

Detection of Spectrum in Cognitive Radio Based on a Hybrid Approach



Kemal Araro Ogato

A Final 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
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**June, 2023
Adama, Ethiopia**

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APPROVAL PAGE OF M.SC. THESIS

We, the advisors of the thesis entitled “**Detection of Spectrum in Cognitive Radio Based on a Hybrid Approach**” and developed by **Kemal Araro Ogato**, 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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DECLARATION

I hereby declare that this Dissertation entitled” **Detection of Spectrum in Cognitive Radio Based on a Hybrid Approach**” is my original work. That is, it has not been submitted for the award of any academic degree, diploma or certificate in any other university. All sources of materials used for this thesis have been duly acknowledged through appropriate citations.

Kemal Araro Ogato

Name

Signature

Date

RECOMMENDATION

We, the advisors of this thesis, hereby certify that we have read the revised version of the thesis entitled” **Detection of Spectrum in Cognitive Radio Based on a Hybrid Approach**” Prepared under our guidance by **Kemal Araro Ogato** submitted in partial fulfillment of the requirement 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 ACRONYMS AND ABBREVIATIONS

AWGN	Additive White Gaussian Noise
AP	Access Point
BPF	Band Pass Filter
BPSK	Binary Phase Shift Keying
BS	Base Station
BTS	Base-station Transceiver System
CAF	Cyclic autocorrelation Function
CDMA	Code Division Multiple Access
CED	Conventional Energy Detection
CFD	Cyclo-stationary Feature Detection
CLT	Central Limit Theorem
CR	Cognitive Radio
CRN	Cognitive Radio Network
CROC	Complementary Receiver Operating Characteristics
CSS	Cooperative Spectrum Sensing
DSA	Dynamic Spectrum Access
DSM	Dynamic Spectrum Management
ED	Energy Detection
EGC	Equal Gain Combining
FC	Fusion Center
FCC	Federal Communications Commission
FSA	Fixed Spectrum Allocation
FFT	Fast Fourier Transform
IEEE	Institute of Electrical and Electronic Engineers
MF	Matched Filter
MFD	Matched Filter Detection
MInT	Ministry of Innovation and Technology
MS	Mobile Station
NCA	National Communication Authority
NCC	Nigerian Communications Commission
OSA	Opportunistic Spectrum Access
Pd	Probability of Detection

Pfa	Probability of False Alarm
Pm	Probability of Missed Detection
PSD	Power Spectral Density
PU	Primary User
RF	Radio Frequency
ROC	Receiver Operating Characteristics
RSS	Received Signal Strength
SCF	Spectral Correlation Function
SDR	Software Define Radio
SLC	Square Law Combining
SNR	Signal-to-Noise Ratio
SS	Spectrum Sensing
SU	Secondary User
Tv	Television
USRP	Universal Software Radio Peripheral
WiMAX	Worldwide Interoperability for Microwave Access
WLAN	Wireless Local Area Network
WSS	Wide-Sense Stationary

ABSTRACT

Recent years have seen a sharp increase in the number of wireless devices, which has led to a shortage of radio spectrum due to static spectrum allocation. The licensed spectrum bands, however, are not being used to their full potential, according to numerous studies on static allocation. Spectrum shortage and underuse have been problems that have been thought to be overcome via cognitive radio. To find spectrum holes, spectrum sensing (SS) is a crucial component of cognitive radio. To detect the presence or absence of primary user signals, many conventional spectrum sensing techniques such as Energy Detection (ED), Matched filter Detection (MFD), and Cyclo-stationary Feature Detection (CFD) have been developed. There are numerous difficulties in performance detection for these techniques. For instance, high susceptibility to noise uncertainty, high sensing time and need for prior knowledge of the primary user's signal are limitations of ED, CFD, and MFD respectively. In this thesis, a hybrid SS method consists of ED, MF, and CFD are proposed to exploit their merits and overcome their challenges. The proposed hybrid method aims to improve the detection performance of the existing hybrid technique over the Additive White Gaussian Noise (AWGN) channel and under the Rayleigh fading channel. Also, a performance comparison among conventional SS techniques, conventional hybrid based on ED and CFD, hybrid based on ED and MFD, and MFD and CFD SS over the AWGN channel are performed. The performance of the proposed hybrid approach is additionally enhanced by the cooperative detection methods. Parameters including the probability of detection, probability of false alarm, probability of miss detection, receiver operating characteristic (ROC) curve, and complementary receiver operating characteristic (CROC) curve are used to assess the effectiveness of SS. According to simulation results, the proposed hybrid technique significantly outperforms about 1.5 dB, 3.5 dB, and 5.5dB in SNR wall when compared to the hybrid method from MFD and CFD, ED and MFD, and conventional hybrid based on ED and CFD, respectively under AWGN. Additionally, under Rayleigh fading channel, the proposed technique achieves 1 dB, 1.5 dB, and 5.6 dB respectively. In contrast, a cooperative proposed hybrid technique involving two users shows a 6 dB and 4.5 dB performance improvement over single node proposed hybrid techniques under AWGN and Rayleigh fading channel respectively.

Keywords: Cognitive radio, Spectrum sensing, Spectrum holes, Energy detection, Matched filter detection, Cyclo-stationary feature detection, Hybrid method

CHAPTER ONE

1. INTRODUCTION

1.1 Background of the Study

In recent years, the need for adaptable and reliable wireless transmission has become more pronounced. To provide users with a broad range of services, mobile communication systems, and internet technologies are seen as the key to the future of wireless networks. Traditionally, the leasing of the spectrum and its use result in static and ineffective use. Spectrum shortage and uneven frequency use are caused by the demands of various technologies and the market(Akyildiz, Lee, et al., 2006). While the Ministry of Innovation and Technology (MInT) is in charge in Ethiopia, the government regulates the use of radio spectrum in many other nations through national regulatory organizations like the Federal Communications Commission (FCC) in the United States, the Nigerian Communications Commission (NCC) in Nigeria, and the National Communications Authority (NCA) in Ghana. This administrative body is in charge of allocating spectrum bands to various operators. All frequency bands, or licensed bands, are exclusively granted to certain users under the existing spectrum allocation policy over very long periods with the intention that only licensees will use them. The Fixed Spectrum Allocation (FSA) policy is the name of this approach. Using a specific methodology, it can temporarily use the spectrum that is presently available without interfering with the main user who paid to be serviced in that area(Ridhima & Singh Buttar, 2019).

Due to the enormous number and variety of wireless devices and applications, the development of new applications, and the ongoing demand for faster communication speeds, the Radio Frequency (RF) spectrum is becoming increasingly congested. Cognitive radio (CR), a promising technique, provides a solution to the spectrum shortage issue by dynamically utilizing the underutilized area of the frequency range(Wilfred & O.R., 2016). It refers to a radio or system that can dynamically modify the radio operating environments in response to the operational environment it can sense and comprehend. Cognitive radio, a wireless technology, makes it feasible to share the spectrum without interfering with the primary user (Moghaddam, 2018). Wireless communication technologies are developing quickly to satisfy peoples' ever-changing needs. Radio spectrum is becoming more necessary as cellular technology and systems progress. Utilizing natural resources like frequency, and time, effectively are the goal of CR (Walko, 2005). Spectrum sensing is the first step in employing a CR system. A secondary user (SU) or cognitive user (CU) can utilize the

primary user's (PU's) spectrum when the PU isn't there by sensing the PU's band and recognizing the PU's activity. PU signal or license band is the fundamental component of spectrum sensing (Abed & Abdullah, 2022). The SU cannot in any way obstruct the PU in cognitive radio networks for there to be progress. The two types of spectrum detection techniques are cooperative and non-cooperative. The three main methods used for spectrum sensing are energy detection (ED), matching filter detection (MFD), and cyclo-stationary feature detection (CFD). The MFD, which increases the received SNR in communication networks, is the best detector. It presents a problem for MF to comprehend the specifics of the PU signal's characteristics, such as the packet structure, pulse shaping, and kind of modulation. Cyclo-stationary detectors are not the best option. CFD can be used to remove the PU data from the noise. Due to its ability to reject noise, it works well in low SNR environments (Moghaddam, 2018). The MFD cannot be utilized as an ideal detector if the CR doesn't have sufficient understanding of the PU signal. A cyclostationary detector has a long sensing time, which is occasionally desired, but it also has a high computational complexity. Because it is less complicated to process than other methods, the ED spectrum sensing technique is more popular. However, when the signal-to-noise ratio (SNR) is low and the channel conditions are poor, the ED is unable to distinguish between the PU signal and the noise.

Performance monitoring is enhanced by the use of cooperative spectrum sensing (CSS) (Brito, Sebastiao, et al., 2021). Fading and shadow in wifi channels could be eliminated by CSS. CSS has both centralized and distributed fundamental structures. A fusion center (FC) receives the local judgments that SUs individually communicate after perceiving the spectrum in CSS. FC is in charge of making the final choice by implementing some type of fusion logic scheme (Meena et al., 2021). Choice fusion rules are available in two varieties: hard and soft. In a soft fusion rule, the SUs transmit their sensing data to the FC without making local judgments, in contrast to a hard fusion rule where each SU independently makes the local binary decision depending on the activity of the PU. At FC, a combining formula is used to make the choice. A hidden PU transmitter, range problems, fading effects, and SNRs are only a few of the challenges in identifying PU signals. In this instance, just one CR user may recognize the PU signal. The effectiveness of PU signal detection is lower for the same reasons. To overcome the drawbacks of single CR users in CSS, the PU signal must be detected by more than one number of CR users (Abed & Abdullah, 2022). In the distributed method, there is no FC. The CSS environment is built using the OR, AND, and

Majority rule algorithms. The algorithm only declares that PU is present when all CR users concur that it is, by the AND rule. Additionally, according to the OR rule, the algorithm asserts that PU exists whenever one of the CR users does. When 50% or more CR users report that the PU is present FC under the Majority rule ($M/2$ out of M), the algorithm determines whether the PU is present or absent in all other circumstances (Subhedar & Birajdar, 2011), (Bani & Kulkarni, 2022). The use of the spectrum efficiently and for next-generation wireless transmission has been made possible by cognitive radio technology. This enables us to further reduce the amount of energy we use for transportation. Nodes with cognitive radios can utilize the unlicensed portion of the spectrum flexibly with the help of this technology. The licensed user's usage habits determine whether these unutilized portions of the spectrum are accessible. The basic characteristics of the cyclic spectrum are used to classify PU signals (Divya Lakshmi & Rangaiah, 2019).

The permitted spectrum is not being used effectively for many frequencies, periods, and locations, according to a spectrum study done by the Federal Communication Commission (FCC) of the United States (Kaur, 2017). The wireless spectrum is a finite natural resource that is getting more crowded due to the increase of wireless devices and apps. By 2021, there will be more than 35.85 billion cellular connections, and the majority of them are likely to demand internet access. The policy for allocating radio spectrum has been created, assigning certain users with licenses for specific wireless technologies frequency channels. The ability to transmit and receive data from those portions is granted to licensed users. To allow access to all of these devices, static wireless spectrum management is no longer sufficient. According to a recent study, the percentage of spectrum used in the US under the fixed spectrum allocations (FSA) regime ranges from 15% to 85%. According to FCC measurements, some frequency bands are often used while other frequency ranges are generally underutilized. White spaces or "spectrum holes" are areas of the radio spectrum that have been allotted to principal users (PUs) but are not currently in use (Mishra et al., 2016). The term "spectrum hole" describes a frequency band set aside for a heavy user that is periodically underutilized in a specific location or time frame. This results in radio spectrum abuse. The FCC is the governmental body in charge of allocating fixed radio spectrum to license holders for a range of uses, such as cellular, television, and military. The demand for the limited radio spectrum is rising due to users of multimedia applications with high data rates and Quality of Service (QoS) requirements. This issue of the limited and underutilized radio spectrum can be resolved with the help of the dynamic spectrum access

(DSA) concept, which enables unlicensed users to opportunistically access the unused spectrum of lawful users without harming the existing users(Ridhima & Singh Buttar, 2019).

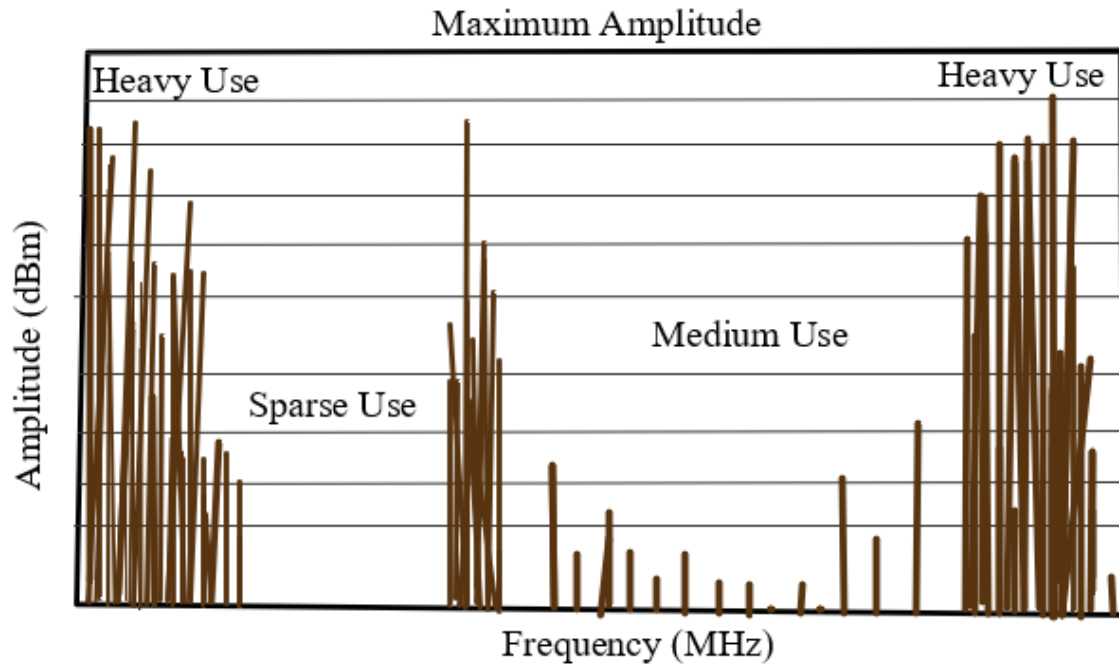


Figure 1.1: Radio Spectrum Occupancy (Akyildiz, Lee, et al., 2006)

The major drawbacks of the underutilized wireless spectrum are restricted Utilization, depletion, and poor use of the spectrum. Rapid action is consequently necessary to enhance radio access to the spectrum and achieve high network capacity. By regularly managing the issue without interfering with PU communications and sharing available channels with unlicensed users, sometimes known as secondary users, a safer solution to the problem of spectrum scarcity can be found. The use of DSA, or opportunistic spectrum access (OSA), has been implemented to address the problems with frequency allocation (Mishra et al., 2016). The DSA allows OSA between licensed and unlicensed users by dividing the spectrum into numerous frequency bands that are each allotted to one or more users, in contrast to the FSA.

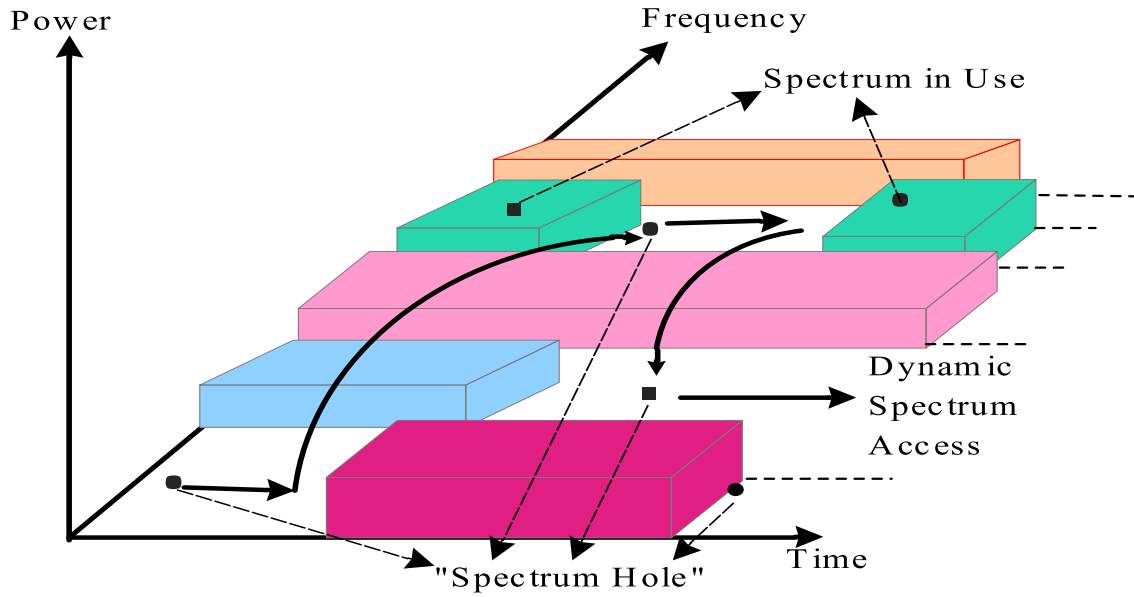


Figure 1.2: Dynamic Spectrum Holes(Mishra et al., 2016)

There have been many recent studies on the effective use of frequency bands that are either unoccupied or not being used to their maximum capacity. The use of the OSA has been advanced by several methods, including cognitive radio (CR). A software-based adaptive technology called CR looks for unused frequency bands and modifies the radio's operating parameters so that it can interact in those bands. A CR device can sense the radio spectrum in the surrounding region and choose to use the unlicensed primary spectrum's free channels. CR's main objective is to find a spectrum hole using clever methods. According to (Develi, 2020), the opportunistic use of frequency bands with few resources and current underutilization is made possible by CR, a vital technology (Nikonowicz & Jessa, 2016). Bands can be classified as either permitted or unlicensed (Gupta & Onumanyi, 2019).

1.2 Statement of the Problem

There are numerous limitations on how the accessible radio spectrum, a limited and precious resource, can be exploited as a result of the rising demand for wireless services. The recent explosive rise of cellular communications has made the issue of spectrum utilization even more critical. Additionally, because a significant portion of the licensed spectrum is not being used properly, a fixed policy for allocating spectrum has resulted in underutilization of the available spectrum. To address the issue of spectrum underutilization, spectrum sensing (SS), which identifies spectrum gaps (underused frequency bands), is a crucial task for cognitive radio (CR). CR has proven to be a workable method for improving the efficiency of the radio spectrum use that is currently available. As was mentioned in the background section, there are several different SS techniques. The easiest and clearest of

these processes is the energy detection (ED) method. However, because of noise uncertainty, ED performance rapidly declines at low SNR signals. By contrast, matched filter detection (MFD) can detect PU signals at low SNR levels and maximize SNR. But it is unable to recognize PU when there is no prior knowledge of the PU signal. Additionally, cyclostationary feature detection (CFD) takes more time to detect the existence or absence of a PU signal, but it can detect a PU signal at low SNR by rejecting noise. To solve the problems caused by noise uncertainty at low SNR, the absence of prior knowledge of PU, and the limitations of CFD, this study introduces a hybrid based on MFD, CFD, and ED. Additionally, a hybrid SS technique made up of the three fundamental SS techniques (ED, MFD, and CFD) is developed to enhance the performance of the conventional SS techniques (ED, MFD, and CFD) and the existing hybrid SS method.

1.3 Objectives

1.3.1 General Objective

The main objective of this thesis is to improve the spectrum sensing (SS) performance by using a hybrid SS method that consists of ED, MFD, and CFD to exploit their merits and overcome their challenges over the AWGN channel and Rayleigh fading channel.

1.3.2 Specific Objectives

The specific objectives of this thesis are:

- ❖ To study and analyzes the performance of energy detection (ED), matched filter detection (MFD), and cyclostationary feature detection (CFD) in terms of P_d vs SNR, ROC curve, and CROC curve.
- ❖ To compare the performance of conventional spectrum sensing (SS) with conventional hybrid based on ED and CFD, hybrid based on ED and MFD, and MFD and CFD.
- ❖ To develop a hybrid SS technique using ED, MFD, and CFD for SS of cognitive radio.
- ❖ To evaluate how well the proposed hybrid SS technology performs in comparison to existing hybrid methods (ED and CFD, ED and MFD, and MFD and CFD).
- ❖ To evaluate the performance of cooperative detection for conventional hybrid based on ED and CFD, hybrid based on ED and MFD, MFD and CFD and proposed hybrid SS.

1.4 Scope of the Study

The primary objective of this thesis is to enhance spectrum sensing (SS) for cognitive radios (CR). The non-cooperative SS approaches that will be used include energy detectors (ED), matching filter detection (MFD), and cyclo-stationary feature detection (CFD). Hybrid detection approaches are used to address the problems of performance degradation at low SNR due to noise uncertainty in ED, to improve the performance detection of the MFD when it lacks sufficient information about a PU signal or at very low SNR values, and to address the problem of the detection of the PU signal taking longer in CFD. Hybrid SS for CR is created by employing ED, MFD, and CFD to further enhance the performance of SS. Finally, the effectiveness of the proposed hybrid SS, traditional hybrid technique, and conventional SS over the AWGN channel and Rayleigh fading channel is evaluated. The proposed detector is completely simulated using MATLAB software communication tools.

1.5 Significance of the Study

The demand for bandwidth has greatly increased as a result of the sharp rise in the number of devices linked to wireless systems in recent years. There is a severe spectrum scarcity issue as a result in some bands. Cognitive radio network (CRN) technology has been suggested as a solution to the bandwidth shortage issue. Thus, the significance of this thesis is that it reduces bandwidth scarcity using CRN. The ED technique is critical for CR since it functions independently without requiring any PU signal information and is the simplest to implement. Due to noise uncertainty, ED has poor spectrum sensing performance at low signal-to-noise ratio (SNR) values. MFD is the optimum technique for primary users when the transmitted signal's contents are known because it can boost the received signal's SNR. However, because the CFD technique can distinguish between the signal and the noise and because its functions depend on PU signal information, it performs better than ED. But it requires a lot of sensing time. Hybrid SS methods have been proposed to significantly enhance the performance of both traditional hybrid and conventional spectrum sensing (SS) systems. As a result, the main contribution of this thesis is the use of a proposed hybrid SS technique to enhance the performance of traditional hybrid and conventional SS methods.

1.6 Thesis Contribution

The following are the primary contributions of this thesis:

- i. To reduce the performance loss of the conventional technique, and traditional hybrid spectrum sensing (SS) technique which happens at low SNR situations due to noise uncertainty and lack of prior information of the primary user we employed various

fundamental SS and traditional hybrid detection methods. Moreover, the performance comparisons among traditional hybrid SS techniques with fundamental SS techniques are performed to choose to compare with the proposed hybrid.

- ii. Using hybrid SS approaches which have ED, MFD, and CFD, are devised to improve detection performance.
- iii. The proposed hybrid SS technique's cooperative detection is used to boost the single-node technique's performance even more.

1.7 Limitation of the Study

Only results from simulations are included in this thesis. That indicates that only simulation data are used to evaluate the effectiveness of all detecting approaches.

1.8 Thesis Outline

This is how the thesis' five chapters are organized.

Chapter one concisely explains the study's background context. Here, the problem statement, study scope, thesis significance, and thesis objectives are also listed along with their limitations.

Chapter two begins with a quick overview of Cognitive Radio Network (CRN) and Dynamic Spectrum Access (DSA). The presentation includes a thorough explanation of DSA and CRN.

Then a brief discussion of cognitive radio's functions follows. Next, an in-depth discussion of the classification of spectrum sensing (SS) techniques follows. The final section of this chapter discusses a connected thesis.

Chapter three explains the research methodology utilized to create the thesis as well as the system models for the fundamental SS approach and the proposed hybrid approaches. Additionally, this chapter explained the tools that were used to simulate the outcomes.

Chapter four covers the findings and analysis of the proposed hybrid methods, conventional techniques, and traditional hybrid SS techniques. Additionally, the outcomes of the cooperative detection are shown for the proposed hybrid approach and traditional hybrid SS method.

Finally, the thesis's **Conclusion and Recommendation** are given.

CHAPTER TWO

2. LITERATURE REVIEW

2.1 Introduction

The electromagnetic wireless spectrum is becoming more scarce as its utilisation rises. The old approaches to spectrum management and allocation as well as the current rigidity in operating frequency bands, however, result in the underutilization of the available spectrum. The majority of the useful radio spectrum has already been allotted, making it challenging to launch new services or enhance those that are already accessible. As a result, unoccupied bands are hard to discover. The dynamic spectrum access (DSA) approach was developed to improve spectrum use (Gupta & Onumanyi, 2019). The DSA approach set the way for the creation of cognitive radio network (CRN) technology, a solution to the spectrum underutilization issues in wireless communication.

2.2 Cognitive Radio (CR)

In cognitive radio (CR), a form of wireless communication, a transceiver can enter available channels while avoiding ones that are already occupied. CR is an example of wireless communication. Another name for CR is a wireless communication system that actively changes and assimilates information from its environment. Full CR and Spectrum Sensing CR are the two types of CR:

Full Cognitive Radio: It considers every aspect a system is capable of knowing. In other words, it is a radio that takes into account every characteristic that could be measured by a wireless node (network).

Spectrum Sensing CR: It's a radio that simply considers the radio frequency spectrum. There are only radio frequency bands found.

2.2.1 Basic Definitions of Cognitive Radio

For many networking and communication networks, the term "cognitive" has gained popularity. One of the most common definitions of "cognitive" in the Oxford English Dictionary is "pertaining to cognition or to the activity or process of knowing." Cognition is described as "the mental process of gaining knowledge through, experience, and the senses." As a result, CR can be referred to as a cognitive radio. In a 1999 study, Joseph Mitola introduced the idea of "cognitive radio," which he later defined as "a radio that employs model-based reasoning to achieve a specified level of competence in radio-related domains" (MAGUIRE, 1999). Six years after Joseph Mitola's paper on the topic was published, Simon Haykin defined cognitive radio (CR) as follows: "With two main objectives in mind, an

intelligent wireless communication system that is aware of its surroundings (i.e., the outside world) uses the understanding by building methodology to learn from the environment and adapt its internal states to statistical variations in the incoming RF stimuli. The system then adjusts certain operating parameters in real-time, such as transmission power, carrier frequency, and modulation strategy:" (Walko, 2005).

- Whenever and wherever required, highly reliable communications;
- Judicious use of the electromagnetic spectrum

A wireless communication system with intelligence that can change the transceiver's parameters in response to interactions with its operating surroundings is referred to as a CR by the FCC. The definitions provided by IEEE USA in 2019 however specify that it is "a type of radio in which communication systems are aware of their environment and internal state and can make decisions about their radio operating behavior based on that information and predefined objectives." According to cognitive principles, unlicensed users (secondary users) can use the free spectrum bands without interfering with the primary users.

To accommodate numerous users, a transceiver automatically distinguishes between communication channels that are in use and those that are not (i.e., "spectrum holes") and quickly accesses the free channels while avoiding the occupied ones. This is known as CR. The CR users access the spectrum using the DSA method, as shown in Figure 2.1 (Ridhima & Singh Buttar, 2019).

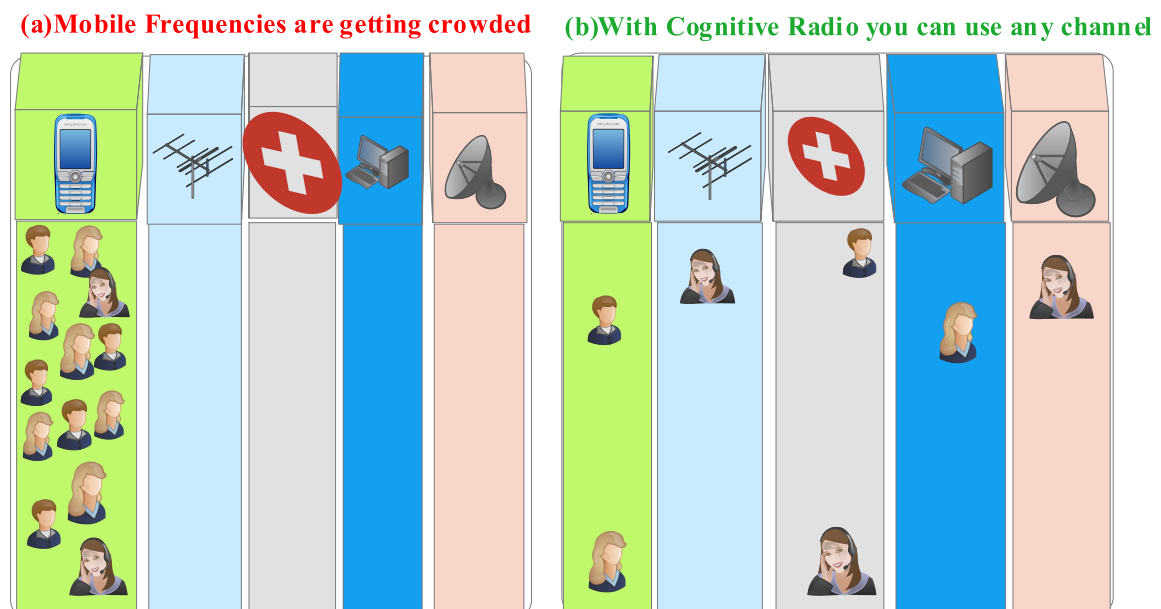


Figure 2.1: Dynamic Spectrum Access by CR users (Ridhima & Singh Buttar, 2019)

2.2.2 Cognitive radio characteristics

Two primary cognitive radio characteristics are explained below:

Cognitive Capability: It describes the radio technology's capacity to gather data from its environs (i.e., radio environments). Joseph Mitola described cognitive ability as "a CR that constantly monitors the surroundings, orients itself, forms plans, decides and then acts" in terms of the cognitive cycle.

Re-configurability: Cognitive capabilities enable spectrum awareness, whereas reconfigurability describes a radio's ability to change its functionality, enabling the CR to be dynamically configured in reaction to the radio environment.

2.2.3 The Architecture of Cognitive Radio

Cognitive radio networks (CRNs) are made up of interconnected Cognitive Radio devices that exploit the licensed electromagnetic range as secondary users. CRNs should be viewed as heterogeneous networks in the ideal scenario. This is because such networks utilize a variety of cellular access technologies and comprise various networks, communication systems, and endpoints. But it is still possible to create three basic network architectures for CRNs.

2.2.3.1 Ad-hoc Architecture

There is no definite network architecture for coordinating data flow between end devices in these types of topologies. (Akyildiz, Melodia, et al., 2006). As a consequence, an ad-hoc network is created when mobile stations connect to other suitable devices nearby. As a result, these designs use the multi-hop method for communication.

2.2.3.2 Infrastructure Architecture

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

2.2.3.3 Mesh Architecture

Ad hoc and infrastructure designs are combined to create mesh architecture. In this design, an MS can communicate directly with the BS or employ other mobile stations as multi-hop relay nodes. According to (Akyildiz, Melodia, et al., 2006), in cases like this, there is frequently some wireless contact between the BS.

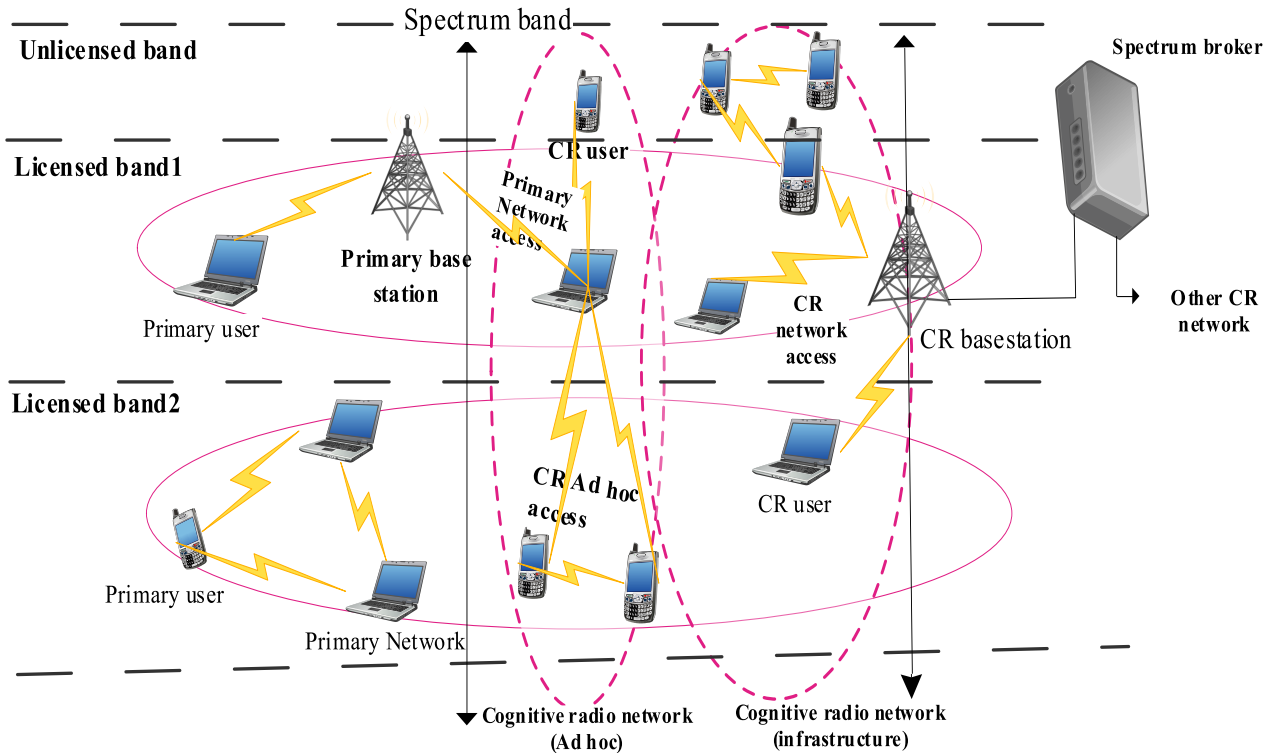


Figure 2.2: Cognitive Radio Network Architecture(Akyildiz, Melodia, et al., 2006),(Nath, 2015)

Generally, there are two categories for CRN architecture:

- Primary Network
- Cognitive Radio Network

The Primary Network: Its access to the particular spectrum bands is restricted to the pre-existing equipment (Subhedar & Birajdar, 2011), (Akyildiz, Melodia, et al., 2006). WiMAX, TV transmission networks, CDMA, and cellular networks are prominent examples of this type of network. The primary User (PU) and Primary BS are the main network elements. A licensed base station user who has been given authorization to perform in a band with a license is referred to as a Primary User (PU). A main BS (licensed base station) is a piece of fixed network infrastructure that is licensed to use certain technology in a specific spectrum band. Consider integrating a Base-station transmission system (BTS) into a cellular network.

The Cognitive Radio Network (CRN): Does not have a monopoly on access to a licensed frequency; rather, it is given opportunistic access to the spectrum. Secondary User (SU), Cognitive Radio BS (Unlicensed BS), and Spectrum Broker are the parts that make up the CRNs.

Unlicensed users who are only occasionally allowed to utilize the airwaves are referred to as Secondary Users (SU). The term Cognitive Users can also be used as SU. A fixed

infrastructure component called Cognitive Radio BS (Unlicensed BS) has Cognitive Radio capabilities and offers users of Cognitive Radio a single-hop link. In cooperative SS, the Cognitive radio BS serves as a Fusion center (FC) that compiles local measurement data from cooperating users before making the ultimate SS determination. A centralized network body called a "Spectrum Broker" controls how spectrum resources are distributed among users of cognitive radio.

Primary Users (PU) and Secondary Users (SU) are two categories for users in CRN.

Primary user (PU): A user with a greater priority for using a particular spectrum band.

The secondary user (SU): A low-priority user who uses the airwaves without interfering with PUs.

2.3 Spectrum Access Techniques

Due to the expansion of wireless services and applications over the past 20 years, as we already stated in the previous chapter, Spectrum resources are in high demand, and as a result, there are concerns about shortage (Akyildiz, Melodia, et al., 2006). In a wider sense, these problems are a result of the prevalent conventional spectrum management paradigms. But numerous studies reveal that there is relatively little ongoing usage of the licensed spectrum, which results in very low spectrum utilization. The massive underutilization of the spectrum has motivated numerous regulatory organizations in charge of communications to investigate ways to improve spectrum management and access methods (Heng & Niversity, 2012) as a consequence, Dynamic Spectrum Access (DSA) was developed as a strategy.

