ENERGY EFFICIENCY ANALYSIS OF COMPRESSIVE SENSING BASED COOPERATIVE SPECTRUM SENSING IN COGNITIVE RADIO

M.Sc. Thesis

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A THESIS SUBMITTED TO THE
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This is to certify that the thesis entitled" **Energy Efficiency Analysis of Compressive Sensing Based Cooperative Spectrum Sensing in Cognitive Radio**" submitted in partial fulfilment of the requirements for the degree of Master'**s** in Communication Engineering and Networking**,** the Graduate Program of the **Department of Electrical and Computer Engineering,** and has been carried out by Tsega Teklewold Id. No PGComR/008/10, under my supervision. Therefore, I recommend that the student has fulfilled the requirements and hence hereby can submit the thesis to the department.

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Final approval and acceptance of the thesis is contingent upon the submission of the final copy of the thesis to the Department of Graduate Council (DGC) of the candidate's department.

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Dedication

This thesis is dedicated to my family and many friends whose words of encouragement and a push for tenacity ringing in my ears.

Declaration

I, Tsega Teklewold declare that this MSc thesis is my original work and has not been presented for a degree in any other university, and all sources of material used in this thesis have been duly acknowledged.

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

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Place and Date of Submission: Hawassa, December 2020

Abstract

A range is a scant and valuable asset and a matter of worry with the quickly developing wireless communications. Wireless communication industries are increasing at a very fast pace as the wireless technologies are attracting the interest of many users, so the demand increases and researchers are looking for alternative adaptive measures. ***.*** *The essential usefulness to empower dynamic range access for CR is wideband spectrum sensing to discover more temporarily available frequency bands to fulfill the growing needs of wireless services. Also, the need to occasionally detect and an expansion in the quantity of channels to be detected further builds the energy interest. Thus, one of the principal challenges that limit the implementation of cognitive radio networks especially in the battery-powered terminal is due to its high energy consumption. Consequently, energy-proficient CSS in a CR network utilizing the CS based maximum minimum subband ED is the focal point of this thesis. The number of participating CRs in the cooperative spectrum sensing, sensing duration, data transmission duration, and fusion threshold play vital roles in designing an energy-efficient CSS system. In other words, increasing the number of participating CRs in the system leads to an increase in both consumed energy during CSS process and delay time; moreover, longer sensing time duration increases detection precision, but on the other hand, decreases spectrum efficiency and increases the consumed energy during sensing phases (i.e., sensing overhead).In the essence of above-mentioned facts, tackling a trade-off between performance improvement and overhead is our main focus research point in this thesis.*

Evaluation and analysis of performance are done by using MATLAB software. *The simulation result shows that the Compressive sensing-based Max-Min subband ED has better performance than traditional Max-Min subband ED based on Shannon-Nyquist sampling theorem. Also, it shows that strategies remarkably increase the energy efficiency of the cooperative system; furthermore, it is shown optimality of Majority rule over other two hard decision fusion rules. Finally, optimization of sensing time, number of sensing users and fusion threshold for a cognitive radio is considered. Finally, the energy efficiency is enhanced by 74.6% when compared with the conventional energy detection-based EE*

Keywords: Cognitive Radio Network; Compressive sensing; CSS; Energy efficiency

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AWGN	Additive white Gaussian noise
CAF	Cyclic autocorrelation function
CDMA	Code division multiple access
CSMA/CA	Carrier Sense Multiple Access/Collision Avoidance
CR	Cognitive Radio
CSD	Cyclic Spectral Density
CS	Compressive sensing
CSS	Cooperative spectrum sensing
CU	Cognitive User
DSA	Dynamic spectrum access
ED	Energy detection
EMC	Electromagnetic compatibility
EMI	Electromagnetic interference
ETA	Ethiopian telecommunication agency
FDMA	Frequency division multiple access
FC	Fusion Center
FCC	Federal Communications Commission
FSA	Fixed spectrum allocation
IEEE	Institute of Electrical and Electronics Engineers
IR	Infrared
ISM	Industrial, scientific, and medical band
ISP	Internet Service Provider
ITS	Intelligent transportation systems
MAC	Medium Access Control
MInT	Ministry of Innovation and Technology
MRC	Maximal Ratio Combining
NTSC	National Television System Committee
NU	Noise Uncertainty
OBU	On-board unit
PU	Primary user
Pd	Probability of detection
Pf	Probability of false alarm

QoS	Quality-of-Service
RF	Radio frequency
RSU	Roadside unit
ROC	Receiver operating characteristic
SC	Selection combining
SC-CR	Soft combination with contention-based reporting
SC-TR	Soft combination with threshold-based reporting
SDR	Software define radio
SNR	Signal to noise ratio
SPTF	Spectrum Policy Task Force
SLC	Square law combining
SU	Secondary user
TDMA	Time division multiple access
TSEEOB	Time saving energy efficient one bit
USA	United States of America
UWB	Ultra-wideband
V2R	Vehicle-to-roadside
VANET	Vehicular unplanned network
Wi-MAX	Worldwide Interoperability for Microwave Access
WRAN	Wireless regional area network
WSP	Wireless Service Provider
WSS	Wide-sense stationary
Qd	Global probability of detection for CRN
Qf	Global probability of false alarm for CRN
$\sigma_n{}^2$	Noise power
$\sigma_s{}^2$	Signal power
τ	Sensing time
$\mu(N)$	Energy efficiency metric

Chapter 1 : Introduction

1.1 Background

From the beginning of wireless communications, the utilization of the available RF spectrum has been a matter of concern because the RF spectrum is a limited natural resource. Then again, a static spectrum allocation policy adopted by governments of many countries has caused underutilization of spectrum because a huge segment of the licensed radio spectrum is not efficiently used. Conventional, licensed spectrum is allocated over relatively long periods and is meant to be used only by licensed users.

A government organization is responsible for allocating spectrum bands to operators. In Ethiopia, the ministry of innovation and technology (MInT) is responsible for this exercise; as the federal communications commission (FCC) is for the USA. This approach is termed as the fixed spectrum allocation (FSA) scheme and with this, the RF spectrum is divided into bands allocated to distinct technology-based services, e.g. mobile telephony, radio, and TV broadcast services [1]. The FSA supervision structure guarantees that the radio frequency spectrum is entirely licensed to an authorized party (primary user (PU)) without interference.

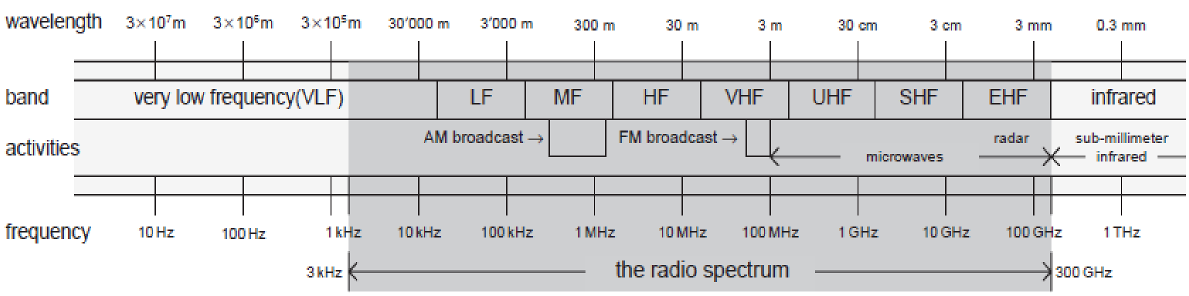

Figure 1-1 Radio Spectrum

The modern trend of wireless technologies has further increased the amount of services that can be provided, leading to the substantial demand for access to the RF spectrum in an efficient manner[2]. On one side, the rising diversity (voice, short message, Web, and multimedia) and demand of high QoS applications have resulted in overcrowding of the allocated FSA spectrum bands leading to significantly reduced levels of user satisfaction. The challenge is particularly serious in communication-intensive situations such as in the case of people gatherings or a substantial emergency. On the opposite side, major licensed bands such as those that are allocated for TV broadcasting be highly underutilized which resulting in spectrum wastage. For example, the study report of FCC shows that the spectrum utilization in the 0–6 GHz band varies from 15% to 85% [3].

In Ethiopia's case, the national RF spectrum allocation table from ETA shows that the spectrum in the 960MHz–3GHz band as highly underutilized.

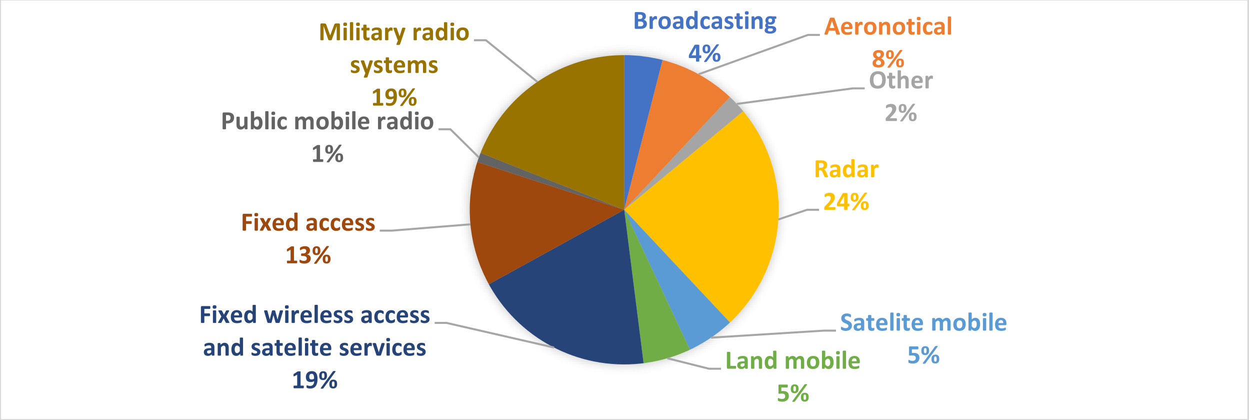

Figure 1-2 Traditional radio spectrum allocations

Firstly, any economic failure of licensed radio services and systems may lead to an idle spectrum which leads to spectrum wastage. For example, In the US, Wi-MAX appears to be commercially unsuccessful. Wi-MAX spectrum has been allocated and licensed in many countries, but appears not to be used at all by cross country network administrators. Wi-MAX spectrum is hence considered wasted for the time being. Secondly, public safety and military radio systems require spectrum for occasional operation, which leads to an additional amount of unused spectrum. Thirdly, technological progress in communications results in the improvement of the spectrum1 efficiency of existing licensed communications systems likes, for example, the digitalization of television (TV) broadcasting, so that less RF spectrum is required to provide the same service. As a result of all these observable trends, large parts of the spectrum are currently used inefficiently. This makes the benefit of CR significant to open licensed bands to be used by SUs which is known as DSA. Accordingly, the IEEE has formed a working group IEEE 802.22 to develop an air interface for opportunistic secondary access or DSA via CR technology[4].

CR as a new concept was first proposed by Joseph Mitola III and Gerald Maguire was introduced as an expansion of SDR improving the adaptability of personal wireless services with the radio domain model and computational intelligence [5]. CR, therefore, is an exciting and new way of thinking about wireless communications. It is now being considered as one of the key applicant advancements for the 5G wireless systems which aim to provide a higher data rate transmission, adequate capacity, cost efficiency, and highly sophisticated services[6]. CR plans to increase spectrum utilization and efficiency of spectrum usage by opportunistically accessing the licensed spectrum without interfering with the PUs.

To avoid utilizing the spectrum simultaneously with the PUs, CR has to determine the availability of the PU by sensing the wireless spectrum. It can communicate to its receiver if the spectrum is empty or idle. However, when PUs retransmits again, SUs should stop their transmission immediately to abstain from interfering with the PUs. Hence, spectrum sensing is crucial for CR. The better CR knows about the PU's existence the better it can communicate and utilize the spectrum. There are several types of SS techniques for CR such as non- cooperative sensing, cooperative spectrum sensing, and Interference based sensing.

Energy efficiency is a criterion that compromises the performance (i.e., throughput) and overhead (i.e., consumed energy). The criterion is characterized as the proportion between achievable throughput and incurred energy consumption. The energy consumed for local sensing is equivalent to the product of the quantity of CUs, the sensing time, and the sensing power. Thus, reducing energy utilization in the sensing stage can be accomplished in two different ways, either reducing the quantity of CUs or by reducing the sensing time. Energy efficiency has gained increasing importance and has received a lot of interest in recent times[7]. This attention is occurred due to the finite energy resources that are available at the CRs, which is often accompanied by big demand for data rates. This research work is all about CSS, where the local decisions are taken by all the CRs within a network and then these decisions are fused in FC to give the combined decision about the status of the radio spectrum whether it is occupied by the PU or not, also this research work will investigate the energy efficiency based on optimization of sensing time, number of users and fusion threshold optimization.

1.2 Statement of the Problem

The limited spectrum availability and the rising popularity of wireless service over-weight the available RF band because of licensed spectrum management which results in the licensed band is underutilized. To utilize the licensed band by unlicensed without influencing the QoS being accommodated for PUs, CR is proposed to relocate the spectrum dynamically. In this research, CS-based Max-Min subband ED method is used for SS. Wideband SS has been supported as a successful way to deal with increment in spectrum access opportunity of SUs. Then again, due to the expansion in sampling rate and sensing time duration cost by the ADC, energy saving has been a significant problem for wideband spectrum sensing. Therefore, the possibility of settling a compromise between improving the performance and reducing the overhead by designing an energy-efficient system is a considerable target and primary center point in this thesis work.

1.3 Review of Related Work

Some of the researches related to this work are shortly reviewed below.

In[8], the energy utilization is minimized based on different techniques by using the minimum CUs that satisfy predefined threshold values on the detection accuracy. An energy efficiency optimization problem is formulated by limiting the number of participating SUs while satisfying predefined constraints on the detection and false-alarm probabilities. However, considering a limited frame length duration, limiting the number of participating SUs does not automatically maximize energy efficiency. In limited frame length, changing the time which is given for a sensing stage will affect the time distribution for other stages in CSS. Hence, limiting the number of participating SUs may decrease the reporting time but it gives major time for data transmission which consumes more energy. Similarly, the authors of [9]considered two parameters which are reducing the sum of energy consumed in the sensing stage which includes sensing, reporting, and transmissions. The second is maximizing energy efficiency. In this paper, optimization is based on limiting the number of SUs and optimizing the sensing time. They have assumed to use a single transmitter in CR which is TDMA based. In this manner, the CR can't both transmit and sense, which implies one needs to hold up till the continuous transmission is finished. On the off chance that it requires some investment, it will deplete vitality too. In any case, it tends to be decreased on the off chance that we utilize various channels for detecting and transmission because both can happen simultaneously.

In [10]a centralized CR network with two CSS techniques has been proposed and used to minimize the extra reporting overhead; a soft combination with threshold-based reporting (SC-TR) and a soft combination with contention-based reporting (SC-CR). The proposed techniques essentially reduce the reporting overhead, which helps to minimize the energy utilization in the CR system with a slight sacrifice in detection performance. The reporting channel between FC and SU is thought to be error-free. The above paper is limited to error-free data but the wireless channel in the real world is full of error, so it has to be considered.

In[11] the algorithm is based on limiting the number of secondary users in CSS. The selection of the participating SU is not random but instead, those SU that consumes higher energy are prevented from participating in CSS. In this paper, as they are using non-identical local sensing, the channel condition among users, and also the influence of shadowing in sensing and reporting channels in the overall performance is not considered.

In[12], the less amount of participating SUs that satisfy two constraints on the detection and false-alarm probabilities is numerically formulated. Unlike[11], in [12] only the energy utilized in the sensing stage is considered, while energy consumed in results' reporting and data transmission has not been taken into consideration. It merits referencing that the attention in [11], [12]has been focused on energy consumption not to EE, representing a drawback in all of them. Additionally, they have expected that indistinguishable sensing performance for all CUs, which is an absurd presumption considering distinctive channel conditions including the multi-path fading and shadowing.

From [8] up to [12] they have considered or used conventional energy detection mechanism which is based on narrowband spectrum sensing with energy detection mechanism, but this research work considers compressive sensing which is one type of wideband SS.

In [13] proposed a cooperative compressive sensing scheme, in which a gathering of spatially distributed nodes sense the presence of a phenomenon independently, and send a compressed summary of observations to an FC where a global decision is made about the availability of the phenomenon. This scheme was designed to compensate for the performance loss due to compression, and it was shown that the amount of loss can be improved and recovered through cooperative detection. Specifically, it was shown that as the level of compression is reduced, for example keeping number of sensing nodes fixed, or as the number of sensing nodes is increased, i.e., keeping the level of compression fixed, the overall probability of error in detection can be made arbitrarily small. Nonetheless, the study in [13] never tended to energy efficiency and was restricted to the detection performance of the cooperative compressive detection scheme, in a non-CR context. In this research work, we derive the formulation for the average energy utilization, and the average achievable throughput of CS based Max-Min subband ED. Next, we derive a formulation for the energy efficiency for these techniques and formulate an optimization issue that maximizes the energy efficiency, subjected to constraints on P_d and P_f

In[14], the throughput improvement issue in CRN is analyzed by improving the boundaries of local sensing and cooperative decision making. The target work is settled in two levels: improvement of local sensing parameters which is sensing time and threshold value (τ, λ), and joint optimization of sensing time and number of SUs in a single slot, however in this research work we are going to do joint optimization based on Compressive sensing.

In [15], they have considered EE of compressed conventional collaborative sensing (CCCS) scheme focusing on balancing the trade-off between EE and detection accuracy in CR. Maximization of EE is posed as non-convex optimization problem to find the number of sensing that satisfies a given constraint on probability of detection and false alarm probability. However, in this research work, we have considered CS based Max-Min subband cooperative spectrum sensing. Maximization of EE is based on bisection algorithm to find the optimal number of nodes and sensing time that satisfies P_d and P_f.

1.4 Objective of the Research

1.4.1 General Objectives

The general objective of this research work is to improve the energy efficiency of compressive sensing based cooperative spectrum sensing for a cognitive radio network.

1.4.2 Specific Objectives

To achieve the general objective, the research has the following specific objectives

- To study different SS method and derive an analytical expression for subband energy threshold, probability of false alarm, and the probability of detection.
- To evaluate the performance for CS-based Max-Min subband ED in terms of P_d Vs P_f.
- Proposing a simple iterative algorithm that can find the optimal number of SU and sensing time that improves the EE while reducing the resulting interference by satisfying a predefined constraint on detection probability.
- To examine the effect of OR, AND, and Majority fusion scheme on CSS performances

1.5 Methodology

In this thesis, we propose an energy efficient CSS based on CS based maximum-minimum subband ED technique. The essential endeavour is to review different literature about compressive sensing-based energy efficiency optimization and spectrum detection to build up a solid understanding of the thesis work have been done. The subsequent task is to derivate the test statistic from both subband energies, decision stage is executed after deciding the maximum and minimum of the subband energies. The difference between the maximum and minimum values of subband energies is contrasted with a predefined threshold. Contingent upon the aftereffect of correlation of maximum and minimum values and furthermore with the assistance of hard fusion schemes the decision device decides whether the PU is present or only noise is present in the RF band. At last, utilizing average throughput and energy utilization minimization we will assess energy efficiency based on parameters which are basic building blocks for energy optimization.

1.6 Scope of the research

This research work focuses on centralized cooperative spectrum sensing based on energy detection tests. A group of spatially placed SUs sense a PU in a cooperative spectrum network. The models are analyzed based on the local probability of detection (P_d), and the probability of false alarm (P_f) performance metrics. The decisions of SUs are transmitted to the FC through wireless fading channels where global detection probability Q_d is made. Optimization is done on the hard-fusion techniques to improve on the SS and energy consumption in CRN.

