spectrum bands, which exploited to get the spectrum band appropriate requirements of the user. Spectrum decision refers to a cognitive radio decides the data rate, determines the transmission mode, and the transmission bandwidth. Then, the appropriate spectrum band selected according to the spectrum characteristics and user requirements. [16].
- **Spectrum Sharing:** Cognitive radio assigns the unused spectrum (spectrum hole) to the secondary user (SU) as long as primary user (PU) does not use it. This property of cognitive radio refers as spectrum sharing.
- **Spectrum Mobility:** When a licensed user detected, the CR vacates the channel. This property of cognitive radio describes the spectrum mobility and called handoff. This process allows the CR user to change its operating frequency. In additions, the CR networks try to use the spectrums dynamically to operate in the best available frequency band and maintain transparent communication [17].

2.5 Spectrum Sensing Techniques for Cognitive Radio Networks

There are different methods can that be used to enhance the spectrum detection probability and proposed to identify the presence of signal transmission between the transceivers. Therefore, there are three types of techniques for spectrum detections in [17]:

1. Transmitter / Non-cooperative spectrum detection techniques.

2. Cooperative spectrum sensing technique.
3. Interference based detection spectrum sensing technique

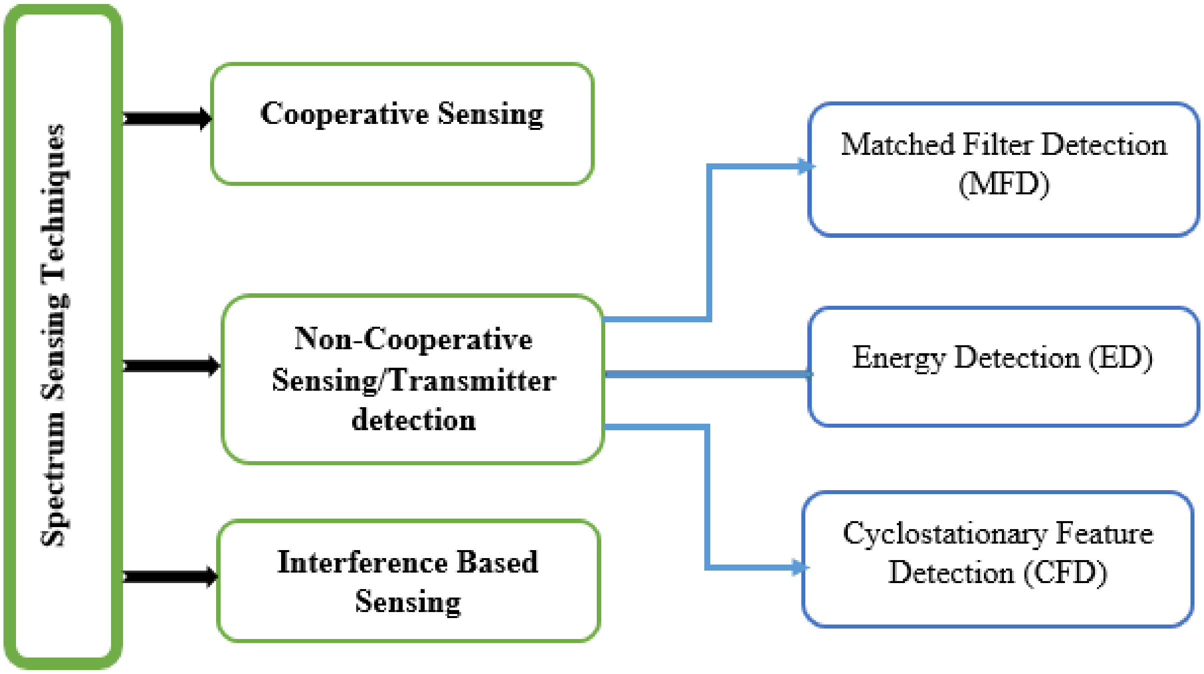

Figure 2- 3: General Classification diagram of Spectrum Sensing Techniques.

2.5.1 Transmitter/Non-cooperative Spectrum Detection Techniques.

The key functions of transmitter detection are to detect the unused or vacant spectrum by sensing the presence of primary users and to analyses the received signal. In [18], this type of spectrum detection techniques further classified into three methods: -

- Matched filter detector (MFD)
- Energy Detections (ED)
- Cyclo-stationary Feature Detections (CFD)

2.5.1.1 Matched Filter Detector (MFD)

The matched filter detector (MFD) is one of the prominent sensing techniques, which requires perfect knowledge of the transmitted signal or where information from the known signals is decoded at the receiver end and the channel responses for its coherent processing at the demodulator. In additions, MFD is a linear filter, which, enhance the signal to-noise ratio (SNR) of the PU under additive white Gaussian noise (AWGN). Since it requires the perfect knowledge of the channel response, its performance degrades dramatically when there is lack of channel knowledge due to rapid changes of the channel conditions [18]. However, the output (O/P) SNR is maximized by convolution of the transmitted signal which is unknown signal with a filter whose impulse response h (n) is time shifted version of the known (reference) signal. Generally, MFD is used when a prior information like modulation type, spread code, shape of the pulse etc. In equation (2.1), the MFD operations expressed mathematically [18]:

$$y(n) = \sum_{n=-\infty}^{\infty} h(n-l)x(l), \qquad \text{Eq (2.1)}$$

Where, y (n) = denotes the received signal

x = denotes the transmitted or unknown signal

h = denotes the channel impulse response of MFD, which is match with the known signal for increasing the output SNR [18]. The block diagram of MFD shown in figure 2-4:

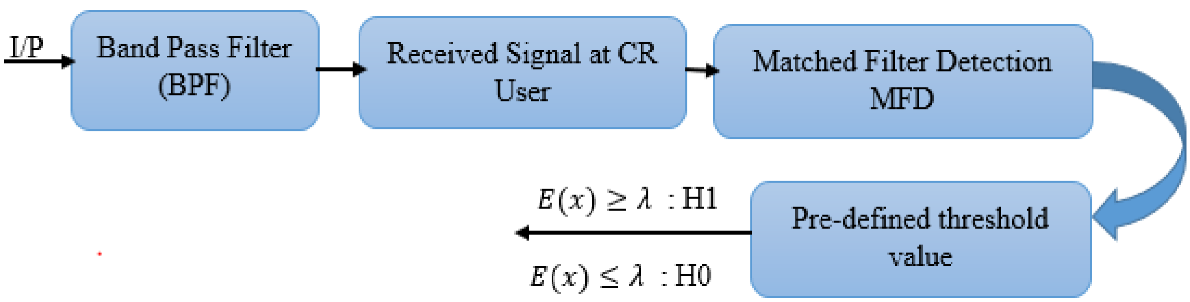

Figure 2- 4: A Block diagram of Matched Filter Detection (MFD) techniques

Pros of Matched Filter Detections (MFD)

- MFD have most useful applications in digital communication systems and radars, due to its objectives of detecting a signal achieved in the noisy environment.
- MFD achieved the certain probability of detection and false alarm probability in a very fast way.
- Have optimal performance and low computational cost.

The Limitations of MFD

- In a cognitive radio network, the transmitted signal characteristics are usually unknown.

- ❖ It requires a specific sensing receiver for different types of the primary user's signals. Therefore, the MFD performance decrease which leads to unwanted signal detection.
- ❖ Large power consumption due to the execution of different receiver algorithms for the detection.
- ❖ It requires for a prior knowledge.

2.5.1.2 Energy Detections (ED)

This detection method measures the energy of the received signal within the pre-defined bandwidth and within specific time duration. Therefore, the measured energy compared with a pre-defined threshold value to determine the status (presence/ absence) of the transmitted signal. Not requiring channel gains and other parameter estimates, the energy detector is a low-cost option. However, it performs poorly under high noise uncertainty and background interference [19]. There are difficulties originate in MFD techniques when sufficient information about the PU is not found in the Secondary Users end. It is the mostly used scheme due to it does not requires a prior knowledge about the PU and the implementation complexity is simple. ED may only need the information about the SNR of PU for calculating the threshold value in order to compare its output SNR.

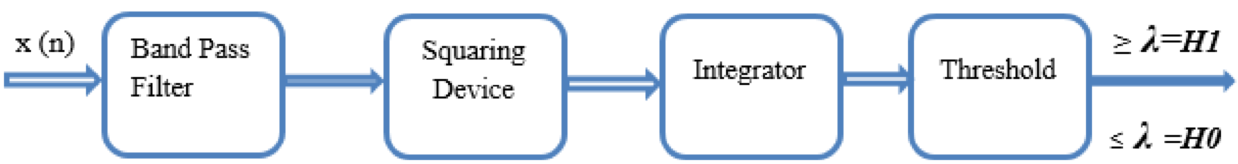

Figure 2- 5: A Block diagram for Energy Detection (ED) Techniques

The working process of ED, shown in the above figure 2-5 for calculating the O/P signal energy of PU from the Band pass filter is squared and integrated and then the final summation of the each added signal energy value compared with the predetermined threshold value for spectrum occupancy details of PU**.**

Pros of ED schemes

- ❖ It is Robust in low signal to noise ratio
- ❖ Highly robust to prevent the interferences.

Drawbacks of ED schemes

- It has Low performance when noise uncertainty is avail.
- It requires prior knowledge

2.5.1.3 Cyclo-stationary Feature Detections (CFD)

The transmitted signal from the primary users PUs has a periodic pattern refers to Cyclo stationarity and used to detect the presence of a licensed user. Periodicity occurs in the signal due to spread code, modulation, synchronization etc. Nevertheless, the noise signal is a stationary signal without periodicity. Therefore, using correlation function noise can be retrieved or bring back from the received signals. If periodicity properties introduced intentionally to the modulated signals, the statistical parameters of received signal such as mean, and autocorrelation may vary periodically. Such periodicity of statistical properties used in the Cyclo-stationary detections. Its input-output (I/O) spectral correlation density may extract Cyclo-stationary detection properties of the received signal. Therefore, the signal absence status identified easily because the noise signal does not have Cyclo-stationary properties. While this detector is able to distinguish among the primary user (PUs) signals, secondary user (SUs) signals, and interference. Cyclo-stationary detection needs a high sampling rate and a large number of samples, thus increases the computational complexity in [19].

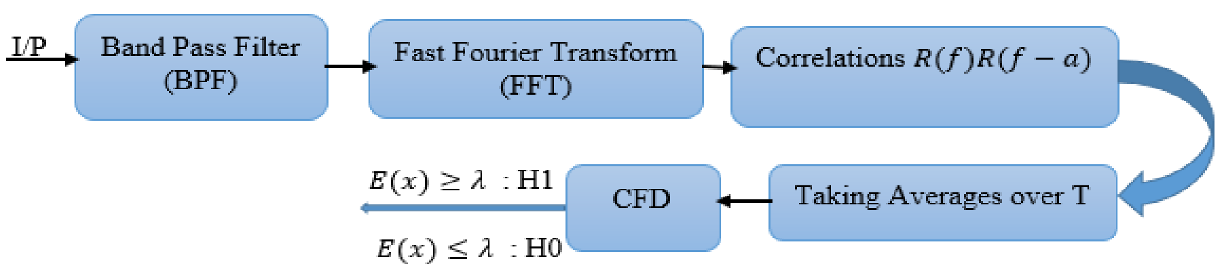

Figure 2- 6: A Block diagram for Cyclo-stationary detection (CFD) techniques

The process of CFD based sensing method applied as seen in the above figure; the process of CFD is more effective in an environment where the levels of noise are uncertain. However, the noise uncertainty occurs because of the spectral correlation function of the AWGN channel is zero due to the stationary property [19]. The input signals spectral components computed through the fast Fourier transformer, and then spectral correlation functions carried out on the input signal and then estimated. Then after, the presence/ absence of the PU signal distinguished by calculating the spectral correlation of the PU signal at the CFD [20]. Lastly, the output of the CFD compared with the predefined threshold value to determine the presence/absence of the PU's signal.

- **Limitations of the CFD**

The CFD is more robust to uncertain levels of noise and gives much better performance in low SNR Regions [20]. However, this technique has its own limitations:

- ✓ High computational complexity.
- ✓ Long sensing time.

Table 2- 1: Comparison of the spectrum detection techniques

Performance metrics	Energy Detections (ED)	Cyclostationary Feature Detections (CFD)	Matched Filter detections
Detection Accuracy	High noise power could be a false detection High performances at high SNR values	Best performance at all SNR value	Optimal Performance
Complexity	Low Computational /operational complexity	Moderate complexity	Most complex
Robustness	No need of any prior knowledge of PU's signal Requires knowledge of noise power	No need of prior PU's signal	The receiver must know PU's signals

2.5.2 Cooperative Spectrum Sensing Technique

The cooperative spectrum detection method refers to where the cognitive radio network's (CNR) share their individual sensing information in order to improve the overall sensing/detection information about their primary users. This implies that a solution to improve the spectrum detection performance, the facility to collectively detect the spectrum holes and making it easier for the secondary users collaborate with primary user. But, in this type of spectrum sensing technique the cognitive radio network users have to perform the sensing technique only at particular periodic time intervals as the detected data will be quick because of the factors such as mobility, channel weakness etc. [20].

2.5.3 Interference Based Detection Spectrum Sensing Technique

The interference-based detection technique is very new concept for the dynamic spectrum access (DSA). The cognitive radio hubs treat the licensed clients and unlicensed (unauthorized) clients within the similar network without interference. The higher interference prompts lower Signal-to-interference proportion (SIR), which implies that the lower limit is reachable for a specific sign's transfer speed. Not at all like the essential collector identification, the fundamental thought of impedance temperature executives to set up an upper obstruction limit for the given recurrence band in a particular geographic area. Therefore, spectrum-sensing techniques mainly depends on the total number of samples and their sensing threshold. So that, taking a large number of samples will improve the detection capability to maximum up to a certain value of SNR and makes the more reliable Cognitive networks. Due to the increase in the number of samples also increases the sensing time proportionally [19, 20].

2.6 The Applications of Cognitive Radio Networks

A cognitive radio has capability to increase the capability of spectrum efficiency and overall network capacity through interference-free spectrum sharing among several wireless communication systems. In addition, CR system is one of the most intensively researched paradigms in recent wireless network communication systems. Some of most common application areas includes [20]:

- ❖ Next-Generation (5G and beyond) wireless communication networks
- ❖ Intelligent transportation system (ITS)
- ❖ E-Health care and medical applications
- ❖ Military network etc...

2.6.1 Next-Generation (5G and beyond) Wireless Communication Networks

The 5G of wireless communication standards and CRNs believed to be the solution for present day data intensive applications. CR offers dynamic spectrum sharing to achieve higher spectrum efficiencies as required as 5G architecture. CR will provide intelligence to both the user-side and provider-side equipment to manage the air interface and network efficiently. At the user-side, a mobile device with multiple air interfaces (e.g., Wi-Fi, WiMAX, cellular) can observe the status of the wireless access networks (e.g., transmission quality, throughput, delay, and congestion) and choose by selecting the access network to attach with the wireless devices. At the provider-side, RF resources from multiple networks often optimized for the given set of mobile users and their Qos requirements. Based on the mobility and traffic pattern of the users, efficient load balancing mechanisms often implemented at the service provider’s infrastructure to distribute the traffic load among multiple available networks to scale back network congestion [20].

2.6.2 Intelligent Transportation System (ITS)

Intelligent transportation system will progressively utilize diverse remote access advancements to fortify the effectiveness and security of transportation by vehicles. In additions, there are two kinds of interchange situation emerges in ITS framework vehicle-to-roadside (V2R) and vehicle-to-vehicle (V2V) communication. In V2R correspondences, information traded between the roadside unit (RSU) and the on-board unit (OBU) during a vehicle. In V2V communications, a unique kind of unplanned network, namely, a VANET, is made among vehicles to exchange safety-related information. The high portability of the vehicles and rapid variations in network topologies pose significant challenges to efficient V2R and V2V communications. CR ideas frequently used in both OBUs and RSUs so they will adjust their transmissions to manage the fast varieties inside the surrounding frequency environment. With multi-radio capabilities at the OBUs, they ought to be ready to choose adaptively the radio to speak with the RSUs [20].

2.6.3 E-Health Care and Medical Applications

There are several wireless technologies are adopted in healthcare and medical application services to enhance the efficiency of patient care and healthcare management. However, using wireless communication devices in healthcare applications is constrained by EMI (electromagnetic interference) and EMC (electromagnetic compatibility) requirements. Since the medical equipment and bio-signal sensors are sensitive to EMI, the transmit power of the wireless devices has to be carefully controlled. In addition, different biomedical devices (e.g., surgical equipment, diagnostic, and monitoring devices) use RF transmission. Spectrum usage of those devices has carefully chosen to avoid interference with one another. Many wireless medical sensors designed to work within the ISM band, which may use CR concepts to settle on suitable transmission bands to avoid interference [20, 21].

2.6.4 Military Networks

The wireless communication parameters are often dynamically adapted supported the time and site of the target. Because of the mission of the soldiers. For instance, if some frequencies are jammed or noisy, the CR transceiver can look for and access alternative frequency bands for communication. In addition, location-aware CR can control the transmitted waveform during a particular region to avoid interference to the high priority military communication systems [21].