To reduce spectrum scarcity and boost spectrum utilization, a novel spectrum-sharing approach called DSA, also known as dynamic spectrum management (DSM) makes use of frequency gaps. By allowing secondary usage in licensed frequency bands, DSA aims to address the problems of scarce spectrum and inefficiency. In (Clancy, 2009) as long as they don't obstruct main users, secondary users (SU) or unlicensed users are permitted to transmit in the licensed bands. According to Figure 2.3, DSA can be in general terms there are three main models. The fundamental technology that has been heavily utilized to accomplish DSA objectives is cognitive radio (CR) technology (Zhang, 2008).

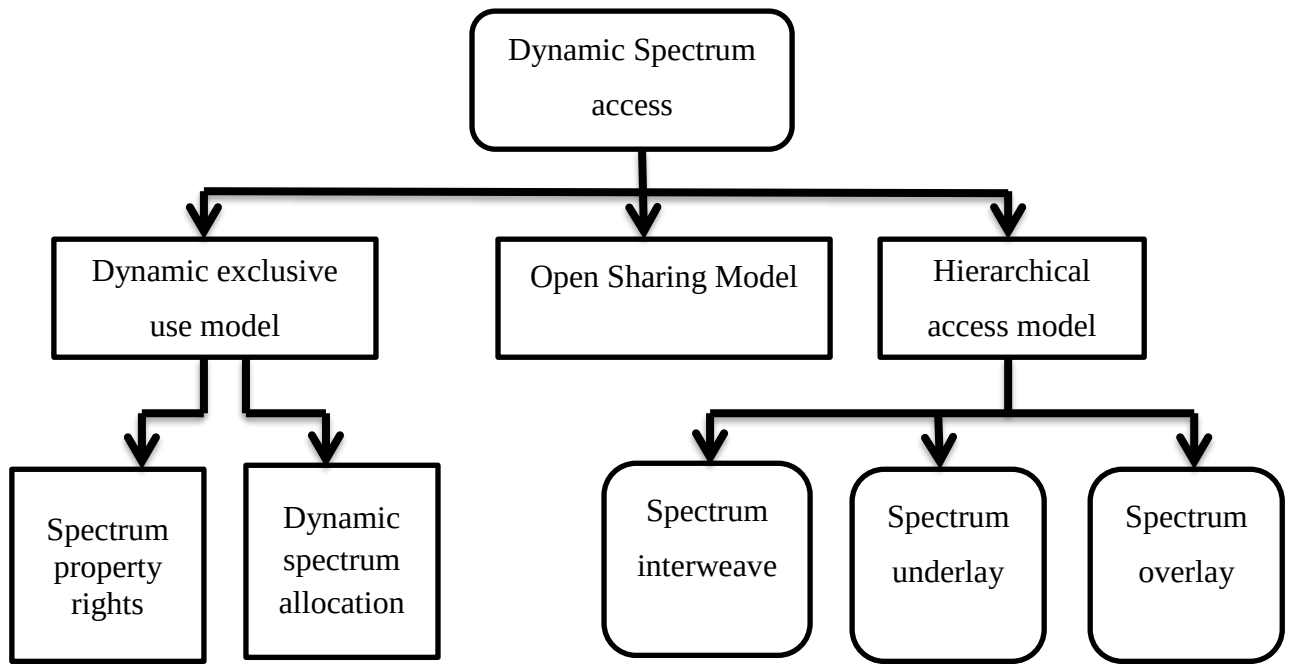


Figure 2.3: Classification of DSA(Clancy, 2009)(Nasser et al., 2021)

2.3.1 Dynamic Exclusive Use Model

It adds flexibility while maintaining the fundamental structure of the existing spectrum management policies. This increases the efficiency of spectrum utilization. Two strategies have been put forth in this model to add dynamicity: Spectrum Property Rights and Dynamic Spectrum Allocation. Licensees have the freedom to sell and trade the acquired spectrum as well as select the technology that best meets their requirements in terms of spectrum property rights. Dynamic spectrum allocation aims to improve spectrum efficiency by using spatial and temporal traffic information for a variety of applications and services (Prasad, 2009), (Rodriguez, 2015).

2.3.2 Open-Sharing Model

The spectrum common model is also referred to as the open-sharing paradigm. This enhances spectrum efficiency by enabling users to share resources freely, similar to earlier successful models like wireless services that operate in the unlicensed Industrial, Scientific, and Medical (ISM) radio band (Heng & Niversity, 2012).

2.3.3 Hierarchical Access Model

This model generates dynamicity in the spectrum via a hierarchical access mechanism. Users can be divided into two groups in this model: primary users and secondary users. Three techniques are employed to achieve spectrum sharing between primary and secondary users in the hierarchical paradigm (Prasad, 2009), (Rodriguez, 2015). As seen in Figure 2.4, these

are the spectrum interweave approach, spectrum underlay approach, and spectrum overlay method.

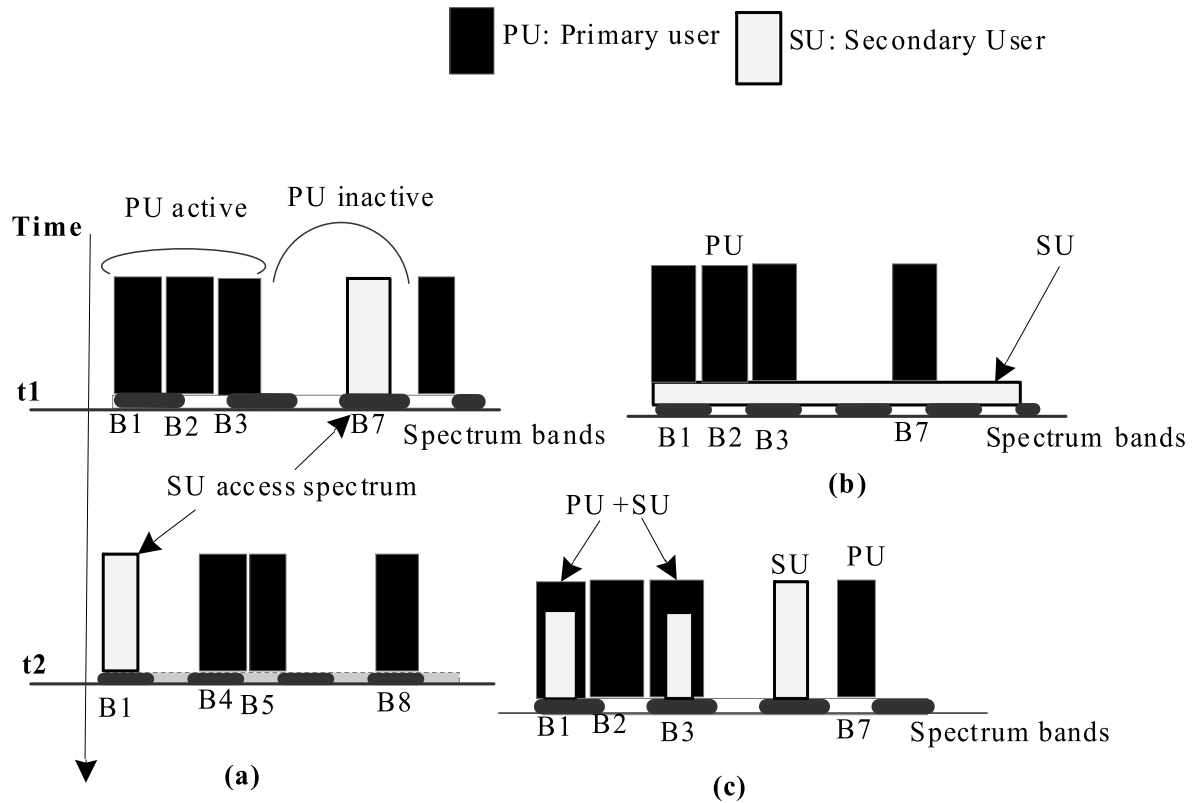


Figure 2.4: DSA models: a) interweave DSA model; b) underlay DSA model; c) overlay DSA model. (Heng & Niversity, 2012)

The method that has drawn the most notice and is generally regarded as the de facto standard for DSA is the spectrums interweave approach. In contrast to the spectrum overlay and underlay methods, SU is not permitted to use a licensed spectrum frequency if a PU is already using it. In addition, whenever the PU starts to access the band, any SU accessing it must stop. This is because the PU has the highest precedence in the spectrum band. The interweave DSA model is also referred to as opportunistic spectrum access as a consequence. Figure 2.4 (a) shows the dynamic availability of the spectrum as well as how SUs employ an integrated strategy to find and utilize free spectrum bands (Heng & Niversity, 2012).

The spectrum underlay approach permits SUs to operate on a licensed band of the spectrum whether or not the PU is utilizing it if the sum of all SU interference is less than a particular threshold that the PU can tolerate. There are two ways to adhere to this constraint. The transmitted power of the SU is scattered throughout a wide range of spectrums, which greatly reduces the interference to the PU on each allowed band compared to the threshold in the first technique. This tactic is used by Ultra-wideband (UWB) technology. Short-range

situations are best suited for this technique. The second strategy is the interference temperature technique. This technique allows SUs to function at greater power levels on a licensed spectrum band, provided that the total interference from all SUs on the band is below a predetermined threshold. The spectrum underlay methods in Figure 2.4 (b) show how SUs share a large amount of spectrum with PUs on each band (Heng & Niversity, 2012). The spectrum overlay method allows SUs to use an approved spectrum band while the PU similarly uses the band to the underlay method (Heng & Niversity, 2012). The restriction is different, though. The overlay method focuses on keeping or preserving the PU performance rather than restricting SUs transmit power to reduce SUs interference to the PU. As long as the performance of the PUs is not adversely affected, SUs are allowed to broadcast simultaneously as shown in Figure 2.4 (c) (Heng & Niversity, 2012)

2.4 Cognitive Radio Cycle

A Cognitive radio (CR) device can locate open channels, identify the spectrum, and select which of those channels to use. The Cognitive Cycle describes the categorization of spectrum sensing and allocation techniques into four main groups. Spectrum sensing (SS), spectrum management, spectrum sharing, and spectrum mobility are all tasks carried out by CR devices.

- i. **Spectrum sensing:** SS continuously scans the spectrum to identify the principal user's presence or absence. Real-time environment monitoring by CR identifies the unoccupied spectrum. SS may be carried out by a single cognitive radio or by a network of cognitive radio terminals working together.
- ii. **Spectrum management:** The secondary user's ability to choose and decide on the best channel that meets specific targeted goals is made possible by the spectrum management function. To identify the most accessible spectrum, CR looks at data rates, transmission types, and customer needs before using the spectrum hole or white space. For CR to choose when to start operating, the operating frequency, and the associated technical challenges, a decision must be made based on SS data.
- iii. **Spectrum sharing:** Due to the possibility of many SUs using the available gaps in the spectrum, it is necessary to provide a fair scheduling method for coexisting users.
- iv. **Spectrum Mobility/Handoff:** To avoid colliding with the main licensed user when they begin transmitting, CR must immediately stop operating or leave the radio spectrum that is presently in use. For the application currently running at the secondary user, the handoff should be seamless, and CR should maintain

communication during the move to a better white space, ensuring that the application is unaffected and suffers minimum performance loss. For radio to keep flawless transmission, alternate spectrum gaps must be constantly searched for.

The figure illustrates the cognitive cycle through which a cognitive radio interacts with its surroundings 2.5 below.

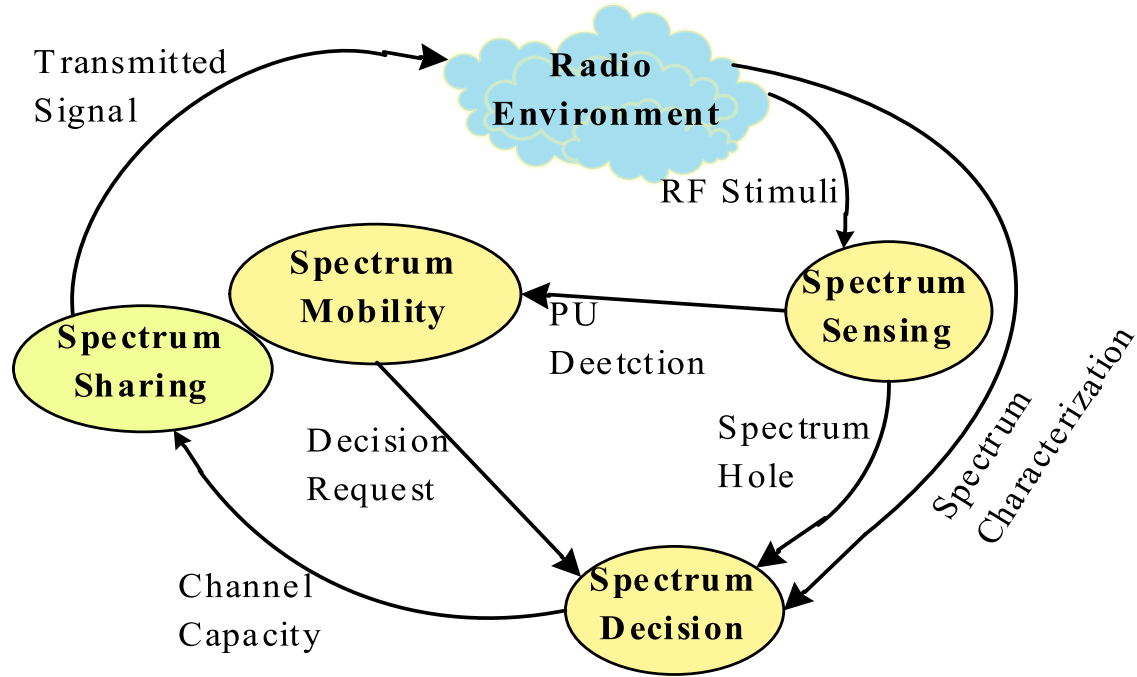


Figure 2.5: Cognitive Radio Cycle(KUMAR, 2015) (Eappen & Shankar, 2020)

2.5 Spectrum Sensing Techniques

It is essential for cognitive radio (CR) function that secondary users correctly and promptly identify spectrum opportunities(Suhag & Malhotra, 2016). The secondary user will lose the chance to transmit its data if a main transmission has been discovered while the primary user is not using the device. If the secondary user transmits at the same time as the primary user despite being unable to identify it, there will be a degradation in service and interference. Therefore, it is essential to understand how CR makes use of spectrum detection. The method of locating signals in a frequency range is called range sensing. The process of gathering information about how spectrum resources are being used in a specific geographic area is known as spectrum sensing (SS). This data is then used to accommodate SUs without interfering with other users of the spectrum(Suhag & Malhotra, 2016). Due to SS, CR can observe, understand, and be aware of their working environments, including the spectrum's availability and the level of interference. When the PU determines that a particular spectrum band is underutilized at a particular time in a particular place, indicating the presence of a spectrum opportunity, the SUs are permitted to use that band. In light of this, SS applies to

the dimensions of frequency, time, and space. Thanks to recent developments in beam-forming technology, multiple users can utilize the same frequency bands (channels) at the same time in the same place (Sobron et al., 2015). As a result, if a PU is not broadcasting in all directions, spectrum openings for SUs in the unoccupied directions may be formed, and SS must also take the angle of arrivals into account. Generally speaking, SS accomplishes the following duties. Spectrum holes are found, the spectral resolution for each one is determined, the spatial coordinates of an incoming interfering signal are estimated, and the signals are classified.

Spectrum hole detection, the most important of the aforementioned SS tasks, is looked into using a binary hypothesis-testing issue. Out-of-band sensing and in-band sensing are two subsets of the so-called SS, which determines the presence or absence of PUs in the underlying band. Out-of-band sensing entails searching the spectrum band for openings that SUs can use for transmission, while in-band sensing entails searching for the PU return in the spectrum band where the CR is currently operating.

Wideband and Narrowband are the two sets of SS techniques that have emerged during the last few decades depending on the relevant bandwidth for spectrum sensing. While Wideband SS analyzes numerous frequencies at once, Narrowband SS only looks at one frequency band at a time. Another way to categorize sensing techniques is the requirement of prior knowledge of PU signals, which are separated into coherent and non-coherent detection (Huang et al., 2010). But there are three basic types of spectrum-detecting methods, as shown in Figure 2.6: three types of detection: interference-based, receiver-based, and transmitter-based (non-cooperative). In this paper, transmitter-based detection techniques are employed.

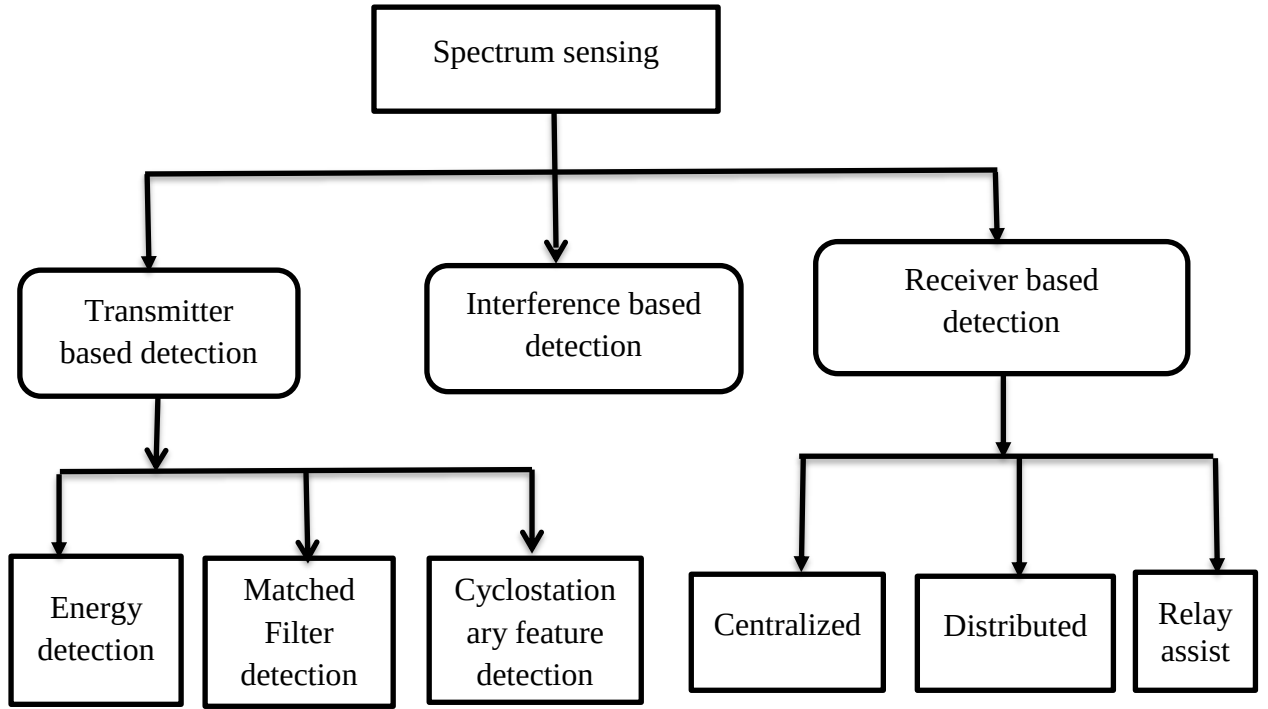


Figure 2.6: Classification of Spectrum sensing technique (Divya Sahithi et al., 2020)

2.5.1 Transmitter-based detection technique

It belongs to one of the main groups of spectrum sensing (SS) methods. Another term for it is the Non-cooperative SS approach. Non-cooperative detection is when there is only one terminal available to sense the spectrums or when the sensing terminals do not collaborate. As a result, decisions regarding spectrum sensing are dependent on regional measurements and secondary users' observations (Lavate, 2017). The cognitive device is typically believed to be unaware of the location of the primary transmitter in transmitter-based detection strategies, and the examination of the signal that was received at the SUs reception end serves as the sole foundation for the detection model.

Cognitive users can only do SS using local observations and the identification of weak signals from the main transmitter as a result. The spectrum occupancy around a cognitive device is not completely understood. As a result, PUs cannot be protected from harmful interference. Furthermore, a concealed terminal issue cannot be prevented by transmitter-based detection. Transmitter-based detection falls within the categories of energy detection, matching filter detection, cyclo-stationary feature detection, etc. Noncooperative algorithms are straightforward, inexpensive, and simple to apply in real-time environments.

2.5.1.1 Energy Detection

The most prevalent spectrum sensing (SS) method for assessing the presence or absence of a PU signal without having any prior knowledge of the PU signal's properties is the Energy

Detector (ED). The ED approach, which can be used with CRs, is the best way to find any unknown signals with zero-mean constellation when the PU signal is unknown. Given that it ignores the characteristics of the received information, an ED is known as a blind detector(Digham et al., 2007). Since ED doesn't require prior knowledge of the primary signal, it is resistant to changes in the primary signal (Nair et al., 2010). To identify a PU signal, the energy of an incoming signal is used in the energy detection method. If the energy present is noticeably more than just background noise, a signal is considered to be present in the channel. The ED filter initially filters out the unwanted signal from the unwanted frequency band. After that, the sampled filter output is squared, and the signal energy is added. The test statistics generated from the output of signal energy are compared with a threshold (λ) to ascertain whether a licensed user is present(Clancy, 2009).

The ED process can be carried out or realized in the time domain and occasionally in the frequency domain and also it can be implemented as analog and digital; Hereafter, we concentrate on the digital time domain implementation strategy. The signal received by the secondary user is first routed through a BPF to measure the signal power in a certain frequency range in the time domain. The output of the filter is then squared and integrated over a specified time interval. By comparing the final signal to the detection threshold, the signal power is statistically evaluated. To do frequency domain detection, the time domain signal must first be converted using FFT into the frequency domain signal, after which the overall signal power across all frequency bins must be compared to the decision threshold (Lakshmi et al., 2013).

Since the threshold must differentiate between signals and noise, setting the right threshold is challenging. The easiest method for finding spectrum holes is ED. However, because of the uncertainty of the noise level, it is necessary to have previous knowledge(Tandra & Sahai, 2008). The threshold value as well as the sample size are the primary factors considered in the design of the ED. The SNR and noise variance affect the energy detector's performance, but in practice, designers do not influence these factors because they are dependent on the wireless channel environment. The quantity of samples is another essential element in the design of the ED. The ED functions best when the signal is nondeterministic and only its average strength is known.

Constraints of the Energy Detector

- It might take more time to reach the target detection probability.
- The noise's ambiguity affects the effectiveness of the detection.

- It is challenging to discern between different PU signals because ED is unable to distinguish between the sources of received energy (Akyildiz, Melodia, et al., 2006).
- It can't detect spread or dispersed signals(Akyildiz, Melodia, et al., 2006).

2.5.1.2 Matched Filter Detection

When the SU is aware of the PUs signal beforehand, the matched filter (MF) is the best identification method. Given that it requires prior knowledge of the PU signal, it is a coherent detection technique(Lu et al., 2012). Under ideal circumstances, the coherent detection method performs very well. In matched filter detection (MFD), the following details must be known by SUs: bandwidth, order, modulation type, carrier frequency, packet structure, and pulse shape (Li et al., 2011). An MF's primary function is to increase the incoming or output SNR for a specific input signal (Subhedar & Birajdar, 2011). The operation of an MF is analogous to that of a correlation scheme; where the reference signal's mirror and time-shifted version of the filter's impulse response are convolved with the unknown signal (Kumar Verma et al., 2012). A matched filter convolves a time-reversed version of the known signal with the received signal $r(t)$ in operation (Kumar Verma et al., 2012). An MF works similarly to a correlation scheme in that the reference signal's impulse response is mirrored in the unknown signal's impulse response, which is then convolved with the reference signal. In use, a matched filter combines a time-reversed form of the known signal with the received signal $r(t)$ (Bluthenthal & Fehring, 2011).

$$r(t) \oplus s(T - t + \tau) \quad (2.1)$$

Where T denotes a symbol time duration and τ is refer to a shift in the known signal.

MFD is a method of detection that contrasts newly acquired signal samples with pilots that have already been gathered and stored from the same stream of PU signal. The saved pilots are mixed with the signal samples that were received, averaged over N samples to produce the decision statistics, and finally contrasted to a predetermined cutoff to produce the sensing choice. The PU signal is regarded as present if the convolution result surpasses a threshold value; otherwise, it is regarded as absent. The MF method offers better detection performance at low SNR values, and it is ideal in that it only needs a small number of samples to achieve a maximum probability of detection in a brief sensing period. However, MF detection needs prior information on some PUs signal characteristics. This detection method is impractical because this information is frequently unavailable(Giweli & Shahrestani, 2016).

Limitations of Matched Filter Detection

- The broadcast signal characteristics in a CRN are frequently unknown. The performance of the MFD, therefore, degrades, which causes the detection of undesirable signals (Akyildiz, Melodia, et al., 2006).
- Different PU signals required a different sort of detecting receiver.

2.5.1.3 Cyclostationary Feature Detection

A signal is considered to be cyclo-stationary, in cyclo-stationary feature detection (CFD) if its statistics, such as its mean or auto-correlation, are a periodic function over a specific time. Typically, a licensed user's signal has a periodic rhythm that it transmits. Cyclo-stationary, another name for the periodic pattern, is used to identify the presence of a licensed user. Feature detection is the process of obtaining features from a signal that has been received and performing detection based on those characteristics. By utilizing the information in the primary user signal that noise lacks, CFD can separate the primary user (PU) signal from noise at very low SNR detection levels. One of the main advantages of CFD algorithms is their ability to distinguish between PU signals and noise signals (Nafkha et al., 2014). This is so because noise lacks correlation with the PU signal and is wide-sense stationary (WSS) (Zhang, 2008). The CFD is also called the auto-correlation-based sensing technique.

Limitations of the Cyclo-stationary Feature Detection

In sites with low SNR, the CDF performs noticeably better and is more tolerant to noise levels with uncertainty (Akyildiz, Melodia, et al., 2006). However, this method has certain drawbacks:

- High computational complexity
- long sensing times; and
- large power consumption as a result of the use of several receiver algorithms for detecting (Akyildiz, Melodia, et al., 2006).

Table 2.1: An overview of transmitter-based spectrum detection methods

Spectrum Sensing Techniques	Advantages	Disadvantages
Energy Detection	➤ Does not need any prior information about PU signal ➤ Ease to implement or easy for deployment ➤ Very less sensing time ➤ Low computational complexity	➤ Poor performance in a low SNR environment ➤ Very low sensing accuracy ➤ Difficulty in identifying PU signal from noise
Matched filter Detection	➤ Optimal detection performance ➤ Shorter sensing time	➤ Requires prior knowledge of the PU signal ➤ Requires a large number of receivers
Cyclostationary feature detection	➤ Robust in low SNR ➤ Robust to interference ➤ It can identify PU signals from noise ➤ High sensing accuracy	➤ Requires a partial knowledge of primary users ➤ High computational complexity ➤ Large sensing times

2.5.2 Interference-based detection

CRs concentrate on figuring out the interference at the receiver terminal when using this method. Due to background transmissions and impending radio noise, the energy that could interfere with the PU is always present at the receiver at any given moment. As a consequence, the main receiver experiences the majority of the interference(Akyildiz, Melodia, et al., 2006). Therefore, main transmissions are made to function at a particular distance from the transmitter and over a particular noise level. However, because the noise

in the radio environment is unpredictable, the noise level may change, further interfering with the PU. By using this method, the SU can broadcast at the same time as the PU, but it must also monitor the interference environment to ensure that it doesn't go over the PU's tolerance for interference. The interference threshold, also known as the interference temperature limit, is depicted in Figure 2.7 and acts as a boundary for the interference caused by the licensed users in a certain frequency band at a particular location. The SU may use the channel if the primary signal level measured is below the interference temperature limit. Furthermore, an SU is free to use any frequency parameter it chooses as long as its transmission strength stays below the interference gap. This approach is characterized as a spectrum underlay scheme since it is expected that the secondary users will be permitted to operate concurrently with the primary users under strict interference avoidance requirements. The main issue with this approach is that CR users are required to know the precise location of the adjacent PUs; otherwise, it is difficult to measure the interference.

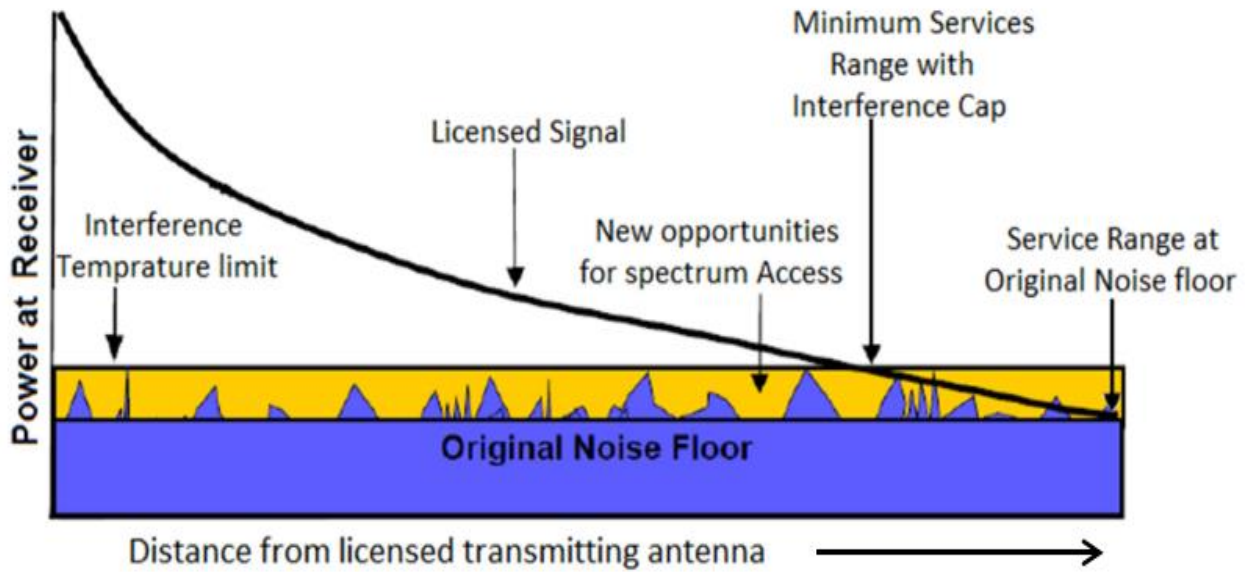


Figure 2.7: interference temperature Management(Subhedar & Birajdar, 2011),(Akyildiz, Melodia, et al., 2006),(FCC, 2002)

2.5.3 Cooperative Detection

In transmitter-based detection, each CR user assesses the spectrum occupancy using their local data. A dynamic variation in channel fading and shadowing circumstances is explained by several unknowns, including channel uncertainty. The performance of the receiver operating characteristic can be impacted by noise uncertainty, which makes it challenging to detect a transmitted signal from authorized users in a CRN environment, and aggregated interference uncertainty, which occurs when too many unauthorized users interfere with one

another in the same CRN. The problem of hidden terminals is seen as a serious impediment in SS, as shown in Figure 2.8 below.

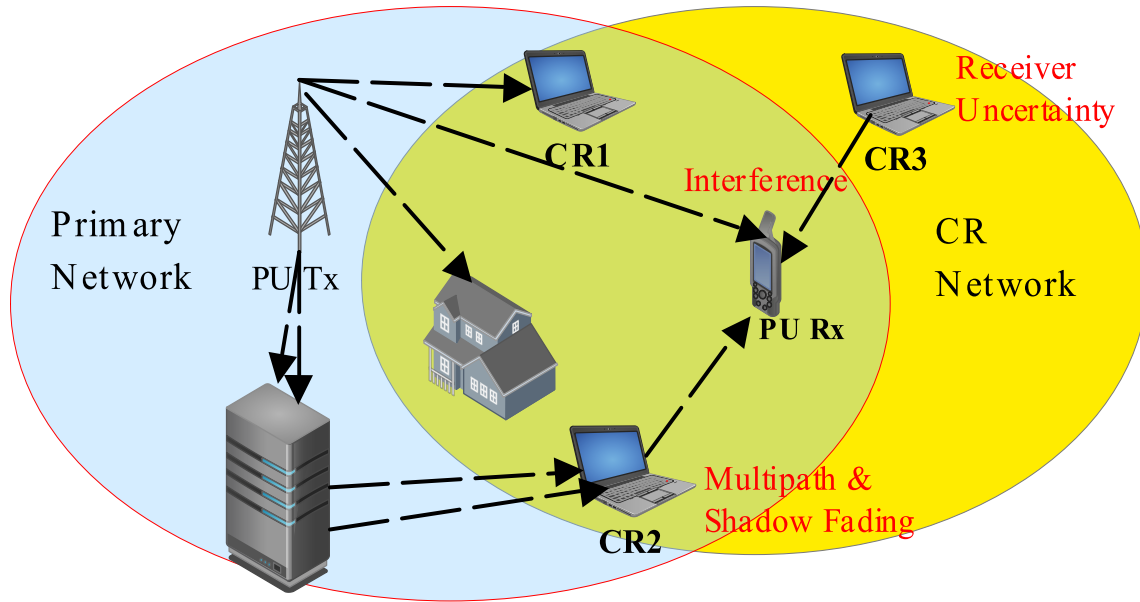


Figure 2.8: Shadowing, Multipath fading and Receiver Uncertainty(Akyildiz, Melodia, et al., 2006)

According to Figure 2.8 above, CR1 and CR2 are present inside the PU transmission range, whereas CR3 is present outside of the PU transmission range. Due to multipath fading and shadowing effects brought on by obstruction from homes, CR2 misidentifies the main transmission. Additionally, neither the primary user transmission nor the presence of a primary receiver within a range is known to CR3. If CR3 starts transmitting in the same frequency band and at the same time as primary users, a phenomenon known as the receiver uncertainty issue may interfere with PU transmission.

Secondary users need two channels for local sensing to decide on joint spectrum sensing. First, to conduct local sensing, secondary users connect to the primary transmitter; this connection between the many cooperating SUs and the primary transmitter is referred to as the sensing channel. A reporting or control line (the channel between SU and fusion center (FC)) is required to share local sensing data with other parties or with the FC. The switching between these two channels has been orchestrated so far by a medium access protocol (Umar & Sheikh, 2013). Following are the two phases of cooperative spectrum sensing. The detection of PU and reporting are those. The principal unused channel is searched after by SU during the PU detection phase, while during the reporting phase, the FC is informed of the information found. Cooperative spectrum sensing (CSS) is widely categorized as

centralized, distributed (decentralized), and relay-assisted depending on how cooperating SUs transmit sensing data within the network (Akyildiz, Melodia, et al., 2006).

2.5.3.1 Centralized approach

In this method, as depicted in Figure 2.9, the central processor node or fusion center (FC) gathers sensing data from all SU radios that are within its range. FC decides whether spectrum possibilities are available based on the data gathered from cooperating users. Either the FC efficiently handles the sensed spectrum usage opportunities to effectively manage traffic, or it broadcasts this opportunity to all secondary users. In wireless local area networks (WLAN), any node (once recognized) can serve as a master to coordinate CSS, unlike cellular networks where the FC might be either the base station (BS) or the access point (AP).

In a centralized strategy, the availability of the primary user is assessed using two different techniques. These processes are known as hard combining (decision fusion) and gentle combining (data fusion). When utilizing the data fusion technique, collaborating nodes transmit locally gathered sensory data to the FC, allowing it to carry out data fusion and make a centralized decision regarding the availability of the spectrum through a process known as soft combining. Soft combining techniques include Square Law Combining (SLC), Equal Gain Combining (EGC), Maximal Ratio Combining (MRC), and Linear Weighted Combining. In the instance of decision fusion, each node has determined if a PU signal is there or not. The FC then receives the binary decision and decides collectively on the PU activity. Hard choice rules can be classified as either OR rules, AND rules, or majority rules.

2.5.3.2 Distributed approach

Decentralized collaborative spectrum sensing is another name for distributed cooperative spectrum sensing (CSS). The idea of a fusion center (FC) or central computing is not used in this strategy. As depicted in Figure 2.9, each cognitive radio can instead communicate the sensing data it has collected with other radios that are under its preview.

