

Two-Stage Spectrum Sensing for Cognitive Radio Using Energy and Entropy Detection over AWGN Channel



Mustefa Badri Usman

A Thesis Submitted to

The Department of Electronics and Communication Engineering

School of Electrical Engineering and Computing

Presented in Partial Fulfillment of the Requirement for the Degree of Master's in
Electronics and Communication Engineering

Office of Graduate Studies

Adama Science and Technology University

June, 2022

Adama, Ethiopia

**Two-Stage Spectrum Sensing for Cognitive Radio Using Energy
and Entropy Detection over AWGN Channel**

Mustefa Badri Usman

Major Advisor: Dr. Ram sewak Singh

Co-Advisor: Dr. S. Raj Kumar

A Thesis Submitted to

The Department of Electronics and Communication Engineering

School of Electrical Engineering and Computing

Presented in Partial Fulfillment of the Requirement for the Degree of Master's in
Electronics and Communication Engineering

Office of Graduate Studies

Adama Science and Technology University

June, 2022

Adama, Ethiopia

APPROVAL PAGE OF M.SC. THESIS

We, the advisors of the thesis entitled “**Two Stage Spectrum Sensing for Cognitive Radio using Energy and Entropy Detection over AWGN channel**” and developed by **Mustefa Badri Usman**, hereby certify that the recommendation and suggestions made by the board of examiners are appropriately incorporated into the final version of the thesis.

Dr. Ram sewak Singh

Major Advisor

Signature

Date

Dr. S. Raj Kumar

Co-advisor

Signature

Date

We, the undersigned, members of the Board of Examiners of the thesis by **Mustefa Badri Usman** have read and evaluated the thesis entitled “**Two Stage Spectrum Sensing for Cognitive Radio using Energy and Entropy Detection over AWGN channel**” and examined the candidate during open defense. This is, therefore, to certify that the thesis is accepted for partial fulfillment of the requirement of the degree of Master of Science in Electronics and Communication Engineering.

Chairperson

Signature

Date

Internal Examiner

Signature

Date

External Examiner

Signature

Date

Finally, approval and acceptance of the thesis is contingent upon submission of its final copy to the Office of Postgraduate Studies (OPGS) through the Department Graduate Council (DGC) and School Graduate Committee (SGC).

Department Head

Signature

Date

School Dean

Signature

Date

Office of Postgraduate Studies, Dean

Signature

Date

DECLARATION

I hereby declare that this Master Thesis entitled “**Two stage Spectrum Sensing for Cognitive Radio using Energy and Entropy Detection over AWGN channel**” is my original work. That is, it has not been submitted for the award of any academic degree, diploma or certificate in any other university. All sources of materials that are used for this thesis have been duly acknowledged through citation.

Mustefa Badri Usman

Name of the Student

Signature

Date

RECOMMENDATION

We, the advisors of this thesis, hereby certify that we have read the revised version of the thesis entitled “**Two stage Spectrum Sensing for Cognitive Radio using Energy and Entropy Detection over AWGN channel**” prepared under our guidance by **Mustefa Badri Usman** submitted in partial fulfillment of the requirements for the degree of Masters of Science in Electronics and Communication Engineering. Therefore, we recommend the submission of revised version of the thesis to the department following the applicable procedures.

Dr. Ram sewak Singh

Major Advisor

Signature

Date

Dr. S. Raj Kumar

Co-advisor

Signature

Date

ACKNOWLEDGMENT

First of all, I would like to thank the Almighty God who gave me the strength and ability to complete the thesis successfully. After the almighty God, I would like to express my earnest gratitude and regards to my advisor **Dr. Ram Sewak Singh** for being the cornerstone of this work. He had perpetual motivation and guidance during the period of doubts and uncertainties, that has helped me to carry on with this thesis. I am also thankful to my co-advisor **Dr. S. Raj Kumar** for his valuable suggestions and continuous support. I would also like to express my special gratitude to the program of Electronics and Communication Engineering (ECE) for giving me the golden opportunity to do this wonderful thesis on the topic “Two-stage Spectrum Sensing for Cognitive Radio using Energy and Entropy Detection over AWGN channel”, which will also help me in the future in doing a lot of research and also come to know about so many things. I am really thankful to them.

I would like to thank all of my classmates, especially **Mr. Hise Teferi, Mr. Zelalem Melak, Mr. Wendwossen Desalegn** and **Mr. Eyasu Kefale** for their advice while I faced challenges on my thesis.

Finally, I would like to thank my parents for their endless advice and also I want to express my gratitude's to those who directly or indirectly supported me during my thesis.

Table of Contents

APPROVAL PAGE OF M.SC. THESIS.....	i
DECLARATION.....	ii
RECOMMENDATION.....	iii
ACKNOWLEDGMENT.....	iv
LIST OF TABLES.....	viii
LIST OF FIGURES.....	ix
LIST OF ACRONMYS AND ABBREVIATIONS.....	xi
ABSTRACT.....	xiii
CHAPTER ONE: INTRODUCTION.....	1
1.1 Background of the Study.....	1
1.2 Statement of the Problem.....	5
1.3 Objectives.....	5
1.3.1 General Objective.....	5
1.3.2 Specific Objectives.....	6
1.4 Scope of the Study.....	6
1.5 Significance of the Study.....	6
1.6 Thesis Contribution.....	7
1.7 Limitation of the Study.....	7
1.8 Organization of the Thesis.....	7
CHAPTER TWO: LITERATURE REVIEW.....	9
2.1 Introduction.....	9
2.2 Dynamic Spectrum Access.....	9
2.2.1 Dynamic Exclusive Use Model.....	10
2.2.2 Open Sharing Model.....	10
2.2.3 Hierarchical Access Model.....	10
2.3 Cognitive Radio (CR).....	12
2.3.1 Fundamental Meanings of Cognitive Radio.....	12
2.3.2 Characteristics of Cognitive Radio.....	13
2.3.3 Cognitive Radio Architecture.....	13
2.3.4 Cognitive Radio Cycle.....	16

2.4 Spectrum Sensing Techniques	17
2.4.1 Transmitter based detection technique	19
2.4.2 Interference based detection	26
2.4.3 Cooperative Detection	27
2.5 Issues and Challenges in Spectrum Sensing	31
2.6 Additive White Gaussian Noise (AWGN) Channel	32
2.7 Central Limit Theorem	33
2.8 Related Works	33
2.8.1 Previous work on Energy Detection	33
2.8.2 Previous work on Entropy Detection	35
2.8.3 Previous work on Two-stage Spectrum sensing	35
CHAPTER THREE: METHODOLOGY AND SYSTEM MODEL	38
3.1 Overview	38
3.2 Materials	38
3.3 Methodology	38
3.4 System Model for Spectrum Sensing	39
3.4.1 System Model of Energy Detection Technique	42
3.4.2 System Model of Entropy Detection Technique	44
3.4.3 System Model of Proposed Two-Stage Spectrum Sensing	47
3.5 Cooperative Spectrum Sensing	48
3.5.1 OR Rule	49
3.5.2 AND Rule	49
3.6 Performance Metrics of Spectrum Sensing	50
CHAPTER FOUR: RESULT AND DISCUSSION	52
4.1 Results of Conventional Energy Detection (CED)	53
4.1.1 Probability of detection versus SNR for CED	54
4.1.2 Effects of varying probability of false alarm on detection performance of CED	55
4.1.3 Probability of detection versus probability of false alarm (ROC Curve) for CED	56
4.1.4 Probability of miss detection versus probability of false alarm (CROC Curve)	57
4.1.5 Effects of varying number of samples on detection probability of CED	58
4.1.6 Cooperative detection for CED	58
4.2 Performance comparison among various types Entropy Detection	62

4.2.1 Probability of detection versus SNR	62
4.2.2 Receiver Operating Characteristic (ROC) Curve.....	64
4.2.3 Complementary Receiver Operating Characteristic (CROC) Curve	65
4.2.4 Effects of varying number of bins on the performance of Renyi Entropy detection	65
4.2.5 Cooperative detection for Renyi Entropy techniques	66
4.3 Results of Proposed Two-Stage Spectrum Sensing	68
4.3.1 Probability of detection versus SNR for comparing the proposed technique with conventional methods.....	68
4.3.2 Receiver Operating Characteristics (ROC) Curve	70
4.3.3 Complementary Receiver Operating Characteristics (CROC) Curve.....	71
4.3.4 Effects of varying probability of false alarm on the performance of proposed technique	72
4.3.5 Effects of varying number of samples on the performance of proposed technique..	73
4.4 Results of Cooperative detection for Proposed techniques.....	74
4.4.1 Pd vs SNR for cooperative detection of proposed two-stage technique	74
4.4.2 ROC curve for Cooperative detection of proposed two-stage technique.....	75
4.4.3 CROC curve for Cooperative detection of proposed two-stage technique	76
5. CONCLUSION AND RECOMMENDATION	77
5.1 Conclusion	77
5.2 Recommendation	78
6. REFERENCES	80
7. APPENDICES	86
Appendix A: Algorithm of Conventional Energy Detection	86
Appendix B: Algorithm of Entropy Detection.....	87
Appendix C: Algorithm of Two-stage spectrum sensing technique.....	88
Appendix D: Alternative Algorithm for Two-stage spectrum sensing technique	89

LIST OF TABLES

Table 2. 1: A Summary of transmitter based spectrum sensing technique.....	26
Table 2. 2: A Summary of some related work.....	37
Table 4. 1: Parameters used for Simulations.....	53
Table 4. 2: performance comparison among single node CED, AND rule and OR rule CSS at Pf=0.1, SNR=-12 dB, N=1500 and NU=4	60
Table 4. 3: Performance comparison on different types of entropy detection at various SNR values.....	63
Table 4. 4: Performance comparison between proposed two-stage SS and Single stage SS at various SNR values	69

LIST OF FIGURES

Figure 1.1: Radio Spectrum utilization (Akyildiz et al., 2006), (Venkatapathi et al., 2019)	2
Figure 1.2: Spectrum hole and DSA concepts (Akyildiz et al., 2006), (A & A, 2012).....	3
Figure 2.1: classification of DSA	10
Figure 2.2: DSA model a) interweave b) underlay c) overlay (Heng & Niversity, 2012)	11
Figure 2.3: Cognitive Radio Network Architecture (Akyildiz et al., 2008).....	14
Figure 2.4: The Cognitive cycle (Akyildiz et al., 2006).....	16
Figure 2.5: Classification of Spectrum sensing technique (Divya Sahithi et al., 2020).....	18
Figure 2.6: Process of energy detection (A & A, 2012), (Xuping & Jianguo, 2007).....	20
Figure 2.7: Block diagram of Matched filter detection (Divya Sahithi et al., 2020).....	22
Figure 2.8: Cyclostationary feature detection (Birajdar2, 2011).....	24
Figure 2.9: interference temperature Management (Birajdar2, 2011), (Akyildiz et al., 2006) .	27
Figure 2.10: Shadowing, Multipath fading and Receiver Uncertainty (A & A, 2012), (Akyildiz et al., 2011)	28
Figure 2.11: Centralized approach of Cooperative SS (Birajdar2, 2011), (A & A, 2012).....	29
Figure 2.12: Distributed approach of Cooperative SS (Birajdar2, 2011), (A & A, 2012)	30
Figure 2. 13: Relay-assisted approach of Cooperative SS (Birajdar2, 2011), (Akyildiz et al., 2011)	31
Figure 2. 14: Model for received signal passed through an AWGN channel.....	33
Figure 3. 1: Methodology	39
Figure 3. 2: Modeling of the received signal (Manesh et al., 2016).....	40
Figure 3. 3: Hypothesis testing and probable outcomes, along with their probability (Abdo-tuko, 2015)	40
Figure 3. 4: General Model of Spectrum Sensing (Manesh et al., 2016)	41
Figure 3. 5: Block Diagram of Energy Detection.....	42
Figure 3. 6: Block Diagram of Entropy Based Detector	47
Figure 3. 7: System model for Proposed Two-stage Spectrum Sensing	48
Figure 4. 1: Pd vs SNR for CED at Pf=0.1 and N=1500.....	54
Figure 4. 2: Pd vs SNR for CED at Pf=0.1, 0.2 ,0.3 and N=1500.....	55
Figure 4. 3: Pd vs Pf for CED at SNR=-11dB.....	56
Figure 4. 4: Pm vs Pf for CED at SNR=-11dB	57

Figure 4. 5: Pd vs Pf for CED at various number of samples (N).....	58
Figure 4. 6: Pd vs SNR for cooperative CED at different number of users for OR/AND Rule	59
Figure 4. 7: ROC curve for cooperative CED	60
Figure 4. 8: CROC curve for cooperative CED.....	61
Figure 4. 9: Pd vs SNR at Pf=0.1 and $\alpha=4$ for various types of Entropy Detection	63
Figure 4. 10: ROC Curve for various types of Entropy Detection at SNR=-19dB	64
Figure 4. 11: CROC Curve for various types of Entropy detection at SNR=-21dB	65
Figure 4. 12: Pd vs SNR for Renyi Entropy detection at various number of bins (L)	66
Figure 4. 13: ROC Curve for Cooperative renyi entropy detection at SNR=-25dB	67
Figure 4. 14: CROC Curve for Cooperative renyi entropy detection at SNR=-25dB.....	67
Figure 4. 15: Pd vs SNR for comparing proposed two stage, Renyi entropy and CED at Pf=0.1	69
Figure 4. 16: ROC curve that compares proposed two stage, Renyi entropy and CED at SNR=- 24dB	70
Figure 4. 17: CROC curve that compares proposed two stage, Renyi entropy and CED at SNR = -21dB	71
Figure 4. 18: performance comparison of proposed two-stage SS technique at various values of false alarm probability	72
Figure 4. 19: ROC curve of proposed two stage SS technique at different number of samples	73
Figure 4. 20: Pd vs SNR for Cooperative two-stage SS at Pf=0.1	74
Figure 4. 21: ROC curve for Cooperative two-stage SS at SNR=-24dB	75
Figure 4. 22: CROC curve for Cooperative two-stage SS at SNR=-26dB.....	76

LIST OF ACRONMYS AND ABBREVIATIONS

ADC	Analog to Digital Converter
AWGN	Additive White Gaussian Noise
AP	Access Point
BPF	Band Pass Filter
BPSK	Binary Phase Shift Keying
BS	Base Station
BTS	Base-station Transceiver System
CAF	Cyclic autocorrelation Function
CD	Cyclostationary Detection
CDMA	Code Division Multiple Access
CED	Conventional Energy Detection
CLT	Central Limit Theorem
CR	Cognitive Radio
CRN	Cognitive Radio Network
CROC	Complementary Receiver Operating Characteristics
CSS	Cooperative Spectrum Sensing
DSA	Dynamic Spectrum Access
DSM	Dynamic Spectrum Management
ED	Energy Detection
EGC	Equal Gain Combining
EnD	Entropy Detection
FC	Fusion Center
FCC	Federal Communications Commission
FSA	Fixed Spectrum Allocation
FFT	Fast Fourier Transform
IEEE	Institute of Electrical and Electronic Engineers
ISM	Industrial, Scientific and Medical
MF	Matched Filter
MFD	Matched Filter Detection
MInT	Ministry of Innovation and Technology

MRC	Maximal Ratio Combining
MS	Mobile Station
NCA	National Communication Authority
NCC	Nigerian Communications Commission
OSA	Opportunistic Spectrum Access
P_d	Probability of Detection
P_f	Probability of False Alarm
P_m	Probability of Missed Detection
PSD	Power Spectral Density
PU	Primary User
RF	Radio Frequency
ROC	Receiver Operating Characteristics
RSS	Received Signal Strength
SCF	Spectral Correlation Function
SLC	Square Law Combining
SNR	Signal-to-Noise Ratio
SS	Spectrum Sensing
SU	Secondary User
T_v	Television
WiMAX	Worldwide Interoperability for Microwave Access
WLAN	Wireless Local Area Network
WSS	Wide-Sense Stationary

ABSTRACT

The numbers of wireless devices have grown dramatically in recent years, resulting in a scarcity of available radio spectrum due to static spectrum allocation. However, many studies on static allocation show that the licensed spectrum bands are underutilized. Cognitive radio has been considered as a viable solution to overcome the problem of spectrum scarcity and underutilization. Spectrum sensing is an important part in cognitive radio for detecting spectrum holes. To detect the presence or absence of primary user signals, many spectrum sensing techniques such as Energy Detection, Matched filter Detection, and Cyclostationary feature Detection have been developed. Among these, Energy detection has received the most attention from researchers due to its ease of implementation, fast sensing time, and low computational complexity. However, the performance of conventional energy detector degrades rapidly at low Signal-to-noise Ratio (SNR) due to its sensitivity to noise uncertainty. To mitigate noise uncertainty problem, Shannon, Tsallis, Kapurs, and Renyi entropy-based detection have been used in this study, and their performances are compared to choose the best performer. The comparison results have shown that Renyi entropy detection has a significant improvement of about 11 dB, 10 dB and 7 dB in SNR wall compared to Tsallis, Shannon and Kapurs entropy, respectively. In this thesis, two-stage spectrum sensing are proposed using Energy detection as the coarse stage and Renyi entropy-based detection as the fine stage to improve the performance of single-stage detection techniques. Also, a performance comparison among conventional energy detection, entropy-based detection, and proposed two-stage spectrum sensing over the Additive White Gaussian Noise (AWGN) channel are performed. In addition, the cooperative detection techniques are performed to further improve the performance of the proposed two-stage techniques. Simulation results show that the proposed two-stage technique has a significant improvement of about 15 dB and 0.5 dB in SNR wall when compared to Conventional Energy Detection and Renyi entropy, respectively, whereas a cooperative two-stage technique with two users indicates a 2 dB performance improvements in SNR wall compared to single-node two-stage techniques. To evaluate the performance of spectrum sensing, parameters such as probability of detection, probability of false alarm, probability of miss detection and receiver operating characteristics curve are used.

Keywords: *Cognitive radio, Kapurs entropy, Shannon entropy, Renyi entropy, Tsallis entropy, Spectrum Sensing, Spectrum holes, Single-stage, Two-stage*

CHAPTER ONE

1. INTRODUCTION

1.1 Background of the Study

Nowadays, wireless communication technologies are rapidly evolving to accommodate people's demands and requirements, which are changing exponentially (Develi, 2020). As wireless technology advances, the demand for spectrum resources grows, which has been resulted in spectrum scarcity due to the finiteness and limitedness nature of radio spectrum (Dubey & Verma, 2015). The government regulates the use of radio spectrum within many countries through national regulatory agencies such as the Federal Communications Commission (FCC) in the United States, the Nigerian Communications Commission (NCC) in Nigeria and the National Communications Authority (NCA) in Ghana whereas the Ministry of Innovation and Technology (MInT) is in charge in Ethiopia (A & A, 2012). This governmental agency is in charge of assigning spectrum bands to different operators. In the current spectrum allocation policy, all frequency bands (i.e., licensed bands) are exclusively assigned to specific users over very long time periods and are intended to be utilized solely by licensees. This method is known as Fixed Spectrum Allocation (FSA) policy.

The FSA management system ensures that the radio frequency spectrum is licensed only to authorized parties without interference. As a result of wireless applications and devices grows, the need for high data rate has increased and spectrum resources become scarce because of current allocation policy. On the contrary, recent studies on current spectrum allocation show that underutilization of allocated spectrum for licensed user at both the temporal or/and spatial domains. For instance, high utilization is appearing in the cellular and FM radio bands, whereas low utilization is seen in other bands. The majority of license holders do not always transmit at all times in all geographic areas covered by their license. According to the measurements from FCC, the spectrum allotted to most license holders has a utilization range of 15% to 85% (Akyildiz et al., 2006). Figure 1.1 depicts the radio spectrum utilization in which some channels are heavily used while others are partially or sparsely used. The vacant spectrum band which is not in use by any user in the temporal and/or spatial domains are called spectrum holes or white spaces. It opens up a lot of possibilities for wireless communications.

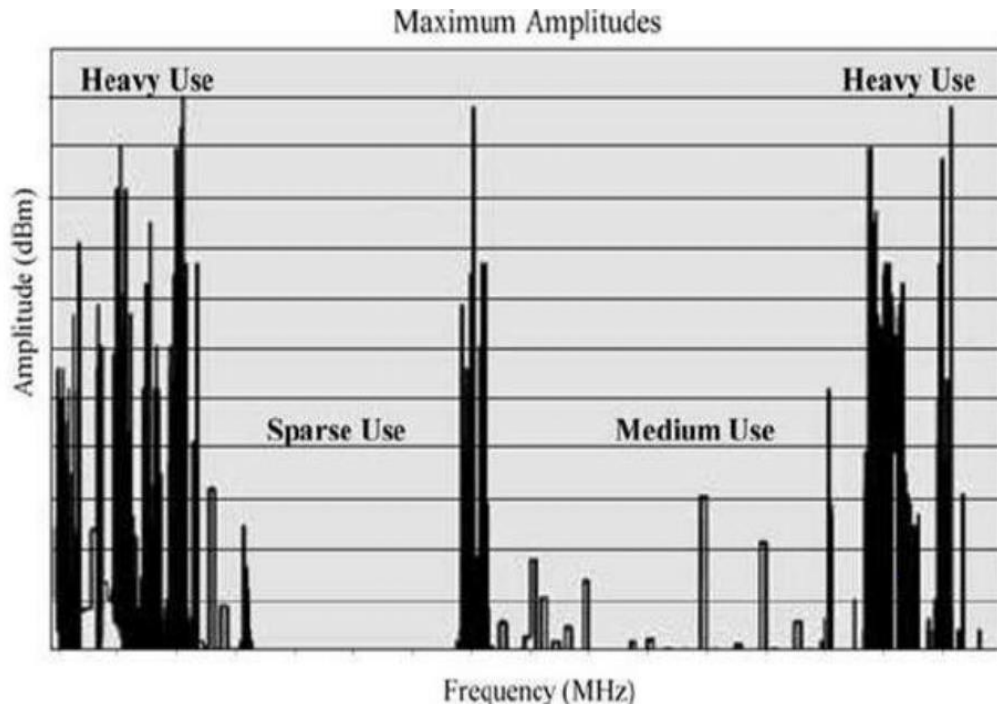


Figure 1.1: Radio Spectrum utilization (Akyildiz et al., 2006), (Venkatapathi et al., 2019)

The FSA policy has been effective in preventing radio spectrum interference among users, and it grants licensed users the right to use a specific portion of the spectrum exclusively. However, it has resulted in less spectrum utilization efficiency. The FCC is urged to reconsider how the radio frequency spectrum is used since the scarcity of radio spectrum has occurred due to a rigid allocation policy rather than a shortage of natural resources. As a result, the FCC recommends the Dynamic Spectrum Access (DSA) approach to overcome the problem of spectrum scarcity and underutilization. DSA is a novel spectrum sharing approaches that enables secondary users (SUs) to access the plentiful spectrum holes in the licensed spectrum bands. It is a viable solution for reducing the problem of spectrum scarcity and increasing spectrum utilization (Heng & Niversity, 2012). The main idea behind DSA is that SUs can use frequency bands that aren't being used by their licensed users (PUs) as long as they don't pose any harmful interference to PUs (A & A, 2012). With DSA, SUs dynamically search for vacant spectrum bands, and temporarily access them for wireless communications. To prevent interfering with PUs, SUs constantly checks the spectrum bands and yield to PUs whenever PUs starts using a band. The key enabling technology for the DSA approach is Cognitive radio. Figure 1.2 illustrates the concept of spectrum holes and DSA.

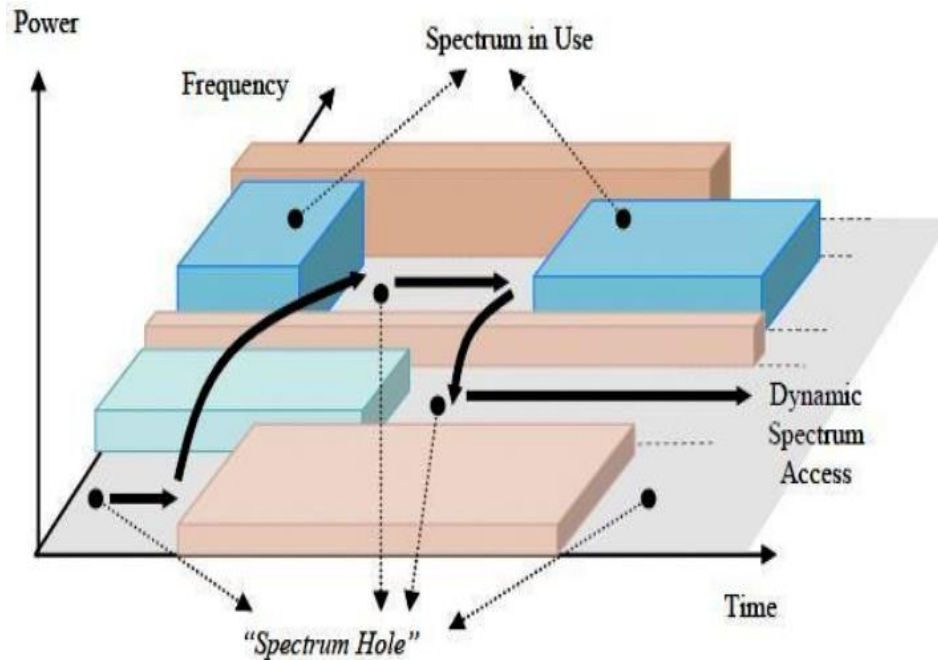


Figure 1.2: Spectrum hole and DSA concepts (Akyildiz et al., 2006), (A & A, 2012)

Cognitive radio (CR) is a critical technology that allows an opportunistic usage of frequency bands that are currently underutilized and have limited resources (Develi, 2020), (Nikonowicz et al., 2016). CR is also described as a wireless communication system that learns and adapts to its surroundings intelligently. There are two kinds of bands: licensed and unlicensed. Licensed bands are those that can only be used by authorized parties or users, whereas unlicensed bands can be used by everyone who wants to use them (Dubey & Verma, 2015). Depending up on the priority of accessing licensed band there are two kinds of users in CR networks (CRN): Primary Users (PUs) and Secondary Users (SUs) (Develi, 2020). The users who have a higher priority of using the licensed band are known as “Primary users (PUs)”, while the users who have a lower priority of using the licensed band are called “Secondary Users (SUs)”.

CR has four main tasks/functions: Spectrum Sensing (SS), Spectrum Decision/Management, Spectrum Sharing/Allocation and Spectrum Mobility/Handoff. SS is used to determine the portion of spectrum that are vacant and senses the presence of licensed primary users (PUs). Spectrum Management selects the most suitable vacant spectrum holes among the detected ones. The goal of Spectrum sharing is to evenly or fairly distribute the spectrum holes among the Secondary users (SUs). Spectrum Mobility aims to maintain communication while transitioning to a better spectrum holes (Fawzi et al., 2020), (Tomar et al., 2016).

Among all of the functions of CR, Spectrum Sensing is regarded as the most critical component in its establishment. A number of SS methods have been suggested in recent decades, which can be classified into two categories based on the bandwidth of interest for spectrum sensing: Wideband and Narrowband. Narrowband Spectrum Sensing examines a single frequency band at a time, whereas Wideband Spectrum Sensing analyzes multiple frequencies simultaneously (Arjoune & Kaabouch, 2019). Another way to categorize sensing techniques is by the requirement for prior information about PU signals, which are classified as Coherent and Non-Coherent Detection. However, spectrum sensing techniques are popularly classified into three different techniques for sensing spectrum holes: Transmitter based (Non-cooperative), Interference based and Receiver based (Cooperative) detection. In this thesis, we look at transmitter based detection and cooperative detection. Under transmitter based detection many techniques are presented such as Eigenvalue detection, Energy detection (ED), Cyclostationary feature detection (CFD), Matched filter detection (MFD), etc.

In this thesis, ED is generally adopted for SS due to its non-coherent method, in which the SU receiver requires no prior information about PU signals. It has a low computational complexity as well as a fast sensing time. However, noise uncertainty, which is the random or unpredictable and unavoidable variation of noise in any wireless communication system, severely reduces ED performance, especially when SNR is low (Prieto et al., 2018). Many methods have been proposed to address the challenges of ED. Among those methods, Entropy detection becomes the most robust one to the noise uncertainty at low SNR values. Furthermore, because it doesn't require prior information about primary signals, its implementation complexity is comparable to that of ED. There are many types of Entropy Detection, such as Shannon, Renyi, Kapurs, and Tsallis Entropy. So, by comparing these types of entropy with each other, the one that outperform better is investigated in this study.

In this thesis, to address the challenges of ED and to further enhance the performance of Entropy-based detection, two-stage SS techniques are proposed, using conventional energy detection (CED) and best performer entropy types. Because it accomplishes SS within the shortest time and provides accurate detection at high SNR values, ED is used as the coarse stage (first stage) for the proposed technique. However, due to its robustness to noise uncertainty in low SNR values, the best performer Entropy detection technique is used in the fine stage (second stage).