2.7 Dynamic Spectrum Access (DSA)

The Cognitive radio technology concepts includes two types of users: Primary users (the licensed users) who are usually granted preferential access to the spectrum and these main users are the original users, which can access their dedicated spectrum unconditionally anytime, anywhere. The second type of users are Secondary users (the unlicensed users), who can utilize the spectrum that PUs are licensed to use only when the PU are not actively using the spectrum. [22]. The CR networks can be also designed to manage the radio frequency spectrum more efficiently by utilizing the spectrum holes in primary users' licensed frequency bands. Therefore, dynamic spectrum allocation refers to alter the spectrum resources practice in a near-real-time method to answer to the changing circumstance and goal. For examples, accessible channel and kind of applications), a transformation of radio state (e.g., transmission mode, battery status, and location), and changes in external environment and constraints (for examples, radio propagation, operational policy) and it has a good possibility to improve spectrum usage and in perspective allowing next-generation mobile networks access to the attractive frequency spectrum bands.

2.8 Cognitive Radio Network Architecture

Cognitive radio network architectures classified in to two types of nodes or networks in cognitive radio system are the primary networks and cognitive radio networks details in [22]:

2.8.1 The Primary Networks

The networks with access right to certain spectrum bands, for instance TV broadcast networks and common cellular system users refers to as primary network users. They have the right to operate in licensed spectrum users of certain primary network do not care of other primary or secondary networks users. The key components of the primary networks are:

- ❖ Primary user (licensed user): a user, which has a permit to work in an authorized band and its activity ought not to be influence the tasks of CR clients.
- ❖ Primary base-station (licensed base-station): a fixed foundation network part with spectrum license.

2.8.2 The Cognitive Radio Networks

The users of these networks known as secondary users and do not have a license to work in the authorized spectrum band, its spectrum permit to access opportunistically. The categories of the secondary or cognitive radio networks are:

- ❖ CR user (unlicensed user): a client who has no permit over the spectrum. CR clients can get to the spectrum opportunistically only when PU is not present and CR clients must empty the channel promptly when the PU is recognized.
- ❖ CR base-station (unlicensed base-station): a fixed foundation segment with CR capacities giving a solitary bounce association with CUs.
- ❖ Spectrum broker (scheduling server): a central network entity that controls spectrum resource sharing among the CR users.

Chapter 3

Literature Review

In this thesis work proposed, a comparative analysis of decision thresholds based on Energy detection of dual-hop cognitive radio networks. Therefore, the non-cooperative spectrum sensing technique of energy detection-based decision threshold analysis on this work, in [4, 5, 6,7], due to its minimum complexity, high spectrum sensing speed, robust in low signal-to-noise ratio environments, highly robust to prevent the interferences and easy for practical implementation. A review of relevant works done based on it:

In [7], the author proposed the evaluation of energy detection (ED) performances based variable thresholds under the probability of false alarm vs probability of detection. In this work proposal, the energy detection considered to examine the primary user spectrum band and to increase the probability of detection of free holes. In addition, the considered evaluation parameters on the author's work, the maximum number of signal sample size 2048, with a primary user transmitting modulation scheme of quadrature-phase shift-keying (QPSK), to improve the received signal energy and achieve improved sensing time during emerge a gain of the primary user signals resulted. However, the limitation of this work is on comparative analysis of decision thresholds of energy detection with primary user-transmitting signals of orthogonal frequency division multiplexing with quadrature phase-shift keying modulation scheme under minimum and high signal-to-noise ratio environments.

In [11], Proposed, the performance analysis of energy detections based on evaluation metrics, detection probability, and false alarming probabilities. In addition, performance evaluations and comparisons on edge of the signal pulse detector and Energy detector in two-hopes based on predefined decision thresholds in order to determine the efficient detection algorithm for spectrum band utilization. The limitation of the author's presentation, the performance of detection probability on low signal-to-noise ratio environments with different false alarming probabilities. In addition, the performance evaluation, and comparisons of decision thresholds of ED (variable thresholds and constant thresholds) under different signal–to–noise ratio conditions.

The authors in [14] - Proposed an adaptive decision threshold of local spectrum-sensing scheme (i.e., Energy detection) in cognitive radio networks. The evaluation metrics considered in his work, the effect of receiver curve plots under signal-to-noise ratio vs detection probability with varying noise uncertainty parameters during energy detection process through adaptive decision thresholds. However, the obtained results throughout the authors work, the detection probability of ED performs better during low noise uncertainty and SNR conditions. Therefore, the authors work is limited with, the evaluation of energy detection based adaptive decision thresholds of receiver operating characteristic curve plots under signal-to-noise ratio versus detection probability at different number of sample size and false alarm probability in order to obtain better detection probability during energy detection operations. Moreover, comparative analysis on ED of decision thresholds with and without noise uncertainty under false alarm probability vs detection probability considered in this thesis work.

The authors in [15], proposed the efficient non-cooperative spectrum sensing technique (i.e. energy detection) with deferent noise uncertainty in cognitive radio networks through pre-defined decision thresholds. The considered evaluation metrics for the proposed work, the receiver operating characteristic curves under false alarm probability vs detection probability through different noise uncertainty parameters at low SNR conditions. Therefore, the obtained result through the authors works operations, the energy detection technique detection probability increases when noise uncertainty decreases with the considered specific ranges 0.6 to 0.1 during low false alarm probability conditions. Therefore, the authors work is limited to evaluating ED of adaptive threshold of ROC curve plots under false alarm probability vs probability of detections with NU parameter ≥ 1, considering at low SNR and relatively high N conditions.

The author in [18]**:** Proposed performance evaluations of hard decision rules for fixed thresholds of energy detection. Then, the performance evaluations on the fusion logic rules (OR-Logic rules and AND-Logic rules) of energy detection with considering low false alarm probability and signal-to-noise ratio conditions. Therefore, during receiver operating characteristic curve plots under probability of false alarm vs probability of detection of energy detection, the obtained results from the authors work were, the OR-Logic fusion rule outperforms than considered AND-Logic rules during ED of fixed threshold process. However, the proposed work is limited with evaluating the performance of ED of adaptive thresholds with complementary receiver operating characteristic curve plots under false alarm probability vs missed-detection probability of fusion rules with considering minimum signal-to-noise ration environments.

However, this thesis investigated the performance analysis and comparison of decision thresholds on dual-hop CRNs based on energy detection techniques. Therefore, during the ED process determined the performances of both variable and constant decision thresholds through the effect of known noise variance and NU under P_D and P_{FA} by using inverse cumulative density function (ICDF) approaches. In addition, adopted the comparative analysis of variable and adaptive threshold techniques at different SNR conditions to determine decision thresholds performances. Moreover, determined the effect of noise uncertainty on the PU signal decision thresholds based on the number sample size during the energy detection process at the fusion center.

Chapter 4

System Model and Problem Description

4.1 Thesis Flow Chart

This thesis proposed the performance analysis and comparison of decision thresholds on dual-hop cognitive radio networks based on Energy detection. The fundamental endeavor is to review different Literature, books, journals, and websites about the analysis and comparison of decision thresholds on dual-hop cognitive radio networks based on Energy detection to build up a solid understanding of the thesis work have done. Subsequently, the mathematical analysis has been done for the proposed system model, to compare and analyzes both constant and adaptive threshold techniques based on ED under evaluation metrics: signal-to-noise ratio (SNR), noise uncertainty, number of sample sizes, receiver operating characteristic (ROC) curves of detection probability and false alarming probability, and complementary receiver operating characteristic (ROC) curves. On the other hand, the effect of noise uncertainty on the performances ED of decision thresholds. Lastly, to enhance the chance of detection accuracy of PU signals used fuzzy combined logic sensing approach over specified ranges of SNR levels. The process flow diagram from the proposed system model at the fusion center of cognitive radio networks, which is considered as a methodology for this thesis work in figure 4.1.

The process flow diagram from the proposed system model at the fusion center of CRN:

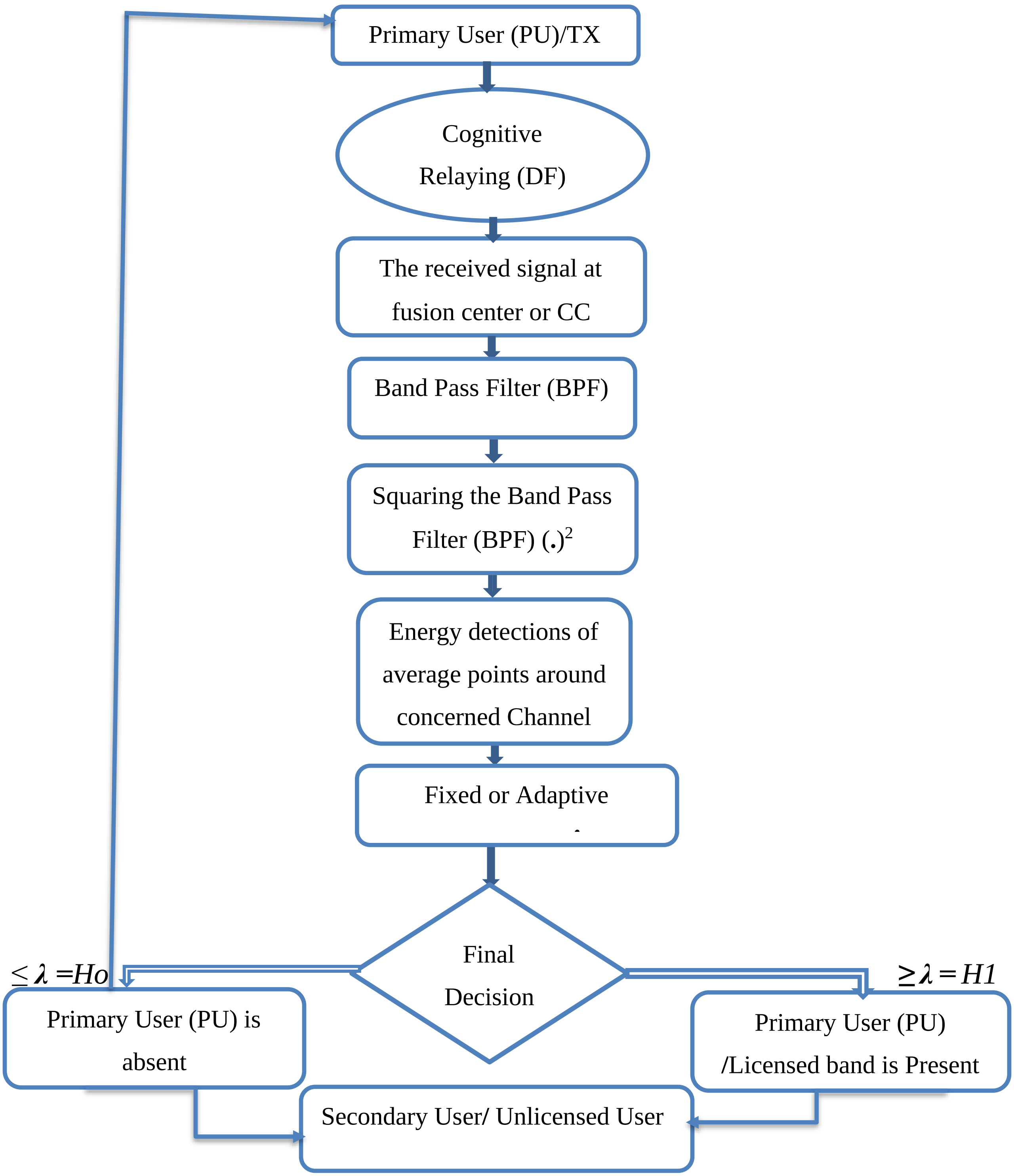

Figure 4- 2 Energy detector (ED) Process flow diagram at the fusion center of CRN

4.2 The Performance Evaluation Metrics

An energy detector is a spectrum sensing technique and used to determine the presence or absence of the primary user spectrums. In addition, ED detects the PU spectrum by using the following techniques: binary hypothesis test static theorems, decision thresholds technique (either fixed or adaptive) with the assistance of hard decision of fuzzy logic at fusion center, receiver operating characteristics (ROC) curve plots for detection and false alarm probabilities of energy detections through the simulation software MATLAB2018a for this thesis work.

The considered performance evaluation metrics on this thesis work includes:

- The probability of detection (P_D) which implies that the probability of SU declaring that a PU is present when the spectrum is indeed occupied by the PU.
- The Probability of false alarm (P_{FA}): which implies that the probability of SU declaring that a PU is present when the spectrum is actually free.
- The Probability of miss-detection (P_{MD}): describes the probability of a SU declaring that a PU is absent while the spectrum has been occupied in actual.
- Signal-to-noise ratio (SNR): Which is determines the transmitted signals strength with respect to the noise power. The common factors that affect the signal to noise ratio (SNR) of secondary users or cognitive radio users are Path loss, the propagation channels, shadowing, and the PU signal strengths [59]. The IEEE 802.22 WRAN standards, the desired probability of detection and probability of false alarming, ($P_D \geq 0.9$ and $P_{FA} \leq 0.1$) respectively to achieve the minimum signal to noise ratio [60]-[63].
- Number of sample sizes (N): Based on the desired probability of detection and probability of false alarming, the number of sample sizes effect and determining the proportionality with P_D, P_{FA} and signal-to-noise ratio.
- Receiver operating characteristics (ROC) curves: The ROC curves, which is determining the performance of spectrum detection algorithms and eliminating the noise uncertainty at different SNR values.
- Complementary ROC curves to determine the trade-off between the probability of detection and miss-detection probability during ED process.

- Noise Uncertainty (NU): During energy detection, process excludes any irregularity of noise power at the secondary user side called noise uncertainty.

4.3 CR System Model for Transmitter Detection Technique on Dual hops

The main problems in wireless transmission medium are noise and fading, which makes become complex the received data streams for decoding and due to the wrongly received signals, occasionally made the error at the receivers. Then, to obtain error-free and reliable data at the destination, the dual-hop communication process is completed by using orthogonal frequency-division multiplexing schemes between the primary user and secondary user proposed in figure 4.2. Therefore, in the first hop, the encoded data broadcasted into the wireless medium. Then, the transmitted data reached the destination through the direct and indirect path, which includes the CRs. Although, during the communication process the second hop received data by the CRs estimated by using the ML decoding and further transmitted towards the fusion center. The fusion center is responsible for the final decision-making about the presence or absence of the licensed user spectrum. In addition, due to the spectrum sensing, the energy detection technique implemented during the process. The entire spectrum sensing technique decision thresholds and fusion rule logics operate at the fusion center in the cascade to come up with reliable result about the licensed spectrum. Furthermore, the dual antennas at transmitter and receiver considered, due to trans-receive signals with full-duplex capability between source and destination respectively, but CRs with half-duplex feature implemented for the proposed operations. Therefore, let consider the received information through the direct and indirect path at destination conveys mathematically:

$$\mathrm{y(n)_{SR}} = \mathrm{h^{SR}} * \mathrm{x(n)_{SR}} + \mathrm{w(n)} \qquad \text{Eq (4.1)}$$

$$\mathrm{y(n)_{RD}} = \mathrm{h^{RD}} * \mathrm{x(n)_{RD}} + \mathrm{w(n)} \qquad \text{Eq (4.2)}$$

Therefore, adding the Eq (4.1) and Eq (4.2), then obtained the simplified results to calculate the total received information at destination expressed:

$$\mathrm{y(n)}_{SD} = \mathrm{h^{SD}} * \mathrm{x(n)_{SD}} + \mathrm{w(n)} \qquad \text{Eq (4.3)}$$

Where, $\mathrm{y(n)_{SR}}$ and $\mathrm{y(n)_{RD}}$ the received information through the direct path at CRs and at destination respectively $\mathrm{h^{SR}}$ and $\mathrm{h^{RD}}$ = denotes the channel coefficients at cognitive relays and destination. w(n), denotes the AWGN added in signal during transmission through the wireless channel from PU to the receiver end. On the other hand, as shown in figure 4.1, the separation distance between the primary and cognitive relays denoted by d1, at the same time the distance between the CRs and the secondary user called d2. Then, d represents the total separation distance between PU and fusion center or cognitive controller. Therefore, the 2-hopes relations for channel mean power at wireless links because of the effect of path loss mathematically expressed in equations:

$$h^{SR} = \in^{-\alpha} * d_1 \qquad \text{Eq (4.4)}$$

$$h^{RD} = (1-\in)^{-\alpha} * d_2 \qquad \text{Eq (4.5)}$$

Therefore, the channel mean power throughout wireless links from source to destination

$$h^{SD} = \in^{-\alpha} * d_1 + (1-\in)^{-\alpha} * d_2 \qquad \text{Eq (4.6)}$$

Where, h^{SR}= the channel mean power between primary user and CRs.

h^{RD} = the channel mean power between CRs and fusion center.

h^{SD} = the channel mean power between source and destination.

$\in$ = is the distance control factor in between PU and fusion center.

α = is the path loss exponent during propagation.