1.7 Thesis Outline

This thesis is organized into five chapters. The first chapter deals with the general introduction of the study including a background of the study, statement of the problem, objectives, methodology, and scope of the research. The second chapter discusses the cognitive radio network basics and functions of the cognitive radio network. Also, it describes the spectrum sensing concept based on PUs and SUs in detail. The third chapter discusses the system model and performance analysis of CSS. The fourth chapter deals with the result and discussion. Finally, chapter five presents a conclusion that summarizes the major points of the research and recommendations have been forwarded for further research.

Chapter 2 : Cognitive Radio System

2.1 Introduction

Cognitive radio is a new worldview of planning wireless communications systems which intends to improve the proper usage of the RF spectrum. The inspiration driving cognitive radio is a shortage of the accessible RF spectrum, expanding request, brought about by the rising distinctive wireless applications for mobile users. A large portion of the accessible RF spectrum has already been dispensed to existing wireless systems, however, and only small parts of it can be licensed to new wireless applications. Regardless, an investigation by the Spectrum Policy Task Force (SPTF) of the Federal Communications Commission (FCC) has indicated that some frequency bands vigorously utilized by licensed systems in particular locations and at particular times, however there are additionally numerous frequency bands which are only partially occupied or largely unoccupied. For instance, spectrum bands allocated to cellular networks in the USA reach the highest utilization during working hours but remain largely unoccupied from midnight until early morning[16].

The main consideration that prompts wasteful utilization of the RF spectrum is the spectrum licensing mechanism itself because, in traditional spectrum allocation mechanism which depends on the command-and-control model, where the radio spectrum allocated to licensed users is can't be used by unlicensed users and applications [17]. Because of this static and inflexible allocation of spectrum, legacy wireless systems need to work just on a dedicated spectrum band, and can't adjust the transmission band according to the changing environment. For example, if one spectrum band is heavily used, the wireless system can't change to operate on another more lightly used band.

The privilege to use the spectrum (or license) is generally defined by frequency, space, transmit power, spectrum owner (i.e., licensee), type of use, and the duration of the license. Normally, a license is assigned to a licensee, and the utilization of the spectrum by this licensee must conform to the specification in the license (e.g., maximum transmit power, location of the base station). In the current spectrum licensing scheme, the license cannot change the type of use or transfer the privilege to other licensees This restricts the proficient utilization of the frequency spectrum and results in low use of the frequency spectrum. Basically, because of the current static and inflexible spectrum licensing scheme, spectrum holes or spectrum opportunities arise[18]. Spectrum holes are defined as frequency bands that are allocated, but not utilized by, PUs, and therefore, could be accessed by SUs[19].

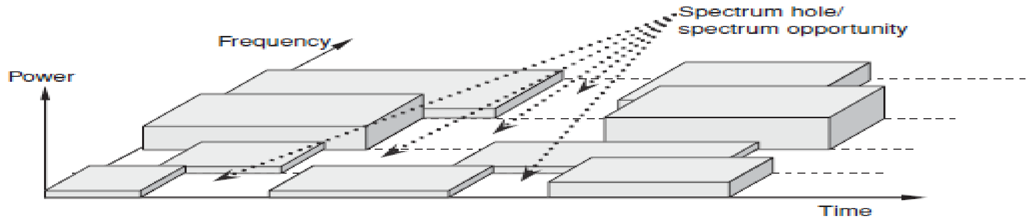

Figure 2-1 Spectrum hole (or spectrum opportunity).

The limitations in spectrum access due to the static and inflexible spectrum licensing scheme can be summarized as follows:

- **Fixed type of spectrum usage**: In the current spectrum licensing mechanism, the type of spectrum use cannot be changed. For example, a TV band which is allocated to the National Television System Committee (NTSC)-based analog TV cannot be used by digital TV broadcast or broadband wireless access technologies. However, this TV band would remain largely unused in many locations due to cable TV systems.
- **Licensed for a large region:** When a spectrum is licensed, it is usually allocated to a particular user or wireless service provider (WSP) in a large region. However, the WSP may use the RF only in areas with a good number of subscribers, to gain the highest return on investment. Consequently, the allocated RF spectrum stays unused in different zones, and different users or service providers are disallowed from getting to this RF.
- **A huge piece of the authorized spectrum:** A wireless service provider is commonly authorized with a huge lump of RF spectrum (e.g., 50 MHz). For a service provider, it may not be conceivable to get a permit for a little spectrum band to use in a specific region for a brief timeframe to meet an impermanent traffic load. For instance, a CDMA2000 cellular service provider may require a spectrum with a bandwidth of 1.25MHz or 3.75MHz to give brief wireless access service in a hotspot area.
- **Disallowed spectrum access by unlicensed users:** In the current spectrum authorizing mechanism, just a PU can get to the corresponding RF spectrum, and SU are prohibited from accessing the spectrum even though it is unoccupied by the PUs. For example, in a cellular system, there could be areas in a cell with no users. In such a case, SUs with short-range wireless communications would not be possible to access the RF spectrum, even though their transmission would not interfere with cellular users.

To improve the efficiency and viable use of the available RF spectrum, these limitations are helped by altering the spectrum licensing mechanism. The essential thought is to make spectrum usage more adaptable by permitting SUs to access the RF specific limitations.

Since the legacy wireless systems were intended to work on a devoted frequency spectrum band, they can't use the improved adaptability gave by this spectrum licensing mechanism[20]. The primary objective of CR is to give versatility to the wireless transmission through DSA so that the performance of wireless transmission can be optimized, just as improving the use of the RF. The major functions of a CR system include spectrum sensing, spectrum management, spectrum mobility, and spectrum sharing. Through spectrum sensing, the information of the target RF (e.g. the type and current activity of the PU) has to be obtained so that it can be utilized by the cognitive radio user[21]. The spectrum detecting data is misused by the spectrum management function to investigate the spectrum opportunities and make decisions on spectrum access. If the status of the target spectrum changes, versatility capacity will control the difference in RF bands for the SUs.

2.1.1 Cognitive Radio Features and Capabilities

Cognitive Radio is essentially a class of software radios (SR's) with additional capabilities and functionalities such as environment sensing, learning, and decision-making, which enable it to reach the required dynamic performance. On the software level, CR empowers the running of elevated level application SRs to imitate a personal digital assistant (PDA). A SR is defined as a transceiver whose communication functions are realized as programs running on a suitable processor. Hence, an SR comprises all the protocol stack layers of a communication system. Based on the same hardware, the adaptation of transmitter/receiver algorithms can be done on software to match different transmission standards. A wide-band antenna attached to the hardware allows its operation over different bands. SR is henceforth, exceptionally adaptable and versatile, which meets the quintessence of the CR details. An ideal SR straightforwardly tests the antenna output and converts these samples to the digital domain, and then the entire baseband signal processing is done in the digital domain. SR is fairly a hypothetical model because legitimately digitizing the wide-band antenna output yield will prompt the digitization of an unnecessary huge bandwidth filled with different signals of no interest. This is neither technologically nor commercially desirable. A SDR is a common-sense version of an SR; the received signals are inspected after an appropriate band choice to diminish testing and digitizing complexity. Basic difference between an SDR and a conventional receiver is the reconfigurability feature in SDR, where transmission parameters can be modified via a control bus. For SDRs, reconfigurability implies that the radio can handle signs of various guidelines or even signals that are not normalized yet exist in explicit applications [22].

2.1.2 Cognitive Radio Architecture

Cognitive Radio network design can be categorized into two groups; the primary network and the cognitive radio network[23].

The primary network is an existing infrastructure that has an elite right over certain spectrum bands for example the cellular networks and TV broadcast networks. The components of the primary networks are

- **Primary User (licensed user):** a user which has a permit to work in an authorized band. The PU activity ought not to be influenced by the tasks of CR clients.
- **Primary Base-Station (licensed base-station):** a fixed foundation network part with spectrum license.

The CR network doesn't have a permit to work in an authorized band its spectrum access is allowed opportunistically. The parts of the cognitive radio networks are:

- **Cognitive Radio User (unlicensed user):** a client who has no permit over the spectrum. CR clients can get to the spectrum opportunistically only when PU is not present and CR clients must empty the channel promptly when the PU is recognized.
- **Cognitive Radio Base-Station (unlicensed base-station):** a fixed foundation segment with CR capacities giving a solitary bounce association with CUs. In CSS, the CR also serves as an FC to gather the information from cooperative users and make the final spectrum sensing decision.
- **Spectrum Broker (scheduling server):** a central network entity that controls spectrum resource sharing among the CR users.

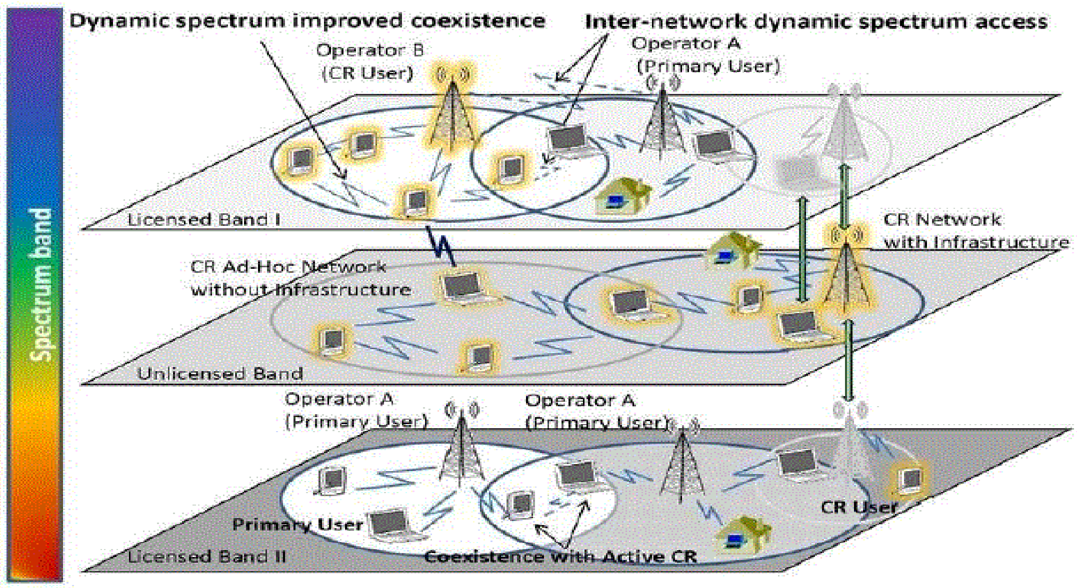

Figure 2-2 Cognitive radio structure

2.1.3 Functions of Cognitive Radio

The primary elements of CR to help and proficient DSA are as per the following:

- **Spectrum sensing:** The objective of SS is to decide the status of the spectrum and the movement of the authorized clients by occasionally detecting the objective recurrence band. Specifically, a CR handset distinguishes an unused spectrum (i.e. band, location, and time) and decides the strategy for getting to it (for example, transmit power and access duration without meddling with the transmission of a PU) [24]. SS can be either centralized or distributed. In centralized SS, a sensing controller (base station) senses the target RF band, and the information thus obtained imparted to different hubs in the framework. Centralized SS can diminish the complexity of user terminals since all the sensing functions are performed at the sensing controller. However, centralized SS experiences area decent variety. For instance, the detecting regulator will be unable to distinguish an SU at the edge of the cell. In distributed spectrum sharing, SUs performs SS autonomously, and the SS results can be either utilized by individual CRs (i.e., non-cooperative sensing) or shared with other users (i.e., cooperative sensing). Although cooperative sensing incurs a communication and processing overhead, the accuracy of SS is higher than of non-cooperative sensing[25].
- **Spectrum analysis (spectrum management):** The information obtained from SS is used to schedule and plan spectrum access by SUs. For this situation, the communication requirements of SUs are also used to optimize the transmission parameters. Spectrum analysis and spectrum access advancement are significant parts of spectrum management are. In spectrum analysis, data from SS is investigated to pick up information about spectrum holes (e.g., interference estimation, duration of availability, and the probability of collision with a PU due to sensing error). At that point, a choice to get to the spectrum (e.g. frequency, bandwidth, modulation mode, transmit power, location, and time duration) is made by optimizing the system performance given the desired objective (e.g. maximize the throughput of the SUs) and constraints (e.g. maintain the interference caused to licensed users below the target threshold)[24]. Spectrum analysis is needed after the completion of the spectrum sensing. The reason for the spectrum decision is making preparations for spectrum sharing by confirming the access parameters (including modulation encoding and the transmitted power) based on the spectrum sensing and the spectrum analysis. Spectrum analysis and spectrum decisions belong to the scope of spectrum management.

- **Spectrum access (spectrum sharing):** After a decision is made on spectrum access based on spectrum analysis, the spectrum holes are accessed by the SUs. Spectrum access is performed based on a cognitive MAC protocol, which intends to avoid collision with PUs and also with other SUs[26]. The CR transmitter is also required to perform negotiations with the CR receiver to synchronize the transmission so that the transmitted data can be received successfully. A cognitive MAC protocol convention could be founded on a fixed distribution MAC (e.g. FDMA, TDMA, CDMA) or a random access MAC (e.g. ALOHA, CSMA/CA)[25].
- **Spectrum mobility:** It is a capacity that is identified with the difference in the working RF band of CUs. At the point when an authorized begins getting to a RF band that is at present being utilized by a SU, the SU can change to a RF band that is idle or free. This adjustment in the working frequency band is referred to as spectrum handoff. During the spectrum handoff, the protocol parameters at the different layer's convention stacks must be changed per coordinate the new working frequency band. Spectrum handoff must try to ensure that the data transmission by the SU can continue in the new spectrum band.

The core idea of CR technology is that the SUs can intelligently detect and analyze the spectrum in a wireless environment, and then identify the free spectrum in a specific time or specific position. In this manner, the SUs can access the chosen optimal spectrum to understand spectrum sharing and therefore the improved spectrum utilization. To achieve this goal, the SUs needs to implement SS to seek out the PU and detect the idle spectrum resources. Once the working band is selected, the SU can transmit the signal in this band, however, the SU opportunistically access the spectrum in CRN, because the available spectrum is changed dynamically in different space and time. When the PU appears, the SU must release the occupied spectrum and switch to another available spectrum to realize seamless handoff, which is named spectrum handoff. Within the preparation of spectrum handoff, the way to make sure the continuity and reliability of the SU's transmission and realize the fast-seamless handoff are difficult, which firstly requires that the SU should continuously perform SS to detect the availability of the free spectrum resources. Multiple SUs may use the same idle spectrum to communicate simultaneously when the idle spectrum is detected, therefore, to avoid the SUs interference with each other, spectrum sharing is needed. In the spectrum sharing, the SUs transmissions can be appropriately coordinated and managed by certain resource allocation strategies which are similar to the MAC media access protocols in the existing systems.

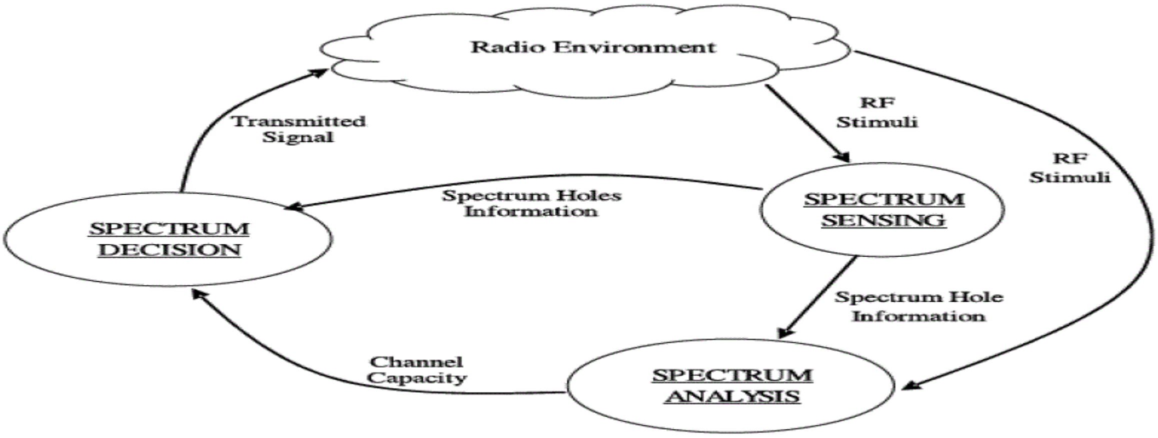

Figure 2-3 Cognitive cycles.

The most basic and the most important step in the process of the CR cycle is the SS technique on which the entire operation of the CR depends. This step gains the attention of many researchers as it is responsible for performing the two important functions: first, it has to carefully detect the presence of all the spectrum holes and second it has to make the best use out of these spectrum holes so that they can add to increase the overall spectrum efficiency.

2.1.4 Dynamic Spectrum Access (DSA)

DSA can be defined [27] as an instrument to alter the spectrum resource practice in a near-real-time method to answer to the changing circumstance and goal (e.g. accessible channel and kind of applications), a transformation of radio state (e.g. transmission mode, battery status, and location), and changes in external environment and constraints(e.g. radio propagation, operational policy). It has a good possibility to improve spectrum usage and in perspective allowing next-generation mobile networks access to the attractive RF bands. There are three major models of DSA, namely, commons use, shared-use, and exclusive-use models. In the commons-use model, the spectrum is open for access to all users. This model is as of now in utilizing within the ISM band[28]. In the shared-use model, PUs is allocated the RF bands which are opportunistically accessed by the SUs when they are not occupied by the PUs. In the exclusive-use model, a PU can grant access to a particular RF band to an SU for a certain time [29]. This model is more flexible than the traditional command-and-control spectrum licensing model since the type of use and the licensee of the spectrum can be dynamically changed. With OSA, SU can exploit unused in-band segments without causing interference to the active PU. There are two basic approaches for OSA: spectrum underlay and spectrum overlay. The underlay approach constrains the transmission power of the SUs so that they operate below the interference temperature limit of PUs. One possible approach is to transmit signals in a very wide RF band (e.g., UWB transmission) so that a high data rate is achieved with extremely low transmission power. It is based on the worst-case scenario that the PUs transmits all the time. Therefore, it doesn't exploit spectrum holes. The overlay approach doesn't force any serious limitation on the transmission control by SUs. It permits SUs to distinguish the spectrum holes defined in space, time, and frequency. This approach is compatible with the existing spectrum allocation, and, therefore, the legacy systems can proceed to function without being influenced by the SUs[30].

In any case, the attachment for SUs got to be characterized by the administrative bodies to guarantee compatibility with legacy systems.

2.1.5 Applications of Cognitive Radio

CR concepts can be applied to a variety of wireless communications scenarios, a few of which are described below:

A. Next-generation wireless networks

Cognitive Radio is predicted to be a key technology for Next-generation wireless networks. It will provide intelligence to both the user-side and provider-side equipment to manage the air interface and network efficiently. At the user-side, a mobile device with multiple air interfaces (e.g., Wi-Fi, WiMAX, cellular) can observe the status of the wireless access networks (e.g., transmission quality, throughput, delay, and congestion) and choose by selecting the access network to attach with. At the provider-side, RF resources from multiple networks are often optimized for the given set of mobile users and their QoS requirements. Based on the mobility and traffic pattern of the users, efficient load balancing mechanisms are often implemented at the service provider's infrastructure to distribute the traffic load among multiple available networks to scale back network congestion[31].

B. Coexistence of various wireless technologies

New wireless technologies (e.g., IEEE 802.22-based WRANs) are being developed to reuse the RF spectrum allocated to other wireless services (e.g., TV service). CR may be a solution to supply coexistence between these different technologies and wireless services. For instance, IEEE 802.22-based WRAN users can opportunistically use the TV band when there's no TV user nearby or when it is not broadcasting. SS and spectrum management are crucial components for IEEE 802.22 standard-based WRAN technology to avoid interference to TV users and to maximize throughput for the WRAN users[31].

