Performance Enhancement of Spectrum Sensing for Cognitive Radio Network Using Three-Stage Detection Technique Over AWGN Channel

Megersa Lamesa Hunde

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, 2023

Adama, Ethiopia

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Major Advisor: Dr. Ram sewak Singh

Co-Advisor: Mr. Eshetu Tesema

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APPROVAL PAGE OF M.SC. THESIS

We, the advisors of the thesis entitled "**Performance Enhancement of Spectrum Sensing for Cognitive Radio Network Using Three-Stage Detection Technique Over AWGN Channel**" and developed by **Megersa Lamesa Hunde**, hereby certify that the recommendation and suggestions made by the board of examiners are appropriately incorporated into the final version of the thesis.

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We, the advisors of this thesis, hereby certify that we have read the revised version of the thesis entitled "**Performance Enhancement of Spectrum Sensing for Cognitive Radio Network Using Three-Stage Detection Technique Over AWGN Channel**" prepared under our guidance by **Megersa Lamesa Hunde** 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.

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LIST OF ACRONOMYS

2-stage	Two-stage
ADC	Analog to Digital Converter
AWGN	Additive White Gaussian Noise
AP	Access Point
BPF	Band Pass Filter
BS	Base Station
BTS	Base-station Transceiver System
CAF	Cyclic autocorrelation Function
CD	Cyclostationary Detection
CDMA	Code Division Multiple Access
CED	Conventional Energy Detection
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
ED+KE	Energy Detection and Kapurs Entropy
ED+RE	Energy Detection and Renyi Entropy
ED+KE+RE	Energy Detection, Kapurs and Renyi Entropy
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
KE	Kapurs Entropy
MF	Matched Filter
MFD	Matched Filter Detection

MIMO	Multiple-Input Multiple-Output
MInT	Ministry of Innovation and Technology
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
QPSK	Quadrature Phase Shift Keying
RE	Renyi Entropy
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
Tv	Television

ABSTRACT

The use of wireless communication resources, namely energy and spectrum, has significantly expanded recently. Considering its scarcity and improper, spectrum becomes an even more important and severe resource to deal with. Radio spectrum is one of the world's most extremely regulated and restricted natural resources that has suffered even more limitation due to a rapid increase in the availability of wireless device, which has greatly expanded their applications. According to many studies on static allocation, the licensed spectrum bands are not fully utilized heavily. In order to mitigate incongruity ideas of spectrum scarcity and spectrum underutilization, the Cognitive radio (CR) technology considered as an optimistic solution. In CR, spectrum sensing is a critical step in identifying the spectrum gaps or spectrum holes. To detect whether primary user is present or not, many spectrum sensing techniques such as Energy detection (ED), Entropy detection, Matched filter and Cyclostationary feature detection have been developed. Among those, Energy detection (ED) has public the most observance from researchers due to its fast sensing time, simplicity on implementation and low computational complexity. Nevertheless, due to noise uncertainty problem, the performance of conventional detector is very low at low signal to noise ratio (SNR). In this thesis, three-stage spectrum sensing technique is proposed to improve the performance of single stage and two-stage spectrum sensing techniques and also to overcome the problem occurred due to uncertainty of noise at low SNR values. Furthermore, the performance comparison among three stage, two stage and single stage spectrum sensing techniques are performed over Additive white Gaussian noise (AWGN) channel. The proposed three-stage detection technique has an about 1 dB and 2.5 dB performance improvement as compared to two-stage ED+ Renyi Entropy (RE) and two-stage ED+ Kapurs Entropy (KE) respectively. The cooperative three-stage detection technique using OR rule has an about 4 dB and 5 dB performance improvement as compared to single node and AND rule cooperative spectrum sensing (CSS) technique respectively at NU=5. The parameters like Receiver operating Characteristic (ROC) curve, Complementary ROC (CROC) curve and Probability of Detection (Pd) at various SNR are used to estimate the performance of Spectrum sensing approach.

Keywords: Cognitive Radio (CR), Cooperative Detection, Energy Detection, Kapurs Entropy, Renyi Entropy, Spectrum holes, Spectrum Sensing, Single-Stage, Two-Stage, Three-stage

CHAPTER ONE

INTRODUCTION

1.1 Background of the Study

The need for spectrum resources has grown significantly over the past two decades, particularly in the domain of wireless communication systems to meet the changing demands and requirements of people. Hence, the available radio spectrum is a limited natural resource, a day by day adding of wireless system and network leads us to failure of spectrum resource because of conventional spectrum allocation policy which is known as static allocation. The deficit of radio frequency spectrum, which has yet to be overcome, is one of the most critical challenges at the van of future network research. Traditionally, radio spectrum has been distributed to licensees (Primary user) for lengthy periods of time and is intended to be used solely by licensees. The allocation of spectrum bands to operators is the responsibility of a governmental agency. In utmost of the countries, National regulatory agencies, such as the Federal Dispatches Commission(FCC) in the United States, the Nigerian Communications Commission (NCC) in Nigeria, and National Communications Authority (NCA) in Ghana, are in charge of regulating how the frequency spectrum is utilized, although the Ministry of Innovation and Technology(MInT) is in charge of this activity in Ethiopia.

The Recent statistical research on radio spectrum usage shows that the pre-allocation of spectrum bands to particular wireless communication applications leads to poor spectrum utilization in terms of many dimensions like frequency, time, and geographic space. According to an FCC report, 70% of the allocated PU licensed spectrum band called whitespace/spectrum holes remains unused at any one point of time as shown in the Figure 1.1. In order to solve the impending spectral scarcity and underutilization allocated spectrum, Cognitive radio (CR) has been considered as a promising technology (Srinu et al., 2012),(Sabat et al., 2012).

A crucial technology that enables the sparse and inefficiently used frequency bands to be exploited more effectively with an opportunistic approach is cognitive radio (CR) (Develi, 2020). Also, CR is defined as a wireless communication system, which is intelligently learns and adapts itself according to the environment. There are two types of band one is licensed band and other is unlicensed band. Depending on the priority of accessing licensed band there is two types of user

in Cognitive Radio Network (CRN): Primary Users (PUs) and Secondary Users (SUs), depending on the priority of accessing the licensed band. Users who prioritize using a licensed band are referred to as Primary Users (PUs), whereas users who lower prioritize using a licensed band are called as Secondary Users (SUs) (Dubey & Verma, 2015).

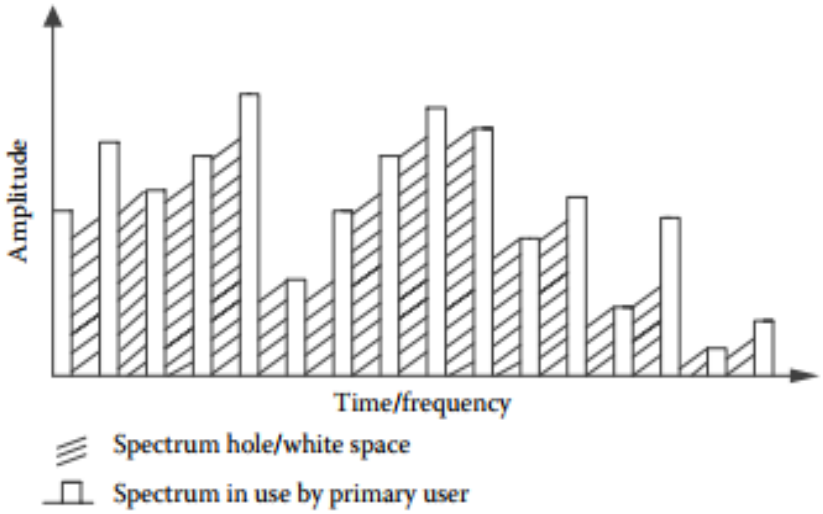

Figure 1. 1: CRN Concepts; Spectrum holes

Generally, CR users must be able to sense all spectrums, choose the best vacant spectrum, communicate selected spectrum information to nearby cognitive users, and ultimately, provide seamless connectivity during data transmission. To sustain such conditions, four basic or fundamental/tasks are required which includes Spectrum Sensing, Spectrum Management/Decision, Spectrum Sharing/Allocation and Spectrum Mobility/Handoff. Spectrum sensing identifies which portion of spectrum are vacant and senses the presence of licensed PUs. It identifies all the possible and available spectrum holes to avoid interference. Spectrum Management captures the best available vacant spectrum holes among the detected ones. Spectrum Sharing aims at distributing the spectrum holes fairly between the SUs. Spectrum Mobility targets to keep communication during the transition to a better spectrum holes (Fawzi et al., 2020),(Tomar et al., 2016).

From all functions given above, Spectrum Sensing is considered as the essential element in the establishment of CR. Over the last decade, a number of spectrum sensing techniques have been proposed which can be classified into two categories based on the bandwidth of spectrum of interest for sensing: Narrowband and Wideband. Narrowband Spectrum Sensing analyzes one

frequency channel at a time while Wideband Spectrum Sensing analyzes a number of frequencies at a time (Arjoune & Kaabouch, 2019). Another way to classify spectrum sensing technique is based on the requiring a prior knowledge of PUs: Coherent and Non-Coherent Detection. In general, we can classify spectrum sensing technique into three different techniques for sensing spectrum holes, as shown in the Figure 1.2.

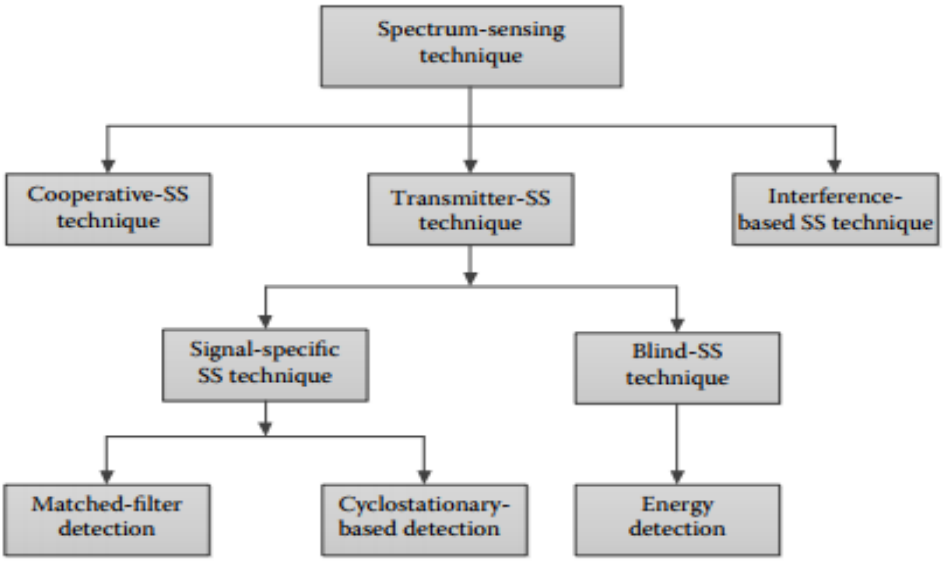

Figure 1. 2: Classification of Spectrum Sensing technique

In this thesis, Energy Detection is generally adopted for Spectrum sensing because it doesn't need a prior information of the primary signal and enjoys low computational and implementation complexities. However, the random and unavoidable variation of the noise present in every wireless communication system, also known as noise uncertainty, significantly reduces the performance of ED, especially when the SNR is low (Prieto et al., 2018). There are many numerous proposed to overcome the challenges of ED. Among those methods Entropy Detection becomes a robust one to the noise uncertainty at low SNR values. Also, its implementation complexity is similar to ED since it does not require any prior knowledge of primary signals. There many types of Entropy Detection (EnD) such as Shannon, Renyi, Kapurs, Tsallis and Escort Tsallis, Entropy. Among these types of entropy detection, Kapurs and Renyi entropy are used for proposed techniques since they have a better spectrum sensing performance compared to others (Usman, Singh, & Rajkumar, 2022).

To further improve the performance of spectrum sensing the three-stage spectrum sensing techniques are developed using the individual advantages of Energy Detection, Kapurs Entropy and Renyi Entropy Detection. ED is used as the Course stage (first stage) for proposed technique, because it performs spectrum sensing within the shortest time and gives a reliable detection at high SNR values while Kapurs Entropy detection detection is used in the alternative stage. However, in the third stage the Renyi Entropy detection method is used due to its robustness to noise query in low SNR value.

1.2 Statement of the Problem

The expanding demand for wireless operation has placed numerous limits on the use of the available radio spectrum, which is a scarce and precious resource. The recent rapid rise of wireless communications has aggravated the problem of spectrum utilization. Furthermore, a fixed spectrum assignment has resulted in spectrum underutilization, as a large amount of licensed spectrum is not adequately exploited. Cognitive radio (CR) has emerged as a result for improving the usage efficiency of the existing electromagnetic spectrum in order to address the issue of spectrum underutilization. Spectrum sensing is a critical task for CR since it aids in the detection of gaps in the spectrum (underutilized frequency bands). There are so many techniques for sensing the spectrum as explained in the background section above. Among those techniques ED method is the simplest and easiest ones. But at low SNR signal, the performance of ED deteriorates rapidly due to noise uncertainty. In order to overcome the problem occurred due to noise uncertainty at low SNR, different types of EnD are introduced in (Usman, Singh, & Rajkumar, 2022). Even though the noise uncertainty problem overcome by entropy detection, the performance of spectrum sensing is very poor below -20 dB. So, to enhance the performance of spectrum sensing at low SNR signal a Three-Stage Spectrum Sensing technique are developed, which consists of ED as a first stage, Kapurs entropy as a second stage and Renyi entropy as a third stage.

1.3 Objectives of the Study

1.3.1 General Objectives

The main goal of this work is to enhance performance of spectrum sensing for Energy Detector (ED) and two-stage SS at low SNR over AWGN channel using Three-stage detection method which is orderly form of Energy Detection, Kapurs Entropy and Renyi Entropy.

1.3.2 Specific Objectives

The following are the precise goals of this thesis proposal:

- To develop three-stage spectrum sensing technique using Energy detection, Kapurs Entropy and Renyi Entropy Detection.
- To enhance the performance of spectrum sensing at low SNR using three-stage technique.
- To compare the performance of proposed three-stage technique with Energy Detection and two-stage techniques in terms of ROC curve, CROC curve and P_d Vs SNR.
- To evaluate the performance of cooperative detection for proposed three-stage SS technique in terms of ROC curve, CROC curve and P_d vs SNR.

1.4 Significance of the Study

There has been a significant increment in the number of devices connected to wireless networks in recent times, which has resulted in a substantial increase in bandwidth demands. As a result, certain bands of the spectrum became moderately scarce. Cognitive radio network (CRN) technology is proposed to address the issue of bandwidth scarcity. As a result, the main significance of this thesis is to use CRN to alleviate bandwidth shortage. The Energy Detection technique is critical for CR since it functions independently without requiring any information from the PU signal and is the simplest to implement. Even so, ED has low spectrum sensing performance at low SNR values due to noise uncertainty. In order to counteract the noise uncertainty problem Entropy detection are proposed in (Usman, Singh, & Rajkumar, 2022). In order to further improve the performance of both single stage ED and two-stage SS, three stage spectrum sensing techniques are proposed. As a result, enhancing the performance of Energy detectors at low SNR especially below -20 dB using three-stage SS method becomes the main significance of the thesis.

1.5 Scope of the Study

This study mainly focuses on enhancing the performance of spectrum sensing technique for cognitive radio networks at low SNR values especially below -20 dB. Single-stage Energy Detection spectrum sensing techniques will be chosen for implementation since it doesn't require prior knowledge of PU. Also, Kapurs entropy detection and Renyi Entropy detection technique will be performed to overcome the problem of performance degradation at low SNR due to noise uncertainty in ED. In addition, 2-stage SS for CRN are performed using ED as a coarse stage and Renyi Entropy Detection as a fine stage. To further improve the performance of spectrum sensing (i.e., single-stage and two-stage), Three-stage SS for CRN are developed using ED as a first stage, Kapurs entropy (KE) detection as a second stage and Renyi Entropy (RE) Detection as a third Stage. Finally, the performance comparison among Single-Stage ED, Two-stage SS and proposed three-stage spectrum sensing over AWGN channel are performed. All simulation of proposed detectors is done using MATLAB software communication tools.

1.6 Thesis Contribution

The major contribution of this thesis are:

- The comparison among single-stage detection techniques such as Energy, Kapurs and Renyi are performed in order to select the best performer one.
- There are two different two-stage SS approaches developed. The first ones developed by using energy detection as a first stage and kapurs entropy as a second stage while the second ones developed using energy detection as a first stage and renyi entropy as a second stage. Additionally, developed two-stage SS method comparison is also carried out.
- The three-stage SS technique is developed using Energy detection, Kapurs entropy and Renyi entropy.

1.7 Limitation of the Study

The results of this thesis are limited to simulation level only.

1.8 Thesis Organization

This thesis has been structured or organized under five chapters.

Chapter 1 briefly discusses the background of the study. The problem statement, scope of the study, significance of the thesis , and thesis's objectives and constraints are also listed. 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 Energy detection (ED), Kapurs entropy (KE), Renyi entropy (RE), two-stage SS techniques and the proposed three-stage spectrum sensing technique.Also, this chapter introduced materials that have been used for simulating the results. Chapter 4 includes the results and discussion for ED, Kapurs entropy, Renyi entropy, two-stage techniques using ED+KE and ED+RE and also the result of proposed three-stage SS technique are presented. In addition to this, the cooperative detection results are presented for Renyi, two-stage ED+RE and three-stage SS. Lastly, the Conclusion and Recommendation of the thesis are presented.

CHAPTER TWO

LITERATURE REVIEW

2.1 Overview of the Chapter

In this chapter, the fundamental concepts of Cognitive Radio Network (CRN), classification of Spectrum Sensing techniques, and the concept of Dynamic Spectrum Allocation (DSA) are discussed and presented, with a view to deepen the understanding. The goal is to first present a broad overview of CR before looking deeply into spectrum sensing methods, primarily those that are the subject of this study. The most current methods for SS that are described in the literature are then focused on, along with research gaps.

2.2 Introduction to Cognitive Radio Network

The word "cognition" refers to the processes of knowing, understanding, and learning about the world around us. As a result, cognitive radio can be defined as a method of becoming familiar with the radio environment's parameters and changing their values to suit the demands of users (Mitola, 2002). According to cognitive theory, secondary users (SU) use unoccupied frequencies in the free spectrum without interfering with authorized users (PU).

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): “With two main goals in mind, an intelligent wireless communication system that is conscious of its environment (the outside world) and uses the method of understanding by building to learn from the environment and adapt its internal states to statistical variations in the incoming RF stimuli through the implementation of corresponding changes in some operating parameters (e.g. transmit power, carrier frequency, and modulating strategy) in real-time”

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

Technically, CR is described as a smart radio that has the ability to sense its environment and adjust its transmission parameters in response to the environment in order to increase spectral efficiency. (Kolodzy, 2005). The CR technology is intended to make it possible to recognize, utilize, and manage vacant spectrum, also referred to as a "Spectrum Hole (Agrawal et al., 2022).

According to (Akyildiz et al., 2006), and the objective of cognitive radio (CR) technology is to increase spectral efficiency using dynamic access by unlicensed users. According to (Akyildiz et al., 2006), and (Hofmeyer et al., 2008) opportunistic spectrum access (OSA) allows for the exploitation of local spectrum availability without negatively affecting the PU. The OSA serves as the cornerstone around which the CR paradigm is formed. With this paradigm, devices would be able to quickly exploit frequency bands that are not currently in use by primary users while causing no harm to the older system by detecting the environment across broad swaths of spectrum to find spectral voids. The secondary user basically locates and utilizes "gaps" in the spectrum, often known as spectrum holes or white spaces.

These spectrum holes result from either completely or partially unoccupied portion of the PU such as Digital TV broadcasters. After the white spaces in the spatio-temporal domain are found, the secondary communication can be carried out (Baldini et al., 2012). Therefore, the purpose of spectrum sensing is to identify the frequencies that the PU occupies in order to be aware of the spatiotemporal electromagnetic environment.

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 Cognitive Radio Network Architecture

CRN architecture includes various heterogeneities in networks. Such diversity may exist within the interconnections of CR terminals, base station (BS) utilities, hardware modules of APs and mobile terminals (MTs), and networking protocols, etc. CR mainly carries out sensing of the spectrum holes and accordingly applies the spectrum reuse. Figure 2.1 shows the modeling of CR architecture. Variety of wireless access technologies are available to be used by terminals and wide range of service providers (Akyildiz et al., 2005). CR technology empowers the users to access the channel anytime, anywhere with tolerable levels of interruptions. Moreover, the system operators are vested with the liability of delivering better services to mobile users. The operators also manage the highly constrained radio resources and other network utilities, necessary for delivering more packets per unit bandwidth in a suitable way (Tabaković, 2011), (Haykin, 2008), (Joshi et al., 2013), (Arshad et al., 2014).

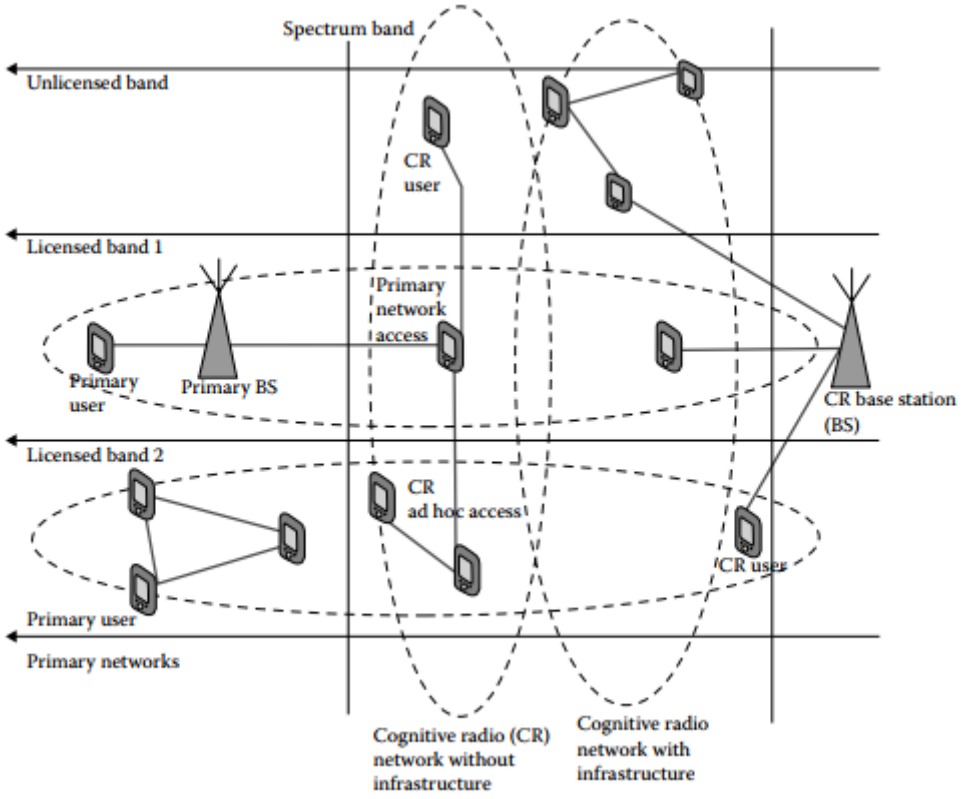

Figure 2. 1: CRN Architecture

CRNs can be designed in three ways to solicit the official as well as unofficial applications. Key constituents of CRNs are MTs, BS/APs, and backbone networks. Three categories of CRNs architecture include infrastructure-based, ad hoc, and mesh architectures. These are described in this section.