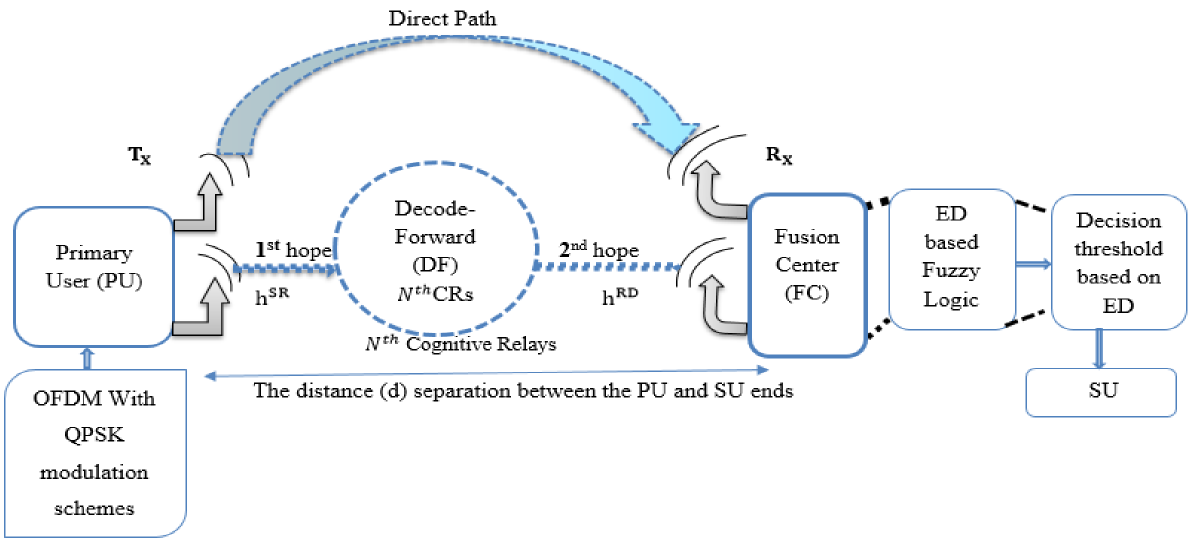

Figure 4-2: CR system model for transmitter detection technique of ED based decision thresholds under dual-hop transmissions.

4.4 Cognitive Relaying System

The basic cooperative relaying scheme refers to that the source transmitter sends the information to both the relays and the destination, then the received information is processed to achieve reliability and spatial diversity at relaying station in between the transmitter and the receiver end [23]. The relay receives the same signal from the source and then retransmits it to the destination. The destination merges the received signal from both the relay and source to boost reliability. In [23], the whole process described in figure 4-1.

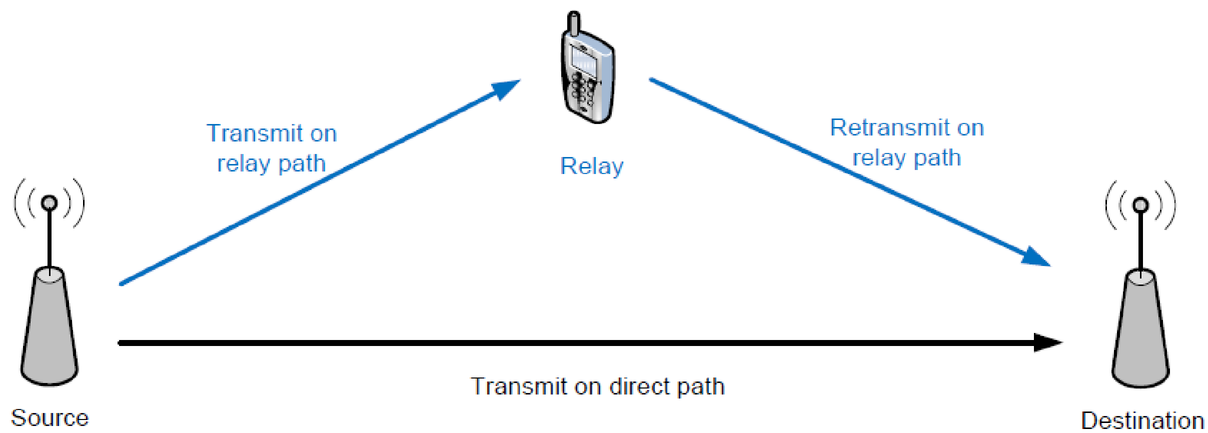

Figure 4- 3: The basic operational principle of cognitive relaying system

4.4.1 Dual-hop Cognitive Relaying Communication System

The wireless cognitive relays used when the distance between source and destination to transmit the source information to destination ends. The working principle of wireless relays, which receives the broadcasted data streams from source. Then making decode and then process it and finally, forwards to receiver ends. In additions, transmitter spectrum sensing plays an important role in CRN to improve the detection probability of licensed spectrum. The data streams traveling through wireless communication mediums face a lot of problems due to noise, fading, hidden terminal problem, multipath reflection, etc. However, the data streams transmitted from source arrive at destination through digital relays in dual hops using orthogonal frequency division multiplexing schemes, [24]. Furthermore, in [24], the basic cognitive relaying schemes process carried out by: Decode and Forward (DF) schemes, Amplify-Forward (AF) schemes and Decode-Amplify and Forward (DAF). In this work, considered only Decode and Forward (DF) Schemes to minimize the unwanted interferences from the wireless medium.

4.4.1.1 Decode and Forward (DF) schemes

In [24, 53,56], in this non-cooperative relaying scheme, the relay node is going to decode the sending information's from the source and then re-encodes it prior to forwarding it to the destination. If the source signal detected properly, the relay supports direct path communication. Otherwise, wrongly decoded information at the relay considered as the lower performance of the system due to error propagation. Furthermore, the final received information at the destination is represented mathematically in the below equation (4-1) in [24].

$$Y(n) = H^{SD} \cdot X(n) + W(n) \qquad \text{Eq}(4.7)$$

Where,

X (n) = is the transmitted/the-input signal,

H^{SD} = denotes the channel mean power from source to destinations.

W (n) = is the AWGN fading channel

Y (n) = is the received signal at the destination. Therefore, the DF relaying protocol decodes the primary user signal X (n) and then transmit primary user signal from relay towards the destination. However, let be assumed the received information at the destination is become = Y (n), at the relaying station the received signal is designated by, X_r (n), then at the end of the DF schemes amplify the received signal at the relaying stations with the amplification factor (β), where, the whole process explained mathematically below in the Equation (4.8).

$$Y(n) = \beta * X_r(n) + W(n) \qquad \text{Eq (4.8)}$$

Where, β = is the amplification factor of DF

W(n) = is the additive white Gaussian noise (AWGN).

X_r (n) = is at the relaying station the received signal

Y (n) = is the received information at the destination

Furthermore, with considering when the coefficients of amplification factor of DF, β depends on the Raleigh fading's and variance, as expressed mathematically in the equation (4.9).

$$\beta = \sqrt{\frac{P_t}{\delta_n{}^2 + P_r H^{SD}}} \qquad \text{Eq (4.9)}$$

Where, β = is the amplification factor of DF

H^{SD} = denotes the variance and fading coefficient between the transmitter and the relay.

$\delta_n{}^2$ = is the noise variance

P_t = is the average transmitted signal from source to destination

P_r = is the average transmitted signal from relay.

On the other hand, in [24], Wireless communication is a type of communication media in which the signal transferred between two or more than two points without physical connections. However, communication channel is referring to either wired or wireless mediums between the transmitter and the receiver. Mostly wireless communication channels affected by free path loss, fading, noise; inter symbol interference (ISI), etc. In [25], describes the signal attenuation between a source and destination due to a function of the propagation distance and other parameters is called path loss and it is expressed mathematically in [25].

$$\alpha = \frac{P_t}{P_r} \qquad \text{Eq (4.10)}$$

Where, α = denotes the path loss factor

P_t= is denotes the transmitted power

P_r = is denotes the received power

Therefore, the wireless channel mean power from source to destination affected by path loss as described in [25, 26] and expressed mathematically.

$$H^{SD} = \in^{-\alpha} * d_{sr} + (1 - \in)^{-\alpha} * d_{rd} \qquad \text{Eq (4.11)}$$

Where, ∈ = denotes the distance control factor between PU and FC.

d_{sr} = denotes the separation distance between source to relay

d_{rd} = denotes the separation distance between relay to destinations.

4.5 The Binary Hypothesis of Spectrum Detections

Spectrum detecting is the process of periodically monitoring a particular spectrum band, due to recognizing the presence or absence of primary user's spectrums. The main objectives of the spectrum sensing process are to declare the frequency spectrum band status (unoccupied or occupied), due to the process the secondary user can use the radio spectrum without interfering with the Primary User. Therefore, the thought of non-cooperative spectrum detection is based on a two binary hypothesis is expressed in [30].

$$Y(n) = W(n) \quad , H_O \quad n = 1, 2, 3...N \qquad \text{Eq (4.12)}$$

$$Y(n) = H^{SD} . X(n) + W(n) \quad , H_1 \quad n = 1, 2, 3...N \qquad \text{Eq(4.13)}$$

Where, n, which denotes the sensing time

X (n) = is the transmitted or the-input signal,

H^{SD} = denotes the channel mean power from source to destinations.

W (n) = is the AWGN fading channel

Y (n) = is the received signal at the destination by CR users.

H_O = denotes the Channel is unoccupied given that PU is absent.

H_1 = denotes the Channel is occupied given that PU is present. Therefore, non-cooperative spectrum sensing techniques classified into three (i.e. energy detection, matched filter detection, and Cyclo-stationary feature detection) are possibly used and described in detail in [30]. However, in this thesis work considered, comparative analysis of Energy detection-based decision thresholds proposed on dual-hop cognitive radio networks, due to the key features of ED includes: low operational and computational complexity, not require prior information of PU signals, and it is the most popular detection algorithms as presented in [30]. Furthermore, to make the spectrum decision based on the availability as obtained during spectrum sensing channel allocations, about the primary signal presence, a decision detection threshold, denoted by λ is chosen according to the adopted spectrum sensing technique and then compared to the received output signal is called the test statistic (E). Therefore, to evaluate the performance of detection techniques, a decision threshold (λ) is set constantly or dynamically and compared to the test statistic, that generated from primary users. Generally, in terms of the probability index, the possible outcomes of a two binary hypothesis test H_O and H_1 as per the type of spectrums detection performances described in, [31].

- ❖ The Probability { H_1/ H_1}: Declaring H_1 when H_1 is true (H_1: H_1) Exact decision.
- ❖ The Probability { H_0/ H_0}: Declaring H_0 when H_0 is true (H_0: H_0) Exact decision.
- ❖ The Probability { H_0/ H_1}: Declaring H_0 when H_0 is true (H_0: H_1) missed detection.
- ❖ The Probability { H_1/ H_0}: Declaring H_1 when H_0 is true (H_0: H_1) is false alarming.

4.5.1 Decision Thresholds Based Energy Detection Process at Fusion Center (FC)

In [31,32], the principle of energy detection at the FC is, determining the transmitted signal energy results of binary hypothesis test statics, then compared to the considered decision threshold values. Then, the received signal energy at the fusion center is greater than the decision thresholds value, the hypothesis test static H_1 is declared, which means the PU is present otherwise the signal energy is lower than a predefined threshold, H0 is declared i.e. the PU is absent and there is free spectrum hole. The received data streams at the cognitive controller (CC) or FC is a test statics E (n) compared with a predefined threshold value λ to make the final decision about the absence or presence of the primary user spectrum**.** Therefore, the output of a test statics E (n) of the energy detector compared to a decision threshold value used to make the accurate decision at the end, expressed [32].

- ❖ If E (n) $\geq \lambda$, then PU signal is present. Eq (4.14)
- ❖ If E (n) $\leq \lambda$, then PU signal is absent. Eq (4.15)

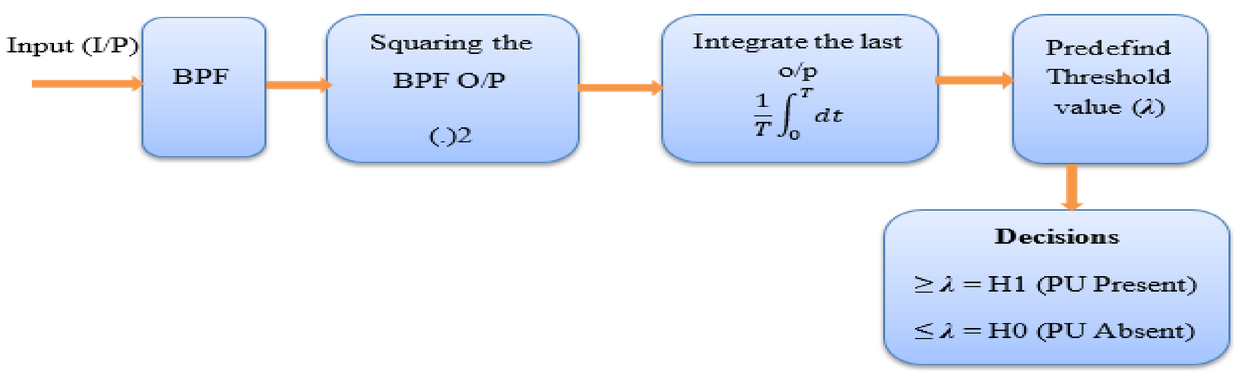

Figure 4- 3**:** Block diagram of Energy detection technique implementation at the FC

In [33], if the ED received a noise power and its test statics expressed as determined in equation (4.13).

$$E(n) = \sum_{n=0}^{N-1} |Y(n)|^2 \qquad \text{Eq (4.16)}$$

Where, $E(n)$ = denotes the test statics for the energy detection technique.

N = Number of signal sample sizes.

$Y(n)$= denotes the sequence of the received signals.

As depicted in Eq (4.13), a binary hypothesis test static rule is used to determine the decision thresholds in energy detections, with considering the AWGN mean value = 0 and variance is unity. Therefore, during energy detection operation the decision thresholds operate by using either dynamic or constant decision thresholds. Moreover, the dynamic decision thresholds operate dynamically by adjusting the frequency resolution and number of sample sizes for reliability and detection accuracy [33]. However, the Neyman-Pearson hypothesis used to determine the performance of decision thresholds of energy detection between probability density functions of the alternative and null hypothesis, described mathematically in [33]:

$$\frac{\text{Log Prob}(Xo,X1,X2,\ldots\ldots X(N-1)|H_1)}{\text{Log Prob}(Xo,X1,X2,\ldots\ldots X(N-1)|H_0)} \lessgtr \lambda \text{, results for } H_1 \text{ or } H_0\text{ ,} \qquad \text{Eq (4.17)}$$

Where, Prob $(X|H_1)$ = denotes the probability of density function for H_1 (PU is present).

Prob $(X|H_0)$ = denotes the probability of density function for H_0 (PU is absent).

In [34], to expressing the presence of the PU signal ($E(n) > \boldsymbol{\lambda}$), the Non-central chi-squared distribution with N degrees of freedom is used. However, central chi-squared distribution with N degrees of freedom is used, where N represents a number of signal samples used in the energy detection process in the case of PU signals absence ($E(n) < \lambda$). Therefore, when the noise variance is well known and noise uncertainty (NU) is not considered, the central-limit theorem yields the following normal distribution approximations of the hypothesis test statistics in [34]:

$$E(n) = \begin{cases} N\left(\delta n^2, \frac{\delta n^4}{N}\right) & , \quad H_0 \\ N((\delta n^2 + P), \frac{2}{N}(\delta n^2 + P)^2 & , \quad H_1 \end{cases} \qquad \text{Eq (4.18)}$$

Where,$P = \frac{1}{N}\sum_{n=1}^{N} |Y(n)|^2$ denotes the average transmitted signal power. In [34, 35], the most suitable values of the PU signals of Tx power are characteristically based on OFDM commutation systems such as WLAN (100 mW) or wireless systems (1 W and 10 W). On the other hand, the decision thresholds of energy detection technique, the noise power and the transmitted signal considered an IID RV (independent and identically distributed random variables) with zero mean or $\delta\mu^2 = 0$ and $\delta n^2 = 1$. In addition, the signal-to-noise ratio (SNR) is to be considered γ :

$$\gamma = \frac{\delta\mu^2}{\delta n^2} \qquad \text{Eq (4.19)}$$

However, based on central limit theorem, when the number of sample size gets increase, the $E(n)$ has a normal distribution with μ_i mean and variance δ_i under the hypothesis test statics H_i, where, i= 0, 1. Hence, each described to be μ_i = for i =0, 1 and δ_i = for i = 0,1, therefore;

$$\mu_0 = \delta_{n^2}, \text{ but } \quad \delta_0 = \frac{\delta_{n^2}}{N^{\frac{1}{2}}} \qquad \text{Eq (4.20)}$$

$$\mu_1 = \delta_{n^2} * (1+\gamma) \text{ , } \delta_1 = \delta_0 * (2\gamma+1)^{\frac{1}{2}} \qquad \text{Eq (4.21)}$$

In [35], when the number of signal sample size increases, the mathematical analysis is consent for decision threshold of energy detection technique, in terms of probability of false alarm (p_{FA}), detection probability (p_D) and probability of miss-detections (p_{MD}) can be determined as:

$$P_D = P\{E(n) > \lambda | H1\} = Q_m\left(\frac{\lambda_D - N(\delta_{\mu^2}+\delta_{n^2})}{(2N)^{\frac{1}{2}}(\sqrt{(\delta_{\mu^2}+\delta_{n^2})^2})}\right) \qquad \text{Eq (4.22)}$$

$$P_{FA} = P\{E(n) > \lambda | H0\} = Q_m\left(\frac{\lambda_{FA} - N\delta_{n^2})}{(\sqrt{2N\delta_{n^4}}}\right) \qquad \text{Eq (4.23)}$$

$$P_{MD} = 1 - P_D \qquad \text{Eq (4.24)}$$

Where, $Q_m(.)$ = denotes the standard Gaussian complementary distribution functions.