C. E-Health services

Various sorts of wireless technologies are adopted in healthcare services to enhance the efficiency of patient care and healthcare management. However, using wireless communication devices in healthcare applications is constrained by EMI (electromagnetic interference) and EMC (electromagnetic compatibility) requirements. Since the medical equipment and bio-signal sensors are sensitive to EMI, the transmit power of the wireless devices has to be carefully controlled. Also, different biomedical devices (e.g., surgical equipment, diagnostic, and monitoring devices) use RF transmission. Spectrum usage of those devices has to be carefully chosen to avoid interference with one another. Many wireless medical sensors are designed to work within the ISM band, which may use CR concepts to settle on suitable transmission bands to avoid interference[31].

D. Intelligent transportation system (ITS)

ITS will progressively utilize diverse remote access advancements to fortify the effectiveness and security of transportation by vehicles. Two kinds of interchanges situations emerge in an ITS framework vehicle-to-roadside (V2R) and vehicle-to-vehicle (V2V) communication. In V2R correspondences, information is traded between the roadside unit (RSU) and the on-board unit (OBU) during a vehicle. In V2V communications, a unique kind of unplanned network, namely, a VANET, is made among vehicles to exchange safety-related information. The high portability of the vehicles and rapid variations in network topologies pose significant challenges to efficient V2R and V2V communications. CR ideas are frequently used in both OBUs and RSUs so they will adjust their transmissions to manage the fast varieties inside the surrounding frequency environment. With multi-radio capabilities at the OBUs, they ought to be ready to adaptively choose the radio to speak with the RSUs[31].

E. Emergency networks

Public safety and emergency networks can cash in of the CR concepts to supply reliable and versatile wireless communication. For instance, during a disaster scenario, the quality communication infrastructure might not be available, and therefore, an adaptive wireless communication system (i.e., an emergency network) may have to be established to support disaster recovery. Such a network may use the CR concept to enable wireless transmission and reception over a broad range of the RF spectrum[31].

F. Military networks

With cognitive radio, the wireless communication parameters are often dynamically adapted supported the time and site also because of the mission of the soldiers. For instance, if some frequencies are jammed or noisy, the CR transceiver can look for and access alternative frequency bands for communication. Also, location-aware CR can control the transmitted waveform during a particular region to avoid interference to the high priority military communication systems [32].

2.2 Spectrum Sensing in Cognitive Radio Network

Due to the rapid growth in the field of communication, there is an increasing demand for higher data rates. Static frequency assignment cannot fulfill the requirements of higher data rates. The foremost compelling way to distinguish the accessibility of a few parcels of the spectrum is to identify the PUs that are receiving data within the range of a CR. However, it is difficult for the CR to have a direct measurement of a channel between a primary transmitter and receiver. Hence, most existing spectrum sensing algorithms focus on the detection of the primary transmitted signal based on the local observations of the CR.

To enhance the detection probability, many signal detection techniques can be used in spectrum sensing[33]. It is the process of performing measurements on the part of the spectrum and the idea of measured data making a choice related to spectrum usage. As the requirement and quantity of users are getting increased day by day, ISPs (internet service providers) must have a large amount of spectrum to achieve the QoS. This leads the interest in unlicensed spectrum access and spectrum sensing is a vital concept of this. In a situation where there are licensed users and any unlicensed exists, a licensed user is to be protected and no unlicensed user can interfere with any PU's operation and such cases SS is also useful to detect the existence or non-existence of a PU. It is also is an important concept for exploring spectrum opportunities for secondary spectrum usage in real-time. It detects the unused spectrum and shares it without any noticeable interference with other users. It is a crucial requirement of CR to sense spectrum holes. In CR communication, spectrum sensing is the way toward observing the frequency bands by the SUs and sensing any activity of a licensed user, which helps in detecting the spectrum holes. By spectrum sensing, the white holes are determined and these holes are used efficiently. There are various sensing techniques, which are utilized in CR to detect the supply of a spectrum

- Transmitter detection
- Interference detection
- Cooperative detection and

2.2.1 Transmitter Detection (Non-cooperative)

This mechanism detects the spectrum holes by detecting the availability of PU transmitter. In this method, weak signals of the PU transmitter are detected based on local observations of the CU. The essential hypothesis model here is that if PU, the received signal at the CU would contain the PU's signal and noise. Otherwise, it might be noise only just in case that PU doesn't exist. There are different transmitter detection techniques in CR networks we've mentioned the foremost popular sorts of SS which are shown below.

- Energy detection
- Matched filter detection
- Cyclostationary feature detection
- Wavelet detection
- Compressive detection

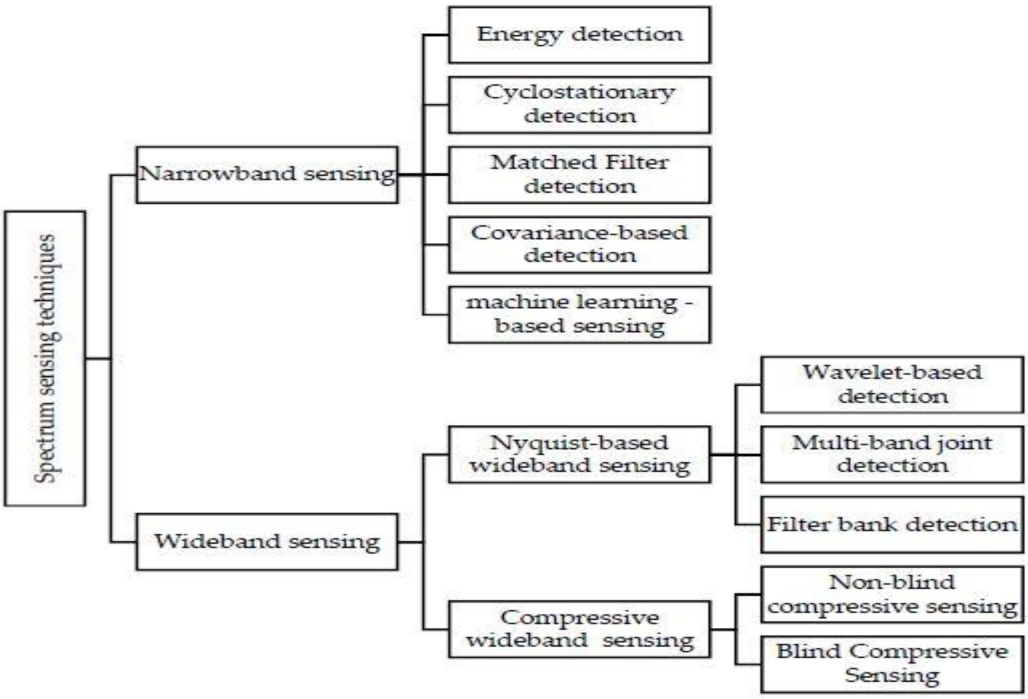

Figure 2-4 Classification of spectrum sensing techniques[34]

A. Energy detection

It is a simple detector which detects the total energy content of the received signal over specified time duration. It has the following components[35]: -

- **Band-pass filter** -- Limits the bandwidth of the received signal to the frequency band of interest.
- **Square Law Device** – Squares each term of the received signal.
- **Summation Device** – Add all the squared values to compute the energy.

A threshold value is required for comparison of the energy found by the detector. Energy greater than the threshold values indicates the presence of the PU. The principle of energy detection is shown in **Figure 2-5** . Energy detector-based sensing, also known as radiometry, is the optimal spectrum sensing method when the information about the signal of interest is not known. It is easy to implement and has low computational complexity. Since the received energy is compared to a threshold in energy detector-based sensing, the threshold selection affects the performance of the method significantly.

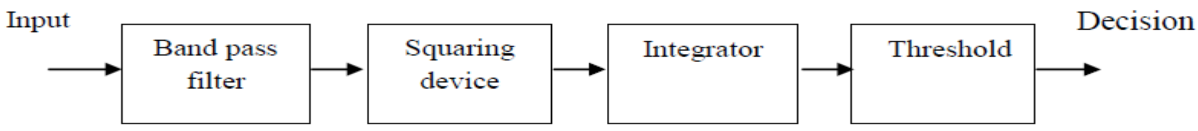

Figure 2-5 Block diagrams of energy detection

B. Matched filter detection (MFD)

The Matched Filter Technique is very important in communication as it is an optimum filtering technique which maximizes the signal to noise ratio (SNR). It is a linear filter and prior knowledge of the primary user signal is very essential for its operation. The operation performed is equivalent to a correlation. The received signal is convolved with the filter response which is the mirrored and time shifted version of a reference signal. **Figure 2-6** shows an implementation of the matched filtering method[35]. Matched filtering is the optimal SS method when the information about the signal of interest is known. To achieve a certain probability of false alarm, this method requires a shorter time as compared to the ED based sensing and cyclostationary-based sensing methods. The need for a priori knowledge is the main disadvantage of the matched filtering method. The requirement of synchronization between the transmitter and the receiver is another disadvantage of this method[36].

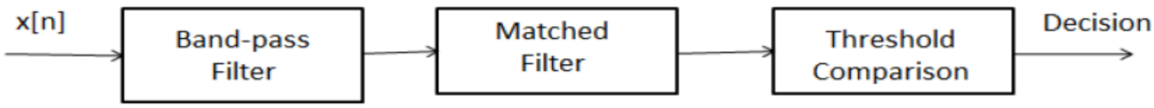

Figure 2-6 Matched filter block diagram

The Operation of the MFD can be expressed as:

$$y(n) = \sum_{l=-\infty}^{\infty} h(n-l)x(l) \qquad (2\text{-}1)$$

Where y (n) is the received signal, x is the unknown signal, h is the impulse response of the MFD which matches the known signal for maximizing the output SNR.

C. Cyclostationary Feature detection (CFD)

In the cyclostationary-based detecting method, cyclostationary features of the modulated signals are abused. Cyclostationary features are the characteristic consequences of the occasional structures of the modulated signals, such as sinusoidal carriers, pulse trains, hopping sequences, or cyclic prefixes. Due to this built-in periodicity, modulated signals are cyclostationary with spectral correlation[36]. **Figure 2-7** shows an implementation of the CFD based sensing method. As seen in this figure, first the spectral components of the input signal are computed through the FFT. Then the spectral correlation is performed on these spectral components and the spectral correlation function is estimated. This spectral correlation function is analyzed to detect the signals in the cyclostationary-based SS method. The biggest advantage of this method is that it is robust to noise uncertainty. This robustness comes from the fact that the noise is a WSS process with no spectral correlation, whereas the modulated signals are cyclostationary with spectral correlation. On the other hand, CFD sensing has increased computational complexity and requires longer observation time than the ED-based sensing schemes[36]. The output of this detection is compared with the predefined threshold value to determine the availability of PU's. The cyclic spectral density function of the received signal can be obtained as:

$$S(f,\alpha) = \sum_{\tau=-\infty}^{\infty} R^{\alpha}{}_{y} e^{j2\pi\alpha t} \tag{2-2}$$

Where $R^{\alpha}{}_{y} = E[Y(t+\tau)Y^{*}(t-\tau)e^{j2\pi\alpha t}]$, $R^{\alpha}{}_{y}$ is the cyclic autocorrelation function and α is the cyclic frequency. When the cyclic frequency is equal to the fundamental frequencies of the transmitted signal $x(n)$, the peak values can be obtained by the CSD function.

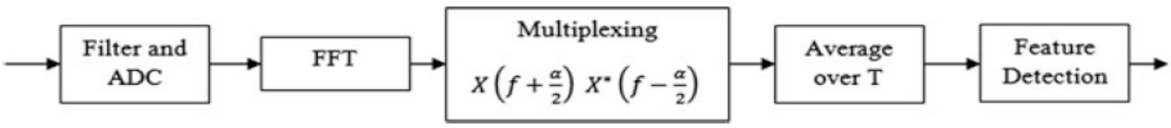

Figure 2-7 Cyclostationary feature detection block diagram

D. Wavelet detection (WD)

This method uses the principle of wavelet transformation where multi-resolution analysis mechanisms decompose the input signal into different frequency components. Wavelet transform uses irregularly-shaped wavelets as basic functions and offers better tools to represent sharp changes. To distinguish the areas of idle RF bands, the whole wideband is modelled as a train of consecutive sub-bands where the facility spectral properties are smooth within each sub-band but change suddenly on the border of two neighbouring sub-bands.

By analysing the irregularities in the PSD properties with wavelet transformation, the spectrum hole can be located. Its advantage is that it can perform optimally without a priori knowledge information of the PU's signal[35].

E. Compressive sensing (CS)

On account of the unusualness of PU, quick and prompt moving over the detected void channel is of incredible significance and is a troublesome task. To moderate this issue, a fast and productive SS strategy is required. This quick sensing is cultivated by acquiring a compressed version of the wideband SS and reconstructing that spectrum by a lower number of estimations than those needed by the Shannon-Nyquist hypothesis. In this way, CS speeds up the cycle of wideband SS in distinguishing the unoccupied RF. This CS-based wideband SS technique grants conquering the need of an extremely quick ADC to get a wideband and a fast DSP to handle such a wideband, which need to work at or over the Shannon-Nyquist rate. This section examines the three-essential cycle of CS: sparse representation, measurement, and sparse recovery. Besides, the impact of CS on SNR is examined.

1. **Sparse representation**

   It contains finding a reasonable change premise that makes the signal sparse and packs the data into a couple of significant coefficients. Sparse signal demonstrating of data is a capacity to describe helpful signals characteristic as linear combinations of couple of components from another change premise. The achievement of the change premise depends upon how the signal is compactly represented by that transform basis which is called the sparse representation of the signal. So sparse signal has a few significant components that license to disposing of coefficients with generally little sufficiency without presenting distortion in the reproduced signals. This empowers us to achieve high rates of compression and the sampling would itself be able to be intended to procure only essential information[37].

2. **Measurement**

   The subsequent cycle is measurement or investigation to assemble the data, which is a huge part that the essential trouble for some engineering and scientific activities. While getting the straight measurements, the denser measurement matrix is, the additionally detecting time it costs, the huge the extra room and prompts the high cost. In CS, the measurement is needed to detect and diminish the compression of the signal simultaneously, which is obtaining the compressed version of signals straightforwardly by taking just a couple of measurements from the sparse signals. This dimensional decrease in CS is done by linear projecting of the sparse signal by a set of deliberately picked measurement matrix[38].

$$Y + n = \varphi BX = AX \quad (2\text{-}3)$$

Where $Y \in R^M$ measurements, $A = \varphi B \in R^{NxM}$ is measurement matrix, $X \in R^N$ sparse signals, n is noise containing measurement errors, quantization error, and model imperfection which is generally modeled as an independent zero-mean Gaussian distributed with a variance σ_n^2, B is sparsity bases in this case Fourier transform and φ is dimensional reduction matrix.

3. **Sparse Recovery**

The essential task in CS is to precisely recover the sparse signals from the accessible noisy measurement which has a reduced size of components. The recovery issue ought to consider measurement noise and extra noise[38]. Generally, from linear algebra, when the quantity of unknown variables (dimensionality of sparse signal X), surpasses the quantity of observation (dimensionality of measured signal Y), the framework is an underdetermined arrangement of linear equations which have endless many solutions. That infers there exists an endless possible number of signal X that may explain the observation vector Y. The issue of reconstructing X from Y appears, hence, somewhat infeasible. To narrow the choice to one well-known solution, it is necessary to specify additional criteria[39]. The information of signal X just holds a few nonzero entries comparative with signal measurement, permits us to recover the signal remarkably inside high probability. In this way, we need to introduce a target or regularization function $O(X)$ to assess the attractive quality of an answer X and the extra property of signal which is sparsity. This objective function significantly reduces the set of candidates for X and adequately explains the perception without superfluous complexity[40]. Along these lines, the signal recovery from noisy measurement is formulated as a constrained optimization issue.

$$minimize\ O(X) \text{ subject to } \|Y - AX\|_2 < \eta \quad (2\text{-}4)$$

The ideal trait of a sparse signal which has the sparsest arrangement can be characterized as the arrangement with the most modest number of nonzero sections. The target work is l_0-norm and given by $|X|_0$ to account the nonzero components in the signal. In this way, the l_0 minimization is given by:

$$min_X\ |X|_0 \text{ subject to } \|Y - AX\|_2 < \eta \quad (2\text{-}5)$$

Effect of Compressive Sensing in SNR

Now the SNR in the recovered spectrum when all spectrum samples being used.

$$SNR_0 = 10 \log\left(\frac{\sum_{n=0}^{N-1} X_n^2}{\sigma_n^2}\right) \quad (2\text{-}6)$$

However, it is understood that the energy of the spectrum is concentrated in a few Fourier coefficients because of the sparse nature of spectrum usage. Likewise, normally, the spectrum can be sparsely represented in the frequency domain. In any case, noise is spread over the entire domain that implies noise is not sparse in a frequency transform domain. To give a profitable signal reconstruction it is critical to isolate those (N-K) having a place with the noise component part from signal components. To isolate the signal from noise component we have to characterize the probability that non-signal samples in the frequency domain are below a threshold λ.The probability that all (N-K) values comparing to noise value are beneath λ is given by[41].

$$P(\lambda) = \left[1 - \exp\left(\frac{-\lambda^2}{\sigma^2}\right)\right]^{N-K} \approx \left[1 - \exp\left(\frac{-\lambda^2}{\sigma^2}\right)\right]^{N} \tag{2-7}$$

A predefined probability of error guarantees that the signal components isolated from spectral noise and for the desired value of $P(\lambda)$ are given as.

$$\lambda = \sqrt{-\sigma^2 \log\left(1 - P(\lambda)^{\frac{1}{N}}\right)} \tag{2-8}$$

Accordingly, one can avoid the influence of noise on signal component detection by keeping only some large Fourier transform coefficients utilizing the appropriately thresholding level and discard other insignificant components below the threshold. During the reconstruction of the spectrum from these coefficients, one can undoubtedly expand the underlying SNR by giving the denoised form of the original full signal. On account of a reduced set of measurements from N to M, only M available measurement of the observed noise energy is reduced[41],[42].

$$\sigma_{R_s}^2 = \frac{N^2}{M^2}\sigma_n^2 \tag{2-9}$$

Since only $K\ out\ of\ N$ coefficient is utilized in the reconstruction, the energy of the reconstruction error is limited by the factor of $\frac{K}{N}$

$$\sigma_{R_s}^2 = \frac{K}{N}\frac{N^2}{M^2}\sigma_n^2 = \frac{KN}{M^2}\sigma_n^2 \tag{2-10}$$

Using the fact that the variances in measurements are the same $\frac{1}{M}\sigma_n^2 = \frac{1}{N}\sigma_n^2$

$$\sigma_{R_s}^2 = \frac{KN}{M^2}\sigma_n^2 = \frac{KN}{M}\frac{1}{M}\sigma_n^2 = \frac{KN}{M}\frac{1}{N}\sigma_n^2 = \frac{K}{M}\sigma_n^2 \tag{2-11}$$

Substitute (**2-11**) to (**2-6)** and we get the SNR due to reduced measurement

$$SNR = 10\log\left(\frac{\sum_{n=0}^{N-1} X_n^2}{\sigma_{R_s}^2}\right) = 10\log\left(\frac{\sum_{n=0}^{N-1} X_n^2}{\frac{K}{M}\sigma_n^2}\right)$$

$$= 10\log\left(\frac{\sum_{n=0}^{N-1} X_n^2}{\sigma_n^2}\right) - \log\left(\frac{K}{M}\right)$$

$$= SNR_0 - \log\left(\frac{K}{M}\right) \tag{2-12}$$

Where K is the number of active PU, M is the number of measurements, SNR is the SNR of the recovered spectrum and SNR_0 is the SNR when all signal sampled used (without CS).