The two most important parameters used to evaluate the performance of any SS method are Probability of detection (P_d) and probability of false-alarm (P_f). The probability of correctly detecting the presence of a primary (licensed) user is denoted by P_d . As a result, a high P_d is preferable because it ensures less interference to primary users. The P_f is the probability of incorrectly declaring the primary user presence.

1.2 Statement of the Problem

The increasing demand for wireless services has put a lot of restrictions on how the available radio spectrum, which is a finite and valuable resource, can be used. Because of the recent rapid rise of wireless communications, the issue of spectrum utilization has become even more critical. In addition to this, a fixed spectrum allocation policy has resulted in spectrum underutilization, as a large amount of licensed spectrum is not adequately exploited. In order to overcome the problem of spectrum underutilization, cognitive radio (CR) has emerged as a viable solution for increasing the efficiency of available radio spectrum utilization. Spectrum sensing is an essential task for CR since it helps in the detection of the spectrum gaps (underutilized bands of frequency). As mentioned in the background section, there are a variety of spectrum sensing techniques. Among those techniques Energy Detection (ED) method is the simplest and easiest ones. But at low SNR signal, the performance of ED deteriorates rapidly due to noise uncertainty. So, in order to overcome the problem occurred due to noise uncertainty at low SNR, different types of Entropy Detection (EnD) are introduced in this study. Furthermore, to improve the performance of ED and EnD at low SNR a Two-Stage Spectrum Sensing technique is developed that consists of Coarse Stage using ED and Fine Stage using EnD.

1.3 Objectives

1.3.1 General Objective

The main objective of this thesis is to improve the spectrum sensing performance of Conventional Energy Detectors (CED) at low SNR over the AWGN channel using a two-stage technique, which is composed of CED and EnD.

1.3.2 Specific Objectives

The specific objectives of this thesis are:

- ❖ To study and analyzes the performance of conventional energy detection (CED) in terms P_d vs SNR, ROC curve and CROC curve.
- ❖ To evaluate the performance of various Entropy detection in terms ROC curve, CROC curve and P_d vs SNR.
- ❖ To develop and apply two-stage spectrum sensing using Energy and Entropy Detection.
- ❖ To compare the performance of CED and Entropy Detection (EnD) with proposed two-stage Spectrum sensing in terms of ROC curve, CROC curve and P_d Vs SNR.
- ❖ To evaluate the performance of proposed two-stage spectrum sensing technique at different sampling values and P_{fa} .
- ❖ To evaluate the performance of cooperative detection for proposed two-stage spectrum sensing in terms of P_d vs SNR, ROC curve, and CROC curve.

1.4 Scope of the Study

This thesis focuses on improving the performance of spectrum sensing for cognitive radios. The Energy Detector non-cooperative spectrum sensing techniques are chosen for implementation. Also, Shannon, Tsallis and Renyi Entropy detection technique are performed to overcome the problem of performance degradation at low SNR due to noise uncertainty in CED. The performance comparison among Shannon, Tsallis, Kapurs and Renyi Entropy are conducted. To further improve the performance of spectrum sensing, Two-stage spectrum sensing for CR are developed using Energy Detection as a coarse stage and best performer Entropy Detection as a Fine Stage. Finally, the performance comparison among Single-Stage ED, Single-Stage EnD and proposed two-stage spectrum sensing over AWGN channel are evaluated. All simulation of proposed detector is done using MATLAB software communication tools.

1.5 Significance of the Study

In recent years, there has been a significant growth in the number of devices connected to the wireless systems because of this; there has been a significant increase in bandwidth demands. As a result, there is a severe spectrum scarcity problem in some bands. In order to overcome the scarcity problem of bandwidth, cognitive radio network (CRN) technology has been proposed.

Thus, the significance of this thesis is that it reduces the bandwidth scarcity using CRN. The ED technique is critical for CR since it functions independently without requiring any PU signal information and is the simplest to implement. However, ED has low spectrum sensing performance at low SNR values due to noise uncertainty. In order to counteract the noise uncertainty problem, various Entropy detections are proposed. To further improve the performance of both single stage SS (i.e. Energy and Entropy Detection), two-stage SS techniques are proposed. Therefore, the main significance of this thesis is that it improves the performance of conventional Energy Detection at low SNR using a proposed two-stage spectrum sensing (SS) technique.

1.6 Thesis Contribution

The main contributions of this thesis are follows:

1. We applied different types of entropy-based detection to alleviate the performance degradation of CED, which occurs at low SNR condition due to uncertainty of noise. Moreover, the performance comparisons among various types of entropy detection are performed in order to choose the best performer method.
2. Depending upon the results found from the comparison, two-stage spectrum sensing techniques are developed by using CED as a coarse stage and the best performer entropy detector as a fine stage.
3. The cooperative detection of the proposed two-stage technique is performed to further improve the performance of the single-node technique.

1.7 Limitation of the Study

This thesis is limited only to simulation based results. That means the performance of all detection techniques are evaluated based on simulation results only.

1.8 Organization of the Thesis

The thesis has been organized into five chapters.

Chapter 1 briefly discusses the background of the study. The problem statement, scope of the study, significance of the thesis and thesis objectives are also laid out here with its limitation.

Chapter 2 starts by discussing a brief introduction about Dynamic Spectrum Access (DSA) and Cognitive Radio Network (CRN). The detailed explanation about DSA and CRN are presented. Then functions of cognitive radio are discussed in short. After that, spectrum sensing techniques are clearly presented with its classification. Lastly, this chapter covers a related work of thesis.

Chapter 3 presents the research method that has been used in the thesis and the system models for conventional energy detection (CED), entropy detection and proposed two-stage techniques. Also, this chapter introduced materials that have been used for simulating the results.

Chapter 4 includes the results and discussion for CED, entropy detection and proposed two-stage techniques. And also, the cooperative detection results are presented for each of them.

Lastly, the Conclusion and Recommendation of the thesis are presented.

CHAPTER TWO

2. LITERATURE REVIEW

2.1 Introduction

The electromagnetic radio spectrum is becoming increasingly scarce as its use grows. However, due to the conventional method of spectrum allocation and management, as well as the existing inflexibility in operating frequency bands, the given spectrum is underutilized. As the majority of useable radio spectrum has already been allotted, detecting unoccupied bands to either introduce new services or enhance existing ones is difficult. Dynamic spectrum access (DSA) approach has been introduced to improve the spectrum utilization (Y. Zhang, 2008). Cognitive radio network (CRN) technology, which is a result of the DSA approach, intends to address the issues related to spectrum underutilization in wireless communication.

2.2 Dynamic Spectrum Access

As we have already mentioned in the previous chapter, there is an increasing demand for spectrum resources due to the growth of wireless services and applications in the past two decades, which has led us to spectrum scarcity problems. In a broader sense, these issues occur because of the conventional spectrum management paradigms that are currently in use (Akyildiz et al., 2006). However, many reports show that the licensed spectrum is rarely used constantly, resulting in very low spectrum utilization. Due to huge underutilization of the spectrum, many communication regulatory agencies have been motivated to investigate enhancing spectrum management and access techniques. This has resulted in the development of Dynamic Spectrum Access (DSA) approach (Heng & Niversity, 2012).

Dynamic spectrum access (DSA), also known as dynamic spectrum management (DSM), is a novel spectrum sharing model that takes advantages of frequency gaps to alleviates spectrum scarcity while also increasing spectrum utilization. DSA aims to alleviate the issues of spectrum scarcity and inefficiency by permitting secondary use in licensed frequency bands (Y. Zhang, 2008). Secondary user (SU) or unlicensed users are allowed to transmit in the licensed bands as long as they do not interfere with primary users. DSA can be broadly classified into three major models as shown in the Figure 2.1. Cognitive Radio (CR) technology is the fundamental technology that has been used extensively to achieve DSA goals (Clancy, 2015).

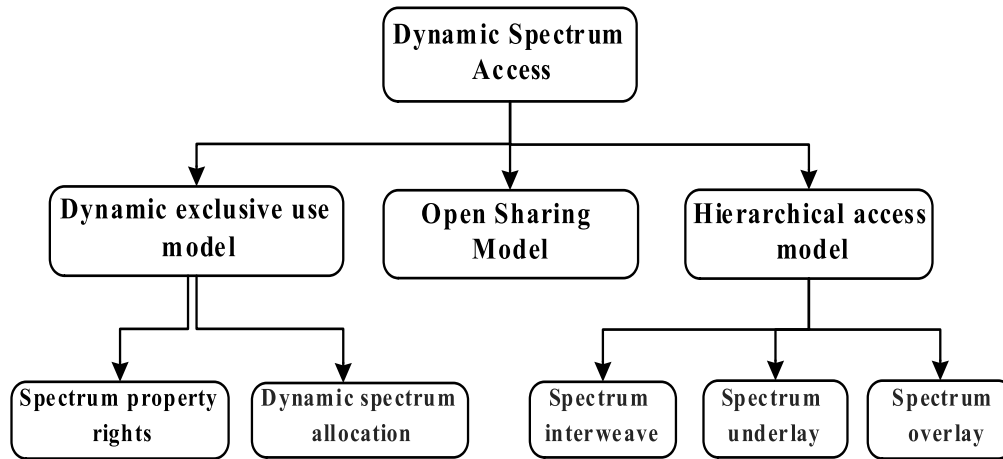


Figure 2.1: Classification of DSA

2.2.1 Dynamic Exclusive Use Model

The Dynamic Exclusive Use Model maintains the basic framework of the current spectrum management policies while adding flexibility to increase spectrum utilization efficiency. In order to introduce dynamicity two approaches: Spectrum Property Right and Dynamic Spectrum Allocation, have been proposed in this model (Prasad, 2009). In terms of spectrum property right, licensees have the freedom to sell and exchange their acquired spectrum as well as choose the technology that best suits their needs. Dynamic spectrum allocation: the goal of dynamic spectrum allocation is to improve spectrum efficiency by utilizing spatial and temporal traffic information for various applications and services (Prasad, 2009), (Rodriguez, 2015).

2.2.2 Open Sharing Model

Open sharing model, also known as spectrum common model. It increases spectrum efficiency by allowing users to share resources openly; this is comparable to previous successful models, such as wireless services that operate in the unlicensed Industrial, Scientific and Medical (ISM) radio band (Prasad, 2009), (Rodriguez, 2015).

2.2.3 Hierarchical Access Model

In order to create dynamicity in the spectrum, this model uses a hierarchical access structure. Two kinds of users: primary users and secondary users are included in this model. Under hierarchical model three approaches are employed to achieve the spectrum sharing between primary and secondary users (Prasad, 2009), (Rodriguez, 2015). These are spectrum interweave approach, spectrum underlay approach and spectrum overlay approach as shown in Figure 2.2.

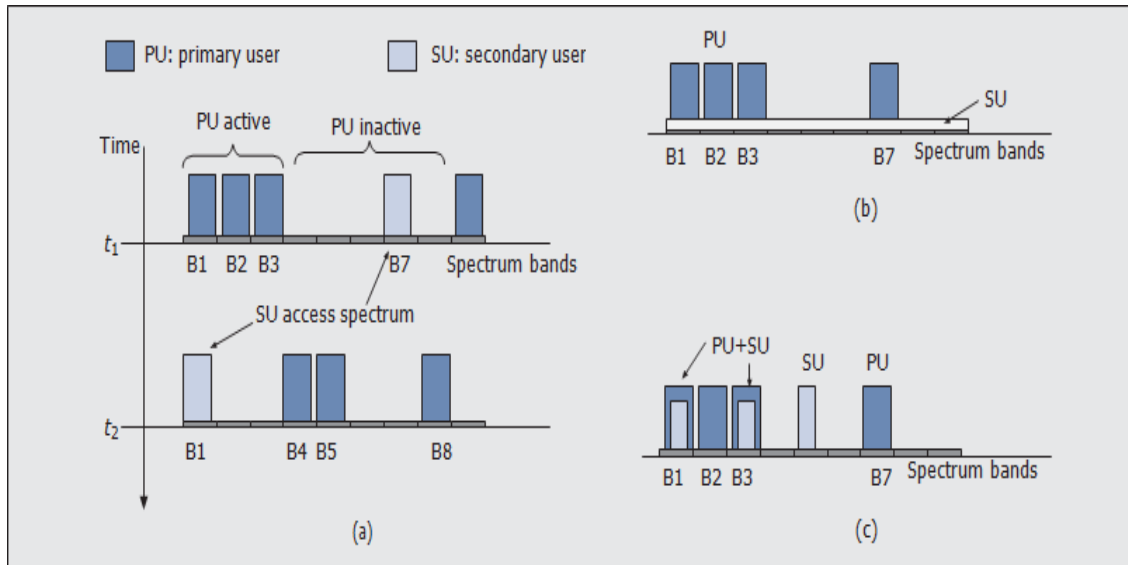


Figure 2.2: DSA model a) interweave b) underlay c) overlay (Heng & Niversity, 2012)

The **spectrum interweave approach** is the one that has received the most attention in the literature and is widely accepted as the de facto standards for DSA. Unlike the spectrum underlay and overlay approaches, SU cannot utilize a licensed spectrum band if a PU is using it (Heng & Niversity, 2012). In addition, the PU has the highest priority in the spectrum band, and any SU accessing the spectrum band must vacate it, whenever the PU begins to access the band. As a result, the interweave DSA model is also known as opportunistic spectrum access (OSA). The dynamical availability of spectrum is depicted in Figure 2.2 (a), along with how SUs use an interweave approach to search for and access idle spectrum bands (Heng & Niversity, 2012).

The **spectrum underlay approach** permits SUs to operate on a licensed band of spectrum whether or not the PU is using it, as long as the total interference from all SUs is below a certain threshold that the PU may tolerate. This constraint can be met in two approaches. In the first approach, the transmitted power of SU spreads across a wide range of spectrum so that the interference to the PU on each licensed band is considerably below threshold. The Ultra-wide band (UWB) technology employs this strategy. This method is best used for short-range scenarios. The interference temperature method is the second approach. SUs can operate at higher power levels on a licensed spectrum band using this method, as long as the overall interference from all SUs on the band is less than a certain threshold. Figure 2.2 (b) depicts how SU in the spectrum underlay approaches shares a wide range of spectrum with PUs on each band (Heng & Niversity, 2012).

The **spectrum overlay approach** permits SUs to operate on a licensed spectrum band while the PU is using the band like underlay approach (Heng & Niversity, 2012). However, the constraint is different. Instead of limiting SUs interference to the PU by restricting SUs transmit power, the overlay approach focuses on maintaining or preserving the PU performance. SUs are permitted to transmit concurrently with PUs as long as PUs performance is not degraded. This approach is depicted in the Figure 2.2 (c) (Heng & Niversity, 2012).

2.3 Cognitive Radio (CR)

Cognitive radio (CR) is a type of wireless communication in which a transceiver can intelligently detect which communication channels are occupied and which are not, and move into unused channels while avoiding occupied ones. CR is also described as a wireless communication system that learns and adapts to its surroundings intelligently.

There are two types of Cognitive Radio which is Full CR and Spectrum Sensing CR:

Full Cognitive Radio: it considers all parameters that a system can know about. In other word, it is a radio in which every possible parameter observable by a wireless node (network) is considered.

Spectrum Sensing CR: it is a radio in which only the radio frequency spectrum is considered. It only detects radio frequency channels.

2.3.1 Fundamental Meanings of Cognitive Radio

The word “cognitive” has become a buzzword for several networking and communications systems. One of the most common definitions of “cognitive” according to the Oxford English dictionary is “pertaining to cognition or to the activity or process of knowing.” The word cognition means: “the mental process of gaining knowledge through thought, experience and the senses.” As a result, CR could be defined as a radio that is cognitive.

In the 1999 Joseph Mitola first invented the term “cognitive radio” in his paper and he defined it as (MAGUIRE, 1999): “a radio that employs model based reasoning to achieve a specified level of competence in radio-related domains.”

Six years after Joseph Mitola’s paper on cognitive radio, Simon Haykin explained the concept of CR as (Haykin, 2005): “An intelligent wireless communication system that is aware of its

surrounding environment (i.e., outside world), and employs the methodology of understanding by building to learn from the environment and adapt its internal states statistical variations in the incoming RF stimuli by making corresponding changes in certain operating parameters (e.g. transmit power, carrier frequency and modulating strategy) in real-time, with two primary objectives in mind:”

- Highly reliable communications whenever and wherever needed;
- Efficient utilization of the radio spectrum

The FCC defines a CR as: “an intelligent wireless communication system capable of modifying its transceiver parameters based on interaction with the environment in which it operates.” However, according to IEEE USA it is defined as (Definitions, 2019) “a type of radio in which communication systems aware of their environment and internal state and can make decisions about their radio operating behavior based on that information and predefined objectives.”

According to cognitive principles, unlicensed users (secondary users) can use the free spectrum bands without interfering with the primary users.

2.3.2 Characteristics of Cognitive Radio

Cognitive radio has two main characteristics (Akyildiz et al., 2006) that are explained below.

Cognitive Capability: it defines the ability to detect the information from its surroundings (i.e. radio environments) of the radio technology. The cognitive capability first explained by Joseph Mitola in terms of cognitive cycle as “a CR that constantly monitors the surroundings, orients itself, forms plans, decides and then acts.”

Re-configurability: Spectrum awareness is provided through cognitive capabilities while re-configurability refers to the ability of a radio to modify its functionality, allowing the CR to be dynamically configured in response to the radio environment.

2.3.3 Cognitive Radio Architecture

Cognitive radio networks (CRN) are made up of interconnected Cognitive Radio devices that operate in the licensed spectrum band as secondary users (SUs). Ideally, CRNs are best viewed as heterogeneous networks. This is due to the fact that such networks use a variety of wireless

access technologies and are made up of various networks, communication systems, and end devices. Nonetheless, three fundamental network architectures for CRNs can be developed.

2.3.3.1 Ad-hoc Architecture

In these types of topologies, there is no clearly specified network infrastructure for coordinating communication flow between end devices (Akyildiz et al., 2006). As a result, mobile stations connect to other suitable devices in the area, resulting in an ad-hoc network. Thus, the communication in these architectures follows the multi-hop approach (Akyildiz et al., 2006).

2.3.3.2 Infrastructure Architecture

In this topology, the CRN is built around a set of base stations (BS) or access points. As a result, a mobile station (MS) only has to make one hop (single hop) to communicate with the nearest BS within transmission range. The communication among BS which is routed through core networks are called inter-cell communication. A dedicated network infrastructure is present in this architecture (Akyildiz et al., 2006), (Akan et al., 2009).

2.3.3.3 Mesh Architecture

Mesh architecture is a hybrid of an ad-hoc and infrastructure architectures. A MS can interact directly with the BS or use other mobile stations as multi-hop relay nodes in this architecture. In this kind of cases, there is typically certain wireless communication between the BS (Akyildiz et al., 2006).

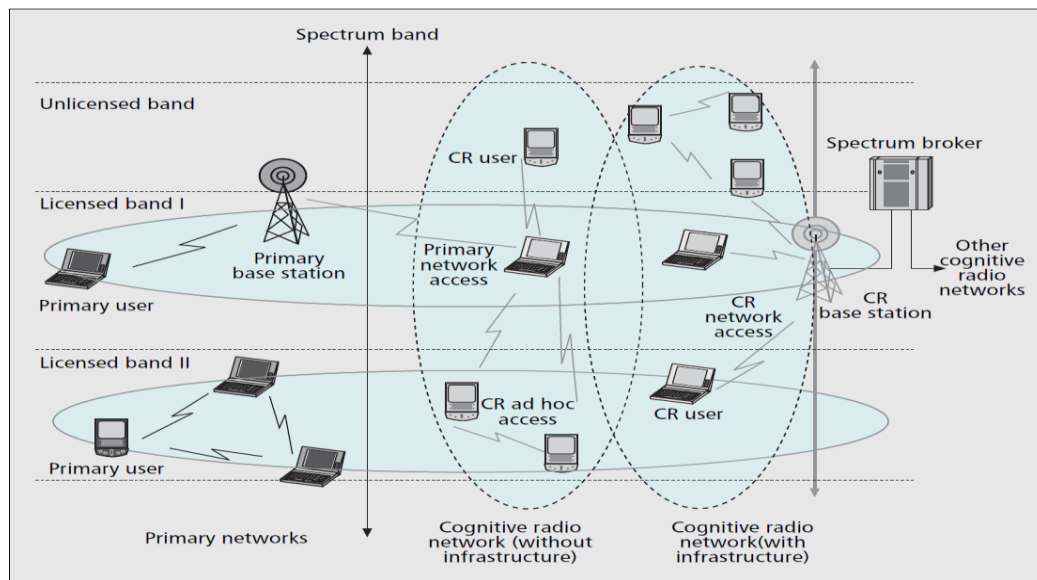


Figure 2.3: Cognitive Radio Network Architecture (Akyildiz et al., 2008)

Generally, CRN architecture can be classified into two groups (Akyildiz et al., 2006):

- Primary Network
- Cognitive Radio Network

The Primary Network: it's the pre-existing infrastructure that has an exclusive rights to access the specific spectrum bands (Akyildiz et al., 2006). The well-known example of this network is WiMAX, Tv broadcast networks, CDMA and cellular network. The primary networks components are Primary User (PU) and Primary BS (Licensed base-station). Primary User (PU) is a user who has been granted permission to operate in a licensed band. Primary BS (Licensed base-station) is a fixed infrastructure network component that has a license on certain spectrum bands for a particular technology. Example, include Base-station transceiver system (BTS) in a cellular system.

The Cognitive Radio network (CRN) does not have an exclusive right of accessing a licensed band and its access of the spectrum is allowed opportunistically. The components that comprise the CRNs are Secondary User (SU), Cognitive Radio BS (Unlicensed BS) and Spectrum Broker. Secondary User (SU) is a user without a license who is only allowed to utilize the spectrum opportunistically. The SUs can also be replaced by another term which is Cognitive Users.

Cognitive Radio BS (Unlicensed BS) is a fixed infrastructure component that have Cognitive Radio capabilities which provides a single-hop connection to Cognitive radio users. In cooperative SS, the Cognitive radio BS is a Fusion center (FC) that gathers the information of local measurements from collaborating users to make the final SS decision. Spectrum Broker is a central network entity that manages the sharing of spectrum resources among cognitive radio users.

In CRN, the users are classified into primary User (PU) and Secondary User (SU).

- Primary user (PU): A user who has a higher priority of using a certain spectrum band.
- Secondary user (SU): A low priority user exploiting the spectrum without causing interference to PUs.

2.3.4 Cognitive Radio Cycle

The set of activities that a CR executes to effectively perform its function is known as the cognitive radio cycle. The cognitive cycle depicts how a cognitive radio systematically responds to external stimuli in the form of radio transmissions within the environment it operates as shown in the Figure 2.4 below (Abolarinwa & Achonu, 2013). The cognition cycle is continuously conducted by the cognitive radio devices in order to discover spectral opportunities and to observe the presence or absence of the primary user. It also allows the cognitive radio devices to dynamically reconfigure themselves independently based on the underlying environmental conditions.

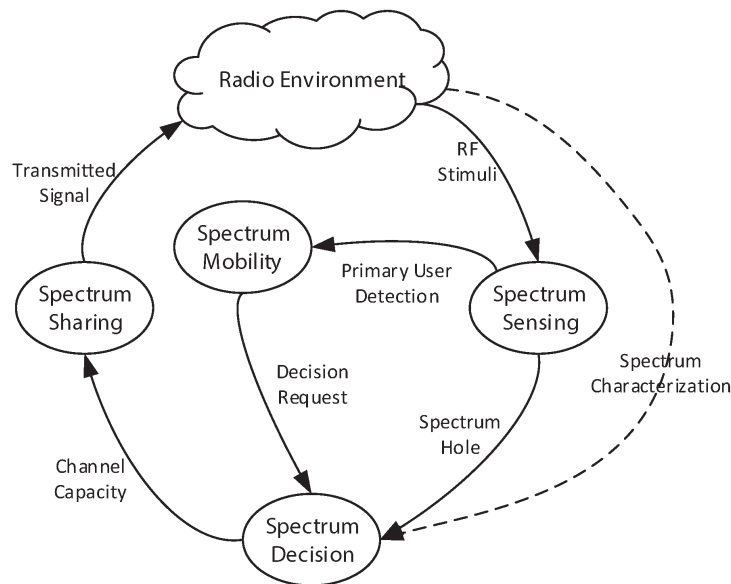


Figure 2.4: The Cognitive cycle (Akyildiz et al., 2006)

The cognition cycle of CRN includes four main functions/tasks that are described as follows:

Spectrum Sensing: it defines all the possible and available spectrum holes to avoid interferences. Spectrum sensing determines which portion of the spectrum vacant and senses the presence of licensed PUs.

Spectrum Management/Decision: it captures available vacant spectrum holes among the detected ones.

Spectrum Sharing/Allocation: the task of providing fair spectrum scheduling method among the coexistence users.

Spectrum Mobility/Handoff: if the spectrum in use by a CR user or secondary user is required for primary user (PU), CR user leaves the present band and switches to another vacant spectrum band in order to provide seamless connectivity.

Spectrum sensing is an important and a sensitive task out of these four functions in Cognitive Radio since interfering with other users is illegal. Therefore, this thesis focuses only on SS among other functions of CR.

2.4 Spectrum Sensing Techniques

In cognitive radio function, it is critical to that spectrum opportunities are timely and accurately detected by the secondary user. If a primary transmission is detected when in fact the primary user is idle, this scenario translates to a missed opportunity by the secondary user to transmit its data (Suhag, 2015). If the secondary user fails to detect a primary user transmission and transmits at the same time, this will result in interference and service degradation. It is thus imperative to understand the role of spectrum sensing in cognitive radio (Develi, 2020). Detecting the presence of signals in the frequency spectrum is called spectrum sensing. By definition, spectrum sensing is the task of collecting spectrum information regarding spectrum resource utilization in a given geographical area and this information is used to accommodate SUs on a non-interfering basis (Suhag, 2015).

Spectrum sensing (SS) allows cognitive radios to monitor, learn and be aware of their operating environment, such as the availability of spectrum and interference status (A & A, 2012). When a given spectrum band is detected as being underutilized by the PU at a certain time in a specific position, the SUs can use the spectrum, indicating that a spectrum opportunity occurs. Therefore, SS can be carried out across the frequency, time and space domains (Arslan, 2009). Multiple users can utilize the same frequency bands (channels) simultaneously in the same geographical area at the same time because of the recent advancements in beamforming technology. As a result, if a PU is not transmitting in all directions, spectrum opportunities might be introduced for SUs in the directions that are not in use and SS must also consider the angle of arrivals (Arslan, 2009). In general, spectrum sensing performs the following tasks (Reed & Ieee, 2009): [1] Detection of spectrum holes, [2] Determination of spectral resolution for each spectrum hole, [3] Estimation of the spatial directions of an incoming interfering signal and [4] Signal classification.

Among the above tasks of SS, spectrum hole detection is the most essential tasks, and it is investigated using a binary hypothesis-testing problem. Therefore, detecting of the spectrum holes on a narrow frequency band is commonly known as spectrum sensing (SS), which identifies the existence or absence of PUs in the underlying band. SS can be divided into two categories: out-of-band sensing and in-band sensing. Out-of-band sensing entails scanning the spectrum band for gaps that can be used by SUs as a transmission opportunity. In-band sensing entails the scanning of spectrum band in which the cognitive radio is currently operating on for the return of primary user.

A number of spectrum sensing methods have been suggested in recent decades, which can be classified into two categories based on the bandwidth of interest for spectrum sensing: Wideband and Narrowband. Narrowband Spectrum Sensing examines a single frequency band at a time, whereas Wideband Spectrum Sensing analyzes multiple frequencies simultaneously. Another way to categorize sensing techniques is by the requirement for prior information about PU signals, which are classified as Coherent and Non-Coherent Detection (Akyildiz et al., 2011). However, spectrum sensing techniques are popularly classified into three different techniques for sensing spectrum holes as shown in the Figure 2.5: Transmitter-based (Non-cooperative), Interference based and Receiver-based (Cooperative) detection. The transmitter based detection methods are used in this thesis.