N = denotes the number of signal sample size

δ_{μ^2} = denotes the noise with mean value zero

δ_{n^2} = denotes the noise with variance value unity.

λ = denotes the decision thresholds

Furthermore, $Q_m(.) =$ denotes the standard Gaussian complementary distribution function and determined in [35]:

$$Q(t) = \frac{1}{\sqrt{2\pi}} \int_t^\infty e^{-\lambda^2}/_2 \, dt \qquad \text{Eq (4.25)}$$

4.5.2 Decision Threshold Selection for Energy Detection (ED) Algorithms

In cognitive radio networks, the energy detection algorithm, which is used to determine the test statics hypothesis under consideration of the unoccupied or occupancy of the PU's signal in frequency spectrum bands. In addition, it is measuring the electromagnetic energy present in a specific frequency band and comparison with a certain predefined decision threshold value. i.e. when the test statics is above the predefined threshold value, a primary user is said to be present in the sensed frequency spectrum bands in [35] [38]. Hence, the test statistic is below the predefined threshold value, the frequency spectrum band considered empty. Therefore, the threshold accuracy has an important role in determining the frequency spectrum band's presence or absence and it depends on the capability to choose a proper decision threshold. The decision threshold techniques broadly categorized as two: variable or adaptive thresholds and fixed or constant decision thresholds. In this thesis considered, comparative analysis on decision thresholds of ED technique based on Neyman-Pearson theorem in order to minimize the effects of impairments of signal introduced by non-stationary noise and wireless channels. Therefore, the key features of both types of decision thresholds in [39] [43], presented here to understand the details. Firstly, the adaptive decision threshold techniques during energy detection provide an adjustment to the noise variation in the environment over the time interval in which the spectrum kept track. In addition, no need for prior knowledge of the PU's signal information and its adaptability achieved through analyzing the statistical properties of the received spectrum measurements in that the standard deviation gives the dispersion level of spectral measurement data around a mean value. Therefore, if the data varies widely the dispersion of the received signal will change more rapidly and vice versa. On the other hand, the basic features of constant threshold technique in [43]: It uses a static threshold value that is predefined above the noise floor to judge spectrum presence or absence, the threshold value is constant and it does not change based on the perceived signal to noise ratio is called constant/fixed threshold. In addition, it requires a priori knowledge of the noise power and spectrum activity. Moreover, based on decision thresholds operational key feature, the inverse cumulative density function (ICDF) considered in this thesis work, to determine the performances of both variable and constant decision thresholds of energy detection approaches as explained in [34].

4.5.3 Energy Detections (ED) Process without Noise-Uncertainty (NU)

In [34, 35], the existing analyses of the spectrum-sensing methods are based on the consideration that prior information about noise power is surely known at the position of SU. Thus, this method implies that during the ED process excludes any irregularity of noise power at the secondary user side called Noise Uncertainty (NU). In this work, inverse cumulative density function (ICDF), which used to determine the performances of both variable and constant decision thresholds of energy detection approaches as described in [34]. However, based on Neyman-Pearson threshold detections, in the case of the adaptive ICDF approach, the decision threshold is a function of the false alarm probability (P_{FA}) and a function of detection probability (P_D) in the case of constant decision threshold methods for energy detection during the spectrum-sensing process in [34] and derived below from the above equations (4.22) and (4.23) respectively. For example, in [34], the decision thresholds during energy detection operation depend on the following input parameters: M is the transceiver antenna number, P_D , P_{FA} and the number of sample sizes (N). Furthermore, then determining the decision threshold estimation of ED, without NU is described mathematically through below equations (4.26) and (4.27).

$$\lambda_{PFA\ ,ED} = Q^{-1}(P_{FA})\delta n^2\sqrt{\frac{2}{MN}} + \delta n^2 \qquad \text{Eq (4.26)}$$

$$\lambda_{PD\ ,ED} = Q^{-1}(P_D)(P + \delta n^2)\sqrt{\frac{2}{MN}} + (P + \delta n^2) \qquad \text{Eq (4.27)}$$

Where,

$\lambda_{PFA\ ,ED}$ = denotes variable values of false alarming probability of decision thresholds during adaptive ICDF of ED proccess without noise uncertainty.

$\lambda_{PD\ ,ED}$ = denotes constant value of detection probability of decision thresholds during fixed ICDF of ED proccess without noise uncertainty.

$Q^{-1}(.)$ = denotes the inverse standard Gaussian complementary distribution functions.

$P =$ The average primary user signal power.

M = The number of transceiver antennas.

$\delta n^2 =$ The noise variance.

However, in [34], far accurate primary user detection during ED sensing time, determine the number of signal sample size and correlate with the required performance evaluation metrics: the detection probability (P_D), probability of false alarming (P_{FA}) and the signal-to-noise ratio (SNR) derived through below equations. Let as consider, $\mu_0 = \delta n^2$ and $\delta_1 = \delta_0 * (2\gamma + 1)^{\frac{1}{2}}$ substituted in Eq (3.22) and Eq (3.23) to obtain the minimum overall number of sample size:

$$\text{No\_ of sample size (N)} = \frac{1}{\gamma^2}\left[\frac{1}{Q}(PFA) - \frac{1}{Q}(PD) * \sqrt{2SNR + 1}\right]^2 \quad \text{if SNR} = \gamma$$

$$= \frac{1}{\gamma^2}\left[\frac{1}{Q}(PFA) - \frac{1}{Q}(PD) * (1 + \gamma)\right]^2$$

$$= \frac{2[Q^{-1}(PFA) - Q^{-1}(PD)]^2 * [(1+SNR)]^2}{SNR^2} \qquad \text{Eq (4.28)}$$

Therefore, the Eq (4.28), shown that the inverse relations between the number of sample sizes and signal-to-noise ratio could be obtained if the existence of noise power is perfectly known. Then, in an energy detection process, the higher number of samples size yields higher detection probability, regardless of the decision threshold set as per noticed that in the Eq (4.28). Furthermore, the Eq (4.28), describes the number of samples is minimum during energy detection process due to obtain energy detection for a specific combination of detection probability, signal-to-noise ratio, and false alarming probability. On the other hands, in [35], the performance evaluation metrics with having great effects on PU signal detection probabilities the level of signal-to-noise ratio, false alarming probability and number of signal sample sizes. In additions, the interdependencies between the detection probability and false alarming probability, which obtained from Eq (4.28), and mathematically expressed in [35].

$$P_D = Q\left(\frac{Q^{-1}(P_{FA}) - \sqrt{\frac{N}{2}}SNR}{1+SNR}\right) \qquad \text{Eq (4.29)}$$

4.6 Energy Detection Process with Estimation of Noise Uncertainty

The fundamental analysis of the Energy detection (ED) spectrum sensing technique with considering that the noise power is exactly known and detected by secondary users. However, in actual application, it is not possible to acquire the exact information about noise uncertainty power, which is random changes in the time and space domain. Because of that secondary user, usually experiences noise uncertainty in the noise power estimation or detection called as noise uncertainty (NU) in [36]. Therefore, the Energy detection performance of the cognitive radio network considering without NU means avoiding realistic conditions in the network. In order to have a realistic performance detection of the energy detection technique modeled by taking into account the noise uncertainty effect on the overall energy detection processes. For this reason, a mathematical model provided to visible the impact of the noise uncertainty on the performance evaluation of Energy detection processes.

In [36, 37, 38], the variations in the noise power usually affects the energy detection technique performance. However, proposed the idea of signal-to-noise ratio wall that presents that there is a critical value of signal-to-noise ratio below which it is impossible for the energy detection to sense the primary user's signal in a spectrum is known as signal-to-noise ratio wall ($\mathrm{SNR}_{\mathrm{Wall}}$). So, for an uncertainty factor (ρ), in noise power detection, where, $\rho > 1$, in [37], because of the appearance of noise uncertainty of the wireless communication channels in cognitive radio networks, there may be a distributional uncertainty of the noise power (δn^2) exists and can vary in the intervals:

$$\delta n^2 \epsilon \left[\frac{1}{\rho}\delta n^2, \rho\delta n^2\right] \qquad \text{Eq (4.30)}$$

Which means, in the worst conditions the minimum value of noise power is considered, $\frac{1}{\rho}\delta n^2$ then the received signal power should be greater than $\rho\delta n^2$ which is expressed mathematically,

$$P + \frac{1}{\rho}\delta n^2 \geq \rho\delta n^2 \qquad \text{Eq (4.31)}$$

Where, P, denotes the primary user's signal power, and then simplified the Eq (4.31), in order to find critical value of signal-to-noise ratio (SNR) during ED operations:

$$\frac{P}{\delta n^2} \geq \left(\rho - \frac{1}{\rho}\right) \qquad \text{Eq (4.32)}$$

Then, the value of signal-to-noise ratio wall(SNR_{Wall}), in [38] which the energy detection does not detect or impossible to detect the primary user signal. i.e.

$$SNR_{Wall} = \left(\frac{P}{\delta n^2}\right)_{minimum} = \rho - \frac{1}{\rho} = \frac{\rho^2 - 1}{\rho} \qquad \text{Eq (4.33)}$$

Therefore, the proposed Energy detection technique can sense even though in case scenario of NU as long as the signal-to-noise ratio is above the minimum value of SNR wall (SNR_{Wall}). Eventually, due to the limits of noise variance of additive white Gaussian noise affected with noise uncertainty (NU) expressed in the Eq (4.30) the detection probability and false alarm probability considered in a case of maximum and minimum value of noise variance intervals, then the Eq (4.22) and (4.23) is replaced by the limiting values and described as [38] [39]. Therefore, when the noise variance is unknown, then to determine P_D and P_{FA} with considering NU factor expressed respectively:

$$\left(P_D{}^{NU}\right)_{Min} = Qm\left(\frac{\lambda_D{}^{NU} - (P + \frac{\delta n^2}{\rho})}{\sqrt{\frac{2}{N}(P + \frac{\delta n^2}{\rho})^2}}\right) \qquad \text{Eq (4.34)}$$

$$\left(P_{FA}{}^{NU}\right)_{Max} = Qm\left(\frac{\lambda_{FA}{}^{NU} - \rho\delta n^2}{\sqrt{\frac{2}{N}(\rho\delta n^2)^2}}\right) \qquad \text{Eq (4.35)}$$

In [38], when the noise variance is known and without considering NU, then P_D and P_{FA} described respectively,

$$P_D = Qm\left(\frac{\lambda_D - (P + \delta n^2)}{\sqrt{\frac{2}{N}(P + \delta n^2)^2}}\right) \qquad \text{Eq (4.36)}$$

$$P_{FA} = Qm\left(\frac{\lambda_{FA} - \delta n^2}{\sqrt{\frac{2}{N}(\delta n^2)^2}}\right) \qquad \text{Eq (4.37)}$$

Where, $P_D{}^{NU}$, denotes the Energy detection probability of PU signals affected by NU.

$P_{FA}{}^{NU}$, denotes the probability of false alarming reception of PU signals affected by NU.

P, denotes the transmitted power of PU signal.

N, denotes number of sample size.

λ_D , denotes the probability of detection threshold.

λ_{FA} , denotes the probability of false alarm threshold.

Moreover, to determining the probability of detection threshold for constant value of ${P_D}^{NU}$ and ${P_{FA}}^{NU}$ in the case NU obtained and simplified from the Eq (4.34) and Eq (4.35) respectively expressed as [39].

$$\lambda_D{}^{NU} = Q^{-1}\left({P_D}^{NU}\right)\left(P + \frac{\delta n^2}{\rho}\right)\sqrt{\frac{2}{MN}} + \left(P + \frac{\delta n^2}{\rho}\right) \qquad \text{Eq (4.38)}$$

$$\lambda_{FA}{}^{NU} = Q^{-1}\left({P_{FA}}^{NU}\right)\delta n^2\sqrt{\frac{2}{MN}} + \rho\delta n^2 \qquad \text{Eq (4.39)}$$

In [37, 38], a minimum number of signal sample size (N^{NU}) for performing energy detection in a case of PU signal affected by NU, the mathematical model is determined by simplifying from the Eq (4.28) expressed as:

$$N^{NU} = \frac{2\left[\rho Q^{-1}({P_{FA}}^{NU}) - (\frac{1}{\rho} + SNR)Q^{-1}({P_D}^{NU})\right]^2}{\left[SNR - \left(\frac{\rho^2-1}{\rho}\right)\right]^2} \qquad \text{Eq (4.40)}$$

Where, N^{NU}, denotes during Energy detection process the number of signal samples used for reliable and an accurate detection of the primary user signal with considering NU. In additions, the Eq (4.33) determines that the ED cannot sense the primary user signal when its power is less than SNR wall of the noise uncertainty power. For this reason, if the noise power has a larger value than the PU signal, it is difficult to distinguish the PU signal from noise signal**s.** So that, in the calculation of a number of samples scaling the noise uncertainty parameter is considered. When the NU factor $\rho = 1$, then $P_D = {P_D}^{NU}$ and $P_{FA} = {P_{FA}}^{NU}$ becomes equal as per the relations of Eq (4.28) and Eq (4.40). However**,** When the NU factor $\rho > 1$, for low SNR conditions, to have accurate detection the number of sample sizes must increases or approaches to infinity, which means the detection duration must extremely large and it is impossible to become fully aware in practice or in low SNR values. In additions, the cognitive radio networks performance is highly impacted by the NU parameter levels, signal-to-noise ratio and number of samples or sensing durations and their interdependence in between ${P_{FA}}^{NU}$ and ${P_D}^{NU}$ for different values of the NU parameter derived from Eq (4.40) and the impact of NU on detection probability expressed as in [38, 39]:

$$P_D{}^{NU} = Q\left(\frac{\rho Q^{-1}(P_{FA}{}^{NU}) - \left(SNR - \frac{\rho-1}{\rho}\sqrt{\frac{N^{NU}}{2}}\right)}{\frac{1}{\rho}+SNR}\right) \qquad \text{Eq (4.41)}$$

4.7 Receiver Operating Characteristic (ROC) Curves

To analysis, the performance of spectrum sensing techniques used several evaluation metrics such as the probability of detections, false alarm probability, miss detection probability, SNR and number of sample sizes. However, P_D , and P_{FA} evaluation metrics are the most common. The probability that the secondary user correctly declares that a primary user is present, when the PU is surely present in the spectrum called detection probability. The probability of false alarming is defined as the probability that a secondary user incorrectly declares that the primary user is present when the PU is absent as the truth [40]. In addition, the relation between the P_D and P_{FA} has been usually described through ROC plot curves as described in figure 4-5. The area above and below the diagonal that identify the performance of Energy detections. Generally, the ROC curve space above the diagonal shows better detection results than the random-access line, while the space below the random-access line represents the worse performance of Energy detection than the random-access line. Consequently, the energy detections will be less accurate when the curve is closer to the diagonal line of the receiver operating curves as per shown in figure 3-5. The closer the curve follows the upper border of the ROC area and the left-hand border; the detection process shown more accurately in figure 4-5. The area under the curve (AUC) is also a measure of the energy detection accuracy. If a larger AUC means that there is, better energy detection accuracy and vice versa. The receiver operating characteristic curve plots idea, as a frequently used concept for analyzing the efficiency of primary user signal detections and is further used in this thesis work at the results section. The overview properties of receiver operating curves (ROC) on detection probability in [41, 43, 44]:

- ROC curve determines the tradeoff between false alarm rate and P_D for providing a sensitivity, accuracy and an optimum threshold performance of the system

- ❖ It is a technique for visualizing, organizing, and selecting classifiers (true positive (TP), false positive (TF)) based on their performance.
- ❖ Widely applicable in signal detection algorithms and estimation for radar operations.
- ❖ It is represented by a two-dimensional (x-y) axis graphically, plot where the P_{FA} vs P_D.
- ❖ The ROC curve classifiers can be discrete and mapped as a single point on ROC space and can be coordinated as a pair of points from (0, 0) to (1, 1) as shown below figure.
- ❖ Area under Curve (AUC) is the portion of the area of the unit square used to calculate the area of the ROC curve its value is always between 0 and 1

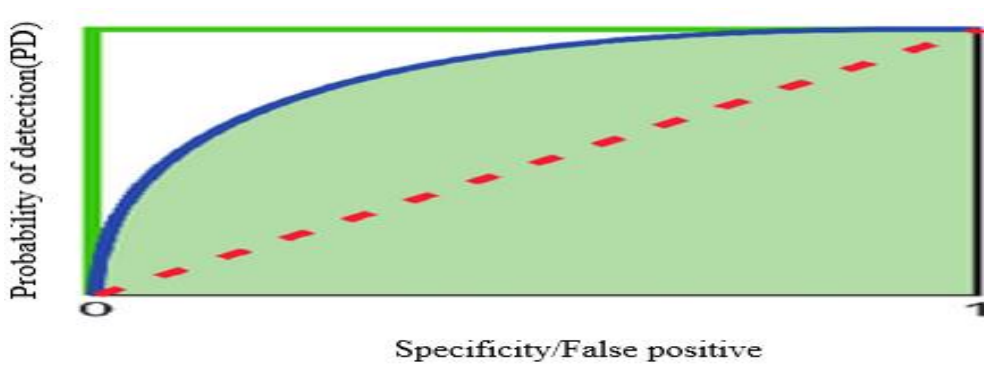

Figure 4- 5: The receiver operating characteristic curve plots region representation

As depicted in the figure 4-5, each point on the ROC curve resembles the different possible combinations of detection probability and probability of false alarming with different decision thresholds during the detection algorithms operation. In addition, the spectrum detection accuracy is a measure of the AUC. The performance of the spectrum detector becomes high when the area is closer to 1-unit squares. Accordingly, the possible and efficient closer area is around 0.5 and 1-unit square. In this thesis work, the performance analysis of decision thresholds of Energy detection algorithm based on the receiver characteristic curves evaluated with different signal-to-noise ratio (SNR) environment.