Comparative Analysis of Spectrum Sensing Techniques

To go further on those SS techniques, it is better to study their advantages and disadvantages.

Table 2-1 Comparison of Spectrum Sensing

SS techniques	Advantages	Disadvantages
ED	✓ Low complexity ✓ No prior knowledge required	✓ Poor performance for low SNR
MFD	✓ Optimal performance ✓ Low computational cost	✓ Requires prior information
CFD	✓ Robust in low SNR region ✓ Robust against interference	✓ Requires prior information ✓ High computational cost
WD	✓ Efficient for wideband signal detection	✓ Requires high sampling rate ADC ✓ High computational cost
CS	✓ Low sampling rate ✓ Low signal acquisition cost ✓ Efficient for wideband detection	✓ Sensitive to design imperfections

2.2.2 Cooperative spectrum sensing

Spectrum sensing employing using single Cognitive radio features has several limitations. Firstly, the sensitivity of one sensing device might be limited due to energy constraints. Furthermore, in wireless channels, the hidden terminal problem will lead to a very low SNR. Although the CR might be out of sight from the PU's transmitter, this does not mean it is also blocked from the PU's receiver. As a result, the PU is not detected but the secondary transmission could still significantly interfere with the PU's receiver[43]. These issues can be resolved using cooperative spectrum sensing (CSS). In this CSS adjacent SU cooperate in SS a joint PU signal transmission by sharing local sensing observation between them before making a final decision. There are three methodologies to implement this CSS which are listed below:

- Centralized
- Distributed
- Relay assisted

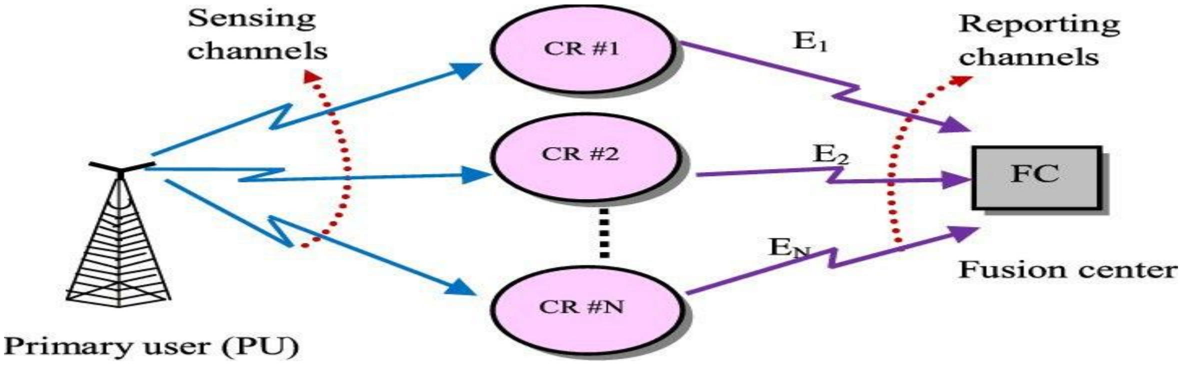

Figure 2-8 Cooperative Spectrum Sensing in a Cognitive Radio Network

I. Centralized Cooperative Spectrum Sensing

In this scheme of CSS, a group of CRs senses the existence of the PU in a specific geographic location and RF channel. Periodically, every single CR in the system measures the signal of the PU independently, based on its local observation, a CR makes its decision about the existence of the PU and then forwards its decision as either one-bit form (i.e., hard decision) or as energy form (i.e., soft decision) to the FC. Finally, the FC collects the decisions of the collaborating CRs fuses them to have a final decision about the presence of the PU. As shown in **Figure 2-9** the FC is that the master node and SU1-SU5 are the cooperative SUs performing local sensing and reporting the sensing data back to the FC. The FC collects sensing information, identifies the vacant spectrum, and broadcasts the information to SU1-SU5[44]. The centralized CSS can occur in either a centralized or distributed CR networks. In centralized CR networks, a CR base station is naturally the FC. Alternatively, in CR ad-hoc networks (CRAHNs) where a CR base station is not present, any SU can act as an FC to coordinate CSS and combine the sensing information from the cooperating neighbours.

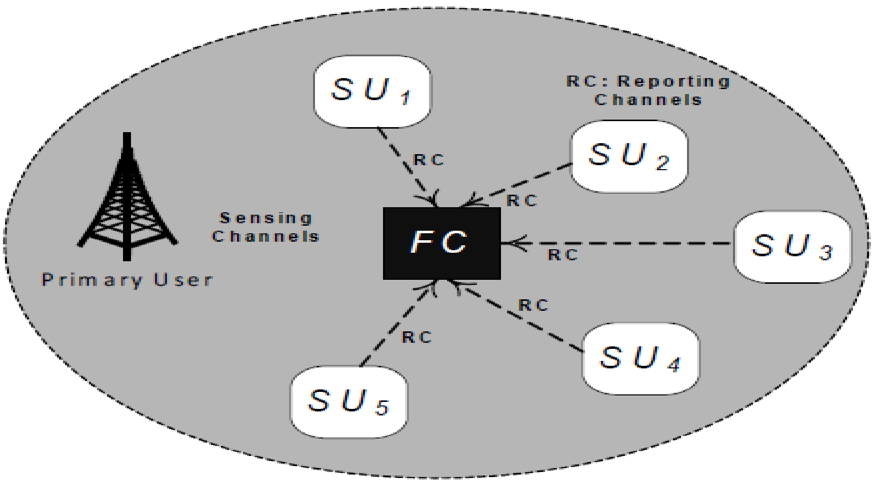

Figure 2-9 Centralized Cooperative Spectrum Sensing[45]

Generally, the centralized system requires establishing a network backbone (i.e., common control channel) to convey data between the FC and the CRs in the network. Though the centralized CSS scheme significantly improves the detection performance (i.e., probability of detection and throughput), however, the information exchanges and data fusion lead to incurring an extra overhead (i.e., bandwidth, computational requirements, energy consumption, and time). Therefore, the trade-off between improving the performance and incurred overhead should always be considered in designing CSS.

II. Distributed Cooperative Spectrum Sensing

In this model of CSS, the CSS process goes through four iterative stages. First, each CR senses the PU signal independently and periodically. Second, every CR establishes communication links with other CRs having the desired channel characteristics; afterward, each CR exchanges its local information with its neighbors. Third, every CR combines the collected information with its local observation to make its decision. Finally, the consensus among the neighbors about the existence of PU should be achieved, however, if consensus is not met, the first three stages of the process should be iteratively repeated till achieving consensus. The principle of consensus is inspired by biological phenomena, specifically, the collective animal behavior in a group deciding the higher level and the individual's communication at the lower level. As shown in **Figure 2-10** after local sensing, SU1-SU5 share their local sensing results amongst each other and make their own decisions as to which part of the spectrum they can utilize. If there are no evident decisions after this initial process, SUs pass their combined results to other users and repeat the sensing process until a decision is reached.

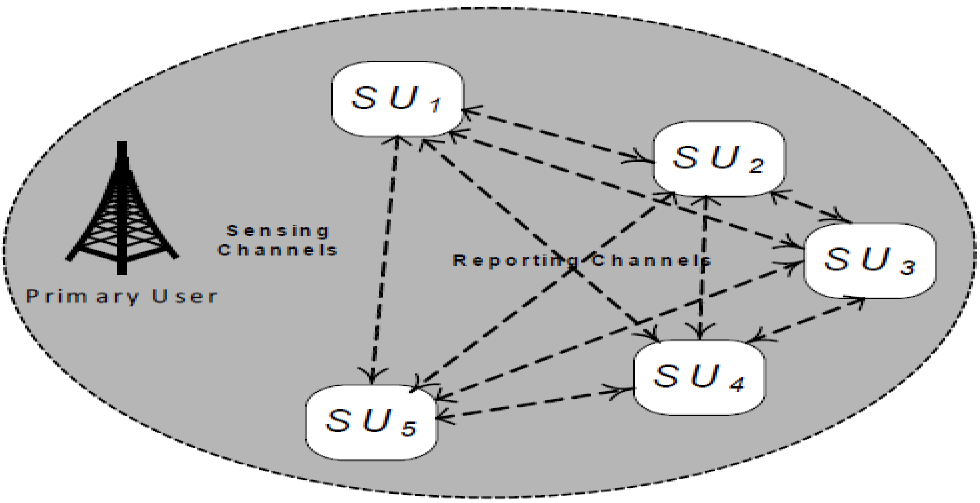

Figure 2-10 Distributed Cooperative Spectrum Sensing[45]

The disadvantage of distributed CSS is a decision delay possibility because several iterations may be required to reach a cooperative decision hence increasing the chance of the PU interference. To overcome this limitation, different decision strategies may be used, which result in different delay[45].

III. Relay-assisted Cooperative Spectrum Sensing

This model is considered as a low complexity cooperative diversity that mitigates the influence of fading induced by multipath propagation in a wireless network. A relay-assisted CSS can be used to overcome the imperfection in both sensing and reporting channels. Meaning, a SU experiencing a weak sensing and a strong reporting channel, and a SU experiencing a strong sensing channel and a weak reporting channel can complement and collaborate to improve the overall performance of the CSS. In **Figure 2-11** SU1, SU4, and SU5, who observe strong PU signals, may suffer from a weak reporting channel. SU2 and SU3 who have strong reporting channels serve as relays to assist in forwarding sensing results from SU1, SU4, and SU5 to the FC. The reporting channels from SU2 and SU3 are known as relay channels. When the sensing results got to be forwarded by multiple hops to succeed in the intended receive node, all the intermediate hops are relays. Thus, if both centralized and distributed structures are one-hop CSS, the relay-assisted structure can be considered as multi-hop CSS[46]. Depending on the type of data shared by SUs, fusion schemes can be classified as hard and soft fusion schemes[47].In this work we only consider Hard fusion scheme.

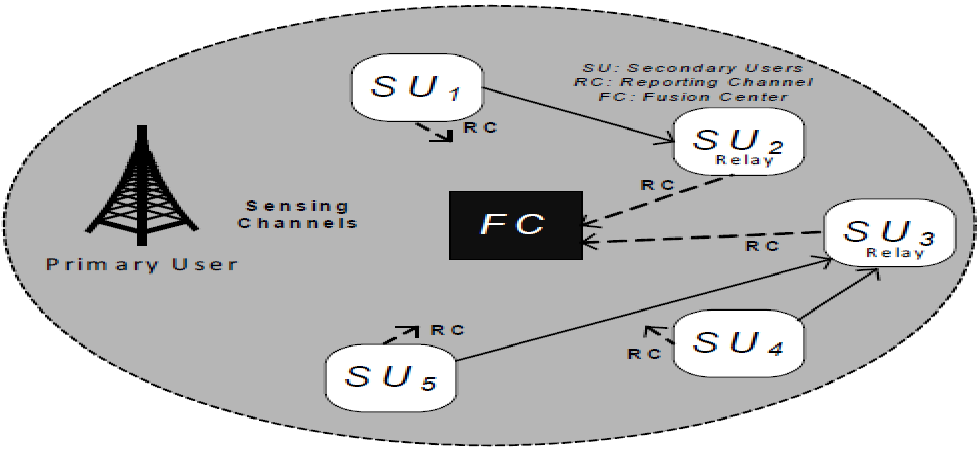

Figure 2-11 Relay-assisted Cooperative Spectrum Sensing

Decision Fusion (Hard based decision)

In this scheme, the final decision is reached by taking into consideration the individual local decisions reported by each SU. Process each data separately, and make individual decisions.

The final decision is then made by fusing those decisions. The main advantage of this method is the easiness because it needs limited bandwidth. The global probability of detection Q_d and the global probability of false alarm Q_f of the CSS system can be determined according to the employed fusion rule, as illustrated below.

1) ***"Logic-OR (LO)" Rule:*** LO rule is a simple decision rule which is described as if one of the decisions says that there is a PU, then the final decision declares that there is a PU. The global probability of detection and false alarm can be evaluated by setting $k = 1$.

$$Q_{f,OR} = 1 - (1 - P_f)^{N_s} \tag{2-13}$$

$$Q_{d,OR} = 1 - (1 - P_d)^{N_s} \tag{2-14}$$

Clearly, it can be noticed that both of $Q_{d,OR}$ and $Q_{f,OR}$ are expanding by expanding N_s. In different words, expanding the $Q_{d,OR}$ prompts improve the PU assurance from CR's obstruction, while expanding the $Q_{f,OR}$diminishes range productivity (i.e., more unfortunate range proficiency).

2) ***"Logic-AND (LA)" Rule:*** LA rule works as follows: if all decisions say that there is a PU, then the final decision declares that there is a PU. The global probability of detection and false alarm can be evaluated by setting $k = N_s$.

$$Q_{f,AND} = {P_f}^{N_s} \tag{2-15}$$

$$Q_{d,AND} = {P_d}^{N_s} \tag{2-16}$$

Clearly, $Q_{f,AND}$ diminishes by expanding N_s which means better range productivity, notwithstanding, $Q_{d,AND}$ additionally diminishes by expanding N_s which implies more unfortunate PU security.

3) ***Majority Rule (k* out of *N):*** If half of the decisions or more say that there is a PU, then the final decision declares that there is a PU. global probability of detection and false alarm can be evaluated by setting $k = \frac{N_s}{2}$.

$$Q_{f,AMAJORITY} = \sum_{i=k}^{N_s} \binom{N_s}{i} P_f (1 - P_f)^{N_s - i} \tag{2-17}$$

$$Q_{d,MAJORITY} = \sum_{i=k}^{N_s} \binom{N_s}{i} P_d (1 - P_d)^{N_s - i} \tag{2-18}$$

where $\binom{c}{k} = \frac{c!}{k!(c-k)!}$

The k out of N rule compromises between improving the PU protection and the spectrum efficiency. Moreover, k out of N rule is the optimal fusion rule in terms of the total detection error rate.

Advantages of Cooperative Spectrum Sensing

Naturally, cooperative spectrum sensing isn't applicable altogether applications, but where it's applicable, considerable improvements in system performance are often gained: -

1. **Diversity gain:** Since the signal strength varies with the CRs location, the worst fading conditions are often avoided, if multiple CRs in several spatial locations share their local sensing measurement, i.e., cash in of the spatial diversity. Taking advantage of spatial diversity results in higher accuracy of detection of the first thanks to higher accuracy in detection multipath, shadowing, and native interference.
2. **Robustness:** Robustness to changing networks and fast convergence [48].
3. **Sensing time:** The longer the sensing time of a CR the upper the probability of detecting the PU signal but the less the throughput. Using multiple CRs the sensing time is often reduced. CSS reduces the sensing time, and thus it increases transmission throughput.

2.2.3 Interference Based Detection

This model attempts to regulate interference at the primary receiver. The CR users are allowed to transmit on the RF band as long as they do not exceed the interference temperature limit. That is, during the interference-based detection, the CRs need to measure the interference temperature and adjust their transmission during thanks to avoiding raising the interference temperature over the interference temperature limit. Typically, CUs transmitters control their interference by regulating their transmission power (their out-of-band emissions) supported their locations concerning PU. The CUs are allowed to coexist and transmit simultaneously with PUs using low transmit power that's restricted by the interference temperature level to not cause harmful interference. However, the main drawback of interference-based detection is that the CUs cannot transmit their data with higher power even if the licensed system is completely idle since they are not allowed to transmit with higher than the present power to limit the interference at PUs. It is noted that the CR users during this method are required to understand the situation and corresponding upper level of allowed transmit power levels, otherwise they're going to interfere with the PU transmissions[49].

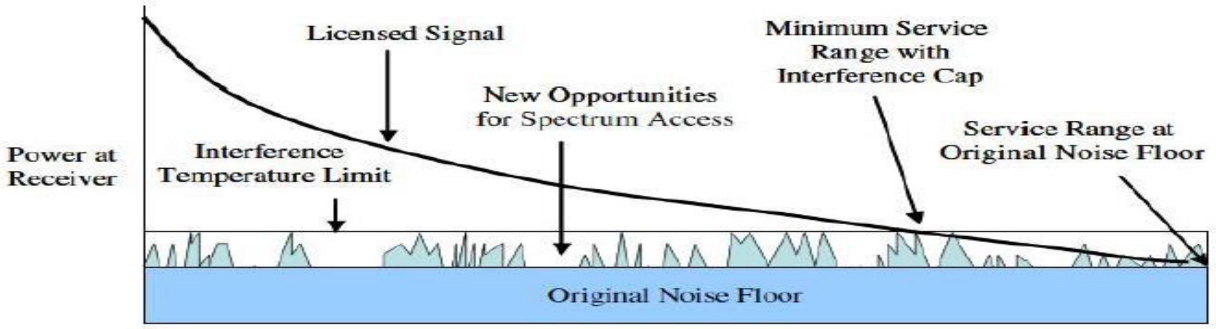

Figure 2-12 Interference Temperature Model

The SU may exploit the channel if the detected PU's signal level is below the interference temperature limit. More so, if the power of transmission of an SU stays below the interference gap, it may utilize any frequency parameter of its choice. With this approach it is hypothesized that the SUs will be allowed to transmit concurrently with the PUs under stringent interference avoidance constraints; wherein it is categorized as a spectrum underlay scheme. This method is far more challenging; since the prime problem faced with an implementation of this technique will be in determining specific receiver interference temperature levels for the various communication standards

2.3 Tradeoff between Cooperation Gain and Cooperation Cost

Investment of cooperation (i.e., spatial diversity) in a group of CRs in spectrum sensing results in an apparent improvement in the detection performance, however, the gained improvement has a penalty of incurring cooperation cost (i.e., extra energy consumption, time, and complexity) which limits attainable cooperation gain (i.e., detection performance improvement), Therefore, balancing between cooperation gain and cooperation cost is very crucial in designing CSS in CRNs. To compromise many factors should be taken into consideration.

2.3.1 Channel impairments

The impact of the channel impairments on the performance of the CSS technique mainly depends on the employed detection techniques and underlying transmission technique. In more detail, the sensing performance of the ED technique severely deteriorates in weak radio conditions such as low SNR scenarios, noise uncertainty, heavy shadowing, and deep multipath fading. Moreover, noise uncertainty in very low SNR prevents ED from detecting the existence of the PU. The effect of noise uncertainty is called the SNR wall (i.e., an SNR value beyond which the detector cannot sense the PU signal no matter how long sensing time is)[50].

2.3.2 Sensing Time

In a centralized CSS system, all CRs in the system detect the PU periodically in a synchronized manner and then report their local observations to the BS. The observations are collected using the time-division multiplexing (TDM) technique. Selecting a proper sensing time for the CSS system is a challenge since long sensing time improves detection efficiency, however, it reduces transmission data duration which possibly results in decreasing the throughput. In other words, increasing the sensing time can effectively reduce spectrum efficiency[51]. Therefore, selecting an optimal sensing time is essential to design factors for CSS systems.

2.3.3 Energy efficiency (EE)

Energy efficiency is a criterion that compromises the performance (i.e., throughput) and overhead (i.e., consumed energy). It is defined as the ratio between attainable throughput and incurred energy consumption. For a non-cooperative SS system, selecting a joint optimal sensing and transmission durations that maximize the achievable energy efficiency of the system in terms of spectrum exploitations of idle PUs RF band was studied in detail in[52]. The study considered three spectrum exploitation scenarios that are fully utilizing the idle PU band with sufficient average power capacity, partially utilizing the idle band with limited power capacity and interim between two previous scenarios. However, the work has not considered the PU traffic (i.e., the possibility that PU reoccupies the idle band during CR transmission duration)[53]. Based on the PU activity model, authors established a mathematical formula for designing an energy-efficient CR system in terms of sensing and transmission durations under constraints of interference to the PU. The work showed that there is a joint optimal sensing and transmission duration that maximizes energy efficiency.