2.5.3.3 Relay-assisted cooperative

The aforementioned system's reporting and sensing channels might not work as intended under real-time conditions. For instance, certain secondary users' reporting channels may be powerful due to multipath and shadowing effects while their sensing channels are weak, whereas another SU's sensing channels may be weak while its reporting channels are extremely strong (Akyildiz, Melodia, et al., 2006),(Umar & Sheikh, 2013). To mitigate the impacts of fading in the wireless channel between the SU and the fusion center (FC), relay cognitive radios are used, as shown in Figure 2.9. This improves SS's precision. The

distributed and centralized system is known as one-hop cooperation, but the relay-assisted approach is known as a multi-hop cooperative.

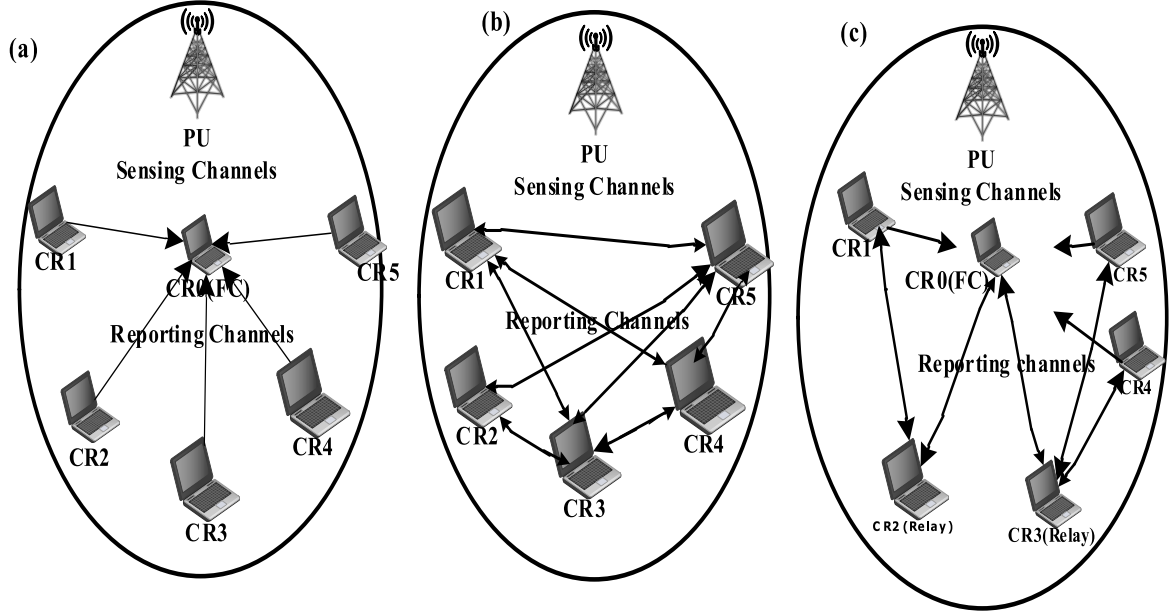


Figure 2.9: Classification of cooperative spectrum sensing, (a) Centralized, (b) Distributed and (c) Relay-assisted(Subheddar & Birajdar, 2011)

2.6 Problems and Difficulties in Spectrum Sensing

SS CRNs handle several issues including sensing interference limit, noise uncertainty, and channel uncertainty.

- **Channel uncertainty:** In wireless communication networks, received signal strength (RSS) can be muddled by channel fading or shadowing. The PU signal sees a significant decline in SS, which the SU may perceive as white spaces. The SU signal may then interfere with PU operations. To differentiate a faded or shaded PU signal from white space, CRs must be more sensitive. This problem was addressed by the development of cooperative sensing, which involves a group of CRs exchanging local data and deciding on the licensed band's occupancy condition jointly.
- **Noise Uncertainty:** The detection sensitivity is the lowest signal-to-noise (SNR) level at which the cognitive radio can trustable identify the PU signal.

$$\gamma_{\min} = P_p \frac{L(D+R)}{N} \quad (2.2)$$

where N is the noise power, P_p is the primary transmitter's transmitted power, R is the maximum distance between the primary transmitter and its associated receiver, and D is the interference range of the secondary transmitter.

- **Limitation:** In a practical setting, determining noise power is challenging and must be approximated, which may result in calibration errors due to variations in thermal noise. Therefore, to estimate noise uncertainty, a higher sensitive detector is needed.
- **Aggregate interference:** In the future, there is a greater chance that SUs using the same licensed frequency will be widely deployed; this could lead to uncertainty known as aggregate interference. Aggregate interference can cause white space recognition to be inaccurate even if the PU is outside of an SU's interference range. More sensitive detectors must be used to improve the precision of detection.
- **Sensing interference:** Spectrum sensing's main objective is to identify any potential occupied or inactive spectrum so that unauthorized users can gain access. The interference measurement errors, however, are the main problem encountered in reality. Unlicensed users (SUs) must be informed of the location of licensed users (PUs) to calculate the level of interference caused by SUs to PUs. However, position determination becomes challenging when the PU device turns passive. When determining the sensing interference limit, these variables need to be given more consideration.

2.7 Additive White Gaussian Noise (AWGN) Channel

As the data passes over an AWGN channel, white Gaussian noise is introduced. This basic noise model is used by information theorists to replicate the impact of several random occurrences that occur in nature. In AWGN channel models, wideband or white noise with a Gaussian amplitude distribution and constant spectral density is frequently included as the sole transmission barrier. This model does not account for fading, frequency selectivity, interference, non-linearity, or dispersion. The AWGN channel serves as a useful model for many deep-space and satellite transmission links. For the majority of terrestrial links, it is not a suitable model due to multipath, terrain blocking, interference, etc.

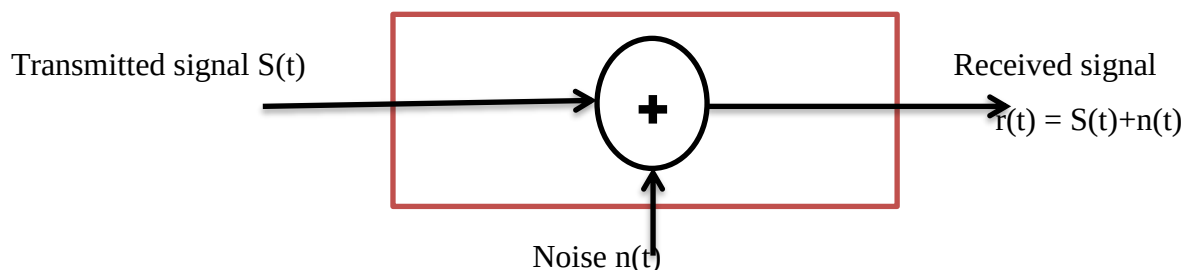


Figure 2.10: Model for received signal passed through an AWGN channel

AWGN is a straightforward and well-liked noise model that replicates a variety of random processes found in nature. Let's dissect each of those words for greater comprehension:

Additive: When noise is added to a transmission, it is referred to as additive. In other words, the received signal is made up of both the sent signal and the noise signal. Additionally, the signal and noise are generated at random and have distinct probabilities, suggesting that the occurrence of one does not affect the likelihood of the other.

White: The idea that noise has a uniform power distribution across all frequencies is referred to as "white." White noise hence has a constant PSD across all frequencies, where PSD is a measure of a signal's strength about frequency. Power spectral density is referred to as PSD. The idea of white noise is comparable to the color white, which is made up of all observable spectrum frequencies.

Gaussian: The noise samples' distribution is Gaussian.

2.8 Rayleigh fading channel

A statistical model known as Rayleigh fading is frequently used to explain how wireless communication channels behave when radio waves take several different routes between the receiver and transmitter. As a result, there is signal interference and fading, which can lead to unpredictable fluctuations in the strength of the signal over time. The Rayleigh fading model assumes that the magnitude and phase of the received signal have a Rayleigh distribution. The interference from the numerous paths, which can be both advantageous and destructive, causes the received signal's power to fluctuate arbitrarily in a Rayleigh fading channel. As a result, the bit error rate (BER) and signal-to-noise ratio (SNR) of the received signal change with time. Only a few of the factors that could determine how severe the fading is are the distance between the transmitter and receiver, the frequency of the broadcast signal, the presence of barriers and reflections in the environment, and the mobility of the transmitter and receiver. Different methods can be used in cognitive radio systems to reduce Rayleigh fading. Spectrum sensing techniques can be used to evaluate the level of channel interference and dynamically change the transmission parameters, such as power, modulation, and coding, to maintain reliable communication.

Overall, the effectiveness of cognitive radio systems in the face of Rayleigh fading depends on the effectiveness of these techniques as well as the complexity and adaptability of the underlying algorithms and protocols. By changing these characteristics, cognitive radio systems can improve spectral efficiency, dependability, and spectrum utilization.

2.9 Central Limit Theorem

It is one of the fundamental results of probability theory. According to this claim, under specific circumstances, the sum of a large number of random variables (RV) is

approximately normal (Gaussian distribution). We present a generalization of the central limit theorem for independently and identically distributed (iid) RVs.

2.10 Related Works

2.10.1 Previous Work on Matched Filter Detection

In (Kumar et al., 2023) It is clear that as sample counts rise, the system will get more sophisticated, and detection times will lengthen. Nevertheless, spectrum-sensing algorithms now perform better. To provide a cutting-edge 5G spectrum sensing approach, this work combines two matched filter detections (MFD) into a hybrid-matched filter method. The author evaluated the efficiency of hybrid-matched filter detection to traditional MFD in Rayleigh fading and Rician channels. The algorithm has been shown to perform better than the conventional MF. Additionally, it can be claimed that although the system uses a lot of computational resources, it performs far better in noisy conditions than existing approaches. But the author didn't consider the effect when prior knowledge of the PU signal is not present.

In (Pandi & Kumar, 2017) uses the matched-filter detection approach to compare the likelihood of detection to the likelihood of a false alarm, the likelihood of detection to the signal-to-noise ratio (SNR), and the likelihood of detection to the bit error rate (BER) to the SNR for each OFDM architecture. Although the BER for OFDM with cyclic prefix (CP) and OFDM without cyclic prefix (CP) are about comparable, the BER performance of OFDM with cyclic prefix (CP), which helps prevent interference between OFDM signals, is substantially better than without it when SNR is increased. Results show that OFDM with cyclic prefix (CP) is in many respects superior to OFDM without CP. Since it is quicker, more effective, and requires less SNR for signal detection, spectrum sensing with matched-filter detection is better than all other spectrum sensing methods now employed in cognitive radio.

In (Rao et al., 2019) to detect primary users in a wireless channel that is fading, a matched filter detector spectrum sensing technique is suggested. Energy characteristics observed for various SNR values are compared with the receiver operating characteristic operating matched filter properties of the suggested. For lower SNR values, the matched filter-based detection performs better. The matching filter also shows a higher probability of detection for concentrations with a lower likelihood of false alarms, it has been noticed. The primary user's prior knowledge is necessary for the matched filter detection approach to have a higher possibility of detection.

2.10.2 Previous Work on Cyclo-stationary feature detection

In (Wang et al., 2021) paper, a method for multi-antenna conventional beam synthesis-based blind cyclo-stationary features detection(CFD) is proposed. The goal is to boost the antenna's signal-pickup capacity and to create the direction of arrival angle necessary for blind detection of cyclo-stationary signals by using beam-forming technology. The detection probability and false alarm probability are calculated by the authors using Wilk's approximation theory and the generalized likelihood ratio test (GLRT), respectively. The simulation results show that the beam synthesis multi-antenna cyclic stationary signal detector can detect unknown cycle signals blindly in low SNR situations. But the author didn't consider the computational complexity of CFD.

In (Shrestha & Telgote, 2020) research propose a spectrum sensor for cognitive radio technology that uses CFD and has a lower sensing time while using less hardware. It has been determined how to successfully apply a difficult frequency-domain-based CFD spectrum sensing method. Particularly, the VLSI architecture of the 2048-point FFT module has been a multi-level resource pooled for optimization. The findings of the performance analysis of the spectrum sensor for various point sizes are also presented. It was determined that the proposed design achieved a reasonable level of detection probability at low SNR. However, the design of such an architecture can be challenging due to the large number of computations involved in FFT processing.

In (George & Prema, 2019) the author proposes a unique approach based on CFD to achieve 100% blind detection performance. The cyclic spectrum's fundamental statistics are used to categorize PU signals. A further method is developed to recognize the signal's modulation scheme and categorize it without using any training algorithms. The proposed method can consistently detect PU for low SNR without knowing anything about PU or channel noise beforehand. But the author didn't consider as the blind cyclostationary feature detection technique may be computationally expensive, especially for signals with high data rates.

2.10.3 Previous Work on Energy Detection

In (Luo et al., 2022) whenever noise variation is present uncertainty, the ED method's detection performance may considerably deteriorate. This work suggests an ED-based sensing approach to reduce the effects of noise variance uncertainty. The decision statistic is created using the same technique as ED by combining these signal samples from several antennas. The decision threshold is constructed using a novel technique that renders it immune to variance in noise. Because of this, the suggested method is unaffected by noise

variance uncertainty and does not necessitate measuring the noise variance. The simulation results show that, when there are two or more antennas for a Gaussian channel and three or more antennas for a Rayleigh fading channel, the suggested strategy performs noticeably better than the ED method without the noise variance estimate. This is so that, when there are more than two antennas, the detection performance of the recommended method can outperform the ED method without the noise variance estimate. But If the channel state information is not accurately estimated, the performance of the recommended method can degrade significantly, especially in scenarios where the channel is highly correlated or experiences fading.

In (Arjoune et al., 2018) the detection performance of the energy detection technology can be further improved by dynamic selection of the sensing level. The power of noise present in the received signal is assessed in this study using a blind technique to assess a dynamic selection of this threshold. The proposed approach was tested and implemented using the GNU Radio software and USRP equipment. The findings demonstrate that dynamic threshold selection, which is based on detecting the noise level present in the received signal during the detection process, increases the likelihood of detection and reduces the likelihood of false alarms when compared to energy detection methods that use static thresholds. But the author didn't consider the situation in the unreliable estimate of the noise level in the received signal. In practice, obtaining an accurate estimate of the noise level can be challenging, especially in scenarios where the noise is non-stationary or has unknown statistical properties.

2.10.4 Previous Work on Hybrid Spectrum Sensing Technique

In (Fawzi et al., 2020) for cognitive radio systems, a wavelet denoising and energy detection adaptive two-stage spectrum sensor model is provided. With the aid of SNR estimation, two techniques are cascaded in a parallel structure in this. It is only used in high SNR situations to determine whether the main user is present. Since ED performs poorly in low SNR situations, Wavelet Denoising is first triggered to lessen the impact of noise. The SNR estimator starts either of the wavelet denoising or ED techniques in this paper's cascaded parallel structure. When compared to ED alone, the suggested approach increased the likelihood of detection. But the limitation of this two-stage spectrum sensor model is that it may require a longer processing time compared to traditional energy detection methods.

In (Eappen & Shankar, 2020) describes a two-stage spectrum sensing method for cognitive radio networks. The ED at low SNR issue is solved using the two-stage approach. After choosing a complex method with excellent detection performance at low SNR, a complicated

approach with low computing cost is used for initial sensing. Maximum Eigenvalue (ME) detection is used in this paper's second detection stage. The purpose of using two stages is to perform ME for verification whenever the main user's absence is determined in the first stage. With maximum eigenvalue detection, the suggested technique achieves roughly the same sensing performance, while requiring less sensing time when compared to ED and ME. The author didn't consider the absence of required accurate knowledge of the noise power level. The energy detection stage requires an estimate of the noise power level to determine the detection threshold. If the noise power level is not accurately estimated, the detection threshold may be set incorrectly, leading to degraded detection performance.

In (Abdullah et al., 2020) the ED problem in low SNR scenarios is addressed in this study by proposing two-stage spectrum sensing for cognitive radios, which combines two spectrum sensing algorithms in two phases. Due to its computational complexity and lengthy sensing time, cyclo-stationary detection is used as the second stage in this work instead of ED as the first. The main objective is to use the advantages of the Cyclo-stationary detector in low SNR scenarios. However, the author failed to take into account the effect of not having correct knowledge of the signal and noise statistics, which can be challenging to collect in practice and have an impact on the method's performance.

In (Mashta et al., 2021) research describes a practical multi-stage spectrum sensing strategy for cognitive radio networks in noisy situations. In this study, two spectrum sensing techniques ED and maximum-minimum eigenvalue detection are coupled. The first stage of ED is designed to quickly recognize the primary consumers. CMME is employed when the first stage, or at low SNR, is unable to detect the main user's presence. The outcome of the simulation demonstrates that the suggested method outperforms those individual methods in low SNR situations; however, due to its computational complexity, it requires more time for spectral sensing.

In (Bani & Kulkarni, 2022) the spectrum hole could be located using the available spectrum resources using a hybrid detector (HD), according to research. The HD technique is based on an energy detector (ED) and a matching detector. HD can detect the signal more precisely than a single detector like an ED or MD. HD can operate in either scenario, regardless of whether the primary user (PU) information is available. Both cooperative and non-cooperative spectral sensing environments are being examined for HD. Four users were utilized to apply the OR, AND, and majority methods for CSS with low SNR walls. The IEEE Wireless Regional Area Network (WRAN) 802.22 standard for accessing TV spectrum gaps served as the foundation for the HD standards. The OR rule was used by the

author to achieve the best results for the HD models. But the proposed technique is unable to detect the spread spectrum signal which is characterized by weak signal and wide bandwidth since energy detection and matched filter detection do not detect it.

In (Abed & Abdullah, 2022) the detection performance of both matched filter and cyclo-stationary approaches has improved, and their computational cost has decreased. To simplify the convolution process between the incoming received signal (the PU signal) and its impulse response, which is stored, the matched filter of the spectrum sensing technique receives the PU signal and senses the half number of samples by choosing one and skipping another. When the detector doesn't have a greater understanding of the PU, it switches to the cyclo-stationary approach to combat the drop-in performance detection. The PU signal in the cyclo-stationary stage is likewise detected by sensing one sample and omitting one to reduce the computational complexity of the autocorrelation method. As a result, the suggested approach helps the author achieve high-performance detection while reducing computing complexity. But The author did not consider when prior knowledge of PU was not available.

In (Usman et al., 2022a) as a result of the research, a novel and intriguing spectrum sensing alternative called energy detection (ED) with entropy technique methodology is presented. The recommended ED using the entropy technique gives improved sensing capability in low SNR scenarios compared to standard ED. Simulated results show that the proposed method works significantly better than ED at low SNR. But the author only evaluates the performance of the proposed technique on the AWGN which is not more practical.

Table 2.2: A Summary of some related work

Authors	Year	Title	Techniques and Concepts Covered	Gaps or Concept not Covered
(Bani & Kulkarni, 2022)	2022	Hybrid Spectrum Sensing Using MD and ED for Cognitive Radio Networks	This paper overcoming the problem of noise uncertainty.	Both techniques may not be able to detect spread spectrum signals because these signals are designed to have a wide bandwidth and a low power spectral density.
(Abdullah et al., 2020)	2020	Complexity reduction of cyclo-stationary sensing technique using improved hybrid sensing method	These techniques use the SDFT and only need half as many samples in the autocorrelation process, which reduces the computing complexity.	This paper does not focus on the detection of performance improvement.
(Brito, Sebastiao, et al., 2021)	2021	Hybrid Matched Filter Detection Spectrum Sensing	To understand the effects of changing the given parameters, such as the signal-to-noise ratio, chance of false alarm, and the number of samples (N), these methods have each been examined individually.	The author did not consider when prior knowledge of PU was not available.
(Usman et al., 2022b)	2022	Improving Spectrum Sensing for Cognitive Radio Network Using the Energy Detection with Entropy Method	Improve spectrum sensing capability when compared to the CED in low SNR scenarios. This strategy is used by the author to get over the difficulty of ED at low SNR.	To improve the performance of detection, the paper only concentrates on the AWGN channel model.
(Fawzi et al., 2020)	2020	Adaptive two-stage spectrum sensing model using energy detection and wavelet denoising for cognitive radio systems.	Proposed model combines energy detection (ED) and wavelet denoising (WD). The performance of spectrum sensing can be improved by reducing the effects of noise and interference.	The method can be computationally intensive, particularly if the wavelet transform and denoising algorithms are applied to a large amount of data.

CHAPTER THREE

3. METHODOLOGY AND SYSTEM MODEL

3.1 Introduction

In this thesis, previous researchers' studies about the conventional algorithm with its performance issue were revised. Also, to alleviate the problem of conventional spectrum sensing many researchers put forward their proposed method such as hybrid spectrum sensing. Having a basis on the previous works and keeping in mind the problem of conventional spectrum sensing, the methodology of this thesis is depicted.

3.2 Materials

All models in this thesis are performed using MATLAB/R2020a software tools. Matrix LABoratory is what the word MATLAB stands for. A high-performance language for technical processing is called MATLAB. Additionally, it is computer software made up of Simulink and technological boxes. We can build models and applications, analyze data, and develop algorithms using MATLAB.

3.3 Methods

3.3.1 System Design

- Analyzing the mathematical model of conventional spectrum sensing (SS) in terms of Probability of Detection, Probability of False Alarm, and Probability of Miss Detection.
- Analyzing the mathematical model of traditional hybrid SS and proposed hybrid SS.

3.4 System Model for Spectrum Sensing

Spectrum sensing (SS) can often be described as a binary hypothesis problem in the detection theory and provided (Alghorani et al., 2015):

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

Where $n = 1, 2, 3, \dots, N$, h is channel gain (that mean $h = 1$ for AWGN and to obtain a Rayleigh fading channel gain with a specific variance, we can multiply the complex Gaussian random variable by the square root of the variance.), N stands for the sample number in the received sampled signal; $y(n)$ stands for the sampled signal received by secondary users; and $w(n)$ stands for zero-mean additive white Gaussian noise (AWGN) with variation (δ_w^2) . H_0 and H_1 reflect the absence and presence of the PU, respectively. The PU signal $s(n)$, multiplied by the PU's transmitter to SU's receiver channel strength h , and

the additive white Gaussian noise $w(n)$ are added to determine the received signal by an SU, as shown in Figure 3.1 below.

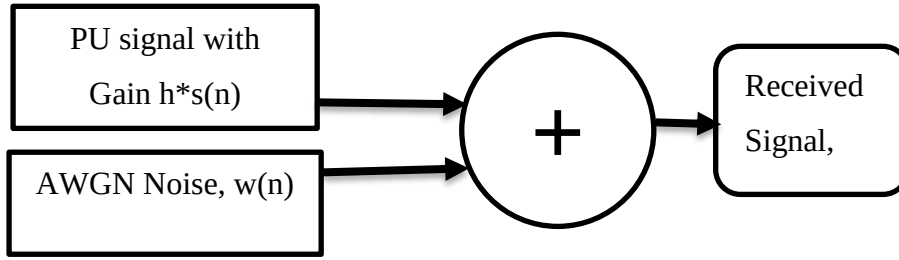


Figure 3.1: Modeling of the received signal (Manesh et al., 2016)

The identification issue was all that remained after determining the number of eligible PU in the specified spectrum band. The structured hypothesis test for this is:

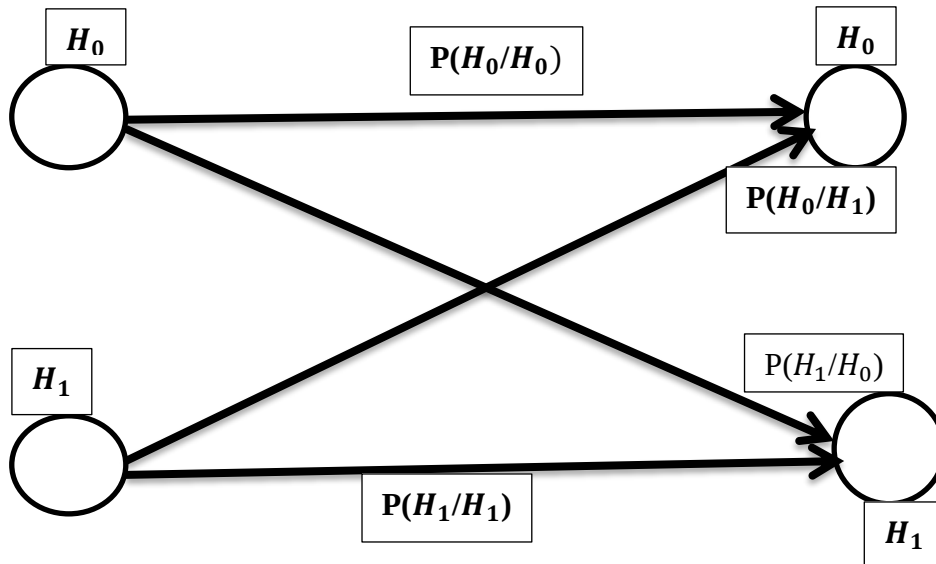


Figure 3.2: Testing hypotheses and likely results, along with the likelihood of each (Abduttuko, 2015)

H_0 and H_1 are the perceived states for the absence and presence of a signal, respectively.

Next, we can discuss four instances of the signal that was discovered, as illustrated in Figure 3.2:

- 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 a false alarm can be used to assess the efficacy of spectrum sensing ($P_{fa} = P(H_1/H_0)$), and the probability of detection $P_d = P(H_1/H_1)$. P_{fa} is the likelihood that a secondary user may mistakenly think a primary user (PU) is active while they are idle. It

demonstrates how severely the SU has lost access options. P_d is the likelihood that an SU will conclude that the PU is active when it is. The likelihood of missing a detection ($P_m = 1 - P_d$) reveals the level of interference a secondary user (SU) introduces to the primary user (PU). P_m is often limited to being below an acceptable level to safeguard the PU (Abdoutuko, 2015).

3.4.1 System Model of Matched Filter Detection Technique

One of the best techniques for spectrum sensing (SS) is matched filter detection (MFD), provided information about the main user (PU) broadcast is known. Communication is where the MFD, an SS method that maximizes the signal-to-noise ratio, is most frequently applied. The signal from the PU must be known for an MFD, a type of linear detector, to sense. In this method, filtering is carried out by comparing the received signal to a stored and archived pilot of the same PU signal stream (Ziafat et al., 2011).

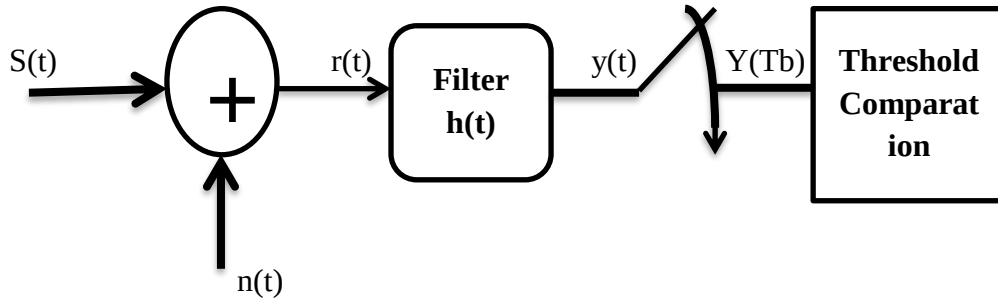


Figure 3.3: Matched filter

From the figure the received signal

$$r(t) = s(t) + n(t) \quad (3.2)$$

Where $s(t)$ is the input signal, and $n(t)$ is the noise signal.

The output of the filter

$$y(t) = r(t) * h(t) \quad (3.3)$$

$$y(t) = [s(t) * h(t)] + [n(t) * h(t)] \quad (3.4)$$

In white Gaussian noise, the constant power spectral density is $\frac{N_o}{2}$ on PSD vs frequency curve. Then the output PSD is:

In the frequency domain, multiplication is equivalent to convolution in the time domain.

$$(PSD)_o = (PSD)_i |H(f)|^2 \quad (3.5)$$

Where $H(f)$ is the frequency domain of impulse response. The output due to noise is:

The output power of noise is:

$$N_p = \frac{N_o}{2} \int_{-\infty}^{\infty} (|H(f)|^2) df \quad (3.6)$$

Signal power: $y_s(t) = s(t) * h(t)$ the by Fourier transform the frequency domain is: $Y_s(f) = S(f).H(f)$ but by inverse Fourier transform:

$$S_p = |y_s(T_b)|^2 = \left| \int_{-\infty}^{\infty} (S(f).H(f))e^{j2\pi f T_b} df \right|^2 \quad (3.7)$$

The maximum signal-to-noise ratio is:

$$SNR = \frac{S_p}{N_p} = \frac{\left| \int_{-\infty}^{\infty} (S(f).H(f))e^{j2\pi f T_b} df \right|^2}{\frac{N_o}{2} \int_{-\infty}^{\infty} (|H(f)|^2) df} \quad (3.8)$$

By using Schwartz's inequality:

$$\left| \int_{-\infty}^{\infty} (f_1(t).f_2(t))dt \right|^2 \leq \int_{-\infty}^{\infty} |f_1(t)|^2 dt \cdot \int_{-\infty}^{\infty} |f_2(t)|^2 dt \quad (3.9)$$

Where $f_1(t) = f_2^*(t)$ Then by using this inequality:

$$SNR = \frac{S_p}{N_p} \leq \frac{\int_{-\infty}^{\infty} |S(f)e^{j2\pi f T_b}|^2 df \cdot \int_{-\infty}^{\infty} |H(f)|^2 df}{\frac{N_o}{2} \int_{-\infty}^{\infty} (|H(f)|^2) df} \leq \frac{2}{N_o} \int_{-\infty}^{\infty} |S(f)|^2 df \quad (3.10)$$

$$SNR_{\max} = \frac{2E_s}{N_o} \quad (3.11)$$

This equation is possible for:

$$h(t) = s^*(T_b - t) \quad (3.12)$$

The enlarged version of matched filter sensing, which generates the sensing decision by comparing the matched filter decision statistic to the matched filter threshold, is depicted as a block diagram in Figure 3.4. To generate the statistic, the received signal and pilot signals are convolved and averaged over N samples (Abdo-tuko, 2015).

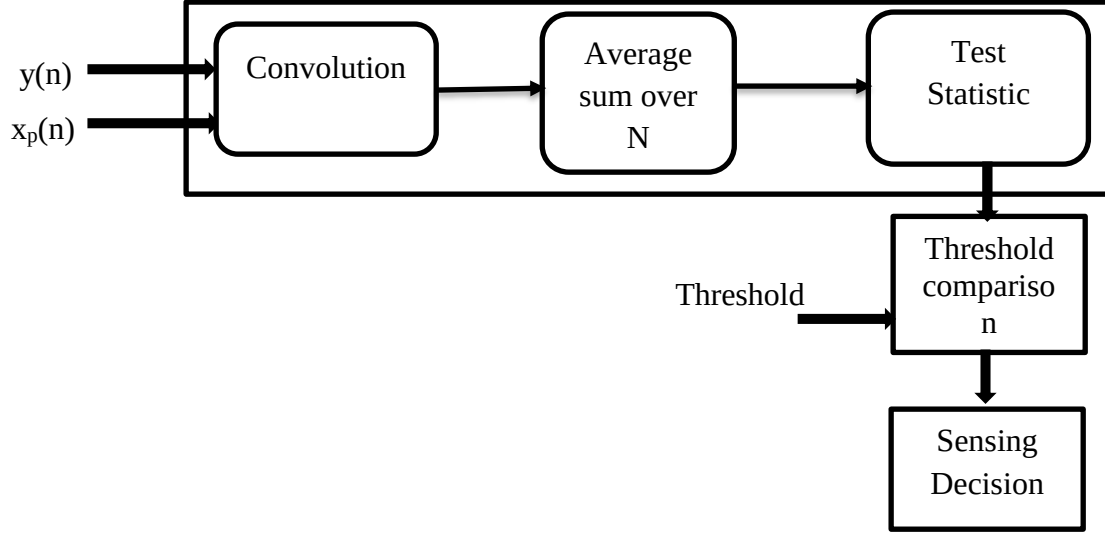


Figure 3.4: Block diagram of Matched filter detection model

The test statistic is expressed as:

$$T_{MFD} = \frac{1}{N} \sum_{n=1}^N y(n) * x_p(n) \quad (3.13)$$

Where T_{MFD} stands for the test result of the matched filter detector, the PU signal is denoted by x_p , and the received SU signal is denoted by y . After that, a threshold and the test statistic (T_{MFD}) are compared to ascertain the spectrum availability. The received signals from the SU and PU are broadly modeled by Gaussian random variables. Additionally, T_{MFD} is estimated as a Gaussian random variable using a linear combination of Gaussian random variables.

$$\begin{cases} \text{If } T_{MFD} \geq \lambda, & \text{PU signal present} \\ \text{If } T_{MFD} < \lambda, & \text{PU signal absent} \end{cases} \quad (3.14)$$

The probability of being detected and the probability of a false alarm are given based on the Neyman-Pearson criterion (Ziafat et al., 2011):

$$P_d = Q\left(\frac{\lambda - E}{\sqrt{E\delta_w^2}}\right) \quad (3.15)$$

$$P_{fa} = Q\left(\frac{\lambda}{\sqrt{E\delta_w^2}}\right) \quad (3.16)$$

Where E is the energy of the PU signal, λ is the sensing threshold, $Q(\cdot)$ is the Q-function, and δ_w^2 is the noise variance.

$$\lambda = Q^{-1}(P_{fa})\sqrt{E\delta_w^2} \quad (3.17)$$

3.4.2 System Model of Cyclo-stationary Feature Detection Technique

The main modulated waveform is typically coupled with cyclo-stationary elements that add periodicity to the signal, such as sine carriers, pulse trains, repeated spreading, hopping sequences, or cyclic prefixes. Cyclo-stationary feature detection (CFD) is based on the fundamental guiding principle of the auto-correlation function. Multiply the received signal $y(n)$ by its delay variation to obtain the autocorrelation. The cyclic spectrum (CS) displays the signal's spectral content as a function of frequency and cyclic frequency (Wilfred & O.R., 2016). The estimated cyclic autocorrelation function (CAF)'s Fourier transform is then used to determine the CS. Based on the CS, a test statistic is calculated. For instance, the greatest value of the CS over a variety of cyclic frequencies can be used to calculate the test statistic. Due to its ability to distinguish between the data and the noise, this approach outperforms ED. However, it has a high computational complexity because it needs a lot of detecting time. A signal is considered to be cyclo-stationary if its autocorrelation is a repeating function of time t with a particular period. a discrete-time signal with a discrete CAF, constant (l) lag, and $y(n)$.

$$R_{yy}^{\alpha} = \lim_{N \rightarrow \infty} \frac{1}{N} \sum_{n=0}^{N-1} y(n)y^{*}(n+l)e^{-j2\pi\alpha n\Delta n} \quad (3.18)$$

Where Δn is the sampling interval, $y[n]$, $\alpha = m/T$ is the cyclic frequency with integer m , and N is the number of samples for the signal. The discrete Fourier transform of R_{yy}^{α} yields the following CS:

$$S_{yy}^{\alpha}(f) = \sum_{l=-\infty}^{\infty} R_{yy}^{\alpha}(l)e^{-j2\pi fl\Delta l} \quad (3.19)$$

The CS of the received signal is then compared to the threshold, and a cyclo-stationary signal is identified when the CS is higher than the threshold. No cyclo-stationary signal is identified if the CS is below the threshold (Mourougayane et al., 2019).

$$\lambda = \sqrt{\frac{2(\sigma^2)}{2N+1}} * \log(P_{fa}) \quad (3.20)$$

Where λ pre-defend threshold N is the number of samples, P_{fa} is the likelihood of a false alarm, and σ^2 is the variance of the received signal.

$$P_d = 1 - \left(1 - e^{-\frac{\lambda^2}{2\sigma_A^2}}\right)^l \quad (3.21)$$

$$P_{fa} = 1 - [1 - Q(\frac{\sqrt{2\gamma}}{\sigma}, \frac{\lambda}{\sigma_A})]^L \quad (3.22)$$

Where δ^2 variance $\delta_A = \delta^2 / (2N + 1)$ in which N is the number of samples for detection, L is the number of diversity branches, γ is instantaneous SNR, $Q_1 (.,.)$ is the generalized Marcum Q-function and λ is the predetermined threshold (Ejaz et al., 2012).