4.8 OFDM Systems for Cognitive Radio Networks

As stated by the Federal Communications Commission (FCC) a cognitive radio network is "a radio or a system that detects its operational electromagnetic environment and can dynamically adjust its radio operating parameters to modify system operations such as maximize throughput, facilitate interoperability, access secondary users and mitigate interferences through using different modulation schemes" [45]. Thus, spectrum-detecting algorithms advanced to facilitate spectrum sensing and enable wireless applications to identify bands with adequate resources. Therefore, the considered modulation scheme for this work is orthogonal frequency division multiplexing (OFDM), due to its implemented currently in some of the major wireless technologies such as Worldwide Interoperability for Microwave Access (WiMAX) and long-term evolutions (LTE/LTE-Advanced) [46, 47]. In additions, the basic working principle behind OFDM is the separation of high-rate data stream into number of low-rate data streams by different mapping schemes. Consequently, there is a serial to parallel conversion to prepare different data groups for different OFDM subcarrier. The mapped signals modulated into N orthogonal subcarrier by the IFFT. A cyclic prefix (CP) then added to the multiplexed IFFT output. Finally, the obtained signals converted to a time continuous analog signal before it transmitted through the channel at the transmitter or primary user side. At the receiver side, an inverse operation carried out and the information data finally detected. Moreover, OFDM is a modulation technique where a transmitter to form a composite high data rate transmission combines multiple low data rate carriers in [47].

4.9 Cognitive Radio Networks Fusion Rules

Cooperative spectrum sensing plays an important role in cognitive radio network, due to enhance the detection probability of licensed spectrum and used different relaying approaches in between the cognitive radio users, which are acts as a repeater for wireless communications between source and destinations. Relays are the access points that are found between transmitter and receiver, then apply many relaying protocols on the received signal and forward it to the destination. The data streams that transmitted through wireless mediums affected with number of challenges: fading, hidden terminal problem, noise, multipath reflection. In the dual-hop digital relaying system, the transmitter cooperates with the cognitive relays for the successful transmission of the data stream towards the destination. Most of the time, to implement the cooperative spectrums by using two fusion methodologies [48, 49]: Soft decision fusion and Hard decision fusion. In this thesis work, considered the hard decision rule considered, due to it provide better overall system performance than soft cooperation as per reviewed in the most of literatures.

4.9.1 Hard Decision Fusion Rules

As per the working principle of cognitive radio networks (CRNs), CR user makes its own decision regarding whether the PU Present or absence, and forwards the binary decision bits, 1 or 0 to cognitive controller for data fusion. Furthermore, the PU is located far away from all cognitive radios and all the cognitive radio users receive the primary user signal with same local mean signal power that means, all cognitive radios form a cluster with distance between any two or more cognitive radios negligible compared to the distance from the PU to a CR. In this thesis considered, the channel fading statics and the average signal-to-noise environments are the same for every cognitive radio user. i.e., assumed that the channels between the fusion center and cognitive radio is noiseless or ideal channels. For the reason of considering independent decisions, the cognitive controller center issue where, k out of N cognitive radio users are necessary for final decision can be determined by distributions of binomial under Bernoulli trials where every trial shows the CR user decision processes. Therefore, at the cognitive controller center with considering uncorrelated decisions for N detectors by applying K-out-of-N decision fusion rule where a decision is reached once k out of N detectors agree or indicate the presences of PU or H1, the effective detection probability, false alarming probability and probability of miss-detections at fusion center is stated in [49,50,51]:

$$P_D = \sum_{1=k}^{N} \binom{N}{1} P_{d,i\,(1-P_{d,i})}{}^{N-1} \qquad \text{Eq}(4.42)$$

Where, $P_{d,i}$ =denotes the detection probability of each specific cognitive radio user.

N = denotes, the number of CR users sensing the PU signals or alternatively we can use the following equation (4.43).

$$P_X(_{X=D \text{ or } FA}) = \sum_{i=k}^{N} \prod_{j=1}^{i} P_X^{(j)} \prod_{j=i=1}^{N} (1 - P_X^{(j)}) \qquad \text{Eq}(4.43)$$

Where, (X= detections or false Alarm) that means, the false alarm probability and the detection probability. Therefore, the global probability of detection P_D and the global probability of false alarm P_{FA} of the CR spectrum sensing systems analyzed according to the implemented logic of fusion rules determined as follows.

4.9.1.1 The ‘’Logic-OR’’ Rules

In [52, 53, 54], this type of decision rule is a simple decision rule, which is determined as if one of the decisions be said that there is a primary user (PU), then the final decision declares that there is a primary user. In order to evaluate the adaptive thresholds of ED performance with ‘’Logic-OR’ ’fusion rules, the global detection probability and false alarming can be determined by setting K = 1.

$$P_{FA}, OR = 1 - (1 - P_{FA})^{N} \qquad Eq(4.44)$$

$$P_{D}, OR = 1 - (1 - P_{D})^{N} \qquad Eq(4.45)$$

With clarity, as obtained that of P_D, OR and P_{FA}, OR are increasing by increasing the signal sampling sizes. i.e., when the detection probability P_D, OR expanding improves the PU positive declarations from CR’s interference, while false alarming probability P_{FA}, OR increases, the interval of productivity become reduced.

4.9.1.2 The ‘’Logic-AND’’ Rules

In this scheme, if all decisions to be said that there is a primary user, and then the final decision declares that there is a Primary user. Then, k can determine the global detection probability and false alarming with equal to i.e. K=N. In [56, 57, 58], in additions, the same scenario followed throughout working process and the adaptive thresholds of ED performance with these rules obtained as:

$$P_{D}, AND = {P_{d,i}}^{N} \text{ or } \text{Prob(Fusion Decision} = 1|H1) = \prod_{i=1}^{N} PD, i \qquad Eq(4.46)$$

$$P_{FA}, AND = {P_{FA}}^{N} \text{ or } \text{Prob(Fusion Decision} = 1|H0) \prod_{i=1}^{N} P_{FA}, i \qquad Eq(4.47)$$

$$P_{MD}, AND = 1 - {P_{d,i}}^{N} \text{ or } 1 - (\prod_{i=1}^{N} PD, i) \qquad Eq\ (4.48)$$

In [59] - [61], generally the working process of hard decision fusion rule includes:

- Every cognitive relay terminal makes its own individual decision based on the received data from the source. Then each CR forwards the individual decision towards the CC.
- The CC is responsible for making the final decision based on the received individual decisions. Finally, it gives confirmation to relays about the presence or absence of the PU.

Chapter 5

Simulation Results and Discussions

5.1 Simulation Parameter Types and Considerations

In this thesis work, the performance analysis and comparison of adaptive and fixed thresholds energy detector (ED) under the considered evaluation parameter described through simulations. The outputs resulted and compared the binary hypothesis test statistics with decision thresholds of the receiver signal strength through MATLAB2018a simulation tool. In additions, the parameters used for simulations for this thesis work, described in the below Table 5.1.

Table 5 - 1: Simulation Parameters Type and Values

S/No	Simulation Parameters	Type and Values
1	Transmitted Signal (PU Signal)	OFDM with QPSK schemes
2	Detection Algorithms	Energy Detections
3	Channel models	Rayleigh fading
4	Number of sample sizes/FFT sizes	128,256,512,1024,2048
5	SNR Ranges	-25dB to 0 dB
6	Mean and Variance	0 & 1
7	Number of Transceivers (Tx and Rx)	2,2
8	Threshold Techniques	Adaptive and Fixed thresholds
9	PD and PFA	0 to 1
10	Noise Uncertainty factors	ρ = 1, 1.01, 1.03 and 1.05
11	Number of Monte Carlo iterations	10000
12	Simulation Platform	MATLABR2018a

5.2 The Performance Evaluation of Adaptive and Fixed Thresholds with effect of relatively low SNR condition on the Energy detection process.

In [52,53], the IEEE 802.22 Wireless LAN standards for Probability of false alarming and Probability of detection is P_{FA} ≥0.1 and P_D ≥0.9, used in Cognitive radio networks communication respectively and considered in this thesis work. The performance evaluations among adaptive and fixed threshold energy detector using MATLAB R208a software. The expected ROC curve plots for both thresholds of energy detector on dual hop CRNs would be not similar except the input parameters. However, the ROC curve plots are resulted in figure 5-1, for both decision thresholds of ED with the minimum SNR value -20dB. For example, the performance of adaptive threshold energy detector is better than fixed thresholds of energy detector when the value of $P_{FA} \leq 0.21$. In addition, when the range of probability of false alarming (P_{FA}) increases from 0.21 to 0.51, the performance of fixed threshold energy detector is relatively performing better than adaptive threshold energy detector at the same ranges of P_{FA}, during used the specified SNR conditions. On the other hand, as depicted in the below figure 5 -1, the adaptive threshold energy detector outperforms the fixed threshold of ED throughout detection probability ranges from 0 to 0.32 and 0.6 to 1. Subsequently, the P_{FA} increases from 0 to 0.21 and 0.56 to 1, the P_D increases proportionally. Therefore, the P_D of adaptive thresholds of ED are outperforms than fixed thresholds at the minimum signal-to-noise ratio environments.

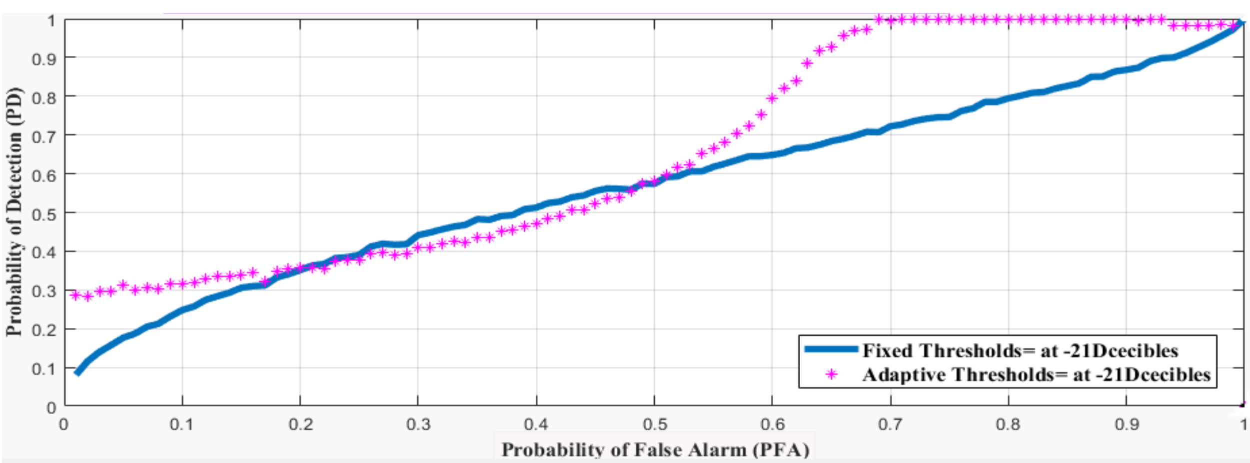

Figure 5- 1: The performance comparatives of fixed threshold and adaptive threshold energy detector (ED) at SNR value -21dB.

5.3 The performance comparison of fixed and adaptive thresholds with effect of relatively high SNR condition on the energy detection process.

The comparison of constant threshold and adaptive threshold by using receiver operating characteristic curve plots at higher signal-to noise ratio conditions presented in the figure 5-2. For examples, when the Probability of false alarming enhancing from zero to 0.5, the detection probability of fixed threshold performs better than adaptive threshold of ED through considered specific SNR value -11dB. Therefore, the constant thresholds of energy detectors are considered better to detect the PU signals in case of higher Signal to noise ratio conditions except weaker signals which might be embedded in spread spectrum signal or in too noisy conditions. In addition, obtained results from the simulation, the receiver operating characteristic (ROC) curve plots of adaptive and fixed threshold of energy detection probability slightly the same when the probability of false alarming value ranges increased from 0.5 to 1, when used the specified higher signal-to- noise ratio (SNR) value is -11dB.

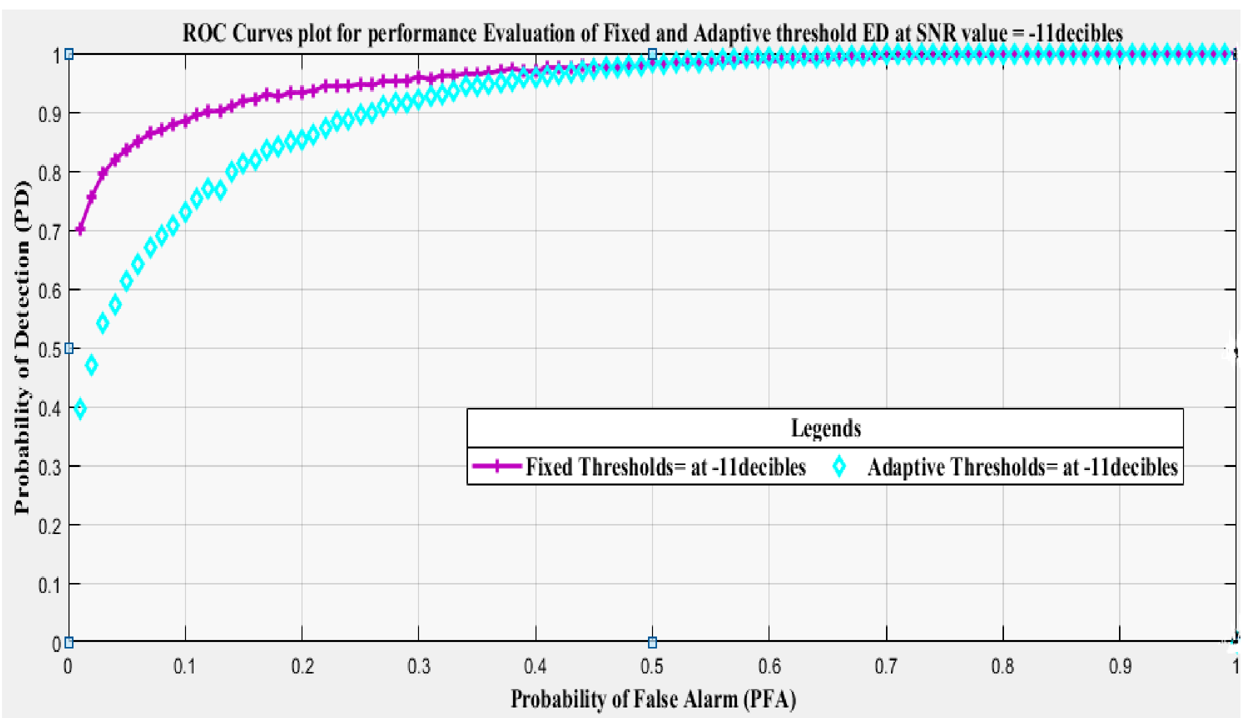

Figure 5- 2: The performance comparatives of fixed threshold and adaptive threshold of energy detector (ED) at SNR value -11dB

5.4 The impact of the number of signal sample sizes on the energy detection process

In the figure 5-3, plotted SNR vs P_D in this work, with the operating ranges of the signal-to-noise ratio = -25dB to 0 decibels versus the detection probability ranges from 0.1 to 1 with considered fixed false alarming probability value 0.01, to determine the effect of number of signal sample sizes with varying values. On the other hand, as depicted from figure 5-3, when the signal-to-noise ratio increases with detection probability also increases, thus implies the strength of receiving signal increases the detection probability of primary user's signal also increases proportionally. In addition, the detection probability of PU signal increases even if at minimum signal-to-noise ratio environments, when the considered number of samples becomes high. For example, when the number of signal sample size considered is 2048-sample size, the maximum strength of signal-to-noise ratio obtained at -11.9 dB, then the detection probability of ED increased as per shown in the figure 5-3. Furthermore, the obtained result presents that at the minimum SNR value of -25 dB, all considered number of signal sample size engages in between 0.19 to 0.21 of detection probabilities. Thus implies, regardless of number of signal sample sizes, the PU's signal P_D accuracy of energy detection is not good.