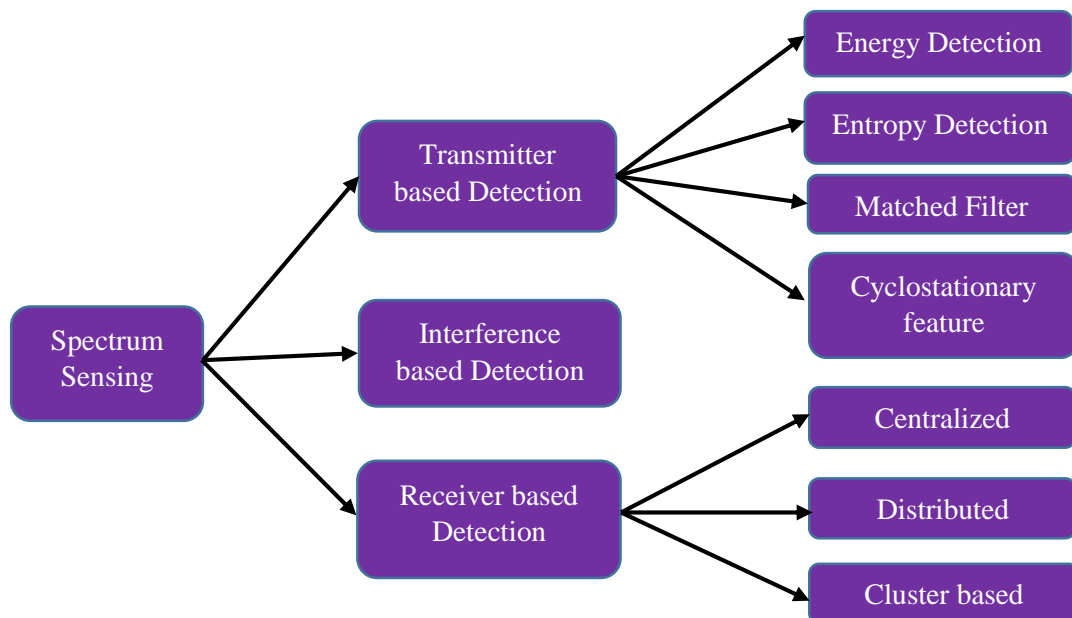


Figure 2.5: Classification of Spectrum sensing technique (Divya Sahithi et al., 2020)

2.4.1 Transmitter based detection technique

Transmitter based detection is one of the major categories of the SS techniques. It is also known as Non-cooperative SS techniques. Non-cooperative detection refers to that the sensing terminal do not cooperate with each other's or the availability of one terminal only for sensing the spectrums. Therefore, it is spectrum sensing decision is made based on the local measurements and observations of secondary users (Lavate, 2017). The detection model is purely based on the analysis of the received signal at the SUs receiver end. Transmitter-based detection methods are commonly based on the assumes that cognitive device is unaware of the primary transmitter's location. As a result, cognitive users have to rely on the detection of weak signals from primary transmitter and use only local observations to carry out SS. A cognitive device is not fully aware of the spectrum occupancy in its vicinity (coverage area). Therefore, totally avoiding harmful interference with PUs is impossible. Furthermore, the transmitter-based detection is ineffective in preventing a hidden terminal problem. Transmitter based detection are further classified as Energy Detection, Matched Filter Detection, Cyclostationary Feature Detection, Entropy Detection etc.

These methods are described in details in the following section except Entropy detection. Entropy detection is discussed in detail on section 3.4.2.

2.4.1.1 Energy Detection

The Energy Detector (ED) is the most well-known SS technique (Digham et al., 2007). It is the most frequently used SS schemes for assessing the existence or absence of a PU signal without needing any knowledge about the nature of the PU signal. When the PU signal is unknown, the ED technique is the best method for detecting any unknown signals with zero-mean constellation and can be used with CRs. Energy detector referred to as a blind detector since it does not take into consideration the characteristics of the received signal.

Energy detection is robust to the variation in the primary signal because it does not need any a prior knowledge of the primary signal. In the energy detection technique, the energy of a received signal is used to detect a primary user signal and the presence of a signal in the channel is detected if the energy present is significantly greater than only noise (Nair et al., 2011). The ED initially filters out the unwanted signal from the undesirable frequency band (Nair et al., 2010). Then the signal energy is computed by squaring and summing the sampled output of the

filter. Finally, the test statistics that is formulated from the output of signal energy is compared with a threshold λ (Clancy, 2015) to identify whether or not a licensed user is present.

The process of ED can be realized or conducted in time domain and sometimes in frequency domain (Xuping & Jianguo, 2007) and also it can be implemented as analog and digital; we focus on the digital time domain implementation approach hereafter. For measuring the signal power in a particular frequency band in time domain, the received signal by secondary user is initially passed through a BPF. After that, the filter's output is squared and integrated over a predetermined time interval. The resultant signal formulates the signal power which is compared against detection threshold as test statistics. The time domain signal should be transformed to frequency domain signal using FFT for the frequency domain detection and the overall signal power across all frequency bins is compared to the decision threshold. Figure 2.6 a, b and c illustrates the process of energy detection for analog time domain, digital time domain and frequency time domain respectively.

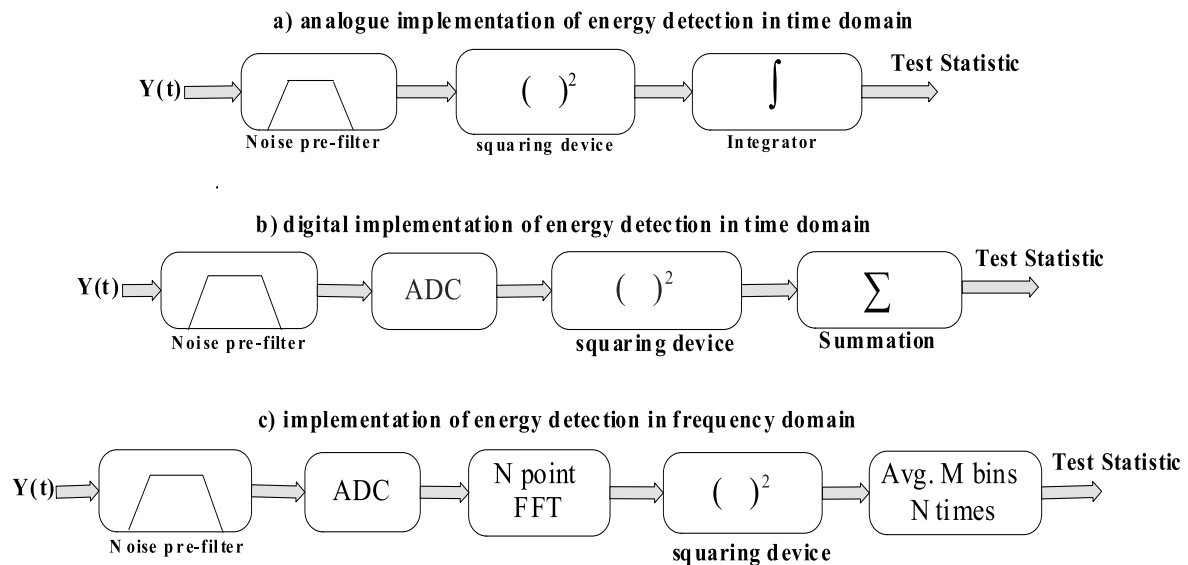


Figure 2.6: Process of energy detection (A & A, 2012), (Xuping & Jianguo, 2007)

Setting the correct threshold is difficult since it must distinguish between the noise and signals. ED is the simplest technique for detecting spectrum holes. However, a prior information of noise level is required, as its uncertainty reduces detector performance (Tandra & Sahai, 2008).

The main parameters considered in the design of energy detector are the threshold value and the number of samples. Although the SNR and noise variance determines the performance of energy detector, practically, designers have no control over these parameters as they depend on the wireless channel environment. The number of samples is also a critical design parameter of the energy detector. Energy detector is the most optimal when the signal is not deterministic and only the average power of the signal is known.

Limitations of Energy Detector

- The time required to achieve the desired detection probability may be longer.
- The detection performance depends on the uncertainty of the noise.
- ED cannot distinguish between the sources of the received energy, it is difficult to distinguish between various PU signals (Akyildiz et al., 2011).
- It can't detect spread or dispersed signals (Akyildiz et al., 2011).
- The computation of the detection threshold value is extremely sensitive to noise levels variations, which leads to a low SNR environment (Akyildiz et al., 2011).

2.4.1.2 Matched Filter Detection

The matched filter (MF) is the optimal detection technique when the SU has prior knowledge of the PUs signal (Lu et al., 2012), (Cabric et al., 2006). It is a coherent detection technique since it requires a prior information of PU signal. The process of coherent detection delivers an excellent performance under ideal conditions. The information that are to be known by SUs in matched filter detection (MFD) are bandwidth, order, modulation type, carrier frequency, packet format and pulse shape (Birajdar2, 2011). The main operation of a MF is to maximize the received or output SNR for a given input signal (Li et al., 2011). The operation of a MF is analogous to that of a correlation scheme; in which the unknown signal is convolved with a filter whose impulse response is a mirror and time shifted version of the reference signal (Verma et al., 2012). In operation, a Matched Filter convolves the received signal $r(t)$ with a time-reversed version of the known signal as (Verma et al., 2012);

$$r(t) \otimes s(T - t + \tau) \tag{2.1}$$

where T refers to a symbol time duration and τ is a shift in the known signal.

MFD is a detection technique that compares the received signal samples with previously collected and saved pilots from the same stream of PU signal. The saved pilots are convoluted with the received signal samples and then averaged across N samples to determine the decision statistics, which are then compared to a predefined threshold to make the sensing decision. If the convolution result exceeds a threshold value, the PU signal is deemed to be present; otherwise, it is considered absent. At low SNR value, the MF technique provides a better detection performance, and it is optimal in the sense that it only requires a few samples to attain maximum probability of detection in short sensing time. However, MF detection needs a prior information of some PUs signal characteristics. This information is frequently unavailable, which makes this detection technique impractical (Giweli et al., 2016).

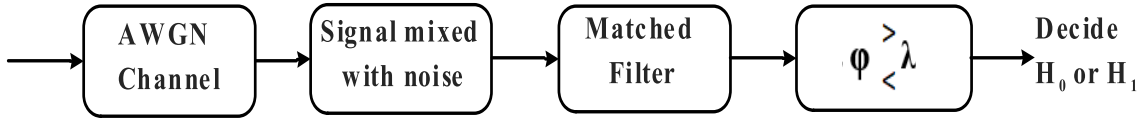


Figure 2.7: Block diagram of Matched filter detection (Divya Sahithi et al., 2020)

The operation of matched filter can be expressed as

$$\phi(y) = \begin{cases} H_0, & \text{if } \sum_{n=1}^N y(n) * x(n) \leq \lambda \\ H_1, & \text{otherwise} \end{cases} \quad (2.2)$$

where $y(n)$ and $x(n)$ represents received signal and correlation coefficient respectively whereas λ represents the threshold.

Probability of detection (P_d) and probability of false alarm (P_f) in accordance to the Neyman-Pearson hypothesis are expressed as (Salem et al., 2014):

$$P_d = Q\left(\frac{\lambda - E}{\sqrt{E\sigma_w^2}}\right) \quad (2.3)$$

$$P_{fa} = Q\left(\frac{\lambda}{\sqrt{E\sigma_w^2}}\right) \quad (2.4)$$

where Q and E respectively represents the Q-function and energy of the received signal. λ is the threshold expressed as (Salem et al., 2014):

$$\lambda = Q^{-1}(P_{fa})\sqrt{E\sigma_w^2} \quad (2.5)$$

The decision is determined by the binary hypothesis and is represented by:

$$\begin{aligned} \phi(y) > \lambda, & \quad H_1 \quad \text{Primary user is present} \\ \phi(y) < \lambda, & \quad H_0 \quad \text{Primary user is absent} \end{aligned} \quad (2.6)$$

The biggest strength of matched filter detection is its ability to detect primary signals in less time. On the other hand, matched filter detection may obtain inaccurate detection results if the correct information about primary user is not adequately incorporated in secondary user design. A dedicated operation to detect each primary user technology is required at the secondary user end, which increases complexity and power consumption (Arslan, 2009).

Limitations of Matched Filter Detection

- In a CRN, the transmitted signal parameters are often unknown. As a result, the MFD performance deteriorates, resulting in signal detection that is undesirable (Akyildiz et al., 2011).
- It requires a specific sensing receiver for different types of the primary user signals.

2.4.1.3 Cyclostationary Feature Detection

In cyclostationary feature detection (CFD), a signal is seen to be cyclostationary if its statistics, i.e. mean or auto-correlation are a periodic function over a certain period. The signal that is transmitted from a licensed user commonly has a periodic pattern. The pattern which is periodic is referred to as cyclostationary and is also used to detect the presence of a licensed user. Feature detection is the process of extracting features from a received signal and performing detection based on those characteristics. CFD can distinguish the primary user signal from noise at extremely low SNR detection by utilizing information present in the primary user signal that is not present in noise. One of the major advantages of cyclostationary feature algorithm is their ability to distinguish PU signals from noise signals (Amor Nafkha, Malek Naoues, Krzysztof Cichon, 2014). This is due to the fact that noise is wide-sense stationary (WSS) and has no correlation with the PU signal (T. Zhang et al., 2009). The cyclostationary feature detection is also called the auto-correlation based sensing technique.

The CFD technique is more effective in noisy environments (i.e. where the levels of noise are uncertain). Because of the stationary condition, the spectral correlation function (SCF) of the AWGN channel is zero, resulting in noise uncertainty. The existence or absence of the primary user signal can be determined by computing the spectral correlation of the primary user signal at the cyclostationary detector. The existence or absence primary users signal is identified by comparing the CFD output with a predetermined threshold value. Figure 2.8 shows a block diagram of the cyclostationary feature detection process.

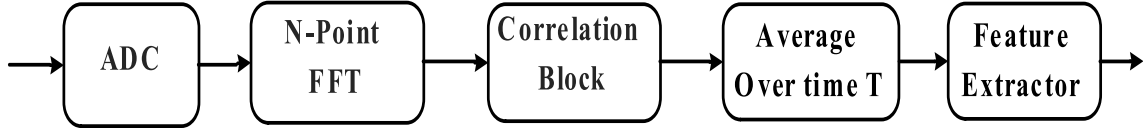


Figure 2.8: Cyclostationary feature detection (Birajdar2, 2011)

A zero mean continuous time signal $x(t)$ is said to be wide sense cyclostationary if it satisfies the following conditions (Mingchuan et al., 2015), (T. Zhang et al., 2009):

$$m_x(t) = E[x(t)] = m_x(t + mT_0) \quad (2.7)$$

$$R_x(t, \tau) = m_x(t + T_0, \tau) \quad (2.8)$$

where T_0 is the period of the signal, τ represents the time offset, $E(\cdot)$ is the signal mean, $R_x(t, \tau)$ is the autocorrelation function of $x(t)$.

cyclostationary feature detection can be performed as follows. First, one calculate the cyclic autocorrelation function (CAF) of the observed signal $x(t)$, $R_x^\alpha(\tau)$, as (Mingchuan et al., 2015), (T. Zhang et al., 2009):

$$R_x^\alpha(\tau) = \lim_{T \rightarrow \infty} \frac{1}{T} \int_{-T/2}^{T/2} x(t + \frac{\tau}{2}) x(t - \frac{\tau}{2}) e^{-j2\pi\alpha t} dt \quad (2.9)$$

where α represents a cyclic frequency. Second, the discrete Fourier transformation of the CAF can be computed to obtain the spectral correlation function (SCF) (Mingchuan et al., 2015), (T. Zhang et al., 2009):

$$S_x^\alpha(f) = \int_{-\infty}^{\infty} R_x^\alpha(\tau) e^{-j2\pi f \tau} d\tau \quad (2.10)$$

Specifically, it is shown that (Mingchuan et al., 2015), (T. Zhang et al., 2009):

$$S_X^\alpha(f) = \lim_{T \rightarrow \infty} \lim_{Z \rightarrow \infty} \frac{1}{TZ} \int_{-\infty}^{\infty} x_T\left(t, f + \frac{\alpha}{2}\tau\right) x_T^*\left(t, f + \frac{\alpha}{2}\tau\right) dt \quad (2.11)$$

where

$$x_T(t, f) = \int_{t-T/2}^{t+T/2} x(u) e^{-j2\pi fu} du \quad (2.12)$$

Spectral correlation function $S_X^\alpha(f)$ is also called cyclic spectrum, which is a two dimensional function in terms of frequency and cyclic frequency. We also note that the power spectrum density is a special case of spectral correlation function for $\alpha=0$.

Compared to matched filter detection, cyclostationary feature detection does not require close synchronization and perfect knowledge of the waveform of the signal of interest, phase or frequency synchronization, making it suitable in cases where this knowledge is unknown. Additionally, this method has strong performance under low SNR as noise signals are random signals with no form of periodicity.

Limitations of the Cyclostationary Feature Detection

the CDF is more robust to uncertainty levels of noise and gives much better performance in low SNR regions (Akyildiz et al., 2011). However, this technique has its own limitations:

- High computational complexity
- Long sensing time
- Large power consumption due to the execution of different receiver algorithms for the detection (Akyildiz et al., 2011).

Table 2. 1: A Summary of transmitter based spectrum sensing technique

Spectrum Sensing Techniques	Advantages	Disadvantages
Energy Detection	<ul style="list-style-type: none"> ✓ Does not need any prior information about PU signal ✓ Ease to implement or easy for deployment ✓ Very less sensing time ✓ Low computational cost 	<ul style="list-style-type: none"> ✓ Poor performance in low SNR environment ✓ Very low sensing accuracy ✓ Difficulty in identifying PU signal from noise
Matched filter Detection	<ul style="list-style-type: none"> ✓ Optimal detection performance ✓ Shorter sensing time 	<ul style="list-style-type: none"> ✓ Requires a prior knowledge on the PU signal ✓ Requires large number of receivers
Cyclostationary feature detection	<ul style="list-style-type: none"> ✓ Robust in low SNR ✓ Robust to interference ✓ It can identify PU signal from noise ✓ High sensing accuracy 	<ul style="list-style-type: none"> ✓ Requires a partial knowledge of primary users ✓ High computational complexity ✓ Large sensing times

2.4.2 Interference based detection

In this technique, CRs focus on calculating the interference at the receiver terminal. The energy that could cause interference to the PU is always present at the receiver at any given time due to ambient transmissions and imminent noise in the radio environment. As a result, the majority of interference occurs at the primary receiver (Akyildiz et al., 2008). Therefore, primary transmissions are designed to operate over a specified noise level at a specific distance from the transmitter. However, due to the unpredictability of noisy in the radio environment, the noise floor may vary, which results in causing further interference to the PU.

In this method, the SU is allowed to transmit at the same time as the PU, but has to measure the interference environment to ensure that the interference does not go above a certain threshold defined by PU tolerance interference. The interference threshold is referred to as the interference temperature limit and is used as a bound for the interference caused to the licensed users in a particular frequency band at a particular location, as shown in Figure 2.9. The SU can utilize the channel if the level of sensed primary signal is less than the interference temperature limit. Moreover, if an SU's transmission power remains below the interference gap, it can use any frequency parameter of it wants. This approach is characterized as a spectrum underlay scheme since it is expected that the secondary users will be permitted to operate concurrently with the primary users under strict interference avoidance requirements. The major problem of this method is that the CR users should know the exact location of the nearby PUs, otherwise it is difficult to measure the interference.

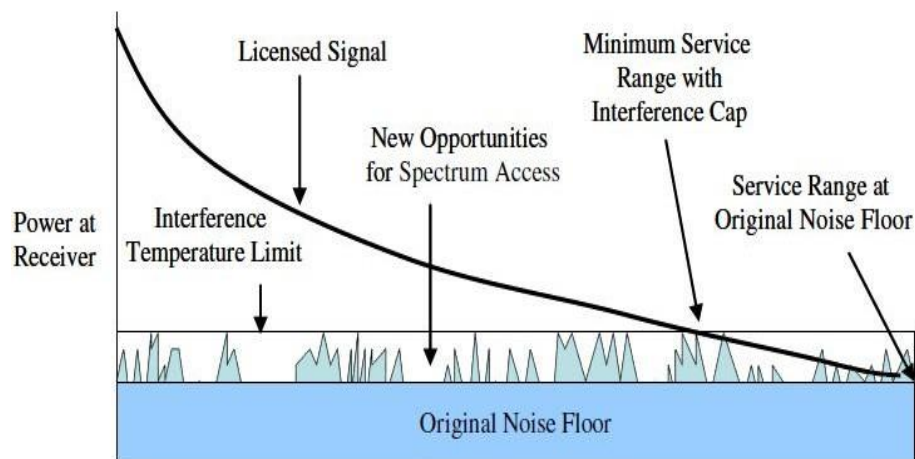


Figure 2.9: interference temperature Management (Birajdar2, 2011), (Akyildiz et al., 2006)

2.4.3 Cooperative Detection

In transmitter-based detection, each CR user behaves individually and assesses the spectrum occupancy depending on its own local observations. Detecting a transmitted signal of licensed users in a CRN environment is difficult due to a number of uncertainties, including channel uncertainty, which refers to dynamic variation in channel fading and shadowing circumstances; aggregated interference uncertainty, which occurs when there are too many unauthorized users in the same CRN that interfere with one another; and lastly, the noise uncertainty which can affect the performance of receiver operating characteristics (ROC) curve and detection

sensibility. In SS, the problem of hidden terminals is also seen a major challenge as shown in Figure 2.10 below.

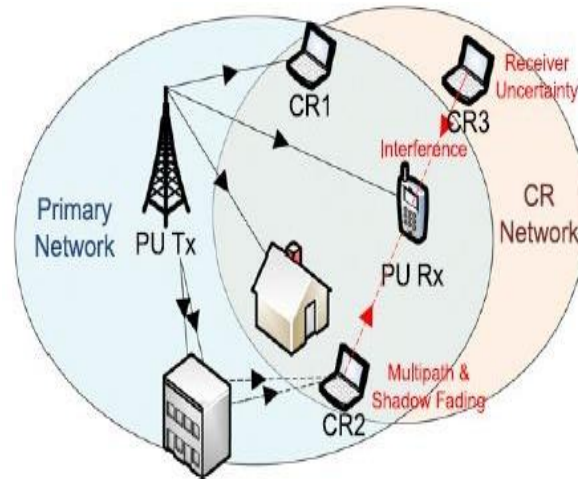


Figure 2.10: Shadowing, Multipath fading and Receiver Uncertainty (A & A, 2012), (Akyildiz et al., 2011)

As illustrated in Figure 2.10 above, CR1 and CR2 exist within the range of PU transmission while CR3 exists out of range of PU transmission. Due to multipath fading and shadowing effect caused by obstruction from houses, the primary transmission is incorrectly detected by CR2. Moreover, CR3 is not aware of the primary user transmission and the existence of a primary receiver within a range. Therefore, the transmission from CR3 may create an interference to PU transmission if it initiates transmission within the same band of frequency and at the same time with primary users; this phenomenon is known as the receiver uncertainty problem.

For cooperative spectrum sensing, secondary users require two channels for local sensing in order to make a decision. Firstly, secondary users establish a connection with the primary transmitter to perform local sensing; this link between the numerous collaborating SUs and primary transmitter is referred to as the sensing channel. A reporting or control channel (the channel between SU and FC) is required to share local sensing data with one another or with the fusion center (FC). Thus far, a medium access protocol has coordinated the switch between these two channels (Umar & Sheikh, 2012). Cooperative spectrum sensing consists of two phases. Those are Detection of PU and Reporting. In Detection of PU phase, SU attempts to detect primary unused channel while in the case of reporting phase, the detected information is reported to the fusion center (FC). Depending upon how collaborated SUs convey sensing data within the network, the CSS is broadly classified as; centralized, distributed (decentralized) and relay-assisted (Akyildiz et al., 2011).

Centralized approach

In this approach, the central processor node or fusion center (FC) collects sensing information from all the SU radios that are within its coverage, as shown in Figure 2.11. Based on the collected information from collaborated users, FC makes a decision on the availability of spectrum opportunities. This opportunity is either broadcasted to all secondary users or the fusion center manages traffic by efficiently managing the sensed spectrum usage opportunities. The fusion center can be BS in a cellular network or access point (AP) in a wireless local area network (WLAN); while in ad hoc networks, any node (once identified) can act as a master to coordinate CSS.

Centralized approach adopts two methods in determining whether primary user is available or not. These are termed soft combining (data fusion) and hard combining (decision fusion) method. In case of data fusion method, the collaborating nodes send locally collected sensing data to the fusion center, letting it to carry out data fusion and make a centralized decision on the availability of spectrum, in a fashion known as soft combining. Soft combining method includes the rule such as Square Law Combining (SLC), Equal Gain Combining (EGC), Maximal ratio combining (MRC) and linear weighted combining. In case of decision fusion, the hard decision regarding the presence or absence of PU signal has taken by the individual nodes and then the binary decision is reported to the FC and FC takes the collaborative decision regarding the PU activity. Mainly there are three types of hard decision rules, namely OR rule, AND rule and Majority rule.

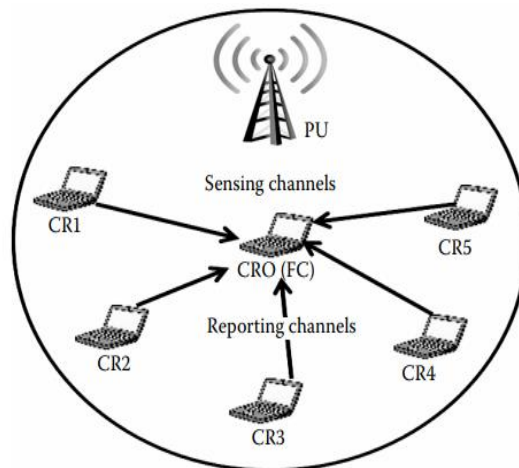


Figure 2.11: Centralized approach of Cooperative SS (Birajdar2, 2011), (A & A, 2012)

Distributed approach

Distributed cooperative spectrum sensing (CSS) is also known as decentralized collaborative spectrum sensing. In this approach, concept of fusion center (FC) or central processing is not adopted. Instead, each cognitive radio can share the sensing information gathered by them with other radios that are within their coverage, as shown in Figure 2.12.

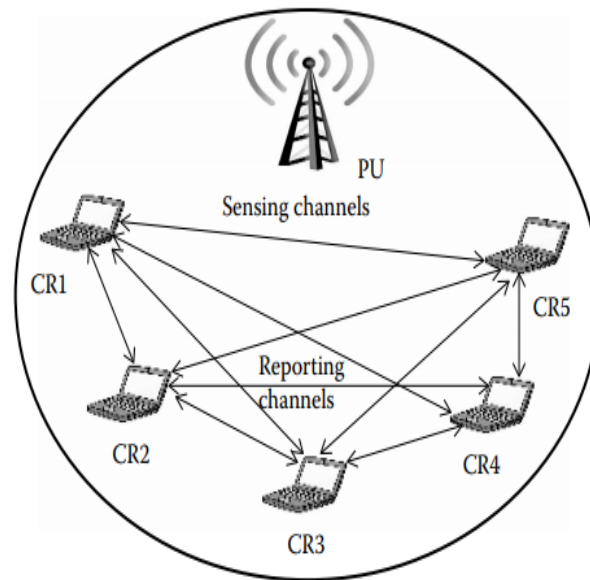


Figure 2.12: Distributed approach of Cooperative SS (Birajdar2, 2011), (A & A, 2012)

Relay-assisted cooperative

In real-time situations, the reporting and sensing channels of the above mentioned system may not work well. For example, a specific secondary users sensing channels may be strong from multipath and shadowing effects while its reporting channel is weak, whereas another SU's sensing channel may be poor while its reporting channel is very strong (Akyildiz et al., 2011), (Umar & Sheikh, 2012). In this approach, relay cognitive radios are used between the SU and fusion center (FC) to mitigate the effect of fading in the wireless medium, as shown in Figure 2.13. This enhance the accuracy of SS. The relay assisted approach is referred to as multi hop cooperative, while the distributed and centralized approach is considered as one-hop cooperation.

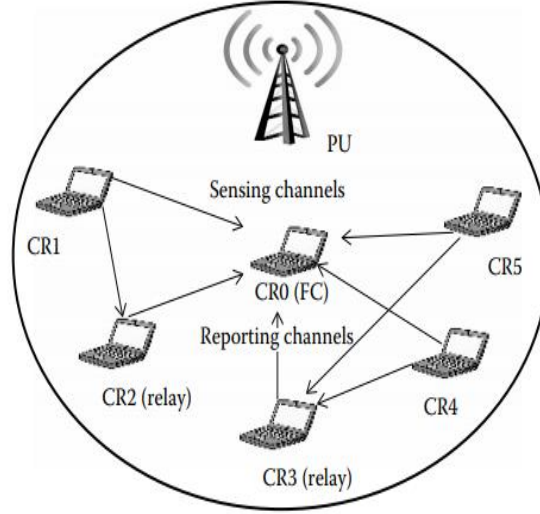


Figure 2. 13: Relay-assisted approach of Cooperative SS (Birajdar2, 2011), (Akyildiz et al., 2011)

2.5 Issues and Challenges in Spectrum Sensing

Various issues such as channel uncertainty, noise uncertainty and sensing interference limit addressed by SS CRNs (Birajdar2, 2011).