2.3.4 Mobility

Mobility is an inherent characteristic of modern wireless communication systems. It has a direct impact on network capacity, coverage, connectivity, and routing. The impact of mobility on SS performance for a single CR terminal with an ED has been investigated in[54]. It was proven that increasing the moving speed of the CR terminal on both urban and suburban environments drastically enhances the Spatio-temporal diversity and consequently, the sensing observation of the CR gets faster uncorrelated which leads to significant improvement in SS performance. It is shown in[54] that higher terminal mobility can effectively improve the sensing performance of the terminal with low RSS in received PU signal.

Chapter 3 : System Model

3.1 Introduction

A CR network with N cognitive users is considered. The sensing channel is assumed to be the AWGN channel with σ_n^2 noise variance. The transmitted signal by the licensed users is assumed to be circularly symmetric complex Gaussian (CSCG) distributed with variance σ_s^2. This research work concentrates on the centralized CSS, where CSS starts with an area sensing performed by each CU individually. In this spectrum sensing adjacent secondary users cooperate in SS a joint PU signal transmission by sharing local sensing observation between them before making a final decision. After local sensing, which is happened by individual CU in CSS the decision is cooperatively made by reporting the local decisions to the FC.

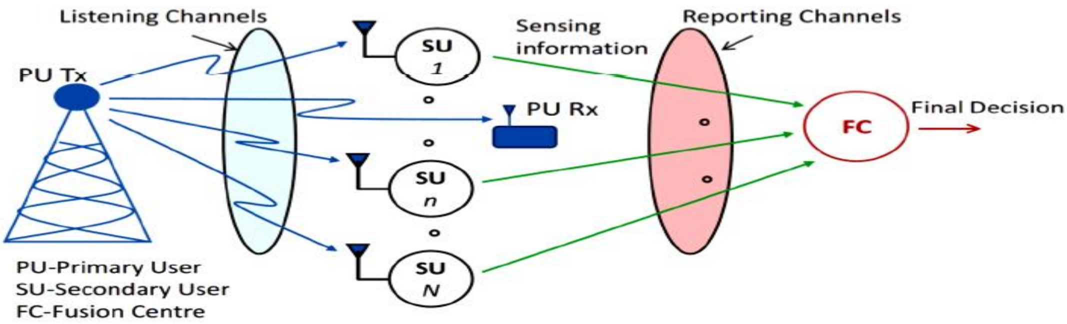

Figure 3-1 System model for cooperative spectrum sensing in cognitive radio

3.2 Performance Metrics

The accuracy of the spectral availability information is defined using sensing quality parameters. This feature makes up performance metrics. Sensing the performance of the energy detector is specified by the following general metrics:

- The probability of detection, (P_d)
- The probability of false alarm, (P_f)
- The probability of missed detection, (P_m)

The probability of detection (P_d) specifies that a detector makes a correct decision that a channel is occupied H_1. P_d is an indicator of the level of interference protection provided to the PU. Hence, a large P_d denotes exact sensing; which translates to a small chance of interference. A false alarm event occurs when the detector assumes H_1; when the right decision is H_0. The probability of this occurrence is specified as a P_f. When a false alarm event occurs the SU would not exploit the free spectrum thus missing a chance to utilize the free channel.

The probability of declaring the spectrum space vacant H_0, when it is indeed occupied H_1 is referred to as the probability of missed detection (P_m). A high P_m implies an increase in the chance of interference between the PU and the SU. If the detection fails or miss detection occurs, the SU initiates a transmission which results in interference with the PU signal.

3.3 Performance Analysis and Spectrum Sensing Preliminaries

The higher the detection probability is, the higher the PUs are often protected. However, from the SUs perspective, the lower the false alarm probability is, the more chances the channel is often reused when it's available, thus the upper the achievable throughput for the SUs[55]. Obviously, for an honest detection algorithm, the probability of detection should be as high as possible while the probability of false alarm should be as low as possible.

3.3.1 Preliminaries for Spectrum Sensing

Suppose that we are interested in the frequency band with carrier frequency fc and bandwidth BW and the received signal is sampled at sampling frequencyf_s. Let τ be the available sensing time and N the number of samples (N is the maximum integer not greater than τf_s, and for notation simplicity, we assume $N = \tau f_s$). When the PU is active, the discrete received signal at the SU are often represented as

$$H_1: \; y(k) = s(k) + n(k) \tag{3-1}$$

If the PU is inactive, then the discrete received signal at the SU can be represented as

$$H_0: \; y(k) = n(k) \tag{3-2}$$

Generally, the received signal for each case is

$$y(k) = \begin{cases} n(k), & H_0 \\ s(k) + n(k), & H_1 \end{cases} \tag{3-3}$$

3.3.2 Conventional Energy Detector

The principle of a conventional energy detection method is finding the energy of the received signal and compares that with predefined threshold to determine the availability of the primary signal[56]. The test statistics for energy detector is given by

$$E_y = \frac{1}{N}\sum_{n=1}^{N} |Y(k)|^2 \tag{3-4}$$

This test statistics is then compared to a threshold λ; to obtain the sensing decision as follows:

$$E_y > \lambda \text{ primary user present}$$

$$E_y < \lambda \text{ primary user absent}$$

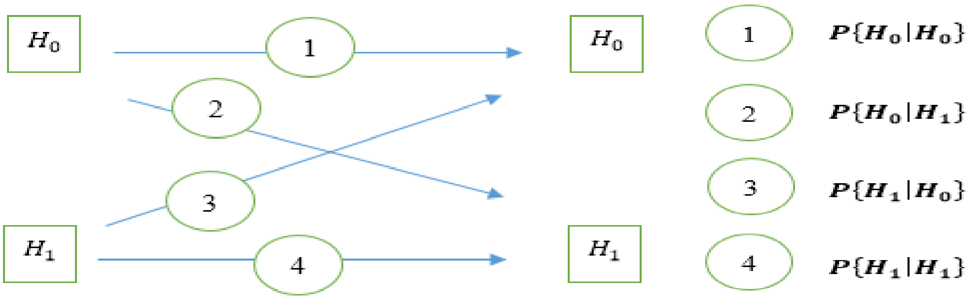

Figure 3-2 Hypothesis test with possible outcomes and their corresponding probabilities

From **Figure 3-2** four possible cases can be defined for the detected signal;

- Declaring H_0 when H_0 is true (H_0: H_0) correct detection
- Declaring H_0 when H_1 is true (H_0: H_1) missed detection
- Declaring H_1 when H_0 is true (H_1: H_0) false alarm
- Declaring H_1 when H_1 is true (H_1: H_1) correct decision.

The goal of the signal detector is to realize correct detection which is the probability of detection all the time. However, this can't be accomplished absolutely in practice due to the statistical nature of the matter. Therefore, signal detectors are designed to function within minimum error levels. A prominent issue for SS is missed detection; because it implies interfering with the primary system and also the P_f has got to be kept as low as possible to enable the system to exploit possible transmission opportunities. In practical cases, the central limit theorem (CLT) proposes that when N is large enough, the sum of N I.I.D random variables with finite mean and variance can be accurately expected to follow the Gaussian distribution. Using CLT the distribution of decision test statistic can be accurately approximated with a normal distribution due to a large number of involved samples, the following expressions are obtained[57].

$$E_y = \begin{cases} Normal\left(\sigma_n{}^2, \frac{1}{N}\sigma_n{}^4\right) & : H_0 \\ Normal\left(\sigma_n{}^2(\gamma+1), \frac{1}{N}\sigma_n{}^4(\gamma+1)^2\right) & : H_1 \end{cases} \tag{3-5}$$

Where $\sigma_n{}^2$ and $\sigma_s{}^2$are the noise variance and signal variance, respectively.

If $E_y \geq \lambda$, it can be concluded that the PU is present and H_1 will be declared. Contrary to that if, $E_y < \lambda$ it can be concluded that the PU is absent and H_0 will be declared. If we choose predefined threshold as λ, the P_f is then given by

$$P_f = P(E_y > \lambda|H_0) = P(E_y < \lambda|H_1) \tag{3-6}$$

According to[58], the false alarm P_f and probabilities of detection P_d are given as follows

$$P_f(\lambda) = Q\left(\left(\frac{\lambda}{\sigma_n{}^2} - 1\right)\sqrt{N}\right) \tag{3-7}$$

Where $Q(x) = \frac{1}{\sqrt{2\pi}}\int_x^{\infty} e^{\frac{-t^2}{2}}dt$ is Q function and N is number of samples

From the above equation, λ is related to the P_f as:

$$Q^{-1}\widetilde{P}_f = \left(\frac{\lambda}{\sigma_n{}^2} - 1\right)\sqrt{N} \tag{3-8}$$

$$\lambda = \sigma_n{}^2\left(\frac{Q^{-1}\tilde{P}_f}{\sqrt{N}} + 1\right) \tag{3-9}$$

For a chosen threshold λ, the P_d :

$$P_d(\lambda) = P\left(E_y > \lambda \middle| H_1\right) \tag{3-10}$$

$$P_d = Q\left(\left(\frac{\lambda}{\sigma_n{}^2(1+\gamma)} - 1\right)\sqrt{N}\right) \tag{3-11}$$

Where γ is the signal to noise ratio

For a target probability of detection $\tilde{P}_d$, the detection threshold λ can be determined by

$$\left(\frac{\lambda}{\sigma_n{}^2(\gamma+1)} - 1\right)\sqrt{N} = Q^{-1}(\tilde{P}_d) \tag{3-12}$$

$$\lambda = \sigma_n{}^2(\gamma+1)\left(\frac{Q^{-1}\tilde{P}_d}{\sqrt{N}} + 1\right) \tag{3-13}$$

Therefore, for a target probability of detection $\widetilde{P}_d$, from (**3-7**) and (**3-13**) P_f is given by:

$$P_f = Q\left(\tilde{P}_d Q^{-1}(1+\gamma) - \gamma\sqrt{N}\right) \tag{3-14}$$

The constraint $\widetilde{P}_D$ is employed to limit the interference at the PUs, caused when a missed detection occurs. However, for a target $\tilde{P}_f$,from (**3-9**) and (**3-11**) P_d is given by:

$$P_d = Q\left(\left(\frac{Q^{-1}\tilde{P}_f - \gamma\sqrt{N}}{1+\gamma}\right)\right) \tag{3-15}$$

The probability of miss detection is obtained using the probability of detection as

$$P_m(\lambda,\tau) = 1 - P_d(\lambda,\tau) = 1 - Q\left(\left(\frac{Q^{-1}\tilde{P}_f - \gamma\sqrt{N}}{1+\gamma}\right)\right) \tag{3-16}$$

As in most communication systems, the noise is an error or unwanted disturbance of a useful information signal. It is a summation of various independent sources including thermal noise, and interferences due to weak signals from transmitters very far away, etc. However, the noise power may fluctuate over time and location, which yields noise uncertainty[59]. To study the effect of noise uncertainty (NU) on the detection performance, we modelled the distributional NU as $\sigma_n^2 \epsilon \left[\left(\frac{1}{\rho}\right)\sigma_n^2, \rho\sigma_n^2\right]$ Where ρ is the parameter that quantifies the NU.

It is noted here that NU is usually expressed as $10\log_{10}\rho$ in dB, ${\sigma_n}^2$ is nominal noise power. The probability of false alarm is calculated by considering the NU is expressed as follows:

$$P_f = Q\left(\frac{\lambda}{\rho{\sigma_n}^2} - 1\right)\left(\sqrt{N}\right) \tag{3-17}$$

$$P_f = Q\left(\frac{1+\gamma}{\rho}\left(Q^{-1}\widetilde{P}_d + \sqrt{N}\right) - \sqrt{N}\right) \tag{3-18}$$

Also, the P_d is calculated by considering the NU factor is expressed as follows:

$$P_d = Q\left(\frac{\lambda\rho}{{\sigma_n}^2(1+\gamma)} - 1\right)\left(\sqrt{N}\right) \tag{3-19}$$

$$P_d = Q\left(\frac{\rho}{1+\gamma}\left(Q^{-1}\widetilde{P}_f + \sqrt{N}\right) - \sqrt{N}\right) \tag{3-20}$$

3.3.3 Subband Energy Detector (SED)

The basic functionality to enable dynamic spectrum access for CR is wideband SS to discover more temporarily available frequency bands to fulfill the growing needs of wireless services. However, the necessity of a very high sampling rate in wideband SS for CR, it is difficult to accomplish. Because, that involves either physical unavailability to take a complete set of measurement or very expensive in implementation, particularly for power-constrained SUs. Compressive sensing (CS) is utilized to replace this high-speed ADC to sense the wideband spectrum by utilizing the sparse nature of spectrum occupancy with the most negligible conceivable number of estimations. This method uses Fourier transform and chaotic sequence in designing measurement matrix to have both determinacy and randomness. The Bayesian method is utilized to reconstruct the spectrum from the available measurement and the Max-Min subband ED to decide whether the PU is absent or present.

Wideband energy detection is performed at the subband level at the output of FFT. $Y_k[m]$ is the subband output signal, where m is the subband sample index and where $k = 0..,K-1$ is the subband index. Concerning SS the subband signals can be expressed as follows[56].

$$Y_k[m] = \begin{cases} n_k(m) & H_0 \\ X_k(m) + n_k(m) & H_1 \end{cases} \tag{3-21}$$

Where $X_k(m) \cong S_k(m)H_k$ denotes the PU signal at m^{th} FFT output sample in subband k. H_k is the complex gain of subband k, and $n_k(m)$ is the corresponding noise sample. Additionally, the noise $n_k(m)$can be modelled as a zero-mean Gaussian random variable with variance as $N(0,\sigma_{n,k}^2)$ and $X_k(m)\sim N(0,\sigma_{s,k}^2)$ with $\sigma_{s,k}^2$ denoting the PU signal variance in subband k. For a uniform FFT, the subband noise variances are assumed to be equal, such that

$$\sigma_{n,k}^2 = \frac{\sigma_n^2}{N} \tag{3-22}$$

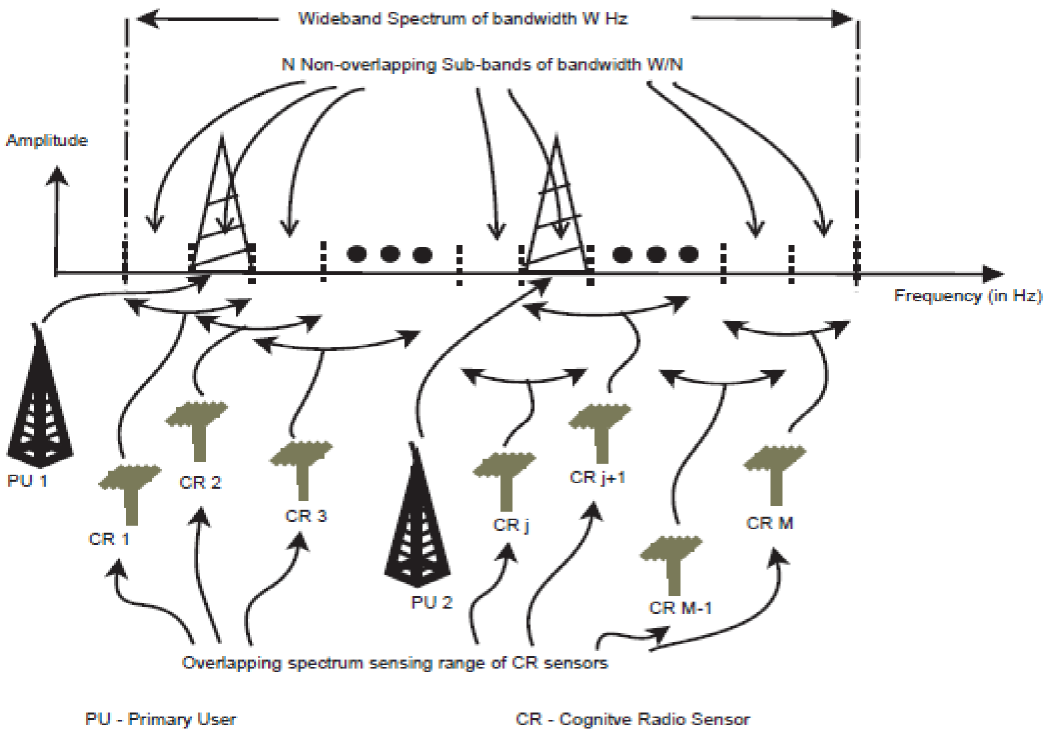

Figure 3-3 Block diagram of sparsely occupied wideband spectrum sensing

The overall subband ED process can be summarized as

$$E_k = \frac{1}{L_t}\sum_{m=1}^{L_t}|Y_k[m]|^2 \tag{3-23}$$

Where $L_t = \frac{N}{N_{FFT}}$ and by using CLT the expected value of energy E_k given by

$$E_k = \begin{cases} N\left(\sigma_{n,k}^2, \frac{2}{L_t}\sigma_{n,k}^4\right) & H_0 \\ N\left(|H_k|^2\sigma_{s,k}^2 + \sigma_{n,k}^2, \frac{2}{L_t}\left(|H_k|^2\sigma_{s,k}^2 + \sigma_{n,k}^2\right)^2\right) & H_1 \end{cases}$$

$$= \begin{cases} N\left(\sigma_{n,k}^2, \frac{2}{L_t}\sigma_{n,k}^4\right) & H_0 \\ N\left(\sigma_{n,k}^2\left(|H_k|^2\frac{\sigma_{s,k}^2}{\sigma_{n,k}^2} + 1\right), \frac{2}{L_t}\left(\sigma_{n,k}^2\left(|H_k|^2\frac{\sigma_{s,k}^2}{\sigma_{n,k}^2} + 1\right)\right)^2\right) & H_1 \end{cases}$$

$$= \begin{cases} N\left(\sigma_{n,k}^2, \frac{2}{L_t}\sigma_{n,k}^4\right) & H_0 \\ N\left(K, \frac{2}{L_t}(K)^2\right) & H_1 \end{cases} \tag{3-24}$$

Where $\zeta_k = \frac{\sigma_{s,k}^2}{\sigma_{n,k}^2}$ is signal to noise ratio of subband k and $K = \sigma_{n,k}^2(|H_k|^2\zeta_k + 1)$

1. **CS-based Maximum-Minimum Energy Detection Based SS**

The Max-Min ED methods are based on subband division and derivation of the test statistic from the subband energies. This method, subdivide and estimate the energies across various subbands over the total detecting frequency band and evaluation of the max-Min subband energy levels or energy differentials. The difference of Max and Min is used as decision measurement and compares with the determined energy threshold.