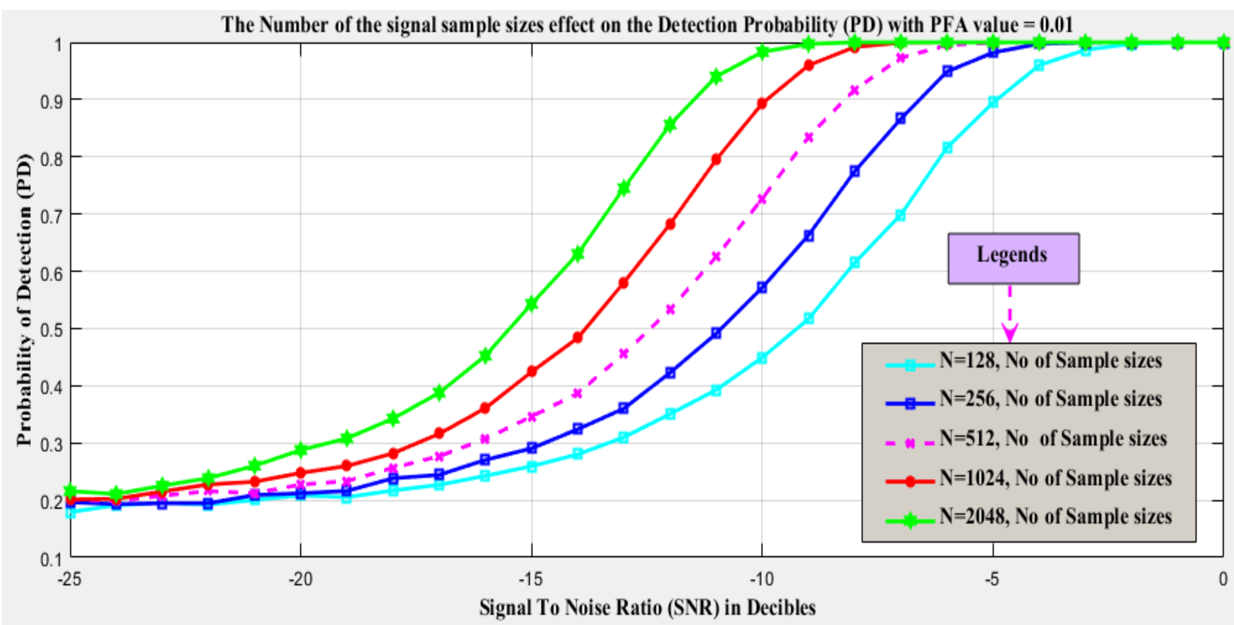

Figure 5- 3: SNR vs P_D of the number of signal sample sizes effect on detection probability with P_{FA} value = 0.01.

5.5 The impact of the probability of false alarm on the energy detection process based on signal-to-noise ratio

In the figure 5-4, presented the receiver operating characteristic curve plots of SNR vs P_D with considering the different P_{FA} values = 0.01, 0.1, 0.25 and sample size, N= 2048. Therefore, as presented in ROC curve plots, the performance of energy detection operates optimally and identifies a PU signal from unwanted noise signals when the signal-to-noise ratio ranges from -9dB to 0dB. In addition, as depicted in the figure, when the false alarming probability values increases from 0.01 to 0.25, similarly increases the energy detection probability at the minimum SNR ranges. Furthermore, as obtained from the plots, the relation of probability of detection and probability of false alarming at specific SNR value, for example, SNR = -13.1dB, with P_{FA} = 0.01, the Probability of detection obtained 0.49, with P_{FA} = 0.1, the Probability of detection obtained 0.72 and with P_{FA} = 0.25, the Probability of detection obtained 0.86. Therefore, similar operations are occurring when the SNR ranges from -25dB to -20dB.

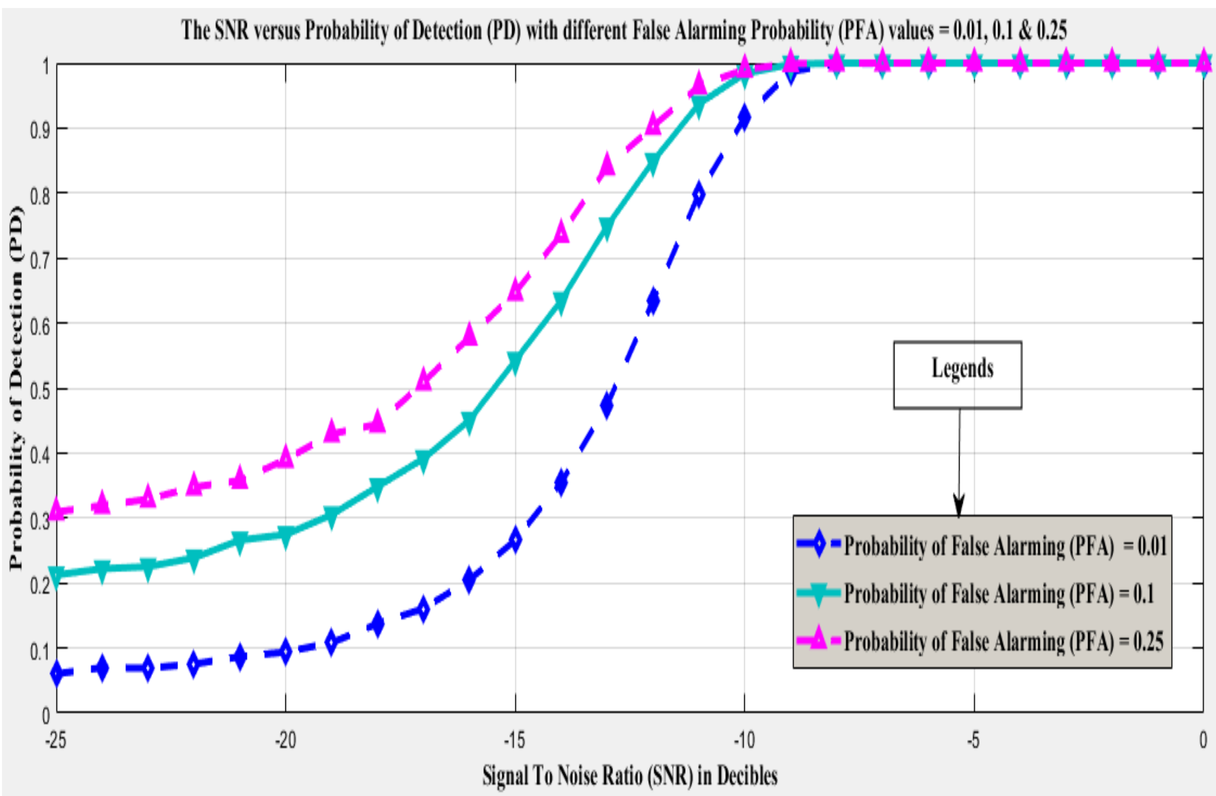

Figure 5- 4: The SNR versus Probability of detection with different false alarming probability

5.6 The effect of the signal-to-noise ratio ROC curve plots on the energy detection process

To provide, a quantitative way of estimating the detection accuracy, ROC curve plots evaluation contributes a statistical framework that calculate and contrasts the false alarming probability and detection probability during ED operations [62]. This thesis work presents, in figure 5-5, every points on the ROC curve plots have a look of the different false alarming probability and detection probability at different signal-to-noise ratio during the detection algorithm operations with considered adaptive thresholds. Therefore, the detection performance becomes high when the area under the curve is closer to one or unity and vice-versa operations obtained when the AUC decreases. For examples, in the figure, ROC curve plots presented with varying signal-to-noise ratios for adaptive decision thresholds of energy detector described, the AUC curve plots become decreases, proportionally the signal-to-noise ratio decreases from -10 decibels to -21dB and the performance of energy detection probability is also decreasing as per minimum SNR conditions. On the other hand, the performance of adaptive thresholds of energy detection algorithm increases, thus the signal-to-noise ratio increases proportionally. For instance, considered at SNR value = -10dBs, the ED probability of detection performs high, and decreases the energy detection performance when the SNR become decreases or at low SNR environments. Finally, in [62] as claimed by IEEE 802.22 WLAN standards, the false alarming probability and detection probability from plot results that the only desired values at signal-to-noise ratio (SNR) = -10dBs.

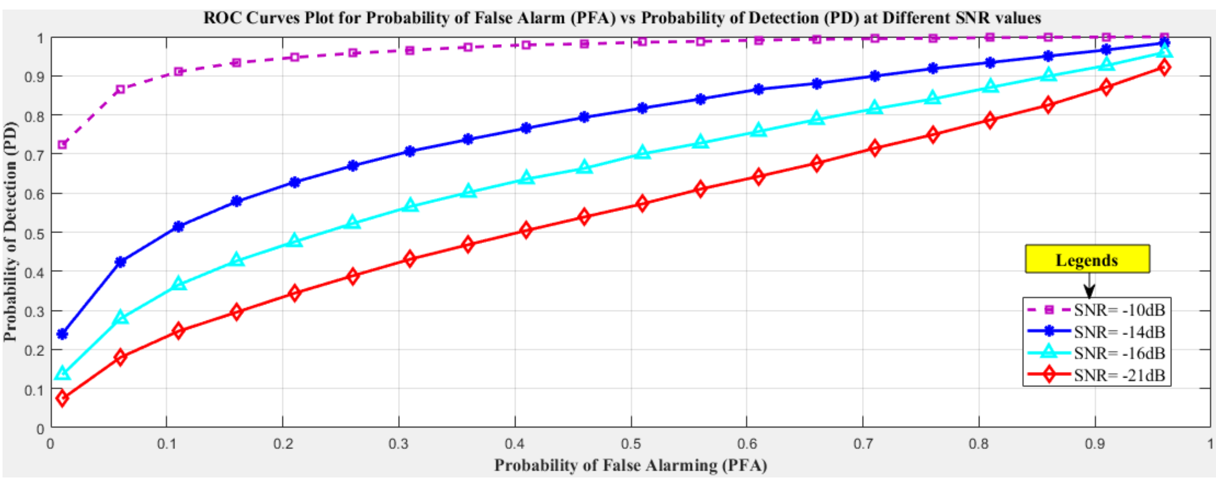

Figure 5- 5: P_{FA} vs P_D of ROC curve plots for energy detector at different SNR values.

5.7 The effect of the signal-to-noise ratio Complementary ROC curve plots on the energy detection process

As depicted in figure 5-6, CROC curve plots under the probability of false alarm versus probability of misdetection with variable SNR conditions. In addition, the miss detection probability reduces when the signal-to-noise ratio and false alarming probability increases respectively. The CROC curve is the inverse operation than the ROC curve plots during detection performance analysis of adaptive energy detection technique. Therefore, when the area under the CROC curve decreases, then increases the adaptive thresholds of energy detections performances. On the other hand, as obtained from the CROC curve plots, when the considered signal-to-noise ratio value increases, the area under the curve reduces and yielding that the miss-detection probability decreased, when the area under the curves become reducing, the possibility of the licensed and unlicensed user's collision decreases. For example, from the P_{FA} vs P_{MD} at different SNR value plots obtained results, when the probability of false alarm = 0.2, with SNR value =-10dBs then, the miss detection probability (P_{MD}) becomes below 0.1. In addition, when P_{FA} = 0.2, with SNR value = -21 dB then, the probability of miss-detection approaches to 0.7. Thus shows, at minimum SNR conditions, the probability of miss-detection increases and decreases relatively at high SNR environments. Furthermore, the probability of miss-detection decreased when the false alarming probability increased.

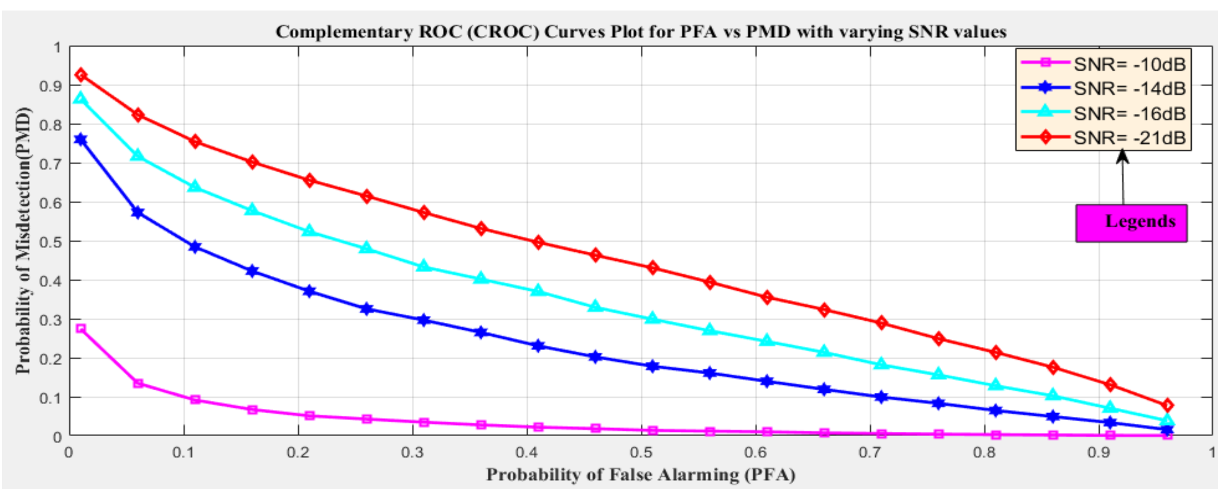

Figure 5- 6: The P_{FA} vs P_{MD} of CROC curves for energy detector at different signal-to-noise ratios.

5.8 The Complementary ROC curve plots for performance comparison of ‘’Logic-OR’’ and ‘’Logic-AND’ ’fusion rules under Rayleigh fading channel

Spectrum sensing technique is the key component of CR technology and compromised when a CR user experience shadowing or fading effects then, cannot distinguish between a free band and a deep fade in [60]. Thus, CR spectrum sensing techniques used a hard decision combining fusion rules to optimize the sensing performances. Therefore, in this thesis work presents a comparison of hard decision combining fusion rule (Logical- OR-rule and Logical- AND-rule) to enhance the performance of adaptive ED during its operation considered under Rayleigh fading environment. Furthermore, the fusion rule performed at fusion center (FC) to make the final binary bits output for decision about the presence/absence of PU.

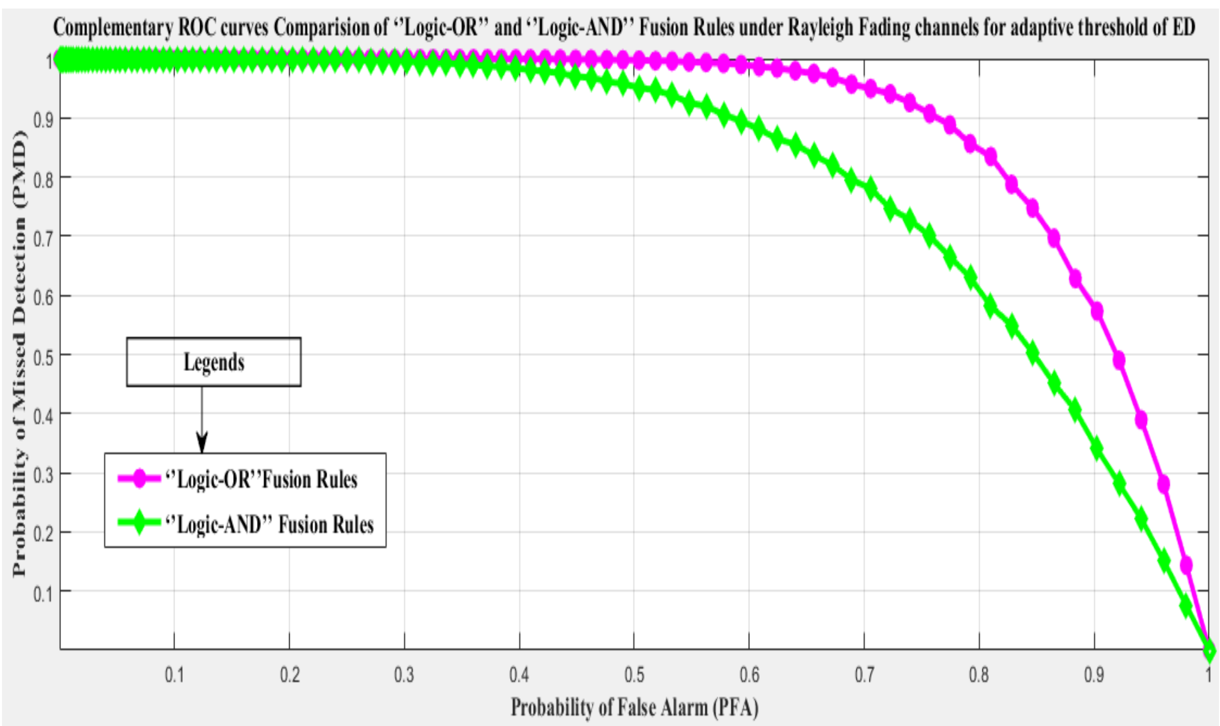

Figure 5- 7: The CROC curve plots P_{FA} vs P_{MD} for performance comparison of ‘’Logic-OR’’ and ‘’Logic-AND’ ’fusion rules.

The simulation results in the figure 5-8, depicted the hard decision rules performance comparisons based on adaptive thresholds of energy detections and the input parameters that are considered for this thesis work includes with the value of SNR = -11dB and the number of CR users (N) = 3 CR users) under P_{FA} vs P_{MD} ranges from 0.1 to 1. Therefore, as presented in the figure 5-7, ROC curve plots, the ''Logic-OR'' fusion rule out performs than the ''Logic-AND'' fusion rules at maximum and minimum ranges of false alarm probability and probability of miss detections during ED operations. For examples, the P_{FA} values from 0.4 to 1 with increasing the detection probability by 10^{-1}or 0.1 and each CR user's local decision information's forwarded to data fusion center and combined to determine the final decision to detect PU signals.