- **Channel uncertainty:** in wireless communication networks, uncertainty in received signal strength (RSS) can arise due to channel fading or shadowing. In SS, the deep fade experienced by PU signal may be wrongly interpreted as white spaces by the SU. Then the SU transmission can become interference to the PU. Hence, CRs have to be more sensitive to distinguish a faded or shadowed PU signal from a white space. Cooperative sensing is the mechanism devised to handle this issue, in which a group of CRs share their local measurements and a collective decision can be taken on the occupancy status of the licensed band.
- **Noise Uncertainty:** the detection sensitivity defined as the minimum signal to noise ratio (SNR) at which the PU signal can be accurately detected by the cognitive radio is given by

$$\gamma_{\min} = \frac{P_p L(D+R)}{N} \quad (2.13)$$

where N is the noise power, P_p is the transmitted power of the PU, D is the interference range of the SU, R is the maximum distance between primary transmitter and its corresponding receiver.

Limitation: Determining noise power is difficult in a practical scenario and needs to be estimated which may contain calibration errors due to change in thermal noise. Therefore, to calculate noise uncertainty, it is necessary to have a more sensitive detector.

- **Aggregate interference:** in future the possibility of widespread deployment of SUs operating over the same licensed band increases; this may result in uncertainty known as aggregate interference. Even though the PU may lie outside the interference range of an SU, detection of white space may become faulty due to aggregate interference. In order to enhance the accuracy of detection, usage of more sensitive detectors becomes mandatory.
- **Sensing interference:** the primary goal of spectrum sensing is to detect the spectrum status which may be either idle or occupied, so that access can be made by the unlicensed user. However, the crucial challenge faced in practice is the errors involved in the interference measurements. In order to compute the level of interference caused by the unlicensed users (SUs) to the licensed users (PUs), SU need to be aware of the location of the PUs. However, when the PU device becomes passive, determination of location becomes cumbersome. These factors need to be given more attention while calculating the sensing interference limit.

2.6 Additive White Gaussian Noise (AWGN) Channel

An AWGN channel adds white Gaussian noise to the signal that passes through it. It is a basic noise model used in information theory to mimic the effect of many random processes that occur in nature. AWGN is often used as a channel model in which the only impairment to communication is linear addition of wideband or white noise with a constant spectral density and a Gaussian distribution of amplitude. This model does not account for fading, frequency selectivity, interference, non-linearity or dispersion. The AWGN channel is a good model for many satellite and deep space communication links. It is not a good model for most terrestrial links because of multipath, terrain blocking, interference etc.

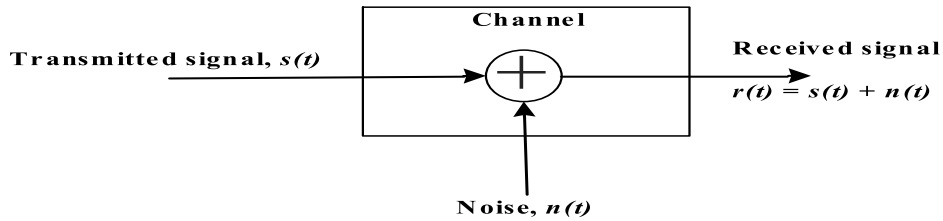


Figure 2. 14: Model for received signal passed through an AWGN channel

AWGN is a simple and widely accepted noise model that mimics numerous random processes seen in nature. For better understanding, let's break down each of those words:

Additive: the term additive refers to the addition of noise to a signal. In other words, the received signal is the same as the noise signal plus the transmitted signal. Furthermore, the noise is generated at random and has a separate probability from the signal, implying that the occurrence of one does not alter the probability of occurrence of the other.

White: the term white refers to the idea that noise has the same distribution of power at all frequencies. As a result, white noise has the same PSD (the measure of a signal's power in relation to frequency) at all frequencies. The PSD denotes power spectral density. The concept of white noise is analogous to the white color, which is made up of all frequencies in the visible spectrum.

Gaussian: the noise samples have a Gaussian distribution.

2.7 Central Limit Theorem

The central limit theorem (CLT) is one of the most fundamental results in the probability theory. It states that, under certain conditions, the sum of a large number of random variables (RV) is approximately normal (Gaussian distribution). We present a version of the central limit theorem that is applicable to RVs that are independently and identically distributed (i.i.d).

2.8 Related Works

2.8.1 Previous work on Energy Detection

In (Divya Sahithi et al., 2020), analysis of the energy detection SS technique in CR is presented. The theoretical concept of different types of spectrum sensing techniques is discussed clearly with their mathematical formulas. In this paper, the ED method is one of the SS techniques that is analyzed in detail. An energy detection method is used to detect the unused portions of the

spectrum and make them available for reuse. By using the energy detection method, we can identify and allocate gaps in the spectrum to secondary users. Also, the effects of fading, shadowing and hidden terminal problems on detection performance are discussed. This paper analyzes energy detection techniques well, but it fails to detect PU signals at low SNR levels.

In (Mahendru et al., 2020), a new mathematical models are proposed for determining the optimal number of samples for energy detection method in the presence of noise uncertainty. The main goal of this study is to find the best number of samples while keeping the metrics of sensing performance within pre-defined limits in the existence of noise uncertainty. The noise uncertainty factor, which degrades sensing performance, is also discussed, along with its effects on the SNR and sample number for different values of P_D , P_{FA} , and ρ . Also, a novel method correlates the sensing duration or sample numbers with SNR to achieve the desired performance in terms of P_D and P_{FA} .

In (Patil et al., 2020), energy detection based spectrum sensing in Rayleigh fading environments is discussed. The closed form mathematical equations for AWGN and Rayleigh channels, including detection probability and probability of false-alarm in respect to the SNR, are derived. The results of simulations and theoretic calculation are compared. According to the comparison, this study confirmed that the probability of detecting a primary signal is lower in Rayleigh channels compared to AWGN channels. The results of this paper show that as the SNR value increases, so does the detection probability. Furthermore, it is evident that an increase in false-alarm probability increases the detection performance.

In (Luo et al., 2022), a novel SS technique based on ED is proposed for cognitive radios. In this paper, a novel method for constructing decision thresholds that are free from the variance of noise is introduced. Thus, the proposed method significantly decreases the impact or effects of uncertainty in noise variance. To decrease the effect of noise variance uncertainty, an ED-based sensing technique is suggested in this study. This technique combines samples of the signal that are sampled by multiple antennas to get the decision statistic as ED does. According to simulation results, the proposed method outperforms the ED technique in both Rayleigh and AWGN channels without noise variance estimation when the antenna number is greater than two.

2.8.2 Previous work on Entropy Detection

In (Muñoz et al., 2020), Rényi Entropy-Based Spectrum Sensing in Mobile Cognitive Radio Networks Using Software Defined Radio are proposed. This paper is proposed to measure the power signals of a PU over time. This paper uses Software Defined Radio (SDR) system to implement a MCRN in order to measure the behavior of primary and secondary in both time and frequency domain using GNU radio and Open BTS as software tools to allow a phone call service between Secondary User(SU).

In (Prieto et al., 2019), Numerical Analysis of Histogram-Based Estimation Techniques for Entropy-Based Spectrum Sensing are proposed. In this paper, Spectrum Detection based on Entropy had been proposed to sense primary transmission in Cognitive radio Network (CRN). To estimate Entropy the histogram method was used. The performance of the Entropy based detection with respect to several rules for calculating the number of bins in the histogram is evaluated. And, its demonstrated that performance of detection is different for each of the aforesaid rules due to the probability distribution of the PU signal. The main focus of this paper are only focuses on the optimal determination of number of bins. However, the current hot research topics on the area of CRs are improving the performance of spectrum sensing.

In (Prieto et al., 2018), spectrum sensing evaluation based on Entropy strategy applied to Cognitive Radio Network is presented. Bartlett Periodogram is used to perform Entropy Estimation. A tradeoff between variance and the spectral resolution for Bartlett Periodogram is presented. This paper tries to do spectrum sensing only by Entropy Detection using Bartlett Periodogram. However, Entropy Detection using Bartlett Periodogram have more computational complexity than two-stage SS using ED and Entropy detection.

2.8.3 Previous work on Two-stage Spectrum sensing

In (Rabie Mohamed et al., 2021), a hybrid sensing model for spectrum detection in CR is proposed to enhance sensing efficiency of traditional techniques of spectrum sensing, which consists of two parallel paths of hybrid detectors . The first path is formed from two sequential detectors whereas the second path is formed two parallel detectors. The individual methods that are used in this papers are Energy and Maximum-Minimum eigenvalue (MME) detector. In the sequential phase, energy detector is used to recognize the PU signal existence where the signal has not been identified. MME used as a second stage to detect the PU existences. In the parallel

phase, ED and MME are separately used to detect the presence of PU. However, the Computational complexity of this paper become high since it uses an eigenvalue detector.

In (Mashta et al., 2021), a new parallel fully blind multistage detectors are proposed. Appropriate stages are assumed based on estimated SNR value that are achieved from the SNR estimator. Energy Detection is used in the first stage for its simplicity and sensing accuracy at high SNR. For low SNR, a maximum eigenvalue detector techniques with different smoothing factors are adopted for higher stages. The sensing accuracy for maximum eigenvalue detector increases with an increase of smoothing factor. And also, they analyzed the performance of two cases of the proposed detector: two-stage and three-stage schemes. However, the computational complexity at the higher stages become increase due to the use of eigenvalue detector and an increase of smoothing factor.

In (Mashta et al., 2020), a novel fully blind sequential multistage spectrum sensing detector had been proposed to overcome the limitation of single stage detector and make use of the advantages of each detector in each stage. This paper proposes a three stage spectrum sensing using energy detection and maximum eigenvalue detector. In the first stage, Energy detection is used because of its simplicity. In second and third stage, the maximum eigenvalues detector is adopted with different smoothing factor in each stage. However, since the maximum eigenvalue detector is used inside a proposed three stage techniques, the overall computational complexity of the proposed systems become high.

In (Fawzi et al., 2020), an adaptive two-stage SS model for cognitive radio system are presented by combining two well-known techniques: ED and wavelet denoising. In this paper, ED technque is employed to identify the existence of primary user signal in the case of high SNR value by comparing the energy of the received signal with a threshold values. However, in the case of low SNR value, the stage of wavelet denoising is exploited prior to the ED are used for reducing the noise effect and detecting the PU signal in the presence of noise.

Table 2. 2: A Summary of some related work

Authors	Year	Title	Techniques and Concept Covered	Gaps or Concept not Covered
G. Prieto et al.	2019	Numerical Analysis of Histogram-Based Estimation Techniques for Entropy-Based Spectrum Sensing.	Entropy based detection are proposed for spectrum sensing. Several rules for determining the number of bins in histogram is evaluated. Those rules are: square root rule, scott rule and Sturges rule.	This paper focuses only on Shannon entropy. It doesn't include other types of entropy like Renyi, Kapurs and Tsallis entropy.
A. Fawzi et al.	2020	Adaptive two-stage spectrum sensing model using energy detection and wavelet denoising for CR systems.	Two-stage spectrum sensing techniques are proposed by combining two well methods: ED and WD.	Even though it improves the performance of SS, the proposed technique is not robust to noise uncertainty at low SNR. Moreover, since WD is integrated with ED at low SNR, sensing time and computational complexity are very high.
A. D. Sahithi et al	2020	Analysis of energy detection spectrum sensing technique in cognitive radio.	Cooperative spectrum sensing using ED are used to overcome the problem of uncertainty occurred due to fading and hidden primary terminal.	This paper does not focus on overcoming the problem of noise uncertainty.
F. Mashta et al.	2021	An integrated parallel Multistage Spectrum Sensing for Cognitive radio.	Two-stage and Three-stage detector for SS are discussed in detail. ED and Maximum eigenvalue detector with different smoothing factor are used.	Even though three-stage and two-stage spectrum sensing are performed, the overall performance of SS is not good at low SNR due to its sensitivity to noise uncertainty. Moreover, since the eigenvalue based detector is used, the complexity of overall system increases.

CHAPTER THREE

3. METHODOLOGY AND SYSTEM MODEL

3.1 Overview

In this thesis, different related papers and articles are reviewed from various journals such as IEEE, Springer and Elsevier and also the books that are related to cognitive radio networks are highlighted. Depending on the reviewed papers and having the statement of the problem in mind the methodology that are listed under section 3.3 are followed to design and simulate the proposed methods/techniques.

3.2 Materials

In this thesis, MATLAB/R2020a software tools are used for all simulations. The name MATLAB stands for MATrix LABoratory. MATLAB is a high performance language for technical computing. Also it is a computing software that consists of technical boxes and Simulink. Using MATLAB we can develop algorithms, analyze data, and create models and applications.

3.3 Methodology

In order to meet the above mentioned objectives of the thesis the following formal methodologies are followed.

Literature Review: This thesis work is inextricably linked to previous research on the subject by experts or scholars. As a result, studying the works of these scholars and getting relevant and important knowledge on the subject is essential. It is reviewed from a variety of sources, including papers, books, journals, the internet, etc. Hence, the literature review consists of reading articles, conferences, papers, books, journals, and searching from various sources on the internet for relevant topics (i.e., Cognitive radio network, Energy detection and Entropy detection spectrum sensing technique).

Problem Identification: based on the paper reviewed from different journals, articles and conferences the problem (research gaps) are identified for research study.

System Designing: after the identification of research gap the systems are designed for proposed work.

Simulation of designed System using MATLAB: after modeling of the proposed system the simulation are done using MATLAB tools.

Result and Discussion: depending up on the results from simulation, discussions are performed on the results and performance evaluation are also done on proposed techniques.

Documentation: After analyzing the results of the designed system, the whole work of the research study is concluded by suggesting an implied recommendation and further work to be done on the areas.

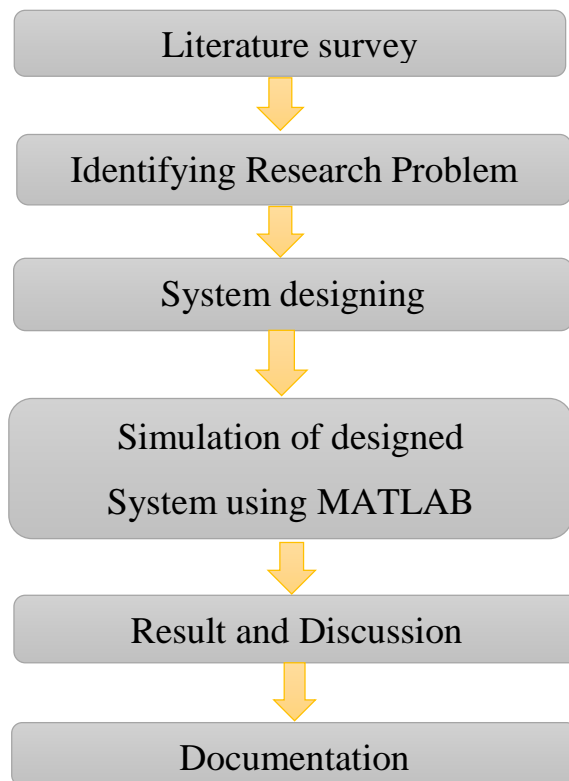


Figure 3. 1: Methodology

3.4 System Model for Spectrum Sensing

The main task of SS in CRNs is to determine whether an authorized PU (primary user) is present or not on a given channel, so that secondary users can efficiently access and exploit the unoccupied or unused spectrum. SS depends on a well-known method known as signal detection. In a noisy environment, Signal detection methods are used to detect the availability of signal. Signal detection could be simplified to a basic identification problem that can be formulated as hypothesis test analytically (Abdo-tuko, 2015). Generally, spectrum sensing can

be modelled as a binary hypothesis problem in the detection theory and can be given as (Bagwari & Tomar, 2013):

$$y(n) = \begin{cases} w(n) & : H_0 \text{ Absence of PU} \\ h * s(n) + w(n) & : H_1 \text{ Presence of PU} \end{cases} \quad (3.1)$$

where $n=1, 2, 3 \dots N$ is the sample number in the sampled signal that has been received, $y(n)$ is the sampled signal that has been received by secondary users, $w(n)$ is zero mean AWGN (additive white Gaussian noise) with variance σ_w^2 , $s(n)$ is the signal from PU with variance σ_s^2 and zero mean, h is the channel amplitude gain between PU transmitter and secondary user (SU) receiver since we use AWGN channel $h=1$. H_0 and H_1 represents absence (null hypothesis) and presence (alternative hypothesis) of the PU respectively.

In spectrum sensing, the received signal by a SU, $y(n)$ is calculated as the sum of PU signal $s(n)$, multiplied by PUs transmitter to SUs receiver channel gain h and the noise of additive white Gaussian noise $w(n)$ as shown in the Figure 3.2 below.

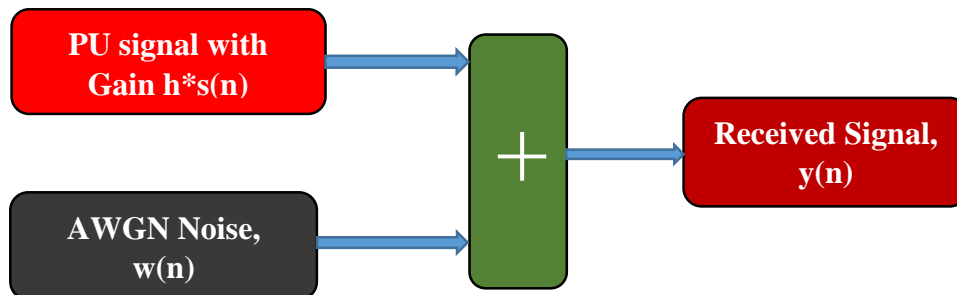


Figure 3. 2: Modeling of the received signal (Manesh et al., 2016)

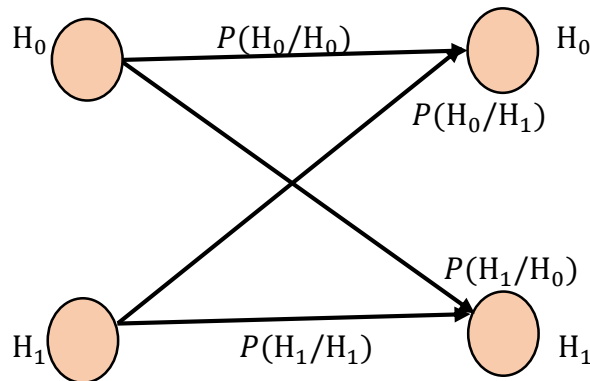


Figure 3. 3: Hypothesis testing and probable outcomes, along with their probability (Abduttuko, 2015)

Figure 3.3 shows four alternative scenarios or cases for the detected signal (Abdo-tuko, 2015):

- Case 1: deciding H_0 when H_0 is active (H_0/H_0);
- Case 2: deciding H_1 when H_1 is active (H_1/H_1);
- Case 3: deciding H_0 when H_1 is active (H_0/H_1);
- Case 4: deciding H_1 when H_0 is active (H_1/H_0);

The probability of detection (P_d), missed-detection probability (P_m) and probability of false-alarm (P_f) are generally defined as (Abdo-tuko, 2015):

$$P_d = P(H_1 / H_1) \quad (3.2)$$

$$P_m = 1 - P_d = P(H_0 / H_1) \quad (3.3)$$

$$P_f = P(H_1 / H_0) \quad (3.4)$$

Thus, the probability of detection is the probability to decide H_1 when H_1 is true and the probability of missed detection is the probability to decide H_0 when H_1 is true. The probability of false alarm is the probability to decide H_1 when H_0 is true. Probability of false alarm indicates the level of SU missed opportunity of accessing the spectrum while missed detection probability refers to interference level caused by SU to PU. Typically, the missed detection probability is kept below an acceptable level in order to protect the PU. The goal of a signal detector is obviously to achieve perfect detection every time, but this will never be possible practically due to statistical nature of the problem. As a result, signal detectors are built or designed to operate within certain error levels.

A summary diagram of the signal detector for spectrum sensing technique is shown in the Figure 3.4 below.

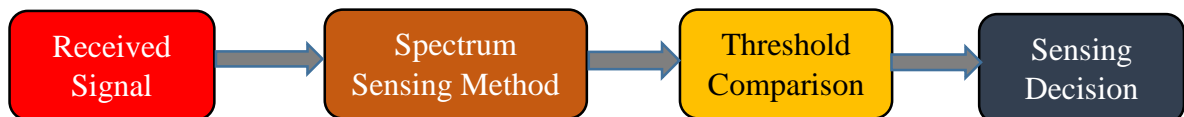


Figure 3. 4: General Model of Spectrum Sensing (Manesh et al., 2016)

3.4.1 System Model of Energy Detection Technique

Energy detection is the most widely used method because of it has low computational complexity and it doesn't require any prior knowledge of the PU signal. The block diagram of energy detection that is used to identify the presence or absence of PU is shown in the Figure 3.5 below. In an energy detector, the received signal is first pre-filtered by an ideal band pass filter which has bandwidth of interest. The filtered signal is then passed through ADC converter. The output signal of ADC is then squared and integrated over a predefined time interval. The resultant signal is used to formulate a test statistics (Develi, 2020). Finally, formulated test statistics is compared with a threshold ' λ_{ED} ', to decide whether the licensed user is present or not. Test statistics of energy detection is given as (Abdo-tuko, 2015), (Manesh et al., 2016):

$$T(y) = \frac{1}{N} \sum_{n=1}^N |y(n)|^2 \quad (3.5)$$

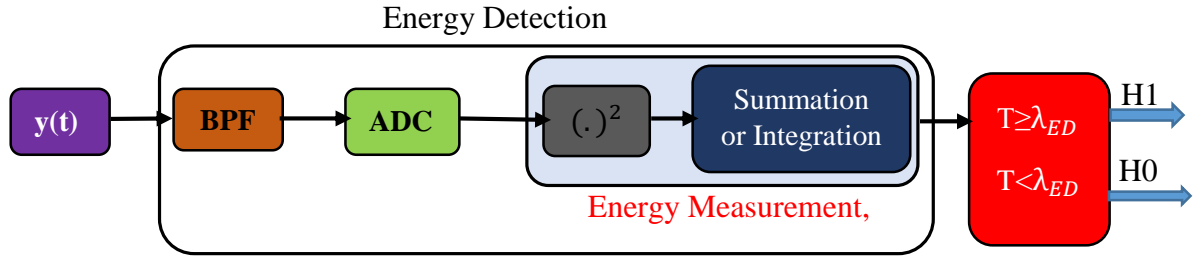


Figure 3. 5: Block Diagram of Energy Detection

Under noise only condition (H_0) of zero mean Gaussian distribution, the test statistics decision of energy detection follows central chi-square distribution with $2TW$ degrees of freedom. Note that TW represents the product of time-bandwidth. On the contrary, under H_1 conditions, the test statistics decision follows a non-central chi-square distribution with non-centrality parameters 2γ and degrees of freedom $2TW$. Here γ represents linear scale of mean SNR. As a result, the decision test statistics for energy detection under H_0 and H_1 hypothesis are given as follows (Abdo-tuko, 2015):

$$Y = \begin{cases} \chi_{2TW}^2 & H_0 \\ \chi_{2TW}^2(2\gamma) & H_1 \end{cases} \quad (3.6)$$

Then probability density function (PDF) of test statistics Y can be expressed as (Abdo-tuko, 2015):

$$f_Y(y) = \left\{ \begin{array}{ll} \frac{1}{2^{TW} \Gamma(TW)} y^{TW-1} e^{-\frac{y}{2}}, & H_0 \\ \frac{1}{2} \left(\frac{y}{2\gamma} \right)^{\frac{TW-1}{2}} e^{-\frac{(2\gamma+y)}{2}} I_{TW-1}(\sqrt{2\gamma y}), & H_1 \end{array} \right\} \quad (3.7)$$

where $\Gamma(\cdot)$ is complete gamma function and $I_x(\cdot)$ is the x^{th} -order modified Bessel function of the first kind. The probability of false alarm and probability of detection are respectively given as (Abdo-tuko, 2015):

$$P_f = P_r(Y > \lambda / H_0) = \frac{\Gamma(TW, \frac{\lambda}{2})}{\Gamma(TW)} \quad (3.8)$$

$$P_d = P_r(Y > \lambda / H_1) = Q_{(N=TW)}(\sqrt{2\gamma}, \sqrt{\lambda}) \quad (3.9)$$

where $Q_{(N=TW)}(\cdot, \cdot)$ is the generalized Marcum Q-function.

Without coherent detection, the samples of primary signal $S[n]$ can be described as a Gaussian process with variance σ_s^2 . As a result, $y[n]$ is a Gaussian process. The number of needed samples N in the low SNR region is high, as can be seen. Whenever the sample number becomes high ($N > 250$), the test statistics can be estimated as a Gaussian distribution using the central limit theorem (Digham et al., 2007). The test statistics is given by equation (3.10) (Abdo-tuko, 2015), (Manesh et al., 2016):

$$Y = \left\{ \begin{array}{ll} N(\mu_0, \sigma_0^2): & H_0 \\ N(\mu_1, \sigma_1^2): & H_1 \end{array} \right\} \quad (3.10)$$

where $N(\mu, \sigma^2)$ is the Gaussian distribution with mean μ and variance σ^2 . The mean and variance for both hypothesis H_0 and H_1 are given respectively as (Abdo-tuko, 2015):

$$\begin{aligned} & \left(\mu_0 = N\sigma_w^2 ; \sigma_0^2 = 2N\sigma_w^4 \right) \text{ and} \\ & \left(\mu_1 = N(\sigma_s^2 + \sigma_w^2) ; \sigma_1^2 = 2N(\sigma_s^2 + \sigma_w^2)^2 \right) \end{aligned} \quad (3.11)$$

The performance of detection is measured by two parameters probability of detection (P_d) and probability of false alarm (P_f). Each pair is associated with a particular threshold λ_{ED} that test the decision statistics (Abdo-tuko, 2015). For the large values of N , P_d and P_f with the substitution of equation (3.11) can be expressed as (Abdo-tuko, 2015), (Manesh et al., 2016):

$$P_d = P(T \geq \lambda_{ED} / H_1) = Q\left(\frac{\lambda_{ED} - N(\sigma_w^2 + \sigma_s^2)}{\sqrt{2N(\sigma_w^2 + \sigma_s^2)^2}}\right), \quad (3.12)$$

$$P_f = P(T < \lambda_{ED} / H_0) = Q\left(\frac{\lambda_{ED} - N\sigma_w^2}{\sqrt{2N\sigma_w^4}}\right), \quad (3.13)$$

where

$$Q(x) = \frac{1}{\sqrt{2\pi}} \int_x^\infty \exp\left(-\frac{y^2}{2}\right) dy, \quad (3.14)$$

where $Q(x)$ is Q-function.

The detection threshold can be given as equation (3.15) (Abdo-tuko, 2015), (Manesh et al., 2016):

$$\lambda_{ED} = \sigma_w^2 [\sqrt{2N}Q^{-1}(P_f) + N]. \quad (3.15)$$

The minimum number of samples needed is dependent on the SNR and can be computed as (Xuping & Jianguo, 2007), (Manesh et al., 2016):

$$N = 2 \left[\left(Q^{-1}(P_f) - Q^{-1}(P_d) \right) SNR^{-1} - Q^{-1}(P_d) \right]^2. \quad (3.16)$$

3.4.2 System Model of Entropy Detection Technique

The performance of conventional detectors' such as Energy detection (ED), Matched filter detection (MFD) and Cyclostationary feature detection (CFD) are degrades rapidly at low SNR due its sensitivity to noise uncertainty (Y. L. Zhang et al., 2010). In order to mitigate this

problem Entropy based detection techniques are proposed in many papers. And also its proved that the entropy detection are robust to noise uncertainty at low SNR region.

Average information, also known as Entropy, is the measure of an event's information or randomness. It is a measure of an event's predictability or the randomness, according to information theory. Entropy increases as the occurrences of event become less predictable. For instance, rain that may or may not fall has a higher entropy than rain that is certain to fall today (Priya et al., 2019). As a result, the entropy of a random variable depends on its distribution. The highest possible entropy for any random variable occurs when it has a uniform distribution (i.e. all its values have equal probability). The detection of the existence or absence of users depends on measure of information. In the time domain, the entropy of a received signal is proportional to its signal power and is sensitive to noise uncertainty (Srinu et al., 2012). As a result, we look at frequency domain based entropy based detection.

The Figure 3.6 below shows the basic block diagram of Entropy based detector. After applying DFT to a binary hypothesis given in equation (3.1), we get (Prieto et al., 2019), (Prieto et al., 2018)

$$\begin{aligned}\bar{y}(k) &= \bar{w}(k) \\ \bar{y}(k) &= \bar{s}(k) + \bar{w}(k)\end{aligned}\tag{3.17}$$

where $\bar{s}(k)$, $\bar{y}(k)$, and $\bar{w}(k)$ are frequency spectrum representation of the primary user (PU) signal, received signal, and noise signal respectively.

Numerous methods for predicting the entropy (randomness) of random variable depending on a limited set of observations have been suggested. Entropy estimation based on histogram is evaluated in this paper due to its lower complexity (Prieto et al., 2018).