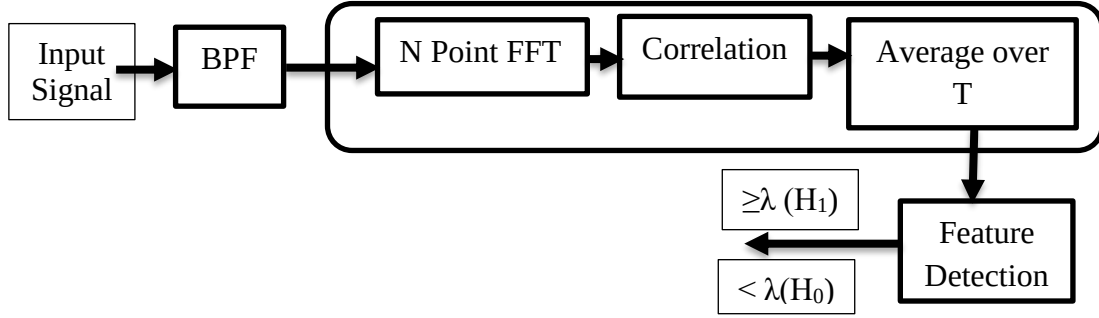


Figure 3.5: Block diagram of Cyclo-stationary feature detection

3.4.3 System Model of Energy Detection Technique

Energy detection (ED), the simplest sensor technique, operates blindly on the PU signal. It operates by comparing the incoming signal's energy to a threshold. The threshold is only affected by the noise intensity. Figure 3.6 illustrates how to construct the decision statistic of an ED using the squared magnitude of the averaged across N samples of the SU received signal. An ED pre-filters the incoming signal using an optimal bandpass filter with an intriguing bandwidth (Develi, 2020). The ADC converter is then used to process the filtered data. Next, a predetermined period is used to square and integrate the ADC's output signal. A test measure is created using the resulting signal. The test statistic is then compared to a threshold (λ) value to see if the licensed user is present or not (Manesh et al., 2016). The test statistic for energy sensing is as follows:

$$T = \frac{1}{N} \sum_{j=0}^{N-1} [s(n)]^2 \quad (3.23)$$

The test statistics for energy detection have a central chi-square distribution with $2TW$ degrees of freedom and the noise-only criterion (H_0) of zero means Gaussian distribution. Keep in mind that TW stands for time capacity multiplied. On the other hand, the test statistics choice under H_1 conditions resembles a non-central chi-square distribution with non-centrality parameters 2γ and degrees of freedom $2TW$. Here, denotes the linear dimension of the mean SNR. The decision test statistics for energy detection under the H_0

and H_1 suppositions are shown below, along with the probability density function (PDF) of the test results Y :

$$f_y(y) = \begin{cases} \frac{1}{2^{TW} \Gamma(TW)} y^{TW-1} e^{\frac{-y}{2}}, & H_0 \\ \frac{1}{2} \left(\frac{y}{2\gamma}\right)^{\frac{TW-1}{2}} e^{\frac{-(2\gamma+y)}{2}} I_{TW-1}(\sqrt{2\gamma y}), & H_1 \end{cases} \quad (3.24)$$

$$Y = \begin{cases} x_{2TW}^2 & H_0 \\ x_{2TW}^2(2\gamma) & H_1 \end{cases} \quad (3.25)$$

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

$$P_{fa}(Y > \lambda / H_0) = \frac{\Gamma(TW, \frac{\lambda}{2})}{\Gamma(TW)} \quad (3.26)$$

$$P_d = P(Y > \lambda / H_1) = Q_{(N=TW)}(\sqrt{2\gamma}, \sqrt{\lambda}) \quad (3.27)$$

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

A Gaussian process with variance (δ_s^2) can be used to describe the samples of the main signal $S[n]$ in non-coherent detection. As a consequence, the process $y[n]$ is Gaussian. In the low SNR area, a high number of samples (N) are needed. The central limit theorem can be used to estimate the test statistics as a Gaussian distribution when the sample size is large ($N > 250$).

$$Y = \begin{cases} N(\mu_o, \delta_o^2) & H_0 \\ N(\mu_1, \delta_1^2) & : H_1 \end{cases} \quad (3.28)$$

Where $N(\mu, \delta^2)$ Gaussian distribution with mean μ and variance δ^2 of both hypothesis H_0 and H_1 respectively (Abdo-tuko, 2015).

$$\mu_o = N\delta_w^2; \delta_o^2 = 2N\delta_w^4 \quad (3.29)$$

$$\mu_1 = N(\delta_s^2 + \delta_w^2); \delta_1^2 = 2N(\delta_s^2 + \delta_w^2)^2 \quad (3.30)$$

The probability of detection (P_d) and the likelihood of false alarms (P_{fa}) are the two factors used to gauge the effectiveness of the detection system. To test the decision statistics, a unique threshold λ_{ED} is utilized for each pair (Manesh et al., 2016). The equation can be expressed as follows by replacing the previously mentioned for the big values of N , P_d , and P_{fa} :

$$P_d = P(Y > \lambda_{ED} / H_1) = Q\left(\frac{\lambda_{ED} - N(\delta_s^2 + \delta_w^2)}{\sqrt{2N(\delta_s^2 + \delta_w^2)^2}}\right) \quad (3.31)$$

$$P_{fa} = P(Y < \lambda_{ED} / H_0) = Q\left(\frac{\lambda_{ED} - N\delta_w^2}{\sqrt{2N\delta_w^4}}\right) \quad (3.32)$$

$$Q(x) = \frac{1}{2\pi} \int_x^\infty \exp\left(-\frac{y^2}{2}\right) dy \quad (3.33)$$

Where $Q(x)$ is the Q-function.

The detection threshold can be expressed as (Manesh et al., 2016):

$$\lambda_{ED} = \delta_w^2 [\sqrt{2N} Q^{-1}(P_{fa}) + N] \quad (3.34)$$

The SNR determines the minimal number of samples required, which can be calculated as

$$N = 2[(Q^{-1}(P_{fa}) - Q^{-1}(P_d))SNR^{-1} - Q^{-1}(P_d)]^2 \quad (3.35)$$

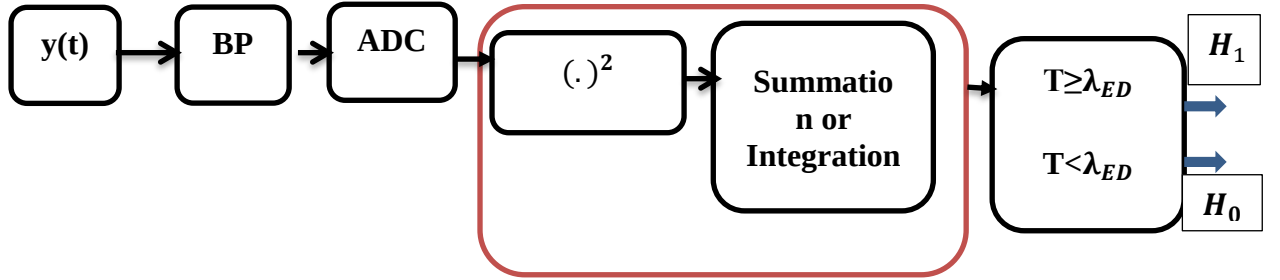


Figure 3.6: Block Diagram of Energy Detection

3.4.4 System Model of Proposed Hybrid Spectrum Sensing

The proposed hybrid sensing approach combines ED, MFD, and CFD to make use of their advantages and get over their drawbacks.

$$P_{do} = P_d^1 + \sum_{i=2}^M (P_d^i \prod_{j=1}^{i-1} (1 - P_d^j)) \quad (3.36)$$

$$P_{fao} = P_{fa}^1 + \sum_{i=2}^M (P_{fa}^i \prod_{j=1}^{i-1} (1 - P_{fa}^j)) \quad (3.37)$$

$$P_{mo} = 1 - P_d \quad (3.38)$$

For a hybrid spectrum sensing system using M approaches, the aforementioned equation (3.36) to (3.38) offers the overall probability of detection, probability of false alarm, and probability of miss detection, respectively (Mashta et al., 2021).

The general mathematical equations for proposed hybrid spectrum sensing (SS) for the probability of detection, probability of false alarm, and probability of miss detection are given as follows respectively in equations (3.39), (3.40), and (3.41).

$$P_d = P_d^{ED} + P_d^{MFD}(1 - P_d^{ED}) + P_d^{CFD}(1 - P_d^{ED})(1 - P_d^{MFD}) \quad (3.39)$$

$$P_{fa} = P_{fa}^{ED} + P_{fa}^{MFD}(1 - P_{fa}^{ED}) + P_{fa}^{CFD}(1 - P_{fa}^{ED})(1 - P_{fa}^{MFD}) \quad (3.40)$$

$$P_m = 1 - P_d \quad (3.41)$$

As shown in Figure 3.7 below, to increase the detection performance hybrid SS approaches made up of three fundamental SS techniques are developed. The average energy of the received signal must be greater than a threshold known as λ_{ED} for the channel to be regarded to be occupied by PU; otherwise, the next approach is used. Because ED has a quicker sensing time than other technologies and is simpler, it is used in the first step. The second approach employs one of the most efficient matched filter detection methods, and to assess whether the channel is idle or occupied, statistical tests are constructed using matched filter formulae and compared with a threshold. If the test statistic is larger than its threshold (λ_{MFD}), the channel is then declared to be occupied by PU; otherwise, we go on to the next approach. The third method involves the application of cyclo-stationary feature detection techniques, followed by the construction of the statistical test utilizing cyclo-stationary formulas and comparison with a threshold called the λ_{CFD} to determine whether the channel is open or occupied.

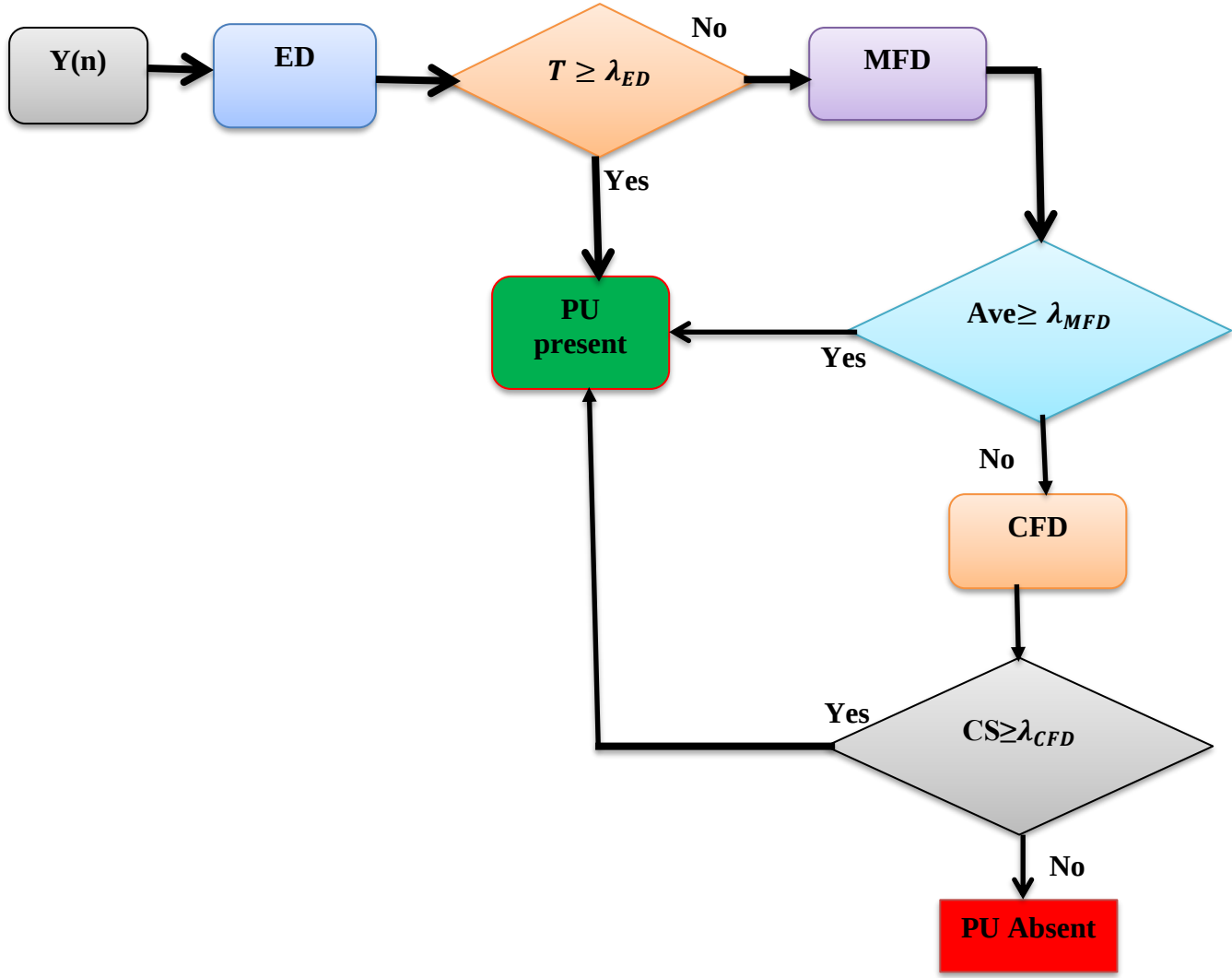


Figure 3.7: System Model for Proposed Hybrid Spectrum Sensing Approach

3.5 Cooperative Spectrum Sensing

The problems that arise in spectrum sensing as a result of noise uncertainty, receiver uncertainty, fading, and shadowing can be resolved through cooperative spectrum sensing (CSS), which was discussed in the previous chapter. To solve the concealed terminal issues that arise with single-node detections, CSS is used specifically. There are three ways to apply CSS, as was already mentioned: centralized, distributed (decentralized), and relay-assisted. In the centralized CSS strategy, each secondary user performs local spectrum sensing using single-node detection techniques before sending the outcome to the fusion center (FC). The FC assesses the combined data as the last stage in the spectrum process and decides using a set of judgment criteria. SU submits its conclusions to FC using either hard decision combining (OR Rule, AND Rule, Majority Rule) or soft decision combining (EGC, MRC, and SLC). In this thesis, we only consider challenging decisions that combine rules, especially OR rule.

The centralized cooperative approach is more flexible and straightforward because each secondary user to the system only needs one connection for communication between the user and the FC, unlike the decentralized cooperative approach which depends on users communicating with one another. The centralized cooperative strategy is therefore best suited for CSS. For this reason, among other CSS schemes, we explore a centralized approach for this thesis (Abdo-tuko, 2015).

3.5.1 OR Rule

In this rule, the FC "ORs" all the decisions it has gotten from SUs. The channel is deemed to be occupied so long as the cognitive outcome of SU is 1. The FC only decides the channel is idle and available when all sensing results are 0. The FC declares the existence of PU if any of the SU judgments result in a 1. In this instance, "1" indicates that PU is present in the channel, whereas "0" indicates that it is not. For the choice made at FC using the OR rule, the following probabilities of overall detection and false alarm are provided:

$$Q_d = 1 - \prod_{j=1}^N (1 - P_{d,j}) \quad (3.42)$$

$$Q_{fa} = 1 - \prod_{j=1}^N (1 - P_{fa,j}) \quad (3.43)$$

$$Q_m = 1 - Q_d \quad (3.44)$$

Where Q_d and Q_{fa} stand for, respectively, the overall probability of detection and the likelihood of a false alarm. For j^{th} secondary users, P_d and P_{fa} stand for the likelihood of detection and false alarm, respectively.

3.6 Measures of Spectrum Sensing Performance

Utilizing success metrics, the effectiveness of the SS method is evaluated. To check if the primary user is properly present in a specific channel system or not, performance metrics are used to calculate values. The following parameters are used to assess how well spectrum sensing methods perform (Digham et al., 2007):

- Probability of detection (P_d).
- The probability of a false alarm (P_{fa}).
- Probability of missed detection (P_m).
- The Receiver Operating Characteristics (ROC) curve.
- The Complementary Receiver Operating Characteristics (CROC) curve.

The probability of detection (P_d) and the probability of a false alarm (P_{fa}) are the two most crucial factors to consider when assessing the effectiveness of any SS technique, though. The possibility of correctly detecting the existence of PUs is implied by the probability of detection (P_d). A high score is therefore preferred because it guarantees that main users won't be hindered. A strong spectrum sensing method increases P_d and offers the PUs more interference protection. Once the sensing method assumes H_1 when the right choice is H_0 , the likelihood of a false alarm (P_{fa}) increases. In detection theory, this is referred to as a false alarm, and P_{fa} stands for the chance that it is one. The likelihood of declaring the main user's absence incorrectly is known as the false-alarm probability (P_{fa}). For high channel throughput amounts, lower P_{fa} values are preferred. In cognitive radio, the P_{fa} is a crucial design factor and ought to be maintained at a reasonable level.

The algorithm of the sensing technique assumes that H_0 when H_1 is the right choice, resulting in a missed-detection probability (P_m). The interference between SU and PU will also grow as a missed-detection probability (P_m) rises. Therefore, P_m should be kept as low as feasible in cognitive radio networks. The receiver's operating characteristics (ROC) curve can be used to visually represent the diagnostic efficacy of a particular test. To evaluate the value of an ideal threshold, ROC curves are used to emphasize trade-offs between detection probability and the likelihood of false alarms, whereas CROC curves are characterized in terms of the probability of missed detection versus false alarm probability.

CHAPTER FOUR

4. RESULT AND DISCUSSION

This chapter presents the simulation outcomes for the proposed hybrid spectrum sensing (SS) technique, matching filter detection (MFD), cyclo-stationary feature detection (CFD), energy detection (ED), and traditional hybrid SS approach. Additionally, the debate and analysis of the outcomes are provided. Performance indicators like as the likelihood of detection, the probability of a false alarm, and the likelihood of missed detection are used to assess the efficacy of SS. All simulations must take into consideration the required detection probability ($\geq 90\%$), false alarm probability ($\leq 10\%$), and miss detection probability ($< 10\%$) for cognitive radio, as per the requirements of IEEE 802.22 standards. The simulation results for all detection methods were produced using 10,000 Monte Carlo simulations and a sample size of 1000. The proposed hybrid spectrum sensing is evaluated through simulations for ED, MFD, CFD, and the traditional hybrid spectrum sensing approach (conventional hybrid based on ED and CFD, hybrid based on ED and MFD, and MFD and CFD) under AWGN channel and Rayleigh fading channel.

The SNR wall is a crucial element that is assessed in all result graphs to compare the proposed methods with those already in use. The SNR wall is the lowest SNR below and discovery is not feasible. The main simulation parameters for this thesis are listed in Table 4.1. In this thesis, the simulation results are discussed under the following four headings:

- Results of conventional SS, and traditional hybrid spectrum sensing technique
- Performance comparison among conventional SS, and traditional hybrid spectrum sensing technique
- Results of proposed hybrid spectrum sensing
- Results of cooperative detection of traditional hybrid spectrum sensing and proposed hybrid techniques

Table 4.1: Parameters used for simulations

Simulation Parameters	Type and Values	Remarks
Cognitive Users	Single User,2,3,4,	It can be vary
Types of Primary Signal	BPSK	Assumption
Detection Types	Cyclo-stationary feature detection, matched filter detection, and energy detection	According to the thesis objective
Ranges of SNR values	-35 dB up to 5 dB	Based on many papers (Brito, Member, et al., 2021), (Shrestha & Telgote, 2020)
Desired Probability of False-alarm	≤ 0.1	According to IEEE 802.22 standards
Desired Probability of Detection	≥ 0.9	According to IEEE 802.22 standards
Number of Samples	1000	Assumption
Monte-Carlo simulation	10,000	Based on many papers (Usman et al., 2022a), (Bani & Kulkarni, 2022),
Channels	AWGN and Rayleigh fading	Assumption
Types of Cooperative SS	Centralized approach (OR rule)	According to the thesis objective

4.1 Results of Matched Filter Detection (MFD)

As discussed in chapter two, there have been a lot of simulations and performance analyses for MFD in the literature. However, the simulation and analysis of MFD are covered in this section for more clarity. Here, the functionality of the MFD over the AWGN channel is replicated. The following simulated outcomes for MFD approaches are discussed:

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

4.1.1 Probability of detection versus SNR for MFD

Figure 4.1 shows the correlation between the probability of detection (P_d) and SNR for MFD at a probability of false alarm ($P_{fa}=0.1$). The graph demonstrates how the detection probability of MFD enhances as the SNR value rises. The performance has declined, as

evidenced by the declining probability of detection. As observed, MFD can distinguish between PU signal and noise signal whenever SNR becomes greater than -22.5 dB according to IEEE 802.22 standards. The SNR wall is the SNR value below which detection is impossible. As a result, the SNR wall for MFD is -22.5 dB because the detection probability below this value is less than 0.9 (< 90%). So, it can be deduced that below the SNR wall of -22.5 dB, MFD performs poorly.

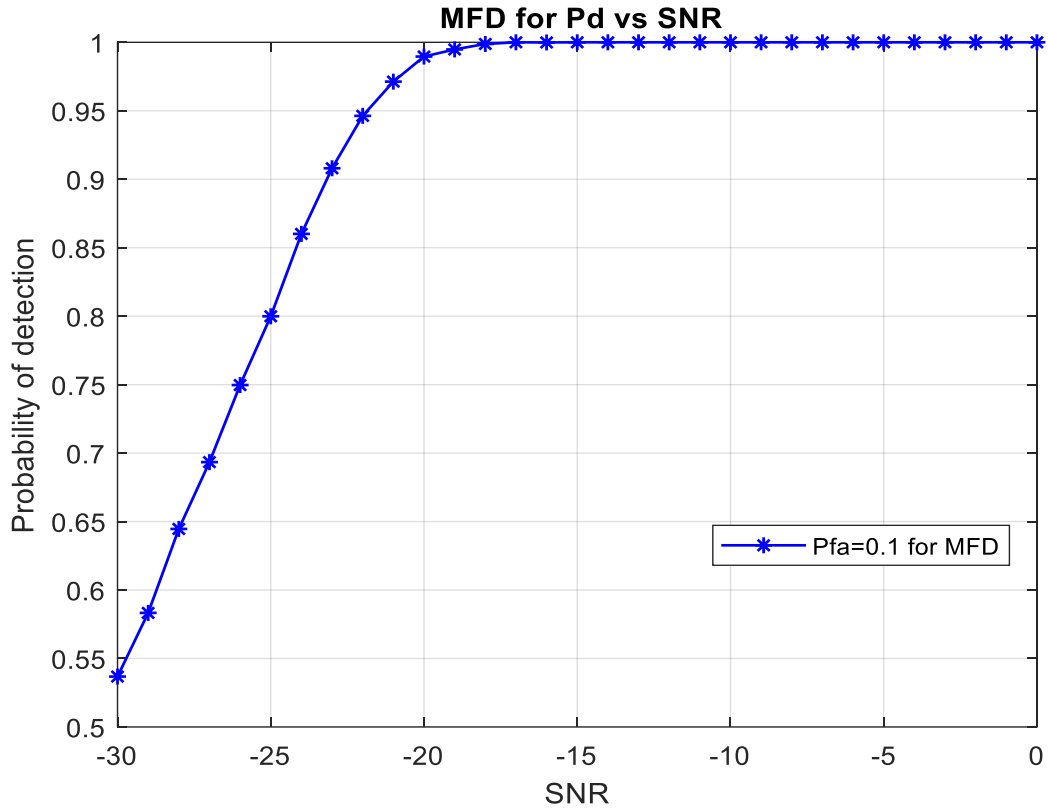


Figure 4.1: P_d vs SNR for CED at $P_{fa} = 0.1$

4.1.2 Effects of the varying probability of false alarm on the detection performance of MFD

The relationship between P_d and SNR is depicted in Figure 4.2 for various false alarm probabilities between 0.1 and 0.2. The graph shows that as the probability of false alarms rises, so too does the probability of detection. However, when SU mistakenly identifies the PU signal when PU is not there, the rising probability of false alarms reduces the efficiency of spectrum usage of SU. As can be seen, the simulations result for $P_{fa} = 0.1$ and 0.2 has SNR wall at -23 dB and -24 dB, respectively. Therefore, as the SNR wall value drops and the signal power weakens, it may be concluded that an increase in the probability of false alarms increases the sensitivity of detection systems.

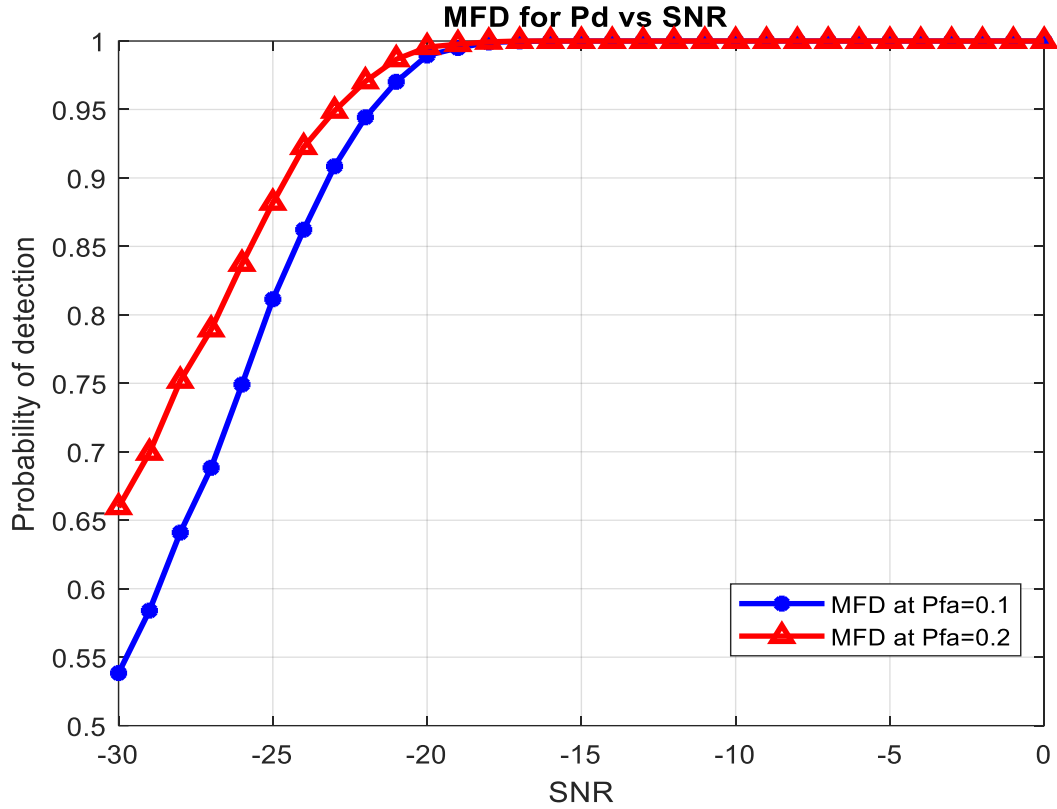


Figure 4.2: P_d vs SNR for MFD at $P_{fa}=0.1$ and 0.2

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

The link between the probability of a false alarm occurring and the probability that an MFD under the AWGN channel will be identified at SNR levels of -23 dB, -25 dB, and -27 dB is depicted in Figure 4.3. The graph demonstrates that as the probability of false alarms rises, so does the probability of detection. However, a significant false alarm probability results in inefficient spectrum use. To provide accurate findings and to avoid secondary user signals obstructing those of the primary user, the frequency of false alarms should be as low as feasible. In addition, these simulation results show the effect of varying SNR values on the performance of MFD. As can be seen, the ROC curve that is plotted using -23dB SNR value has a higher probability of detection compared to the curve that is plotted using -25dB, and -27 dB. Also, the curve that is plotted using the -25 dB SNR value has a higher probability of detection compared to the curve that is plotted using -27 dB. As a result, it can be deduced that an increase in SNR value enhances the performance of MFD.

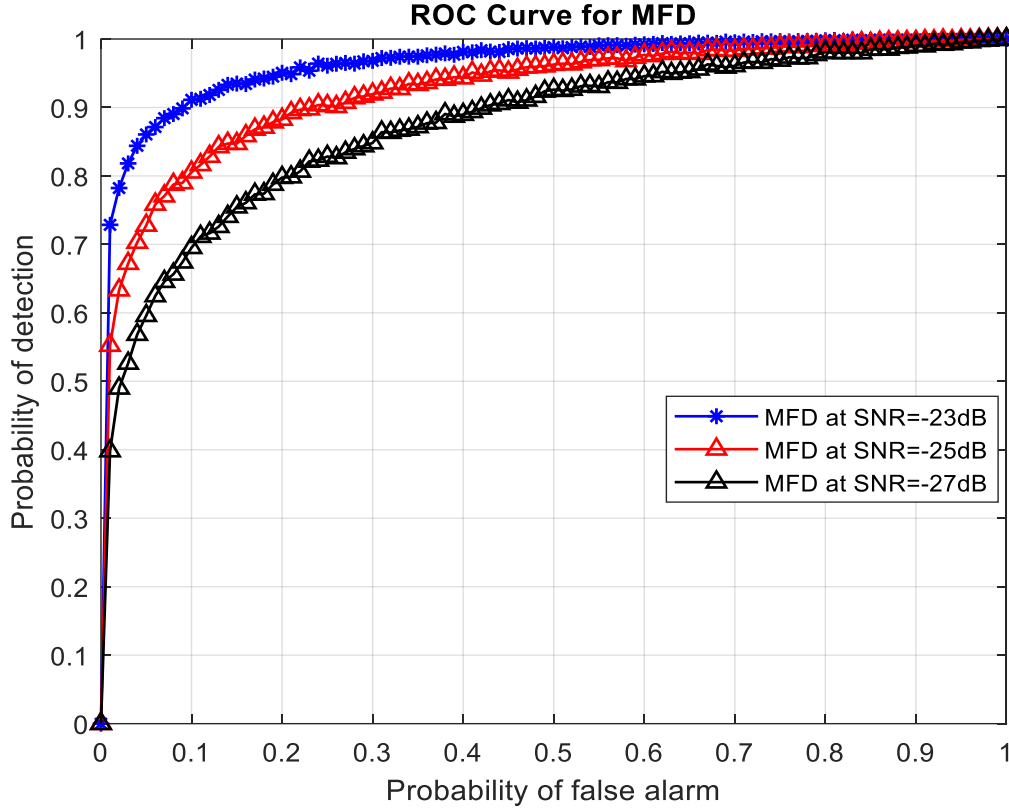


Figure 4.3: P_d vs P_{fa} for MFD at various SNR values

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

The simulation results of the CROC curve for MFD under the AWGN channel are displayed in Figure 4.4. The CROC figure demonstrates the correlation between the probabilities of false alarms and miss-detection. These CROC curves are displayed at -23 dB, -25 dB, and -27 dB SNR levels. The graphic shows that as the probability of a false alarm rises, the probability of a missed detection declines. As the probability of a miss-detection lowers, the performance of the spectrum sensing technology increases. The interference between PU and SU grows along with the probability of a miss-detection. Therefore, a detector that has a lower probability of miss-detection is desirable. Moreover, the impacts of varying SNR values on miss-detection probability are evaluated in this graph. As observed, the CROC curve that is plotted with a -23 dB SNR value has a lower miss-detection probability than those plotted with -25 dB, and -27 dB. Also, the curve that is plotted with -25 dB has a lower probability of miss detection compared to the curve that is plotted with -27 dB. As a result, it is possible to conclude that increasing the SNR value reduces the miss-detection probability, which results in improved performance.

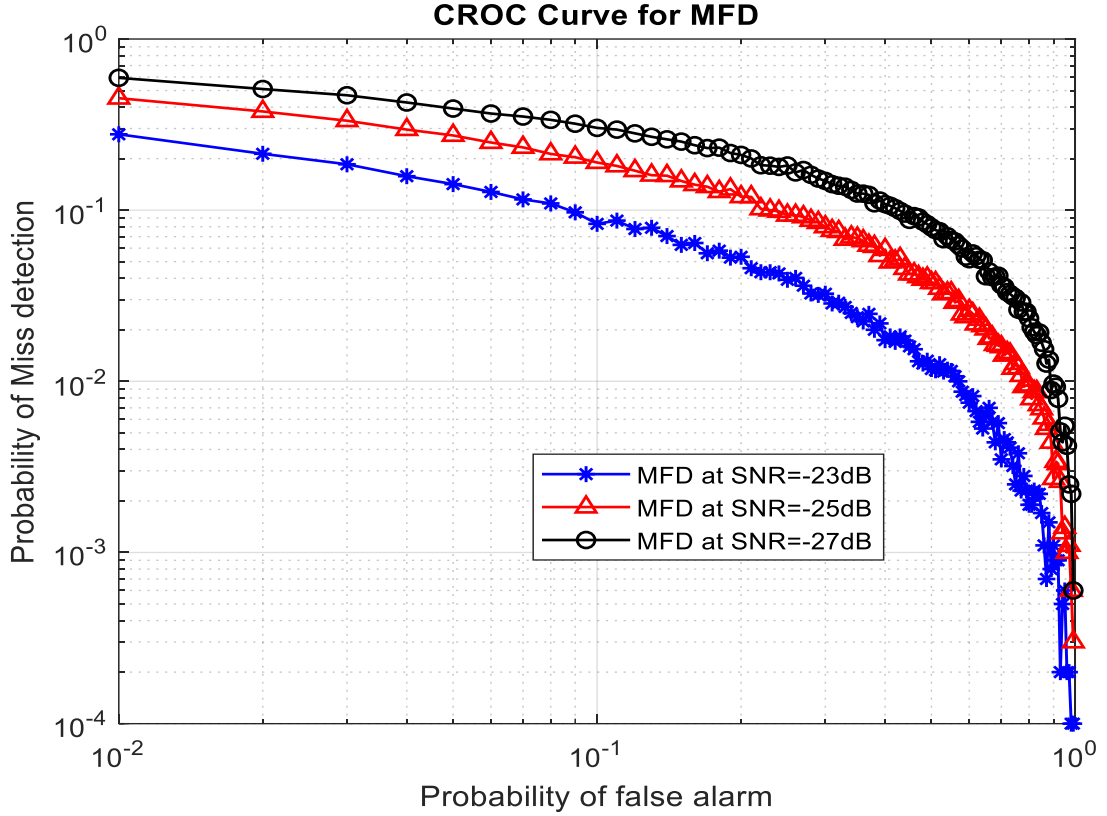


Figure 4.4: P_m vs P_{fa} for MFD at various SNR values

4.2 Results of Cyclo-stationary feature detection (CFD)

There have been several simulations and performance analyses for CFD in the literature, as was covered in chapter two. However, for the sake of clarity, the simulation and analysis of CFD are discussed in this section. Here, the AWGN channel's performance for CFD is simulated. The following simulation outcomes for CFD methods are discussed:

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

4.2.1 Effects of the varying probability of false alarm on the detection performance of CED

The relationship between P_d and SNR is depicted in Figure 4.5 for various false alarm probabilities of 0.1, 0.2, and 0.3. The graph shows that as the probability of false alarms rises, so too does the probability of detection. However, the probability of false alarms enhances if SU incorrectly detects the PU signal when PU is not present, which lowers the effectiveness of SU's spectrum utilization. As can be seen, the simulation result for $P_{fa} = 0.1$ and 0.2 has an SNR wall at -20 dB and -20.5 dB, respectively, while $P_{fa} = 0.3$ has an SNR wall at -21 dB. So, we can conclude that a rise in the probability of false alarms enhances

the sensitivity of detection systems since a weaker signal is produced as the SNR wall value decreases.