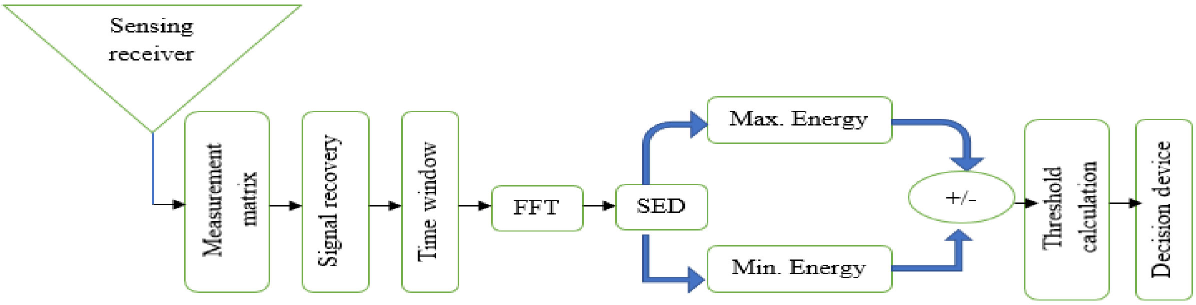

Figure 3-4 Block diagram of CS based ax-Min subband ED

2. **Decision Device and Threshold Calculation**

In the decision stage, the maximum and minimum of the subband energies are resolved. The relating contrast between the maximum and minimum values is compared with a predefined threshold. The desired P_f with the assistance of Gumbel circulation is utilized to acquire the predefined threshold. As per this test when $E_{max-min} = E_{max} - E_{min} > \lambda$

A. Probability of False Alarm and Energy Threshold

The decision statistics rely upon the maximum and minimum value of E_k. Probabilistic extraordinary worth hypothesis manages the stochastic conduct Extreme worth appropriations emerge as restricting distributions arise as limiting distributions for maximums or minimums (extreme values) of a sample of independent, identically distributed random variables. Gumbel emerges concerning the limit of the maximum or minimum of N independent random variables, each with the standard exponential distribution. In view of Gumbel distribution, the maximum extreme value distribution with location parameter a and scale parameter b given by

$$f_{max}(x) = \left(\frac{1}{b}\right) e^{-\frac{x-a}{b}} e^{-e^{-\frac{x-a}{b}}} \tag{3-25}$$

and reversal of the sign of x gives the distribution of the minimum extreme value distribution

$$f_{min}(x) = \left(\frac{1}{b}\right) e^{\frac{x-a}{b}} e^{-e^{\frac{x-a}{b}}} \tag{3-26}$$

Using Gumbel distribution, it is fundamentally basic to determine the expected value and standard deviation of the difference of maximum and minimum value. The n^{th} moment generating a function of the standard extreme value distribution has a simple expression to obtain the moment estimates X which is defined as.

$$E[x^n] = \int_{-\infty}^{\infty} x^n f(x)dx \tag{3-27}$$

When $n = 1$ the corresponding mean value is $\mu = E[x]$ and minimum and maximum energy is derived as:

$$E[E_{max}] = \mu_{max} = \int_{-\infty}^{\infty} x f_{max}(x)dx = \int_{-\infty}^{\infty} x\left(\frac{1}{b}\right) e^{-\frac{x-a}{b}} e^{-e^{-\frac{x-a}{b}}} dx = a - bC \tag{3-28}$$

$$E[E_{min}] = \mu_{min} = \int_{-\infty}^{\infty} x f_{min}(x)dx = \int_{-\infty}^{\infty} x\left(\frac{1}{b}\right) e^{\frac{x-a}{b}} e^{-e^{\frac{x-a}{b}}} dx = -a + bC \tag{3-29}$$

Where $C = 0.577215665$ is the Euler's constant.

Consequently, the expected value of the difference of the maximum and minimum values is expressed as, $\mu_{max-min} = E[E_{max-min}] = a - bC - (-a + bC) = 2a - 2bC$. From equation (**3-24**)expected mean value is $\sigma_{n,k}^2$ and the location parameter can be determined by

$$a = \frac{E[E_{max-min}] + 2bC}{2} = \frac{\sigma_{n,k}^2 + 2bC}{2} \tag{3-30}$$

Likewise, the corresponding variances are obtained by

$$\sigma_{min}^2 = var[E_{min}] = \frac{1}{b}\int_{-\infty}^{\infty} (x - E[E_{min}])^2 e^{\frac{x-a}{b}} e^{-e^{\frac{x-a}{b}}} dx = \frac{\pi^2 b^2}{6} \tag{3-31}$$

$$\sigma_{max}^2 = var[E_{max}] = \frac{1}{b}\int_{-\infty}^{\infty} (x - E[E_{max}])^2 e^{-\frac{x-a}{b}} e^{-e^{-\frac{x-a}{b}}} dx = \frac{\pi^2 b^2}{6} \tag{3-32}$$

By recalling that

$$Var(X \pm Y) = Var(X) + Var(Y) \tag{3-33}$$

When X and Y are mutually independent, it immediately follows that

$$Var(E_{max} - E_{min}) = Var(E_{max}) + Var(E_{min}) \tag{3-34}$$

Which gives

$$\sigma_{max-min}^2 = 2Var(E_{max}) = \frac{\pi^2 b^2}{3} \tag{3-355}$$

and the scale parameter can be determined by

$$b = \frac{\sqrt{3\sigma_{max-min}^2}}{\pi} \tag{3-36}$$

Using the already mentioned parameter representation of the Gumbel distribution with mean and variance values of E_k for the H_0 hypothesis one obtains the expected variance (**3-24**) for H_0 is $Var(E_{max}) = \sigma^2_{max-min} = \frac{2}{L_t}\sigma^4_{n,k}$ the scale parameter which is variance of X is determined as

$$b|^2_{H_0} = \frac{\sqrt{3\sigma^2_{max-min}}}{\pi} = \frac{\sqrt{3\frac{2}{L_t}\sigma^4_{n,k}}}{\pi} = \sqrt{\frac{6}{L_t}}\frac{\sigma^2_{n,k}}{\pi}$$

and the standard deviation is given by

$$b|_{H_0} = \sqrt{\sqrt{\frac{6}{L_t}}\frac{K}{\pi}} = \left(\frac{6}{L_t}\right)^{\frac{1}{4}}\sqrt{\frac{\sigma^2_{n,k}}{\pi}} \tag{3-37}$$

Similarly, the expected mean (**3-24**) difference for H_0 is $E[E_{max-min}] = \sigma^4_{n,k}$

$$a|_{H_0} = \frac{E[E_{max-min}] + 2bC}{2} = \frac{\sigma^4_{n,k} + 2C\sqrt{\frac{6}{L_t}}\frac{\sigma^2_{n,k}}{\pi}}{2} = \frac{\sigma^4_{n,k}}{2} + C\sqrt{\frac{6}{L_t}}\frac{\sigma^2_{n,k}}{\pi} \tag{3-38}$$

The standard Gumbel distribution function is given by

$$P[X \le x] = e^{\left(-e^{\left(\frac{x-a}{b}\right)}\right)} \tag{3-39}$$

Where a is the mean and b standard deviation of X and using equation (**3-37**), (**3-38**), (**3-39**)

$$P_f = P\left(E_{max-min}|_{H_0} > \lambda\right) = 1 - P\left(E_{max-min}|_{H_0} \le \lambda\right)$$

$$P_f = 1 - e^{\left(-e^{\left(\frac{\lambda - a|_{H_0}}{b|_{H_0}}\right)}\right)}$$

$$P_f = 1 - exp\left(-exp\left(\frac{\lambda - \left(\frac{\sigma^4_{n,k}}{2} + C\sqrt{\frac{6}{L_t}}\frac{\sigma^2_{n,k}}{\pi}\right)}{\sqrt{\frac{6}{L_t}}\frac{\sigma^2_{n,k}}{\pi}}\right)\right) \tag{3-40}$$

In realistic situations, NU must be considered in the expressions of P_f and P_d. It is recalled that the noise distribution can be summarized in the range by $\sigma^2_{n,k} \epsilon \left[\left(\frac{1}{\rho}\right)\sigma^2_{n,k}, \rho\sigma^2_{n,k}\right]$ where ρ presents the corresponding NU parameter[56]. As a result, the P_f with NU can be expressed as follows:

$$P_f = 1 - \max_{\sigma^2_{n,k} \epsilon \left[\left(\frac{1}{\rho}\right)\sigma^2_{n,k}, \rho\sigma^2_{n,k}\right]} exp\left(-exp\left(\frac{\lambda - \left(\frac{\sigma^4_{n,k}}{2} + C\sqrt{\frac{6}{L_t}}\frac{\sigma^2_{n,k}}{\pi}\right)}{\left(\frac{6}{L_t}\right)^{\frac{1}{4}}\sqrt{\frac{\rho}{\pi}}\sigma_{n,k}}\right)\right)$$

$$P_f = 1 - exp\left(-exp\left(\frac{\lambda - \left(\frac{\rho\sigma_{n,k}^4}{2} + C\sqrt{\frac{6}{L_t}}\frac{\rho\sigma_{n,k}^2}{\pi}\right)}{\left(\frac{6}{L_t}\right)^{\frac{1}{4}}\sqrt{\frac{\rho}{\pi}}\sigma_{n,k}}\right)\right) \quad (3\text{-}41)$$

The threshold can be determined by

$$\lambda = \frac{\rho\sigma_{n,k}^4}{2} + C\sqrt{\frac{6}{L_t}}\frac{\rho\sigma_{n,k}^2}{\pi} + \left(\frac{6}{L_t}\right)^{\frac{1}{4}}\sqrt{\frac{\rho}{\pi}}\sigma_{n,k}\ln\left(\ln\left(\frac{1}{1-P_f}\right)\right) \quad (3\text{-}42)$$

B. Probability of detection

Using the distribution parameters a and b with mean and variance values of E_k in the case of P_f, the H_1 hypothesis can be expressed as: The expected variance difference for (**3-24**) H_1 is $Var(E_{max}) = \sigma_{max-min}^2 = \frac{2}{L_t}(K)^2$

$$b|_{H_1}^2 = \frac{\sqrt{3\sigma_{max-min}^2}}{\pi} = \frac{\sqrt{3\frac{2}{L_t}(K)^2}}{\pi} = \sqrt{\frac{6}{L_t}}\frac{K}{\pi} \quad (3\text{-}43)$$

$$b|_{H_1} = \sqrt{\sqrt{\frac{6}{L_t}}\frac{K}{\pi}} = \left(\frac{6}{L_t}\right)^{\frac{1}{4}}\sqrt{\frac{K}{\pi}} \quad (3\text{-}44)$$

So, from variance the standard deviation is calculated as shown in (**3-44**)

Similarly, the expected mean difference (**3-24**) for H_1 is $E[E_{max-min}] = K$

$$a|_{H_1} = \frac{E[E_{max-min}] + 2bC}{2} = \frac{K + 2C\sqrt{\frac{6}{L_t}}\frac{K}{\pi}}{2} = \frac{K}{2} + C\sqrt{\frac{6}{L_t}}\frac{K}{\pi} \quad (3\text{-}45)$$

Probability occur when the minimum value of $E_k|_{H_1}$ should greater than the predefined threshold and the corresponding P_d is given by

$$P_d = P\left(E_{max-min}|_{H_1} > \lambda\right) = 1 - P\left(E_{max-min}|_{H_1} \le \lambda\right) = 1 - exp\left(-exp\left(\frac{\lambda - a|_{H_1}}{b|_{H_1}}\right)\right)$$

$$= 1 - exp\left(-exp\left(\frac{\lambda - \left(\frac{K}{2} + C\sqrt{\frac{6}{L_t}}\frac{K}{\pi}\right)}{\left(\frac{6}{L_t}\right)^{\frac{1}{4}}\sqrt{\frac{K}{\pi}}}\right)\right) \quad (3\text{-}46)$$

The probability of detection with noise uncertainty is given as follows

$$P_d = 1 - \min_{\sigma_{n,k}^2 \epsilon \left[\left(\frac{1}{\rho}\right)\sigma_{n,k}^2,\, \rho\sigma_{n,k}^2\right]} e^{\left(-e^{\left(\frac{\lambda - a|_{H_1}}{b|_{H_1}}\right)}\right)} = 1 - exp\left(-exp\left(\frac{\lambda - \left(\frac{K}{2} + C\sqrt{\frac{6}{L_t}}\frac{K}{\pi}\right)}{\left(\frac{6}{L_t}\right)^{\frac{1}{4}}\sqrt{\frac{K}{\pi}}}\right)\right)$$

$$= 1 - exp\left(-exp\left(\frac{\lambda - \left(\frac{K'}{2} + C\sqrt{\frac{6}{L_t}}\frac{K'}{\pi}\right)}{\left(\frac{6}{L_t}\right)^{\frac{1}{4}}\sqrt{\frac{K'}{\pi}}}\right)\right) \tag{3-47}$$

Where $K' = \frac{\sigma_{n,k}^2}{\rho}(|H_k|^2\zeta_k + 1)$

3.3.4 Sensing-Throughput Tradeoff for CS based Max-Min subband ED

In this section, we study the compromise between detecting ability and attainable throughput of the networks. Using the CS based subband Max-Min ED scheme, we'll prove that there indeed exists the optimal sensing time with which the great throughput for the secondary network is accomplished, yet PUs is genuinely ensured.

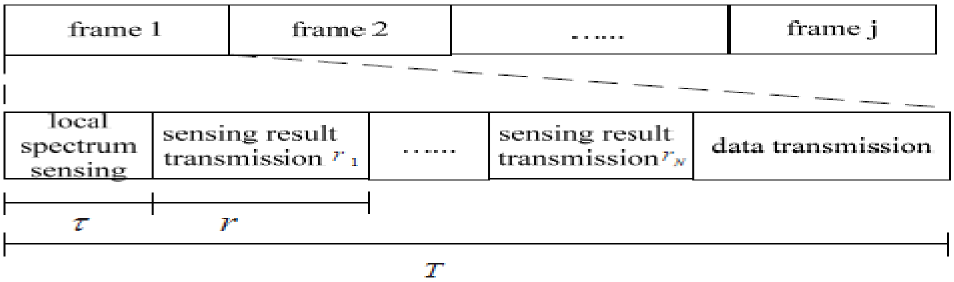

Figure 3-5 Frame structure for cooperative spectrum sensing

Figure 3-5 shows the frame structure designed for CSS in a CR network where each frame consists sensing slot τ and result reporting slot r and data transmission $T_t = T - Nr - \tau$. During data transmission, a CR transmits its data when the channel is idle. Here we are going to see optimization of three parameters to maximize EE. Sensing time, number of SUs and fusion threshold optimization.

A. Sensing time optimization

There is also a tradeoff between the selected N and τ from one side and the achieved throughput from the other side. Increasing the number of SUs leads to higher accuracy in the received sensing results, which improves the attainable throughput. Likewise, expanding the detecting time for every user prompt leads to an increase in the number of energy samples which improves the accuracy of sensing results. Then again, more energy samples will decrease the transmission time, which decreases throughput. Consequently, it is important to choose τ and N so that, the throughput is amplified. Denote C_0 and C_1 to the throughput of the network when it operates within the absence and presence of PUs respectively. For example, if there is just one point-to-point transmission in the secondary network and the SNR for this secondary link is $SNR_s = P_s/N_0$ where P_s the received power of the SU and N_0 is the noise power.

Let Pp be the obstruction intensity of PU estimated at the secondary receiver, and assume that the PU's signal and SU's signal are Gaussian, white, and autonomous of one another. Then

$$C_0 = log2(1 + SNR_s) \tag{3-48}$$

$$C_1 = log2\left(1 + \frac{P_s}{Pp + N_0}\right) = log2\left(1 + \frac{SNR_s}{1 + SNR_p}\right) \tag{3-49}$$

Where $SNR_p = P_p/N_0$ We have $C_0 > C_1$.

Then the average throughput of the CRN in [60]can be written as

$$Th(\lambda, N, \tau) = C_0 P(H_0)(1 - \tilde{P}_f)T_t \tag{3-50}$$

The average energy consumption by the CRN can be expressed as

$$E(\lambda, N, \tau) = f + g\left(1 - \tilde{P}_d\right) + h(1 - \tilde{P}_f) \tag{3-51}$$

Where $f(\tau) = N_s(E_s\tau + E_t\tau)$, $g(\tau) = P(H_1)E_tT_t$, $h(\tau) = P(H_0)E_tT_t$

Then the energy efficiency is given as

$$\mu(\lambda,, N_s, \tau) = \frac{Th(\lambda,, N_s, \tau)}{E(\lambda,, N_s, \tau)} = \frac{C_0 P(H_0)(1 - \tilde{P}_f)T_t}{f(\tau) + g(\tau)\left(1 - \tilde{P}_d\right) + h(\tau)(1 - \tilde{P}_f)} \tag{3-52}$$

let $\omega(\tau) = C_0 P(H_0)T_t$

Here we study the influence of sensing time on energy efficiency. The optimization model is established and relationship between energy efficiency and sensing time is derived.

1. **Establishment of optimization model**

Assuming that λ, N, τ are given, the optimization model of optimizing defined in the equation

$$\underset{s.t\ 0 \le \tau \le \Gamma}{\overset{max}{\tau}} \mu = \frac{\omega(\tau)(1 - \tilde{P}_f)}{f(\tau) + g(\tau)\left(1 - \tilde{P}_d\right) + h(\tau)(1 - \tilde{P}_f)} \tag{3-53}$$

We assume that the distances between SUs are much smaller than the distances between SUs and the PU, so each SU experiences almost similar pathloss, and has the same average PU's signal to noise ratio which is described as γ. Using SED, setting the threshold of the SU as λ, false alarm probability and detection probability can be expressed as

$$P_f = 1 - exp\left(-exp\left(\frac{\lambda - \left(\frac{\rho\sigma_{n,k}^4}{2} + C\sqrt{\frac{6}{L_t}}\frac{\rho\sigma_{n,k}^2}{\pi}\right)}{\left(\frac{6}{L_t}\right)^{\frac{1}{4}}\sqrt{\frac{\rho}{\pi}}\sigma_{n,k}}\right)\right) \tag{3-54}$$

$$P_d = 1 - exp\left(-exp\left(\frac{\lambda - \left(\frac{K'}{2} + C\sqrt{\frac{6}{L_t}}\frac{K'}{\pi}\right)}{\left(\frac{6}{L_t}\right)^{\frac{1}{4}}\sqrt{\frac{K}{\pi}}}\right)\right) \tag{3-55}$$

Using $k\ out\ of\ N$ decision fusion rule or majority rule, the global false alarm probability and detection probability are expressed as follows, respectively

$$Q_{f,AMAJORITY} = \sum_{i=k}^{N_s} \binom{N_s}{i} P_f (1 - P_f)^{N_s - i} \tag{3-56}$$

$$Q_{d,MAJORITY} = \sum_{i=k}^{N_s} \binom{N_s}{i} P_d (1 - P_d)^{N_s - i} \tag{3-57}$$

From (**3-50**),(**3-51)**,(**3-56**),(**3-57**) we can see that τ affects both the average throughput and the energy consumed by the CRN, therefore it has influence on energy efficiency. To save the sensing time and obtain the maximal energy efficiency, the optimization of τ is considered and the solving algorithm is given below.

2. The Characteristic of Objective Function

For the energy efficiency and sensing time, there is the following lemma:

Lemma 1: Energy efficiency is a unimodal function in terms of sensing time τ.