By splitting the ranges of $(y_{\max} - y_{\min})$ of values in y into L bins of constant width A , the data set for histogram which is $y = \{y_0, y_1, y_2, \dots, y_{N-1}\}$ is obtained. let n_k denote the number of items in y that fall within the k -th bins such that $\sum_{k=1}^L n_k = N$ (Prieto et al., 2018), (Prieto et al., 2019), (Vaidehi et al., 2015). After constructing the histogram, the entropy which is denoted by H , is calculated as follows:

The Shannon Entropy formula is given by equation (3.18) (Prieto et al., 2019),(Vaidehi et al., 2015)

$$H_S = - \sum_{k=1}^L p_k \log_2(p_k) \quad (3.18)$$

The Renyi Entropy formula is given by equation (3.19) (Vaidehi et al., 2015)

$$H_R = \frac{1}{1-\alpha} \log\left(\sum_{k=1}^L P_k^\alpha\right) \quad (3.19)$$

The Tsallis Entropy formula is given by equation (3.20) (Vaidehi et al., 2015),(Kumar & Goyal, 2013)

$$H_T = \frac{1}{\alpha-1} \left(1 - \sum_{k=1}^L P_k^\alpha\right) \quad (3.20)$$

The Kapur's Entropy formula is given by equation (3.21) (Kumar & Goyal, 2013)

$$H_K = \frac{1 - \left(\sum_{k=1}^n P_k^\alpha\right)^\alpha}{1-\alpha} \quad (3.21)$$

where α is the order of entropy and p_k is the frequency of occurrences in k-th bins and is given as (Prieto et al., 2019),(Vaidehi et al., 2015)

$$p_k = \frac{n_k}{N} \quad (3.22)$$

By substituting this in equation (3.18), (3.19), (3.20) and (3.21), we got the test statistics (Prieto et al., 2019),(Vaidehi et al., 2015)

$$T(y) = H \quad (3.23)$$

The detection threshold is determined as (Prieto et al., 2019),(Vaidehi et al., 2015)

$$\lambda = H_L + Q^{-1}(1 - P_f)\sigma_n \quad (3.24)$$

where

$$H_L = \ln\left(\frac{L}{\sqrt{2}}\right) + \frac{\gamma}{2} + 1 \quad (3.25)$$

Is a Gaussian noise entropy, number of bins denoted by L, γ represents euler mascheroni constants, P_f is false-alarm probability and σ_n is the standard deviation of H under H_0 .

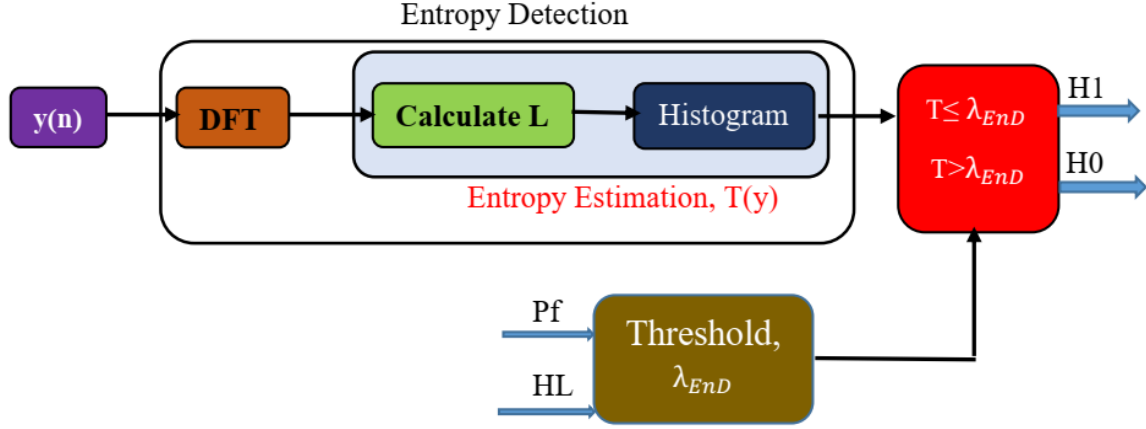


Figure 3. 6: Block Diagram of Entropy Based Detector

3.4.3 System Model of Proposed Two-Stage Spectrum Sensing

Generally, there are three classes of multistage spectrum sensing algorithm. The first one is the sequential Multistage sensing, in which the multiple detection stages are serially linked and each stage is either executed or skipped based on the sensing results of the stages before it. The second is the parallel multistage detection, in which detection is done using many detectors at the same time and the final decision is made by combining the result of these simultaneous decisions. Lastly, the third classes is sequential or parallel detection with an SNR estimation process to decide which stage to use (Mashta et al., 2021). The overall probability of detection for sequential Multistage spectrum sensing that have M stages are given by equation (3.26) (Mashta et al., 2021):

$$P_d = P_d^1 + \sum_{i=2}^M (P_d^i \prod_{j=1}^{i-1} (1 - P_d^j)) \quad (3.26)$$

In this thesis, two-stage SS techniques are developed to enhance the performance of detection as shown in the Figure 3.7 below. In the first stage (coarse stage) ED is used because it has faster sensing time than other methods, and then the average energy of the received signal is compared to a threshold λ_{ED} , if it exceeds λ_{ED} , then the channel is declared to be occupied by PU, else, we proceed to the second stage. In the second stage (fine stage), one of the entropy-based detection methods that outperforms other methods of entropy is used, and then statistical test are constructed using entropy formulas and compare it with a threshold λ_{EnD} to decide if channel is idle or occupied.

The general mathematical equations for false-alarm probability and detection probability in two-stage SS are given as follows, respectively, in equation (3.27) and (3.28) (Mashta et al., 2021):

$$P_f = P_f^{(coarse)} + P_f^{(fine)} * (1 - P_f^{(coarse)}) \quad (3.27)$$

$$P_d = P_d^{(coarse)} + P_d^{(fine)} * (1 - P_d^{(coarse)}) \quad (3.28)$$

where P_{fa} is false-alarm probability of overall system, P_d is detection probability of overall system, $P_f^{(coarse)}$ is false-alarm probability of coarse stage, $P_f^{(fine)}$ is false-alarm probability of fine stage, $P_d^{(coarse)}$ is detection probability of coarse stage, and $P_d^{(fine)}$ is detection probability of fine stage.

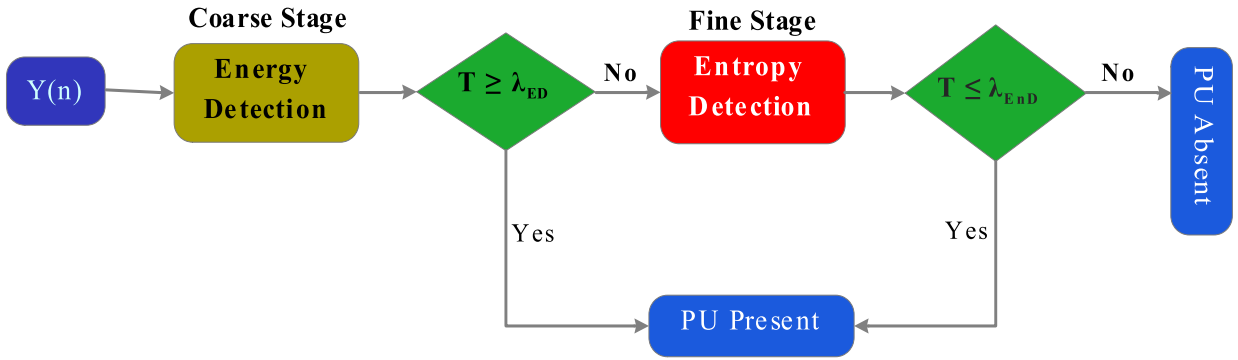


Figure 3. 7: System model for Proposed Two-stage Spectrum Sensing

3.5 Cooperative Spectrum Sensing

As highlighted in previous chapter, cooperative spectrum sensing (CSS) provides a solution to the problem that arise in spectrum sensing due to noise uncertainty, receiver uncertainty, fading and shadowing. Particularly CSS are used to overcome the hidden terminal problems occurred for single node detections. As discussed earlier there are three approaches of CSS; centralized, distributed (decentralized) and relay-assisted approach. Under centralized CSS approach, each secondary users employs the single node detection techniques to perform the local spectrum sensing and then sends the decision result to the fusion center (FC). lastly, the FC analyzes the aggregated information and makes a decision based on certain judgment criteria to complete spectrum process. SU sends their results to FC either by using Hard decision combining (OR Rule, AND Rule, Majority rule) or Soft decision combining (EGC, MRC, SLC) (Padmavathi &

Shanmugavel, 2015). In this thesis, we consider only hard decision combining particularly OR rule and AND rule.

Unlike the decentralized cooperative approach, which needs users to communicate with one another, the centralized cooperative approach relies heavily on the FC to make decisions and each secondary user to the system requires only one communication link between the user and the FC, which is more flexible and simple. As a result, the centralized cooperative approach is the most suitable for CSS. For this reason, we consider a centralized approach for this thesis among other CSS schemes.

3.5.1 OR Rule

In this rule, the FC performs an “OR” operation on all the received decision from SUs. As long as the cognitive result of SU is 1, the channel is determined to be occupied. Only when all sensing results are 0, the FC determines the channel is idle and available. The FC declares the presence of PU if any of the SU decision is 1. Here “1” represents the presence of PU in the channel while “0” represents the absence of PU. The overall probability of detection and the probability of false alarm for the decision taken at FC using OR rule are given as (Padmavathi & Shanmugavel, 2015):

$$Q_d = 1 - \prod_{i=1}^N (1 - P_{d,i}) \quad (3.29)$$

$$Q_f = 1 - \prod_{i=1}^N (1 - P_{f,i}) \quad (3.30)$$

where $P_{d,i}$ and $P_{f,i}$ are the probability of detection and false alarm respectively for i^{th} cognitive users. And also Q_d and Q_f are respectively represents the overall probability of detection and false alarm.

3.5.2 AND Rule

In this rule, the FC performs an “AND” operation on all the received decision from SUs. The FC declares the presence of PU if and only if all SU decision is 1. The overall probability of detection and the probability of false alarm for the decision taken at FC using AND rule are given as (Padmavathi & Shanmugavel, 2015):

$$Q_d = \prod_{i=1}^N P_{d,i} \quad (3.31)$$

$$Q_f = \prod_{i=1}^N P_{f,i} \quad (3.32)$$

where $P_{d,i}$ and $P_{f,i}$ are the probability of detection and false alarm respectively for i^{th} cognitive users. And also Q_d and Q_f are respectively represents the overall probability of detection and false alarm.

3.6 Performance Metrics of Spectrum Sensing

The performance of SS method is analyzed using the value of performance metrics. The values from performance metrics are used to determine whether the primary user is correctly present or not in a given channel system (Digham et al., 2007). The performance of spectrum sensing techniques is measured using the following parameters:

- Probability of detection (P_d).
- Probability of false-alarm (P_f).
- Probability of missed-detection (P_m).
- The Receiver Operating Characteristics (ROC) curve.
- The Complementary Receiver Operating Characteristics (CROC) curve.

However, the most important parameters used to evaluate the performance of any SS technique includes the detection probability (P_d) and false-alarm probability (P_f).

Receivers Operating Characteristics (ROC) curve are a way of graphically displaying the diagnostic performance of a given test. In the perspective of SS, ROC curve are applied to highlight trade-offs between detection probability and probability of false-alarms to determine the value of an optimal threshold. In statistics the probability of detection is complimentary to the probability of miss-detection. ROC curves are the graph that is represented by detection probability versus the false-alarm probability, whereas the CROC curves are expressed in terms of the probability of missed-detection versus false-alarm probability.

Probability of detection (P_d) refers to the likelihood of identifying the existence of PUs accurately. As a result, a high score is preferred because it ensures that primary users are not hampered. A robust spectrum sensing technique gives a higher P_d and provides more interference protection to the PUs.

The probability of false-alarm (P_f) arises once the sensing technique assumes H_1 when in fact the correct decision is H_0 . In detection theory, this is specified as a false-alarm and the associated probability is denoted by P_f . The false-alarm probability (P_f) is the probability of incorrectly declaring the presence of primary user. Lower values of P_f are preferable for high channel throughput levels. The P_f is a very important design parameter in cognitive radio and should be kept reasonably low.

The missed-detection probability (P_m) occurs when the algorithm of sensing technique assumes H_0 when correct decision H_1 . As missed-detection probability (P_m) is increase the interference between SU and PU will also increases. Therefore, in cognitive radio network P_m should be kept low as much as possible.

CHAPTER FOUR

4. RESULT AND DISCUSSION

In this chapter, the simulation results of Conventional Energy Detection (CED), various Entropy based detection (EnD) and proposed two-stage spectrum sensing techniques are obtained using MATLAB version 2020a. In addition to this, the simulation results of cooperative spectrum sensing for CED, best performer EnD and two-stage spectrum sensing are obtained. Furthermore, the discussion and analysis of the obtained results are presented. The widely accepted performance metrics such as probability of detection, probability of false-alarm and probability of missed-detection are used in order to analyze the performance of spectrum sensing. According to IEEE 802.22 standards, all simulations must take into account the requisite detection probability ($\geq 90\%$), probability of false alarm ($\leq 10\%$) and probability of miss detection ($< 10\%$) for CR. 10,000 Monte-Carlo simulations and a sample number of 1500 have been used to generate the simulation results for all detection techniques. Simulations are provided to evaluate the performance of proposed two-stage spectrum sensing with respect to CED and EnD under AWGN channels.

The SNR wall is a key factor evaluated in all graphs of the result to compare the proposed techniques with existing ones. Also, the SNR wall is used to compare various types of entropy-based detection with each other. The minimal SNR below which detection is not possible is referred to as the SNR wall. The main parameters that are used for simulation in this thesis are listed in Table 4.1.

In this thesis, the simulation results are presented under four main topics:

- Results of Conventional Energy Detection (CED)
- Performance comparison among various types of Entropy detection
- Results of Proposed two-stage spectrum sensing
- Results of Cooperative detection of Proposed techniques

Table 4. 1: Parameters used for Simulations

Simulation Parameters	Type and Values	Remarks
Cognitive Users	Single User,2,3,4,5	It can be vary
Types of Primary Signal	BPSK	Assumption
Detection Type	Energy Detection (ED), various Entropy Detection (i.e. Shannon, Renyi, Tsallis & Kapurs)	
Ranges of SNR values	-30 dB up to 5 dB	Based on many papers
Desired Probability of False-alarm	≤ 0.1	According to IEEE 802.22 standards
Desired Probability of Detection	≥ 0.9	According to IEEE 802.22 standards
Number of Samples	1000, 1500, 2500 and 4000	It can be vary
Monte-Carlo simulation	10,000	Based on many papers
Channel	AWGN	Assumption
Types of Cooperative SS	Centralized approach (AND rule and OR rule)	
Order of entropy	4	Assumption
Number of bins	15, 17, 20	Based on many papers

4.1 Results of Conventional Energy Detection (CED)

There have been numerous simulations and performance analysis for CED in the literature as highlighted in chapter two. Nevertheless, for further clarity the simulation and analysis of CED are discussed in this section. The performance of CED through AWGN channel is simulated here. The following simulation results are discussed for CED techniques:

- Probability of detection versus SNR
- Effects of varying probability of false alarm on the detection performance
- Receiver Operating Characteristic (ROC) Curve

- Complementary ROC Curve
- Effects of varying number of samples on the probability of detection
- Cooperative detection for CED

4.1.1 Probability of detection versus SNR for CED

Figure 4.1 shows the relationship between probability of detection (P_d) and SNR for CED at a probability of false-alarm ($P_f=0.1$) and number of samples ($N=1500$). As shown in the graph, the detection probability of CED deteriorates as the SNR value decreases. The decreasing of probability of detection indicates the deterioration of performance. As observed, CED has the ability to distinguish between PU signal and noise signal whenever SNR becomes greater than -8 dB according to IEEE 802.22 standards. The SNR value below which detection is impossible is referred to as the SNR wall. As a result, the SNR wall for CED is -8 dB because the detection probability below this value is less than 0.9 ($< 90\%$). So, it can be deduced that below the SNR wall of -8 dB, CED performs poorly.

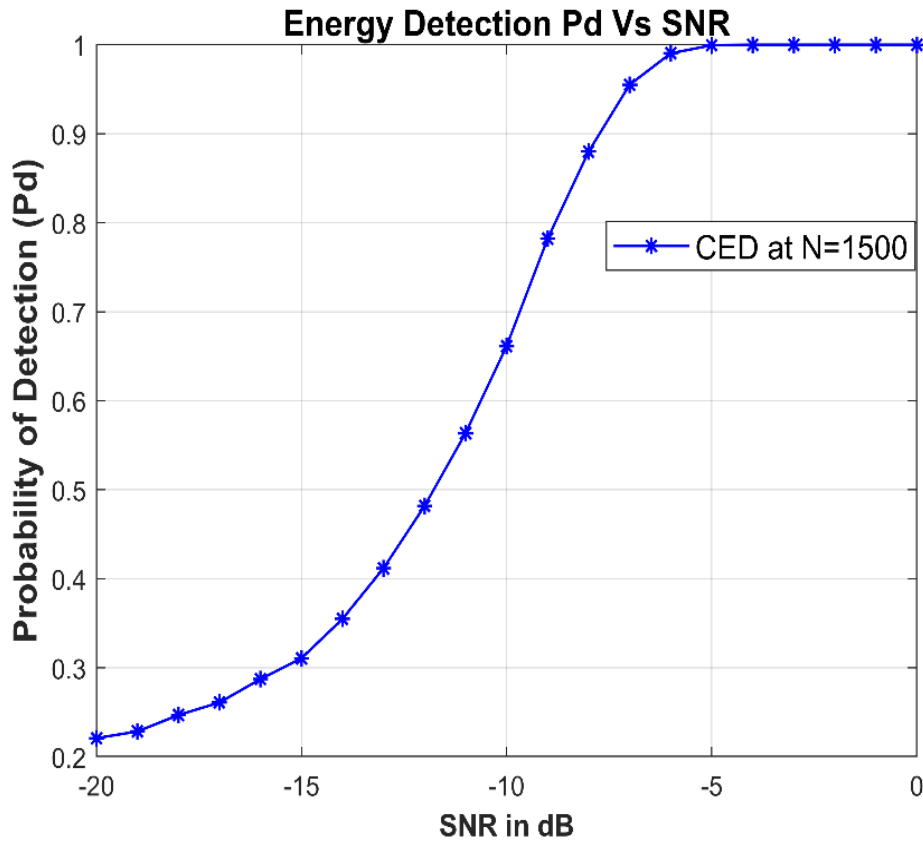


Figure 4. 1: P_d vs SNR for CED at $P_f = 0.1$ and $N = 1500$

4.1.2 Effects of varying probability of false alarm on detection performance of CED

Figure 4.2 shows the relationship between P_d and SNR at various probabilities of false alarm of 0.1, 0.2 and 0.3. As observed from the graph, the detection probability increases as the false alarm probability increases. However, the increasing probability of false alarms degrades the spectrum utilization efficiency of SU since it falsely detects the PU signal while PU is not present. As it can be seen, the simulation result for $P_f = 0.1$ and 0.2 has SNR wall at -8 dB and -8.5 dB, respectively, while $P_f = 0.3$ has SNR wall at -9 dB. So, it can be concluded that a rise in the probability of false alarm enhances the sensitivity of detection techniques since the SNR wall value decreases, resulting in a weaker signal power.

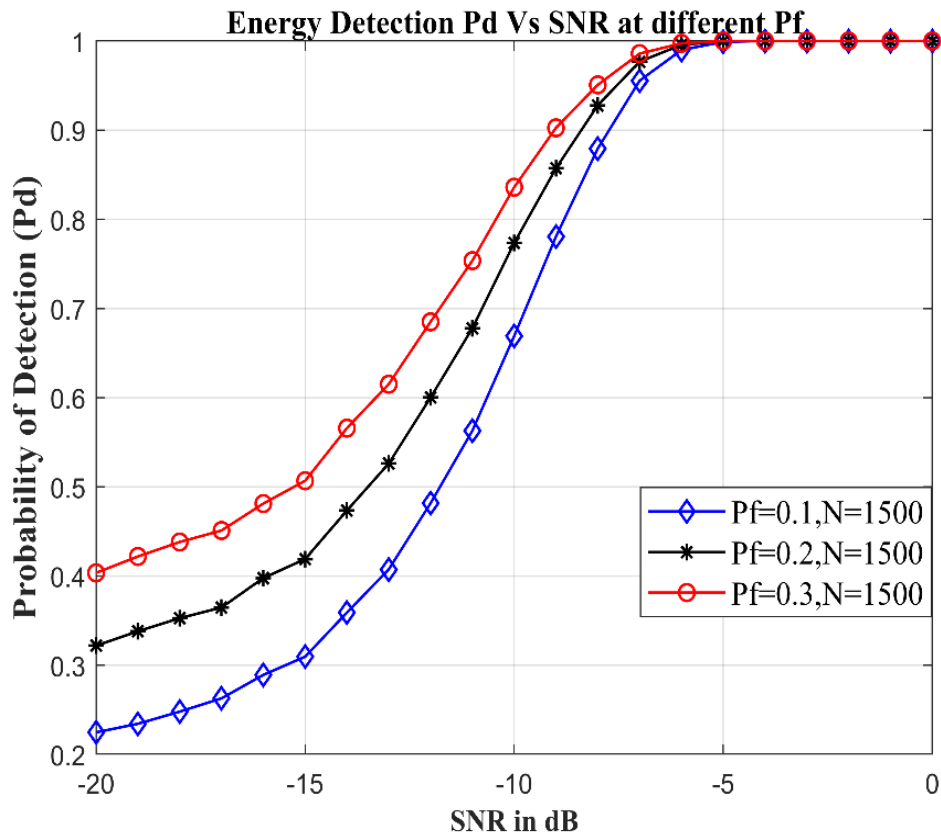


Figure 4. 2: P_d vs SNR for CED at $P_f=0.1, 0.2, 0.3$ and $N=1500$

4.1.3 Probability of detection versus probability of false alarm (ROC Curve) for CED

Figure 4.3 depicts the relationship between the probability of false-alarm and the probability of detection for CED under the AWGN channel at SNR values of -9 dB, -11 dB, -13 dB and -18 dB. As seen from the figure, an increase in the probability of false alarm increases the probability of detection. However, a high probability of false alarm leads to poor spectrum utilization. Hence, the probability of false alarm should be as low as possible for accurate results and also to protect the secondary user signals from interfering with the signals of the primary user. In addition, these simulation results show the effect of varying SNR values on the performance of CED. As it can be seen, the ROC curve that is plotted using -9 dB SNR value has a higher detection probability compared to the curve that is plotted using -11 dB, -13 dB and -18 dB. Also, the curve that is plotted using -11 dB SNR value has a higher probability of detection compared to the curve that is plotted using -13 dB and -18 dB. As a result, it can be concluded that an increase in SNR value increases the performance of CED.

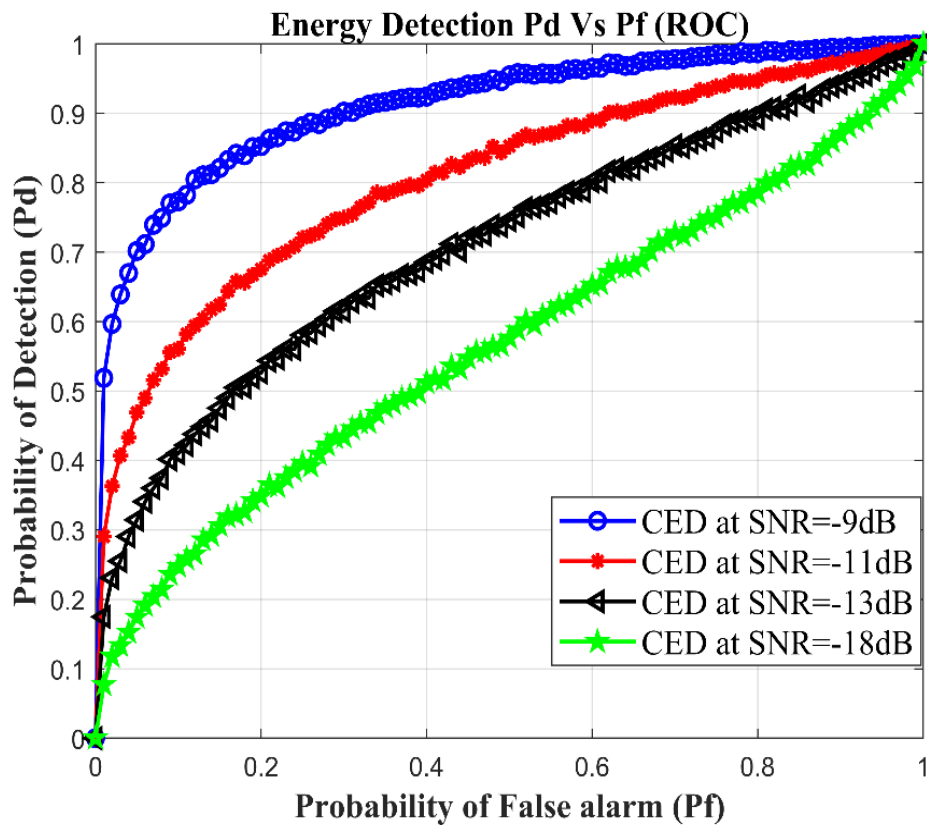


Figure 4. 3: P_d vs P_f for CED at various SNR value

4.1.4 Probability of miss detection versus probability of false alarm (CROC Curve)

Figure 4.4 illustrates the simulation results of the CROC curve for CED under the AWGN channel. The CROC plot shows the relationship between the probability of miss-detection and the probability of false alarm. These CROC curves are plotted at SNR values of -9 dB, -11 dB, -13 dB and -18 dB. As observed from the figure, an increase in the probability of false alarm decreases the probability of miss-detection. The performance of the spectrum sensing technique improves as the miss-detection probability decreases. As the miss-detection probability increases, so does the interference between PU and SU. Therefore, a detector that has a lower probability of miss-detection is desirable. Moreover, the impacts of varying SNR values on miss-detection probability are evaluated in this graph. As observed, the CROC curve that is plotted with a -9 dB SNR value has a lower miss-detection probability than those plotted with -11 dB, -13 dB and -18 dB. Also, the curve that is plotted with -11 dB has a lower probability of miss detection compared to the curve that is plotted with -13 dB and -18 dB. As a result, it is possible to conclude that increasing the SNR value reduces the miss-detection probability, which results in an improved performance.

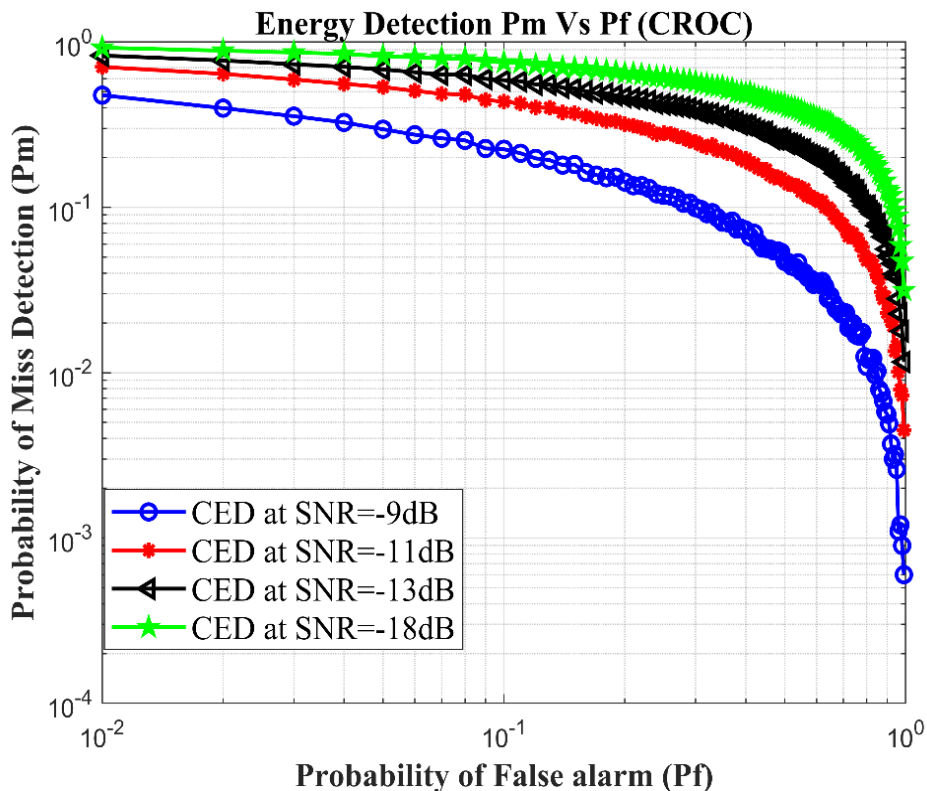


Figure 4. 4: P_m vs P_f for CED at various SNR value

4.1.5 Effects of varying number of samples on detection probability of CED

Figure 4.5 depicts the ROC curve for CED at various sample sizes. In this simulation, the SNR value is set to -12 dB while the probability of false alarm is set to 0.1. In order to see the effects of sample number on detection performance, its value is varied from 1000 to 4000 by increments of 1500. As can be seen from the figure, the detection performance of CED improves with increasing sample sizes. As observed, the ROC curve with a sample size of 4000 has a higher detection probability than the ROC curve with sample sizes of 1000 and 2500. As a result, it is possible to conclude that increasing the sample size enhances the performance of detection techniques.