5.9 The decision thresholds of ED process based on the effects of noise uncertainty

In this section presented, the comparative analysis of decision thresholds (i.e. fixed and adaptive thresholds) based on the effect of noise uncertainty in order to improve the performance of energy detection under P_{FA} vs P_{MD}. In addition, the simulation results carried out in two scenarios, i.e., ED of fixed and adaptive thresholds considered without noise uncertainty and with noise uncertainty under high number of samples size and low SNR environments to achieve a better detection probability during operations. Therefore, as per the obtained results in the figure 5-8, the detection probability of energy detection of adaptive thresholds outperforms than ED of fixed thresholds during with noise uncertainty and without noise uncertainty conditions.

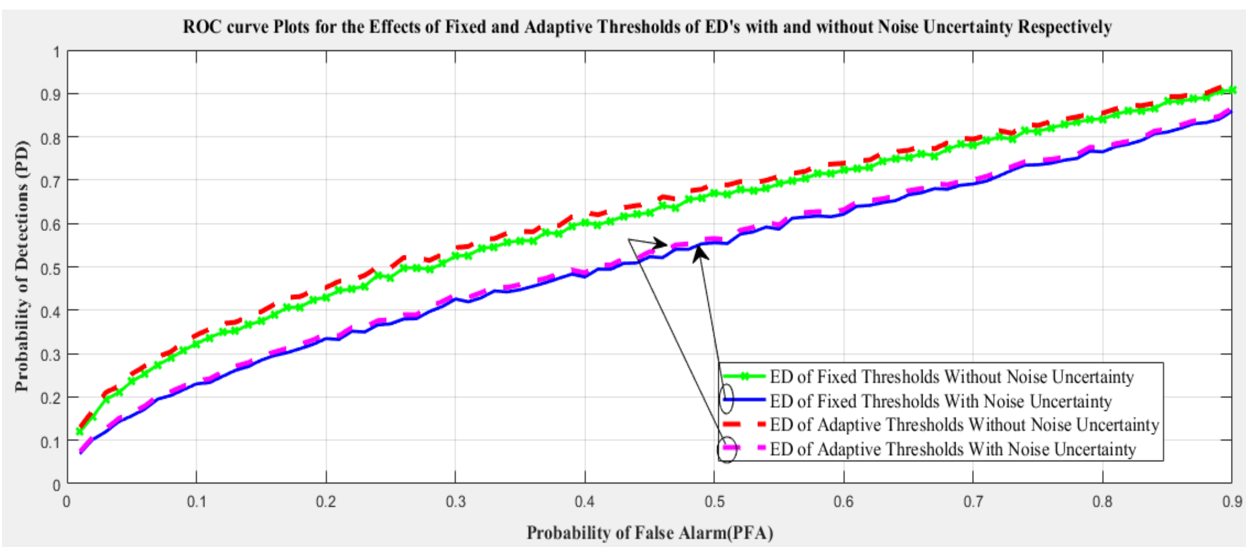

Figure 5- 8: P_{FA} vs P_D of ROC curve plots for performance comparison of decision thresholds with and without noise uncertainty effects.

5.10 ROC curves plots for energy detection of adaptive thresholds with varying noise uncertainty factors

As plotted in the figure 5-9, the ROC curve presents the performance of ED of adaptive thresholds with noise uncertainty parameters (ρ) ≥ 1. Therefore, when the value of noise uncertainty, $\rho > 1$ is becomes a positive metric, which determines the size of noise power uncertainty and the signal sampling complexity based on. On the other hand, when the value of uncertainty parameter increases, the performance of detection probability become decreases even if the considered number of samples is become high with specific signal-to noise ratio value due to SNR wall restriction. For example, when noise uncertainty parameter = 1, the detection performance is better than noise uncertainty parameters ρ = 1.01, 1.03 and 1.05 consecutively. Thus, implies that the detection probability increases when the noise uncertainty is at minimum levels even if the number of sample size approaches to maximum levels or infinity. Furthermore, it is impossible for the energy detection to detect the presence of primary user in a spectrum due to SNR wall features.

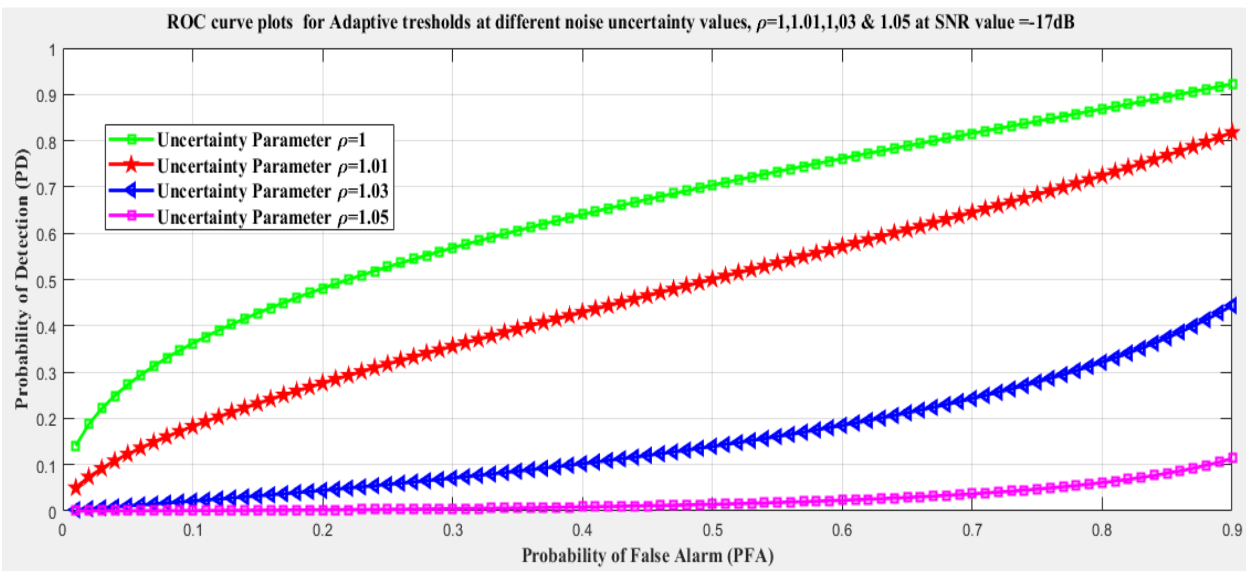

Figure 5-9: The ROC curve plots under $P_{FA\ VS}\, P_D$ for adaptive thresholds with varying NU factors, $\rho = 1, 1.01, 1.03$ & 1.05 at specific SNR value = -17dB and sample size (N) = 1024.

Chapter 6
Conclusion and Future Works

6.1 Conclusions

The 5th generation wireless technology is set apart the absence of difficulty communication of billions of wireless devices connectivity that will strive to gain for spectrum scarcity. In addition, Cognitive radio networks are the possible solution to solve the problems. Therefore, the analysis of spectrum detection technology is a fundamental cognitive radio cycle operation.

In this thesis, a comparative analysis of decision thresholds based on energy detection on dual-hop CRNs to analyze the decision thresholds performance and the effect of noise uncertainty during the ED operations. Therefore, the objectives that achieved through this thesis work expressed as: - Adaptive thresholds performed better than fixed threshold at low SNR conditions, but the constant thresholds relatively having with better performance at high SNR environments and from the obtained results, when the number of sample size increases the detection performance also increases proportionally at perceived SNR ranges. In addition, when the PFA increases from 0.01 to 0.25, then PD increases proportionally, however, the performance of PFA decreases at high SNR value, but the Energy detector achieves high probability of detection at the same SNR environment. And, from the ROC curve plots, the performance of adaptive ED increases when SNR increase and Vic versa. The ‘’Logic-OR’’ fusion rule performs better than ‘’Logic-AND’’ fusion rules, this is attributed to the fact that OR decision fusion rule involves result of a minimum of a single user out of K energy detector nodes to declare the availability or presence of a PU. Moreover, when NU parameter increases, the performance of ED decreases even if the number of samples is become high with specific SNR value. Furthermore, the ED of adaptive threshold with NU has better performance than ED of constant threshold with NU.

6.2 Future Works

This section includes discussions concerning the performance problems and the future scientific demanding tasks related to comparison and performance analysis of decision thresholds of the Energy detection technique based on simulation results presented in the previous discussions.

Therefore, this thesis work limited on detail explanations on the effects of probability of false alarming, the number of samples, signal-to-noise ratio, and noise uncertainty on decision thresholds of matched-filter detection (MFD) and cyclo-stationary feature detection (CFD) techniques through OFDM signals during operations.

In addition, the effects of cognitive relaying and MIMO communication systems with Alamuti STBC schemes considered in my feature work. This thesis works advanced to further the development of energy detection-based adaptive thresholds for real-time software-defined radio platforms using USRP hardware and GNU Radio software. Furthermore, advanced on further study double dynamic thresholds based on ED under low SNR Conditions with varying noise uncertainties.

References

[1] J.(SHMJOS002), "performance analysis of Cognitive Radio (CR) Spectrum Sensing Techniques Through a Rayleigh Fading Channel" Master's thesis in Electrical and computer Engineering-Faculty of Engineering and built Engineering Environment., pp. 70-83, December,2020.

[2] S. D. and A. Kaviarasu, "SNR Based Adaptive Spectrum Sensing in Cognitive Radio Networks" International Journal of Engineering Research & Technology, Vols. Vol. 3- , no. Issue 3, pp. 1438 – 1442., 03.2014.

[3] S. M, L. Y, L.A ,and M. Abdullahi, "Cooperative Spectrum Sensing and Determination of Optimum Threshold in Cognitive Radio System," in International Journal of computer Applications,, vol. Volume 122 – No.23, p. pp. 32 – 38., July 2015.

[4] D. W, Z. L, A. O , and S. Wujian,"EfficiencyAccuracy Trade-off for Spectrum Sensing in Cognitive Network," Instrumentation," in Measurement, Computer, Communication and Control (IMCCC), 2012, pp, Harbin, 1136-1141., 2013 Second International Conference on .

[5] E. D, R. V, R. P, and H. Chye, "Adaptive spectrum sensing method for cognitive radio systems in a fading environment" 2014 71 International Symposium on Wireless Personal Multimedia Communications (WPMC), pp. pp. 451-456, Sydney, NSW, 2015.

[6] S. K, S.Y, M. K, A. R, and W. X. See,"Edge Energy Detection using GNU radio and USRP2: An analysis study,"Communications (MICC),"2014 IEEE Malaysia International Conference on, pp. pp. 87-91., Kuala Lumpur, 2014.

[7] O. O. a. A. Annamalai., "Analysis of detection performance of modified periodogram over fading channels.," in In Consumer Communications and Networking Conference (CCNC),, IEEE, 2014 pages 449–453, 2012.

[8] G. W. a. D. G. D. C. Hou-Shin, "Spectrum sensing using cyclostationary properties and application to ieee 802.22 wran.," in In Global Telecom77 munications Conference, 2010., GLOBECOM ’07. IEEE, pages 3133–3138, 2010.

[9] T. S. S. a. M. Tanany., "A novel adaptive structure of the energy detector applied to the cognitive radio networks.," in IEEE 11th Canadian Workshop on Information Theory,, Jun 5, pages 95–98, 2011..

[10] R. S. R. M. and S.Shobana," Matched Filter Detection (MFD) based spectrum sensing Techniques on cognitive radio for OFDM WLANs." International Journal of Engineering and Technology (IJET), Pages, 2014.

[11] Y. X. S. R. and K.Kim, " Energy detection based spectrum sensing for cognitive radio (CRNs)" An experimental study. In IEEE Globecom,Pages, 56-61, 2013.

[12] J. A. Abolarinwa and A. Achonu, "Cognitive Radio-based Wireless Sensor Networks As Next Generation Sensor Network : Concept , Problems and Prospects" in Cognitive Radio-based WSNs As Next Generation Sensor Network , Bolarniwa.J, vol. 4, no. 8, 2013.pp. 642.

[13] Alewo Michael,"Performance Evaluation of Energy Detection Based Spectrum Sensing for Cognitive Radio Networks," Perforance analysis of Cognitive Radio spectrum sensing techniques, pp. page,65-71,2013.

[14] M. K. F. K, G. K. K. P and C. Sofotasios, "The Area Under a Receiver Operating Characteristic Curve Over Enriched Multipath Fading" AUC curves over Enriched Mulipath Fading Environment, pp.Pages,41-45, 2014.

[15] M. Motta and P. Geete “Analysis of Different Spectrum Sensing Techniques in Cognitive Radio Network,”, chicago, 2016.pp. 573–577.

[16] Electronic Communication Committee (ECC), "Technical and Operational Requirements for the Possible Operation of Cognitive Radio Systems in the White Spaces of the Frequency Band470-790" in European Conference of Postal and Telecommunications Administrations (CEPT),[online], available: and web/paws/current/pdf6LNQT4Lb6S.pdf, Technical Report: ECC Report 159, Jan. 2011.

[17] M. M, A.M and T. Masonta, "“Spectrum decision in cognitive radio networks: a survey" IEEE Communications, Survey and Tutorials, , Vols. Vol. 15, no. 3, pp. pp. 1088-1107, Nov. 2014.

[18] T.Yücek and H. Arslan,"A survey of spectrum sensing algorithms for Cognitive Radio applications" IEEE Communications, Surveys And Tutorials, Vols. Vol. 11, no. 1,, pp. pp. 115-131., First Quarter 2010.

[19] M. Verma and R. Dua, " “Performance Analysis of Energy Detection, Matched Filter Detection & Cyclostationary Feature Detection Spectrum Sensing Techniques" Indian Streams Res., Vols. J., vol. 2, no. 5, pp. Pages. 1296–1301, 2013.

[20] N. Thuoserd,’’An Adaptive Threshold Energy Detection Technique with Noise Variance Estimation for Cognitive Radio Sensor Networks" Masters dissertation, University of Cape Town,pp. Pages 60-63, South Africa, 2015.

[21] M. Abdulsattar and Z.Hussein,"performance evaluation of Energy detection technique for spectrum sensing in cognitive radio: a survey," Vols. Int. J. Comput, vol. 4, no. , pp. pp.223–242, September, 2014.

[22] S. Chaudari, "“Spectrum Sensing for Cognitive Radios: Algorithms, Performance, and Limitations,”," Doctoral dissertation, Aalto University,, Finland, 2012..

[23] K. P, J. T and S. Maharjan, "Energy Detector Prototype for Cognitive Radio System," Japan, 2016.

[24] L. C. B. Y. Z. W. Hou, "Federal Communication Council, “Cognitive Radios" [Online]. Available: www.eecs.berkeley.edu/~dtse/3r_Cognitive_radio_FCC-03-322A1.doc. 27-Nov-2016..

[25] L. C.B, Y. Z, and L. Yang, "Supporting Demanding Wireless Applications with Frequency-agile Radios" in 7th USENIX conference on Networked systems design and implementation,, 2010, pp. 1–14.

[26] D. Nguyen, " “Deployment of Orthogonal Frequency Division Multiplexing systems using GNU Radio and USRP” in Masters dissertation, University of Wollongong , Australia,2014.

[27] M. N, K. C, and K. Nafkha, "Experimental Spectrum Sensing Measurements using USRP Software Radio Platform and GNU-Radio," in in 9th International Conference on Cognitive Radio Oriented Wireless Networks and Communications (CROWNCOM),2014, pp. 1–6.

[28] A. M, N. F, S. K, S. Y, M. H. S. M. and A. Sarijari, "Energy detection sensing based on

GNU radio and USRP: An analysis study in Proceedings " in 2009 IEEE 9th Malaysia International Conference on Communications with a Special Workshop on Digital TV Contents, 2009, , no. December, pp. 338–342.

[29] D. T, N. F, S.P,V. L. and C. Tran, "An Experimental Study of OFDM in Software Defined Radio Systems Using GNU Platform and USRP2 Devices," in International Conference on Advanced Technologies for Communications (ATC2014), in 2014,pp. 658–663.

[30] D. C, A.T, R.W, D. Cabric, "Experimental study of spectrum sensing based on energy detection and network cooperation," Proc. first Int. Work. Technol. policy Access. Spectr , Vols. no. Article no. 12, pp. Pages,660-669, 2008.

[31] C. T. A, H. J and S. Atapattu, "Energy Detection for Spectrum Sensing in Cognitive Radio." Springer International Publishing , pp. pages,25-31, 2014.

[32] H. Z, Q. D, Q. N, G. X. Y. X, and Q. Wang, "“Otsu thresholding segmentation Algorithm based on Markov Random Field," in 2012 Seventh International Conference on Natural Computation, Vols. vol. 2, p. Pages. 969–972. 2012.

[33] A.E,and B.Högskola,"PERFORMANCE ANALYSIS OF HYBRID DECODE-AMPLIFY FORWARD RELAYING PROTOCOLS IN COGNITIVE NETWORKS"[Online].Available:http://www.bth.se/fou/cuppsats.nsf/6753b78eb2944e0ac1256608004f0535/403202d14e696cf 0c12579c2003ae749?OpenDocument, Vols. Vo,1, pp. Pages,37-44, 12-Jun-2012].