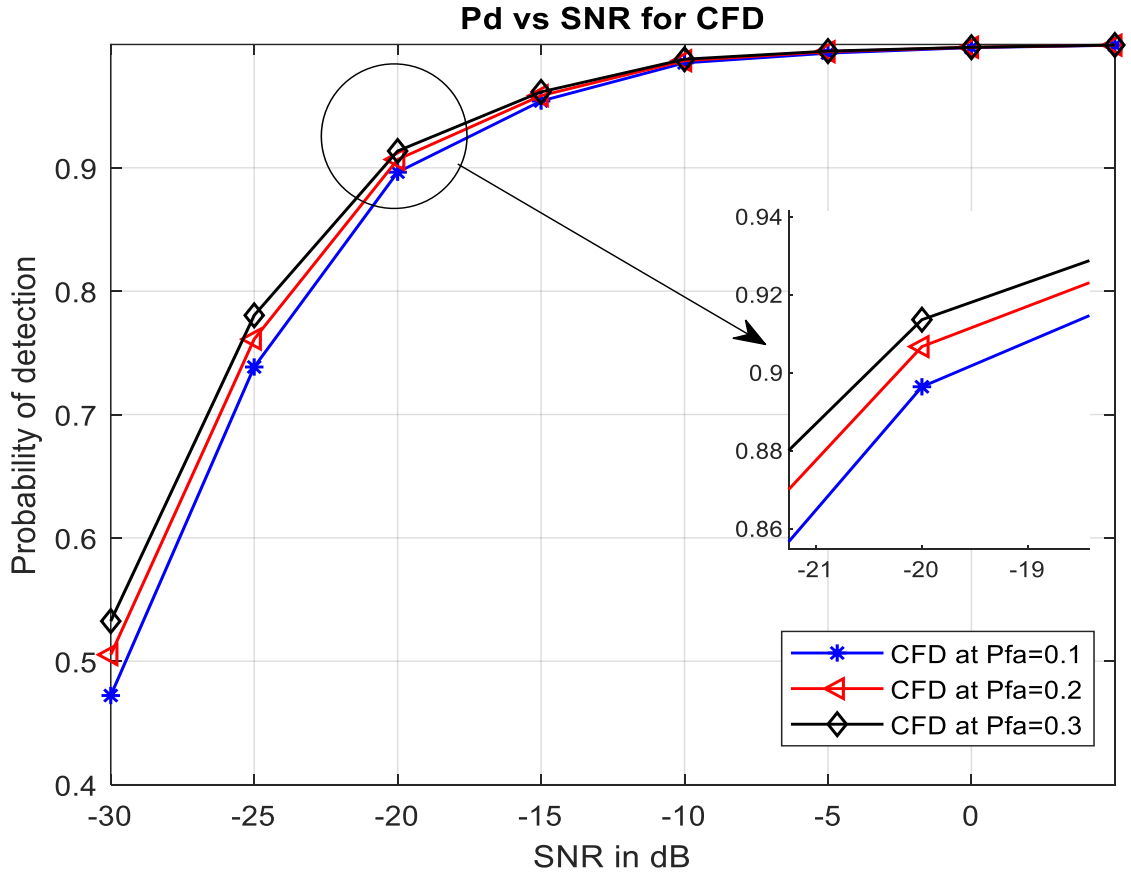


Figure 4.5: P_d vs SNR for CFD at $P_{fa} = 0.1, 0.2$ and 0.3

4.2.2 Probability of detection versus probability of false alarm (ROC Curve) for CFD

Figure 4.6 illustrates the link between the probability of a false alarm and the probability of a PU being detected for the AWGN channel at SNR values of -23 dB, -25 dB, and -27 dB. The graph shows how the probability of detection rises as the probability of false alarms rises. However, inadequate spectrum uses result in a significant probability of false alarms. For accurate findings and to prevent secondary user signals from interfering with those of the primary user, the chance of false alarms should be as low as it can be. In addition, these simulation results show the effect of varying SNR values on the performance of CFD. As can be seen, the ROC curve that is plotted using the -23 dB SNR value has a higher detection probability compared to the curve that is plotted using -25 dB, and -27 dB. Also, the curve that is plotted using the -25 dB SNR value has a greater probability of detection in comparison to the depicted curve using -27 dB. As a result, it can be concluded that an increase in SNR value enhances the performance of CFD.

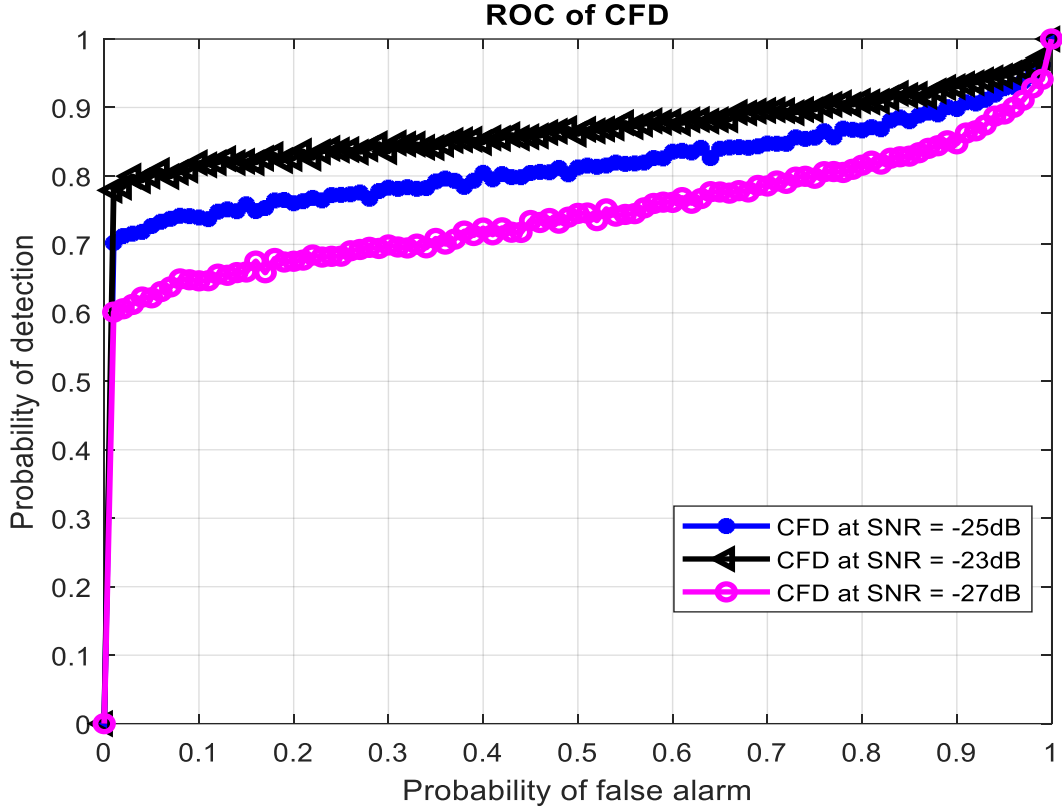


Figure 4.6: P_d vs P_{fa} for CFD at various SNR values

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

Figure 4.7 displays the simulation outcomes for the CROC curve for CFD under the AWGN channel. The CROC figure demonstrates a correlation between the probability of false alarms and the possibility of miss-detection. These CROC curves are shown at SNR levels of -23 dB, -25 dB, and -27 dB. The graph shows how the probability of missing a detection lowers as the probability of a false alarm enhances. As the probability of a miss-detection lowers, the performance of the spectrum sensing technology increases. The interference between PU and SU grows along with the probability of a miss-detection. Therefore, a detector that has a lower probability of miss-detection is desirable. Moreover, the impacts of varying SNR values on miss-detection probability are evaluated in this graph. As observed, the CROC curve that is plotted with a -23 dB SNR value has a lower miss-detection probability than those plotted with -25 dB, and -27 dB. Also, the curve that is plotted with -25 dB has a lower probability of miss detection compared to the curve that is plotted with -27 dB. As a result, it is possible to conclude that increasing the SNR value reduces the miss-detection probability, which results in improved performance.

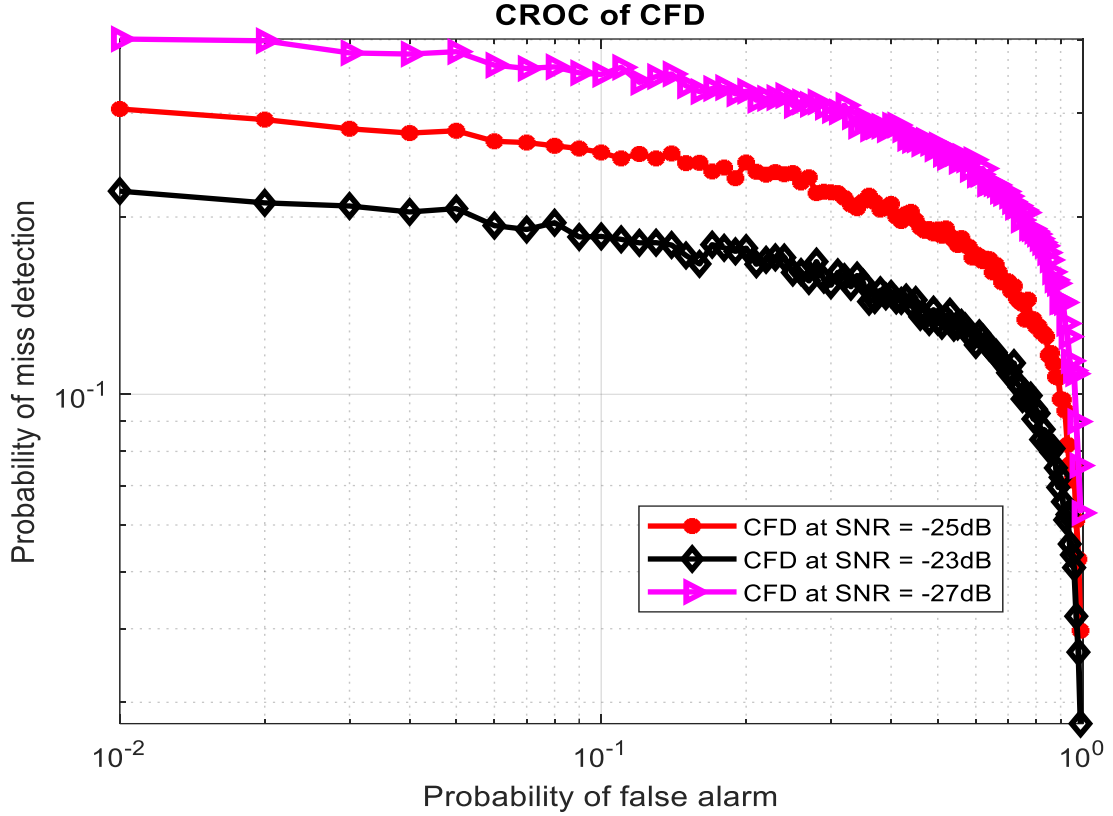


Figure 4.7: P_m vs P_{fa} for CFD at various SNR values

4.3 Results of Energy Detection (ED)

Numerous simulations and performance analyses of ED have been discussed in the literature, as was covered in chapter two. However, for the sake of clarity, the simulation and analysis of ED are covered in this section. In this case, the ED's performance across the AWGN channel is simulated. We discuss the following simulated outcomes for ED methods:

- Effects of varying false alarm probabilities on detection performance
- Receiver Operating Characteristic (ROC) Curve
- Complementary ROC Curve

4.3.1 Effects of the varying probability of false alarm on the detection performance of ED

The correlation between P_d and SNR for various false alarm probabilities of 0.1, 0.2, and 0.3 is displayed in Figure 4.8. The graph demonstrates that as the probability of false alarms increases, the probability of detection also increases. The increased possibility of false alarms, however, limits the effectiveness of SU's spectrum utilization when it incorrectly detects the PU signal when PU is not there. As can be shown, $P_{fa} = 0.3$ has a simulation result with SNR wall at -11 dB while $P_{fa} = 0.1$ and 0.2 have SNR walls at -9 dB and -10.5 dB, respectively. So, it can be concluded that a rise in the probability of false alarms enhances

the sensitivity of detection techniques since the SNR wall value decreases, resulting in weaker signal power.

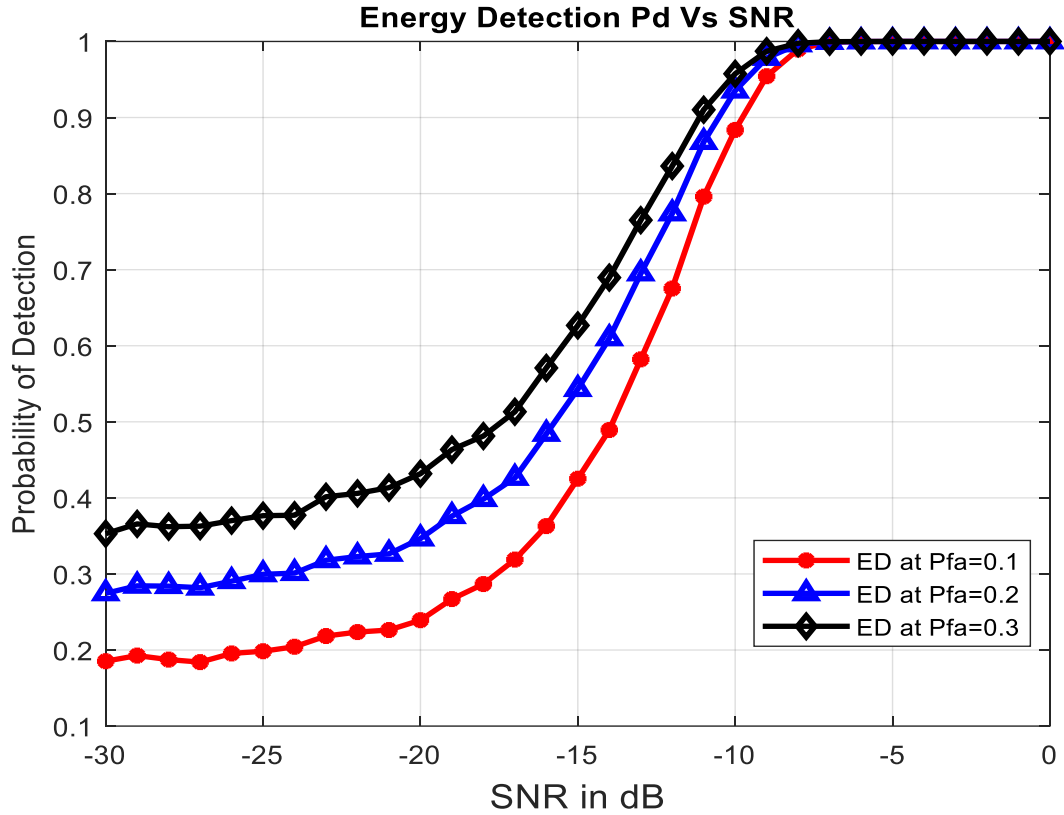


Figure 4.8: P_d vs SNR for ED at $P_{fa} = 0.1, 0.2, 0.3$ and $N=1000$

4.3.2 Probability of detection versus probability of false alarm (ROC Curve) for ED

Figure 4.9 accurately illustrates the link between the probability of a false alarm and the probability of detecting ED under the AWGN channel at SNR values of -10 dB, -14 dB, and -18 dB. The graph shows how the probability of detection enhances as the probability of false alarms rises. However, inadequate spectrum uses result in a significant probability of false alarms. For accurate findings and to prevent secondary user signals from interfering with those of the primary user, the chance of false alarms should be as low as it can be. These simulation results also demonstrate how changing SNR settings affect CED performance. As can be seen, the ROC curve that is plotted using the -10 dB SNR value has a higher detection probability compared to the curve that is plotted using, -14 dB and -18 dB. Also, the curve that is plotted using a -14 dB SNR value has a higher probability of detection compared to the curve that is plotted using -18 dB. Therefore, it may be stated that a higher SNR value improves CED performance.

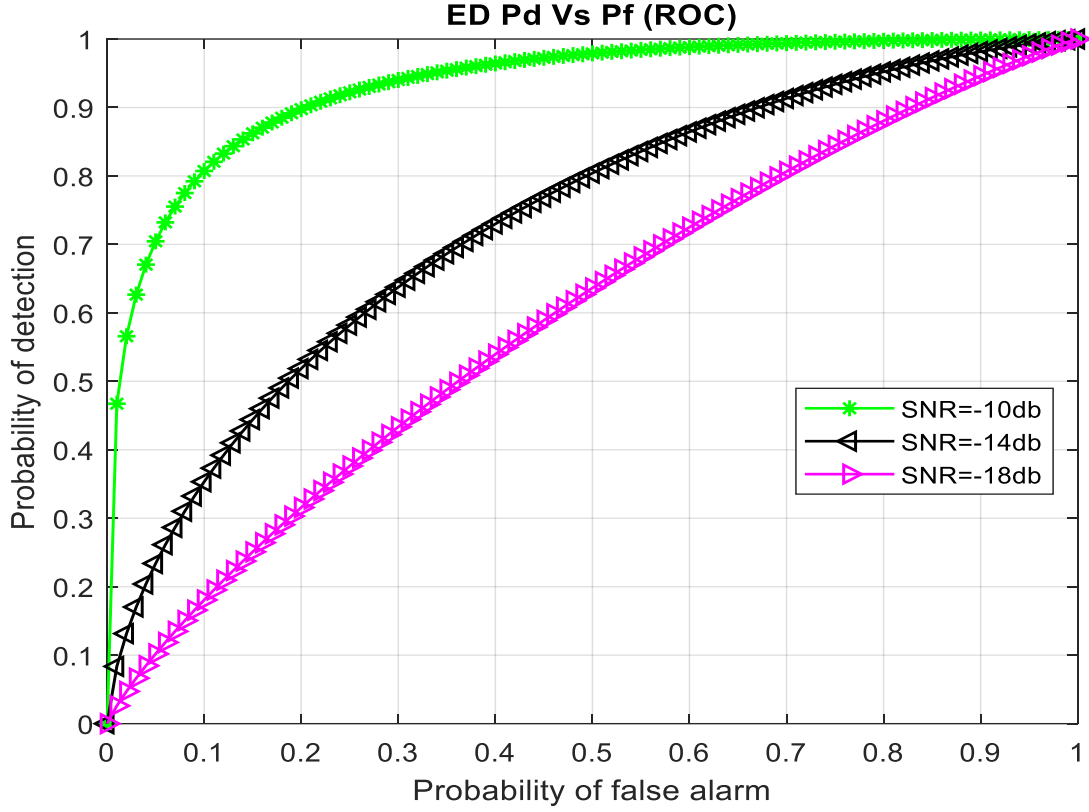


Figure 4.9: P_d vs P_{fa} for ED at various SNR values

4.3.3 Probability of miss detection versus probability of false alarm (CROC Curve) for ED

Figure 4.10 illustrates the simulation results of the CROC curve for ED under the AWGN channel. The probability of false alarms and the probability of miss-detection are correlated, as shown by the CROC figure. These CROC curves are plotted at SNR values of -14 dB, -16 dB, and -18 dB. As observed from the figure, an increase in the probability of false alarms decreases the probability of miss-detection. As the probability of a miss-detection lowers, the performance of the spectrum sensing technology increases. The probability of a miss-detection increases as the interference between PU and SU increases. Therefore, a detector that has a lower probability of miss-detection is desirable. Moreover, the impacts of varying SNR values on miss-detection probability are evaluated in this graph. As observed, the CROC curve that is plotted with a -14 dB SNR value has a lower miss-detection probability than those plotted with -16 dB, and -18 dB. Also, the curve that is plotted with -16 dB has a lower probability of miss detection compared to the curve that is plotted with -18 dB. As a result, it is possible to conclude that increasing the SNR value reduces the miss-detection probability, which results in improved performance.

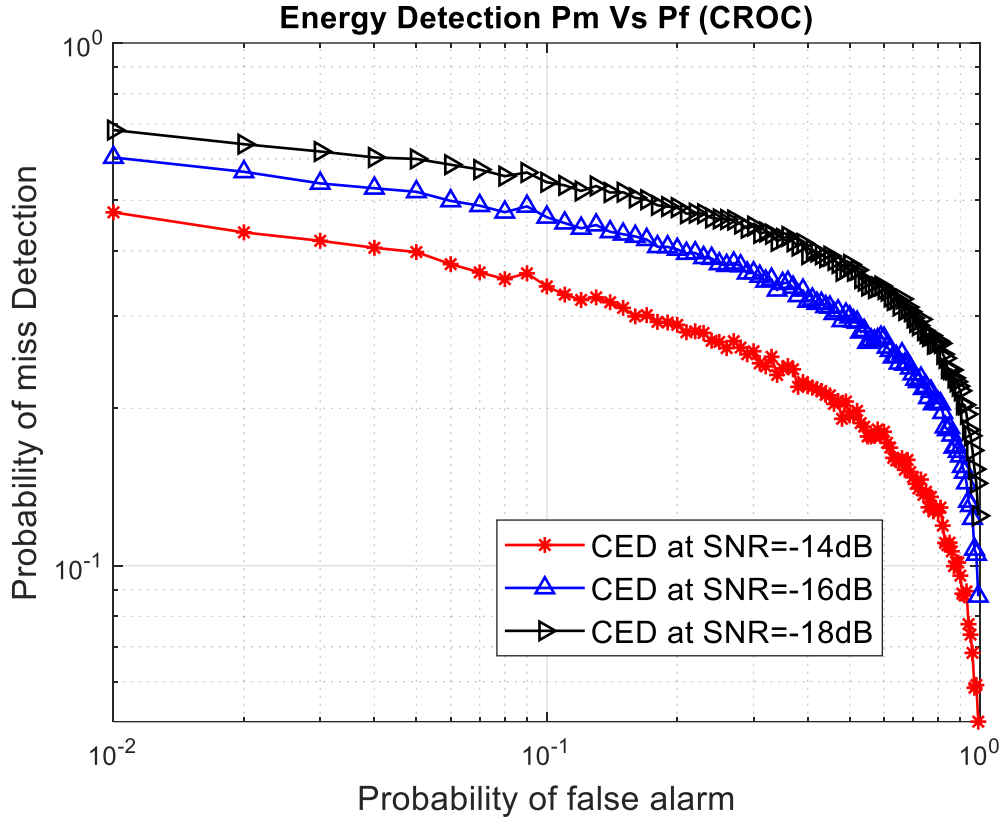


Figure 4.10: P_m vs P_{fa} for ED at various SNR values

4.4 Results of hybrid based on Energy and matched filter detection technique

The performance of the hybrid based on energy detection (ED) and matched filter detection (MFD) spectrum sensing (SS) technique is discussed in this part along with simulation results comparing it to conventional ED and MFD.

For a hybrid based on ED and MFD approaches, the following simulation results are discussed:

- Probability of detection versus SNR for comparing two stages of ED and MFD technique with the conventional method.
- Receiver Operating Characteristics (ROC) Curve.
- Complementary Receiver Operating Characteristics (CROC) Curve.

4.4.1 Probability of detection versus SNR for comparing the hybrid based on Energy detection and matched filter detection technique with conventional methods

Figure 4.11 contrasts this hybrid based on ED and MFD SS, MFD, and ED with a particular probability of false alarm of 0.1. The comparison results show that the hybrid based on ED

and MFD method outperforms MFD and ED by some performance improvement. For example, for a given SNR of -25 dB, the hybrid based on the ED and MFD method has a probability detection of 0.8688, while the detection probabilities for MFD and ED are 0.8 and 0.3406, respectively. In other words, when compared to ED and MFD, respectively, the hybrid based on ED and MFD approach improves the SNR wall by around 12 dB and 1 dB.

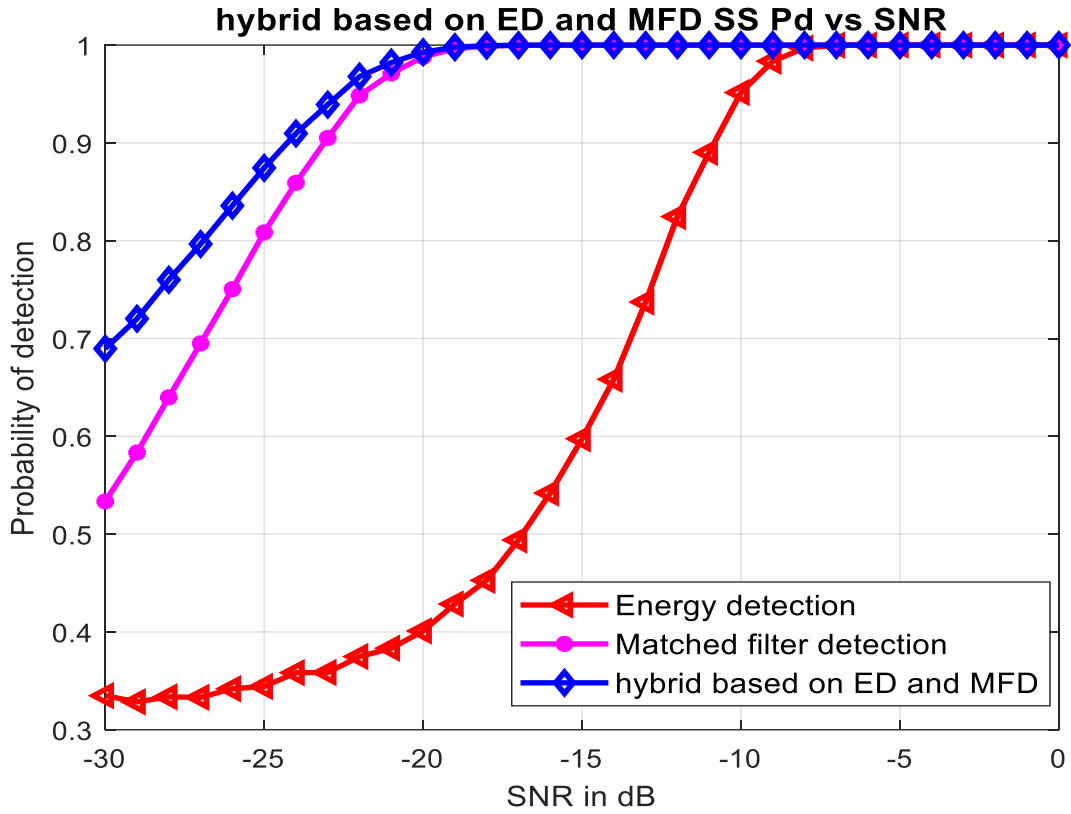


Figure 4.11: P_d vs SNR for comparing hybrid based on ED and MFD, MFD and ED at $P_{fa}=0.1$

Table 4.2: Performance comparison between hybrid based on ED and MFD, ED and MFD SS at various SNR values.

SNR (dB)		-30	-27	-24	-21	-18	-15	-12	-9	-6	-3	0
Detection probability	ED	0.335	0.333	0.358	0.383	0.453	0.59	0.825	0.985	1	1	1
	MFD	0.533	0.695	0.859	0.971	0.998	1	1	1	1	1	1
	Hybrid-based no MFD and ED	0.689	0.797	0.909	0.982	0.999	1	1	1	1	1	1

4.4.2 Receiver Operating Characteristics (ROC) Curve of hybrid based on Energy detection and matched filter detection technique

The ROC Curve that contrasts the hybrid based on ED and MFD SS with MFD and CED at SNR=-25 dB is shown in Figure 4.12. As can be seen, the hybrid based on ED and MFD techniques has a lower probability of false alarms than MFD and CED for identifying PU signals within the proper probability of detection. The hybrid based on ED and MFD detector works better in terms of detection, as shown in the figure. For instance, the detection performance of a hybrid based on the ED and MFD approach is 0.797 at a given probability of false alarm of 0.1, while the detection probabilities of MFD and CED are 0.6938 and 0.3398, respectively. In other words, this hybrid based on ED and MFD SS technique achieves a higher probability of detection than MFD and CED.

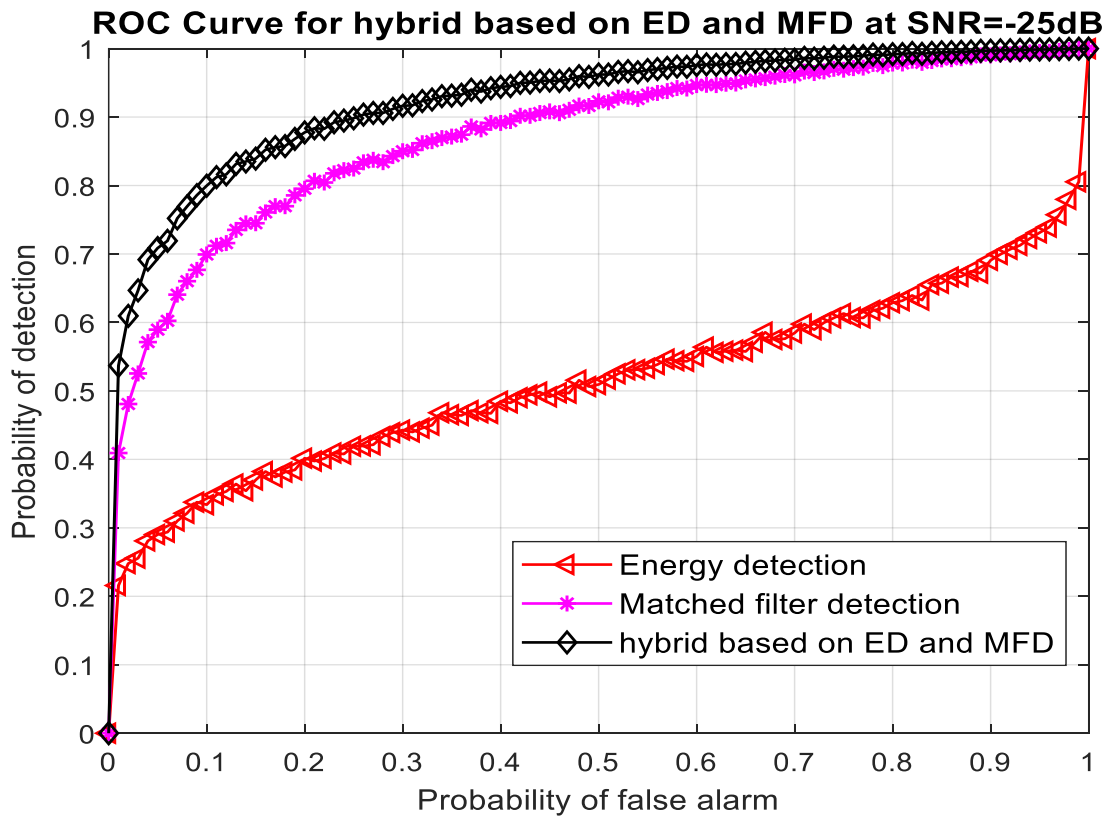


Figure 4.12: ROC curve that compares hybrid based on ED and MFD, at SNR=- 25dB

4.4.3 Complementary receiver operating characteristics curve of hybrid based on energy detection and matched filter detection technique

Figure 4.13 shows the CROC Curve that compares this hybrid based on ED and MFD SS with MFD and CED at SNR=-25dB. The figure shows that the combination of the MFD and ED methods has a better missed-detection probability across all P_{fa} ranges when compared to MFD and CED alone. For example, when the false alarm probability is 0.02, the missed

detection probability of the hybrid approach is 0.3875, while the miss detection probabilities for MFD and CED are 0.5157 and 0.7515, respectively. Less SU interference with PU results from detection methods with lower missed detection probabilities. As a result, it can be inferred from this result that the hybrid technique based on ED and MFD is more effective than MFD and CED at differentiating PU signals from noise signals.

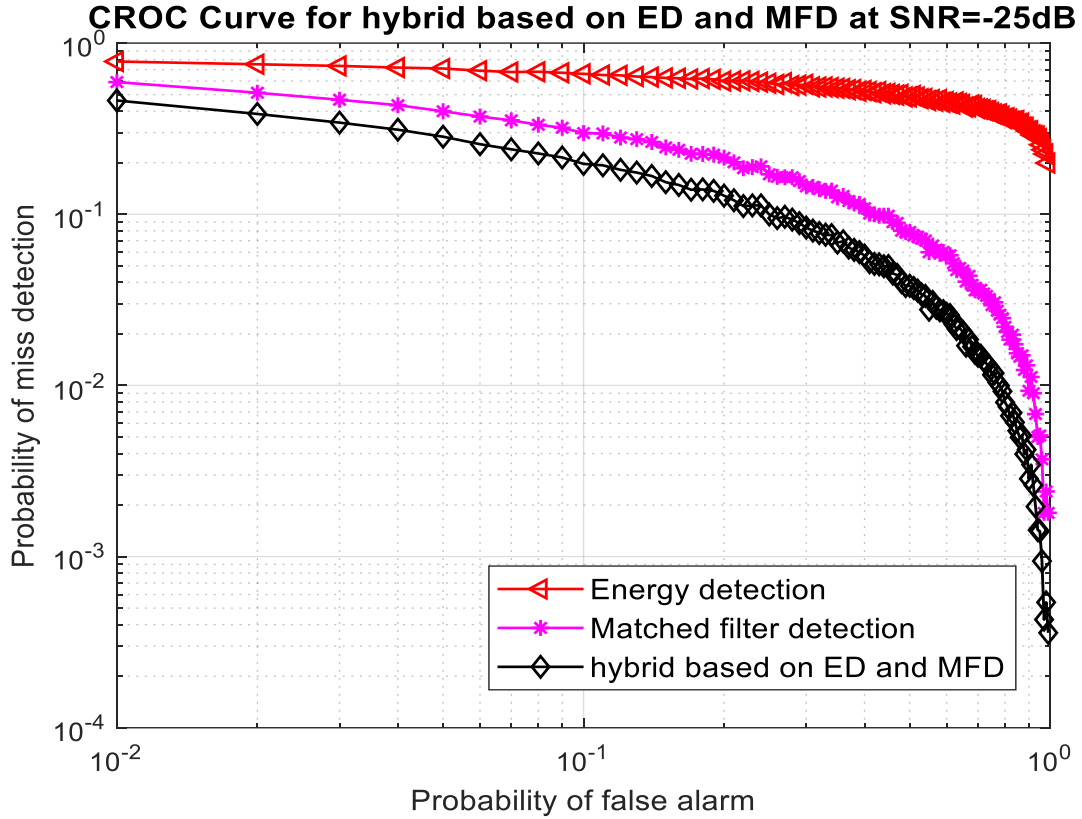


Figure 4.13: CROC curve that compares hybrid based on ED and MFD, MFD and CED at SNR = -25 dB

4.4.4 Results of cooperative detection for a hybrid based on matched filter detection and energy detection techniques

This section gives the results of a simulation that assesses the effectiveness of cooperative detection for the hybrid based on ED and MFD techniques. It is done to compare the proposed technique's single-node and cooperative detection methods. The ROC, CROC, and P_d vs SNR curves are used to evaluate performance.

4.4.5 P_d vs SNR for cooperative detection of hybrid based on ED and MFD technique

In Figure 4.14, the probability of detection is plotted against the SNR for a cooperative hybrid that uses both ED and MFD approaches. The number of samples is fixed at 1000 and the false alarm probability is set to 0.1 ($P_{fa} = 0.1$). Furthermore, the simulation's output

compares a single node (i.e., $NU=1$) with a cooperative hybrid that uses ED and MFD approaches. The number of cooperative users is 2 and 3. The OR rule CSS is used for deciding the final decision of the cooperative approach since it has a higher detection probability compared to the AND rule (Usman et al., 2022b),(Bani & Kulkarni, 2022). As observed from the figure, the cooperative detection of this hybrid based on the ED and MFD technique outperforms a single node of this hybrid based on ED and MFD technique. For instance, a cooperative hybrid technique with two users can detect a PU signal with an SNR of -30dB and above, while a single-node hybrid technique can detect up to -24 dB only. This indicates 6 dB performance improvements in the SNR wall.