Proof: to prove $\mu(\tau)$ is a unimodal function in terms of τ, we need to prove that the derivative of $\mu(\tau)$ is 0. Then there will be only one solution in the domain $[0, T - Nr]$ of τ. Let

$$\mu(\tau) = \frac{B}{A} \tag{3-58}$$

Where $A = f(\tau) + g(\tau)\left(1 - \tilde{P}_d\right) + h(\tau)(1 - \tilde{P}_f)$, and $B = \omega(\tau)(1 - \tilde{P}_f)$

From $\frac{d\mu(\tau)}{d\tau} = 0$, we have $\frac{B'A - A'B}{A^2} = 0$,

$$B'A - A'B = 0 \tag{3-59}$$

Where B' and A' are derivatives of B and A with respect to τ, in order to obtain B' and A'. We need get the following derivatives,

$$\omega'(\tau) = -C_0 P(H_0) \tag{3-60}$$

$$f'(\tau) = N_s E_s \tag{3-61}$$

$$g'(\tau) = -P(H_1) E_t \tag{3-62}$$

$$h'(\tau) = -P(H_0) E_t \tag{3-63}$$

Where E_s energy consumption for local sensing, for reporting E_r, and data transmission E_t

The derivatives of $Q_f(\tau)$ and $Q_d(\tau)$ in terms of τ are shown below

$$\nabla Q_f = \frac{dQ_f(\tau)}{d\tau} = \nabla P_f \sum_{i=k}^{N_s} \binom{N_s}{i} P_f^{i-1} * \left(1 - P_f\right)^{N_s - i} \left(i - (N_s - i)\frac{P_f}{1 - P_f}\right) \tag{3-64}$$

$$\nabla Q_d = \frac{dQ_d(\tau)}{d\tau} = \nabla P_d \sum_{i=k}^{N_s} \binom{N_s}{i} P_d^{i-1} * (1 - P_d)^{N_s - i} \left(i - (N_s - i)\frac{P_d}{1 - P_d}\right) \tag{3-65}$$

Where

$$\nabla P_f = -exp\left(-exp\left(\frac{x - Cy^2z^2}{yz}\right)\right)\left[\frac{Cz}{2y}\left(\sqrt{6N_{FFT}}(\tau f_s)^{\frac{-3}{2}}\right) + \frac{1}{4y^2z}(6N_{FFT})^{\frac{1}{4}}(\tau f_s)^{\frac{-7}{4}}(x - Cy^2z^2)\right] \quad (3\text{-}66)$$

Where $L_t = \frac{N}{N_{FFT}}$ also $N = \tau f_s$ and Let $x = \lambda - \frac{\rho\sigma_{n,k}^4}{2}$, $y = \left(\frac{6N_{FFT}}{\tau f_s}\right)^{\frac{1}{4}}$, and $z = \sqrt{\frac{\rho}{\pi}}\sigma_{n,k}$

$$\nabla P_d = -exp\left(-exp\left(\frac{x - Cy^2z^2}{yz}\right)\right)\left[\frac{Cz}{2y}\left(\sqrt{6N_{FFT}}(\tau f_s)^{\frac{-3}{2}}\right) + \frac{1}{4y^2z}(6N_{FFT})^{\frac{1}{4}}(\tau f_s)^{\frac{-7}{4}}(x - Cy^2z^2)\right] \quad (3\text{-}67)$$

Let $x = \lambda - \frac{K'}{2}$, $y = \left(\frac{6N_{FFT}}{\tau f_s}\right)^{\frac{1}{4}}$, and $z = \sqrt{\frac{K'}{\pi}}$, Where $K' = \frac{\sigma_{n,k}^2}{\rho}(|H_k|^2\zeta_k + 1)$

So, the derivatives of A and B with respect to τ are given as follows,

$$B' = -C_0P(H_0)(1 - \tilde{P}_f(\tau)) - \omega'(\tau)\nabla P_f \quad (3\text{-}68)$$

$$A' = -P(H_1)E_t(1 - \tilde{P}_d(\tau)) - g(\tau)\nabla P_d - P(H_0)E_t(1 - \tilde{P}_f(\tau)) - h(\tau)\nabla P_f \quad (3\text{-}69)$$

Taking the above equation (**3-68**) and (**3-69**) into (**3-59**), according to the method in [61], we can obtain that $\mu(\tau)$ is a unimodal and there is only one optimal value τ in the domain [0,Γ].

Solution by golden section search

Golden Section Search (GSS) algorithm is a valid technique for finding the extremum (minimum or maximum) of a unimodal function[62]. Here, the golden section search is introduced to find the optimal τ maximizing the energy efficiency.

I. Golden Section Search (GSS)

GSS is discovered by Kiefer in 1953. The technique derives its name from the fact that the algorithm maintains the function values for triples of points whose distances form a golden ratio. Consider a function f (x) over the interval $[a, b]$. We assume that f (x) is continuous and unimodal over $[a, b]$, i.e., f(x) has only one minimum in $[a, b]$. Note that the method applies as well to find the maximum. For a unimodal function, we have the following theorem:

Theorem 1: Assuming $f: R \rightarrow R$ is a unimodal function in interval $[a, b]$, $a \leq x_1 < x_2 \leq b$.

$$\text{If } f(x_1) \geq f(x_2),\ x^* \in [x_1, b]$$

$$\text{If } f(x_1) < f(x_2),\ x^* \in [a, x_2]$$

Let $x_1 = a + 0.382\ (b - a)$, and Let $x_2 = a + 0.618\ (b - a)$.

According to Theorem 1, we can remove $[a, x_1]$or $[x_2, b]$by comparing the value of $f(x_1)$ and $f(x_2)$. GSS guarantees the new searching interval just 0.618 times the size of the original interval. The process is iterative and will stop until the size of the searching interval is small.

II. The Optimal Sensing Time by GSS

Since energy efficiency is a unimodal function regarding sensing time in interval [0, Γ], the golden section search algorithm can be utilized to acquire the optimal value. In general, the minimum will be acquired by golden section search. So, we change the object function to minimize the $-\mu(\tau)$to find the optimal sensing time. The sensing time optimization algorithm to maximize the energy efficiency can be separated into 4 steps as follows.

Algorithm 1: Sensing Time Optimization Algorithm

Step 1: Initialization

Let $[a, b]$ be the interval of GSS algorithm whose initial values are $a = 0, b = T - Nr$, respectively. $\tau_1$and τ_2 are corresponding to $x_1$and x_2 respectively in theorem 1. Let ζ be a small number using as the iteration threshold

Step 2: Computation Of τ_1 and τ_2

$$\tau_1 = a + 0.382\,(b - a)$$

$$\tau_2 = a + 0.618\,(b - a)$$

Step 3: Iteration

While $b - a > \zeta$

If $\mu(\tau_2) > \mu(\tau_1)$, we have $a = \tau_1$, $\tau_1 = \tau_2$, $\tau_2 = a + 0.618\,(b - a)$

Else

$b = \tau_2$, $\tau_2 = \tau_1$, $\tau_1 = a + 0.382(b - a)$

Step 4: Obtainment of Optimal Value

The optimal sensing time is

$$\tau^* = \frac{(a + b)}{2}$$

Then, the maximum energy efficiency can be obtained according to equation (**3-58**)

B. Energy Consumption Minimization

In this research, we adopt opportunistic CR access[63], where the spectrum is exploited only if it has been identified as free in the CSS process. Hence, the probability of transmitting data is given by the probability of identifying the spectrum as free during CSS, regardless of the actual status of the spectrum. We denote this probability by P_{free} and it can be computed as follows:

$$P_{free} = P(H_1)(1 - P_D) + P(H_0)(1 - P_f) \tag{3-70}$$

Where $P(H_0)$ and $P(H_1)$ is the probability that the spectrum is unused and used respectively. For both terms we have assumed 0.5.

Since $P_D = \tilde{P}_D$, and $P_f = \tilde{P}_f$according to **(3-9)** and (**3-13**)

$$P_{free} = P(H_1)(1 - \tilde{P}_D) + P(H_0)(1 - \tilde{P}_f) \tag{3-71}$$

Therefore, the energy consumed as a function of N_s is given as follows:

$$E(N_s) = E_s(N_s) + E_r(N_s) + P_{free}E_t \tag{3-72}$$

Where the energies E_s, E_r and E_t are expressed as follows

$$E_s(N) = N\tau\rho_s \tag{3-73}$$

$$E_r(N) = Nr\rho_r \tag{3-74}$$

$$E_t(N) = (T - Nr - \tau)\rho_t \tag{3-75}$$

Where ρ_s, $\rho_r$and ρ_t, are the powers consumed per each SU for local sensing, results' reporting, and data transmission, respectively.

We have seen energy consumption but now we are going to minimize the consumption of energy to have an energy-efficient system. Various numbers of SUs lead to various time distribution between sensing and reporting, and hence different energy consumption. Besides, increasing N results in a lower PF which increases the energy consumed during the data transmission sub-frame. In this subsection, we streamline the number of SUs for minimum energy consumption.

The energy minimization problem can be formulated as follows:

$$\underset{N}{min}\, E(N) = \underset{N}{min}\, E_s(N) + E_r(N) + P_{free}E_t \tag{3-76}$$

By substituting values of $E_s, E_r\ and\ P_{free}$ from (**3-71**), (**3-73**), (**3-74**), and (**3-75**) we get

$$\underset{N}{min}\, E(N) = \underset{N}{min}\, N(\tau\rho_s + r\rho_r) + P(H_1)(1 - \tilde{P}_D) + P(H_0)(1 - \tilde{P}_f)T_t\rho_t \tag{3-77}$$

It is easy to prove that E_T is a concave function of $N \in [1, N_T]$. Because the concavity of E_T can be shown using the second derivative test $\left(\frac{\partial^2 y}{\partial^2 x} < 0\right)$.

Hence, the local minimum values occur at the bounds of the interval, i.e., $N = 1, N_T$. Then, the optimal number of sensing users that limits energy utilization can be expressed as follows:

$$N^{optE} = \begin{cases} 1, & if\ E_T(1) \le E_T(N_T) \\ N_T, & if\ E_T(1) > E_T(N_T) \end{cases} \tag{3-78}$$

Where $E(1)$ and $E(N_T)$ the total energy consumption when the $N = 1, N_T$, respectively, and can be obtained using the energy utilization formula which is expressed in equation (**3-72**).

Notice that the number of accessible CUs is limited by N_{max} . since the time resources are limited, the maximum number of sensing users can be expressed as follows:

$$N_{max} = \left\lceil \frac{T - T_t}{\tau} - 1 \right\rceil \tag{3-79}$$

Where $\lceil . \rceil$ is the ceiling operator

Here, we are going to find N_s which amplifies energy efficiency. To solve this maximization, we will use the bisection algorithm. The procedure of the proposed algorithm is illustrated using the pseudo code as described in Algorithm 1[64].

Algorithm 2: Sensing node optimization

Initialization: set $N_{s,min} = 1$ and $N_{s,max} = \frac{T-T_t}{\tau} - 1$

Define $i = 1$

While $i \neq 1$ do

$N_s = \frac{N_{s,min}+N_{s,max}}{2}$

Compute $\mu(N_s - 1), \mu(N_s), and\ \mu(N_s + 1)$

If $\mu(N_s + 1) > \mu(N_s) > \mu(N_s - 1)$ then

$N_{s,min} = N_s$

end

If $\mu(N_s + 1) < \mu(N_s) < \mu(N_s - 1)$ then

$N_{s,max} = N_s$

end

If $\mu(N_s + 1) \leq \mu(N_s)$ and $\mu(N_s) \geq \mu(N_s - 1)$

${N_s}^{opt\mu}$

end

end

C. Fusion Threshold Optimization

In a CRN, it is conceivable that the FC doesn't criticism any information to the SUs to control their detecting parameters due to a lack of feedback channel. For this situation, the N SUs can choose their own thresholds by fixing their P_f at a predefined value. After the FC gets the N detecting decisions, it will enhance its own fusion rule threshold k, to maximize the EE of the CRN. The problem formulation to be solved by the FC for a given λ, N, and τ is given by[60].

$$\max_{k} \mu(k) = \frac{\omega(\tau)(1 - \tilde{P}_f)}{f(\tau) + g(\tau)\left(1 - \tilde{P}_d\right) + h(\tau)(1 - \tilde{P}_f)} \tag{3-79}$$

Where $\omega(\tau) = C_0 P(H_0)(\Gamma - \tau)$

The k value that maximizes (k, λ) is obtained when $\frac{\partial f(k,\lambda)}{\partial \lambda} = 0$

$$k = \left\lceil \frac{\log\left(\frac{\omega - \lambda z}{\lambda y}\right) - N\log\left(\frac{1-P_d}{1-P_f}\right)}{\log\left(\frac{P_d}{P_f}\right) - \log\left(\frac{1-P_d}{1-P_f}\right)} \right\rceil \tag{3-80}$$

Where $\lceil . \rceil$ ceiling function since $k \geq 1$

$$\log\left(\frac{\omega - \lambda z}{\lambda y}\right) - N\log\left(\frac{1-P_d}{1-P_f}\right) > 0 \tag{3-81}$$

We obtain

$$\lambda < \frac{\omega}{y\left(\frac{1-P_d}{1-P_f}\right)^N + z} \tag{3-82}$$

Algorithm 3: Fusion Threshold Optimization

Initialization $\lambda_{min} = 0, \lambda_{max} = \frac{\omega}{y\left(\frac{1-P_d}{1-P_f}\right)^N + z}; k_{\lambda_{min}} = 1; k_{\lambda_{max}} = N$

While $\lambda_{max} - \lambda_{min} > \rho, \rho$ is tolerable error of λ

$$\lambda = \frac{\lambda_{max} + \lambda_{min}}{2}$$

$$k = \left\lceil \frac{\log\left(\frac{\omega - \lambda z}{\lambda y}\right) - N\log\left(\frac{1-P_d}{1-P_f}\right)}{\log\left(\frac{P_d}{P_f}\right) - \log\left(\frac{1-P_d}{1-P_f}\right)} \right\rceil$$

If $g(\lambda) > 0$ then

$\lambda_{min} = \lambda; k_{\lambda_{min}} = k$

Else

$\lambda_{max} = \lambda; k_{\lambda_{max}} = k$

End if

End while

Output: k

D. Energy Efficiency Maximization

Energy efficiency is characterized as the proportion of throughput to energy consumption. Hence, maximizing it achieves the balance point between energy utilization and average throughput. Energy efficiency can be maximized as follows:

$$\max_{(k, N_s{}^{opt\mu}, \tau^*)} \mu(\lambda^*, k, N_s{}^{opt\mu}, \tau^*) = max \frac{C_0 P(H_0)(1 - \tilde{P}_f)(\Gamma - \tau)}{f(\tau) + g(\tau)\left(1 - \tilde{P}_d\right) + h(\tau)(1 - \tilde{P}_f)} \tag{3-83}$$

Where $f(\tau) = N_s(E_s\tau + E_t\tau)$, $g(\tau) = P(H_1)E_t(\Gamma - \tau)$, $h(\tau) = P(H_0)E_t(\Gamma - \tau)$

Chapter 4 : Results and Discussion

4.1 Introduction

In this chapter, we simulate based on the previous chapter concept and interpret the simulation results using MATLAB R2018a for spectrum sensing techniques. On the other hand, simulations in this work are executed using the Monte Carlo (MC) method which is a stochastic technique based on the use of random numbers. The parameters used for simulation are given in Table 4-1 Performance requirements for the sensing algorithm can be described by metrics including the probability of false alarm, probability of detection, probability of miss detection.

Table 4-1 Simulation Parameters

Parameter	**Value**
Target Probability of detection	≥ 0.9
Target probability of false alarm	≤ 0.1
Energy consumption during data transmission (E_t)	$3w$
Energy consumption during local sensing (E_s)	$0.1w$
Sampling frequency (f_s)	$6MHz$
Frame length (T)	$100ms$
Noise uncertainty (ρ)	$(0-1)dB$
Euler's constant(C)	0.577215665
Length of FFT	$8,16$
Number of samples	10201
Average SNR	$-15\ up\ to - 25dB$

4.2 Result and Discussion for Spectrum Recovery

From Shannon-Nyquist theorem in order to guarantee the recovery of the signal from a lot of consistently dispersed samples the signal must be sampled at a rate which is twice as the highest frequency in the signal's spectrum. Hence, the highest frequency spectrum is 5,000 Hz, so we need 10000sample/sec in order to recover the spectrum. The simulation result shows that the recovered spectrum from only 200 samples without adding distortion in the recovered spectrum.

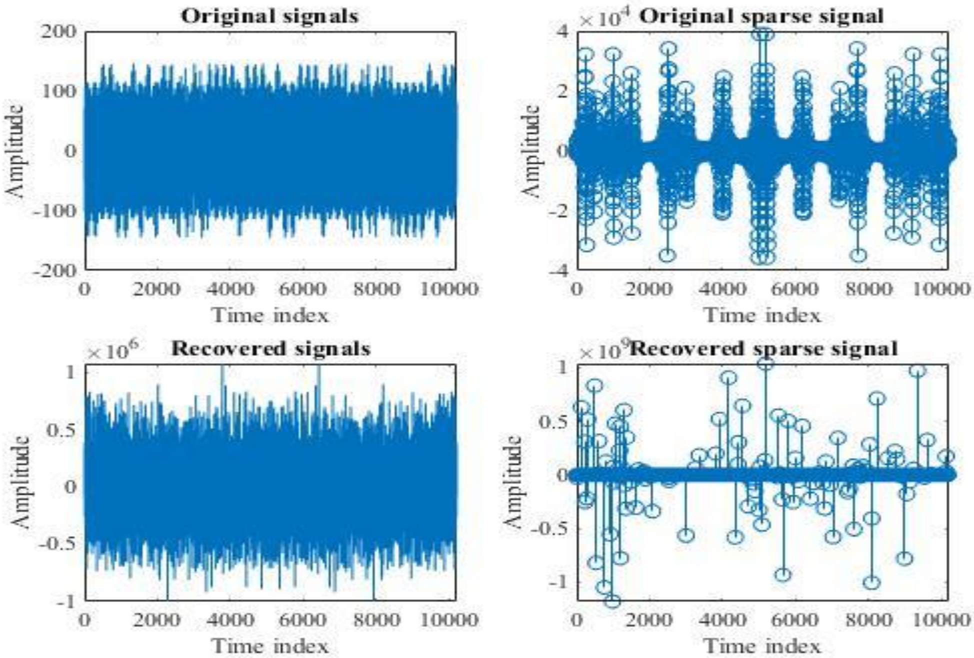

Figure 4-1Spectrum recovery from incomplete sample using Bayesian method

4.3 Result and Discussion for Conventional and CS Based Max-Min Subband ED

Figure 4-2 and ***Figure 4-3*** presents the simulation of Probability of detection and Probability of missed detection Vs probability of false alarm for different NU respectively. Here we have used two N_{FFT} size 8 and 16. The performance is evaluated based on NU from $0 - 1$dB.

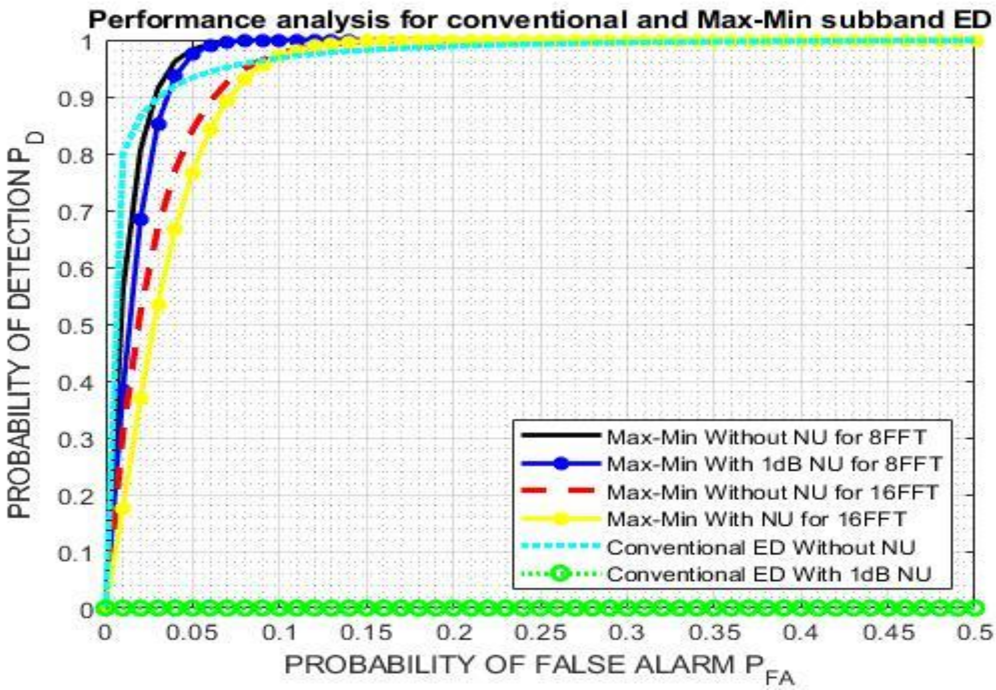

Figure 4-2 Probability of detection Vs probability of false alarm for different NU

The simulation results indicate that the proposed system which is Max-Min subband ED can effectively minimizes the NU effect. The detection performance degrades significantly with a small change in NU in conventional ED. Whereas the detection performance degradation is negligible in the proposed system compared to conventional ED. From this we can understand that the noise uncertainty variation highly influences the detection performances both conventional and max-min subband method, also as the FFT length increases the detection performances decreases as shown in max-min subband method. In the below table we have listed out comparison of conventional and Max-min subband ED using $P_f = 0.05$.