2.3.1 Infrastructure Based Architecture

In infrastructure-based architecture, BSs or APs are accessed by MTs either in direct or multihop manner (Figure 2.2). MTs can communicate with other corresponding terminals through the BS within the same transmission range. To meet the demands of MTs, networking protocols are executed by BS/APs at different layers of protocol stack. Routing of packets among different cells is managed by backbone networks to make the communication feasible among MTs belonging to distinct APs. Various application domains and networking systems can be built from the infrastructure-based model.

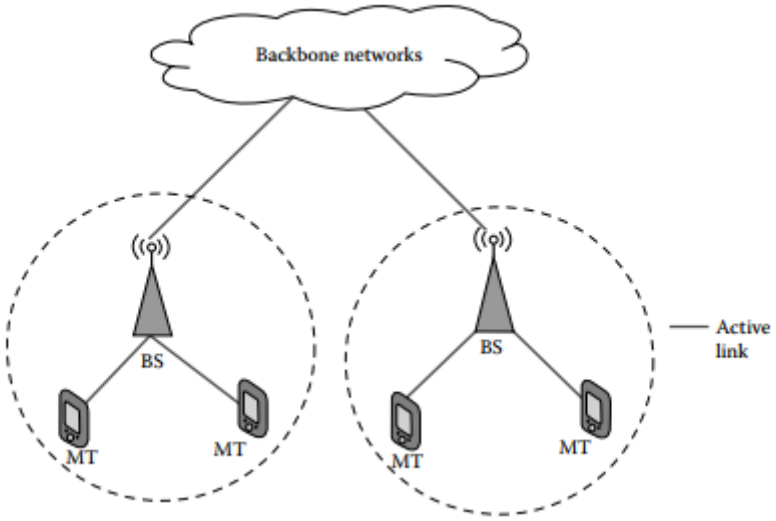

Figure 2. 2: Infrastructure based architecture

2.3.2 Ad Hoc Architecture

Ad hoc architecture is constructed for the special purpose applications where fixed infrastructure is not practical (Figure 2.3). Communication between two or more cognitive terminals is coordinated by several networking protocols and standards, such as Wi-Fi, GSM, Bluetooth, or using spectrum holes dynamically. It is an interconnection of MTs in which if any terminal

perceives signal from the nearby terminal, they can set up a temporary connection with each other by using specific networking technologies.

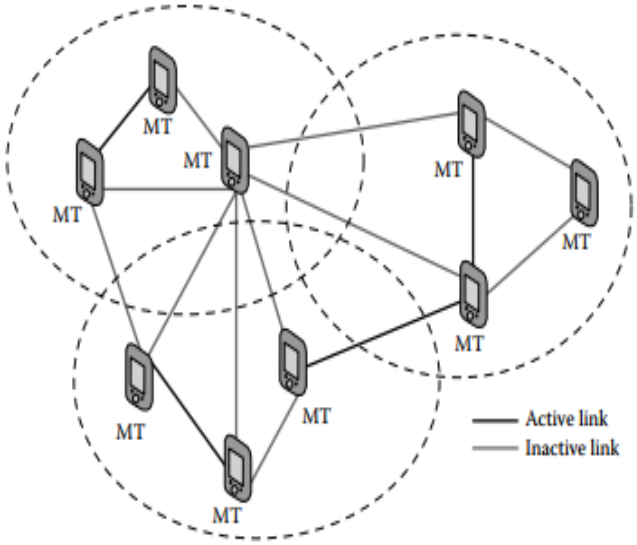

Figure 2. 3: Ad hoc–based architecture.

2.3.3 Mesh Architecture

The combination of both, infrastructure-based and ad hoc–based architectures, is referred to as the mesh architecture (Figure 2.4). It allows wireless connection among MTs, APs, and BSs. Each terminal acts as a transmitter as well as a router to manage the packet forwarding. Therefore, MTs can approach the BS/APs directly or by relaying via intermediate terminals in multiple hops. Moreover, BS/APs often work as gateways to connect the wireless and wired backbone networks together. Therefore, it becomes more cost effective and reliable with improved architectural setup compared to the infrastructure- and ad hoc– based setups. BS/Aps perceive spectrum holes for communicating with each other. They possess cognitive potentiality so that the spectrum holes can be used to fulfill demands of MTs and serve as a wireless backbone.

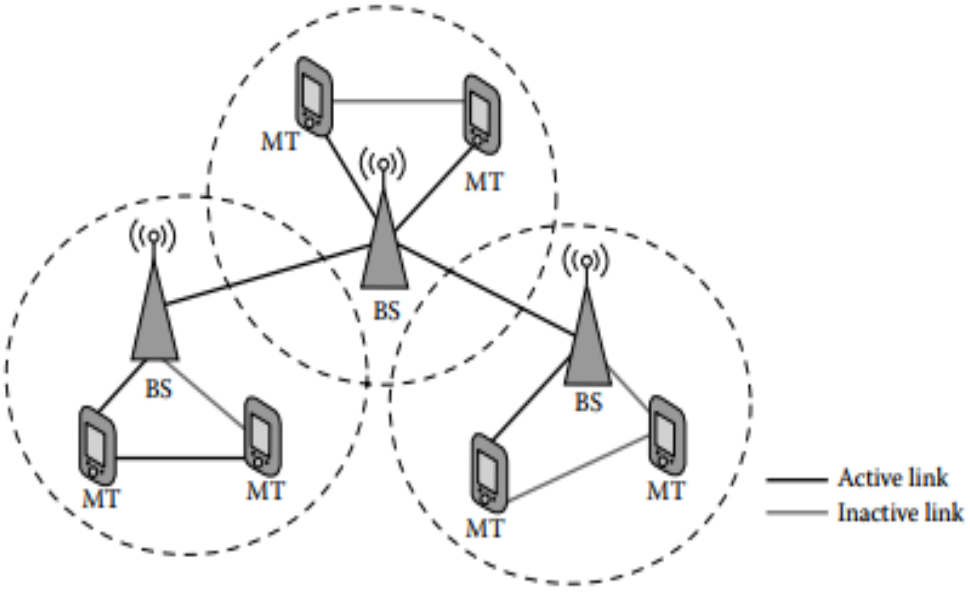

Figure 2. 4: Mesh architecture.

2.4 Spectrum Sensing (SS) Techniques

SS is the process of detecting the presence or absence of a signal in a particular interest of frequency band. It is an essential function in CR systems, which aim to efficiently utilize the available radio spectrum. Recently, research is focusing on the development of tools and methodologies that make it possible to exploit underutilized spectrum resources in the time, frequency, and spatial domains, as shown in Figure 2.5, to meet the spectrum demands for emerging wireless technologies and applications.

For locating spectrum opportunities in a scanned frequency range, several approaches have been put forth (. i.e. a number of techniques has been suggested or proposed for sensing the spectrums). Spectrum sensing is typically divided into three basic detection methods, as depicted in Figure 2.6, namely transmitter-based detection methods, cooperative detection methods, and interference-based methods.

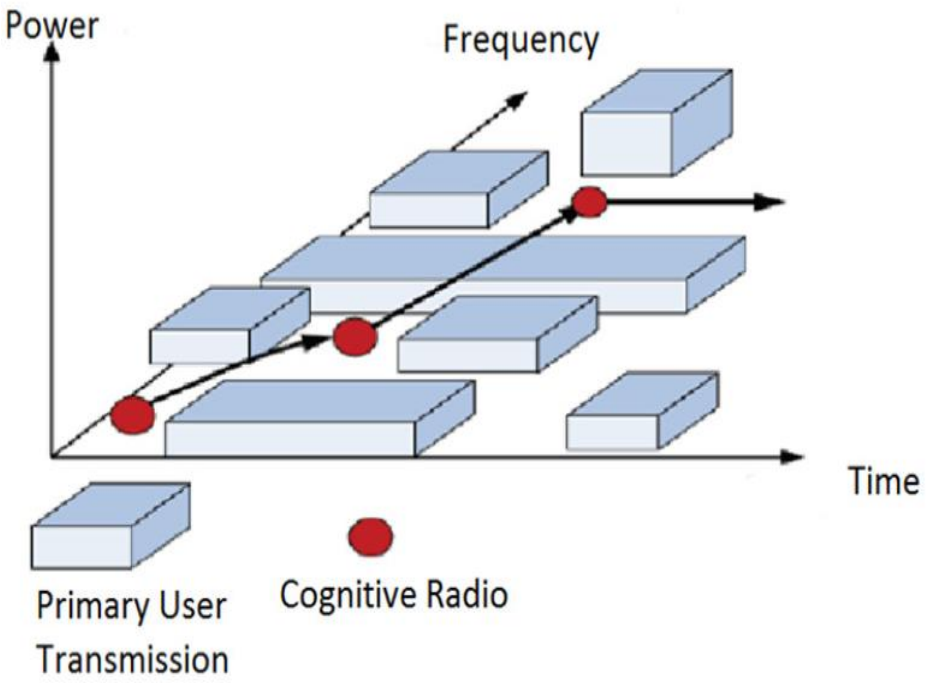

Figure 2. 5: Examples of Illustration of spectrum opportunities in the time and frequency domains (Yadav & Rathi, 2011a)

Transmitter detection methods consist of matched filter (MF), cyclostationary feature (CF) and energy detection (ED) (Umar & Sheikh, 2012). According to some other authors or papers these techniques also includes Entropy detection, Eigen value based detection, wavelet detection, covariance based detection and so on. According to (Tabassam et al., 2011), this techniques can also be further divided into coherent, semi-coherent, or non-coherent categories depending on whether they have full, partial, or no prior knowledge of the broadcaster or transmitter. Centralized, distributed, and cluster/relay assisted based sensing techniques are examples of cooperative detection techniques. Whereas cooperative detection and transmitter approaches "perceive" the spectrum to avoid interfering with primary transmitters, interference-based detection ensures that primary receiver interference is kept to a minimum (Perera & Herath, 2011). The classification of SS techniques is detailed in Figure 2.6. Spectrum overlay refers to the transmitter and cooperative detection strategies, where SUs only transmit across the licensed spectrum when PUs are not using the band.

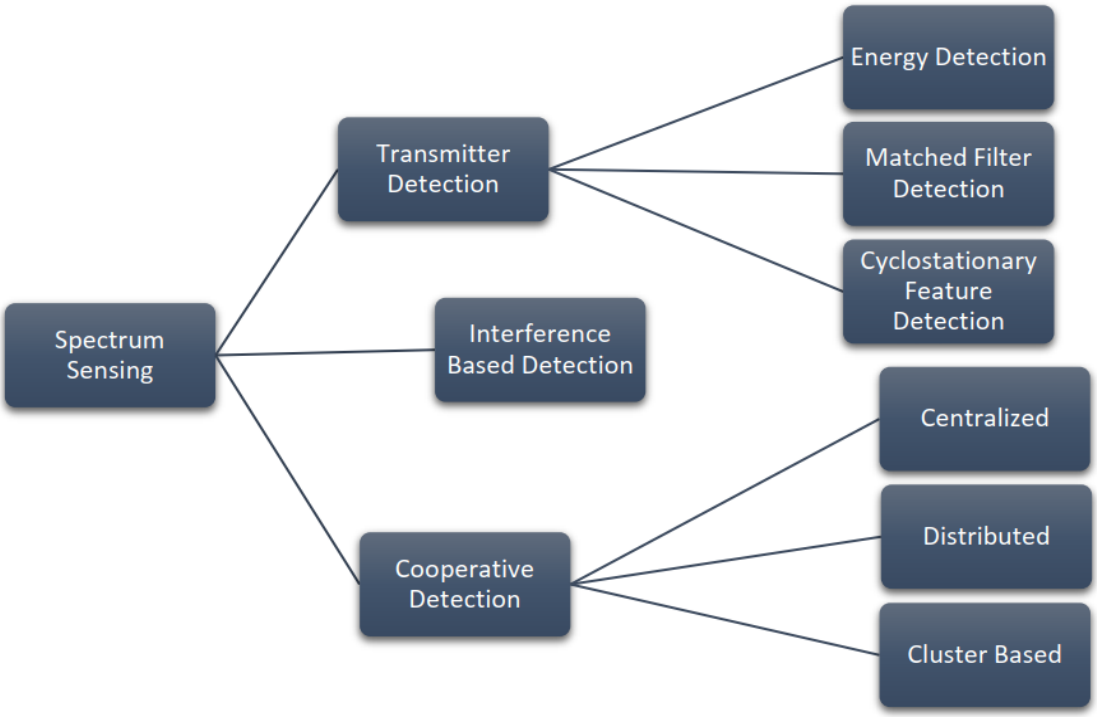

Figure 2. 6: Classification of Spectrum Sensing Techniques

2.4.1 Transmitter Detection

This method is the simplest and most popular way to identify a PU over the operating frequency range (Yadav & Rathi, 2011b). It may be deployed with a minimal system requirements and infrastructure costs. his type of detection technique, however, is lacking in intelligent awareness of the existence of principal users. As a result, the PU is identified using the signal that was received at the end of the SU. The secondary user (SU) determines whether or not the primary user is present by measuring the system energy (CR) level and looking for the presence of a spectrum hole in the system. Based on a binary hypothesis model, the absence or presence of PU is decided. (Yadav & Rathi, 2011b), (Axell et al., 2010), (A Michael Oyibo et al., n.d.).

Detecting the primary receiver within the operational range of a SU is an effective strategy for identifying spectrum opportunities with minimal infrastructure requirements. However, in practice, this is not possible because the SU is not intelligent enough to find a receiver. Hence, spectrum sensing methods rely on detecting the primary transmitter (Umar & Sheikh, 2012). By doing this, a primary user transmitter is identified based on the signal received at the secondary user end. The analysis of the signal received at the secondary user is represented by the primary transmitter detection model. The basic idea is to use nearby data and observations to identify

primary transmitters that are active at a specific period. In order to take use of the empty holes (whitespace) within the channel, the SU uses these techniques to analyze the signal intensity produced by the PU.

Transmitter-based detection, also known as noon-cooperative spectrum sensing, is a technique used in CR systems to improve the spectrum sensing accuracy. Here are some commonly used transmitter based detection SS (spectrum sensing) techniques:

Energy Detection: it is a most common technique used in SS. SUs measures the energy levels in the interest band of frequency and compare it to a predefined threshold. When the measured energy exceeds the threshold, it indicates the presence of a PU.

Matched Filter Detection: it is a technique where SUs correlate received signals with known waveform templates of the PU signals. If the correlation output exceeds a certain threshold, it indicates the presence of the PU signal.

Cyclostationary Feature Detection: it exploits the cyclostationary properties of the PU signals, which arise due to their periodic nature. SUs perform spectral analysis to detect specific cyclic features in the received signals, indicating the presence of PUs.

Covariance-based detection: it involves analyzing the statistical properties of received signals. SUs estimate the covariance matrix of the received signals and compare it to a predefined threshold. Deviations from the expected covariance structure indicates the presence of the PU.

Pilot-based detection: in pilot based detection, PUs periodically transmit pilot signals known to the SUs. SUs exploit these known pilot signals to estimate the channel characteristics. Deviations in the estimated channel parameters indicate the presence of PUs.

The detection techniques that listed above are discussed and explained in details in the below sections.

2.4.1.1 Energy Detection (ED)

Energy Detection is also known as Radiometry. It is a popular spectrum sensing technique used to detect the presence of primary users (PUs) in a frequency band. It is a non-coherent detection method that uses the basic principles of signal detection method. It involves measuring the energy levels of the received signals and comparing them to a predefined threshold. If the measured energy

exceeds the threshold, it indicates the presence of a PU, unless otherwise it indicates the absence of PU.

In ED techniques, the measurement of the signal energy level in the particular interest of frequency band during a given time period serves as the basis for the PU transmission detection. The signal is precisely determined by comparing the output energy of the ED to an acceptable predefined threshold established based on the noise floor (Suseela & Sivakumar, 2015). There are no channel gains, additional parameter estimates, or requirements for prior knowledge of the primary signal for ED. Due to its minimal complexity and cost, ED SS is thus very attractive than other detection methods (Atapattu et al., 2014).

The energy detection concept is predicated on the assumption that the energy level of the signal is always greater than the energy level of the noise. The detection threshold value, sample count, and estimated noise power are the three main variables used in the energy detection technique, it should be noted. The analogue and digital energy detectors, shown in Figure 2.7, are the two models for the energy detector that are theoretically employed in time domain applications. The pre-filter is the first component of the analogue energy detector, which is then followed by a square law device and a finite time integrator. Pre-filters have two functions: band-limiting noise bandwidth and normalizing noise variance. A low pass noise pre-filter, an ADC, a square law device, and a finite integrator comprise the digital ED.

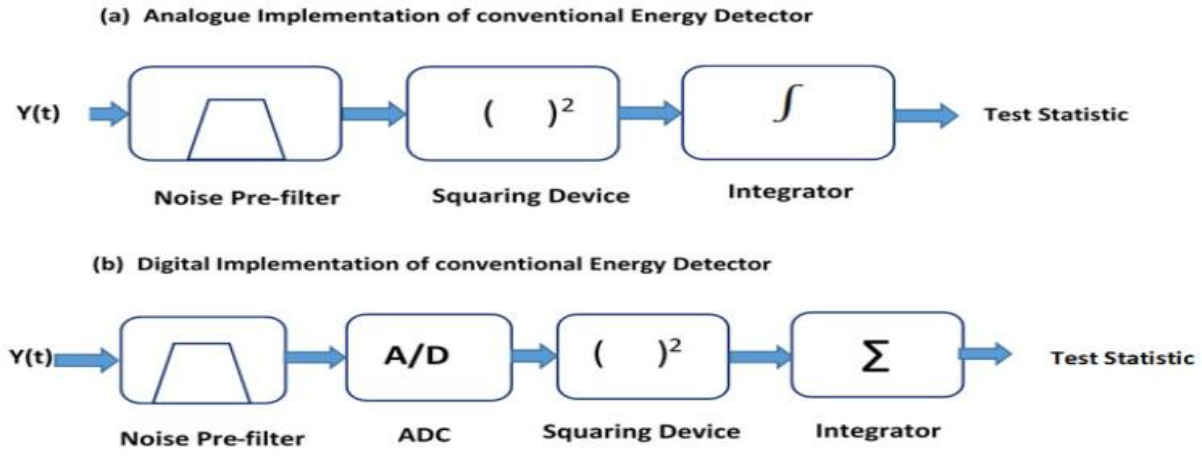

Figure 2. 7: Implementation of CED in Analog and Digital.

Here are some energy detection techniques commonly employed:

1. Fixed Threshold Energy Detection: In this technique, a fixed threshold is set based on the noise floor or the desired detection probability. The received signal's energy is compared to this threshold. If the energy is above the threshold, it is considered as a PU present, otherwise, it is considered as PU absent.
2. Adaptive Threshold Energy Detection: Adaptive threshold techniques dynamically adjust the detection threshold based on the current noise level. This technique accounts for variations in the noise floor, interference, and fading conditions. It provides better adaptability to changing environments.
3. Multiband Energy Detection: In scenarios where multiple frequency bands are of interest, multiband energy detection is employed. It involves performing energy detection independently in each frequency band. The presence of a PU is detected if the energy in any of the bands exceeds the threshold.
4. Cooperative Energy Detection: Cooperative spectrum sensing combines the energy measurements from multiple secondary users (SUs) to improve detection performance. SUs exchange their energy measurements and combine them using techniques like majority voting or weighted averaging. Cooperation mitigates individual detection errors and enhances the overall accuracy.
5. Multiple Antenna Energy Detection: Multiple antennas can be used at the receiver to improve energy detection. By exploiting spatial diversity, the received signal's energy is measured and combined from different antenna elements. This technique helps combat fading and improves detection performance.
6. Sensing Duration Optimization: Energy detection requires a specific sensing duration to accumulate enough samples for accurate energy measurement. Optimizing the sensing duration involves balancing the trade-off between detection performance and sensing overhead. Techniques such as sequential sensing and adaptive sensing duration can be employed to optimize the detection performance.

2.4.1.2 Matched Filter Detection

In the presence of additive Gaussian noise, a matched filter (MF) increases the SNR of the received signal, making it the best detection technique. A matching filter, however, necessitates a priori knowledge of the PU signal at SUs, including information on waveform, pulse shaping, modulation type, code, and packet structure. Accordingly, the MF mechanism is a kind of feature based spectrum sensing. In this scenario, the MF is the optimal detector which maximizes the SNR in the presence of AWGN. Even so, its computational complexity is intolerable high while its performance decreases as the channel response changes snappily, i.e., under short coherence time in fading channels scenarios. The ability to detect the presence of an MF is made possible by correlating a known signal with an unknown signal. Convolution of the unknown signal with a time-reversed version of the presumptive signal is what this amounts to. To determine if the PU signal is present or not, the output of an MF is then compared to a threshold. In operation, a Matched Filter convolves the received signal r(t) with a time-reversed interpretation 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.

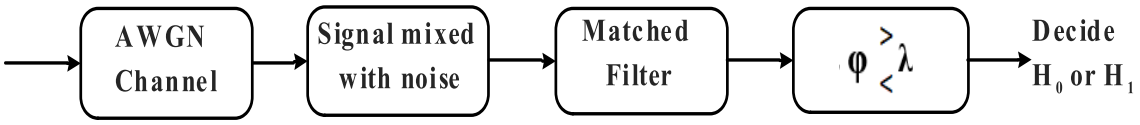

Figure 2. 8: Block diagram of Matched filter detection (Usman, Singh, & Rajkumar, 2022)

The operation of matched filter can be expressed as (Usman, Singh, & Rajkumar, 2022), (Salem et al., 2014)

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

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):

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

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

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):

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

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

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

Matched filter detection is a spectrum sensing technique used to detect the presence of specific signals or waveforms in a received signal. It relies on correlating the received signal with a known waveform template, known as the matched filter, to maximize the detection performance. Here's how matched filter detection works:

1. Matched Filter Design: The first step in MF detection is designing the MF. The MF is designed to have a response that is an exact replica of the desired signal waveform. It is typically created by time-reversing and conjugating the desired signal waveform. The MF is designed to maximize the SNR at its output.
2. Correlation Operation: Once the matched filter is designed, it is applied to the received signal through a correlation operation. The received signal is convolved with the matched filter, which involves sliding the filter over the received signal and computing the inner product at each point.
3. Threshold Comparison: The output of the correlation operation is compared to a predefined threshold. If the correlation output exceeds the threshold, it indicates the presence of the

desired signal or waveform. If the correlation output is below the threshold, it suggests the absence of the desired signal.

4. Detection Decision: Based on the threshold comparison, a detection decision is made. If the correlation output is above the threshold, the presence of the desired signal is detected. Otherwise, it is considered as the absence of the desired signal.

Matched filter detection is particularly effective when the received signal is corrupted by additive white Gaussian noise (AWGN) and when the desired signal waveform is known precisely. It provides optimal detection performance when the received signal matches the waveform used to design the matched filter. 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).