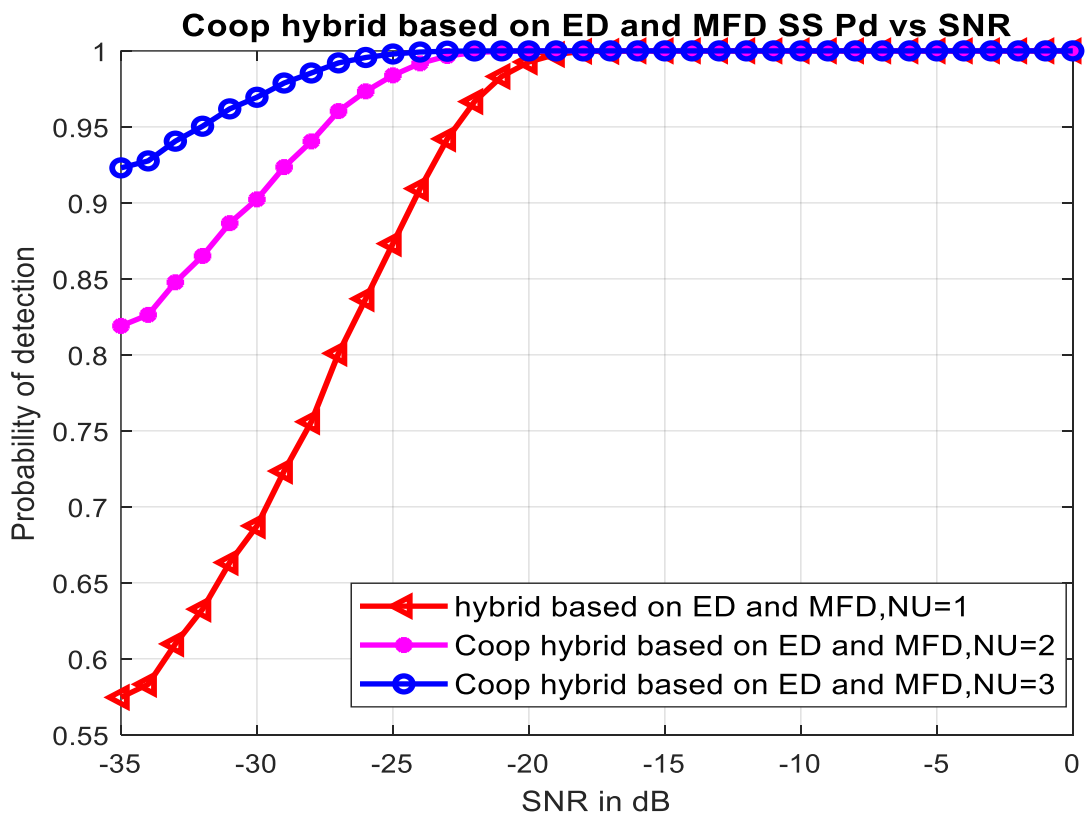


Figure 4.14: P_d vs SNR for Cooperative hybrid based on ED and MFD SS at $P_{fa}=0.1$

4.4.6 ROC curve for cooperative detection of hybrid based on ED and MFD technique

The cooperative hybrid based on the MFD and ED technique's simulation result of the ROC curve at SNR = -25 dB is illustrated in Figure 4.15. The probability detection for the cooperative hybrid based on ED and MFD technique is higher than the single-node strategy, as seen in the figure. Additionally, the outcome demonstrates that the probability detection of the cooperative technique grows with the number of SU. For instance, assuming a specified 0.01 false alarm probability ($P_{fa} = 0.01$), the probability of detection for a

cooperative hybrid based on ED and MFD techniques with $NU = 2$ and 3 is 0.7895 , and 0.9034 , respectively, while the detection probability for single node ($NU=1$) hybrid based on ED and MFD technique is 0.5412 . This finding indicates that the cooperative strategy with a larger number of SU performs better in terms of detection.

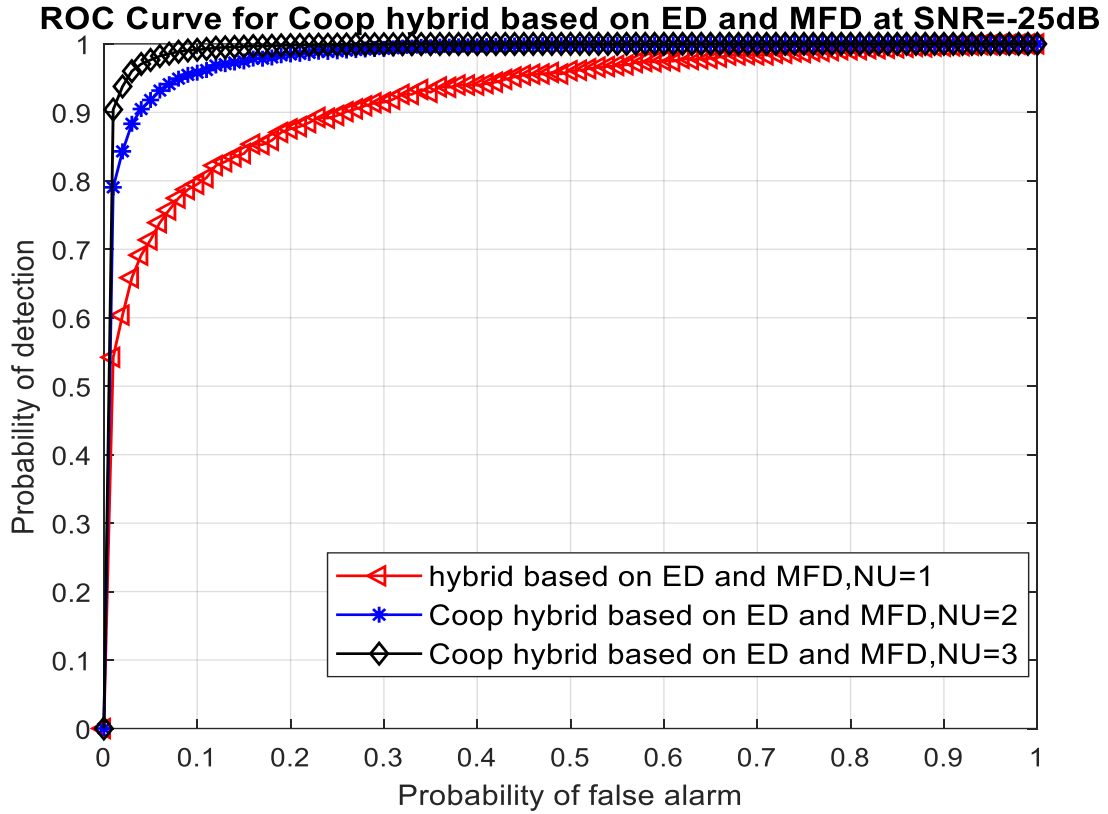


Figure 4.15: ROC curve for Cooperative hybrid based on ED and MFD SS at SNR=-25dB

4.4.7 CROC curve for Cooperative detection of hybrid based on ED and MFD technique

The simulation result of the CROC curve for the hybrid approach that uses both ED and MFD techniques is presented in Figure 4.16, specifically at an SNR of -26 dB. As observed from the figure, the cooperative hybrid based on ED and MFD technique has a lower missed-detection probability compared to the single-node this hybrid based on ED and MFD technique. For instance, at a given false alarm probability of 0.02 ($P_{fa} = 0.02$), the missed detection probability of the cooperative this hybrid based on ED and MFD technique with 3 number users is 0.05981 , while the single-node hybrid based on ED and MFD technique has a 0.3911 probability of miss detection. By comparing this result, the probability of missed detection for a cooperative hybrid based on ED and MFD techniques is decreased by 84.707% compared to a single node hybrid based on ED and MFD methods. This outcome

leads us to conclude that the cooperative technique has better performance than single-node techniques.

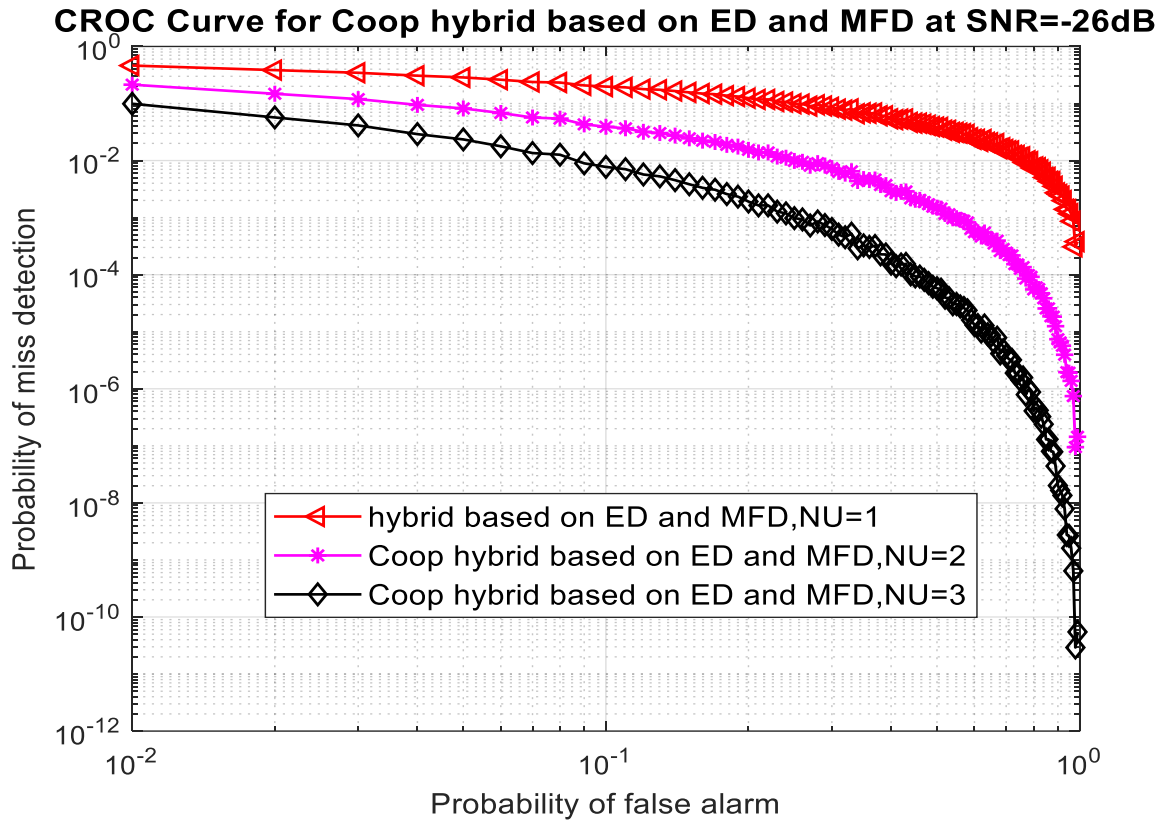


Figure 4.16: CROC Curve for Cooperative hybrid based on ED and MFD at SNR=-26dB

4.5 Results of conventional hybrid from cyclostationary feature detection and energy detection spectrum Sensing

This section presents simulation results that assess the effectiveness of hybrid spectrum sensing methods using cyclostationary feature detection (CFD) and energy detection (ED) in combination with ED and CFD. For this technique, the following simulation outcomes are discussed:

- Probability of detection versus SNR for comparing the hybrid method with the conventional method.
- Receiver Operating Characteristics (ROC) Curve.
- Complementary Receiver Operating Characteristics (ROC) Curve.

4.5.1 Probability of detection versus SNR for comparing the hybrid from ED and CFD technique with conventional methods

At a certain probability of false alarm of 0.1 and 1000 samples, Figure 4.17 compares this hybrid based on ED and CFD spectrum sensing, CFD, and ED. The comparison results

demonstrate that this hybrid technique works somewhat better than CFD and ED. For instance, the detection probability of this hybrid approach is 0.8307 at a given SNR of -25 dB, compared to 0.7417 and 0.3445 for CFD and ED. In other words, when compared to ED and CFD, the hybrid approach improves the SNR wall by approximately 11 dB and 3 dB, respectively.

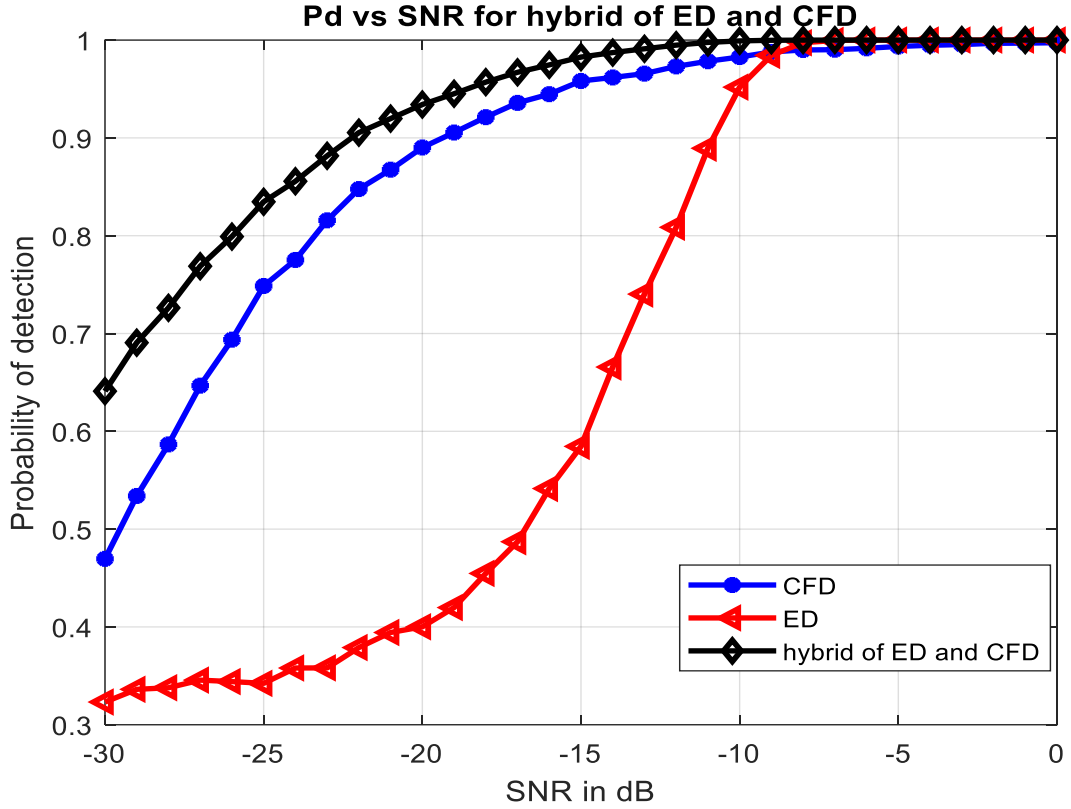


Figure 4.17: P_d vs SNR for comparing the hybrid method from ED and CFD, ED and CFD at $P_{fa} = 0.1$

Table 4.3: Performance comparison between Conventional hybrid based on ED and CFD, ED and CFD spectrum sensing at various SNR values.

SNR (dB)		-30	-27	-24	-21	-18	-15	-12	-9	-6	-3	0
Detection probability	ED	0.333	0.329	0.354	0.396	0.463	0.592	0.81	0.98	1	1	1
	CFD	0.463	0.654	0.784	0.868	0.919	0.957	0.97	0.98	0.99	0.99	1
	Conventional hybrid-based no CFD and ED	0.642	0.768	0.861	0.921	0.956	0.982	0.99	1	1	1	1

4.5.2 Receiver Operating Characteristics (ROC) Curve of conventional hybrid based on ED and CFD

Figure 4.18 displays the ROC Curve for the hybrid SS approach in comparison to CFD and CED, at SNR=-25 dB and N=1000. The figure indicates that the hybrid SS approach has a lower false alarm probability than CFD and CED while maintaining a high probability of detection for PU signals. These results demonstrate that the hybrid approach outperforms the conventional detection methods. For instance, when the false alarm probability is 0.1, the detection performance of the hybrid approach is 0.8312, compared to 0.7404 for CFD and 0.3498 for ED.

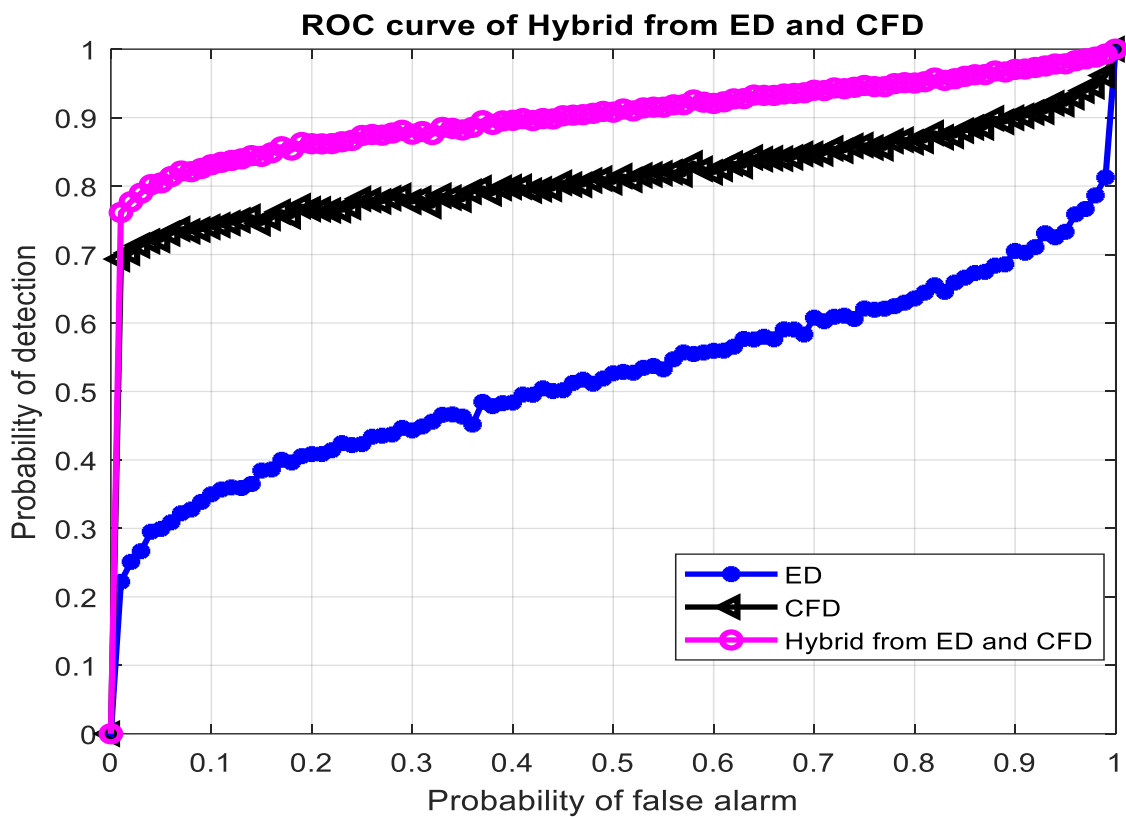


Figure 4.18: ROC curve that compares Hybrid method from ED and CFD, CFD and CED at SNR=- 25dB

4.5.3 Complementary Receiver Operating Characteristics (CROC) curve of conventional hybrid based on ED and CFD

Figure 4.19 shows the CROC Curve that compares the hybrid method from ED and CFD SS with CFD and CED at SNR=-24 dB. The illustration demonstrates that the hybrid approach has a better missed-detection probability than CFD and CED across all Pfa ranges. For example, at a false alarm probability of 0.03, the hybrid approach has a missed detection probability of 0.2146, while CFD and CED have missed detection probabilities of 0.2923

and 0.7341, respectively. Less SU interference with PU results from detection methods with lower missed detection probabilities. Therefore, it may be deduced from this finding that the hybrid approach outperforms CFD and CED.

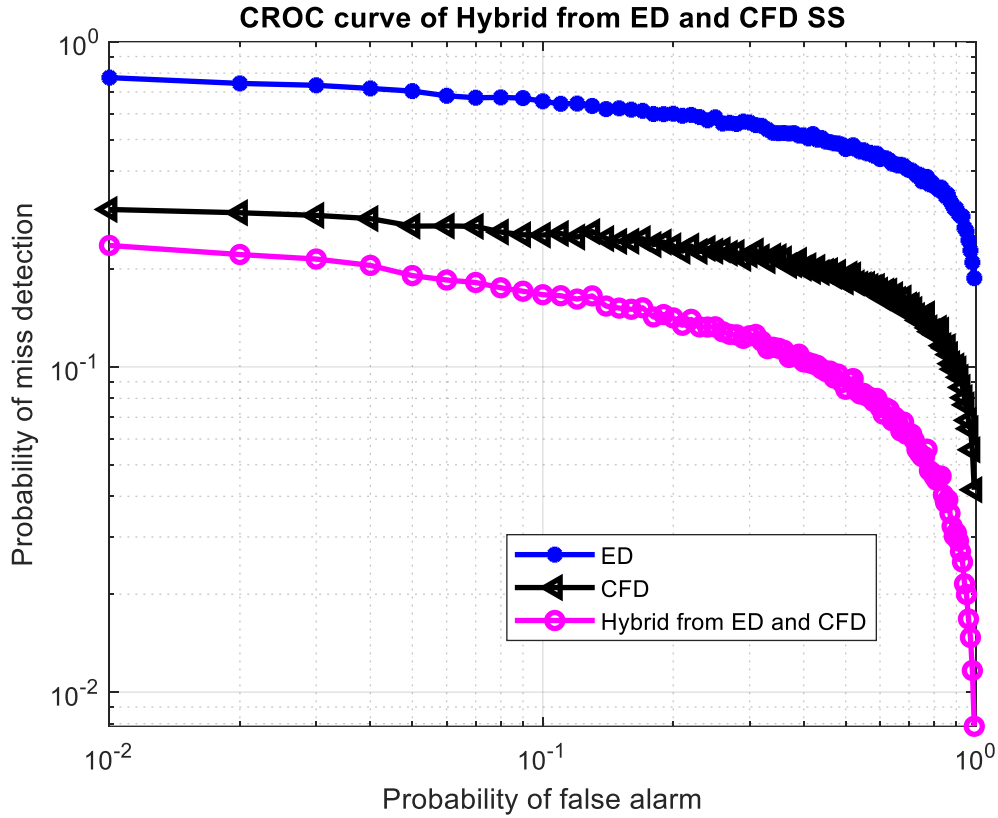


Figure 4.19: CROC curve that compares Hybrid method from ED and CFD, CFD and CED at SNR = -24 dB

4.5.4 Results of cooperative detection for a conventional hybrid based on ED and CFD techniques

This section presents a simulation that assesses the performance of a conventional hybrid approach that uses CFD and ED methods for cooperative detection. The cooperative detection of the hybrid approach is compared to single-node detection. The P_d vs SNR curve, ROC curve, and CROC curve is used to evaluate performance.

4.5.5 P_d vs SNR for cooperative detection of conventional hybrid based on ED and CFD technique

Figure 4.20 shows the relationship between the probability of detection and SNR for a conventional hybrid method that uses CFD and ED techniques for cooperative detection. The false alarm probability is set to 0.1 ($P_{fa}=0.1$) and the number of samples is set to 1000 ($N=1000$). Furthermore, the simulation's output compares a single node (i.e., $N_U=1$) with a cooperative hybrid method. The number of collaborating users is 2 and 3. The OR rule CSS

is used for deciding the final decision of the cooperative approach since it has a higher detection probability compared to the AND rule (Usman et al., 2022b),(Bani & Kulkarni, 2022). As can be seen from the figure, the cooperative detection of a hybrid technique outperforms a single-node hybrid technique. For instance, a cooperative hybrid technique with two users can detect a PU signal with an SNR of -28dB and above, while a single-node hybrid technique can detect up to -22 dB only. This indicates 6 dB performance improvements in the SNR wall.

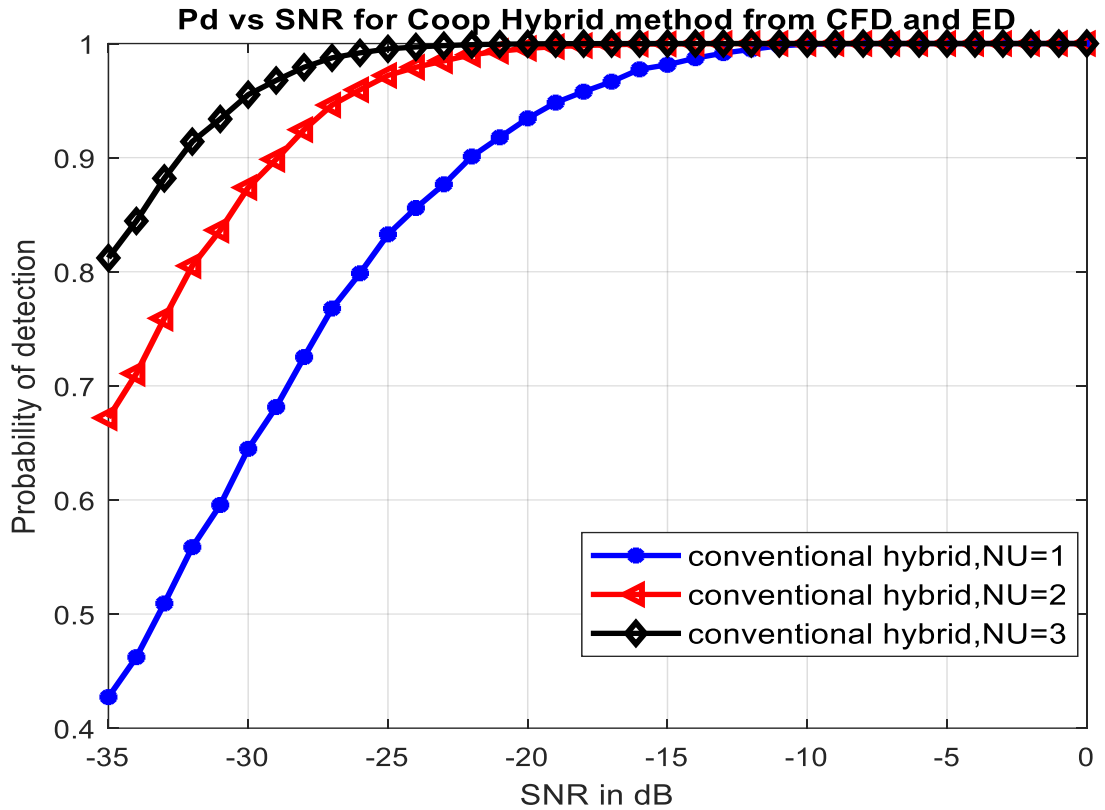


Figure 4.20: P_d vs SNR for Cooperative two-stage SS at $P_{fa}=0.1$

4.5.6 ROC curve for cooperative detection of conventional hybrid based on ED and CFD technique

The cooperative hybrid method from ED and CFD technique's ROC curve simulation result is shown in Figure 4.21 at SNR = -26 dB. The cooperative hybrid approach has a higher probability of detection than the single-node strategy, as seen in the figure. Additionally, the outcome demonstrates that the cooperative technique's detection probability rises as the number of SU increases. For instance, at a given false alarm probability of 0.05 ($P_{fa} = 0.05$), the probability of detection for cooperative hybrid techniques with NU = 2, and 3 is 0.8826, and 0.9598 respectively, while the detection probability for single node (NU=1) hybrid

technique is 0.6574. From this result, it can be concluded that the cooperative method with a higher number of SU has a better detection performance.

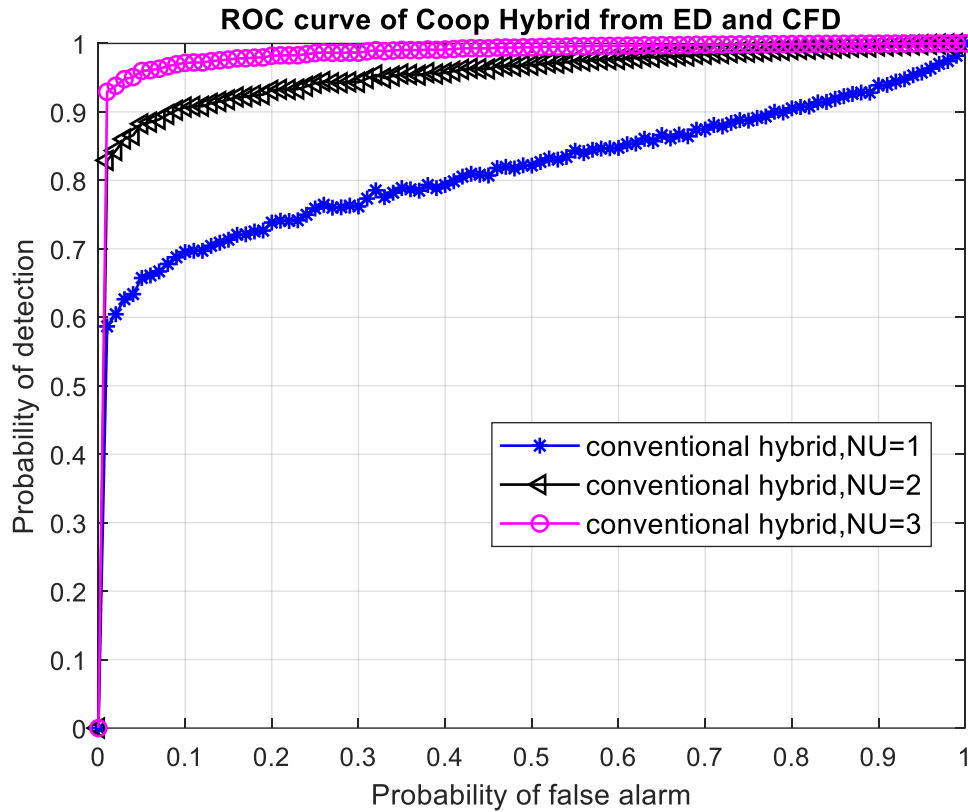


Figure 4.21: ROC curve for Cooperative traditional Hybrid method from ED and CFD SS at SNR=-26dB

4.5.7 CROC curve for cooperative detection of conventional hybrid based on ED and CFD technique

Figure 4.22 display the simulation result of the CROC curve for a cooperative hybrid from the ED and CFD technique at SNR = -26 dB. As seen in the figure, compared to single-node hybrid techniques, the cooperative hybrid technique has a decreased probability of missed detection. For instance, the cooperative hybrid technique with three user numbers has a probability of missed detection of 0.03007 at a given probability of false alarm of 0.1 ($P_{fa}=0.1$), compared to the single-node hybrid technique's 0.311 probability of missed detection. By comparing this result, the probability of missed detection for cooperative the hybrid method is decreased by 90.3% compared to single-node hybrid methods. Based on these results, we can conclude that the cooperative technique performs better than single-node techniques.

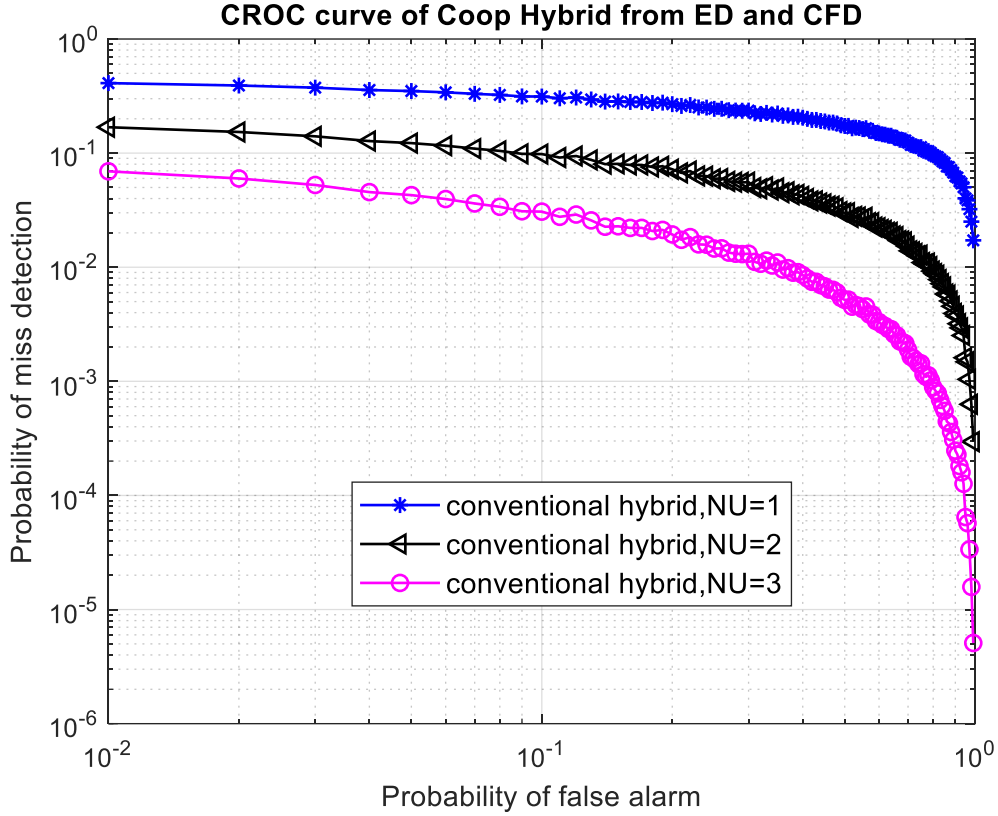


Figure 4.22: CROC curve for Cooperative traditional hybrid technique from ED and CFD
SS at SNR=-26dB

4.6 Results of hybrid method from cyclostationary feature detection and matched filter detection spectrum sensing

This part presents the simulation findings that contrast the effectiveness of the hybrid approach (CFD and MFD) spectrum sensing technology. For the hybrid approach, the following simulation outcomes are discussed:

- Probability of detection versus SNR for comparing hybrid technique with the conventional method.
- Receiver Operating Characteristics (ROC) Curve.
- Complementary Receiver Operating Characteristics (ROC) Curve.

4.6.1 Probability of detection versus SNR for comparing the hybrid method from MFD and CFD technique with conventional methods

In Figure 4.23, the performance of the hybrid methods SS, MFD, and CFD are compared at a false alarm probability of 0.1. The comparison shows that the hybrid approach performs slightly better than MFD and CFD. For example, at an SNR of -25 dB, the hybrid approach has a detection probability of 0.9503, while MFD and CFD have detection probabilities of

0.806 and 0.7436, respectively. In other words, when compared to CFD and MFD, respectively, this hybrid approach improves the SNR wall by around 8 dB and 3.5 dB.

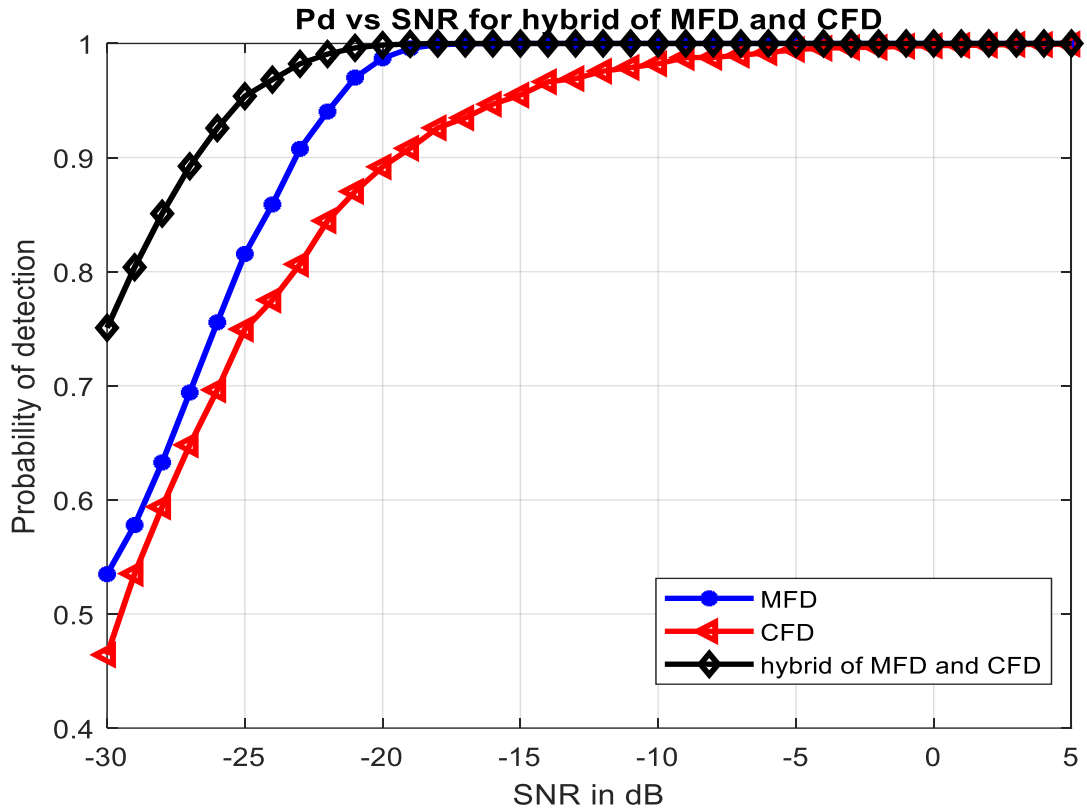


Figure 4.23: P_d vs SNR for comparing the hybrid method of MFD and CFD, MFD and CFD at $P_{fa}=0.1$

Table 4.4: Performance comparison between hybrid based on MFD and CFD, MFD and CFD SS at various SNR values.