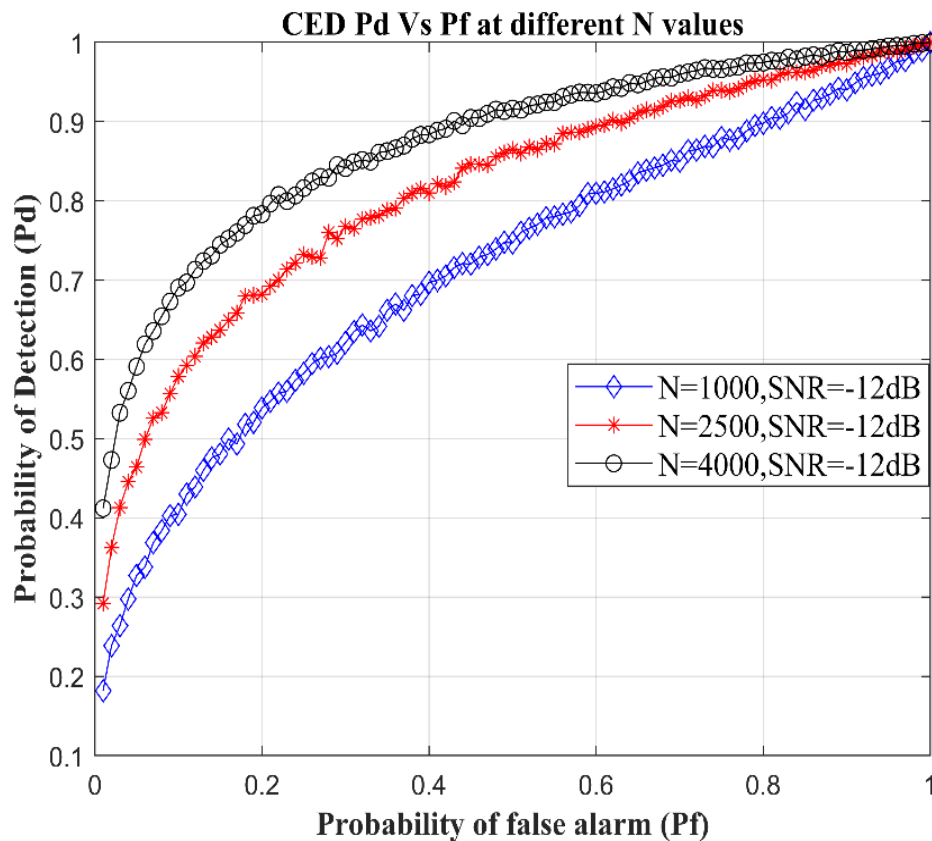


Figure 4. 5: P_d vs P_f for CED at various number of samples (N)

4.1.6 Cooperative detection for CED

In this subsection, the simulation result that evaluates the performance of cooperative CED under the AWGN channel is presented. And also, the comparison among single node CED, AND, and OR rule fusion schemes are discussed. The performance evaluation is done in terms

of ROC curve, CROC curve, and probability of detection versus SNR at different numbers of collaborating SUs.

Figure 4.6 depicts the relationship between P_d and SNR for cooperative CED using the AND rule and OR rule at different numbers of secondary users (i.e. $NU=2,3,4$). And also, the simulation results of a single node (i.e., $NU=1$) CED are presented in this plot. In addition, this graph shows how the AND, and OR rules are affected by increasing number of secondary users (SUs). The figure shows that utilizing OR rule CSS schemes improves spectrum sensing performance when compared to single node schemes, while using AND rule fusion scheme reduces detection probability when compared to single node schemes. As observed, an increasing number of SUs increases the detection probability of the OR rule while it decreases the detection probability of the AND rule. This occurs because the OR rule needs only one SU to become 1 in order to decide the presence of PU, while the AND rule needs all SUs to become 1 to decide the presence of PU. This simulation is done by setting the probability of false alarm to 0.1 and the number of samples to 1500.

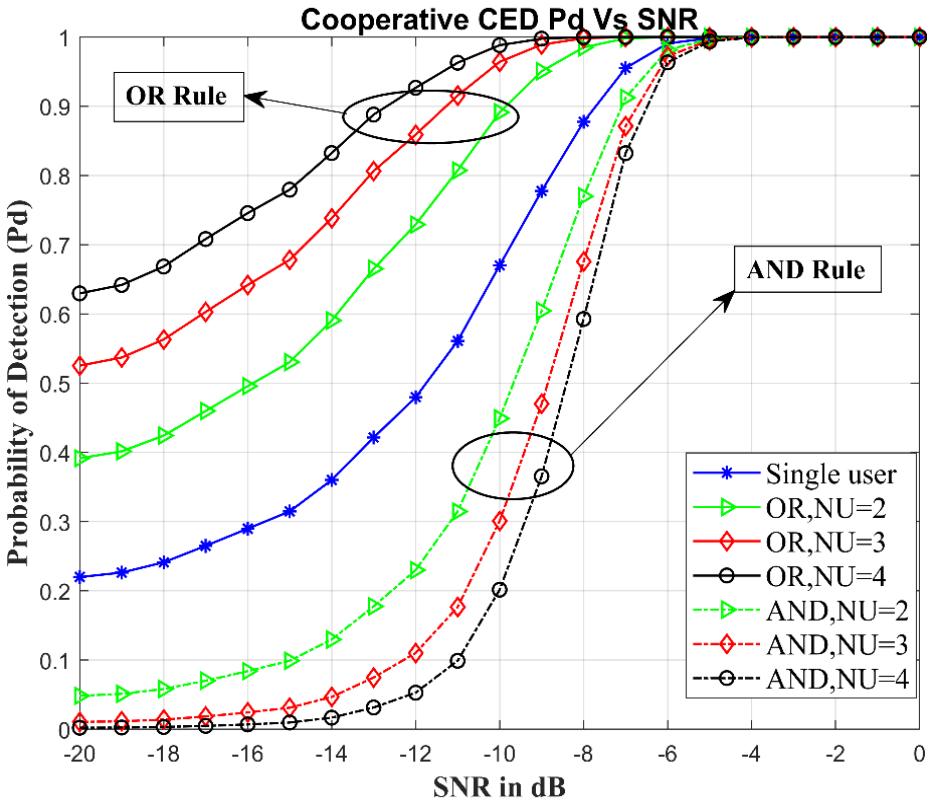


Figure 4. 6: P_d vs SNR for cooperative CED at different number of users for OR/AND Rule

Table 4. 2: performance comparison among single node CED, AND rule and OR rule CSS at $P_f=0.1$, SNR=-12 dB, N=1500 and NU=4

Detectors	Probability of detection	Improvement compared to single node CED
Single user CED	0.4803	-
OR Rule CSS with NU=4	0.9271	93.025%
AND Rule CSS with NU=4	0.05322	-88.919%

Table 4.2 shows a performance comparison between CED and cooperative detection (i.e. AND rule and OR rule CSS) at SNR = -12 dB, $P_f = 0.1$ and N=1500. The results for the AND rule and OR rule are generated with a number of SUs of 4. At this given value, OR rule CSS has a 93.025% performance improvement compared to CED, while the AND rule has an 88.919% performance reduction compared to single node CED.

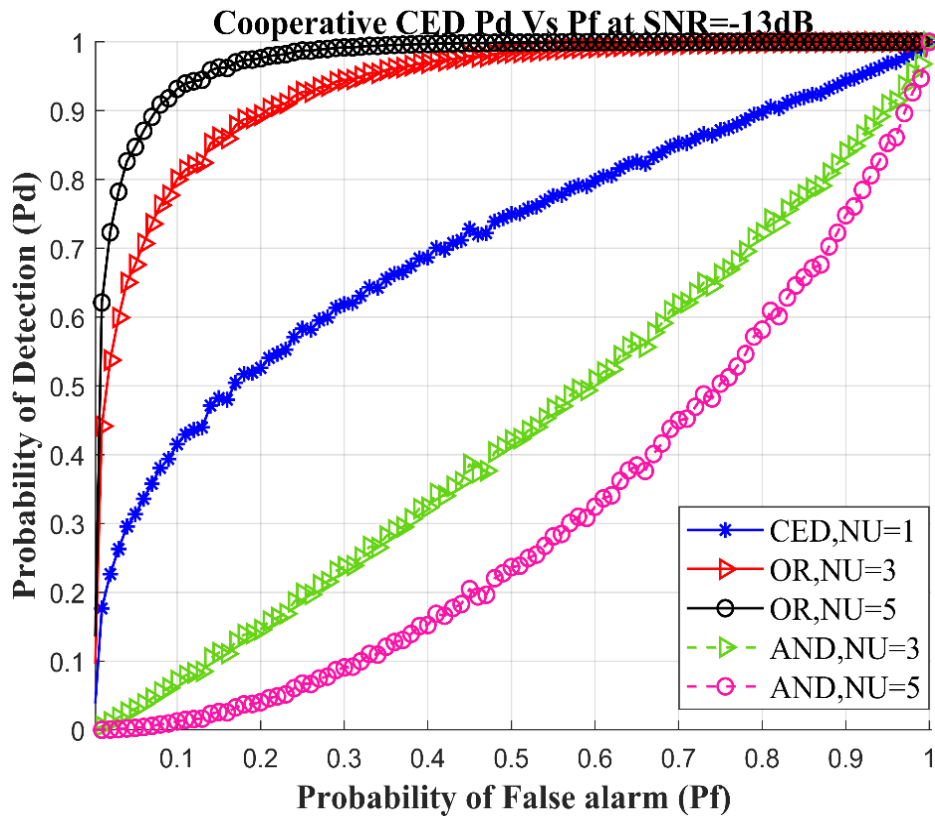


Figure 4. 7: ROC curve for cooperative CED

Figure 4.7 illustrates the simulation result of the ROC curve for cooperative CED when the number of users is 1, 3, and 5 at SNR = -13 dB. From the figure, one can easily understand that an increasing probability of false alarm increases the detection probability of a single node (CED with NU=1), AND rule CSS and OR rule CSS. The detection performance of the OR rule improves dramatically as the number of cooperating SUs increases. However, the detection probability of the AND rule deteriorates with an increasing number of SUs because all of the SUs must decide the existence of PU, which is difficult to achieve since some cognitive users fail to decide due to multipath fading, shadowing effect and hidden terminal problems.

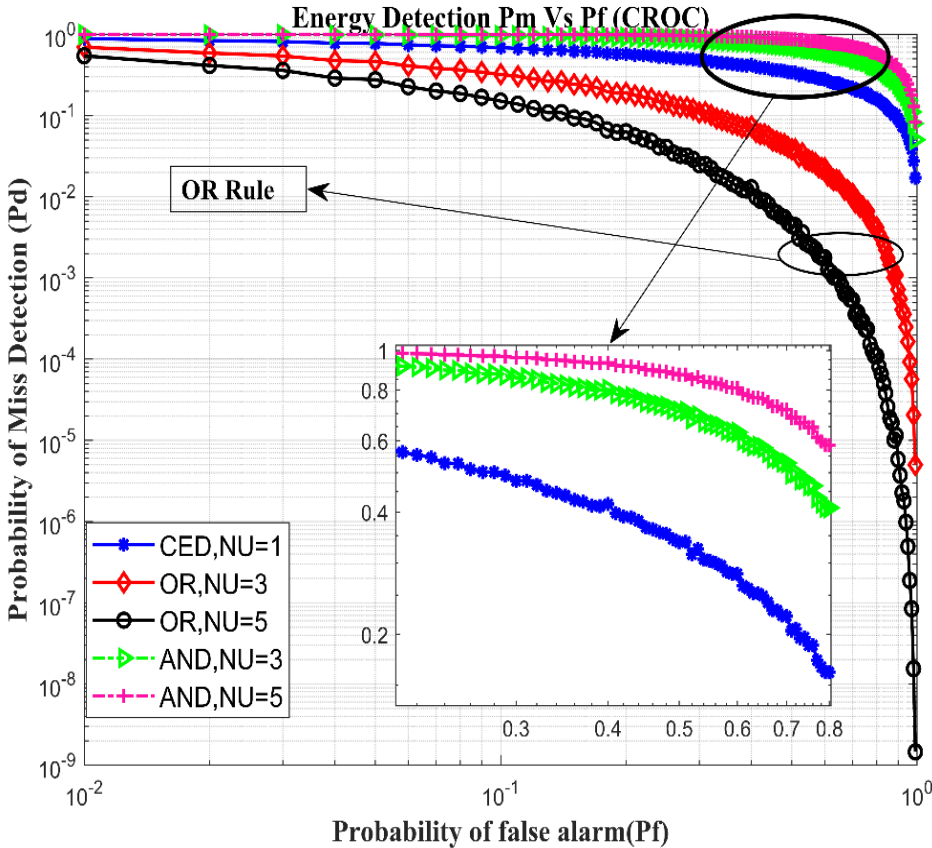


Figure 4. 8: CROC curve for cooperative CED

Figure 4.8 depicts the simulation result of the CROC curve for cooperative CED under the AND rule and OR rule when the number of users is 1, 3 and 5 at SNR = -15 dB. The figure clearly shows that when the probability of false-alarm increases, the missed-detection probability of CED, AND rule CSS and OR rule CSS, decreases. The missed detection probability of the OR rule decreases dramatically as the number of collaborating SUs grows. However, as the number of SUs increases, the missed detection probability of AND rule becomes greatly enhanced. For

instance, at a given probability of false alarm and number of users (NU), 0.1 and 3 respectively, the missed detection probability of OR rule CSS is 0.3214 while for AND rule CSS it is 0.9687. Also, at the same given value of P_f with 5 number of users, the missed-detection probability of OR rule CSS is 0.1508, while it is 0.9963 for AND rule CSS. However, at this value of P_f , the missed-detection probability of single-node CED is 0.685. From this result, it is possible to deduce that the OR rule CSS has create a less interference with PU compared to the AND rule CSS and single-node CED.

4.2 Performance comparison among various types Entropy Detection

In this section, the simulation results that compare the performance of various types of entropy detection are presented. Based upon the obtained results, the method that achieves the highest probability of detection is selected for two-stage spectrum sensing. The comparisons are made in terms of the following metrics:

- Probability of detection versus SNR
- Probability of detection versus probability of false alarm (ROC Curve)
- Probability of miss-detection versus probability of false alarm (CROC Curve)

4.2.1 Probability of detection versus SNR

Figure 4.9 depicts the relationship between P_d and SNR for various types of entropy-based detection at a probability of false alarm ($P_f=0.1$), number of bins ($L = 15$) and order of entropy ($\alpha=4$). Any spectrum sensing technique with a detection probability greater than or equal to 0.9 ($\geq 90\%$) can distinguish PU signal from noise signals, according to IEEE 802.22 standards. As it can be seen, the probability of detection for Tsallis entropy, Shannon entropy and Kapurs entropy becomes greater than 0.9 after SNR of -12 dB, -13 dB and -16 dB respectively. However, the probability of detection for Renyi entropy becomes greater than 0.9 after an SNR of -23 dB. Renyi entropy detection has a significant improvement of about 11 dB, 10 dB and 7 dB in SNR wall compared to Tsallis, Shannon and Kapurs entropy, respectively. Depending on this result, Renyi entropy can detect a weaker PU signal than other entropy methods since it has a lower SNR wall than them. The detection technique with a lower SNR wall value has better sensitivity. Hence, it can be concluded that the Renyi entropy detection outperforms all other types of entropy.

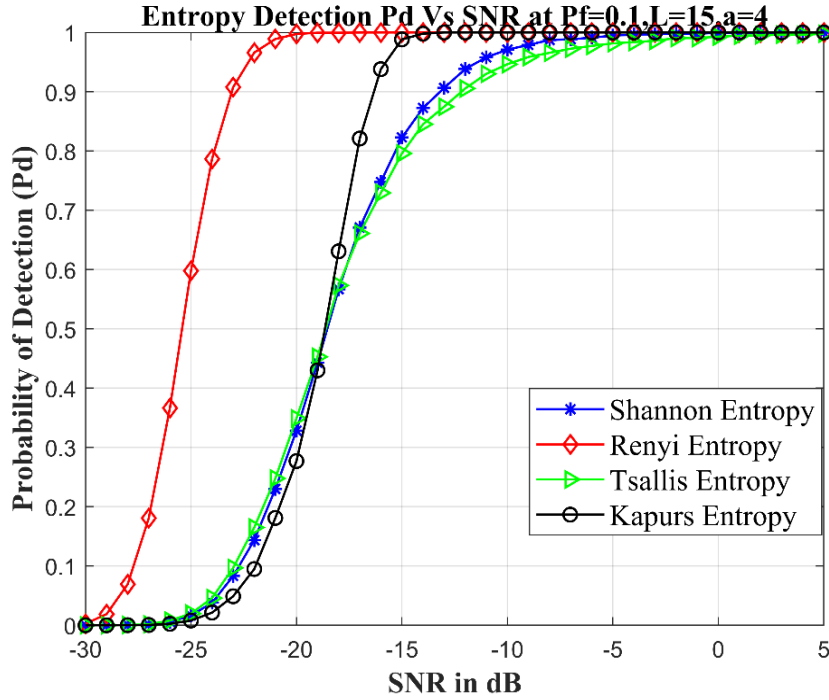


Figure 4. 9: P_d vs SNR at $P_f=0.1$ and $\alpha=4$ for various types of Entropy Detection

Table 4. 3: Performance comparison on different types of entropy detection at various SNR values

SNR (dB)		-23	-20	-18	-16	-14	-12	-10	-8	-6	-4	-2	0
Detection probability of Entropy	Renyi	0.904	0.997	0.999	1	1	1	1	1	1	1	1	1
	Kapur's	0.047	0.288	0.635	0.938	0.999	1	1	1	1	1	1	1
	Shannon	0.081	0.343	0.569	0.758	0.873	0.943	0.97	0.98	0.99	0.99	0.99	0.99
	Tsallis	0.093	0.355	0.572	0.739	0.843	0.909	0.95	0.96	0.97	0.98	0.98	0.99

Table 4.3 depicts the performance comparison among various types of entropy detection in terms of detection probability under various SNR values at $N = 1500$, $P_f = 0.1$, and order of entropy ($\alpha=4$). As observed in the table, the Renyi entropy-based detection has the highest probability of detection compared to other entropy methods at low SNR. After SNR = -12dB, both Renyi and Kapur's entropy attain the maximum probability of detection, while Shannon and Tsallis entropy attain the poorest detection probability compared to them. So, for the proposed schemes, Renyi entropy-based detection is chosen because it has a higher probability of detection at lower SNR than other entropy methods.

4.2.2 Receiver Operating Characteristic (ROC) Curve

Figure 4.10 depicts the ROC curve for various types of entropy detection at SNR = -19 dB. This simulation is done by setting the number of bins to 15 and the order of entropy to 4. As shown in the below graph, an increase in the probability of false alarm enhances the detection probability of entropy. Renyi entropy-based detection achieves the desired probability of detection ($P_d \geq 0.9$) with the lowest probability of false alarm when compared to other methods. As illustrated in the figure, Kapurs entropy has better performance than Shannon and Tsallis entropy. Also, Shannon entropy has a better probability of detection than Tsallis entropy. As observed, Renyi entropy achieves the desired probability of detection with 0.02 probability of false alarm, while Kapurs, Shannon and Tsallis entropy achieves it with 0.17, 0.25 and 0.28 respectively. The detector with a higher probability of false alarm leads to poor spectrum utilization. Hence, it can be deduced that the Renyi entropy outperforms all other methods since it requires a lower probability of false alarm to obtain the required detection probability than the others.

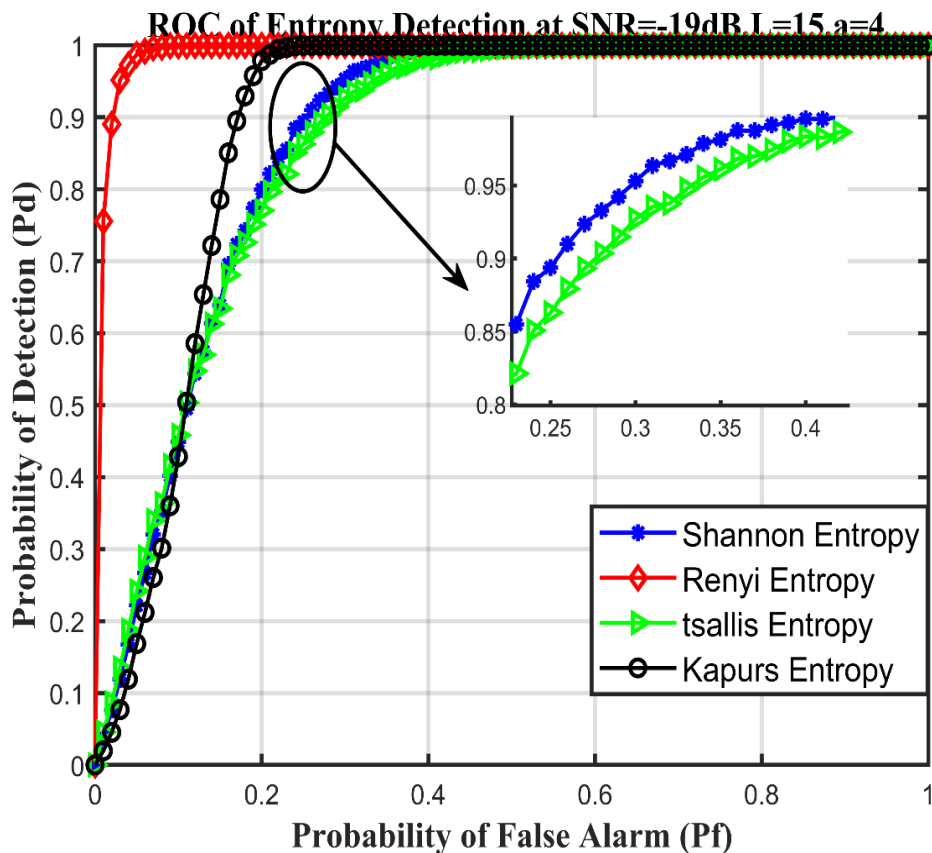


Figure 4. 10: ROC Curve for various types of Entropy Detection at SNR=-19dB

4.2.3 Complementary Receiver Operating Characteristic (CROC) Curve

The performance comparison among various entropy detections can also be analyzed in terms of the CROC curve as shown in Figure 4.11. The results of the CROC curve are simulated at SNR = -21 dB, number of bins ($L = 15$) and order of entropy ($\alpha = 4$). As observed from the plot, an increase in false alarm probability decreases the missed-detection probability. The Renyi entropy detection has the lowest probability of missed detection when compared to other methods, as illustrated in the plot. The method with the lowest missed detection probability can make efficient use of the spectrum holes.

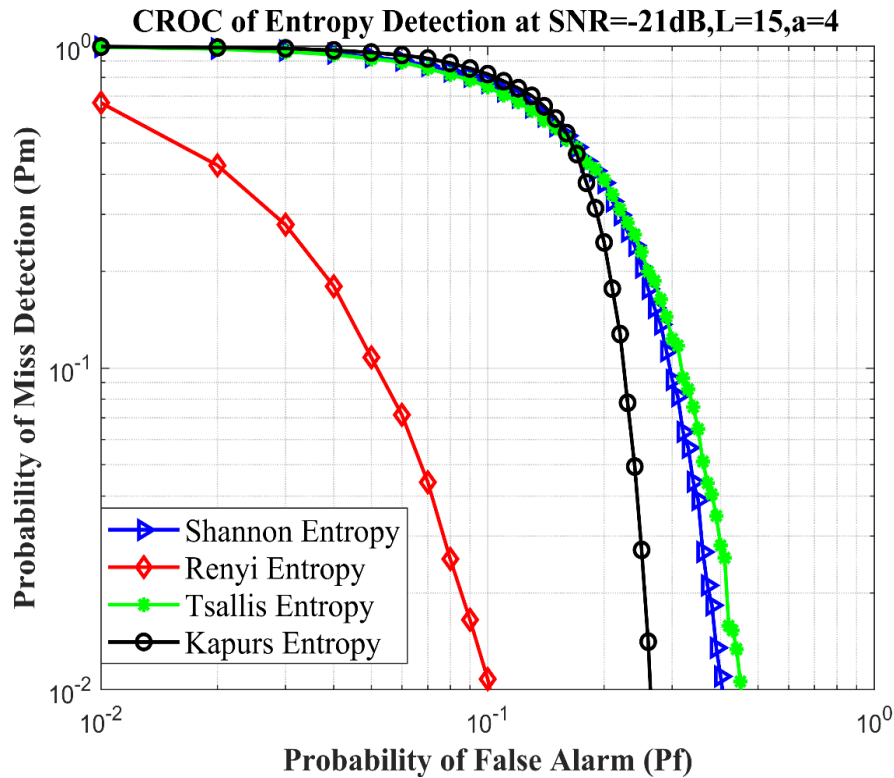


Figure 4. 11: CROC Curve for various types of Entropy detection at SNR=-21dB

4.2.4 Effects of varying number of bins on the performance of Renyi Entropy detection

Figure 4.12 illustrates the impact of the number of bins on renyi entropy based detection. As observed from the figure, the detection probability decreases as the number of bins increases. When the number of bins is 15 ($L = 15$), the renyi entropy detection can detect the primary signal up to -23 dB SNR values, whereas at $L = 17$ and $L = 20$, it can detect the PU signal up to -22 dB and -21 dB, respectively. As a result, it can be deduced that as the number of bins decreases, the sensing performance of entropy detection improves.

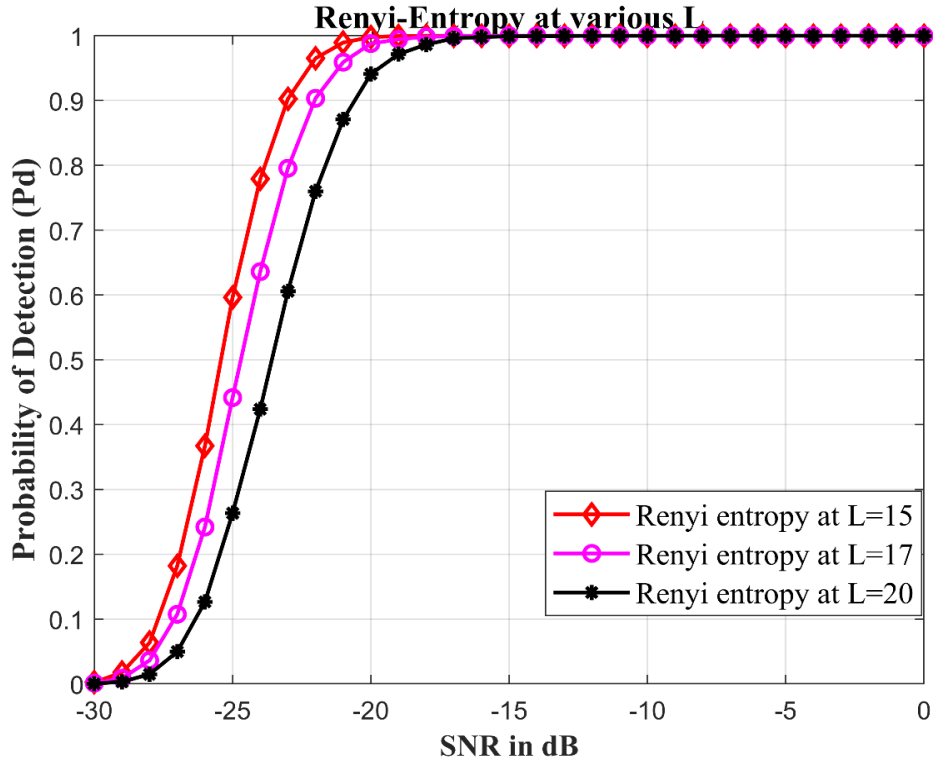


Figure 4. 12: P_d vs SNR for Renyi Entropy detection at various number of bins (L)

4.2.5 Cooperative detection for Renyi Entropy techniques

Figure 4.13 shows the ROC curve for cooperative Renyi entropy detection under both the AND rule and the OR rule at SNR = -25 dB. The detection probability of cooperative entropy detection increases by using the OR rule, while it is decreased by using the AND rule compared to single node renyi entropy. For instance, at a given probability of false alarm of 0.1 ($P_f = 0.1$) and 3 number of users, the detection probability of cooperative renyi entropy using the AND rule and OR rule is 0.206 and 0.9314, respectively, while it is 0.5906 for the single node renyi entropy method. In addition to this, an increasing number of collaborating users greatly improves the performance of spectrum sensing in the case of OR rule CSS. But in the case of the AND rule, an increasing number of collaborating users deteriorates the detection performance of SS technique. For example, at a given probability of false-alarm of 0.1 ($P_f = 0.1$), the detection probability of OR rule CSS is improved from 0.9314 to 0.9885 when the number of user is increased from 3 to 5, while the detection probability of AND rule CSS is decreased from 0.206 to 0.07186.