[34] M. A, S. A, H. D, A. H, A. U, K. T, J. Shazad and A. Malik, "Comparative Analysis of Primary Transmitter Detection Based Spectrum Sensing Techniques In Cognitive Radio

Systems" Australian journal of basic and applied sciences, Vols. vo,1, pp. Pages,51-57, 2010.

[35] M.Hasna and S.Alouini, "Performance analysis of two-hop relayed transmissions over Rayleigh fading channels," in Vehicular Technology Conference, 2003. Proceedings. Vols. vol. 4, pp. Pages 71-78, IEEE 56th, 2003.

[35] M. Alamouti, "A simple transmit diversity technique for wireless communications" Selected Areas in Communications, IEEE Journal on,Vols. vol. 16,pp. Pages, 1451 – 1458, October. 2008.

[36] A. P, G. L. and S. Maleki, "Two-stage spectrum sensing for cognitive radios," in Acoustics Speech and Signal Processing (ICASSP)" 2010 IEEE International Conference on, Vols. Vol,1, pp. Pages, 2946 –2949, 2010.

[37] M.S. A.G, M. K, S and F. Digham, "On the energy detection of unknown signals over fading channels,"in Communications" IEEE International Conference on , Vols. vol. 5, p. pp. 3575 – 3579 vol.5, 2003.

[38] J. K, S.Y, M.H, Y. S, H. Kim, "An effective MIMO Orthogonal Frequency Division Multiplexing transmission scheme for IEEE 802.22 WRAN systems" Proc. 2nd Int. Conf.Cogn. Radio Oriented Wirel. Networks Commun. CrownCom, no. 8, Vols. vol. 55, pp.Pages, 394–399, 2013.

[39] A.P, W.L,and K.Srisomboon,"Two-stage spectrum sensing for cognitive radio under noise uncertainty" Mobile Computing and Ubiquitous Networking (ICMU), 2015 Eighth International Conference on , Hakodate, Vols. Vol,03, pp. Pages, 19-24. 2015.

[40] S.D, A.Kaviarasu, "Signal-to-Noise Ratio (SNR) Based Adaptive Spectrum Sensing in

Cognitive Radio Networks" International Journal of Engineering Research & Technology, vol. Vol. 3 , no. - Issue 3, p. pp. 1438 – 1442. 03.2014.

[41] M. S, X. L, A. N, C. Z, and B. Li,"Energy Detection Based Spectrum Sensing for Cognitive Radios Over Time-Frequency Doubly Selective Fading Channels," in IEEE Transactions on Signal Processing,Vols. vol. 63, no. no. 2, pp. Pages,402-417, Jan.15, 2015.

[42] D. W, Z. L, and S. Wujian,"Efficiency-Accuracy Trade-off for Spectrum Sensing in Cognitive Network," in Instrumentation, Measurement, Computer, Communication and Control (IMCCC), ,2012 Second International Conference on, Harbin, 2012, pp. 1136-1141.

[43] M. R, K.T, A. R,and R. Dzulkifli, "Spectrum occupancy at UHF TV band for cognitive radio applications in " RF and Microwave Conference (RFM), Negeri Sembilan, 2011 IEEE International, Seremban, 2011, pp. 111-114.

[44] K.S, A.S, and M.Sansoy,"Cognitive Radio: Issues and Challenges Journal of Network Communications and Emerging Technologies (JNCET),www.jncet.org, Vols.,Vol. 2, no. Issues and Challenges, 2," pp. Pages, 54 – 58, June 2015.

[45] Y. Z, E. C, Y. P, A. T, H. Y and C. Liang, ""Sensing-Throughput Tradeoff for Cognitive Radio Networks." in IEEE Transactions on Wireless Communications,, Vols. vol. 7, pp. Pages. 1326-1337. no. 4, April 2008.

[46] Y. C, L. K, C.T, and Y. Pei,"Sensing-throughput tradeoff for cognitive radio networks: A multiple-channel scenario," in IEEE 20th International Symposium on Personal, Indoor and Mobile Radio Communications, Tokyo, 02 ,2009, pp. 1257-1261.

[47] W.Lee and F.Akyildiz,"Optimal spectrum sensing framework for cognitive radio networks," in IEEE Transactions on Wireless Communications, , Vols. vol. 7, pp. Pages. 3845-3857, No. 10, October 2008.

[48] E. D, R. V, and H. Chye,"Adaptive spectrum sensing for cognitive radio systems in a fading environment," 2014 International Symposium on Wireless Personal Multimedia Communications (WPMC), Sydney, NSW, Vols. vol,1, pp. pp. 451-456., 2014.

[49] H. Urkowitz,"Energy detection of unknown deterministic signals," in Proceedings of the IEEE,, Vols. vol. 55,, pp. Pageds, 523-531., no. 4, April 1967.

[50] W. H, J. S, and R. Stevenson, "IEEE 802.22: The first cognitive radio wireless regional area network standard," in IEEE Communications Magazine, Vols. vol. 47, pp. Pages,130-138, No. 1, January 2010.

[51] R. Tandra and A. Sahai, "Signal-Noise-Ratio (SNR) Walls for Signal Detection" IEEE Journal of Selected Topics in Signal Processing, Vols. Vol. 2, pp. pp,42-46, No. 1, February 2014..

[52] D. M. Martínez and A. G. Andrade, "Adaptive Energy Detector for Spectrum Sensing in Cognitive Radio Networks" Computers and Electrical Engineering, Vols. Vol. 52, pp. pp. 226–239, 2016.

[53] D. M, M. Plataa et. al, " “Evaluation of energy detection for spectrum sensing based on the dynamic selection of detection-threshold" *in Procedia Engineering* , Vols. vol,3, pp. pp. 135 –143, 2012..

[54] G. Ji and H. Zhu, "A Survey of the Solving Strategies for the SNR walls Problem in

Local Spectrum Sensing" Journal of Convergence Information Technology, Vols. Vol. 6, pp. pp.51-57, No. 8, August 2013.

[55] A. P. and R. Nair, "An Adaptive Threshold Based Energy Detector for Spectrum Sensing in Cognitive Radios at Low SNR" in in proc. ICCS, pp. 574 – 578, 2012.

[56] T. Yucek and H. Arslam, "“A Survey of Spectrum Sensing Algorithms for Congnitive Radio Applications," IEEE Commun. Surv. Tutorials, Vols. ” vol. 97, p. pp. 805–823, no. 5, 2015.

[57] N. T, B.Tam, T.Tran-Thien, T. Do-Hong and Q. Bao,"Performance Analysis of Decode-and-Forward Relaying for Multi-hop Alamouti Transmission Over Rayleigh Fading Channel," in in IEEE International Conference on Advanced Technologies for Communications (ATC), , Ho Chi Minh City,2014.

[58] X. B. and J. Li, " Decode-amplify-forward (DAF) a new class of forwarding strategy for wireless relay channels," in in IEEE International Workshop on Signal Processing Advances in Wireless Communications, , Bethlehem,2015.

[59] K. W. A. M. C. D and W. Bliss, "MIMO Wireless Communication" Lincoln Lab. J., Vols. ol. 15, pp. pp. 97-126, no. 1, 2005.

[60] M. K. and M. Tahseen,"Analysis of OSTBC in Cooperative Cognitive Radio Networks using 2-hop DF Relaying Protocol" in , Master Thesis BTH University , Sweden, 2011.

[61] P. K. Upadhyay and S. Prakriya, "Outage Performance of Two-Way DF Relaying with Alamouti Transmissions and Network Coding" in International Workshop on Cognitive Wireless Systems (UKIWCWS) , New Delhi, 2014.

[62] Z. M, S.A, and W.Ning,"Signal space diversity in decode-and-forward cooperative

communication,"WRI International Conference on Communications and Mobile Computing, Vols. vol. 1, pp. pp. 127–130, 2013.

[63] E. A, Y. C. Liang, " "Sensing Throughput Trade-off for Cognitive Radio Networks" IEEE Transactionson Wireless Communications, Vols. Vol. 7, pp. pp, 1326-1337 ,No. 4 , April 2008.

Appendix's

Appendix 1. The mathematical derivations for Cyclo-stationary feature detections

In case of CFD, both the spectral correlation and the periodic statics features. However, its periodicity depends on; the autocorrelation of $Rx(t,\tau)$ of the signal displays periodic properties with time and the mean value $E(x)$from the cyclostationary signal $x(t)$. The mathematical analysis described as:

$$R_x\left(t+\frac{\tau}{2},t-\frac{\tau}{2}\right)= R_x(t+T_0+\frac{\tau}{2},t+T_0-\frac{\tau}{2}) \qquad \text{Eq (1)}$$

From the above Equation (4-27), the delay τ and $T_0 \neq 0$, then it becomes:

$$R_x\left(t+\frac{\tau}{2},t-\frac{\tau}{2}\right)= E\{x\left(t+\frac{\tau}{2}\right)x\left(\ t-\frac{\tau}{2}\right)\} \qquad \text{Eq (2)}$$

Where, $E\ (.)$ = is denotes the expectation value of the signal.

R_x = is a periodic function

When the periodic function described in FFT:

$$R_x\left(t+\frac{\tau}{2},t-\frac{\tau}{2}\right)= \textstyle\sum_\alpha R_x{}^\alpha(\tau)\, e^{-j2\pi\alpha t} \qquad \text{Eq (3)}$$

Where, α = is denotes the reciprocal of the fundamental period $T_0\ and\ R_x{}^\alpha$ which is cyclic autocorrelation of the signals multiply with the sum of overall integers, when the FFT coefficient is taking in to account by [52].

$$R_x{}^\alpha(\tau)=\frac{1}{T_0}\int_{\frac{-T_0}{2}}^{\frac{T_0}{2}} R_x\left(t+\frac{\tau}{2},t-\frac{\tau}{2}\right)e^{-j2\pi\alpha t}dt \qquad \text{Eq (4)}$$

Where, $R_x^\alpha(\tau)$ = is denotes the CAF (cyclic Autocorrelation function).

In order to obtain the Power Spectral Density (PSD), the FFT of the autocorrelation function in Eq (4-30) becomes:

$$S_x(f)=\int_{-\infty}^{\infty} R_{x(\tau)e^{-j2\pi f\tau}d\tau} \qquad \text{Eq (5)}$$

As per given in the Eq(s), the Spectral Correlation Density (SCD) or CSD (Cyclic spectrum Density), may also be accomplished from the FFT of the cyclic autocorrelation function given by N number of samples of signal, then the estimated spectral correlation function or density SCD is

$$S_x^{\alpha}(f) = \frac{1}{N}\sum_{n=1}^{N} X_L\left(n,\ f + \frac{K\alpha}{2}\right) X^*{}_L\left(n,\ f - \frac{K\alpha}{2}\right) \qquad \text{Eq (6)}$$

Where, $X_L\,(n,k) = \frac{1}{\sqrt{L}}\sum_{n-\frac{L}{2}}^{n+\frac{L}{2}} x(l)\, e^{-j2\pi f\tau}$ Eq (7)

$K\alpha = \alpha L/fs$ = is denotes L point Direct Fourier Transform (DFT) at Nth samples of the received information and is the sampling frequency with corresponding to cyclic frequency α and the Spectral Correlation detection of the received signal, then compared to the pre-defined threshold value. Therefore, for a specific predefined threshold, value λ the mathematical analysis of CFD performance evaluation metrics: probability of detection (PD), probability of false alarm (Pf), and probability of miss-detection (Pm) equations expressed as:

$$P_D = \text{Prob}\left(E(x) > \frac{\lambda}{H1}\right) = Q\left(\sqrt{\frac{2\times SNR}{\delta n^2}}, \frac{\lambda}{\delta A}\right) \qquad \text{Eq (8)}$$

$$P_{FA} = \text{prob}(E(x) > \frac{\lambda}{H0} \quad = \text{Exp}(\frac{-\lambda^2}{2\delta A^2}) \qquad \text{Eq (9)}$$

$$P_{MD} = 1 - P_D = 1 - Q\left(\sqrt{\frac{2\times SNR}{\delta n^2}}, \frac{\lambda}{\delta A}\right) \qquad \text{Eq (10)}$$

Where,

Exp (.) = is denotes the exponential function

SNR $= \frac{P}{\delta n^2}$, P = is average PU signal power, δn^2 = is noise variance

${\delta_A}^2 = \frac{\delta n^2}{2N+1}$, N = is number of samples

Appendix 2: The Mathematical Derivations for Energy Detections (ED)

The presence or absence of PU for a single predefined threshold described as:

$$\begin{cases} E(n) > \boldsymbol{\lambda}, & H1 : \text{Licensed band is Present} \\ E(n) < \boldsymbol{\lambda}, & H0 : \text{Licensed band is Absent} \end{cases}$$

From the central limit theory, if the noise variance is considered fixed, and the noise uncertainty is not considered:

$$E(n) = \begin{cases} N\left(\delta n^2, \frac{\delta n^4}{N}\right) & H0 \\ N((\delta n^2 + P), \left(\delta n^2 + \frac{P)^2}{N}\right) & H1 \end{cases} \quad \text{Eq (1)}$$

In the adaptive threshold energy detection modelling, the noise power and the transmitted signal considered to be an IID RV (independent and identically distributed random variables) with zero mean or $\delta\mu^2 = 0$ *and* $\delta n^2 = 1$.

When, the signal-to-noise ratio (SNR) is to be considered, γ

$$\gamma = \frac{\delta\mu^2}{\delta n^2} \quad \text{Eq (2)}$$

Then, the test statics is given by equations,

$$E(n) = \frac{1}{N}\sum_{n=0}^{N} |X(n)|^{2} \quad \text{Eq (3)}$$

Based on central limit theorem, the number of sample size gets increase, the $E(n)$ has a normal distribution with μi mean and variance δi under the hypothesis test statics Hi, where, i= 0, 1 [46]. Hence, each described to be

μi = for i =0, 1 and $\delta i = for\ i = 0{,}1$, therefore;

$$\mu_0 = \delta n^2, \text{but} \quad \delta_0 = \frac{\delta n^2}{N^{\frac{1}{2}}} \quad \text{Eq (4)}$$

$$\mu_1 = \delta n^2 * (1+\gamma)\ , \delta_1 = \delta_0 * (2\gamma + 1)^{\frac{1}{2}} \quad \text{Eq (5)}$$

When the number sample size increase, the mathematical analysis is consent for adaptive threshold energy detection, in terms of probability of false alarm (PFA) and Detection Probability (PD) can be determined as:

$$P_D = P\{E(n) > \lambda | H1\} = Qm\left(\frac{\lambda - N(\delta\mu^2 + \delta n^2)}{(2N)^{\frac{1}{2}}(\sqrt{(\delta\mu^2+\delta n^2)^2})}\right) \quad \text{Eq (6)}$$

$$P_{FA} = P\{E(n) > \lambda | H0\} = Qm\left(\frac{\lambda - N\delta n^2)}{(\sqrt{2N\delta n^4}}\right) \quad \text{Eq (7)}$$

No_ of sample size (N) $= \frac{1}{\gamma^2}\left[\frac{1}{Q}(PFA) - \frac{1}{Q}(PD) * \sqrt{2SNR+1}\right]^2$ if SNR = γ

$$= \frac{1}{\gamma^2}\left[\frac{1}{Q}(PFA) - \frac{1}{Q}(PD) * (1+\gamma)\right]^2$$

$$= 2\left[Q^{-1}(PFA) - Q^{-1}(PD)\right]^2 * \left[(\gamma - (\rho - \frac{1}{\rho})\right]^{-2}$$

Appendix 3: The mathematical derivations for Matched Filter Detections (MFD)

The mathematical analysis of MFD depicted as:

$$E(x) = \frac{1}{N}\sum_{n=0}^{N-1} x(n) \times S(n) \qquad \text{Eq (1)}$$

Where, $S(n)$ = prior Known signal,

$E(x) =$ is denotes test statics

δn^2 = is denotes the noise variance

In MFD, the test statics expressed as:

$$E(x) = \begin{cases} N\left(0, \frac{\delta n^2}{N}\right) & H0 \\ N\left(NP,\ P\frac{\delta n^2}{N}\right) & H1 \end{cases} \qquad \text{Eq (2)}$$

Where, P = is denotes the average PU signal power.

For probability equations of MFD mathimatical expression for Probability of detection (P_D), Probability of false alarm (P_{FA}), and probability of mis-detection (P_{MD}), are described as :

$$P_D = Prob\left(E(x) > \frac{\lambda}{H1}\right) = Q\left(\frac{\lambda - P}{\sqrt{\frac{P\delta n^2}{N}}}\right) \qquad \text{Eq (3)}$$

$$P_{FA} = Prob\left(E(x) > \frac{\lambda}{H0}\right) = Q\left(\frac{\lambda}{\sqrt{\frac{P\delta n^2}{N}}}\right) \qquad \text{Eq (4)}$$

$$P_{MD} = 1 - Pd = 1 - Q\left(\frac{\lambda - \mathrm{P}}{\sqrt{\frac{\mathrm{P\delta n^2}}{\mathrm{N}}}} \right) \qquad \text{Eq (5)}$$

Where, σn^2 = is variance of the noise

$Q(.)$ = is the Q-function and it is described as:

$$Q(t) = \frac{1}{\sqrt{2\pi}} \int_t^\infty e^{\lambda^2}/_2 \, d\tau \qquad \text{Eq (6)}$$