Matched filter detection is commonly used in applications such as radar systems, communication systems, and acoustic signal processing. It is especially useful in scenarios where the desired signal has a known structure or a specific waveform, allowing for efficient detection and demodulation.

2.4.1.3 Cyclostationary Feature Detection (CFD)

CFD is a spectrum sensing technique that exploits the cyclostationary properties of signals to detect the presence of primary users (PUs) in a frequency band. Cyclostationary signals are those that exhibit statistical properties that vary periodically with time, making them distinguishable from stationary signals.

The cyclic spectral correlation function (SCF) is used in CFD detection technique to detect the presence of a PU signals in the system (Gardner & Spooner, 1992). The cyclostationary signals exhibit periodic statistics as well as spectral correlation. 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. A block diagram of the CFD technique is shown in Figure 2.9.

Figure 2. 9: block diagram of CFD

If a zero mean continuous time signal x(t) meets the following requirements, it is said to be wide sense cyclostationary (Mingchuan et al., 2015), (Zhang et al., 2009):

$$\mathrm{m_x}(t) = E[x(t)] = \mathrm{m_x}(t + m\mathrm{T_0}) \tag{2.7}$$

$$\mathrm{R_x}(t,\tau) = \mathrm{m_x}(t + \mathrm{T_0},\tau) \tag{2.8}$$

Where $\mathrm{T_0}$ denotes the signals period, τ represents the time offset, E(.) is the signal mean, whereas $\mathrm{R_x}(t,\tau)$ denotes the autocorrelation function of x(t).

CFD technique can be performed as follows. First, one calculate the cyclic autocorrelation function (CAF) of the observed signal x(t), $\mathrm{R_x^{\alpha}}(\tau)$, as (Mingchuan et al., 2015), (Zhang et al., 2009):

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

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

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

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

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

where

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

The cyclic spectrum, which is a two-dimensional function in terms of frequency and cyclic frequency, is another name for the spectral correlation function $S_x^{\alpha}(f)$. We also point out that, for α =0, the power spectrum density (PSD) is a specific instance (. i.e. special case) of the spectral correlation function.

Here's how cyclostationary feature detection works:

1. Cyclostationary Property: Cyclostationary signals have statistical properties that exhibit periodicity with respect to time. This periodicity is reflected in their power spectral density (PSD), which contains distinct peaks or spectral lines at specific frequencies or offsets.
2. Spectral Analysis: In CFD, the received signal is analyzed to identify these spectral lines or cyclic features. The analysis is typically performed using methods such as the cyclic autocorrelation function (CAF), cyclic spectrum, or higher-order cyclic moments.
3. Feature Extraction: The goal of spectral analysis is to extract cyclostationary features that indicate the presence of PUs. These features can include cyclic autocorrelation peaks, cyclic spectra peaks, or higher-order cyclic moments. These features are often concentrated at specific offsets or frequencies, corresponding to the cyclostationary characteristics of the PU signals.
4. Threshold Comparison: The extracted cyclostationary features are compared to predefined thresholds. If the features exceed the thresholds, it indicates the presence of PUs. Otherwise, it suggests the absence of PUs.
5. Detection Decision: Based on the threshold comparison, a detection decision is made. If the extracted cyclostationary features exceed the thresholds, the presence of PUs is detected. Otherwise, it is considered as the absence of PUs.

Cyclostationary feature detection is particularly useful when the PU signals exhibit cyclostationary behavior, such as modulated signals with periodic properties. It provides improved detection performance compared to energy detection in scenarios where the noise and interference characteristics are not well-defined or exhibit non-Gaussian properties.

Cyclostationary feature detection has been employed in cognitive radio systems, spectrum sensing for dynamic spectrum access, and interference identification in communication systems. It enables efficient utilization of the spectrum by detecting and identifying signals with cyclostationary properties.

2.4.1.4 Covariance-based Detection

Covariance-based detection, also known as statistical-based detection, is a spectrum sensing technique that utilizes the statistical properties of received signals to detect the presence of PUs in a particular band of frequency. This method involves analyzing the covariance matrix of the received signals to extract relevant information for detection. Here's how covariance-based detection works:

- Covariance Matrix Estimation: The first step in covariance-based detection is to estimate the covariance matrix of the received signals. The covariance matrix represents the statistical relationships and correlations between different samples or antennas in the received signal. The estimation can be performed using techniques such as sample covariance estimation or maximum likelihood estimation.
- Covariance Matrix Analysis: Once the covariance matrix is estimated, it is analyzed to extract features that can indicate the presence of PUs. Various statistical measures or parameters can be derived from the covariance matrix, such as eigenvalues, eigenvectors, determinant, trace, or signal-to-noise ratio (SNR) estimates.
- Threshold Comparison: The extracted features from the covariance matrix are compared to predefined thresholds. If the features exceed the thresholds, it suggests the presence of PUs. Otherwise, it indicates the absence of PUs.
- Detection Decision: Based on the threshold comparison, a detection decision is made. If the extracted features from the covariance matrix exceed the thresholds, the presence of PUs is detected. Otherwise, it is considered as the absence of PUs.

Covariance-based detection can be advantageous in scenarios where the noise and interference characteristics are not well-defined or exhibit non-Gaussian properties. By exploiting the statistical properties of the received signals, covariance-based detection can provide robust detection performance.

This technique is often used in scenarios with multiple antennas, such as in MIMO (Multiple-Input Multiple-Output) systems or cooperative sensing setups. By considering the covariance matrix of the received signals from multiple antennas, spatial diversity can be exploited to improve detection accuracy.

Covariance-based detection is commonly employed in CR systems, where SUs need to reliably detect and utilize spectrum opportunities without causing interference to primary users. It provides an alternative to energy detection and can offer improved performance in certain scenarios.

2.4.1.5 Pilot-based Detection

Pilot-based detection is a spectrum sensing technique that relies on the transmission of known pilot signals by primary users (PUs) to aid in the detection of their presence in a frequency band. It involves the use of these pilot signals to estimate the channel characteristics and make decisions regarding the presence or absence of PUs. Here's how pilot-based detection works:

1. Pilot Signal Transmission: Primary users periodically transmit pilot signals that are known to both the primary and secondary users. These pilot signals serve as reference signals and are typically designed to have specific properties for efficient detection and estimation.
2. Channel Estimation: Secondary users receive the transmitted pilot signals and utilize them to estimate the characteristics of the channel between the primary and secondary users. Channel estimation techniques, such as least squares estimation or maximum likelihood estimation, are employed to obtain an accurate estimate of the channel response.
3. Hypothesis Testing: The estimated channel characteristics are used to formulate hypotheses regarding the presence or absence of primary users. Statistical tests, such as likelihood ratio tests or Neyman-Pearson tests, are often used to make decisions based on the received pilot signals and the estimated channel.
4. Threshold Comparison: The test statistics obtained from the hypothesis testing stage are compared to predefined thresholds. If the test statistics exceed the thresholds, it suggests the presence of PUs. Conversely, if the test statistics are below the thresholds, it indicates the absence of PUs.
5. Detection Decision: Based on the threshold comparison, a detection decision is made. If the test statistics exceed the thresholds, the presence of PUs is detected. Otherwise, it is considered as the absence of PUs.

Pilot-based detection offers advantages in scenarios where the channel characteristics between primary and secondary users can be estimated reliably using the transmitted pilot signals. By exploiting the known reference signals, it can provide more accurate detection compared to techniques that rely solely on received signals and their statistical properties.

This technique is commonly used in wireless communication systems, such as cellular networks, where pilot signals are regularly transmitted for channel estimation and synchronization purposes. In cognitive radio systems, pilot-based detection enables SUs to identify and utilize spectrum opportunities by leveraging the known pilot signals transmitted by primary users.

2.5 Comparison of SS Approaches

Figure 2.10 shows a comparison of various SS approaches. It can be inferred that waveform-based sensing approach is more robust when compared to both energy detector and cyclostationary-based sensing as it involves coherent processing using a deterministic signal component. However, it requires prior information about the characteristics of the PU in the form of pilot or pattern which adds complexity to the sensing module. The performance of energy detector–based sensing is not promising when noise is not stationary and its variance is not known. Further, the effects of baseband filter and spurious tones also influence the performance degradation. From the literature (Sutton et al., 2007), it is observed that cyclostationary-based approach performance may be worse when compared to energy detector–based sensing, whenever noise happens to be stationary.

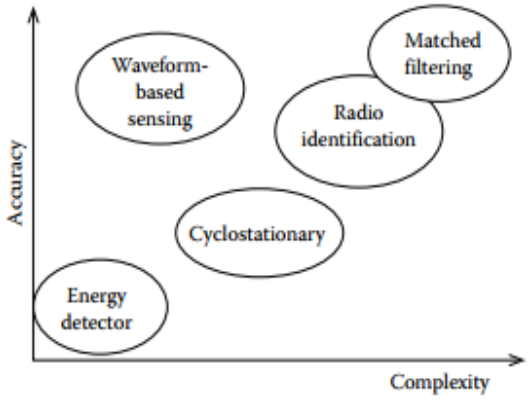

Figure 2. 10: Comparison of various SS approaches

However, noise becomes nonstationary in the presence of co-channel or adjacent channel interferers. Under these circumstances the energy detector–based sensing approach fails, while the cyclostationary-based approach is not affected. On the other hand, cyclostationary features may be completely lost due to channel fading (Sutton et al., 2007). Hence certain trade-offs need to be considered while selecting an SS approach. The characteristics of the PUs are found to be a major design factor in selecting an SS approach. Other factors include required accuracy, sensing duration requirements, computational complexity, and network requirements.

2.6 Interference based spectrum sensing techniques

CRs concentrate on estimating the interference at the receiver terminal in this method. FCC presented a new model of calculating interference mentioned as interference temperature. The interference temperature limit, or the most additional interference that the receiver can tolerate, is the basis for how the suggested model handles interference at the receiver. The model provides an upper limit on the total amount of RF energy that can be accumulated through multiple transmissions. The usage of a specific spectrum band is permitted for CR users as long as their transmissions stay within this restriction. The major problem of the proposed model is that the CR users should know the exact location of the nearby PUs, otherwise it is difficult to measure the interference. The licensed users of the spectrum bands are occasionally denied access by the CR users. This occurs if the transmitting power of a CR is more than the transmitting power of licensed users, and licensed users exist near the CR users. This is a major issue with this model.

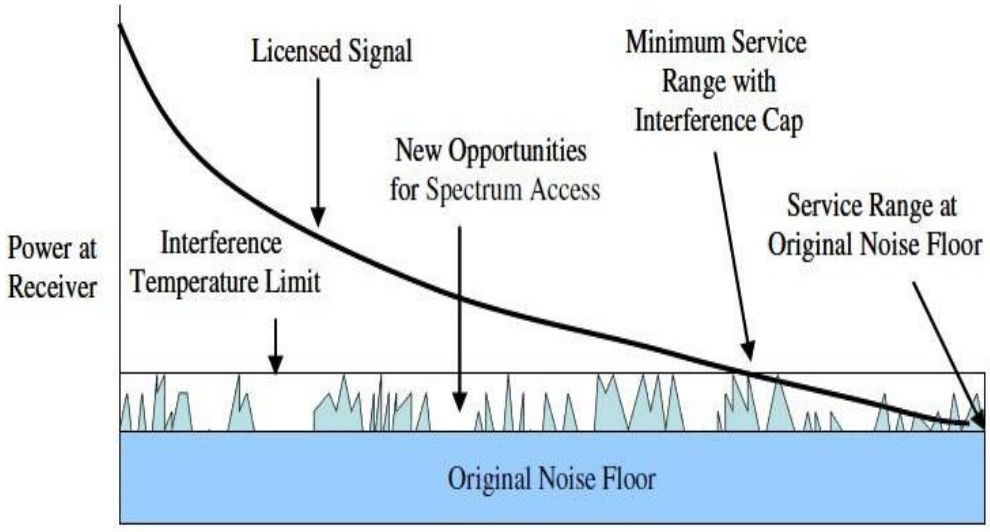

Figure 2. 11: interference temperature Management (Birajdar2, 2011), (Akyildiz et al., 2006)

2.7 Issues in Cognitive Radio Networks

CRNs are a future-based wireless communication technology with various challenges or issues. We are addressing a few significant issues in this part, which are summarized as follows.

2.7.1 Spectrum-Sensing Failure Problem

In the ED-based SS technique, noise uncertainty (Song et al., 2010) makes the perfect threshold level for CR difficult to be set due to which SS reliability reduces (Lee & Akyildiz, 2008). Furthermore, performance of fixed threshold (λ_i)-based ED might dramatically deviate from the desirable targeted performance metrics under low SNRs, hence this may not be the best option.

Figure 2.12 illustrates the signals' power level on the x-axis and their probability on the y-axis. Both the PU signal and noise are represented by two curves. If the two signals are kept apart, the CRN scheme states that it is relatively simple to distinguish between PU and noise. For instance, if ED receives a PU signal, it displays H1, indicating that the channel is occupied, and if it receives a noise signal, it displays H0, indicating that the channel is vacant. It is extremely challenging to detect desirable signals when the PU signal and noise intersect one other. The confused zone in Figure 2.12 refers to the area between the PU and noise curve, or between the upper bound (1) and lower bound (2), where a single threshold is not a successful way to detect a PU signal.

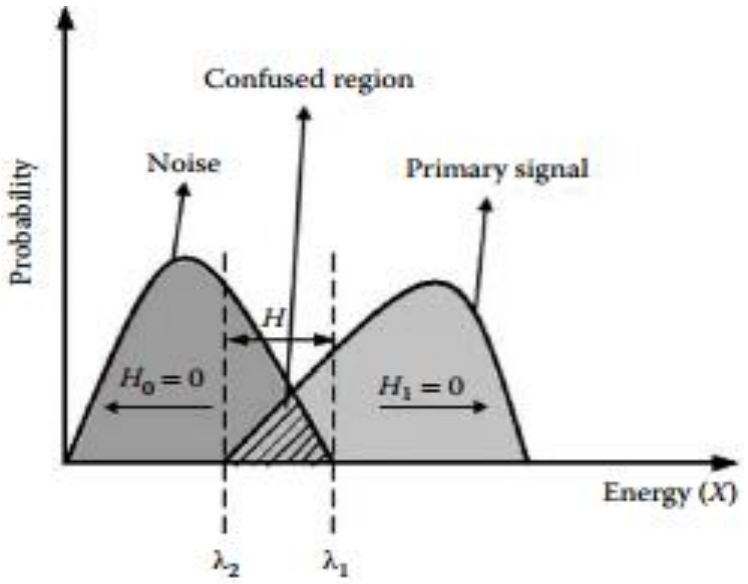

Figure 2. 12: Energy distribution of primary user's signal and noise

2.7.2 Fading and Shadowing Problem

Multipath fading and shadowing is one of the reasons of increasing hidden node problem in carrier sense multiple accessing (CSMA). Figure 2.13 expresses the hidden node problem, where dashed circles indicate the operating ranges of the PU transmitter and the CR. The CR user is not able to sense the PU transmitter signal because of the location of node and creates unwanted interference to the PU receiver.

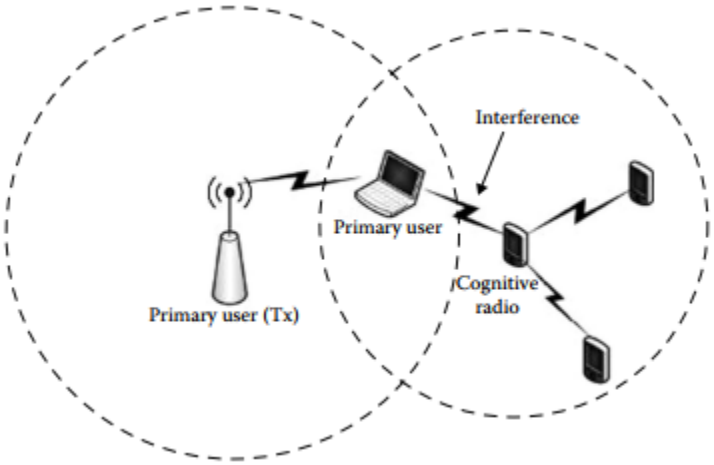

Figure 2. 13: Hidden primary user's problem in CRNs. Tx, transmitter.

2.7.3 Spectrum-Sensing Time

The SS time details the overall amount of time the CR user spent looking for a PU signal. Assume that by lengthening the SS duration, PU may make greater use of its spectrum and that a limit is set beyond which CR cannot continuously interfere. If the SS is high, more PUs will be found, resulting in lower levels of interference. The number of samples received by the CR user determines the sensing time. This situation is known as the sensing effectiveness problem because more time is spent on sensing and less on data transmissions. (Lee & Akyildiz, 2008), (Liang et al., 2008).

2.8 Cooperative Spectrum Sensing Techniques

In this technique, a group of cognitive radios (SUs) share sensing information with each other to enhance the sensing accuracy. In this process, a group of SUs collect the channel occupancy information and represent it as a spectrum map. This information is then periodically transmitted to the central coordinator which determines the set of available ultra-high frequency channels by performing a bitwise-OR operation on the spectrum maps. Then the best available channel is

selected and broadcasted back to the SU. This technique exploits the spatial diversity intrinsic to a multi-user network. It can be accomplished in a centralized or distributed fashion (Sharan & Wankhede, 2013). Cooperative SS adopts three approaches, namely centralized, distributed, and relay-assisted cooperative.

Centralized Approach

In this approach, the fusion center (FC) or central processor node collects sensing information from all the SU radios that are within its coverage, as shown in Figure 2.14. Based on the analyses performed over them, the optimal frequency of operation for the SU can be determined (Cabric et al., 2004).

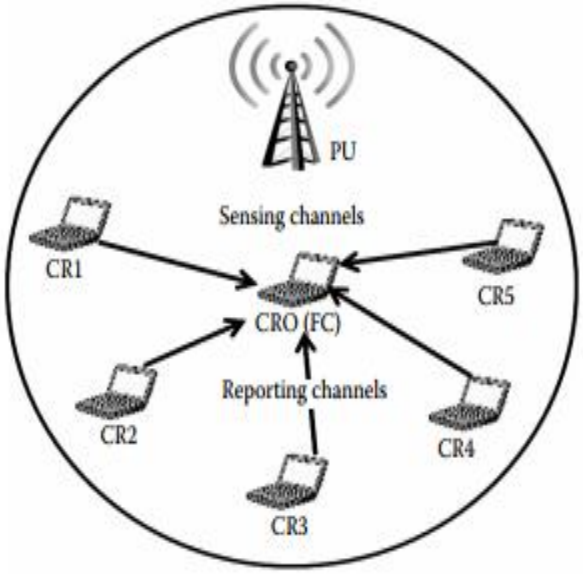

Figure 2. 14: Centralized Approach

Distributed Approach

In this approach, the fusion center (FC) or central processor node collects sensing information from all the SU radios that are within its coverage, as shown in Figure 2.15. Based on the analyses performed over them, the optimal frequency of operation for the SU can be determined (Cabric et al., 2004).

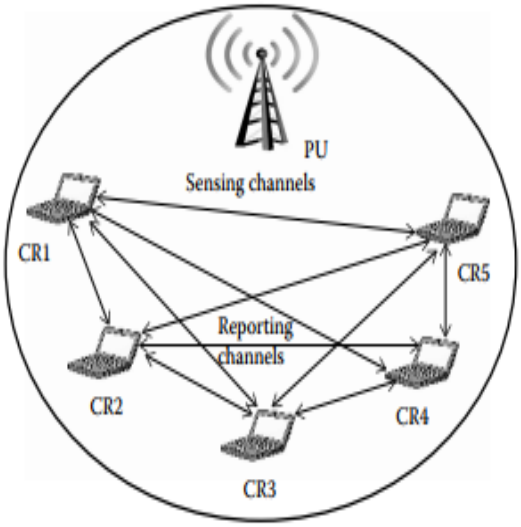

Figure 2. 15: Distributed Approach

Relay-Assisted Approach

In this approach, relay cognitive radios are used between the SU and FC to mitigate the effect of fading in the wireless medium, as shown in Figure 2.16. This enhances the accuracy of SS.

Procedure involved in the cooperative sensing. Cooperative sensing consists of two phases such as detection of PUs and reporting them to the FC.

- Detection of PU: In this phase, the SU attempts to detect primary unused channel.
- Reporting: In this phase, the detected information is reported to the FC for processing.

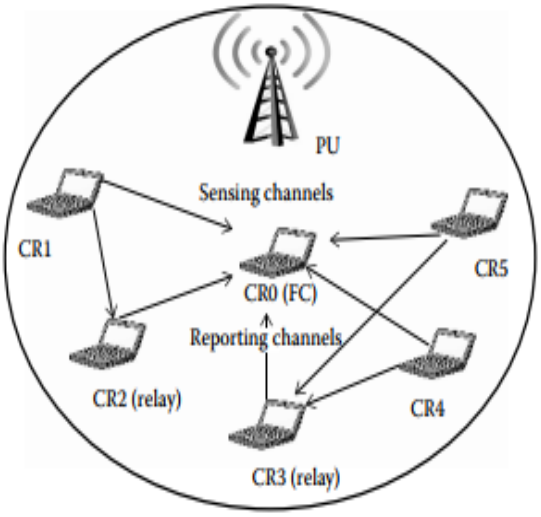

Figure 2. 16: Relay-Assisted Approach

2.9 Previous Related Works

In (Usman, Singh, & Rajkumar, 2022), the study entitled stage SS technique for CRN using ED and EnD detection are presented in well manner. In this paper, different types of entropy method such as shannon, tsallis, kapurs (KE) and renyi entropy (RE) are presented to counteract the noise uncertainity problem that is occurred at low SNR values. Furthermore, 2-stage spectrum sensing techniques which consists of ED as first-stage and RE detection as second-stage are introduced in this study to improve the performance of detection technique for CRN. However, at low SNR values, particularly below -20 dB, the of proposed approach performs poorly.

In (Usman, Singh, Mishra, et al., 2022), the study entitled improving SS for CRN using the ED with entropy detection is discussed in detail. In this paper, a new hybrid spectrum sensing technique is proposed using conventional energy detection and the Gaussian entropy method. The authors in this study tried to overcome the poor performance of CED at low SNR values. The study's suggested technique outperformed ED at -18 dB by 18.5%, as illustrated in the results. However, the achieved result is not good enough to perfectly decide the presence of a PU signal in the given band. In other words, the achieved result is still below the required probability of detection (Pd should be greater than equal to 0.9 i.e. $Pd \geq 0.9$).

In (Rabie Mohamed et al., 2021), a hybrid sensing model for SS in CR is proposed to improve sensing efficiency of traditional techniques of spectrum sensing, which consists of two cognate 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 PU subsistence. However, Computational complexity of this paper become high since it uses an eigenvalue detector.

A brand-new parallel totally blind multistage detector is suggested in (Mashta et al., 2021). On the basis of the estimated SNR value obtained from the SNR estimator, applicable phases are carried out. Due to its ease of use and delicate sensing at high SNR, ED is used in the initial stage. For advanced stages, a maximum eigenvalue detector approach with various smoothing factors is used for low SNR. With an increase in the smoothing factor, the maximum eigenvalue detector's sensing

accuracy rises. Additionally, they examined the effectiveness of the proposed detector's two two-stage and three-stage scenarios. However, the employment of eigenvalue detectors and an increase in the smoothing factor causes the computing complexity at the advanced phases to rise.