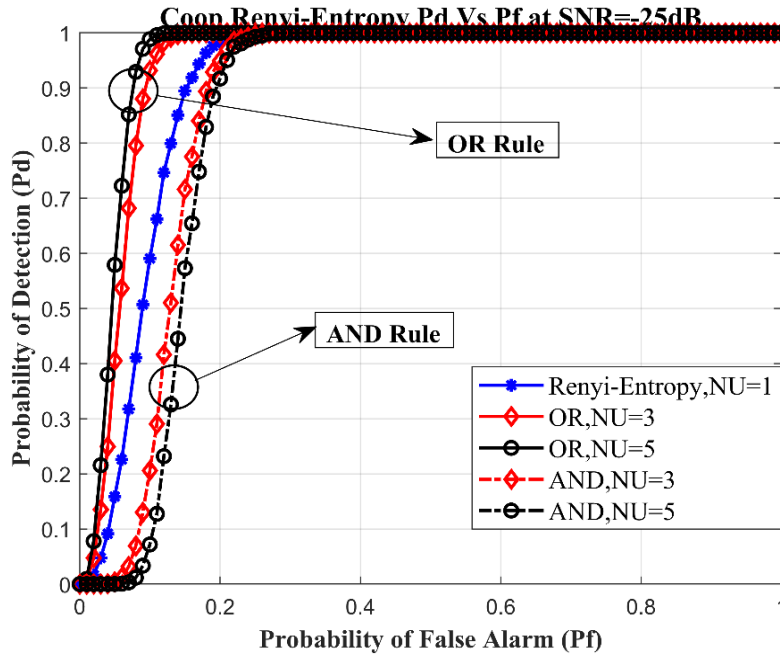


Figure 4. 13: ROC Curve for Cooperative renyi entropy detection at SNR=-25dB

Figure 4.14 shows the CROC curve for cooperative renyi entropy detection at SNR = -25 dB under both the AND rule and the OR rule. This result compares single node and cooperative renyi entropy. As observed from the figure, OR rule CSS has the lowest probability of miss detection compared to both AND rule CSS and single node renyi entropy.

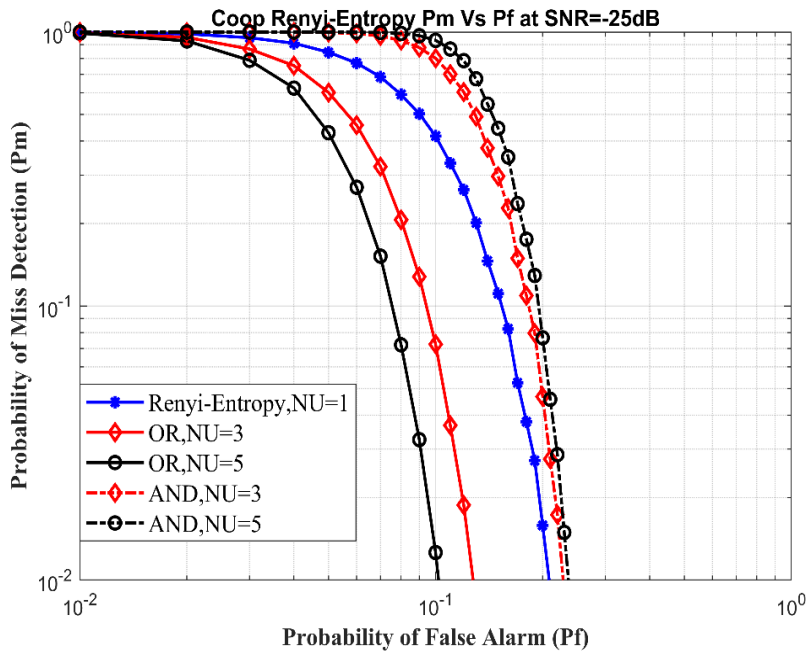


Figure 4. 14: CROC Curve for Cooperative renyi entropy detection at SNR=-25dB

4.3 Results of Proposed Two-Stage Spectrum Sensing

Depending upon the comparison results from the previous section, the Renyi entropy detection is chosen among other entropy methods for developing the proposed two-stage techniques. Renyi entropy is chosen because it has a higher detection probability than other entropies at an assumed order of entropy ($\alpha=4$). In this section, the simulation results that compare the performance of the proposed two-stage spectrum sensing technique with conventional energy detection (CED) and Renyi entropy detection are presented.

The following simulation results are discussed for proposed techniques:

- Probability of detection versus SNR for comparing proposed technique with conventional method.
- Receiver Operating Characteristics (ROC) Curve.
- Complementary Receiver Operating Characteristics (ROC) Curve.
- Effects of varying probability of false alarm on performance of proposed technique.
- Effects of varying number of samples on performance of proposed technique.

4.3.1 Probability of detection versus SNR for comparing the proposed technique with conventional methods

Figure 4.15 depicts the comparison among proposed two-stage SS, Renyi entropy-based detection and Conventional Energy detection (CED) at a particular probability of false-alarm of 0.1, number of bins of 15 and order of entropy of 4. The comparison results show that the proposed method outperforms Renyi entropy and CED by a significant performance improvement. For instance, at a given SNR of -25 dB, the detection probability of the proposed technique is 0.6697 while the detection probability of renyi entropy and CED is 0.5896 and 0.1952 respectively. In other words, the proposed two stage technique has a significant improvement of about 15 dB and 0.5 dB in SNR wall when compared to CED and Renyi entropy, respectively.

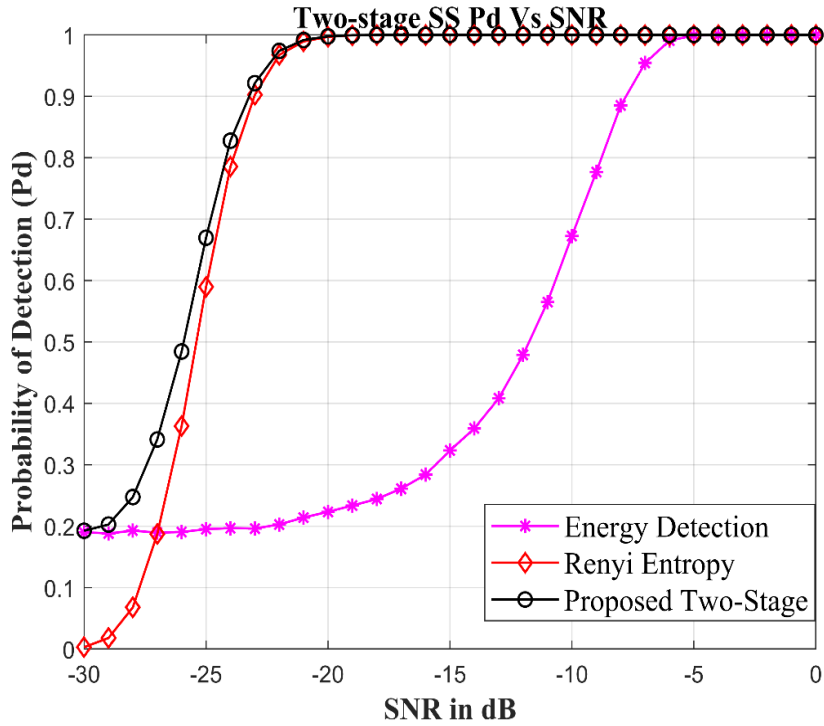


Figure 4. 15: P_d vs SNR for comparing proposed two stage, Renyi entropy and CED at $P_f=0.1$

Table 4. 4: Performance comparison between proposed two-stage SS and Single stage SS at various SNR values

SNR (dB)		-28	-25	-22	-19	-16	-13	-10	-7	-4	-1	0
Detection probability	Energy Detection	0.193	0.195	0.203	0.234	0.284	0.408	0.673	0.954	1	1	1
	Renyi Entropy	0.068	0.587	0.967	0.999	0.999	1	1	1	1	1	1
	Proposed Two-stage	0.247	0.669	0.974	1	1	1	1	1	1	1	1

Table 4.4 depicts the performance comparison between the proposed SS scheme and single-stage spectrum sensing scheme (i.e., Renyi entropy based detection and conventional ED) in terms of detection probability. Each method's performance is evaluated at different values of SNR, as shown in table 4.4. At low SNR values, the proposed two-stage SS technique has the highest probability of detection than both single stage schemes. However, both proposed two-stage and Renyi entropy-based detection achieve a maximum detection probability after SNR = -13 dB, while Energy detection achieves it after SNR=-5dB. So, from this table, it is possible to

deduce that the performance of SS for cognitive radios is enhanced by implementing the proposed two-stage SS scheme rather than single-stage.

4.3.2 Receiver Operating Characteristics (ROC) Curve

Figure 4.16 shows the ROC Curve that compares the proposed two-stage SS with Renyi Entropy and CED at SNR=-24 dB and L=15. As it can be seen, the proposed two-stage methods have a lower probability of false-alarm than Renyi Entropy and CED for detecting PU signals within the desired probability of detection. It is clear from the figure that the proposed detector performs better in terms of detection. For instance, at a given probability of false alarm of 0.1, the detection performance of the proposed technique is 0.826 while the detection probability of renyi entropy and CED is 0.7829 and 0.1984 respectively. In other words, the proposed two-stage SS technique achieves the desired probability of detection with 0.12 probability of false alarm, while Renyi entropy and CED achieves it with 0.13 and 0.96 respectively. As a result, it is possible to deduced that the proposed techniques have better detection performance than both Renyi entropy and CED since it requires a lower probability of false alarm to obtain the desired probability of detection than the them.

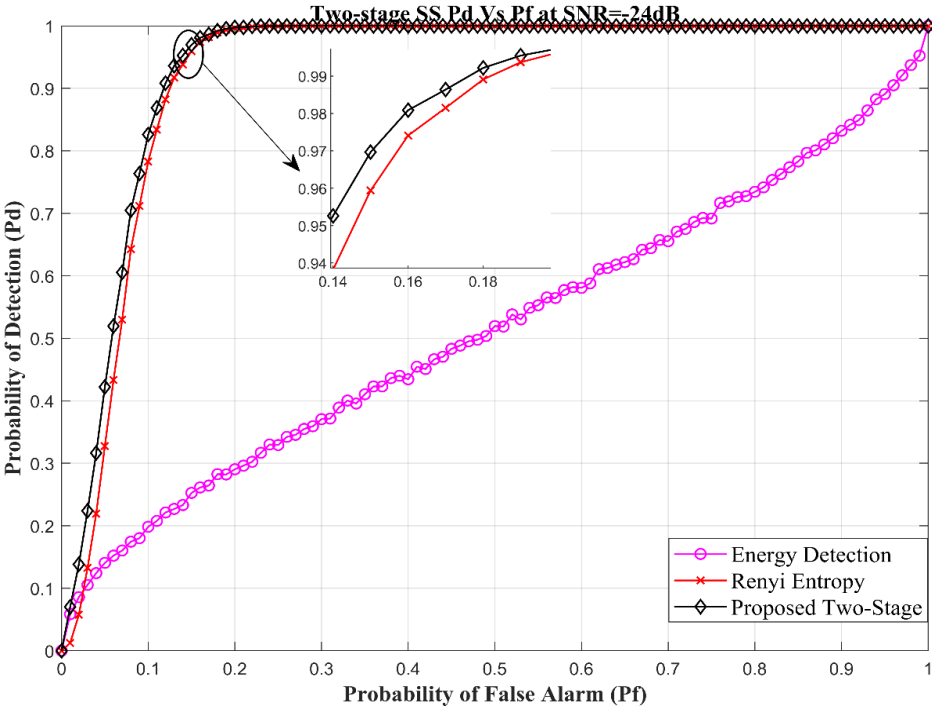


Figure 4. 16: ROC curve that compares proposed two stage, Renyi entropy and CED at SNR=-24dB

4.3.3 Complementary Receiver Operating Characteristics (CROC) Curve

Figure 4.17 shows the CROC Curve that compares the proposed two-stage SS with Renyi Entropy and CED at SNR=-21 dB and L=15. As it can be observed from the figure, the proposed technique has a lower missed-detection probability over all ranges of P_f compared to Renyi entropy and CED. For instance, at a given probability of false alarm of 0.03, the missed-detection probability of the proposed technique is 0.245 while the missed-detection probability of Renyi entropy and CED is 0.276 and 0.887, respectively. The detection technique with a lower probability of missed detection leads to less interference to PU by SU. Therefore, from this result, it can be concluded that the proposed technique is better at distinguishing PU signals from noise signals than Renyi entropy and CED.

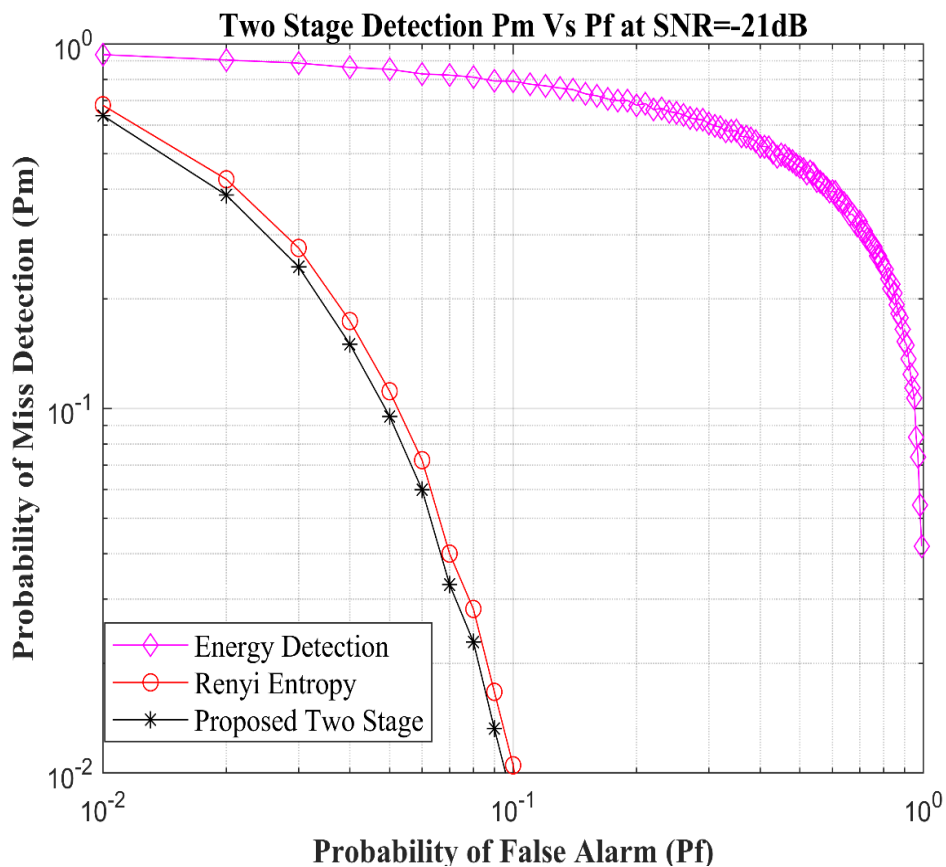


Figure 4. 17: CROC curve that compares proposed two stage, Renyi entropy and CED at SNR = -21 dB

4.3.4 Effects of varying probability of false alarm on the performance of proposed technique

Figure 4.18 shows the detection performance of the proposed two-stage SS scheme at the sample number of 1500 ($N=1500$) for various values of the probability of false-alarm. As illustrated in the graph, the detection probability is increased when the probability of false-alarm increases. As shown from the figure, the curve that is plotted with $P_f = 0.2$ achieves the desired detection probability at an SNR of -27 dB, whereas the curves that is plotted with $P_f=0.15$, $P_f=0.1$ and $P_f=0.05$ achieves it at SNRs of -25 dB, -23 dB and -21 dB respectively. In other words, the curve that is plotted using $P_f=0.2$ has the highest probability of detection when compared to others, while $P_f=0.05$ has the lowest detection performance. However, the maximum acceptable P_f for cognitive radio is 0.1, which cannot be surpassed according IEEE 802.22 standards.

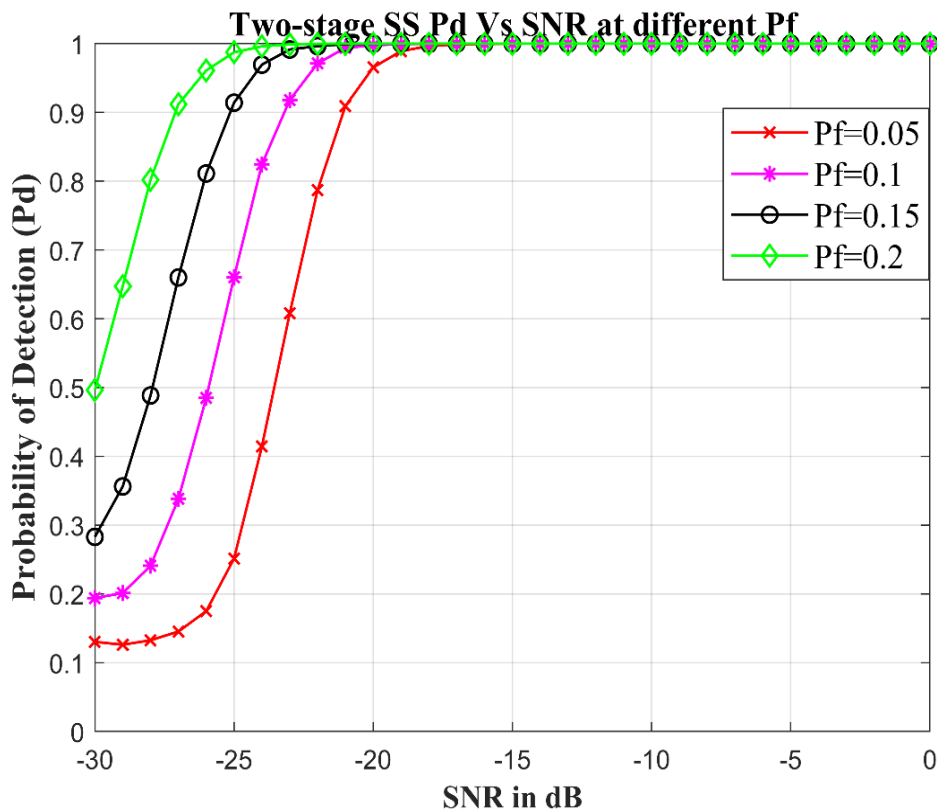


Figure 4. 18: performance comparison of proposed two-stage SS technique at various values of false alarm probability

4.3.5 Effects of varying number of samples on the performance of proposed technique

Figure 4.19 illustrates the ROC curve for the proposed two-stage SS technique at various sample sizes. In this simulation, the SNR value is set to -27 dB. The detection performance improves as the number of samples increases for a particular probability of false-alarm. At a given SNR value, only a sample size of 4000 may attain IEEE 802.22 standards, as seen in the graph. The ROC curve plotted for the proposed two-stage SS technique with 4000 sample sizes achieves the desired probability of detection (i.e., $P_d \geq 90\%$) with 0.05 probability of false alarm, while the ROC curve plotted with 2500 and 1000 sample size achieves it with 0.11 and 0.26 respectively. As a result, it is possible to deduce that the performance of proposed SS technique is enhanced by increasing the sample sizes (number of samples) since an increasing of sample size decreases the false-alarm probability for attaining the required probability of detection.

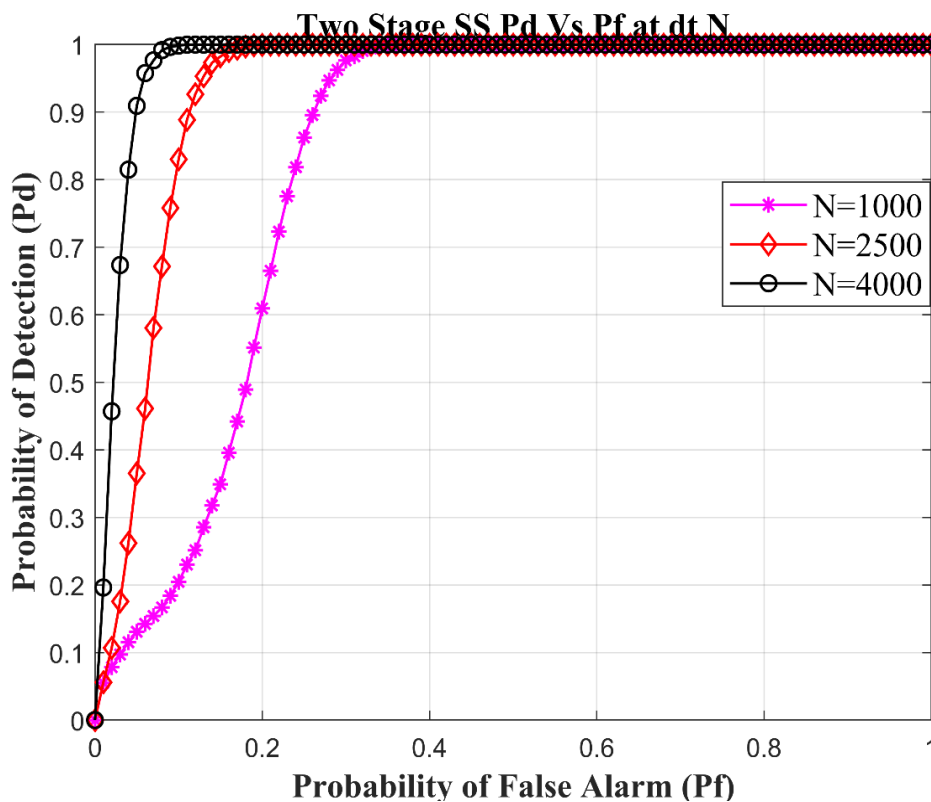


Figure 4. 19: ROC curve of proposed two stage SS technique at different number of samples

4.4 Results of Cooperative detection for Proposed techniques

This section presents simulation result that evaluates the performance of cooperative detection for proposed two-stage technique. The OR rule fusion schemes are applied for implementing cooperative detection since it achieves a good results compared AND rule in the previous section of 4.1.6 and 4.2.5. In addition, the comparison between single-node and cooperative detection of proposed technique is performed. The performance evaluation is done in terms of P_d vs SNR curve, ROC curve and CROC curve.

4.4.1 P_d vs SNR for cooperative detection of proposed two-stage technique

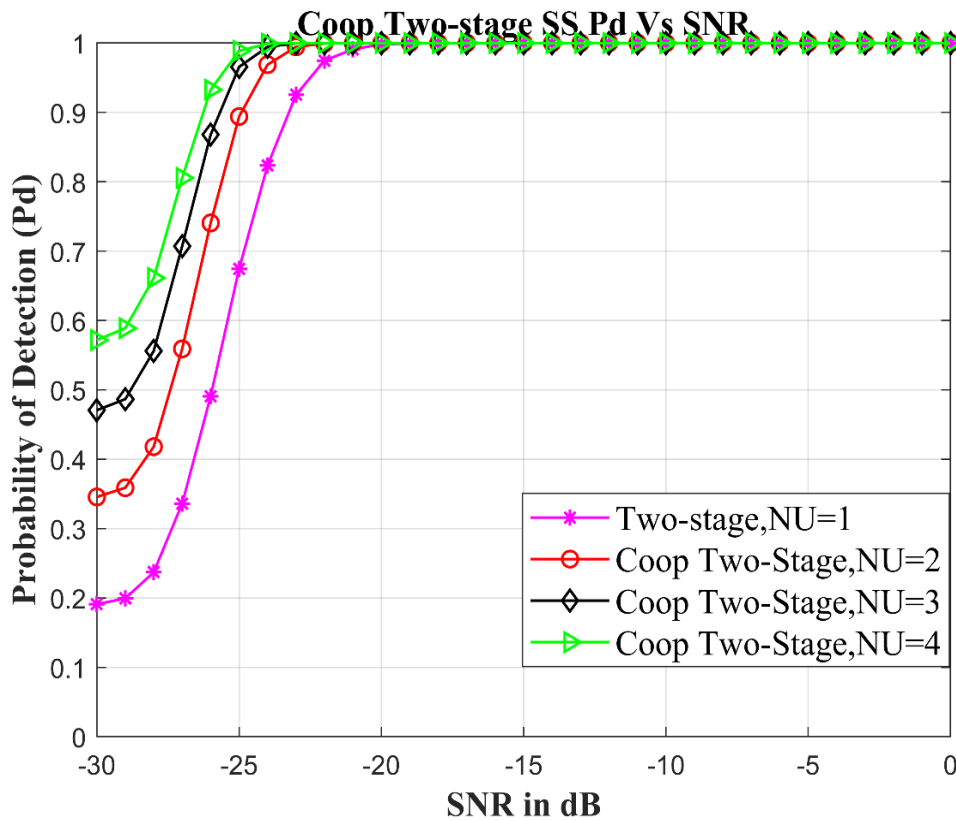


Figure 4. 20: P_d vs SNR for Cooperative two-stage SS at $P_f=0.1$

Figure 4.20 depicts the relationship between detection probability and SNR for cooperative two-stage techniques by setting the probability of false alarm to 0.1 ($P_f = 0.1$), order of entropy to 4 ($\alpha=4$) and number of samples to 1500 ($N=1500$). In addition to this, the simulation result shows the comparison between a single node (i.e. $NU=1$) and a cooperative two-stage technique. The number of collaborating users is 2,3, and 4. The OR rule CSS is used for deciding the final decision of the cooperative approach since it has a higher detection probability compared to the

AND rule. As it can be seen from the figure, the cooperative detection of proposed technique outperforms a single node proposed two-stage technique. For instance, a cooperative two-stage technique with two users can detect a PU signal with an SNR of -25dB and above, while a single node two-stage technique can detect up to -23 dB only. This indicates a 2 dB performance improvements in SNR wall.

4.4.2 ROC curve for Cooperative detection of proposed two-stage technique

Figure 4.21 shows the simulation result of the ROC curve for the cooperative two-stage technique at SNR = -24 dB. As indicated in the figure, the detection probability for the cooperative two-stage technique is greater than the single node technique. In addition to this, the result shows that an increasing number of SU increases the detection probability of the cooperative technique. For instance, at a given probability of false alarm of 0.05 ($P_f = 0.05$), the probability of detection for cooperative two-stage techniques with NU = 2, 3 and 4 is 0.6616, 0.8032 and 0.8855, respectively, while the detection probability for single node (NU=1) two-stage technique is 0.4183. From this result, it can be concluded that the cooperative technique with a higher number of SU has a better detection performance.

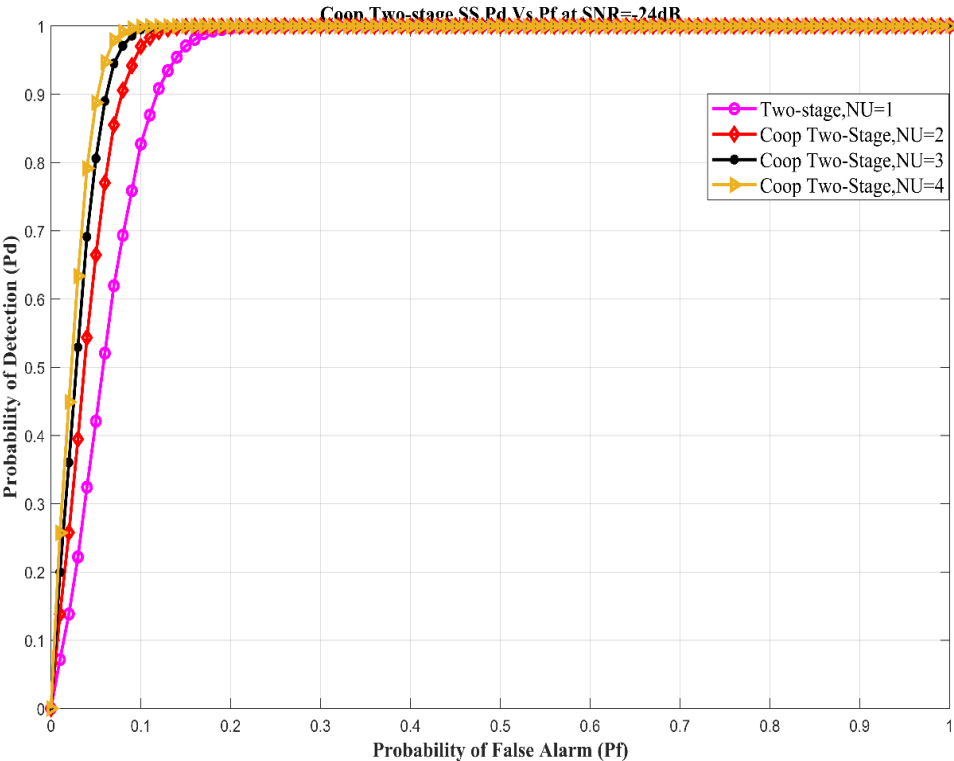


Figure 4. 21: ROC curve for Cooperative two-stage SS at SNR=-24dB

4.4.3 CROC curve for Cooperative detection of proposed two-stage technique

Figure 4.22 shows the simulation result of the CROC curve for cooperative two-stage technique at SNR = -26 dB. As observed from the figure, the cooperative two-stage technique has a lower missed-detection probability compared to single-node two-stage techniques. For instance, at a given probability of false alarm of 0.1 ($P_f = 0.1$), the missed detection probability of the cooperative two-stage technique with 4 number of user is 0.06921, while the single-node two-stage technique has a 0.5129 probability of detection. By comparing this result, the probability of missed-detection for cooperative two-stage techniques is decreased by 86.506% compared to single node two-stage methods. From this result, we can conclude that the cooperative technique has better performance than single-node techniques.