SNR (dB)		-30	-27	-24	-21	-18	-15	-12	-9	-6	-3	0
Detection probability	CFD	0.471	0.646	0.778	0.866	0.922	0.955	0.97	0.98	0.99	0.999	1
	MFD	0.538	0.686	0.864	0.973	0.999	1	1	1	1	1	1
	Hybrid-based no CFD and MFD	0.755	0.888	0.969	0.996	0.999	1	1	1	1	1	1

4.6.2 Receiver operating characteristics (ROC) Curve of hybrid method from MFD and CFD technique

Figure 4.24 shows the ROC Curve that compares the hybrid method from MFD and CFD spectrum sensing (SS) with MFD and CFD at SNR=-26 dB. As can be observed, this hybrid

technique has a lower false alarm probability than MFD and CFD. This hybrid detector works well in terms of detection, as shown in the figure. For example, when the false alarm probability is 0.1, the detection performance of the hybrid technique is 0.8921, compared to 0.6956 and 0.6456 for MFD and CFD, respectively. This means that the hybrid SS method achieves the desired probability of detection with a false alarm probability of 0.12, while MFD and CFD require false alarm probabilities of 0.43 and 0.96 respectively. Therefore, it is reasonable to conclude that the hybrid method has better detection performance than both MFD and CFD because it requires a lower false alarm probability to achieve the target probability of detection.

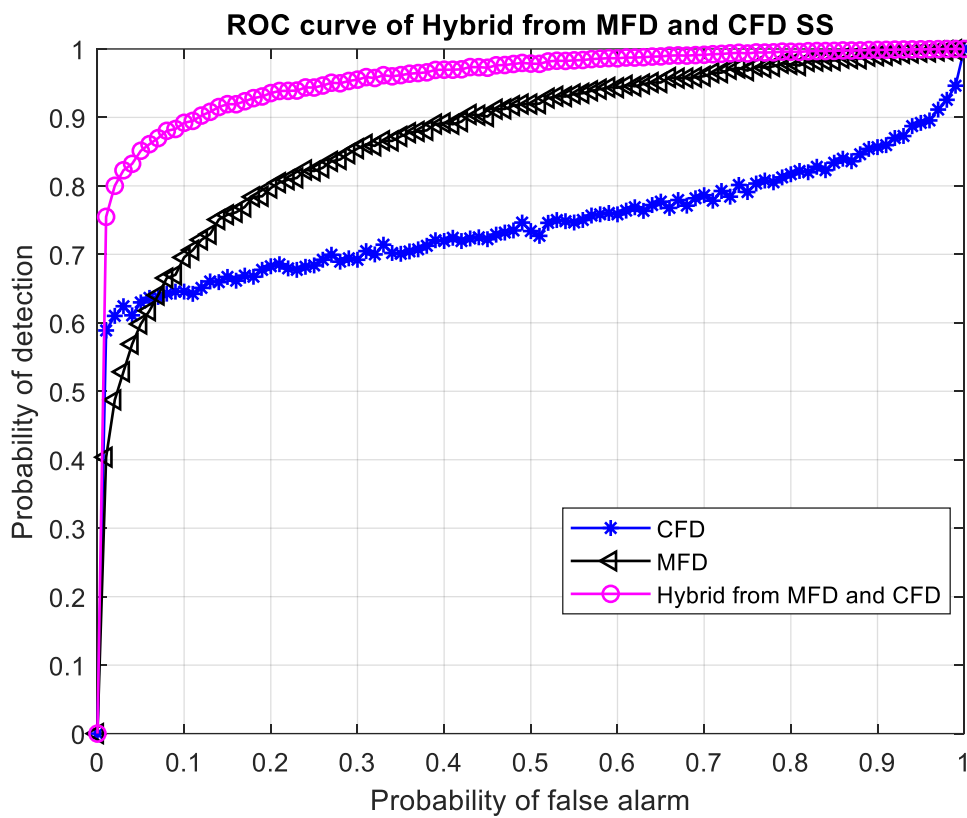


Figure 4.24: ROC curve that compares Hybrid method which from MFD and CFD, MFD and CFD at SNR=- 26dB

4.6.3 Complementary receiver operating characteristics (CROC) curve of hybrid method from MFD and CFD

The CROC curve that compares this hybrid approach, SS with MFD and CFD at SNR=-25 dB, is shown in Figure 4.25. As seen from the figure, the hybrid method outperforms MFD and CFD in terms of missed detection probability throughout all P_{fa} ranges. For instance, this hybrid technique has a probability missed detection of 0.06976 with a given false alarm probability of 0.06, compared to missed detection probabilities of 0.2512 and 0.2777 for

MFD and CFD, respectively. Less SU interference with PU results from detection methods with lower missed detection probabilities. As a result, it can be deduced from this finding that the hybrid technique is superior to MFD and CFD at separating PU signals from noise signals.

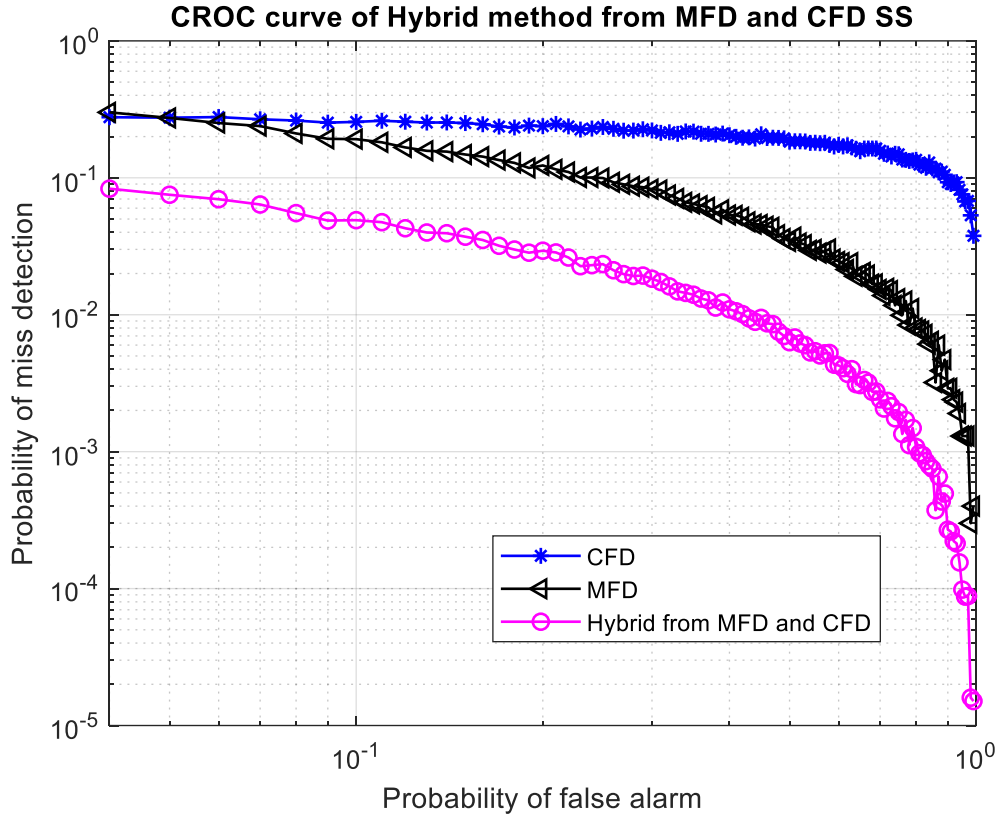


Figure 4.25: CROC curve that compares Hybrid method which from MFD and CFD, MFD and CFD at SNR = -25 dB

4.6.4 Results of cooperative detection for hybrid method from MFD and CFD techniques

This section presents simulation result that evaluates the performance of cooperative detection for the hybrid of methods from CFD and MFD techniques. The comparison between single-node and cooperative detection of hybrid technique is performed. The performance evaluation is done in terms of P_d vs SNR curve, ROC curve, and CROC curve.

4.6.5 P_d vs SNR for cooperative detection of hybrid technique from MFD and CFD

The correlation between detection probability and SNR is shown in Figure 4.26 for the cooperative hybrid method from CFD and MFD techniques by setting the probability of a false alarm to 0.1 ($P_{fa} = 0.1$), and the number of samples to 1000 ($N=1000$). In addition to this, the simulation result shows the comparison between a single node (i.e. $NU=1$) and a

cooperative hybrid technique. The number of cooperative users is 2 and 3. The OR rule CSS is used for deciding the final decision of the cooperative approach. As can be seen from the figure, the cooperative detection of this hybrid technique outperforms a single-node hybrid technique. For instance, a cooperative hybrid technique with two users can detect a PU signal with an SNR of -31dB and above, while a single-node hybrid technique can detect up to -26 dB only. This indicates 5 dB performance improvements in the SNR wall.

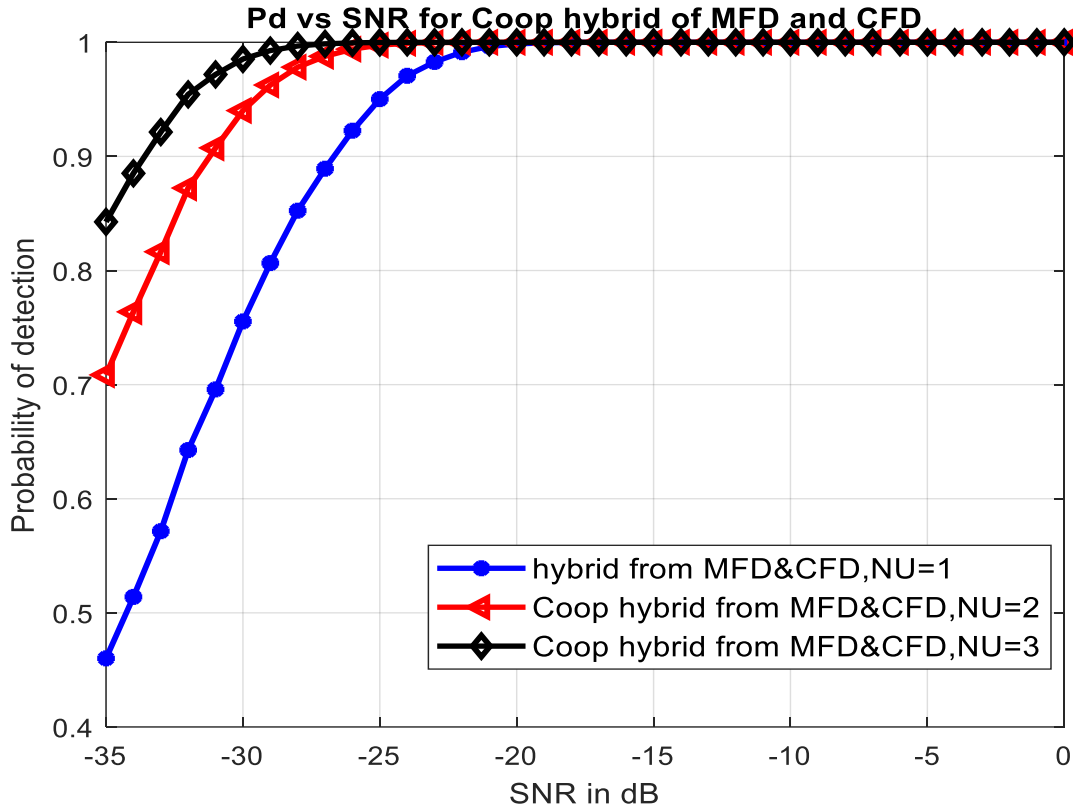


Figure 4.26: Pd vs SNR for the Cooperative hybrid method which is from MFD and CFD
SS at $P_{fa}=0.1$

4.6.6 ROC curve for cooperative detection of hybrid method from MFD and CFD SS technique

The cooperative hybrid technique's simulation result for the ROC curve at SNR = -29 dB is shown in Figure 4.27. The cooperative hybrid technique has a higher probability of detection than the single-node strategy, as seen in the figure. Additionally, the outcome demonstrates that the cooperative technique's detection probability rises as the number of SU increases. For instance, at a given probability of a false alarm of 0.05 ($P_{fa}=0.05$), the probability of detection for the cooperative hybrid method with NU = 2, and 3 is 0.8562, and 0.9455 respectively, while the detection probability for a single node (NU=1) in this hybrid

technique is 0.6208. From this result, it can be deduced that the cooperative approach with a higher number of SU has a better detection performance.

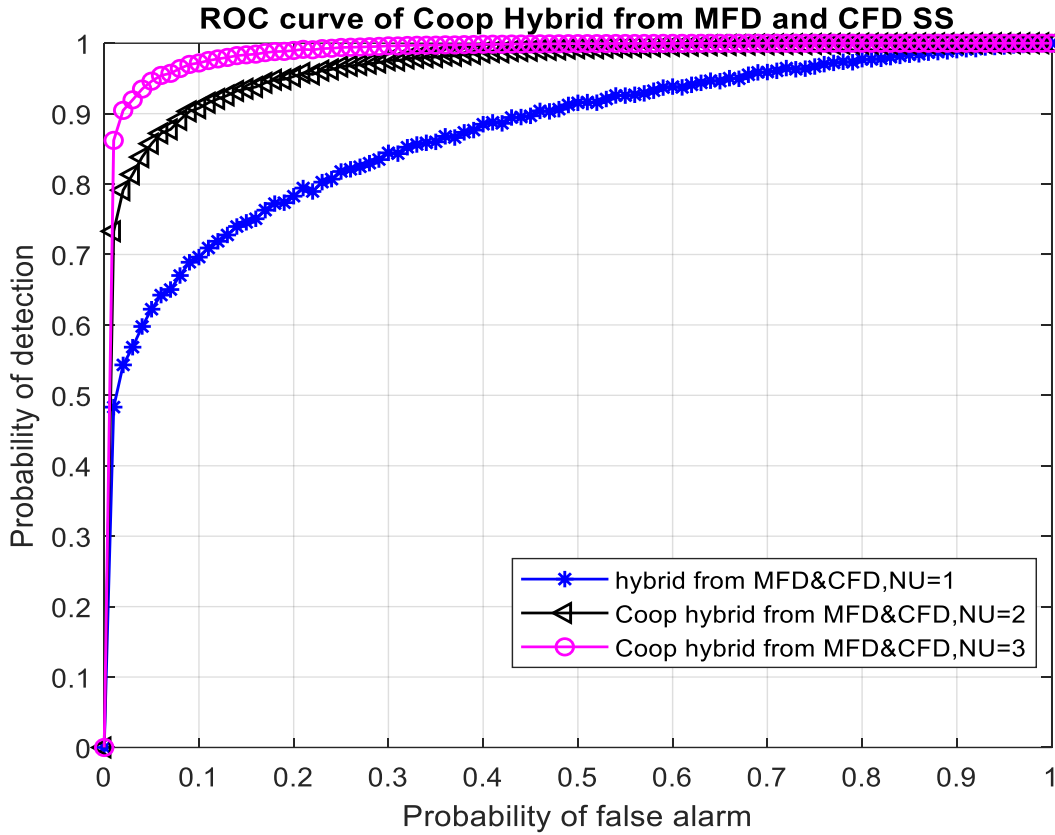


Figure 4.27: ROC curve for Cooperative hybrid method which from MFD and CFD SS at SNR=-29dB

4.6.7 CROC curve for cooperative detection of hybrid method from MFD and CFD SS technique

Figure 4.28 displays the CROC curve simulation results for the cooperative hybrid method using the MFD and CFD SS techniques, with SNR = -26 dB. As seen in the graphic, the cooperative hybrid technique has a reduced probability of missing an object than single-node hybrid strategies. For example, for a given $P_{fa} = 0.1$, the probability of missed detection of the cooperative this hybrid technique with three users is 0.004355, while the probability of detection for the single-node this hybrid technique is 0.0758. By comparing this result, the probability of missed detection for the cooperative this hybrid technique is decreased by 94.25% compared to single-node hybrid methods. From this finding, we can conclude that the cooperative technique has better performance than single-node techniques.

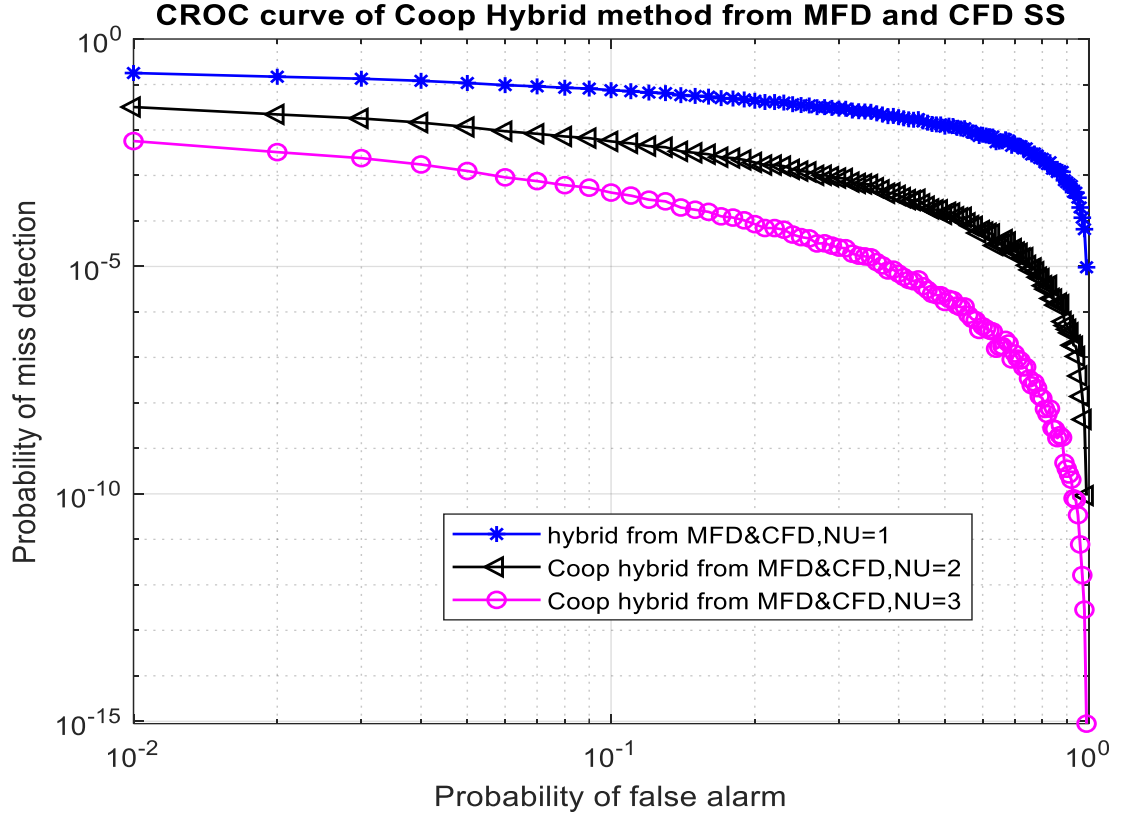


Figure 4.28: CROC curve for Cooperative hybrid method which from MFD and CFD SS at SNR=-26dB

4.7 Results of proposed hybrid spectrum sensing under AWGN

The performance of the proposed hybrid spectrum sensing (SS) approach from ED, MFD, and CFD is compared in this part to that of a conventional hybrid based on ED and CFD, a hybrid based on ED and MFD, and MFD and CFD. The following simulation outcomes for the proposed method are discussed:

- Probability of detection versus SNR for comparing the proposed approach with the conventional method.
- Receiver Operating Characteristics (ROC) Curve.
- Complementary Receiver Operating Characteristics (ROC) Curve.

4.7.1 Probability of detection versus SNR for comparing the proposed technique with conventional methods under AWGN

Figure 4.29 depicts the comparison among proposed hybrid spectrum sensing, a conventional hybrid from ED and CFD, a hybrid based on ED and MFD, and MFD and CFD at a particular probability of false alarm of 0.1. The comparison results show that the proposed hybrid approach performs better than the conventional hybrid based on ED and CFD, the hybrid based on ED and MFD, and MFD and CFD by a substantial performance

enhancement. For instance, the probability detection of the proposed technique is 0.8313 at a given SNR of -30 dB, whereas the detection probabilities of the hybrid based on MFD and CFD, ED and MFD and conventional hybrid based on ED and CFD are 0.7482, 0.682, and 0.6446, respectively. In other words, as compared to the hybrid approach that is based on MFD and CFD, ED and MFD, and conventional hybrid based on ED and CFD, the proposed hybrid approach has a significant improvement of about 1.5 dB, 3.5 dB, and 5.5 dB in the SNR wall respectively.

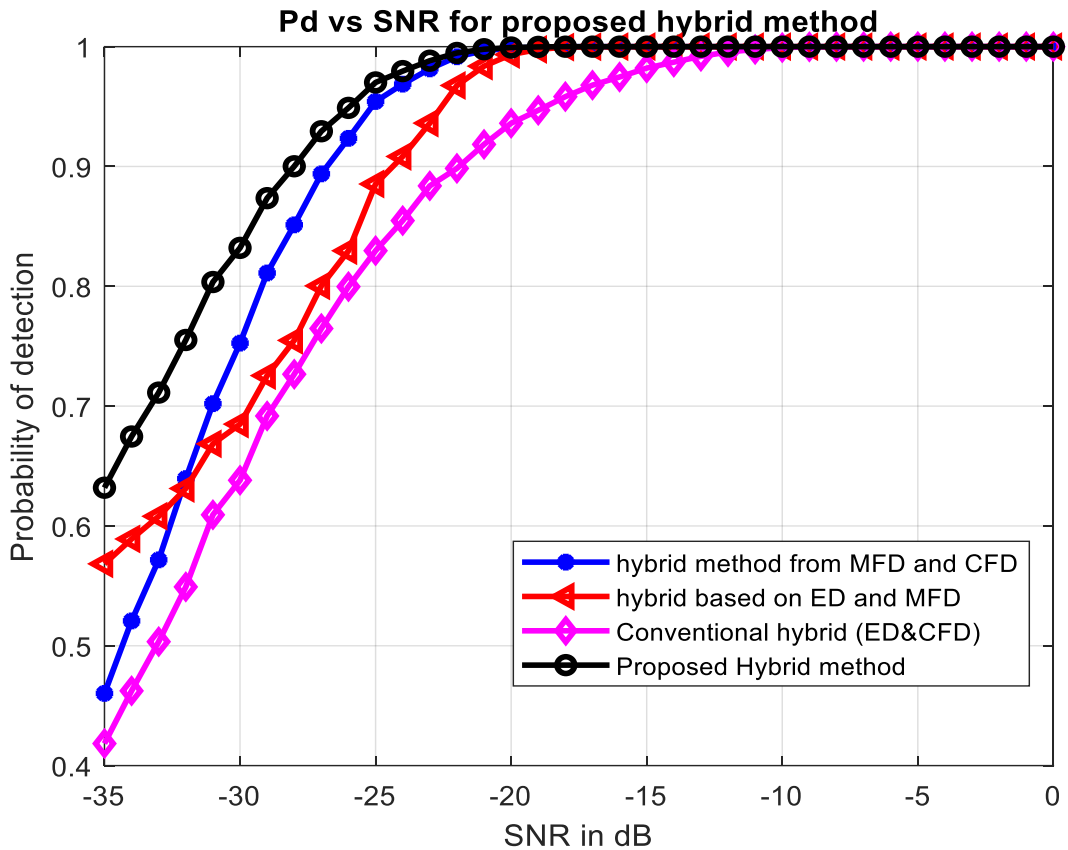


Figure 4.29: P_d vs SNR for comparing the proposed hybrid technique, the hybrid method from MFD and CFD, ED and MFD, and the conventional hybrid based on ED and CFD at $P_{fa}=0.1$ under AWGN

Table 4.5: Performance comparison between the proposed hybrid technique, the hybrid method from MFD and CFD, ED and MFD, and the conventional hybrid from ED and CFD SS at various SNR values under AWGN

SNR (dB)		-30	-27	-24	-21	-18	-15	-12	-9	-6	-3	0
Detection probability	Conventional hybrid (ED and CFD)	0.641	0.765	0.861	0.913	0.959	0.98	0.995	1	1	1	1
	Hybrid based on ED and MFD	0.683	0.798	0.911	0.982	0.999	1	1	1	1	1	1
	The hybrid method from MFD and CFD	0.753	0.892	0.970	0.997	0.999	1	1	1	1	1	1
	Proposed hybrid technique	0.832	0.928	0.981	1	1	1	1	1	1	1	1

4.7.2 Receiver operating characteristics (ROC) curve of proposed technique under AWGN

The ROC curve comparing the proposed hybrid SS to the hybrid methods based on MFD and CFD, ED and MFD, and the conventional hybrid based on ED and CFD is shown in Figure 4.30 at SNR=-26. As can be shown, the proposed hybrid methods to identify primary user signals with the targeted probability of detection have a lower probability of false alarms than the hybrid methods from MFD and CFD, ED and MFD, and the conventional hybrid based on ED and CFD. The proposed detector offers improved detection performance, as seen in the figure. As an example, when the false alarm probability is set to 0.1, the proposed approach has a detection performance of 0.9292, compared to 0.8938, 0.7976, and 0.7669 for the existing hybrid based on MFD and CFD, ED and MFD, and ED and CFD, respectively. In other words, the proposed hybrid SS method obtains the target probability of detection with a 0.06 probability of false alarm, whereas the traditional hybrid based on MFD and CFD, ED and MFD, and ED and CFD achieve it with 0.12, 0.25, and 0.65 correspondingly. As the proposed method requires a lower false alarm probability to achieve the target probability of detection compared to the hybrid methods using MFD and CFD, ED and MFD, and the conventional hybrid based on ED and CFD, it can be concluded that the proposed method has better detection performance.

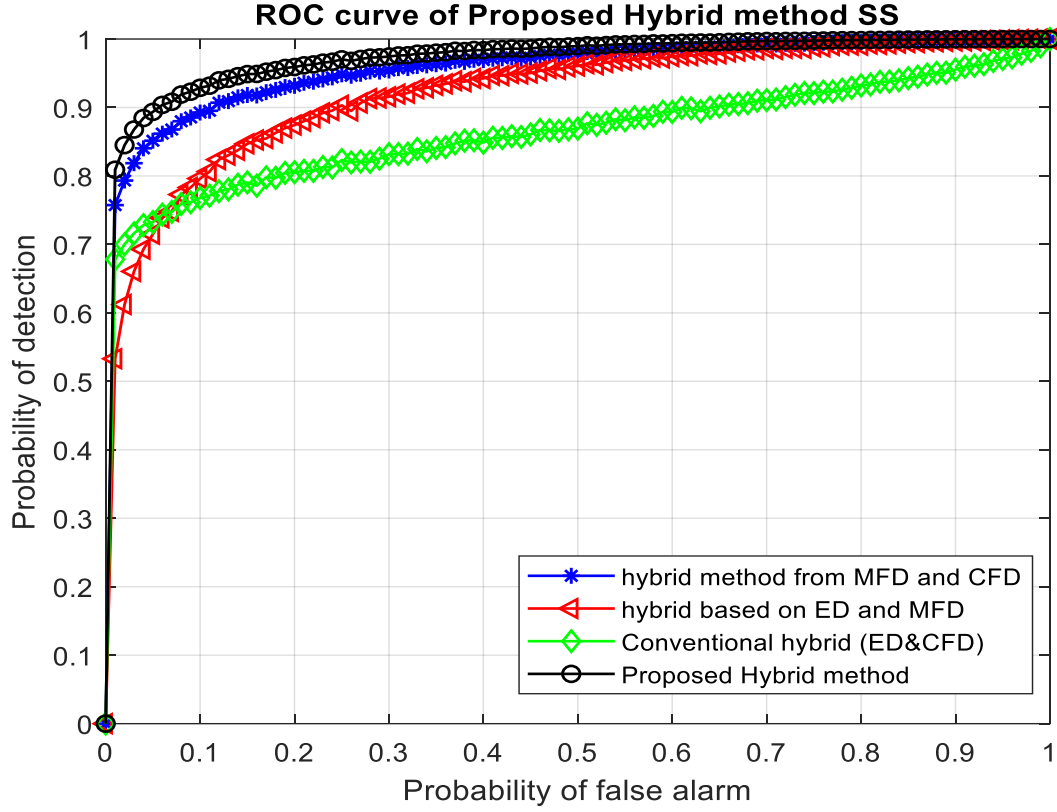


Figure 4.30: ROC curve that compares the proposed hybrid method, hybrid method from MFD and CFD, ED and MFD, and the conventional hybrid based on ED and CFD) at SNR=- 26dB under AWGN

4.7.3 Complementary Receiver Operating Characteristics (CROC) Curve under AWGN

Figure 4.31 illustrate the CROC Curve that compares the proposed hybrid spectrum sensing with the hybrid method from MFD and CFD, ED and MFD, and the conventional hybrid based on ED and CFD at SNR=-25 dB. In comparison to the hybrid methods from MFD and CFD, ED and MFD, and the conventional hybrid based on ED and CFD, the proposed method has the lowest probability of missed detection for all ranges of P_{fa} , as can be seen from the figure. As an example, when the false alarm probability is set to 0.04, the probability of missed detection for the proposed technique is 0.1171 while the probability of missed detection of the hybrid method from MFD and CFD, ED and MFD and the conventional hybrid based on ED and CFD is 0.1626, 0.3117 and 0.2704, respectively. Less SU interference with PU results from detection methods with lower missed detection probabilities. Thus, based on this outcome, it can be inferred that the proposed method has superior performance than the hybrid methods based on MFD and CFD, ED and MFD, and conventional hybrid based on ED and CFD in differentiating PU signals from noise signals.

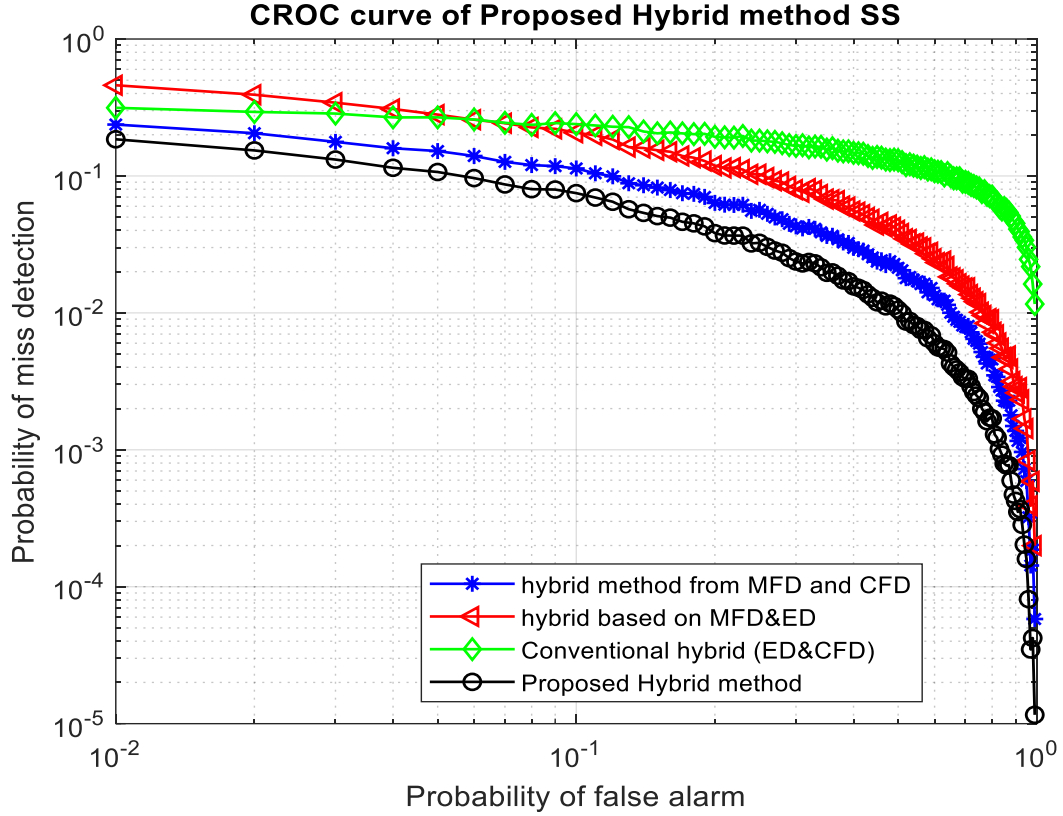


Figure 4.31: CROC curve that compares the proposed hybrid method, a hybrid method which from MFD and CFD, ED and MFD, and a conventional hybrid based on ED and CFD at SNR = -25 dB under AWGN

4.7.4 Results of Cooperative Detection for Proposed Hybrid Techniques under AWGN

The simulation results that assess the effectiveness of cooperative detection for the proposed hybrid method are presented in this section. Since OR rule fusion yields better results, it is used to implement cooperative detection. So, the comparison between single-node and cooperative detection of the proposed technique is performed. The performance evaluation is done in terms of the P_d vs SNR curve, ROC curve, and CROC curve.

4.7.5 P_d vs SNR for cooperative detection of proposed hybrid technique under AWGN

In Figure 4.32, the correlation between the probability of detection and SNR for cooperatively proposed hybrid approaches is shown with the probability of false alarm set to 0.1 and the number of samples at 1000. A comparison between a single node (i.e., $N_U=1$) and a cooperatively proposed hybrid approach is also shown in the simulation result. The number of collaborating users is 2 and 3. The OR rule CSS is used for deciding the final decision of the cooperative approach. As can be observed from the figure, the cooperative

detection of the proposed hybrid technique outperforms a single-node proposed hybrid technique. For instance, a cooperative proposed hybrid technique with two users can detect a PU signal with an SNR of -32 dB and above, while a single node proposed hybrid technique can detect up to -27 dB only. This indicates 5 dB performance improvements in the SNR wall.

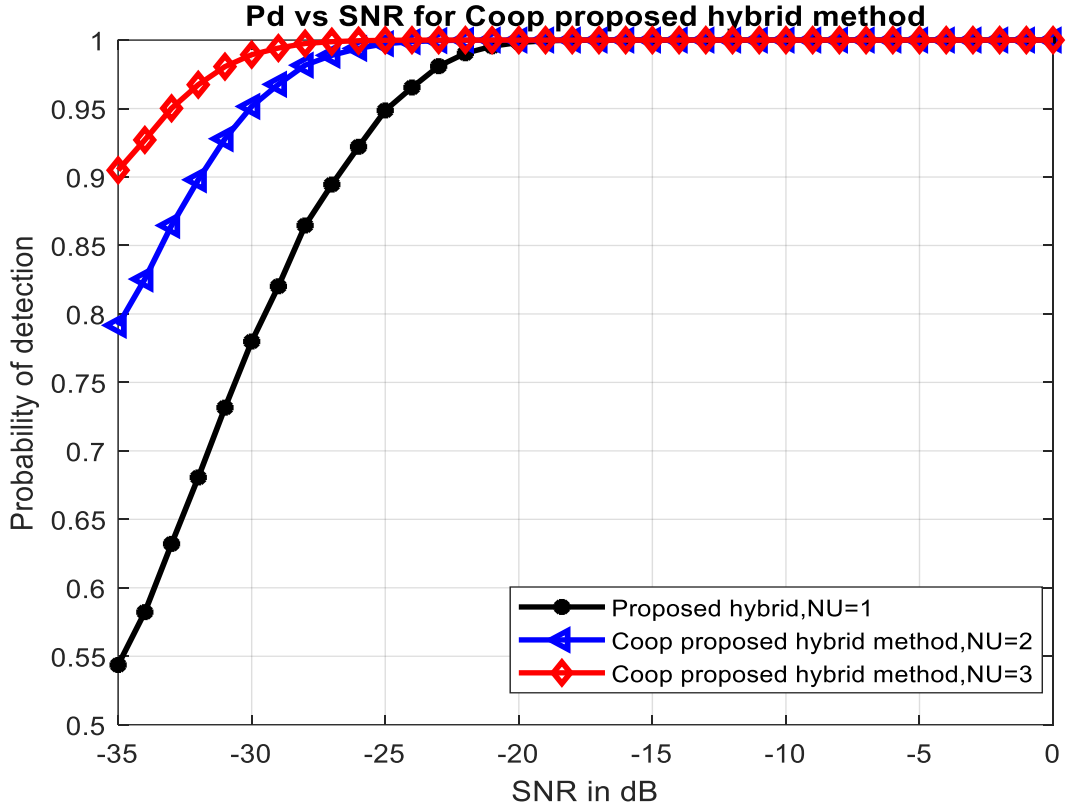


Figure 4.32: Pd vs SNR for Cooperative proposed hybrid method SS at $P_{fa} = 0.1$ under AWGN

4.7.6 ROC curve for cooperative detection of proposed hybrid technique under AWGN

The simulation result of the ROC curve for the proposed cooperative technique is presented in Figure 4.33, specifically at an SNR of -31 dB. The figure demonstrates that the probability of detection for the cooperative proposed method is higher than that of the single-node technique. Moreover, the results indicate that increasing the number of SUs enhances the detection probability of the cooperative technique. For instance, at a given probability of false alarm 0.02 ($P_{fa} = 0.02$), the probability of detection for the cooperative proposed technique with $NU = 2, 3$, and 4 is $0.7792, 0.8963$, and 0.9513 , respectively, while the detection probability for a single node ($NU=1$) proposed hybrid technique is 0.5301 . From this result, it can be deduced that the cooperative technique with a higher number of SU has a better detection performance.