In (Develi, 2020), a new threshold determination system based on online literacy algorithm was proposed to increase SS performance of sensing method and to minimize the total error probability. For optimum decision threshold online learning algorithm are used, which is the most important parameter to decide the presence or absence of the PU signal using historical detection data. Matched filter and Energy detection SS methods are discussed in details. And also, the performance of proposed detector is evaluated under non-fading and fading environments for low SNR. However, in this paper the historical detection data are used which may be difficult to available for online literacy.

The investigation of the ED SS technique in CR is reported in (Divya Sahithi et al., 2020). The idea of many sorts of spectrum sensing techniques is fully presented, along with their mathematical and theoretical formulations. Energy Detection concept, one of the spectrum sensing techniques, is used to identify the unutilized bands of the spectrum and make them accessible for reuse. We can identify the white spaces in the spectrum using this idea and allocate them to secondary users. This research does an excellent job of analyzing energy detection methods; however, it falls short when it comes to picking up Primary User (PU) signals in low SNR scenarios.

An adaptive two-stage SS model for CR systems is proposed (Fawzi et al., 2020), by integrating two effective techniques: energy detection and wavelet denoising. By comparing the energy of the received signal with a threshold value, the energy detection technique is used in this study to decide the presence of PU signal in the situation of high SNR values. However, in cases of low SNR values, wavelet denoising is employed to reduce the noise effect and detect the PU signal in the presence of noise before the ED.

Numerical Analysis of Histogram-Based Estimation Techniques for EnD SS is proposed in (Prieto et al., 2019). In this study, it was suggested to use spectrum detection based on EnD to detect PU signals in CRN. Entropy was estimated or calculated using the histogram approach. The performance or effectiveness of the Entropy-based detection is assessed in relation to several rules for determining the number of bins in the histogram.. Furthermore, it has been shown that the probability distribution of the PU signal causes the detection performance for each of the

aforementioned rules to differ. This paper's primary focus is solely on selecting the right number of bins. But the hottest research areas right now in the field of CRs are enhancing spectrum sensing performance.

A novel mathematical method to determine the best sensing time (number of samples) for an ED technique is proposed (Mahendru et al., 2020). The primary goal of this study is to determine the ideal sample size in the presence of noise uncertainty while keeping the sensing performance metrics within pre-defined levels. he impact of noise uncertainty on the quantity of sensed samples has been examined, and a novel method for achieving the necessary performance in terms of P_{fa} and P_d has been provided (Mahendru et al., 2020).

To get over the drawbacks of single stage detectors and utilize the benefits of each detector in each stage, a novel fully blind sequential multistage SS detector had been developed in (Mashta et al., 2020). This paper proposes a three-stage SS using ED and maximum eigenvalue detector. ED is utilized in the coarse-stage (first-stage) due to its simplicity. The maximum eigenvalues detector is used in the second and third stages, each with a unique smoothing factor. However, since the maximum eigenvalue detector is used inside a proposed three stage techniques, the overall computational complexity of the proposed systems become high.

CHAPTER THREE

METHODOLOGY AND SYSTEM MODEL

3.1 Framework of Research Methodology

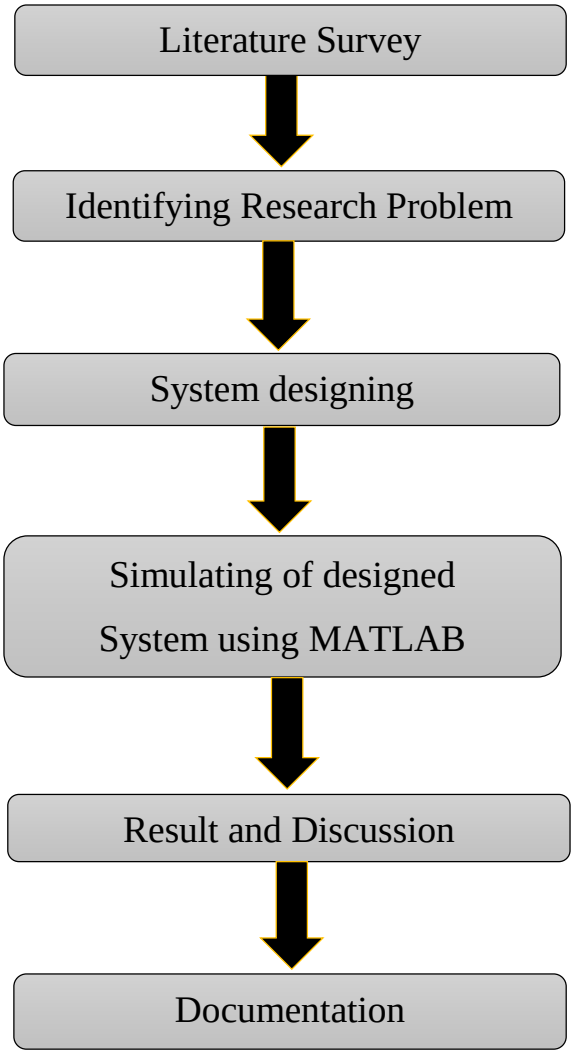

Figure 3. 1: Methodology

- **Literature Review:** This study's work must rely on previous research that has been conducted on the chosen topic by other academics. So, looking into the works of these scholars and obtaining relevant information is crucial to understanding the subject. Different literatures will be reviewed from different available sources such as books, papers, journals, internet, etc. Therefore, literature review will therefore involve reading books, articles, papers, journals, simulation tools, and internet searches relating to ED, EnD, and two-stage SS for cognitive radio network.
- **Problem Identification:** Based on the paper reviewed from different journals, articles and related books the problems are identified for research study.
- **System Designing:** After the identification of research gap, systems will be designed for proposed work.
- **Simulating designed system using MATLAB:** After modeling of the proposed system the simulations are done using MATLAB tools.
- **Result and Discussion:** Depending up on the results from simulation, discussions will be performed on the results and performance evaluation are also done on proposed technique.
- **Documentation:** Upon analysis the results of developed system, every aspect of research study is concluded by suggesting implied recommendation and further work to be done on the areas.

3.2 System Model for Spectrum Sensing

To enable SUs to effectively access and utilize the available unused spectrum, CRNs use spectrum sensing to identify whether the licensed PU is present or missing in a particular channel. Signal detection is a well-known method that is used in spectrum sensing. Methods for signal detection are employed to locate signals in noisy environments. Signal detection can be reduced analytically to a straightforward identification issue that can be expressed as a hypothesis test (Abdo-tuko, 2015). In the detection theory, spectrum sensing can typically be treated as the following binary hypothesis problem:

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

Where n=1,2,3…N is the number of samples of the received sampled signal, y(n) is the received sample signal by the SU, w(n) is the additive white Gaussian noise with zero mean and variance σ_w^2, s(n) is the signal from PU with zero mean and variance σ_s^2, h is the channel gain between PU transmitter and SU receiver since we use AWGN channel h=1. H_0 and H_1represents 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.

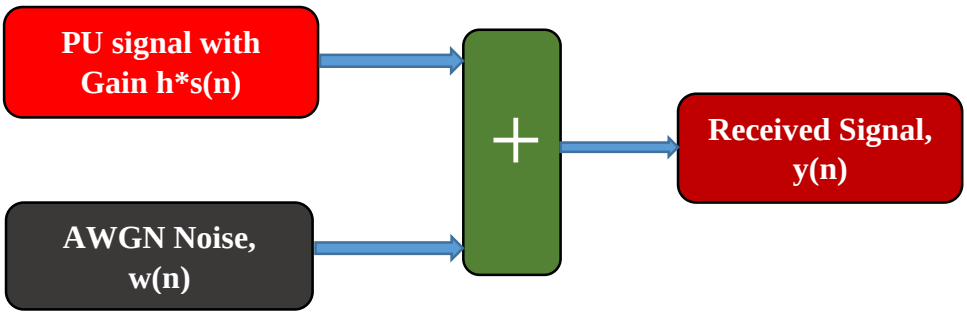

Figure 3. 2: Signal Model representation

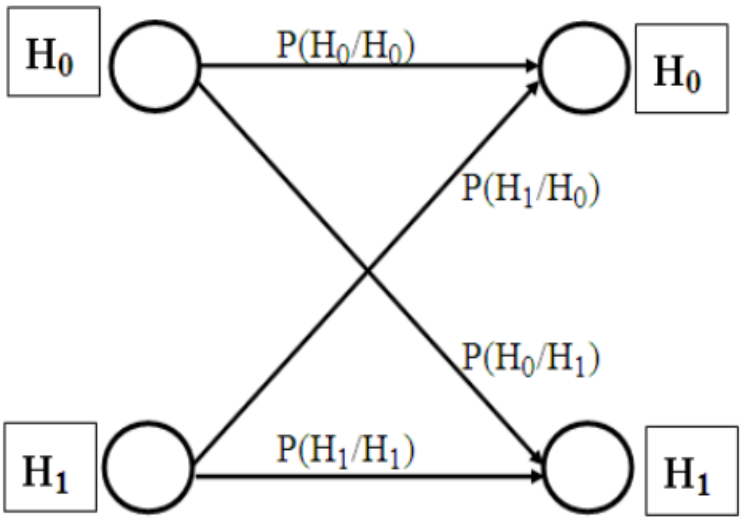

Figure 3. 3: Hypothesis test and possible outcomes with their corresponding probabilities

As seen in the Figure 3.3**,** we can define four possible cases for the detected signal:

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

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

$$P_d = p(H_1/H_1) \quad \text{(3.2)}$$

$$P_m = 1 - P_d = p(H_0/H_1) \quad \text{(3.3)}$$

$$P_f = p(H_1/H_0) \quad \text{(3.4)}$$

Thus the P_d is the probability to decide $H_1$when $H_1$is true and the P_m is the probability to decide $H_0$when H_1 is true. The P_f is the probability to decide $H_1$when H_0 is true.

A summary diagram of the signal detector for spectrum sensing technique is shown in the Figure3.4 below.

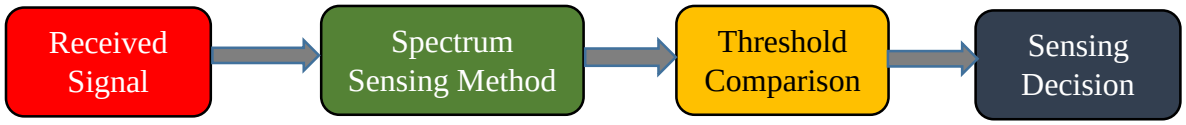

Figure 3. 4: General Model of Spectrum Sensing

3.2.1 System Model of Energy Detection Technique

Energy detection is the most extensively habituated system because of it has low complexity and it doesn't need any prior information of 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. Among detection techniques of spectrum sensing, energy detection is used in this thesis to increase spectrum sensing performance at low SNR values.

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 also passed through ADC converter. The ADC is then squared and integrated over a predefined time interval. The attendant signal is used to formulate a

test statistic (Develi, 2020). Finally, formulated test statistics is compared with a threshold 'λ', to determine whether the licensed user is present or not.

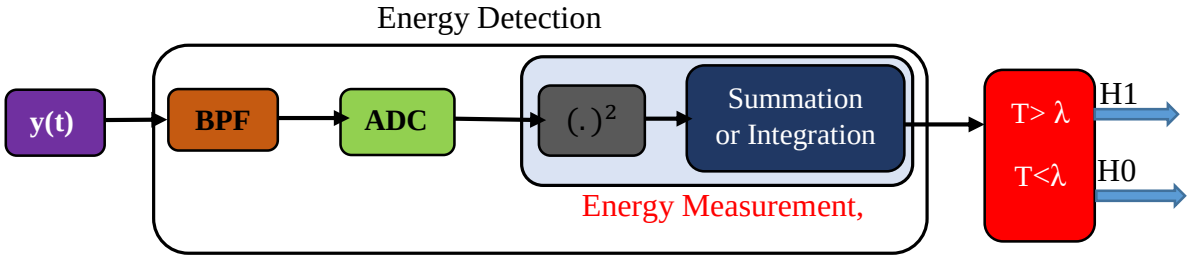

Figure 3. 5: Block Diagram of Energy Detection

In energy detection technique, energy of the received signal is compared with the detection threshold to decide whether PU is active or not. Test statistics for energy detection is given as:

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

In the absence of coherent detection, the signal samples S(n) can be modelled as a Gaussian random process with variance σ_s^2. So y[n] is also a Gaussian random process. It can be show that in the low SNR regime, the number of required samples N is large. By central limit theorem the test statistics can be approximated as a Gaussian distribution.

$$H_0: \quad T \sim Normal(N\sigma_w^2, 2N\sigma_w^4) \quad \text{..... (3.6)}$$

$$H_1: T \sim Normal(N(\sigma_w^2 + \sigma_x^2), 2N(\sigma_w^2 + \sigma_s^2)^2) \quad \text{..... (3.7)}$$

The performance of detection is measured by two parameters P_d and P_f. Each pair is associated with a particular threshold λ that test the decision statistics:

$$P_d = P(T > \lambda / H_1) = Q\left(\frac{\lambda - N(\sigma_w^2 + \sigma_s^2)}{\sqrt{2N(\sigma_w^2 + \sigma_s^2)^2}}\right) \quad \text{..... (3.8)}$$

$$P_f = P(T > \lambda / H_0) = Q\left(\frac{\lambda - N\sigma_w^2}{\sqrt{2N\sigma_w^4}}\right) \quad \text{..... (3.9)}$$

Where

$$Q(x) = \frac{1}{\sqrt{2\pi}} \int_{x}^{\infty} \exp\left(\frac{-y^2}{2}\right) dy \quad \text{..... (3.10)}$$

Where Q(x) is Q-function.

The detection threshold can be given as

$$\lambda = \sigma_w^2[\sqrt{2N}Q^{-1}(P_f) + N] \quad \text{..... (3.11)}$$

3.2.2 System Model of Entropy Detection Technique

The Figure 3.6 below shown the basic block diagram of Entropy based detector. After applying DFT to a binary hypothesis given in equation (3.1), we obtain:

$$\vec{y}(k) = \vec{w}(k) \quad \text{..... (3.12)}$$

$$\vec{y}(k) = \vec{s}(k) + \vec{w}(k) \quad \text{..... (3.13)}$$

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

Numerous methods have been suggested for estimating the entropy of random variable based on finite number of observations. Given its reduced complexity, in this thesis histogram based entropy estimation is considered.

The histogram of data set $y = \{y_0, y_1, y_2, \dots, y_{N-1}\}$ is obtained by dividing the ranges of $(y_{max} - y_{min})$ of values in y into L bins with constant width A. let n_k be the number of elements in y falling inside the k-th bin such that $\sum_{k=1}^{L} n_k = N$ (Prieto et al., 2018),(Prieto et al., 2019),(Vaidehi et al., 2015). Once the histogram is constructed the entropy, denoted H, is estimated as follows

The Renyi Entropy expressed as

$$H_R = \frac{1}{1-\alpha} \log\left(\sum_{k=1}^{L} P_k^{\alpha}\right) \quad \text{..... (3.14)}$$

The Kapurs Entropy expressed as

$$H_K = \frac{1-\left(\sum_{k=1}^{n} P_k^{\frac{1}{\alpha}}\right)^{\alpha}}{1-\alpha} \quad \text{..... (3.15)}$$

Where α is the order of entropy and p_k is the frequency of occurrences in the k-th bin and is given as

$$p_k = \frac{n_k}{N} \quad \text{(3.16)}$$

By substituting this in equation (14), and (15), we got the test statistics

$$T(y)=H \quad \text{(3.17)}$$

The detection threshold is determined as

$$\lambda = H_L + Q^{-1}(1 - P_{fa})\sigma_n \quad \text{(3.18)}$$

where

$$H_L = \ln\left(\frac{L}{\sqrt{2}}\right) + \frac{\gamma}{2} + 1 \quad \text{(3.19)}$$

is a theoretical Gaussian noise entropy, L is the number of bins, γ is Euler-Mascheroni constant, σ_n is the standard deviation of H under H_0 and P_{fa} is the expected probability of false alarm.

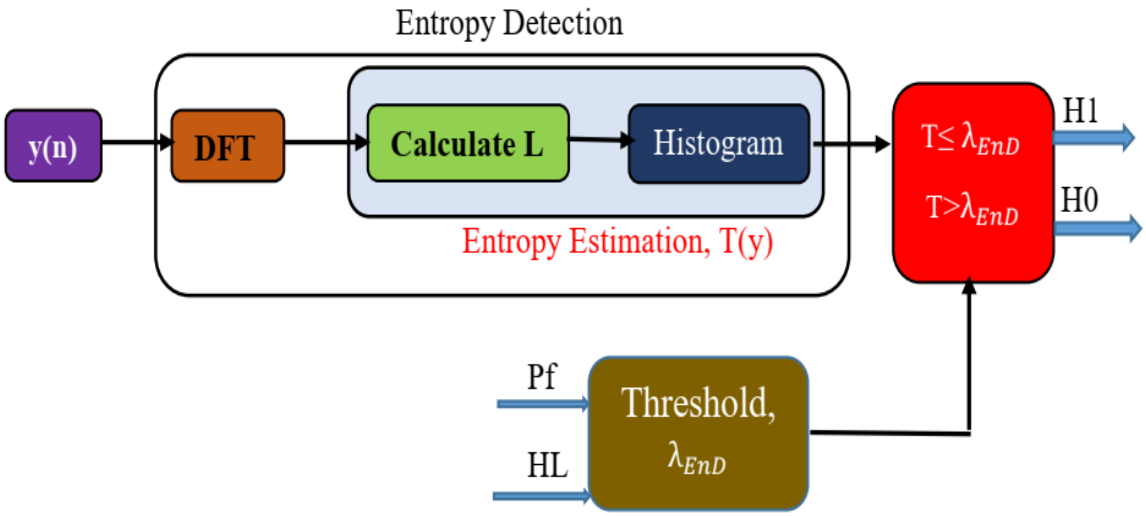

Figure 3. 6: Block Diagram of Entropy Based Detector

3.2.3 System Model of Multistage-Stage Spectrum Sensing Technique

Multistage spectrum sensing (SS) technique are typically broken down into three types. The first is sequential multistage sensing, in which each detection stage is serially connected and is either carried out or skipped depending on the outcomes of the previous stages' sensing. The second type of detection is parallel multistage detection, in which many detectors are used to execute the detection simultaneously, and the combined results of these parallel decisions form the basis of the final determination. The third class, sequential or parallel detection, uses an SNR estimate procedure to determine which stage to employ (Mashta et al., 2021). The overall probability of detection for sequential Multistage spectrum sensing that have M stages are given by

$$P_d = P_d^1 + \sum_{i=2}^{M}(P_d^i \prod_{j=1}^{i-1}(1 - P_d^j)) \quad \text{..... (3.20)}$$

$$P_{fa} = P_{fa}^1 + \sum_{i=2}^{M}(P_{fa}^i \prod_{j=1}^{i-1}(1 - P_{fa}^j)) \quad \text{..... (3.21)}$$

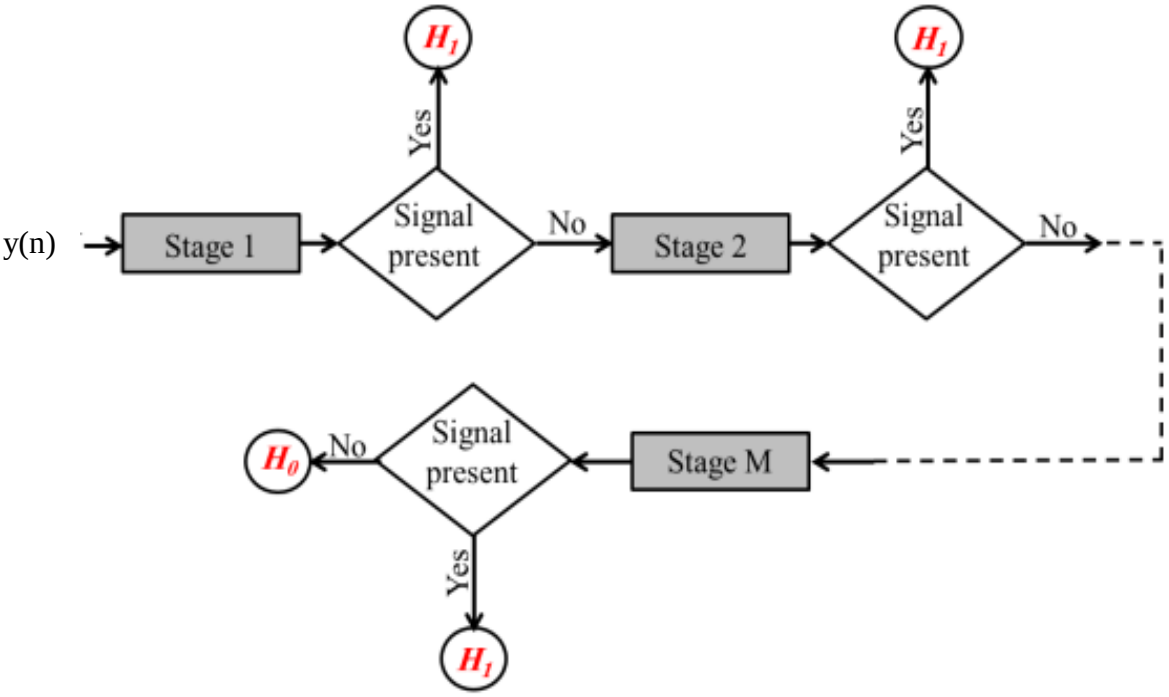

Figure 3. 7: General block diagram for Multistage spectrum sensing techniques

3.2.3.1 System Model of Two-Stage Spectrum Sensing Technique

Considers a sequential two-stage SS for CR as shown in the Figure 3.8. The two-stage SS method can be divided into two phases, which includes a coarse and fine sensing stage. The two stage spectrum sensing overall probability of detection and probability of false alarm mathematical models are expressed as:

$$P_{fa} = P_{fa}^{1} + P_{fa}^{2}(1 - P_{fa}^{1}) \quad \text{..... (3.22)}$$

$$P_{d} = P_{d}^{1} + P_{d}^{2}(1 - P_{d}^{1}) \quad \text{..... (3.23)}$$

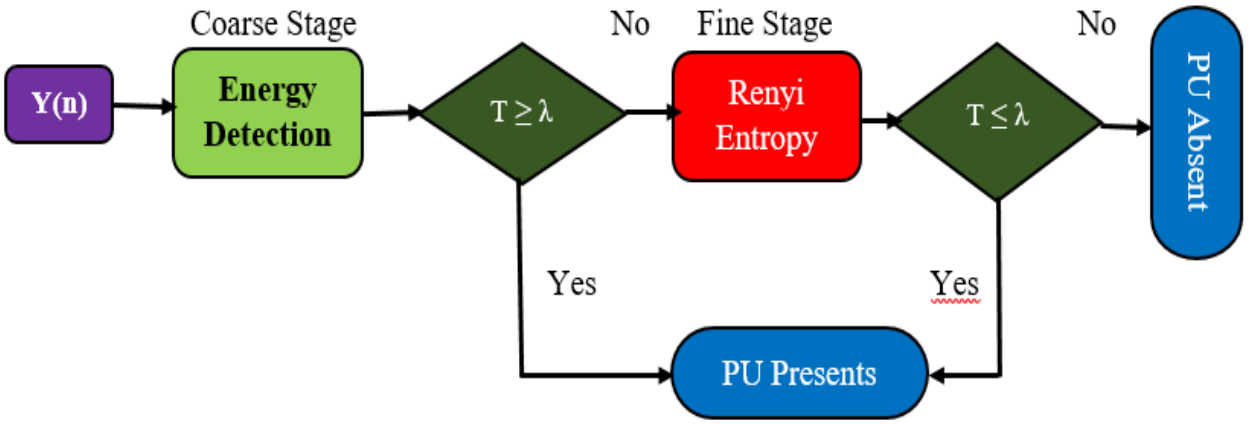

Figure 3. 8: Block diagram of Two-stage SS using Energy and Renyi Entropy detection