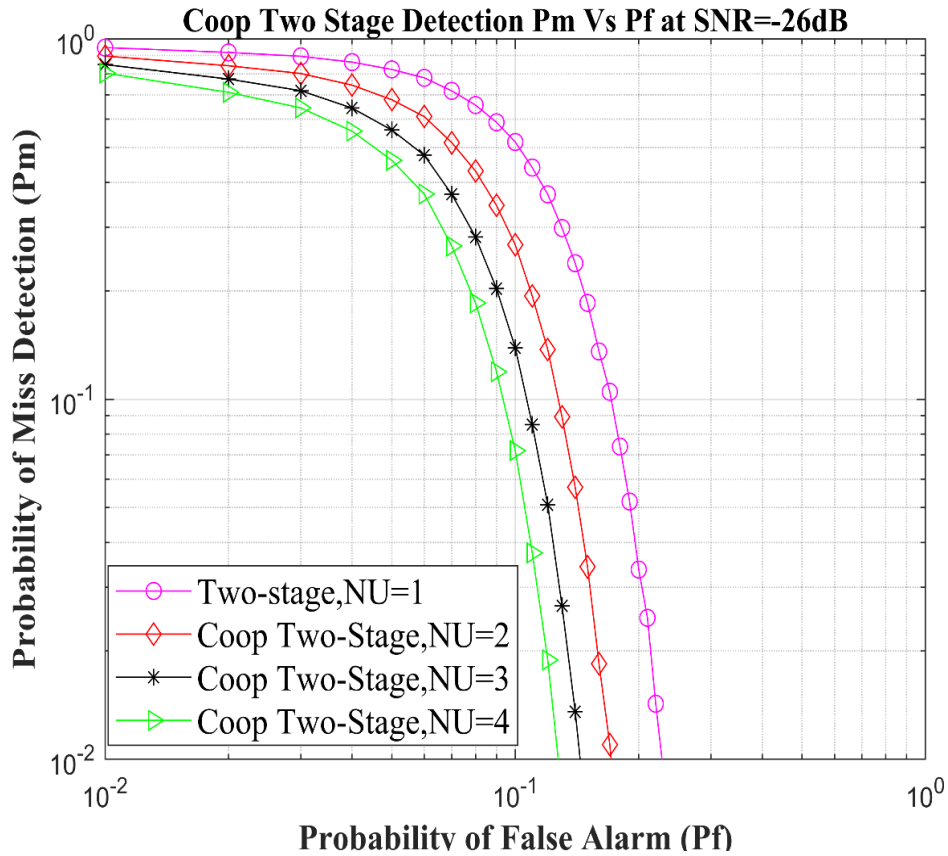


Figure 4. 22: CROC curve for Cooperative two-stage SS at SNR=-26dB

5. CONCLUSION AND RECOMMENDATION

5.1 Conclusion

In this thesis, a two-stage SS scheme for CR has been developed to improve the detection performance. The proposed detector consists of Conventional Energy detection as a coarse stage and Renyi entropy-based detection as a fine stage. The comparison results show that the proposed method outperforms both Renyi entropy and CED with a significant performance improvement. For instance, at a given SNR of -25 dB, the detection probability of the proposed technique is 0.6697 while it is 0.5896 and 0.1952 for renyi entropy and CED, respectively. This indicates that the detection of the proposed technique is improved by 1.14 times compared to Renyi entropy while it is improved by 3.43 times compared to CED. In other words, the proposed two stage technique has a significant improvement of about 15 dB and 0.5 dB in SNR wall when compared to CED and Renyi entropy, respectively.

According to the simulation result, increasing the number of samples improves the detection probability of spectrum sensing. Also, the result shows that the detection probability of the SS technique increases as both SNR and the probability of false alarm increase. In addition, this thesis investigates the performance analysis among four types of entropy detection and the simulation result shows that Renyi entropy is the best one at an entropy order of 4 ($\alpha=4$). Lastly, the cooperative detection of proposed techniques is evaluated using AND fusion and OR fusion rules. The cooperative detection of proposed techniques outperforms a single node proposed two-stage technique by using the OR fusion rule. For instance, a cooperative two-stage technique with 2 users can detect a PU signal with an SNR of -25dB and above, while a single node two-stage technique can detect up to -23 dB only.

Generally, we can conclude that the proposed two-stage technique has a better spectrum sensing performance than both CED and Entropy detection. Depending up on the above view we can say that all objectives of this thesis are achieved.

5.2 Recommendation

In this thesis, the performance of spectrum sensing is evaluated under simulation result only using the MATLAB tools. In the future, the experimental result of spectrum sensing technique should be done using the SDR transceiver such as Universal Software Radio Peripheral (USRP) in real environment and also the signal should be manipulated through GNU radio.

In this thesis, we were assumed that the transmitted signal from PU as a BPSK signal. In the future, the proposed techniques should be evaluated by considering different types of PU signals such as QPSK, M-ary and OFDM signal. Another possibility for future research is to adapt the proposed two-stage SS scheme to analyze its behavior within MIMO detecting circumstances and investigates it is effect on the performance of sensing.

Research Fund Acknowledgment

This research thesis was funded by Adama Science and Technology University under the grant number of ASTU/SM-R/402/22, Adama, Ethiopia.

6. REFERENCES

- A, M., & A, Z. (2012). Energy Detection Technique for Spectrum Sensing in Cognitive Radio: A Survey. *International Journal of Computer Networks & Communications (IJCNC)*, 4(5), 4514. <https://doi.org/10.5121/ijcnc.2012.4514>
- Abdo-tuko, M. (2015). Performance Evaluation and Comparison of Different Transmitter Detection Techniques for Application in Cognitive Radio. *International Journal of Networks and Communications*, 5(5), 83–96. <https://doi.org/10.5923/j.ijnc.20150505.01>
- Abolarinwa, J. A., & Achonu, A. (2013). Cognitive Radio-based Wireless Sensor Networks As Next Generation Sensor Network : Concept , Problems and Prospects. *Journal of Emerging Trends in Computing and Information Sciences*, 4(8), 642–648.
- Akan, O. B., Karli, O. B., & Ergul, O. (2009). Cognitive Radio Sensor Networks. *IEEE Network* •, August, 34–40.
- Akyildiz, I. F., Lee, W., Vuran, M. C., & Mohanty, S. (2006). NeXt generation / dynamic spectrum access / cognitive radio wireless networks : A survey. *Computer Networks*, 50, 2127–2159. <https://doi.org/10.1016/j.comnet.2006.05.001>
- Akyildiz, I. F., Lee, W., Vuran, M. C., & Mohanty, S. (2008). A Survey on Spectrum Management in Cognitive Radio Networks. *IEEE Communications Magazine*, 46(4), 40–48. <https://doi.org/10.1109/MCOM.2008.4481339>
- Akyildiz, I. F., Lo, B. F., & Balakrishnan, R. (2011). Cooperative spectrum sensing in cognitive radio networks : A survey. *Physical Communication*, 4(1), 40–62. <https://doi.org/10.1016/j.phycom.2010.12.003>
- Amor Nafkha, Malek Naoues, Krzysztof Cichon, A. K. (2014). Experimental Spectrum Sensing Measurements using USRP Software Radio Platform and GNU-Radio. *International Conference on Cognitive Radio Oriented Wireless Networks (CROWNCOM)*, 1–6. <https://doi.org/10.4108/icst.crowncom.2014.255415>
- Arjoune, Y., & Kaabouch, N. (2019). A comprehensive survey on spectrum sensing in cognitive radio networks: Recent advances, new challenges, and future research directions. In *Sensors (Switzerland)* (Vol. 19, Issue 1). MDPI AG. <https://doi.org/10.3390/s19010126>
- Arslan, T. Y. and H. (2009). A Survey of Spectrum Sensing Algorithms for Cognitive Radio Applications. *116 IEEE Communications Surveys & Tutorials*, 11(1), 116–130. <https://doi.org/10.1109/SURV.2009.090109>

- Bagwari, A., & Tomar, G. S. (2013). Two-Stage Detectors with Multiple Energy Detectors and Adaptive Double Two-Stage Detectors with Multiple Energy Detectors and. *International Journal Of Distributed Sensor Networks*, 2013(January 2016), 8. <https://doi.org/10.1155/2013/656495>
- Birajdar², M. S. and G. (2011). Spectrum Sensing Techniques in Cognitive Radio Networks: A Survey. *International Journal of Next-Generation Networks (IJNGN)*, 3, No.2. <https://doi.org/10.5121/ijngn.2011.3203>
- Cabric, D., Tkachenko, A., & Brodersen, R. W. (2006). Spectrum Sensing Measurements of Pilot , Energy , and Collaborative Detection. *IEEE Military Communication Conference*, 1–7. <https://doi.org/10.1109/MILCOM.2006.301994>
- Clancy, T. C. (2015). Dynamic Spectrum Access Using the Interference Temperature Model. *Springer: Annals of Telecommunications*, June. <https://doi.org/10.1007/s12243-009-0098-x>
- Definitions, I. S. for. (2019). IEEE Standard for Definitions and Concepts for Dynamic Spectrum Access : Terminology Relating to Emerging Wireless Networks , System Functionality , and Spectrum Management. *IEEE*, 1, 1–15. <https://doi.org/10.1109/IEEESTD.2019.8694195>
- Develi, I. (2020). Spectrum sensing in cognitive radio networks : threshold optimization and analysis. *EURASIP Journal on Wireless Communications and Networking*. <https://doi.org/10.1186/s13638-020-01870-7>
- Digham, F. F., Alouini, M., Member, S., & Simon, M. K. (2007). On the Energy Detection of Unknown Signals Over Fading Channels. *IEEE Transactions on Communications*, 55(1), 21–24.
- Divya Sahithi, A., Lakshmi Priya, E., Ravivek, & Lakshman Pratap, N. (2020). Analysis of energy detection spectrum sensing technique in cognitive radio. *International Journal of Scientific and Technology Research*, 9(1), 1772–1778.
- Dubey, R. K., & Verma, G. (2015). Improved Spectrum Sensing for Cognitive Radio Based on Adaptive Threshold. *Proceedings - 2015 2nd IEEE International Conference on Advances in Computing and Communication Engineering, ICACCE 2015*, 253–256. <https://doi.org/10.1109/ICACCE.2015.70>
- Fawzi, A., El-Shafai, W., Abd-Elnaby, M., Zekry, A., & Abd El-Samie, F. E. (2020). Adaptive

- two-stage spectrum sensing model using energy detection and wavelet denoising for cognitive radio systems. *International Journal of Communication Systems*, 33(16), 1–25. <https://doi.org/10.1002/dac.4400>
- Giweli, N., Shahrestani, S., & Cheung, H. (2016). Selection of spectrum sensing method to enhance QOS in cognitive radio networks. *International Journal of Wireless & Mobile Networks (IJWMN)*, 8(1), 39–50. <https://doi.org/DOI:10.5121/ijwmn.2016.8104>
- Haykin, S. (2005). Cognitive Radio : Brain-Empowered. *IEEE Journal on Selected Areas in Communications*, 23(2), 201–220. <https://doi.org/10.1109/JSAC.2004.839380>
- Heng, X. I. C., & Niversity, G. E. W. A. U. (2012). Dynamic Spectrum Access: From Cognitive Radio to Network Radio. *IEEE Wireless Communications •, February*, 23–29.
- Kumar, V., & Goyel, P. (2013). A Comparative Study of Tsalli ' s and Kapur ' s Entropy in Communication Systems. *International Journal of Computer Applications*, 62(January), 7. <https://doi.org/10.5120/10090-4723>
- Lavate, S. (2017). Transmitter Detection Methods of Spectrum Sensing For Cognitive Radio Networks over Fading Channels. *International Research Journal of Engineering and Technology (IRJET)*, 04(09 | Sep-2017), 912–916.
- Li, D., Xu, Y., Wang, X., & Guizani, M. (2011). Coalitional Game Theoretic Approach for Secondary Spectrum Access in Cooperative Cognitive Radio Networks. *IEEE Transactions On Wireless Communications*, 10(3), 844–856. <https://doi.org/10.1109/TWC.2011.011111.100216>
- Lu, L., Zhou, X., Onunkwo, U., & Li, G. Y. (2012). Ten years of research in spectrum sensing and sharing in cognitive radio. *EURASIP Journal on Wireless Communications and Networking*, 1–16. <https://doi.org/10.1186/1687-1499-2012-28>
- Luo, J., Zhang, G., & Yan, C. (2022). An Energy Detection-Based Spectrum-Sensing Method for Cognitive Radio. *Wireless Communications and Mobile Computing*, 2022, 10.
- MAGUIRE, J. M. 111 A. G. Q. (1999). Cognitive Radio : Making Software Radios More Personal. *IEEE Personal Communication Magazines*, 6(4), 13–18. <https://doi.org/10.1109/98.788210>
- Mahendru, G., Shukla, A., & Banerjee, P. (2020). A Novel Mathematical Model for Energy Detection Based Spectrum Sensing in Cognitive Radio Networks. *Wireless Personal Communications*, 110(3), 1237–1249. <https://doi.org/10.1007/s11277-019-06783-3>
- Manesh, M. R., Apu, S., Kaabouch, N., & Hu, W. (2016). Performance Evaluation of Spectrum

- Sensing Techniques for Cognitive Radio Systems. *In 2016 IEEE 7th Annual Ubiquitous Computing, Electronics & Mobile Communication Conference (UEMCON)*, 1–7.
- Mashta, F., Wainakh, M., & Altabban, W. (2020). Multistage spectrum sensing for cognitive radio using energy and maximum eigenvalues detection. *International Journal of Embedded and Real-Time Communication Systems*, *11*(4), 41–59. <https://doi.org/10.4018/IJERTCS.2020100103>
- Mashta, F., Wainakh, M., & Altabban, W. (2021). An integrated parallel multistage spectrum sensing for cognitive radio. *International Journal of Embedded and Real-Time Communication Systems*, *12*(2), 1–20. <https://doi.org/10.4018/IJERTCS.2021040101>
- Mingchuan, Y., Yuan, L., Xiaofeng, L., & Wenyan, T. (2015). Cyclostationary Feature Detection Based Spectrum Sensing Algorithm under Complicated Electromagnetic Environment in Cognitive Radio Networks. *China Communications*, *12*(9), 35–44. <https://doi.org/10.1109/CC.2015.7275257>
- Muñoz, E. C., Martínez, L. F. P., & Hernandez, C. A. (2020). Rényi Entropy-Based Spectrum Sensing in Mobile Cognitive Radio Networks Using Software Defined Radio. *Journal/Entropy*. <https://doi.org/doi:10.3390/e22060626>
- Nair, P. R., Vinod, A. P., & Krishna, A. K. (2010). An Adaptive Threshold Based Energy Detector for Spectrum Sensing in Cognitive Radios at Low SNR. *IEEE International Conference on Communication Systems*, 574–578. <https://doi.org/10.1109/ICCS.2010.5686712>
- Nair, P. R., Vinod, A. P., & Krishna, A. K. (2011). A Fast Two Stage Detector for Spectrum Sensing in Cognitive Radios. *IEEE Vehicular Technology Conference (VTC Fall)*. <https://doi.org/10.1109/VETEFCF.2011.6092897>
- Nikonowicz, J., Kubczak, P., & Matuszewski, Ł. (2016). Hybrid detection based on (energy and (ntropy \$ nalysis as a 1 ovel \$ pproach for 6 pectrum 6 ensing. *International Conference On Signals And Electronic Systems (ICSES)*, 206–211.
- Padmavathi, G., & Shanmugavel, S. (2015). *Performance Analysis of Cooperative Spectrum Sensing Technique for Low SNR Regime over Fading Channels for Cognitive Radio Networks*. *8*(July), 1–5. <https://doi.org/10.17485/ijst/2015/v8i>
- Patil, H., Nekkanti, S. V., Negi, D., Masanagi, N., & More, S. (2020). Spectrum Sensing Using Energy Detector in Rayleigh Fading Channel. *ITM Web of Conferences*, *02005*, 8–11.
- Prasad, K.-C. C. and R. (2009). *Cognitive Radio Networks* (first edit). John Wiley & Sons Ltd

Registered.

- Prieto, G., Andrade, Á. G., & Martínez, D. M. (2019). Numerical Analysis of Histogram-Based Estimation Techniques for Entropy-Based Spectrum Sensing Numerical Analysis of Histogram-Based Estimation Techniques for Entropy-Based Spectrum Sensing. *IETE Technical Review*, 4602. <https://doi.org/10.1080/02564602.2018.1566029>
- Prieto, G., Andrade, Á. G., Martínez, D. M., & Galaviz, G. (2018). On the Evaluation of an Entropy-Based Spectrum Sensing Strategy Applied to Cognitive Radio Networks. *IEEE Access*, 6, 64828–64835. <https://doi.org/10.1109/ACCESS.2018.2876499>
- Priya, C. G., Sri, S. S., Renganayagi, M., & Varsha, T. M. (2019). Average Information based Spectrum Sensing for Cognitive Radio. *2019 International Conference on Communication and Signal Processing (ICCSP)*, 876–880.
- Rabie Mohamed, A., A. Aziz El-Banna, A., & A. Mansour, H. (2021). Multi-Path Hybrid Spectrum Sensing in Cognitive Radio. *Arabian Journal for Science and Engineering*, 46(10), 9377–9384. <https://doi.org/10.1007/s13369-020-05281-0>
- Reed, J. H., & Ieee, F. (2009). Spectrum Sensing for Cognitive Radio. *Proceedings of the IEEE*, 97(5), 849–877. <https://doi.org/10.1109/JPROC.2009.2015711>
- Rodriguez, J. (2015). *Fundamentals of 5G Mobile Networks Fundamentals of 5G Mobile Networks Edited by* (first edit). John Wiley & Sons, Ltd.,
- Salem, F. M., Ibrahim, M. H., Ali, I. A., & Ibrahim, I. I. (2014). Matched-Filter-based Spectrum Sensing for Secure Cognitive Radio Network Communications. *International Journal of Computer Applications (0975)*, 87(18), 41–46.
- Srinu, S., Sabat, S. L., & Udgata, S. K. (2012). Spectrum sensing using frequency domain entropy estimation and its FPGA implementation for cognitive radio. *Procedia Engineering*, 30(2011), 289–296. <https://doi.org/10.1016/j.proeng.2012.01.863>
- Suhag, C. (2015). Selection of Spectrum Sensing Techniques for. *National System Conference (NSC)*, 39. <https://doi.org/10.1109/NATSYS.2015.7489119>
- Tandra, R., & Sahai, A. (2008). SNR Walls for Signal Detection. *IEEE Journal Of Selected Topics In Signal Processing*, 2(1), 4–17. <https://doi.org/10.1109/JSTSP.2007.914879>
- Tomar, G. S., Bagwari, A., & Kanti, J. (2016). Introduction to cognitive radio networks and applications. In *Introduction to Cognitive Radio Networks and Applications*. <https://doi.org/10.1201/9781315367545>

- Umar, R., & Sheikh, A. U. H. (2012). A comparative study of spectrum awareness techniques for cognitive radio oriented wireless networks. *Physical Communication*. <https://doi.org/10.1016/j.phycom.2012.07.005>
- Vaidehi, G., Swetha, N., & Sastry, P. N. (2015). Entropy based Spectrum Sensing in Cognitive Radio Networks. *International Journal of Advanced Research in Computer and Communication Engineering*, 4(11), 39–43. <https://doi.org/10.17148/IJARCCCE.2015.41110>
- Venkatapathi, P., Khan, H., & Srinivasarao, S. (2019). Performance Analysis of Spectrum Sensing in Cognitive Radio under Low SNR and Noise Floor. *International Journal of Engineering and Advanced Technology*, 9(2), 2655–2661. <https://doi.org/10.35940/ijeat.f8703.129219>
- Verma, P. K., Taluja, S., Rajeshwar, P., & Dua, L. (2012). Performance analysis of Energy detection , Matched filter detection & Cyclostationary feature detection Spectrum Sensing Techniques. *International Journal Of Computational Engineering Research (Ijceronline.Com)*, 2(5), 1296–1301.
- Xuping, Z., & Jianguo, P. (2007). Energy-Detection Based Spectrum Sensing for Cognitive Radio. *IET Conference on Wireless, Mobile and Sensor Networks*, 5–8. <https://doi.org/10.1049/cp:20070306>
- Zhang, T., Yu, G., & Sun, C. (2009). Performance of Cyclostationary Features Based Spectrum Sensing Method in A Multiple Antenna Cognitive Radio System. *IEEE Wireless Communications and Networking Conference*. <https://doi.org/10.1109/WCNC.2009.49178999>
- Zhang, Y. (2008). Dynamic Spectrum Access in Cognitive Radio Wireless Networks. *IEEE Communications Society S*, 4927–4932.
- Zhang, Y. L., Zhang, Q. Y., & Melodia, T. (2010). A Frequency-Domain Entropy-Based Detector for Robust Spectrum Sensing in Cognitive Radio Networks. 14(6), 533–535.

7. APPENDICES

Appendix A: Algorithm of Conventional Energy Detection

Algorithm for Conventional Energy Detection

Inputs: $N=1500$; $\text{snr_db} = -20$ to 0 ; $\text{snr} = 10. \wedge(\text{snr_db./}10)$; $\text{Pf} = 0.1$

Outputs: Decision $\in \{ H_0, H_1 \}$

- 1: Generate modulated waveform of BPSK
- 2: **for** each snr_db value **do**:
- 3: Initialize Detection $\leftarrow 0$
- 4: **for** each trial of Monte-carlo simulation **do**:
- 5: Generate noise signal and BPSK signal
- 6: Generate Received signal as $y = s + n$
- 7: Calculate Energy of received signal
- 8: Calculate Test statistics using Equation (3.5)
- 9: Obtain energy detection threshold using Equation (3.15)
- 10: **if** $T > \lambda_{ED}$
- 11: **THEN** Decision = H_1
- 12: Increment Detection by 1
- 13: **end if**
- 14: **if** $T < \lambda_{ED}$
- 15: **THEN** Decision = H_0
- 16: **end if**
- 17: **end for**
- 18: **end for**

Where N is number of sample, snr_db is SNR value in dB, snr is SNR value in linear scale, Pf is probability of false alarm, y is received signal, s is transmitted signal, n is noise, T is test statistics, λ_{ED} is threshold of energy detection.

Appendix B: Algorithm of Entropy Detection

Algorithm for Entropy Detection

Inputs: $N=1500$; $\text{snr_db} = -30$ to 5 ; $\text{snr} = 10 \cdot 10^{(\text{snr_db}/10)}$; $L = 15$; $a = 4$; $\text{Pf} = 0.1$

Outputs: Decision $\in \{ H_0, H_1 \}$

```
1: Generate modulated waveform of BPSK
2: for each snr_db value do:
3:     Initialize Detection  $\leftarrow 0$ 
4:     for each trial of Monte-carlo simulation do:
5:         Generate noise signal and BPSK signal
6:         Generate Received signal as  $y = s + n$ 
7:         Obtain DFT of received signal
8:         determine spectrum magnitude of the Received signal
9:         do Histogram estimation on spectrum magnitude
10:        obtain Test statistics using Equation (3.18), (3.19), (3.20), and (3.21)
11:        obtain threshold of entropy detection using Equation (3.24)
12:        if  $T < \lambda_{EnD}$ 
13:            THEN Decision =  $H_1$ 
14:            Increment Detection by 1
15:        end if
16:        if  $T > \lambda_{EnD}$ 
17:            THEN Decision =  $H_0$ 
18:        end if
19:    end for
20: end for
```

Where N is number of sample, snr_db is SNR value in dB, snr is SNR value in linear scale, L is the number of bins, a is order of entropy, Pf is probability of false alarm, y is received signal, s is transmitted signal, n is noise, T is test statistics, λ_{EnD} is threshold of entropy detection.

Appendix C: Algorithm of Two-stage spectrum sensing technique

Algorithm for Two-stage Spectrum Sensing Technique (Proposed)

Inputs: $N=1500$; $\text{snr_db} = -30$ to 0 ; $\text{snr} = 10 \cdot 10^{(\text{snr_db}/10)}$; $L = 15$; $a = 4$; $\text{Pf} = 0.1$

Outputs: Decision $\in \{ H_0, H_1 \}$

```
1: Generate modulated waveform of BPSK
2: for each  $\text{snr\_db}$  value do:
3:   Initialize Detection  $\leftarrow 0$ 
4:   for each trial of Monte-carlo simulation do:
5:     Generate noise signal and BPSK signal
6:     Generate Received signal as  $y = s + n$ 
7:     Calculate Energy of received signal
8:     Calculate Test statistics using Equation (3.5)
9:     Obtain threshold of energy detection using Equation (3.15)
10:    Obtain DFT of received signal
11:    determine spectrum magnitude of the Received signal
12:    do Histogram estimation on spectrum magnitude
13:    obtain Test statistics using Equation (3.18), (3.19), (3.20), and (3.21)
14:    obtain threshold of entropy detection using Equation (3.24)
15:    if  $T_{ED} > \lambda_{ED}$ 
16:      THEN Decision =  $H_1$ 
17:      Increment Detection by 1
18:    else if  $T_{ED} < \lambda_{ED}$ 
19:      THEN Decision =  $H_0$ 
20:    if  $T_{EnD} < \lambda_{EnD}$ 
21:      THEN Decision =  $H_1$ 
22:      Increment Detection by 1
23:    else if  $T_{EnD} > \lambda_{EnD}$ 
24:      THEN Decision =  $H_0$ 
25:    end if
26:  end if
27: end for
28: end for
```

Appendix D: Alternative Algorithm for Two-stage spectrum sensing technique

Alternative Algorithm for Two-stage Spectrum Sensing Technique (Proposed)

Inputs: $N=1500$; $\text{snr_db} = -30$ to 0 ; $\text{snr} = 10. \wedge(\text{snr_db./}10)$; $L = 15$; $a = 4$; $\text{Pf} = 0.1$

Outputs: Decision $\in \{ H_0, H_1 \}$

```

1: Generate modulated waveform of BPSK
2: for each snr_db value do:
3:   Initialize Detection_of_energy  $\leftarrow 0$ 
4:   Initialize Detection_of_entropy  $\leftarrow 0$ 
5:   for each trial of Monte-carlo simulation do:
6:     Generate noise signal and BPSK signal
7:     Generate Received signal as  $y = s + n$ 
8:     Calculate Energy of received signal
9:     Calculate Test statistics using Equation (3.5)
10:    Obtain threshold of energy detection using Equation (3.15)
11:    Obtain DFT of received signal
12:    determine spectrum magnitude of the Received signal
13:    do Histogram estimation on spectrum magnitude
14:    obtain Test statistics using Equation (3.18), (3.19), (3.20), and (3.21)
15:    obtain threshold of entropy detection using Equation (3.24)
16:    if  $T_{ED} > \lambda_{ED}$ 
17:      THEN Decision =  $H_1$ 
18:      Increment Detection_of_energy by 1
19:    end if
20:    if  $T_{EnD} < \lambda_{EnD}$ 
21:      THEN Decision =  $H_1$ 
22:      Increment Detection_of_entropy by 1
23:    end if
24:  end for
25:  calculate the overall detection of two-stage SS technique using Equation (3.28)
26: end for

```

Where N is number of sample, snr_db is SNR value in dB, snr is SNR value in linear scale, L is the number of bins, a is order of entropy, Pf is probability of false alarm, y is received signal, s is transmitted signal, n is noise, T_{ED} is test statistics of energy detection, T_{EnD} is the test statistics of entropy detection λ_{ED} is the threshold of energy detection λ_{EnD} is threshold of entropy detection.