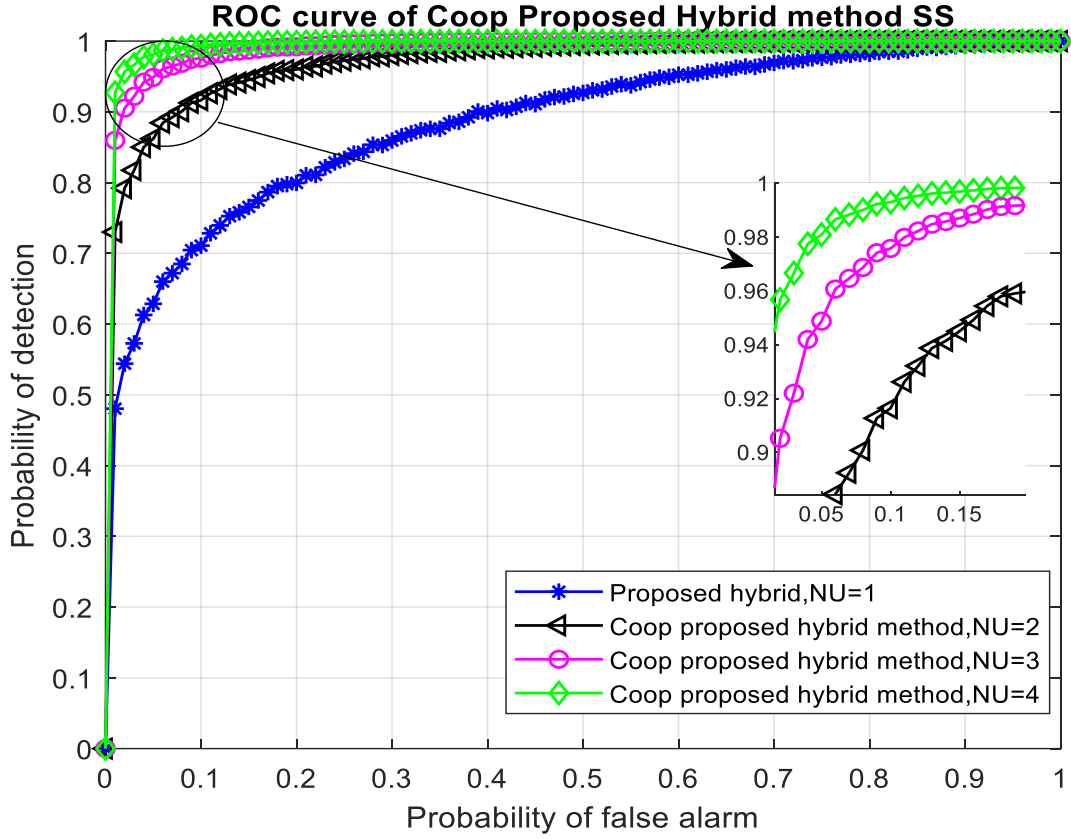


Figure 4.33: ROC curve for Cooperative proposed hybrid SS at SNR=-31dB under AWGN

4.7.7 CROC curve for Cooperative detection of proposed hybrid technique under AWGN

The CROC curve simulation result for the cooperatively proposed hybrid approach at SNR=-31 dB is shown in Figure 4.34. As seen in the figure, compared to single-node proposed hybrid techniques, the cooperative proposed hybrid method has a decreased probability of missed detection. For instance, the probability of missed detection for the cooperative proposed hybrid approach with 4 users is 0.03396 at a given false alarm probability of 0.03 ($P_{fa} = 0.03$), compared to the 0.4293 detection probability for the single-node proposed hybrid method. By comparing this finding, the probability of missed-detection for cooperative proposed hybrid techniques is decreased by 92.08% compared to single node proposed hybrid methods. From this result, we can conclude that the cooperative technique has better performance than single-node techniques.

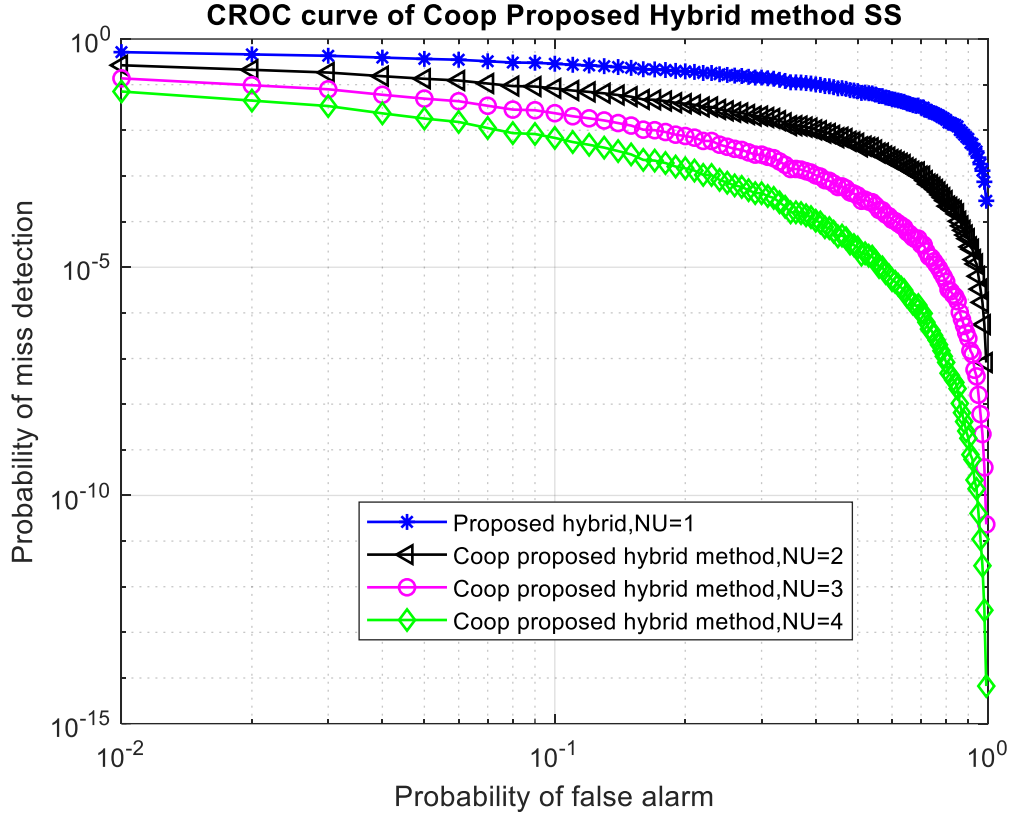


Figure 4.34: CROC curve for Cooperative proposed hybrid SS at SNR=-31dB under AWGN

4.8 Results of Proposed Hybrid Spectrum Sensing under Rayleigh fading channel

The conventional hybrid based on ED and CFD, the hybrid based on ED and MFD, and MFD and CFD are chosen for comparison with the proposed hybrid technique based on the comparison findings from the previous section. These methods were selected because they offer a higher detection probability than the fundamental spectrum sensing approach. In this section, we present simulation results that compare the performance of the proposed hybrid spectrum sensing technique with the conventional hybrid based on ED and CFD, the hybrid based on ED and MFD, and MFD and CFD under a Rayleigh fading channel.

4.8.1 Probability of detection versus SNR for comparing the proposed hybrid technique with the conventional hybrid based on ED and CFD, hybrid based on ED and MFD, and MFD and CFD methods under Rayleigh fading channel

Figure 4.35 depicts the comparison among proposed hybrid spectrum sensing, conventional hybrid based on ED and CFD, hybrid based on ED and MFD, and MFD and CFD methods

under Rayleigh fading channel at a particular probability of false-alarm of 0.1. The comparison results show that the proposed hybrid technique outperforms conventional hybrid based on ED and CFD, hybrid based on MFD and CFD, and ED and MFD methods under Rayleigh fading channel by a substantially better performance improvement. For instance, at a given SNR of -15 dB, the probability of detection of the proposed hybrid method is 0.8387 while the probability of detection of conventional hybrid based on ED and CFD, hybrid based on ED and MFD, and MFD and CFD methods is 0.2197, 0.7964, and 0.8152 respectively. In other words, the proposed hybrid approach has a significant improvement of about 5.6 dB, 1.5 dB, and 1 dB when compared to conventional hybrid based on ED and CFD, hybrid based on ED and MFD, MFD and CFD methods under Rayleigh fading channel.

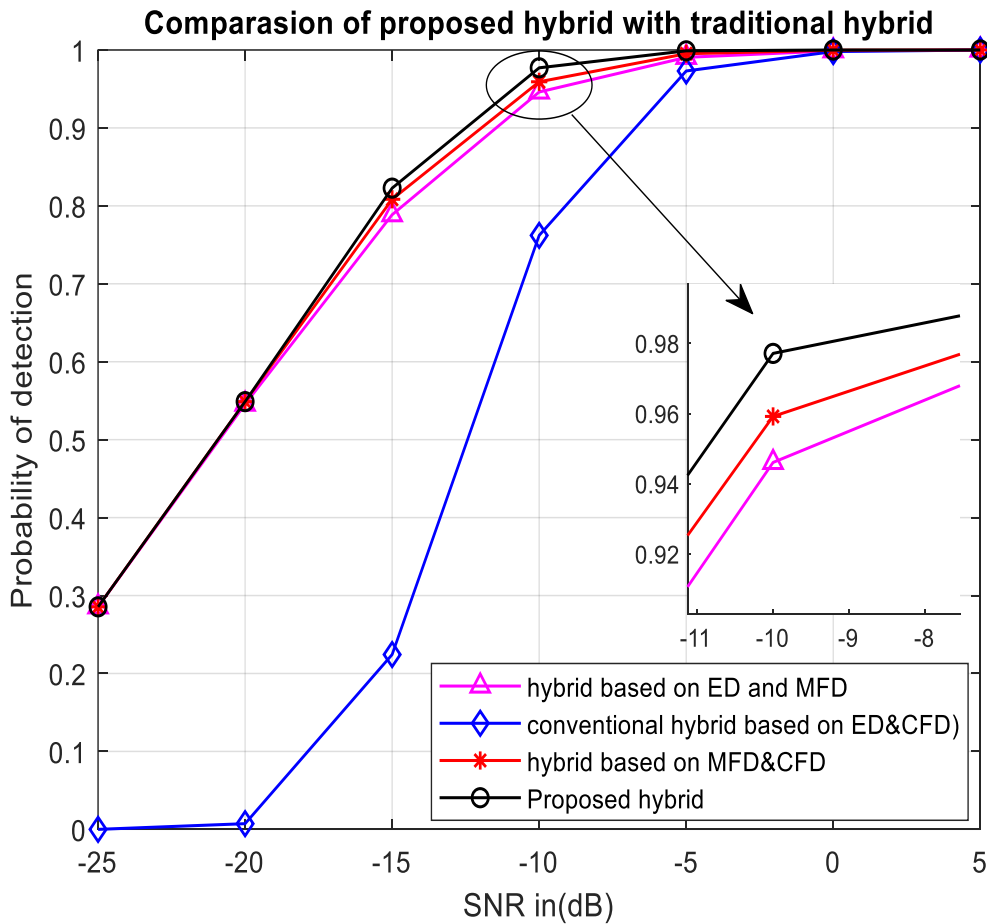


Figure 4.35: P_d vs SNR for comparing proposed hybrid, conventional hybrid based on ED and CFD, hybrid based on ED and MFD, and MFD and CFD methods under Rayleigh fading channel at $P_{fa} = 0.1$

Table 4.6: Performance comparison between the proposed hybrid technique, a hybrid method from MFD and CFD, ED and MFD, and a conventional hybrid based on ED and CFD SS at various SNR values under Rayleigh.

SNR (dB)		-20	-17	-14	-11	-8	-5	-2	1	4	5
Detection probability	Conventional hybrid based on ED and CFD	0.006	0.075	0.326	0.672	0.893	0.971	0.997	1	1	1
	Hybrid based on ED and MFD	0.559	0.71	0.822	0.923	0.971	0.997	0.998	1	1	1
	The hybrid method which is from MFD and CFD	0.559	0.724	0.844	0.941	0.981	0.998	0.999	1	1	1
	Proposed hybrid	0.559	0.727	0.864	0.962	0.997	1	1	1	1	1

4.8.2 Effects of the varying probability of false alarm on the detection performance of the proposed hybrid technique under Rayleigh fading channel

The relationship between P_d and SNR for various false alarm probabilities of 0.1, 0.2, and 0.25 is depicted in Figure 4.36. The graph shows that the detection probability also rises as the probability of false alarms rises. However, the increased probability of false alarms reduces the efficiency of SU's spectrum utilization when it mistakenly detects the PU signal when PU is not there. As can be shown, $P_{fa} = 0.25$ has a simulation result with SNR wall at -14 dB while $P_{fa} = 0.1$ and 0.2 have SNR walls at -13 dB and -13.5 dB, respectively. Therefore, the conclusion is that a rise in the probability of false alarms improves the sensitivity of detection methods since a lower SNR wall value results in a weaker signal.

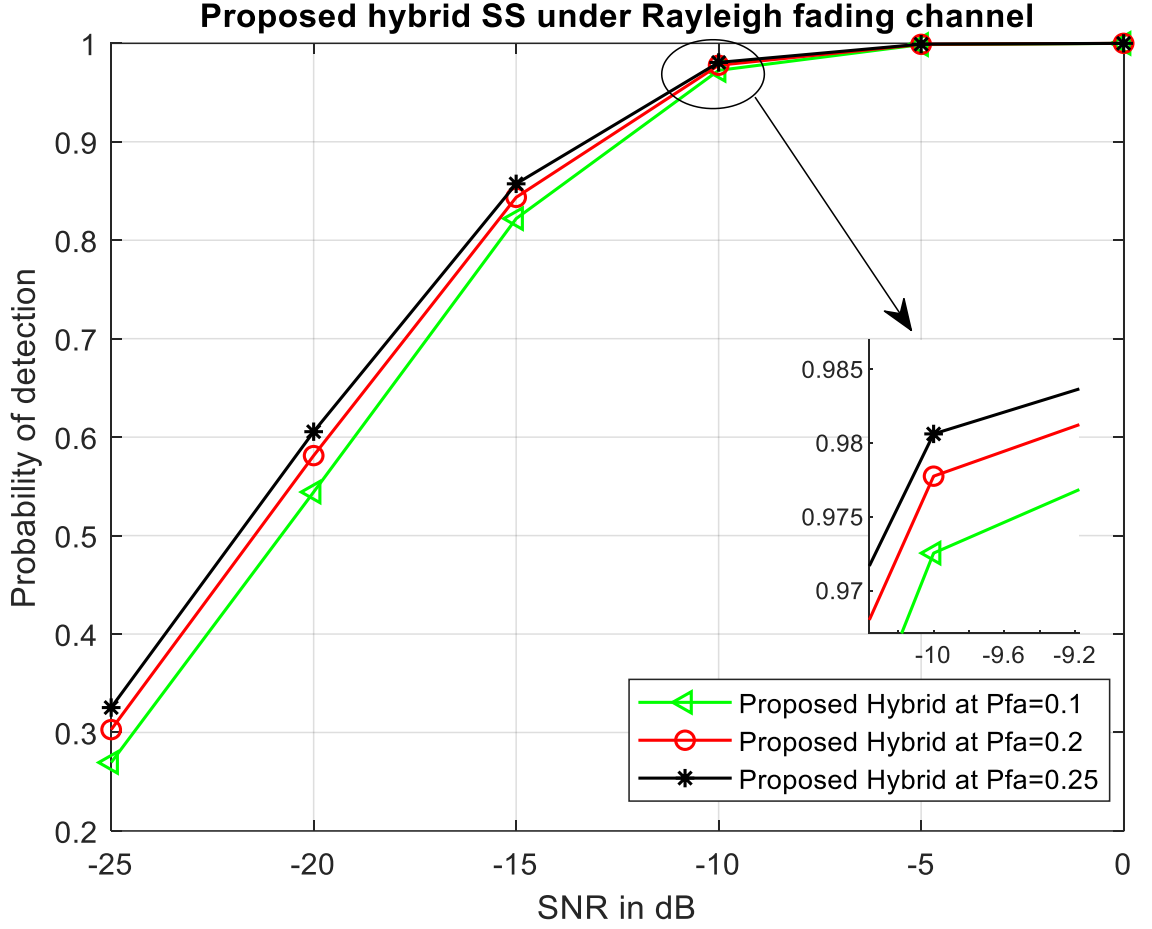


Figure 4.36: P_d vs SNR for the proposed hybrid technique under Rayleigh fading channel at $P_{fa}=0.1, 0.2$, and 0.25

4.8.3 Results of Cooperative Detection for proposed hybrid SS Technique under Rayleigh fading channel

This section presents the results of a simulation that evaluated the efficacy of cooperative detection for the proposed hybrid technique. The OR rule fusion schemes are applied for implementing cooperative detection. Additionally, the proposed hybrid technique's single-node and cooperative detection are compared.

4.8.4 P_d vs SNR for cooperative detection of proposed hybrid SS technique under Rayleigh fading channel

Figure 4.37 shows, for cooperatively proposed hybrid approaches, the relationship between the probability of detection and SNR by setting the false alarm probability 0.1 ($P_{fa} = 0.1$) and the number of samples to 1000 ($N=1000$). Additionally, the simulation's output compares a single node (i.e., $NU=1$) with a cooperatively developed hybrid approach. The number of collaborating users is $2, 3$, and 4 . The OR rule CSS is used for deciding the final decision of the cooperative approach. As can be seen from the figure, the cooperative

detection of the proposed hybrid technique outperforms a single-node proposed hybrid technique. For instance, a cooperative proposed hybrid technique with two users can detect a PU signal with an SNR of -17dB and above, while a single node proposed hybrid technique can detect up to -12.5 dB only. This indicates 4.5 dB performance improvements in the SNR wall.

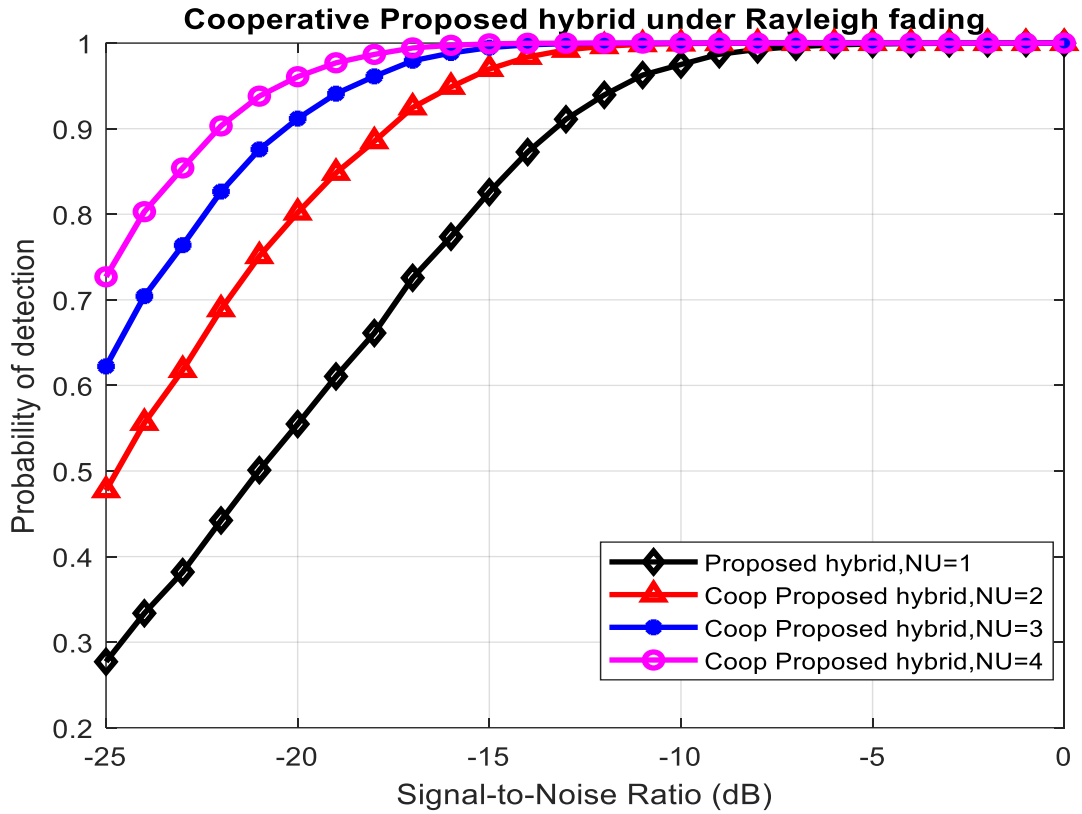


Figure 4.37: P_d vs SNR for Cooperative proposed hybrid SS at $P_{fa}=0.1$ under Rayleigh fading channel

4.8.5 ROC curve for cooperative detection of proposed hybrid SS technique under Rayleigh fading channel

The simulation results for the ROC curve of the proposed cooperative technique are presented in Figure 4.38 at an SNR of -21 dB. The figure reveals that the detection probability for the cooperative proposed technique is higher than that of the single node technique. Furthermore, the results also indicate that the detection probability of the cooperative technique increases as the number of SUs increases. For instance, at a given probability of false alarm 0.03 ($P_{fa}=0.03$), the probability of detection for cooperative proposed hybrid methods with $NU=2$, $NU=3$, and $NU=4$ is 0.7267, 0.8571, and 0.9253, respectively, while the detection probability for a single node ($NU=1$) proposed hybrid technique is

0.4772. From this result, it can be deduced that the cooperative technique with a higher number of SU has a better detection performance.

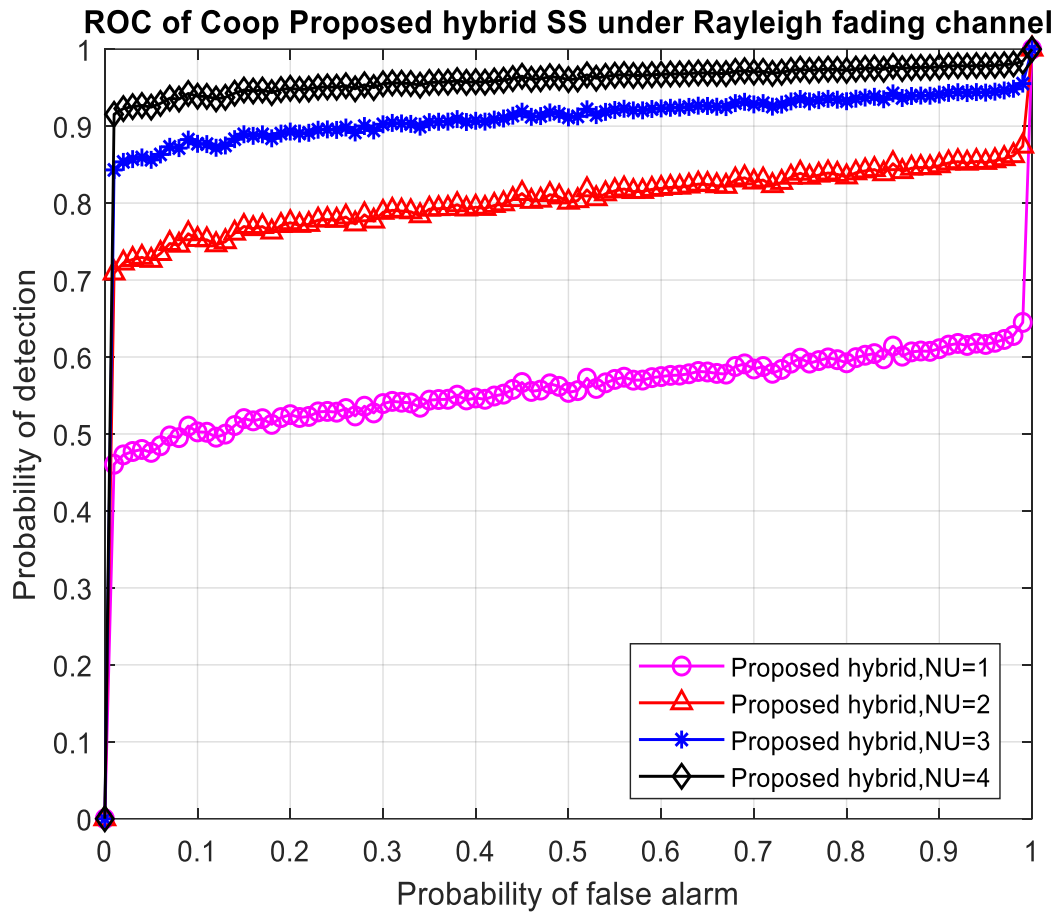


Figure 4.38: ROC curve for Cooperative proposed hybrid SS at SNR = -21 dB under Rayleigh fading channel

5. CONCLUSION AND RECOMMENDATION

5.1 Conclusion

To enhance the detection performance, a hybrid spectrum sensing (SS) method for cognitive radio (CR) has been proposed in this thesis. The proposed hybrid detector utilizes energy detection (ED), matched filter detection (MFD), and cyclo-stationary feature detection (CFD). Comparisons between these methods reveal that the proposed hybrid approach outperforms the conventional hybrid based on ED and CFD, the hybrid based on ED and MFD, and MFD and CFD, resulting in a significant performance improvement. For example, at an SNR of -30 dB, the detection probability of the proposed hybrid method is 0.8313, while the detection probabilities of the hybrid method using MFD and CFD, ED and MFD, and conventional hybrid based on ED and CFD are 0.7482, 0.682, and 0.6446, respectively. To elaborate, the proposed hybrid method exhibits a significant improvement of approximately 1.5 dB, 3.5 dB, and 5.5 dB in the SNR wall when compared to the hybrid method using MFD and CFD, ED and MFD, and conventional hybrid based on ED and CFD, respectively, under AWGN channel. At an SNR of -15 dB, the detection probability of the proposed hybrid technique is 0.8387, while the detection probabilities of the conventional hybrid from ED and CFD, the hybrid based on ED and MFD, and MFD and CFD methods are 0.2197, 0.7964, and 0.8152, respectively. Hence, the proposed hybrid approach yields a substantial improvement of approximately 5.6 dB, 1.5 dB, and 1 dB compared to the conventional hybrid based on ED and CFD, the hybrid based on ED and MFD, and MFD and CFD methods, respectively, under a Rayleigh fading channel.

The result shows that the probability detection of the SS technique increases as both SNR and the false alarm probability rise. In addition, this thesis investigates the performance analysis among hybrid methods from MFD and CFD, ED and MFD, and the conventional hybrid based on ED and CFD. The simulation result shows that the hybrid method which is from MFD and CFD outperforms the other. Lastly, the cooperative detection of hybrid methods which from MFD and CFD, ED and MFD, conventional hybrid based on ED and CFD, and proposed hybrid techniques are evaluated using OR fusion rules. The cooperative detection of proposed hybrid techniques outperforms a single-node proposed hybrid technique by using the OR fusion rule. For instance, a cooperative proposed hybrid technique with two users can detect a PU signal with an SNR of -33.5 dB and above, while a single node proposed hybrid technique can detect up to -27.5 dB only. This indicates 6 dB performance improvements in the SNR wall under the AWGN channel. While a single node

proposed hybrid technique may only detect up to -12.5 dB, cooperative proposed hybrid techniques with two users can identify PU signals with an SNR of -17dB and more. This indicates that 4.5 dB performance improvements have been achieved in the SNR wall under Rayleigh fading channel.

Generally, it can be concluded that the proposed hybrid technique shows better SS performance than the hybrid method which is from MFD and CFD, ED and MFD, and conventional hybrid based on ED and CFD. Based on the aforementioned perspective, we may conclude that this thesis's goals have all been met.

5.2 Recommendation

In this thesis, the performance of spectrum sensing is evaluated solely using MATLAB tools (SS) under simulation results. The experimental results of the SS technique should be performed in the future in a real environment using an SDR transceiver like the Universal Software Radio Peripheral (USRP), and the signal should also be manipulated using GNU radio.

In this thesis, we evaluated the proposed method under both AWGN and Rayleigh fading channels. In future research, it would be beneficial to assess the effectiveness of the proposed method under other types of fading channels. Another possibility in the future the proposed hybrid techniques should be evaluated by considering different types of PU signals such as QPSK, M-ary, and OFDM signals since in this thesis we were assumed that the transmitted signal from PU is a BPSK signal.

Research Fund Acknowledgment

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7. APPENDICES

Appendix A: Algorithm of Matched Filter Detection

Algorithm for Matched Filter Detection

Inputs: $N=1000$; $\text{snr_db} = -30$ to 0 ; $\text{snr} = 10. ^{(\text{snr_db}/10)}$; $P_{fa} = 0.1$

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

- 1: Generate a BPSK waveform with modulation.
- 2: for each snr_db value **Do**:
- 3: Initialize Detection $\leftarrow 0$
- 4: for each trial of Monte-Carlo simulation **Do**:
- 5: Generate noise signal and BPSK signal
- 6: Generate Received signal as $y = s + n$
- 7: Calculate Test statistics using Equation (3.13)
- 8: Obtain Matched filter detection threshold using Equation (3.17)
- 9: **if** $T > \lambda_{MFD}$
- 10: **THEN** Decision = H_1
- 11: Increment Detection by 1
- 12: **end if**
- 13: **if** $T < \lambda_{MFD}$
- 14: **THEN** Decision = H_0
- 15: **end if**
- 16: **end for**
- 17: **end for**

Where N is the number of samples, snr_db is the SNR value in decibels, snr is the SNR value in linear scale, P_{fa} is the probability of a false alarm, y is the signal that was received, s is the signal that was broadcast, n is noise, T is the test statistics, and λ_{MFD} is the threshold for Matched filter detection.

Appendix B: Algorithm of Cyclo-stationary Feature Detection

Algorithm for Cyclo-stationary Feature Detection

Inputs: $N=1000$; $\text{snr_db} = -30$ to 0 ; $\text{snr} = 10. \wedge (\text{snr_db}/10)$; $P_{fa} = 0.1, 0.2, 0.3$

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

```
1: Generate a BPSK waveform with modulation.
2: for each snr_db value Do:
3:     Initialize Detection  $\leftarrow 0$ 
4:     for each trial of Monte-Carlo simulation Do:
5:         Generate noise signal and BPSK signal
6:         Generate Received signal as  $y = s + n$ 
7:         Compute the autocorrelation function of the signal
8:         Compute the cyclic autocorrelation function ( $R_{yy}^\alpha$ ) of the signal
9:         Compute Test statistics using Equation (3.19)
10:        Obtain Cyclo-stationary Feature detection threshold using Equation (3.20)
11:    if  $T > \lambda_{CFD}$ 
12:        THEN Decision =  $H_1$ 
13:        Increment Detection by 1
14:    end if
15:    if  $T < \lambda_{CFD}$ 
16:        THEN Decision =  $H_0$ 
17:    end if
18: end for
```

Where N is the number of samples, snr_db is the SNR value in decibels, snr is the SNR value in linear scale, P_{fa} is the probability of a false alarm, y is the signal that was received, s is the signal that was broadcast, n is noise, T is the test statistics, and λ_{CFD} is the threshold for Cyclo-stationary feature detection.

Appendix C: Algorithm of Energy Detection

Algorithm for Energy Detection

Inputs: $N=1000$; $\text{snr_db} = -30$ to 0 ; $\text{snr} = 10. \wedge (\text{snr_db}/10)$; $P_{fa} = 0.1, 0.2, 0.3$

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

```
1: Generate a BPSK waveform with modulation.
2:           for each snr_db value Do:
3:           Initialize Detection  $\leftarrow 0$ 
4:           for each trial of Monte-Carlo simulation Do:
5:           Generate noise signal and BPSK signal
6:           Compute Received signal as  $y = s + n$ 
7:           Compute Energy of received signal
8:           Compute Test statistics using Equation (3.23)
9:           Obtain energy detection threshold using Equation (3.34)
10:          if  $T > \lambda_{ED}$ 
11:          THEN Decision =  $H_1$ 
12:          Increment Detection by 1
13:          end if
14:          if  $T < \lambda_{ED}$ 
15:          THEN Decision =  $H_0$ 
16:          end if
17:          end for
18: end for
```

Where N is the number of samples, snr_db is the SNR value in decibels, snr is the SNR value in linear scale, P_{fa} is the probability of a false alarm, y is the signal that was received, s is the signal that was broadcast, n is noise, T is the test statistics, and λ_{ED} is the threshold for Energy detection.

Appendix D: Algorithm of Proposed Hybrid Detection

Algorithm for Proposed Hybrid Detection

Inputs: $N=1000$; $\text{snr_db} = -30$ to 0 ; $\text{snr} = 10. \wedge (\text{snr_db}/10)$; $P_{fa} = 0.1, 0.2, 0.3$

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

- 1: Generate a BPSK waveform with modulation.
- 2: for each snr_db value Do:
- 3: Initialize Detection $\leftarrow 0$
- 4: for each trial of Monte-carlo simulation Do:
- 5: Generate noise signal and BPSK signal
- 6: Compute Received signal as $y = s + n$
- 7: Compute Energy of received signal
- 8: Compute Test statistics using Equation (3.23)
- 9: Obtain energy detection threshold using Equation (3.34)
- 10: Calculate Test statistics using Equation (3.13)
- 11: Obtain Matched filter detection threshold using Equation (3.17)
- 12: Compute the autocorrelation function of the signal
- 13: Compute the cyclic autocorrelation function (R_{yy}^α) of the signal
- 14: Compute Test statistics using Equation (3.19)
- 15: Obtain Cyclo-stationary Feature detection threshold using Equation (3.20)
- 16: **if** $T_{ED} > \lambda_{ED}$
- 17: **THEN** Decision = H_1
- 18: Increment Detection by 1
- 19: end if
- 20: **if** $T_{ED} < \lambda_{ED}$
- 21: **THEN** Decision = H_0
- 22: **if** $T_{MFD} > \lambda_{MFD}$
- 23: **THEN** Decision = H_1
- 24: Increment Detection by 1
- 25: end if
- 26: **if** $T_{MFD} < \lambda_{MFD}$
- 27: **THEN** Decision = H_0
- 28: **if** $T_{CFD} > \lambda_{CFD}$

```

29:          THEN Decision =  $H_1$ 
30:          Increment Detection by 1
31:        end if
32:        if  $T_{CFD} < \lambda_{CFD}$ 
33:          THEN Decision =  $H_0$ 
34:        end if
35:      end if
36:    end if
37:  end for
38: end for
39: end for

```

Where N is number of sample, snr_db is SNR value in dB, snr is SNR value in linear scale, P_{fa} is probability of false alarm, y is received signal, s is transmitted signal, n is noise, T_{ED} is test statistics of energy detection, T_{MFD} is the test statistics of Matched filter detection, T_{CFD} test statistics cyclostationary feature detectio λ_{ED} is the threshold of energy detection λ_{MFD} is threshold of Matched filter detection and λ_{CFD} threshold of cyclo-stationary feature detection