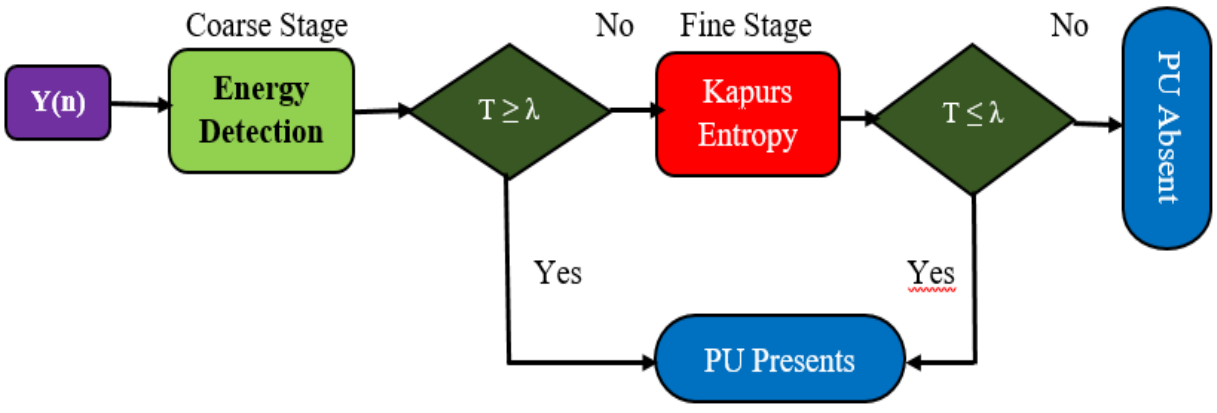

Figure 3. 9: Block diagram of Two-stage SS using Energy and Kapurs Entropy detection

3.2.3.2 System Model of proposed Detection Technique

Considers a sequential three-stage SS for Cognitive Radio network as shown in the Figure 3.9. The strategy of the proposed three-stage spectrum sensing technique can be divided into 3 stages, which includes first stage, second stage and third stage. In the proposed SS technique ED used as a first stage while Kapurs Entropy and Renyi Entropy detection used as a second and third stage respectively. The mathematical models of overall P_f and P_d for three-stage SS are given as:

$$P_{fa} = P_{fa}^1 + P_{fa}^2\left(1 - P_{fa}^1\right) + P_{fa}^3\left(1 - P_{fa}^1\right)\left(1 - P_{fa}^2\right) \quad \text{(3.24)}$$

$$P_d = P_d^1 + P_d^2(1 - P_d^1) + P_d^3(1 - P_d^1)(1 - P_d^2) \quad \text{(3.25)}$$

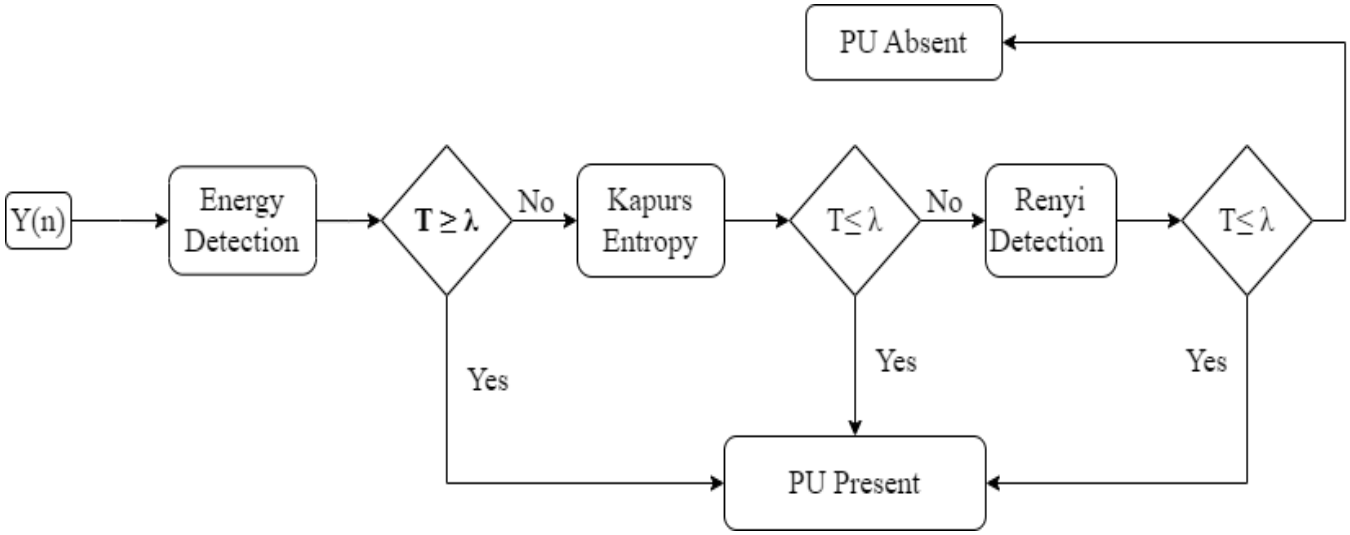

Figure 3. 10: Block diagram of the proposed three-stage SS techniques

3.2.4 Flow Chart of the Proposed Detection Technique

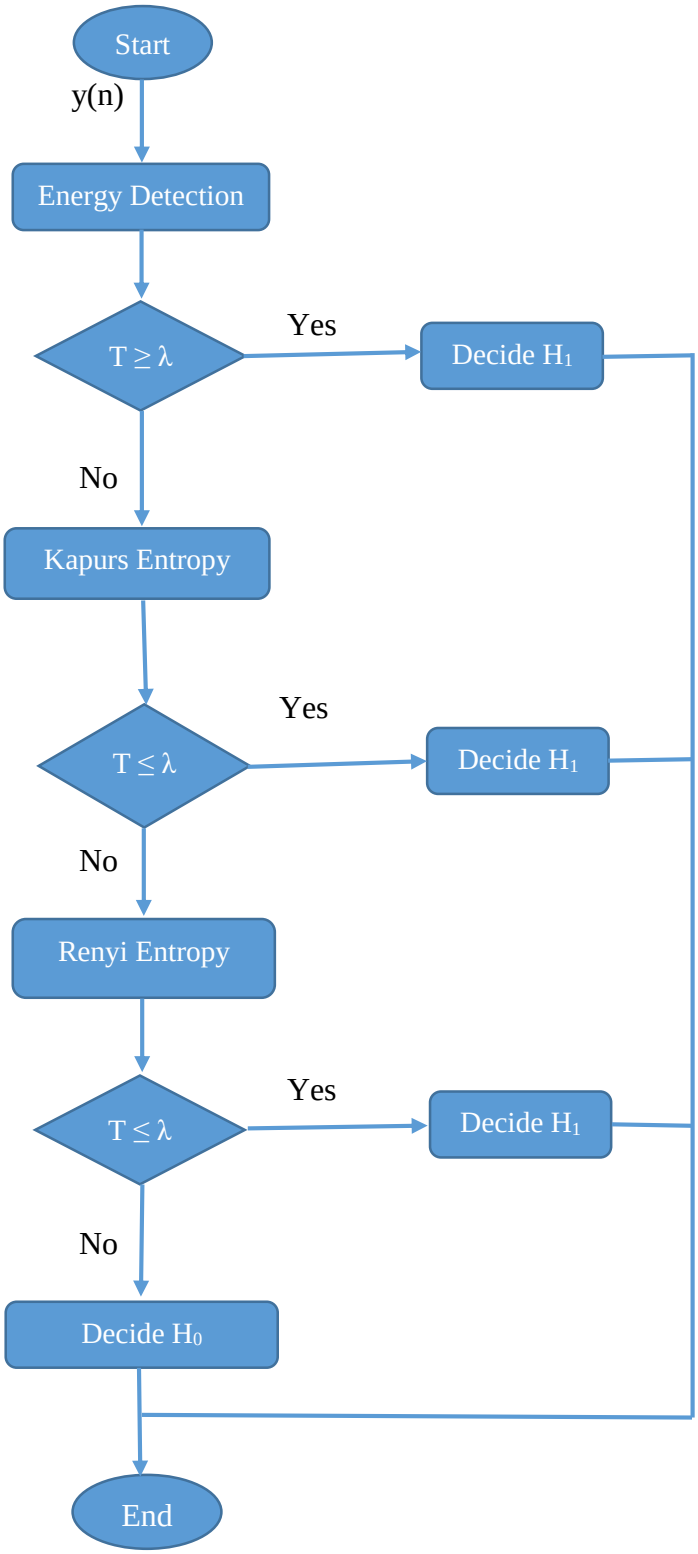

Figure 3. 11: Flow Chart of the proposed techniques

CHAPTER FOUR

RESULT AND DISCUSSION

In the previous chapter, the system model was established with mathematical derivatives to provide a theoretical explanation for signal detection by using different types of SS techniques in a given channel of interests. The effectiveness of spectrum sensing approaches is evaluated using performance standards includes probability of detection (P_d), probability of false alarm (P_f), and probability of missed-detection (P_m). Using the Energy Detection, Kapurs Entropy, Renyi Entropy, two-stage detection, and three-stage detection methods, situations including the sensing of PU signals contained in various forms are described along with simulation results in this section. Simulated results illustrate the P_d at various SNRs, as well as ROC and complementary ROC curves for the SS methods under consideration in the form of plots. All simulations must take into consideration the necessary detection probability (90%), false alarm probability (10%), and miss detection probability (10%) for CR, in accordance with IEEE 802.22 specifications. The SNR wall is the lowest SNR below which detection is not viable. In this thesis, the primary simulation parameters are provided in Table 4.1. The simulation outcome of this thesis are shown in four sections. These are listed as follows:

- Performance comparison among single stage ED, Kapurs Entropy (KE) and Renyi Entropy (RE) detection techniques.
- Performance comparison of Two-stage spectrum sensing methods
- Results of the proposed three-stage SS techniques
- Results of Cooperative detection for the Proposed three-stage SS techniques

Table 4. 1: Parameters that are used for Simulations

Simulation Parameters	**Type and Values**	**Remarks**
Cognitive Users	Single User,2,5	It can be vary
Types of Primary Signal	QPSK	Assumption
Detection Type	Energy Detection, Renyi, & Kapurs Entropy	
Ranges of SNR values	-30 dB up to 0 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	600, 800, 1000, 1200	It can be vary
Monte-Carlo simulation	10,000	Based on many papers
Channel	AWGN	Based on many papers
Types of Cooperative SS	Centralized approach (AND rule and OR rule)	
Order of entropy	4	Based on many papers
Number of bins	15	Based on many papers

4.1 Performance comparison of single stage ED, KE and RE detection techniques

Under this section the comparison among the single stage ED, KE and RE are presented in terms of P_d vs SNR, ROC curve and CROC curve. Depending up on the result, the best detection techniques are selected. For the best detection techniques, the simulation results that shows the effects of varying number of samples on probability of detection, and its cooperative detection are presented as well in this section.

To summarize, the results of single stage SS are presented in terms of:

- Probability of detection (P_d) vs Signal-to-noise Ratio (SNR)
- Receiver operating characteristics (ROC) curve
- Complementary receiver operating characteristics (CROC) curve

- Effects of varying the number of samples on the performance of Renyi Entropy detection
- The results of Cooperative detection for Renyi Entropy

4.1.1 Probability of detection vs SNR for single stage spectrum sensing

Figure 4.1 shows the P_d vs SNR for a single stage ED, KE and RE that are simulated at a P_f=0.1 and 800 number of samples by assuming that the transmitted signal is QPSK. According to IEEE 802.22 standards, any methods of SS should have detection probability which are greater than or equal to 0.9 (≥90%) in order to discern a transmitted PU signal from noise. As its clearly seen in the graph, ED attains the desired probability of detection after -12dB while kapurs entropy and renyi entropy attains it after -20 dB and -21.5 dB respectively. when we compare these three detections, the Renyi entropy has a significant improvement of 9.5 dB and 1.5 dB compared to Energy detection and Kapurs Entropy respectively. So based upon this result, we can say that Renyi entropy can correctly distinguish a PU signal from noise signal at low SNR than ED and kapurs entropy. In general, the Figure 4.1 depicted that as SNR value increases the P_d for all detection techniques increases as well.

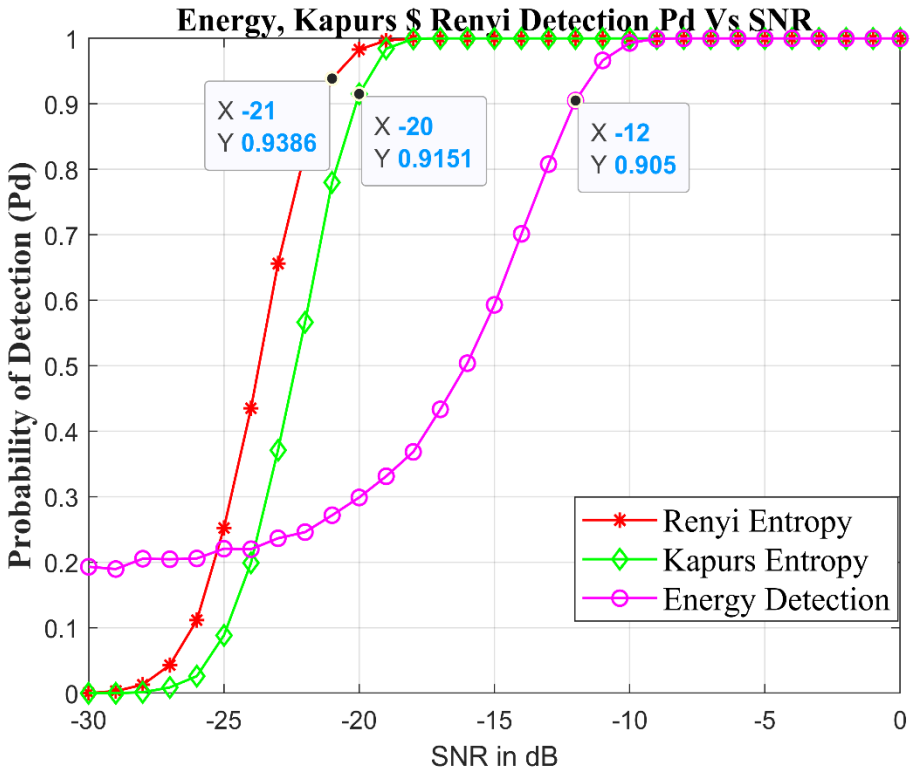

Figure 4. 1: P_d vs SNR for single stage ED, KE and RE detection techniques

Table 4. 2: for Pd vs SNR for Single stage SS such as ED, KE and RE

SNR (dB)		-22	-20	-18	-16	-14	-12	-10	-8	-6
Probability of Detection	Renyi	0.827	0.983	0.999	1	1	1	1	1	1
	Kapur's	0.567	0.915	0.999	1	1	1	1	1	1
	Energy	0.246	0.299	0.368	0.504	0.701	0.905	0.993	1	1

Table 4.2 illustrates the performance comparison among single stage detection techniques (energy, kapurs and renyi) in terms of P_d under various SNR values at N = 800, $P_f = 0.1$. As clearly depicted in the table, the Renyi entropy detection technique has the highest detection probability compared to kapurs entropy and energy detection methods at the poor values of SNR. Beyond -12 dB values of SNR, both Renyi and Kapur's entropy attains the maximum desired P_d for sensing the band of interest, while ED attain the poorest P_d compared to RE and KE. Therefore, in order to develop either two-stage or three-stage SS, it's better to choose the Renyi entropy at last stage of detection technique because it has a higher probability of detection at lower SNR value than ED and KE.

4.1.2 Receiver operating characteristic (ROC) curve

Figure 4.2 depicts that the P_d vs P_f or ROC curve for single stage ED, Kapurs entropy and Renyi Entropy at SNR=-18dB and N=800. This simulation results are performed in order to compare the performance of single-stage ED, KE and RE. As its clearly seen in the graph, an increase in P_f increases the detection performance i.e. P_d. As illustrated in the figure, Renyi entropy attains the desired P_d with $P_f = 0.08$ while Energy detection and Kapurs entropy attains it with $P_f = 0.25$ and $P_f = 0.96$ respectively. In spectrum sensing, the detection techniques that has a higher P_f will have a less utilization on spectrum. Therefore, in this simulation we can conclude that the RE is the best one at low SNR value since it achieves IEEE 802.22 standards with the lowest P_f which is 0.08.

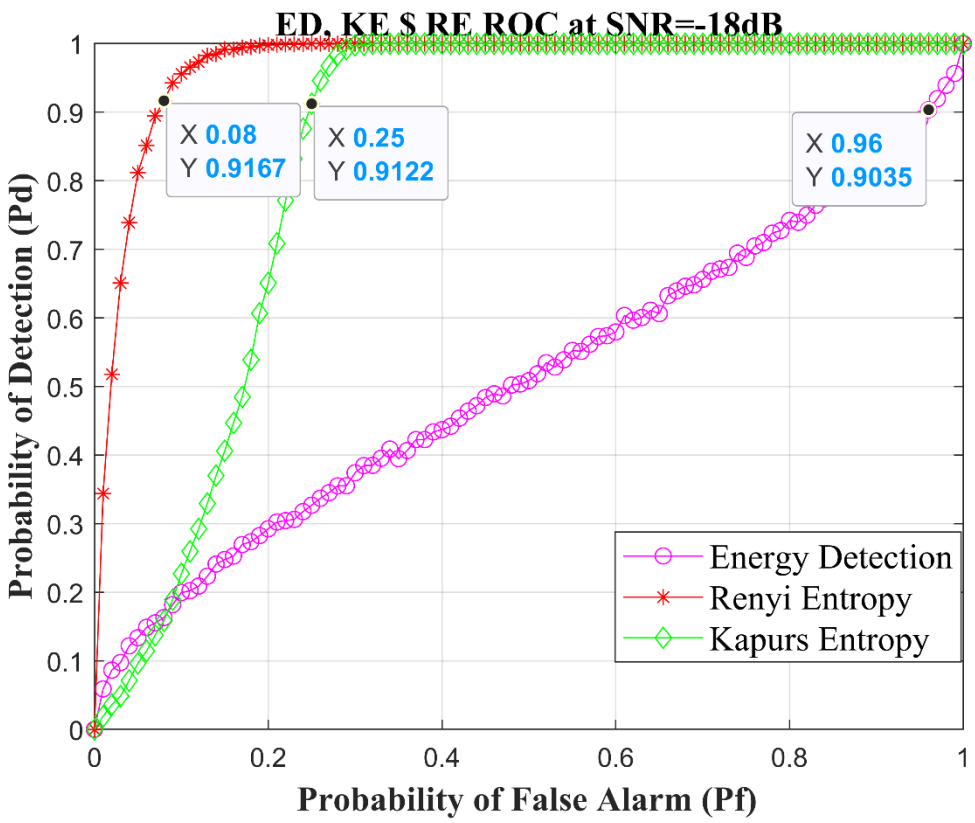

Figure 4. 2: P_d vs P_f for single stage ED, KE and RE detection techniques at SNR=-18dB

4.1.3 Complementary Receiver Operating Characteristics (CROC) curve

Figure 4.3 demonstrates the CROC curve for single -stage ED, KE and RE. This results are simulated by setting SNR at -18 dB and taking number of samples as 800. As its seen in the plot, an increase in P_f decreases the P_m. According to IEEE 802.22 standards the P_f should be less than or equal to 0.1 ($P_f \leq 0.1$) and the P_m less than 0.1 ($P_m < 0.1$). As its observed, the RE has the lowest P_m compared to KE and ED. For example, if we take P_f at 0.1 RE has 0.0462 missed detection probability while KE and ED has 0.7773 and 0.8067 respectively. The techniques that has a lowest missed detection probability creates less interference to PU signal. Among single stage techniques RE is the best one since it has a Pm value which is less than 0.1.

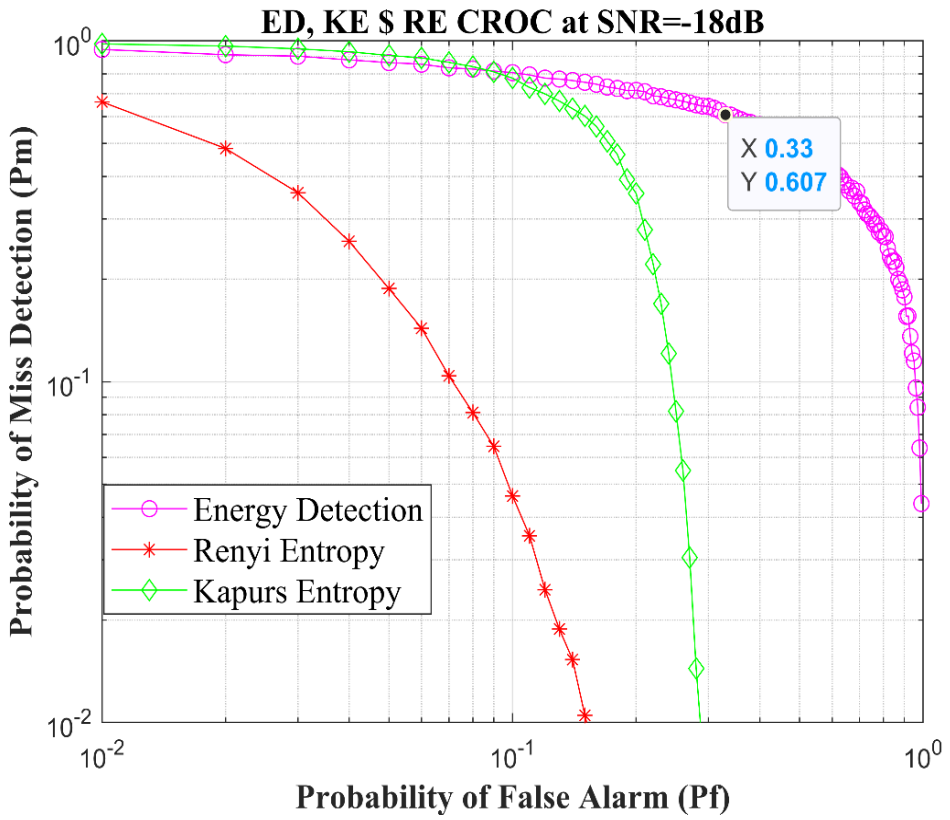

Figure 4. 3: P_m Vs P_f for single stage ED, KE and RE detection techniques at SNR=-18dB

4.1.4 Effects of varying the number of samples on the performance of Renyi Entropy detection

Figure 4.4 shows ROC curve that illustrates the effect of varying sample size on the performance of Renyi entropy. This results simulated by setting the value of SNR to -23dB. To see the effects varying number of samples on the performance of detection, the sample size is varied from 600 to 1200 by an increments of 200. As clearly seen from the graph, the ROC curve that is plotted with N=1200 has a higher P_d when compared to the ROC curve that is plotted with N=1000, N=800 and N=600. In general, we can say that, as the number of sample increases the detection performance of Renyi entropy increases as well. In other word, an adding of number of samples decreases P_f for achieving the requisite detection probability.

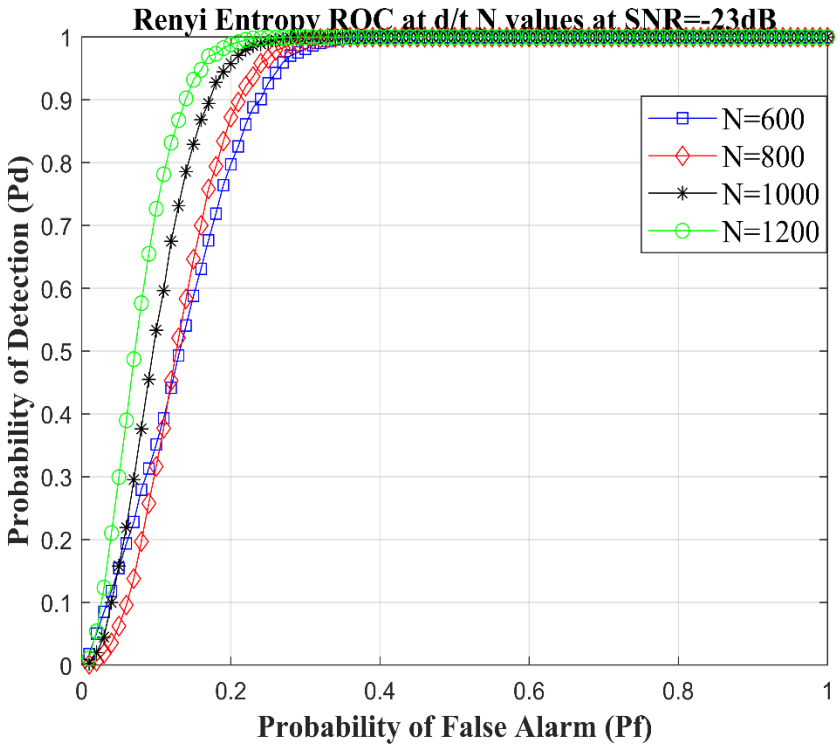

Figure 4. 4: ROC Curve for Renyi Entropy detection at different number of samples

4.1.5 The results of Cooperative detection for Renyi Entropy

Under this subsection, the simulation results that illustrates the performance of cooperative detection for Renyi Entropy in terms of Pd vs SNR, ROC Curve and CROC Curve are presented. In addition to this, the result that compares a single node detection with a collaborated SUs using OR and AND fusion centers (FC) are presented. To sum up, the performance evaluation for cooperative Renyi entropy detection is done in terms of P_d vs SNR, receiver operating characteristic (ROC) and complementary ROC.

Figure 4.5 shows P_d vs SNR for cooperative Renyi Entropy using AND, and OR rule Fusion Center (FC) at different number of SUs. This result is simulated by setting P_f to 0.1 and sample size (N) to 800. Moreover, this figure depicts how AND, and OR rules are affected by increasing number of secondary users (SUs). In addition to that, it illustrates the comparison between AND, and OR FC. As observed from the figure, the plots of OR FC are symbolized by circles while AND FC and single node detection are symbolized by diamond and squares respectively. The simulation result shows the use of OR rule CSS enhances the performance of SS when we compare it to the single node detection techniques. However, the use of AND rule CSS deteriorates the performance

of detection when we compare it to a single node detection technique. As clearly seen, an increasing number of CR users increases the detection performance of OR rule FC while it deteriorates the detection performance of 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. For instance, if we take a given value of SNR to -22 dB the AND rule with 5 and 2 number of SUs has 0.401315 and 0.694056 detection probability respectively while OR rule with 5 and 2 SUs has 0.99987 and 0.972144 P_d values. In addition to this the single node user has 0.8331 P_d at -22 dB SNR value.

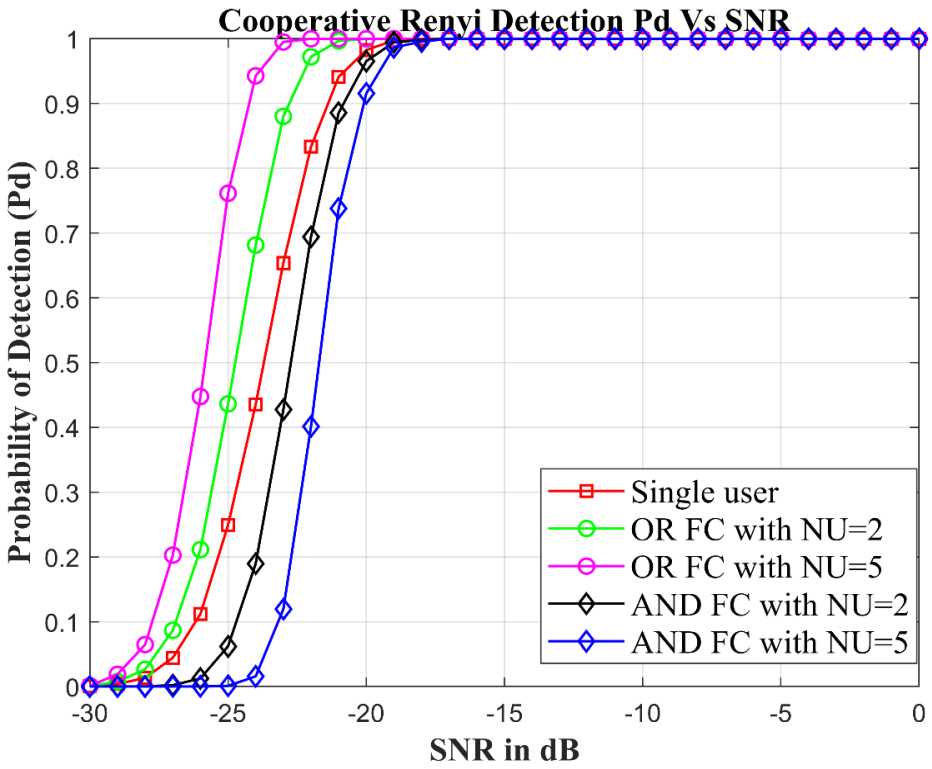

Figure 4. 5: P_d vs SNR for Cooperative Renyi entropy technique

Figure 4.6 depicts the ROC curve for cooperative Renyi entropy detection techniques when the number of SUs is 1, 2 and 5 at SNR = -23 dB. As clearly seen from the figure, an increasing in the P_f increases the detection performance of Single node (NU=1), OR FC CSS and AND FC CSS. As the number collaborated user's increases the detection probability of OR rule is dramatically increased. However, the detection performance of AND rule is decreased as number of collaborated users increased, this occurred because of all of the SUs should decide the existence of PU, which is challenging to attain since some cognitive users fail to decide due to multipath

fading, shadowing effect and hidden terminal problems. For instance, if we take a given value of P_f to 0.1, the AND rule with 5 and 2 number of SUs has 0.119096 and 0.426932 detection probability respectively while OR rule with 5 and 2 SUs has 0.994998 and 0.879868 P_d values. In addition to this the single node user has 0.6534 P_d at 0.1 P_f value.

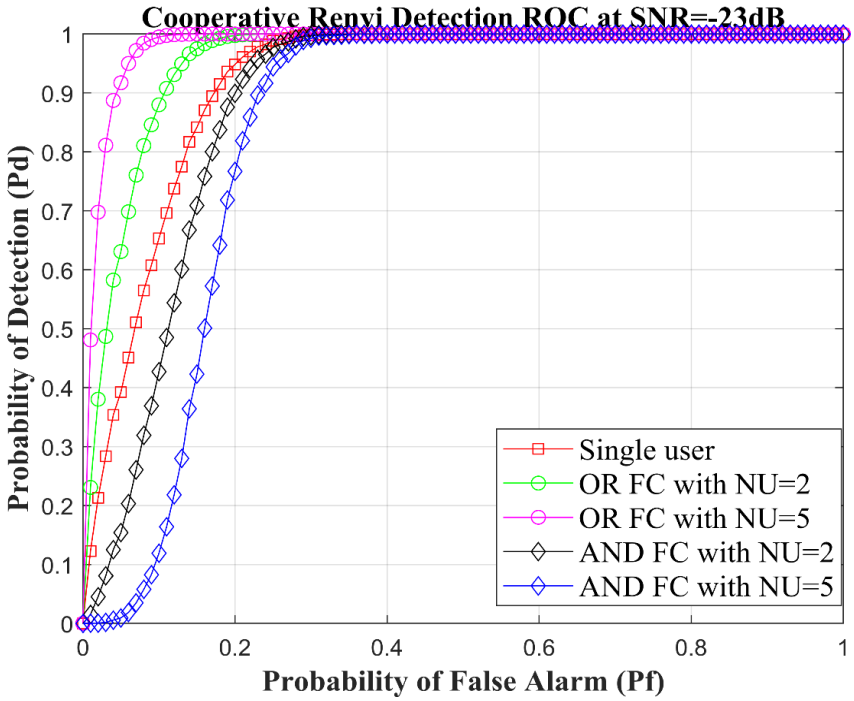

Figure 4. 6: P_d vs P_f for Cooperative Renyi Entropy technique at SNR=-23dB

Figure 4.7 show the CROC curve for cooperative renyi entropy detection technique when the number of SUs is single, 2 and 5 at SNR = -23 dB by using single node, AND, and OR rule CSS. As clearly observed from the figure, an increasing in the P_f decreases the P_m of single node RE, AND rule CSS and OR rule CSS. The missed detection probability of AND rule FC increases dramatically as the number of cooperated SUs increases while Pm of OR rule FC dramatically decreased as the number of collaborated user's increases. For instance, if we take a given value of P_f to 0.1, the AND rule with 5 and 2 number of SUs has 0.996981 and 0.901843 missed detection probability respectively while OR rule with 5 and 2 SUs has 0.152699 and 0.471557 P_m values. In addition to this the single node user has 0.6867 P_m at 0.1 P_f value. Depending up on this results, it is possible to conclude that the OR rule FC CSS has create a low interference with PU compared to the AND rule CSS and single node Renyi Entropy detection techniques.

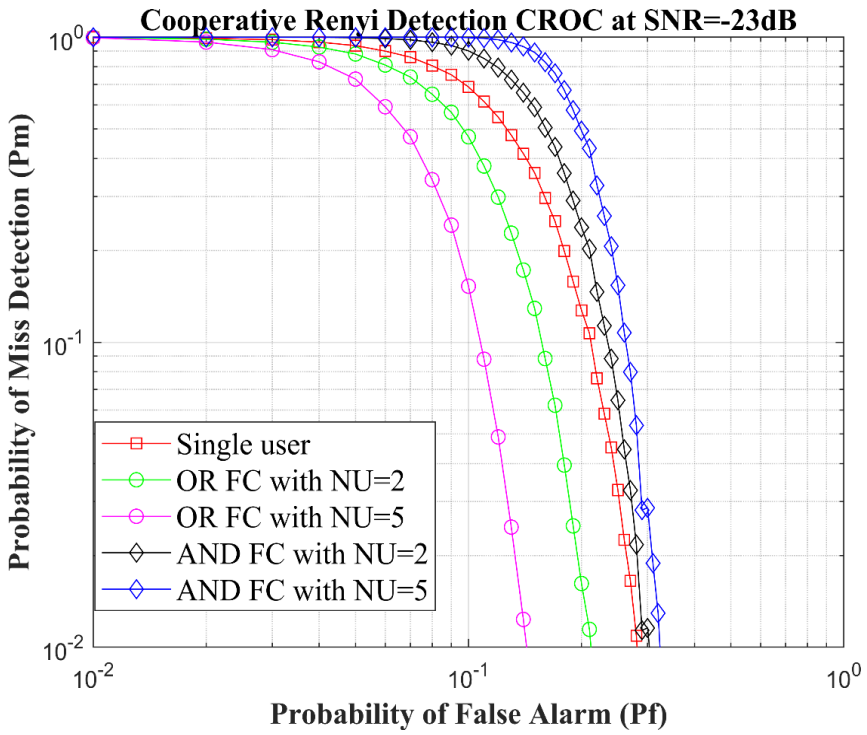

Figure 4. 7: P_m Vs P_f for cooperative Renyi entropy technique at SNR=-23dB

4.2 Performance comparison of Two-stage spectrum sensing techniques

In this section, the results of 2-stage spectrum technique that are developed using energy detection and kapurs entropy as well as energy detection and renyi entropy are presented. The developed two-stage spectrum sensing are compared to each other in terms of Pd vs SNR, ROC curve and CROC curve. Here, the best two-stage SS techniques are selected based on the results of simulations. For the best one, the results of its cooperative detection are performed/simulated in terms of different metrics.

To sum up, the simulation result that compares the developed 2-stage spectrum sensing (. i.e. two-stage ED+KE and two-stage ED+RE) are presented as follows:

- P_d vs SNR that compares two-stage SS
- ROC curve that compares two-stage SS
- CROC curve that compares two-stage spectrum sensing
- Effects of varying number of samples on the performance of two-stage ED+RE detection
- Cooperative detection of Two-stage SS using ED and RE.

4.2.1 P_d vs SNR that compares two-stage spectrum sensing

Figure 4.8 depicts the comparison between 2-stage SS which is developed using ED and Kapurs entropy and the one that is developed using ED and Renyi entropy. In this simulation result we have assumed the transmitted signal as a QPSK. The results are simulated by setting P_f at 0.1 and number of samples at 800. As observed clearly from the plot, an increase in SNR increases the P_d of spectrum sensing method. The 2-stage SS which is developed using ED as a first (fine) stage and RE as a second (coarse) is the best as compared to two-stage SS which is evolved using ED as a first-stage and Kapurs entropy as a second stage. As it seen in the graph, a two-stage ED+RE attains its desired probability of detection at SNR = -21.9 dB while a two-stage ED+KE attains it at SNR = -20.4dB. In other ways, we can say that a two-stage spectrum sensing that is developed using ED and RE has about 1.5 dB improvements compared to a two-stage SS that is developed using ED and KE. For example, at -21 dB SNR value a two-stage ED+RE has a 0.955482 P_d values while a two-stage ED+KE has 0.838714.

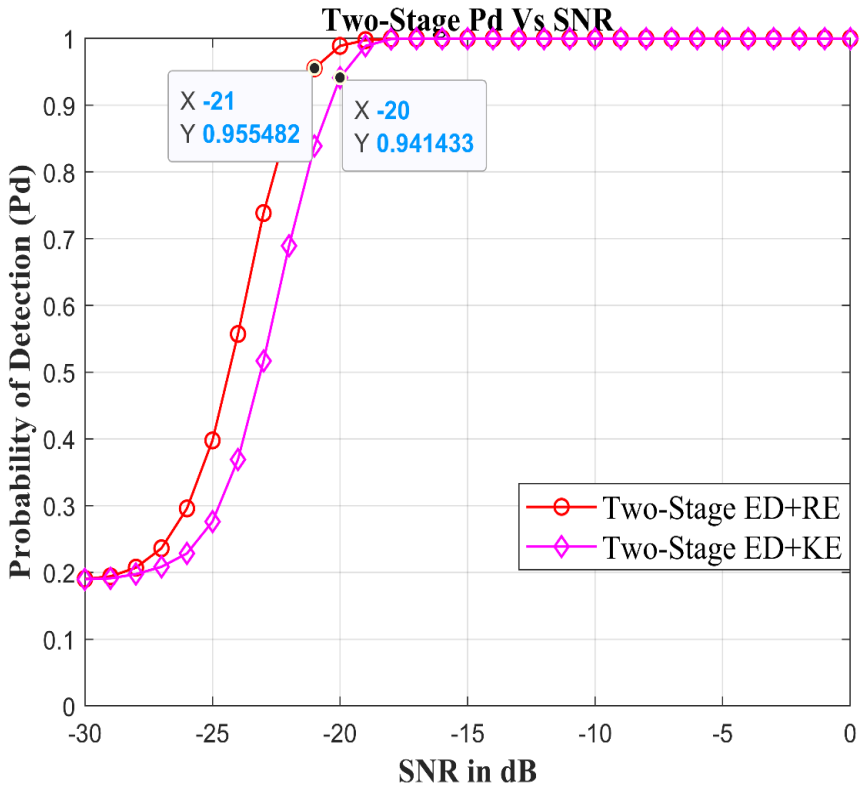

Figure 4. 8: P_d vs SNR that compares Two stage ED+KE vs ED+RE

Table 4. 3: P_d vs SNR for two stage SS such as two-stage Ed+KE and two stage ED+RE

SNR (dB)		-22	-20	-18	-16	-14	-12	-10	-8	-6
Probability of Detection	Two-stage ED+RE	0.877	0.988	0.999	1	1	1	1	1	1
	Two-stage ED+RE	0.689	0.941	0.999	1	1	1	1	1	1

Table 4.3 illustrates the performance comparison between the two-stage ED+RE and two-stage ED+KE SS technique methods in terms of P_d. The detection performance of all methods are evaluated at various values of SNR, as illustrated in table 4.3. At low values of SNR, the two-stage ED+RE SS technique has the highest detection probability compared to two-stage ED+KE detections. However, both two-stage ED+RE and two-stage ED+KE detection achieve a maximum probability of detection after SNR = -16 dB. Therefore, from this table, it is feasible to decide that adopting 2-stage ED+RE SS approaches rather than 2-stage ED+KE detection techniques improves SS performance for CR.

4.2.2 ROC curve that compares two-stage spectrum sensing

Figure 4.9 illustrates the ROC curve that performs comparison between two-stage ED+KE and two-stage ED+RE. These results are simulated by setting a SNR at -18dB and number of samples at 800. As its seen, an increase in the P_f the detection performance of spectrum sensing. 2-stage SS that is developed using ED as first-stage and RE as second-stage achieves the desired P_d with lowest P_f values when compared to a 2-stage SS that is developed using ED as coarse stage and KE as a fine stage. For example, a 2-stage ED+RE achieves the desired P_d at 0.07 probability of false while two-stage ED+KE achieves it at 0.24 P_f values. The detection method with a higher P_f values leads to less spectrum utilization. According to IEEE 802.22 standards, P_f should be less than or equal to 0.1 in order to increase the utilization of the spectrum. Therefore, we can say that two-stage ED+RE SS has a very good spectrum utilization compared two-stage ED+KE SS.

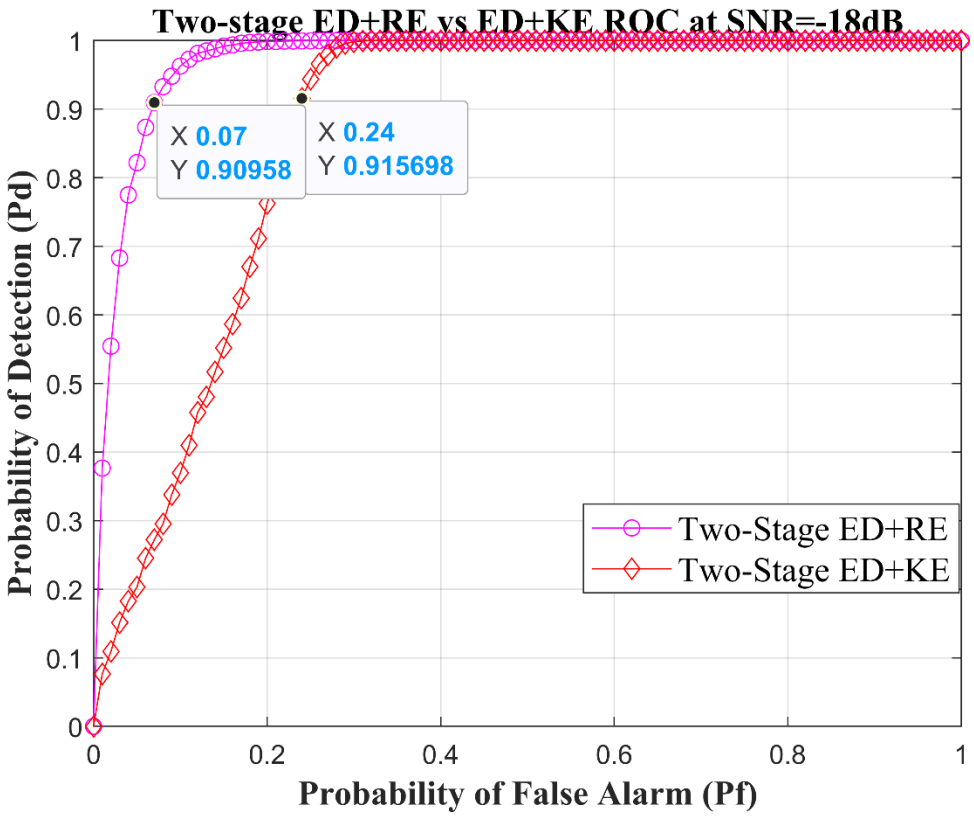

Figure 4. 9: P_d vs P_f that compares Two stage ED+KE vs ED+RE at SNR=-18dB

4.2.3 CROC curve that compares two-stage spectrum sensing

Figure 4.10 depicts the CROC curve that compares a two-stage ED+RE and two-stage ED+KE. The results of this plot are simulated by setting the SNR values to -18dB while sample size is set to 800. In addition to this the transmitted signal is also assumes as QPSK signals. As its seen in the graph, 2-stage SS that is developed using ED as first-stage and RE as second-stage has the lowest probability of missed detection when compared to a 2-stage SS that is elaborated using ED as coarse stage and KE as a second-stage. For example, if we take P_f value at 0.1, two-stage ED+RE has 0.0373502 missed detection probability while two-stage ED+KE has around 0.632928.

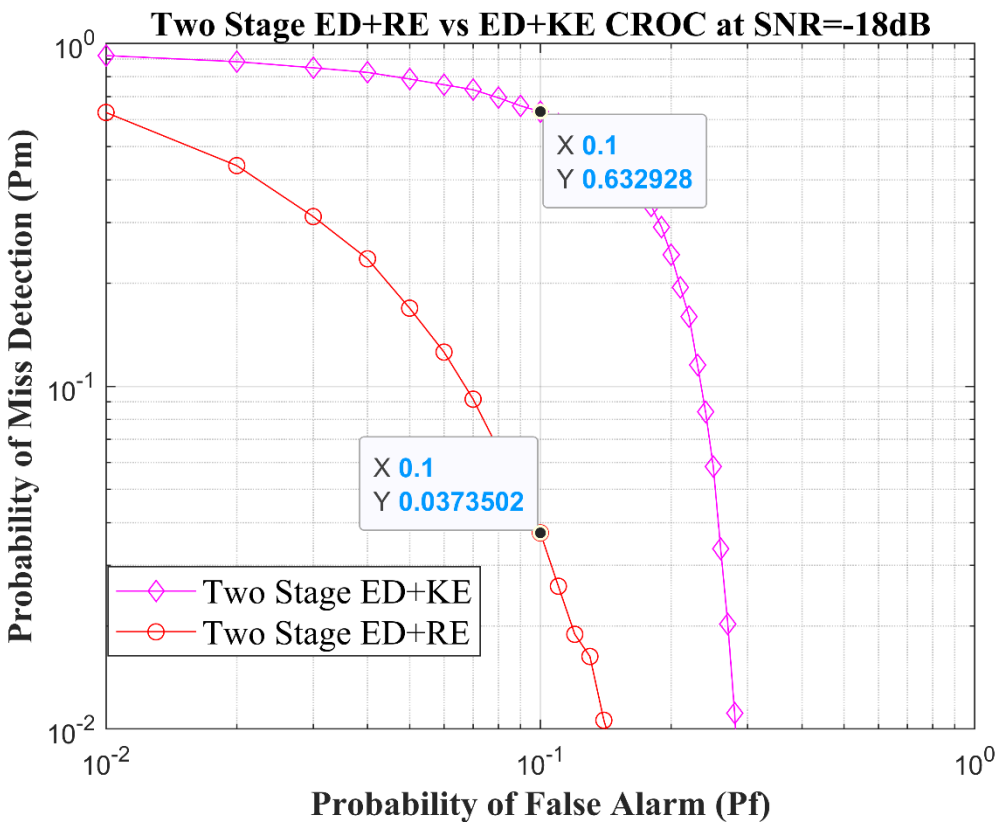

Figure 4. 10: P_m Vs P_f that compares Two stage ED+KE vs ED+RE at SNR=-18dB

4.2.4 Effects of varying number of samples on the performance of two-stage ED+RE detection

Figure 4.11 depicts ROC curve that illustrates the effect of varying sample size on the performance of two-stage ED+RE detection techniques. This simulation results are simulated by setting the value of SNR to -23dB. To see the effects varying number of samples on the performance of detection, the sample size is varied from 600 to 1000 by an increments of 200. As clearly observed, the ROC curve that is plotted with N=1000 has a higher P_d when compared to the ROC curve that is plotted with N=800 and N=600. In general, we can say that, as the number of sample increases the detection performance of two-stage ED+RE SS increases as well. In other word, an adding of number of samples decreases P_f for achieving the requisite detection probability.

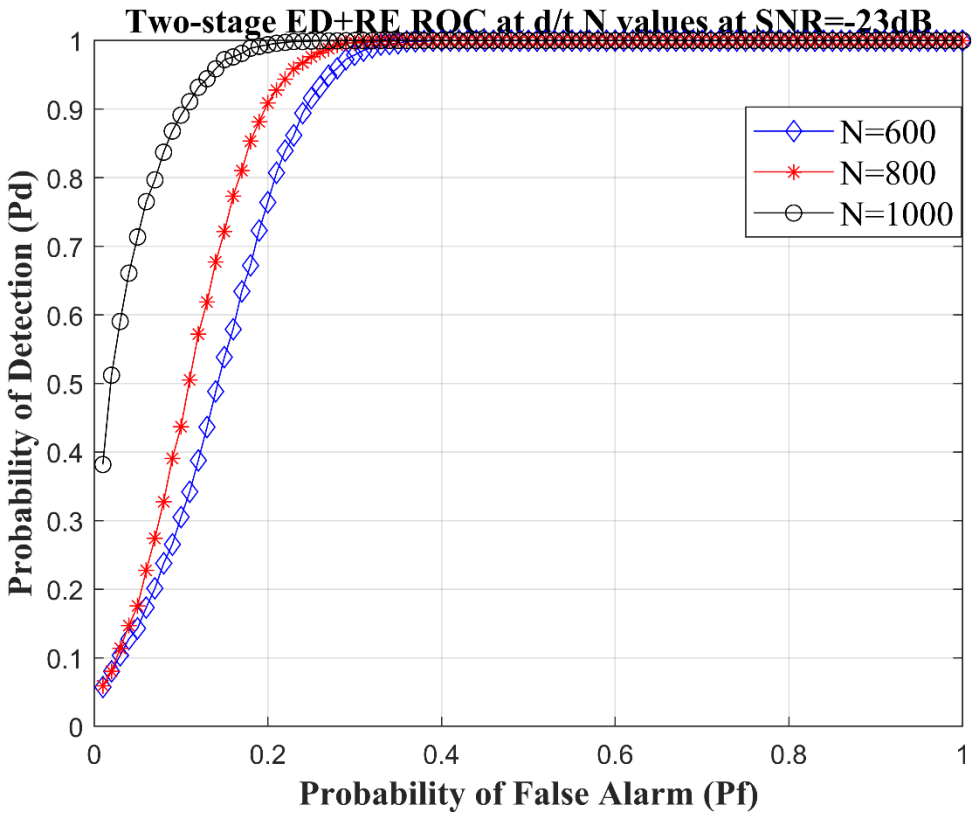

Figure 4. 11: ROC Curve for Two-stage ED+RE detection at different number of samples

4.2.5 Cooperative detection for Two-stage SS using ED and Renyi Entropy

Under this subsection, the results of cooperative two-stage SS using ED and RE are presented in terms of P_d vs SNR, ROC and CROC curves. In order to cooperate the numbers of SUs together the centralized cooperative methods like AND, and OR rule FC are used. Here, the simulation results that compares single user, OR rule and AND rule are discussed in detail as well.

Figure 4.12 illustrates P_d vs SNR for cooperative two-stage ED+RE SS technique using AND, and OR rule Fusion Center (FC) at different number of SUs. This result is simulated by setting P_f to 0.1 and sample size (N) to 800. Moreover, this figure depicts how AND, and OR rules are affected by increasing number of secondary users (SUs). In addition to that, it depicts the comparison between AND, and OR FC. As observed from the figure, the plots of OR FC centers are symbolized by circles while AND FC and single node detection are symbolized by diamond and squares respectively. The simulation result shows the use of OR rule CSS enhances the performance of SS when we compare it to the single node detection techniques. However, the use of AND rule CSS deteriorates the performance of detection when we compare it to a single node

detection technique. As clearly seen, an increasing number of CR users increases the detection performance of OR rule FC while it deteriorates the detection performance of 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. For instance, if we take a given value of SNR to -23 dB the AND rule with 5 and 2 number of SUs has 0.209044 and 0.534681 detection probability respectively while OR rule with 5 and 2 SUs has 0.998597 and 0.927757 P_d values. In addition to this the single node user has 0.731219 P_d at -23 dB SNR value.

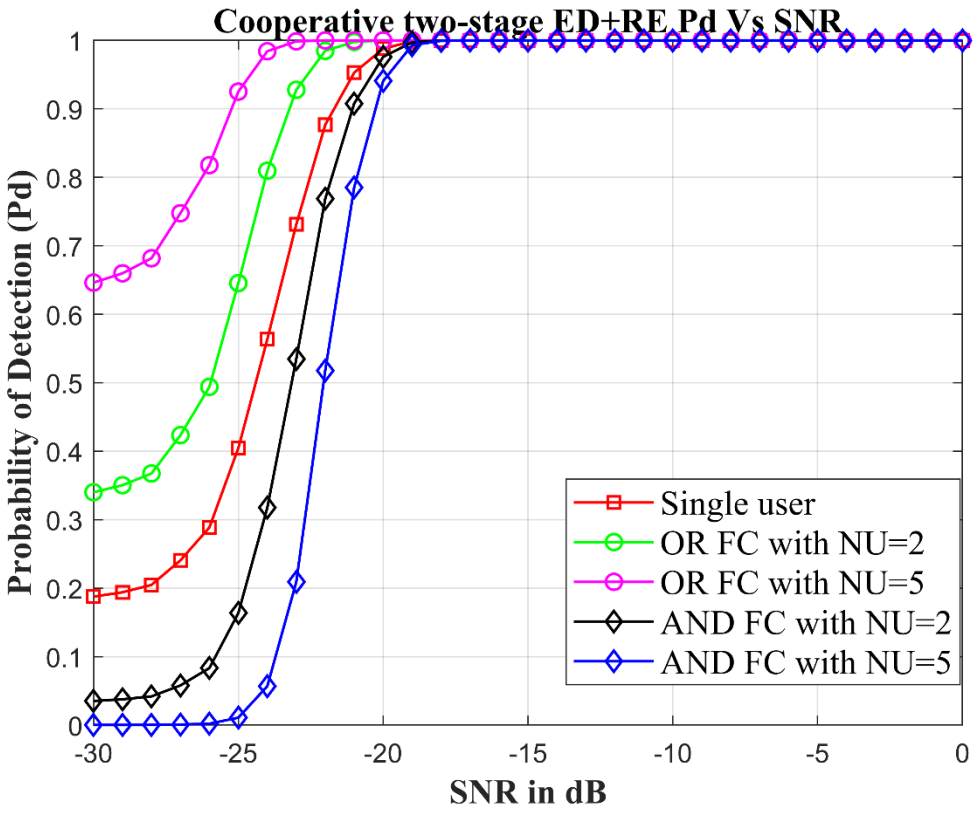

Figure 4. 12: P_d vs SNR for Cooperative Two-stage ED+RE technique

Figure 4.13 depicts the ROC curve for cooperative 2-stage ED+RE detection techniques when the number of SUs is 1, 2 and 5 at SNR = -23 dB. As clearly seen from the figure, an increasing P_f increases the detection performance of Single node (NU=1), OR FC CSS and AND FC CSS. As the number collaborated user's increases the detection probability of OR rule is dramatically increased. However, the detection performance of AND rule is decreased as number of collaborated users increased, this occurred because of all of the SUs should decide the existence of PU, which is challenging to attain since some cognitive users fail to decide due to multipath

fading, shadowing effect and hidden terminal problems. For instance, if we take a given value of P_f to 0.1, the AND rule with 5 and 2 number of SUs has 0.0175384 and 0.198425 detection probability respectively while OR rule with 5 and 2 SUs has 0.947555 and 0.692473 P_d values. In addition to this the single node user has 0.445449 P_d at 0.1 P_f value.

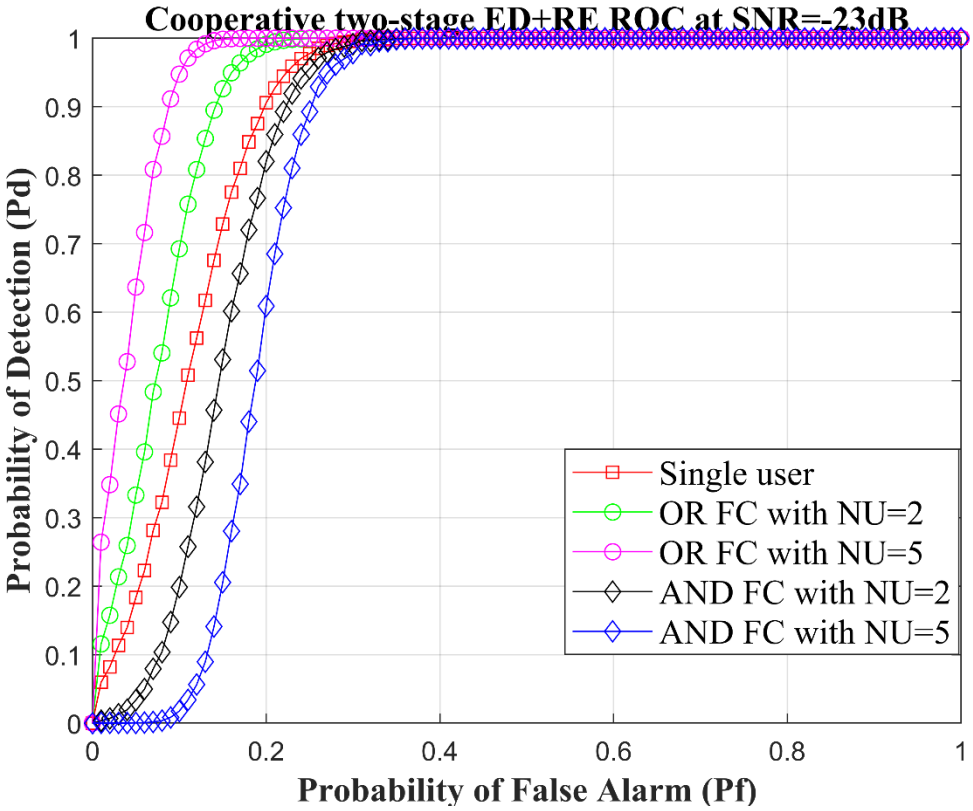

Figure 4. 13: P_d vs P_f for Cooperative Two-stage ED+RE technique at SNR=-23dB

Figure 4.14 show the CROC curve for cooperative two-stage ED+RE detection technique when the number of SUs is single, 2 and 5 at SNR = -23 dB by using single node, AND, and OR rule CSS. As clearly observed from the figure, an increasing in the P_f decreases the Pm of single node two-stage ED+RE, AND rule CSS and OR rule CSS. The missed detection probability of AND rule FC increases dramatically as the number of cooperated SUs increases while Pm of OR rule FC dramatically decreased as the number of collaborated user's increases. For instance, if we take a given value of P_f to 0.1, the AND rule with 5 and 2 number of SUs has 0.982937 and 0.803746 missed detection probability respectively while OR rule with 5 and 2 SUs has 0.0536109 and 0.310243 P_m values. In addition to this the single node user has 0.556994 P_m at 0.1 P_f value. Depending up on this results, it is possible to conclude that the OR rule FC CSS has create a low

interference with PU compared to the AND rule CSS and single node two-stage ED+RE detection techniques.

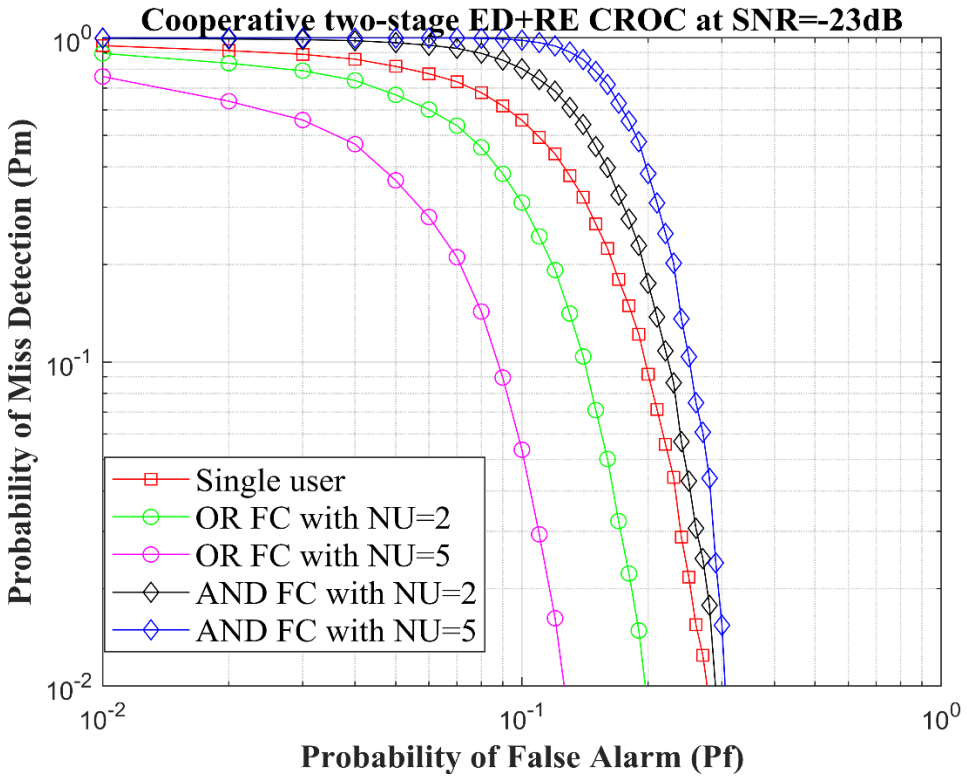

Figure 4. 14: P_m Vs P_f for cooperative Two-stage ED+RE technique at SNR=-23dB

4.3 Results of proposed three stage SS techniques

The proposed techniques are developed by using Energy Detection (ED) as the first stage, Kapurs Entropy as the second stage and Renyi Entropy detection as the third stage. Under this section, the simulation results that compare the performance of the proposed three-stage SS technique with Renyi Entropy and two-stage SS using ED and RE are presented.

To sum up, the simulation result that compares the proposed three-stage SS with two-stage ED+RE and Renyi Entropy are presented in terms of:

- P_d vs SNR for proposed three-stage SS
- ROC curve for proposed three-stage SS
- CROC curve for proposed three-stage SS
- Effects of varying number of samples on the performance of proposed three-stage SS detection.

4.3.1 P_d Vs SNR for proposed Three-stage SS

Figure 4.15 illustrates the simulation results of P_d vs SNR for the proposed three-stage SS while P_f and sample size set to 0.1 and 800 respectively. In addition to this, this results performs a performance comparison among proposed three-stage SS, two-stage ED+RE and Renyi Entropy detection. As it is observed from the graph, the proposed three-stage method exceeds or surpasses two-stage ED+RE and RE by significant amount of improvements. For example, at a particular value of SNR which is -22dB, the P_d of proposed three-stage SS 0.962064 whereas Pd of two-stage ED+RE and Renyi entropy is 0.869366 and 0.8267 respectively. In other word, at a given value of SNR=-22dB, the proposed technique has around 0.092698 and 0.135364 P_d improvement when compared to two-stage ED+RE and Renyi entropy respectively.

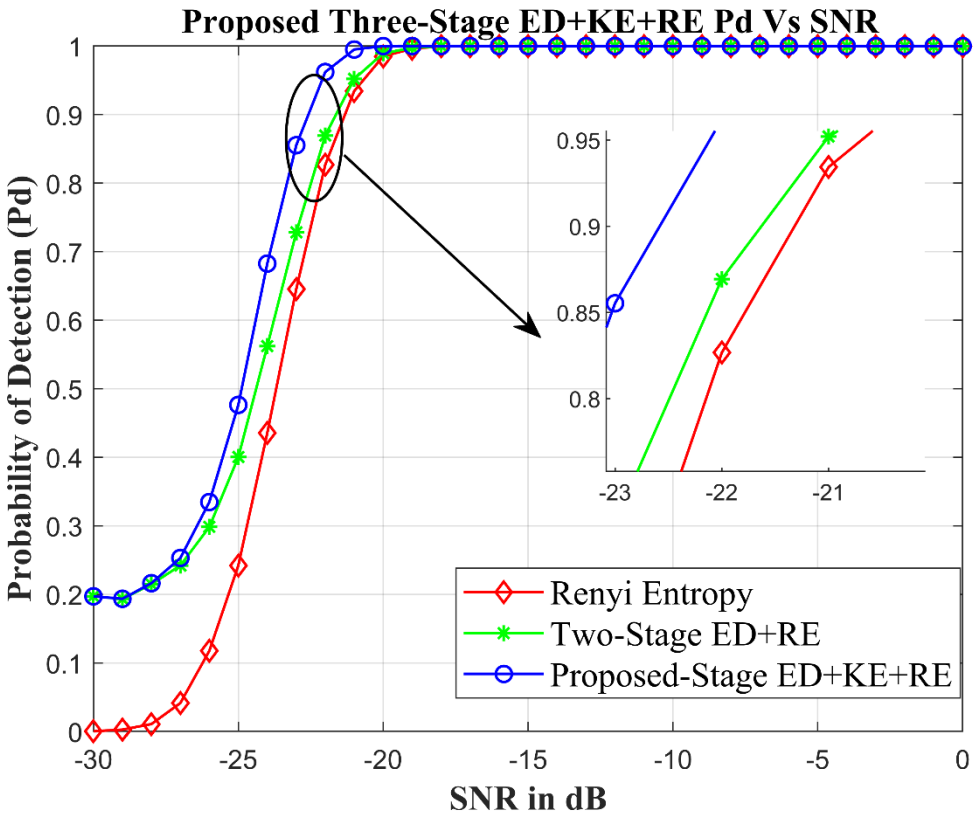

Figure 4. 15: P_d vs SNR for proposed three stage spectrum sensing

Table 4. 4: P_d vs SNR for proposed three-stage SS versus two-stage ED+RE and Renyi Entropy

SNR (dB)		-22	-20	-18	-16	-14	-12	-10	-8	-6
Probability of Detection	Proposed three-stage	0.992	0.999	1	1	1	1	1	1	1
	Two-stage ED+RE	0.869	0.989	0.999	1	1	1	1	1	1
	Renyi Entropy	0.826	0.985	0.999	1	1	1	1	1	1

Table 4.4 shows the performance evaluation among the proposed three-stage SS technique, two-stage ED+RE and Renyi entropy detection methods in terms of probability of detection. The performance of all techniques are investigated at various values of SNR, as depicted in table 4.4. At the very low values of SNR, the proposed three-stage SS technique has the very good detection probability compared to both two-stage ED+RE and renyi entropy detections. However, both two-stage ED+RE and Renyi entropy detection achieve a maximum detection probability after SNR = -16 dB, while proposed three-stage SS achieves it after SNR=-18dB. Therefore, from this table, it is possible to conclude that the performance of SS for CR is improved by employing the proposed three-stage SS techniques compared to both two-stage and single-stage.

4.3.2 ROC Curve for proposed Three-stage SS

Figure 4.16 depicts the ROC curve for proposed three-stage spectrum sensing, two-stage ED+RE and Renyi Entropy. These results are simulated by setting the SNR value at -20dB and number of samples at 800. It is clearly observed; the three-stage SS outperforms better in terms detection performance. If we look at a given $P_f = 0.1$, the P_d of three-stage SS method is 0.9813 whereas P_d of two-stage ED+RE and Renyi entropy is 0.850758 and 0.816 respectively. In other word, at a given value of P_f=-0.1, the proposed three-stage SS technique has around 0.130542 and 0.1653 P_d improvement when compared to two-stage ED+RE and Renyi entropy respectively. Also as its observed from the plot, the proposed three-stage method attains the desired P_d with 0.08 P_f values, while Two-stage ED+RE and Renyi Entropy achieves it with 0.12 and 0.13 respectively. Therefore, it is possible to deduced that the proposed three-stage SS have better P_d than both two-stage ED+RE SS and Renyi Entropy since it requires a lower P_f to gain the desired P_d than the them.

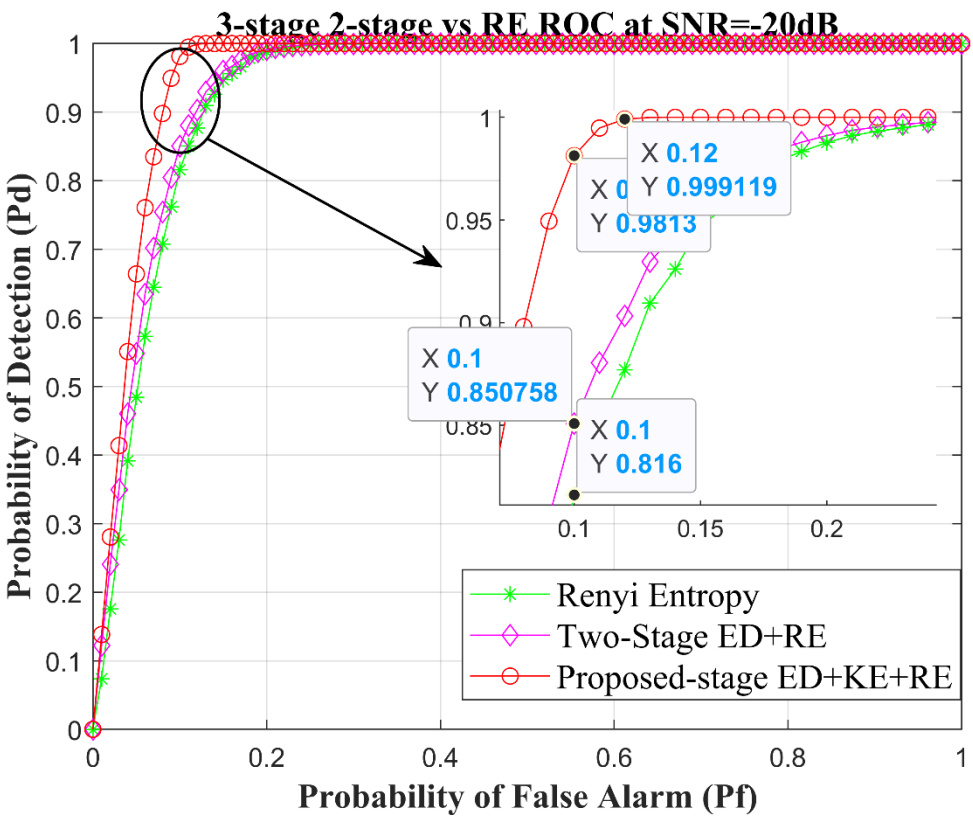

Figure 4. 16: ROC curve for proposed three stage spectrum sensing

4.3.3 CROC Curve for proposed Three-stage SS

Figure 4.17 demonstrates the CROC curve for three-stage SS, two-stage ED+RE and Renyi Entropy detection. Like ROC curve simulated at SNR =-20dB CROC curve also simulated at the same value of SNR values. Also from the figure, its simply understood that an increasing in the Pf decreases the missed detection probability. In this simulation, the comparison among proposed Three-stage technique, Two-stage ED+RE and Renyi entropy are presented. As it is clearly seen from the plot, proposed three-stage SS technique has a lower value of P_m over all ranges of probability of false alarm compared to two-stage ED+RE and Renyi entropy. For example, at a particular value of Pf which is 0.1, the Pm of proposed three-stage SS technique is 0.0190199 while Pm of two-stage ED+RE and Renyi entropy is 0.151312 and 0.185 respectively.

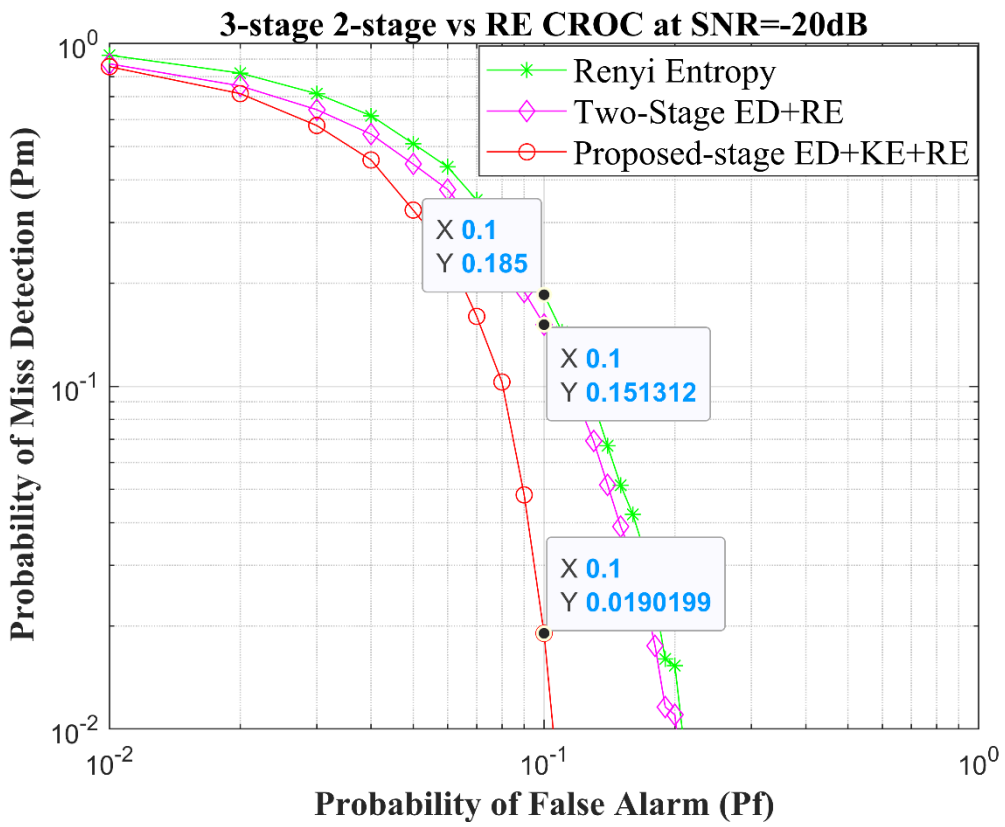

Figure 4. 17: CROC curve for proposed three stage spectrum sensing

4.3.4 Effects of varying number of samples on the performance of three-stage ED+KE+RE detection

Figure 4.18 illustrates the ROC curve that shows the effect of varying sample size on the performance of proposed three-stage ED+KE+RE detection techniques. This simulation results are simulated by setting the value of SNR to -23dB. To see the effects varying number of samples on the performance of detection, the sample size is varied from 600 to 1000 by an increments of 200. As clearly observed in Figure 4.18, ROC curve that is plotted with N=1000 has a higher P_d when compared to the ROC curve that is plotted with N=800 and N=600. In general, we can say that, as the number of sample increases, the detection performance of proposed three-stage ED+KE+RE SS increases as well. In other word, an increasing of sample number decreases probability for attaining the required detection probability.

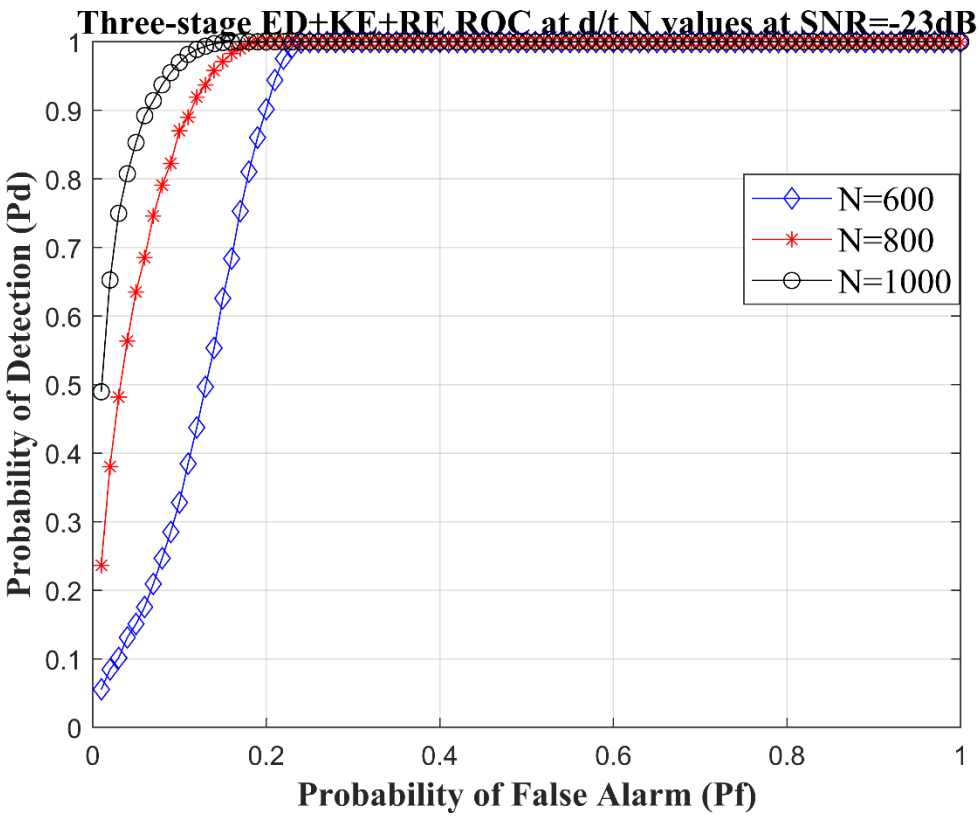

Figure 4. 18: ROC Curve for the proposed Three-stage ED+KE+RE detection at different number of samples

4.4 Cooperative detection for the proposed Three-stage SS technique

In this section, the simulations result that evaluates the detection accuracy of cooperative technique for the proposed three-stage SS are presented in terms of P_d vs SNR, ROC and CROC curve. In addition to this, the comparison between single node and cooperative detection for proposed three-stage SS are presented.

Figure 4.19 depicts P_d vs SNR for cooperative three-stage ED+KE+RE SS technique using AND, and OR rule Fusion Center (FC) at different number of SUs. This result is simulated by setting P_f to 0.1 and sample size (N) to 800. Moreover, this figure depicts how AND, and OR rules are affected by increasing number of secondary users (SUs). In addition to that, it illustrates the comparison between AND, and OR FC. As observed from the figure, the plots of OR FC are symbolized by circles while AND FC and single node detection are symbolized by diamond and squares respectively. The simulation result shows the use of OR rule CSS enhances the

performance of SS when we compare it to the single node detection techniques. However, the use of AND rule CSS deteriorates the performance of detection when we compare it to a single node detection technique. As clearly seen, an increasing number of CR users increases the detection performance of OR rule FC while it deteriorates the detection performance of 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. For instance, if we take a given value of SNR to -24 dB the AND rule with 5 and 2 number of SUs has 0.145433 and 0.462451 detection probability respectively while OR rule with 5 and 2 SUs has 0.996647 and 0.897624 P_d values. In addition to this the single node user has 0.680038 P_d at -24 dB SNR value.

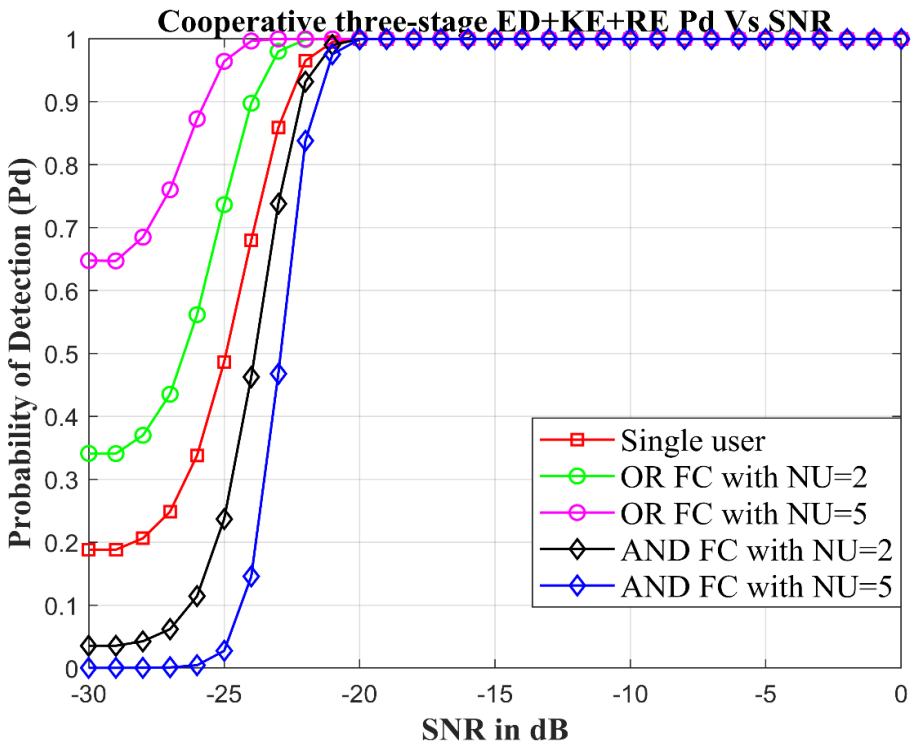

Figure 4. 19: P_d vs SNR for Cooperative three-stage ED+KE+RE technique

Figure 4.20 depicts the ROC curve for cooperative three-stage ED+KE+RE detection techniques when the number of SUs is 1, 2 and 5 at SNR = -23 dB. As clearly seen from the figure, an increasing in the P_f increases the detection performance of Single node (NU=1), OR FC CSS and AND FC CSS. As the number collaborated user's increases the detection probability of OR rule is dramatically increased. However, the detection performance of AND rule is decreased as number

of collaborated users increased, this occurred because of all of the SUs should decide the existence of PU, which is challenging to attain since some cognitive users fail to decide due to multipath fading, shadowing effect and hidden terminal problems. For instance, if we take a given value of P_f to 0.1, the AND rule with 5 and 2 number of SUs has 0.0319884 and 0.252346 detection probability respectively while OR rule with 5 and 2 SUs has 0.969475 and 0.752335 P_d values. In addition to this the single node user has 0.502341 P_d at 0.1 P_f value.

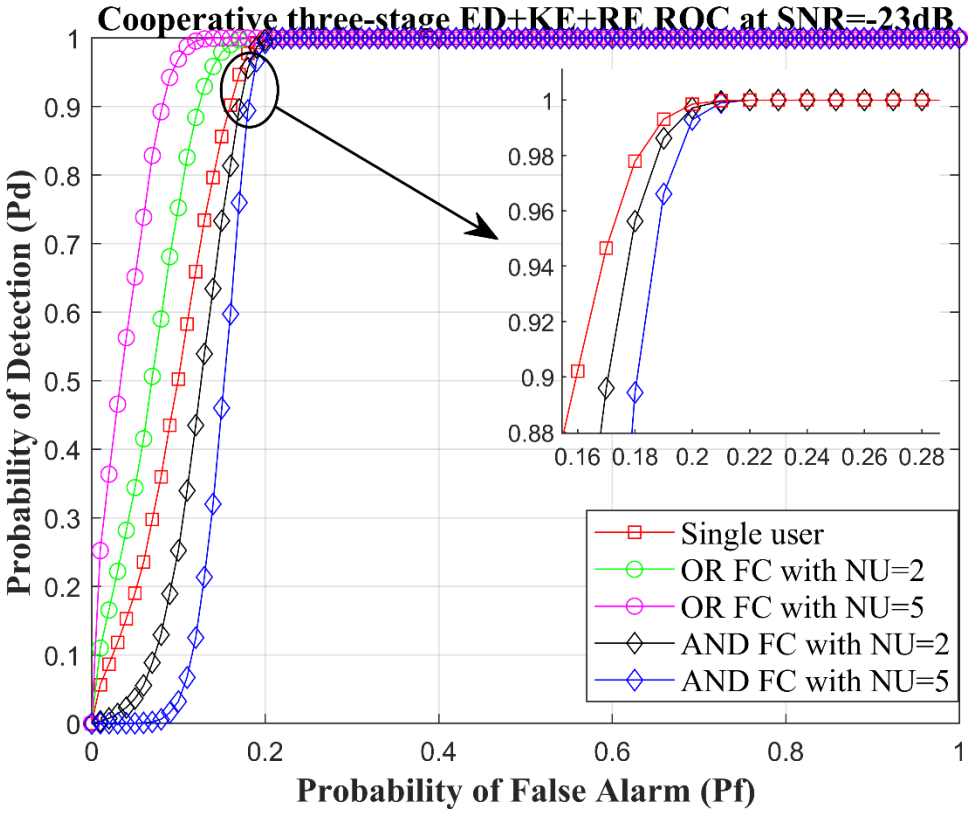

Figure 4. 20: ROC Curve for Cooperative Three-stage ED+KE+RE technique at SNR=-23dB

Figure 4.21 show the CROC curve for cooperative three-stage ED+KE+RE detection technique when the number of SUs is single, 2 and 5 at SNR = -23 dB by using single node, AND, and OR rule CSS. As clearly observed from the figure, an increasing in the P_f decreases the P_m of single node three-stage ED+KE+RE, AND rule CSS and OR rule CSS. The missed detection probability of AND rule FC increases dramatically as the number of cooperated SUs increases while Pm of OR rule FC dramatically decreased as the number of collaborated user's increases. For instance, if we take a given value of P_f to 0.1, the AND rule with 5 and 2 number of SUs has 0.967397 and 0.745725 missed detection probability respectively while OR rule with 5 and 2 SUs has 0.029942

and 0.245761 P_m values. In addition to this the single node user has 0.495743 P_m at 0.1 P_f value. Depending up on this results, it is possible to conclude that the OR rule FC CSS has create a low interference with PU compared to the AND rule CSS and single node three-stage ED+KE+RE SS detection techniques.

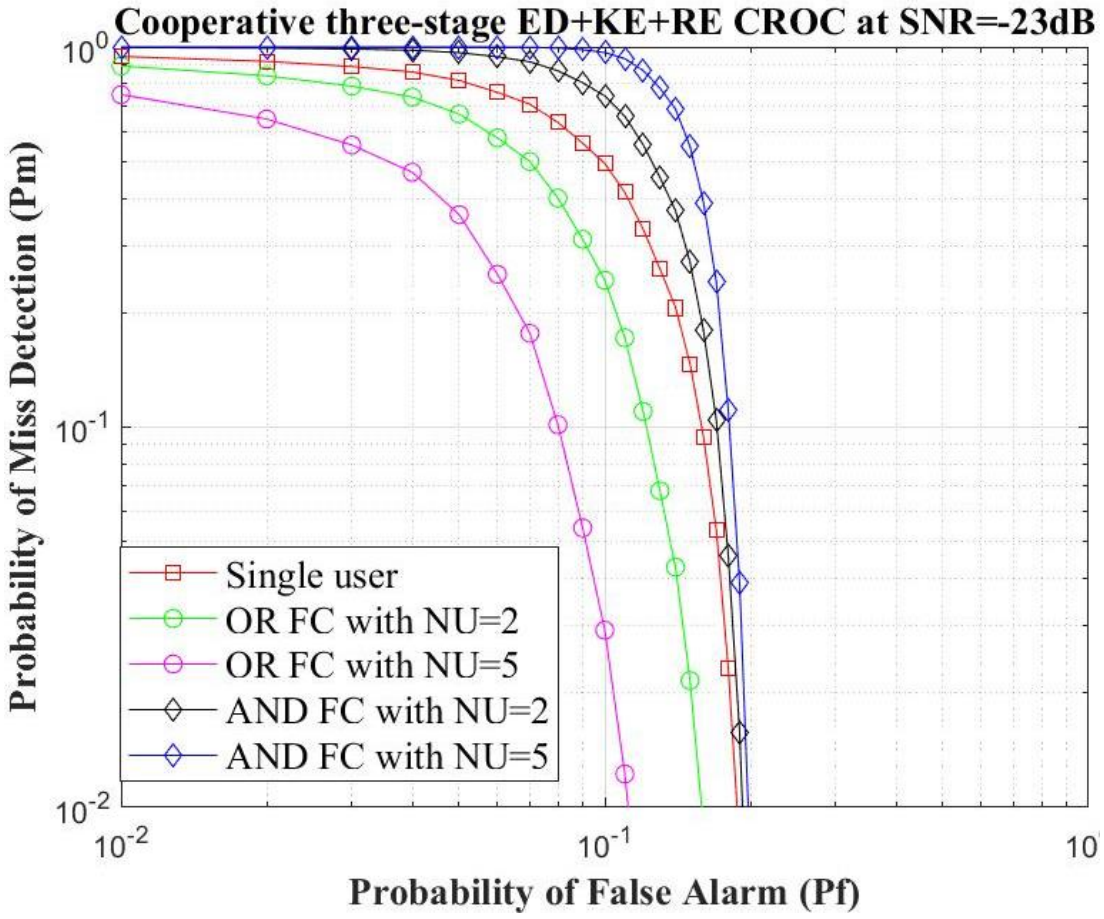

Figure 4. 21: P_m Vs P_f for cooperative Three-stage ED+KE+RE technique at SNR=-23dB

5. CONCLUSION AND RECOMMENDATION

5.1 Conclusion

In this thesis, both single-stage and multi-stage SS are investigated. Particularly, the energy detection (ED) technique is investigated in order to identify its performance at low SNR values. Moreover, the two-stage SS technique that is developed using ED and RE is compared with a technique that is developed using ED and KE. Based on the comparison result the best ones selected. According to simulation results, the two-stage ED+RE achieved the better detection probability compared to a two-stage ED+KE. For instance, a two-stage ED+RE attains its desired probability of detection at SNR= -21.9 dB while a two-stage ED+KE attains it at SNR=-20.4dB. In other ways, we can say that a two-stage spectrum sensing that is developed using ED and RE has about 1.5 dB improvements compared to a two-stage SS that is developed using ED and KE.

For this thesis, the proposed three-stage technique is developed using ED, Kapurs and Renyi entropy detection. The proposed technique consists ED as its first stage, KE as its second stage and RE as its third stage. The performance evaluation among proposed technique, 2-stage ED+RE and RE are performed in this thesis. From the result it can be shown that, the proposed technique has a better detection performance compared to both two-stage ED+RE and RE.

Lastly, this thesis investigates the cooperative detection of proposed three-stage SS techniques using AND rule and OR rule FC. Depending upon the simulation result, it is clearly seen that the cooperative detection using OR rule FC outperforms both AND rule FC CSS and single-node detection techniques. For example, when NU=5 a cooperative proposed technique using OR rule CSS achieves the desired detection probability at -26 dB SNR values while single node (NU=1) and AND rule CSS achieves it at -22 dB and -21 dB respectively. Here it can be concluded that, the OR rule CSS is best in the case of achieving better detection probability (. i.e. according to IEEE standard 802.22).

In general, based on the simulation result the conclusion can be summarized as follows:

- The detection performance of SS techniques is increased by adding the SNR values, sample size and also by adding number of collaborated users in case of OR rule CSS.
- The missed detection probability is decreased as the number of samples, SNR values are increased and also as the number of collaborated SUs are increased in case of OR rule CSS.

- The performance of two-stage ED+RE SS technique is enhanced by 1.5 dB when compared to a two-stage ED+KE SS detection technique.
- The proposed three-stage detection technique has an about 1 dB and 2.5 dB performance improvement as compared to two-stage ED+RE and two-stage ED+KE respectively.
- The use of OR rule CSS technique improves the detection performance of SS as compared to single-node detection techniques. However, the use of AND rule CSS deteriorates the performance of detection as compare to a single node detection technique.
- The cooperative three-stage detection technique using OR rule has an about 4 dB and 5 dB performance improvement as compared to single node and AND rule CSS technique respectively at NU=5.

5.2 Recommendation

In this thesis, the results of proposed technique are evaluated at simulation level only by using MATLAB tools. For the future, its suggested to investigate the practical performance of proposed technique using real-time platform environment such as SDR transceiver, Universal Software Radio Peripheral (USRP) and also its signal should be manipulated through GNU radio.

The proposed three-stage SS method was investigated under AWGN channel model only. For future, its suggested to evaluate under different channel models like Rayleigh, Rician and Nakagami-m fading channels.

In this thesis, the proposed technique was developed using ED as a first-stage, KE as a second-stage and RE as a third-stage. For the future, it's better to combine Energy and Entropy detection as one technique.

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