Table 4-2 Pd comparison between conventional and Max-min subband ED with d/t NU

NU	Spectrum sensing method		
	Conventional ED	Max-Min subband ED	
		8FFT	16FFT
0dB	0.945	0.975	0.825
1dB	0	0.985	0.815

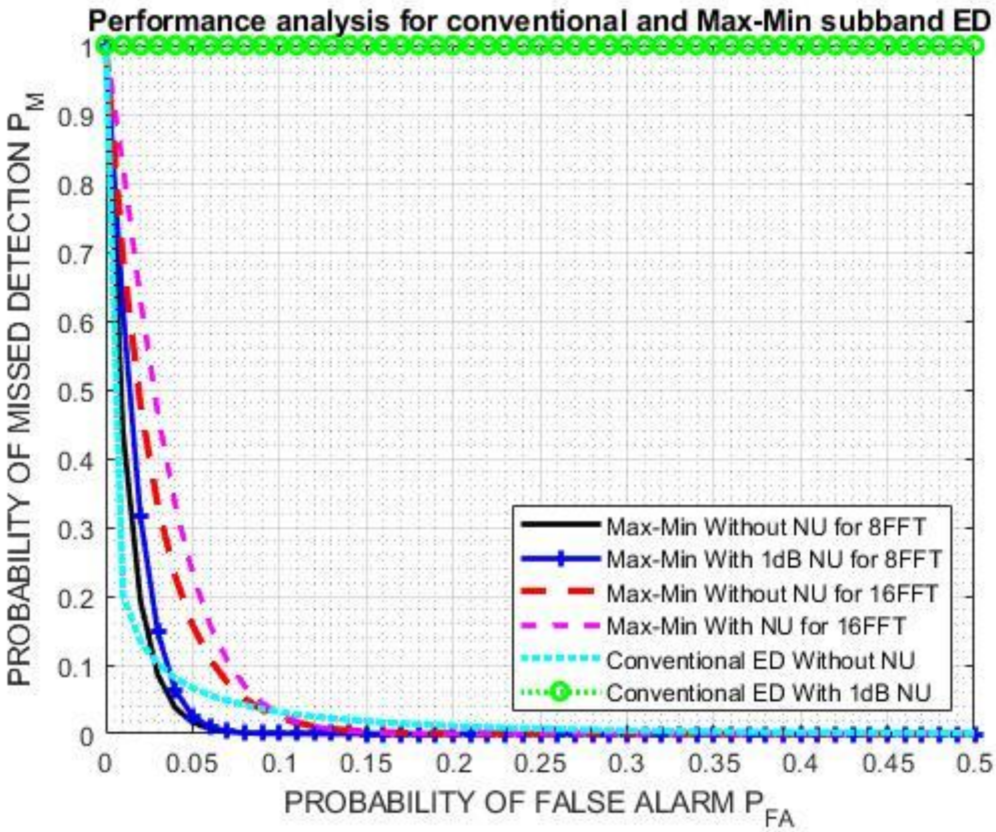

Figure 4-3 Probability of missed detection Vs probability of false alarm for d/t NU

Table 4-3Pm comparison between conventional and Max-min subband ED with d/t NU

Noise uncertainty	Spectrum sensing method		
	Conventional ED	Max-Min subband ED	
		8FFT	16FFT
0dB	1	0.05	0.15
1dB	0.095	0.045	0.2

4.3 Result and Discussion for Applying CS in Max-Min Subband ED

Probability of detection and missed detection Vs false alarm probability is evaluated using different values of NU in **Figure 4-4,** and **Figure 4-5** respectively for applying CS on Max-Min subband ED. Conventional narrowband spectrum sensing can be used with Max-Min ED whereas here we use both with and without CS, which means Max-min using narrowband and wideband spectrum sensing. In these figures we have uses N_{FFT} of 8 and 16 with and without noise uncertainty.

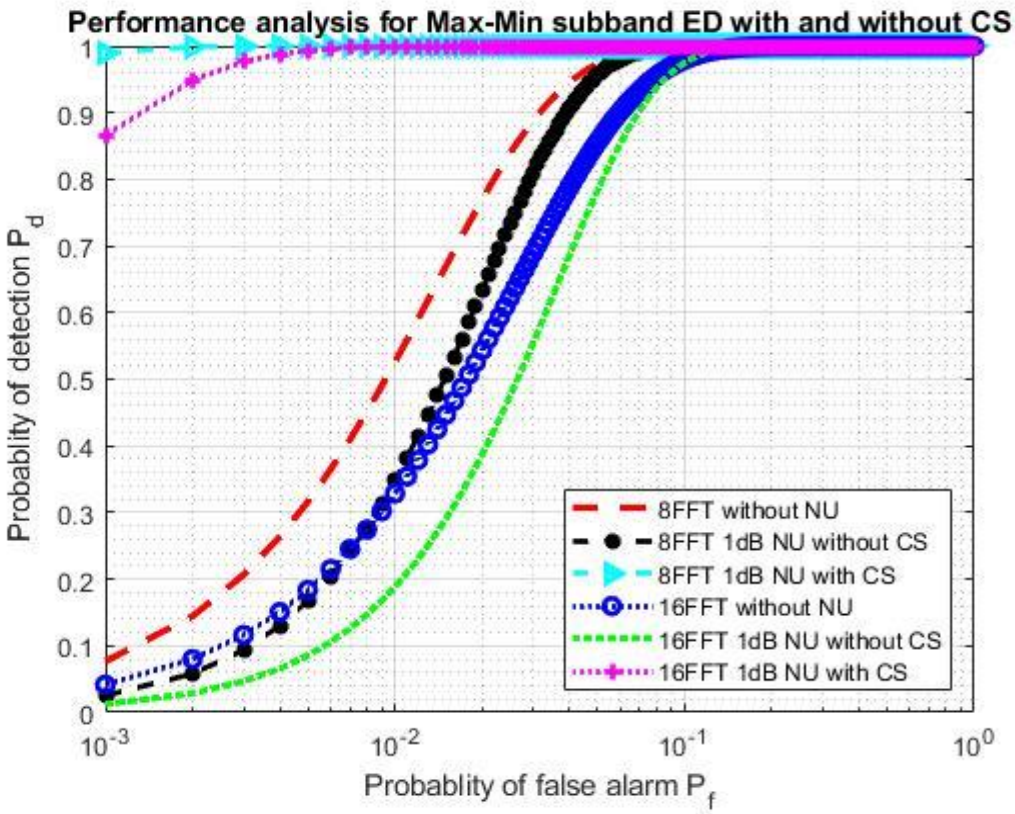

Figure 4-4Probability of detection Vs probability of false alarm for proposed

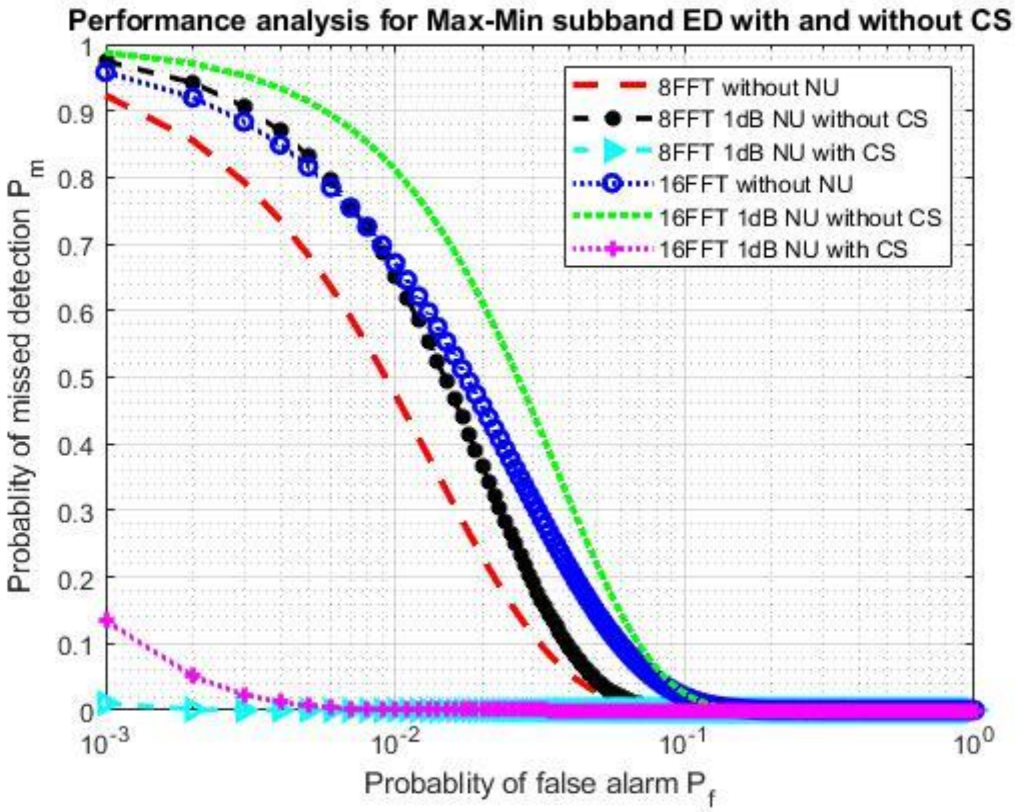

Figure 4-5 Probability of missed detection Vs probability of false alarm for proposed method

Figure 4-4 and **Figure 4-5** shows that 8 FFT with 1dB NU with compressive sensing (CS) and 16 FFT with 1dB NU with CS performs better performance than the remaining ones. This means the detection performance of our proposed method which is CS based max-min subband ED performs better than the Shannon-Nyquist sampling method without CS. This improvement is because of randomly positioned unavailable samples of a signals could also result from heavily corrupted part of signal which is better to declare as idle. Therefore, remove the samples corrupted by noise and compute the transform using the remaining incomplete set of samples. That the reason we need to introduce applying CS try to reconstruct the signal with a few available due to noisy sample elimination. The removal of corrupted samples can significantly improve the detection performance.

4.4 Result and Discussion for Spectrum Sensing Time in CR

The SUs is permitted to use the RF bands of PUs when the bands are not currently being utilized. Consequently, the SUs is required to free the medium as fast as possible with the least possible number of received samples for effective usage of the RF spectrum.***Figure 4-6*** and ***Figure 4-7*** presents the P_d and P_m) Vs sensing time at a fixed stationary level of P_f. Pd vs sensing time which is expressed with the help of $N = \tau f_s$

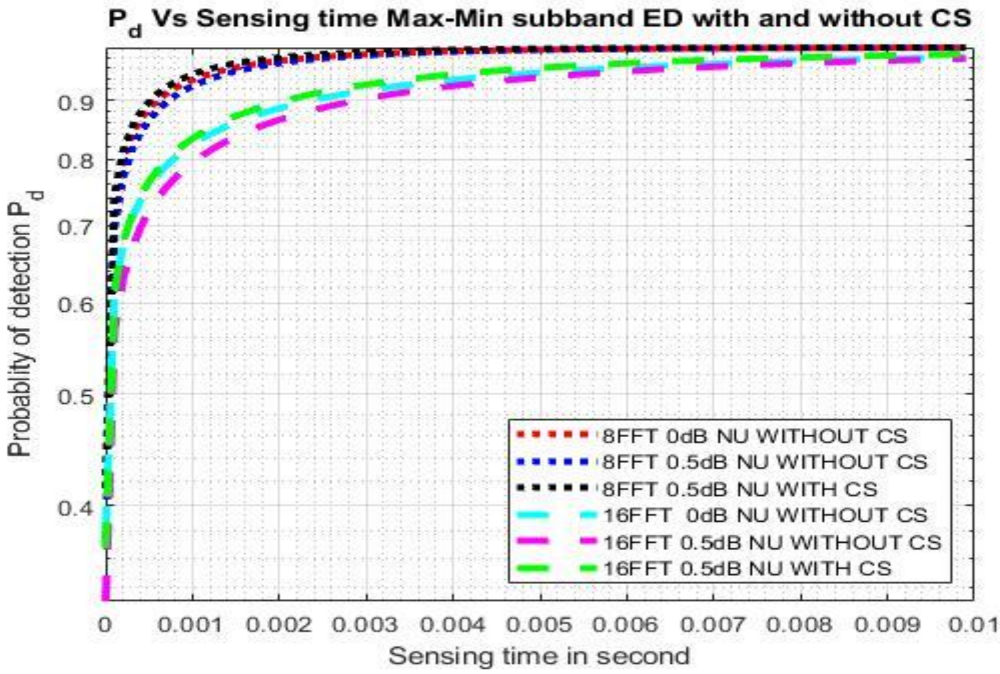

Figure 4-6 P_d Vs sensing time for Max-Min ED with and without applying CS

The simulation shows that increasing the sensing time in SS leads to an increasing of P_d and a decreasing of P_m. Furthermore, for a given sensing time applying CS on Max-Min subband ED have better performance in P_d and P_m. In general, to obtain better detection performance, longer sensing time required. During the sensing period, the transmission of SUs is not allowed. So, from SU point of view this longer time in the sensing process will decrease the data transmission time for SUs and subsequently results in less throughput for SUs.

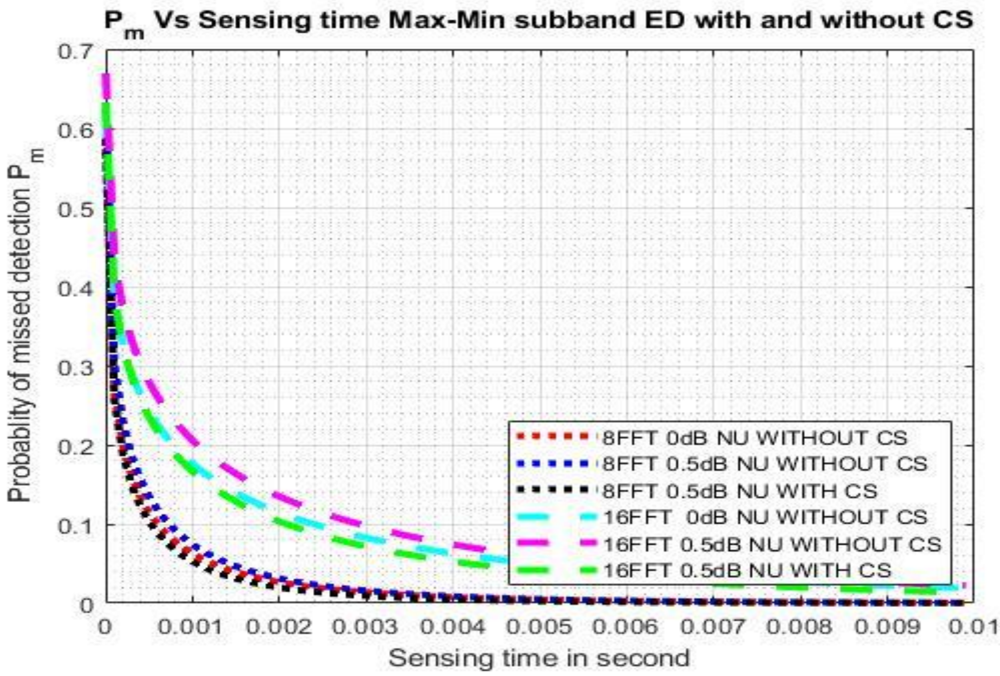

Figure 4-7 P_m Vs sensing time for Max-Min ED with and without CS

The simulation shows that increasing the sensing time in SS leads to a decreasing of P_m. Furthermore, for a given sensing time applying CS on Max-Min subband ED have better performance in P_m. In the above figure as the number of sensing time increases the probability of miss detection is increasing constantly, this shows that to obtain less missed detection performance, longer sensing time required.

4.5 Result and Discussion for Optimal Sensing Time Vs Number of SUs with decision rules

Figure 4-8 shows the optimal sensing time versus the number of sensing users when various decision fusion schemes are applied and $SNRp = -15dB$. As it is mentioned in earlier, we have used hard fusion schemes techniques. Here we have used three basic hard fusion schemes OR, AND, and Majority rule in order to evaluate the performance of CSS.

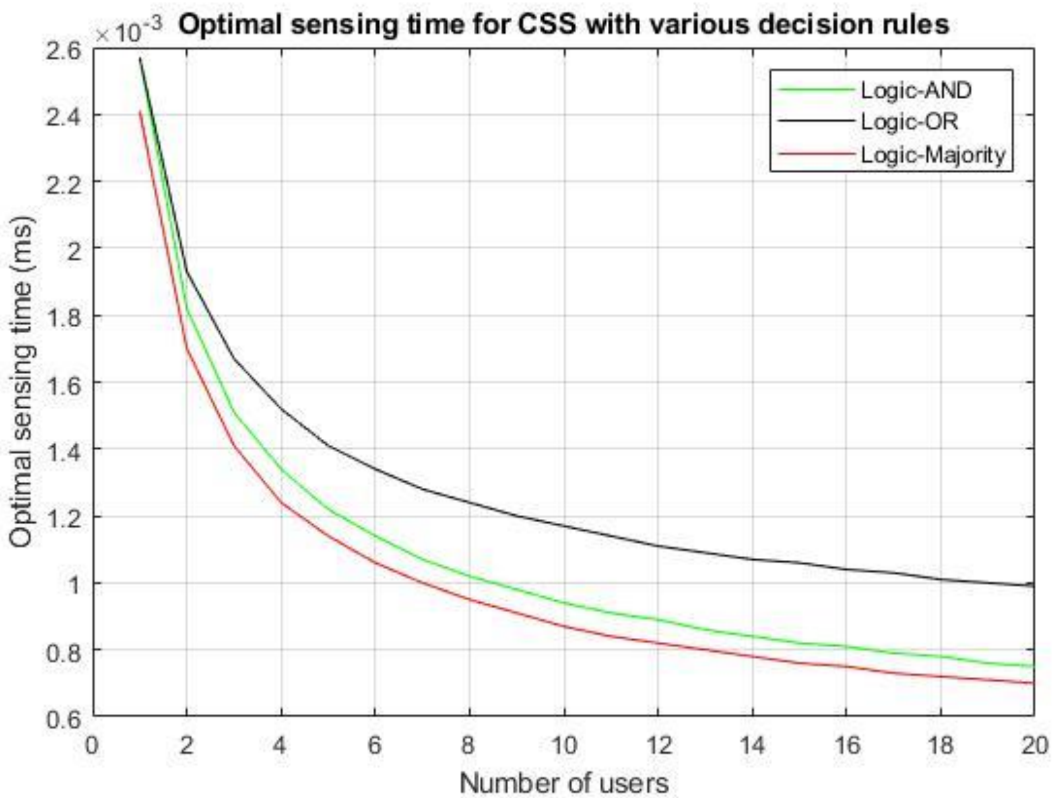

Figure 4-8 Optimal sensing time for CSS with various decision rules using CS based ED

It is seen that for every fusion scheme, the optimal sensing time decreases gradually when the number of users increases. For $N = 10$ those three rules have $0.954ms$, $1.25ms$ and $0.75ms$, respectively. From this result we can conclude that Majority rule performs better than that of the remaining two fusion mechanisms. For further comparison we will take this logic to compare with conventional ED

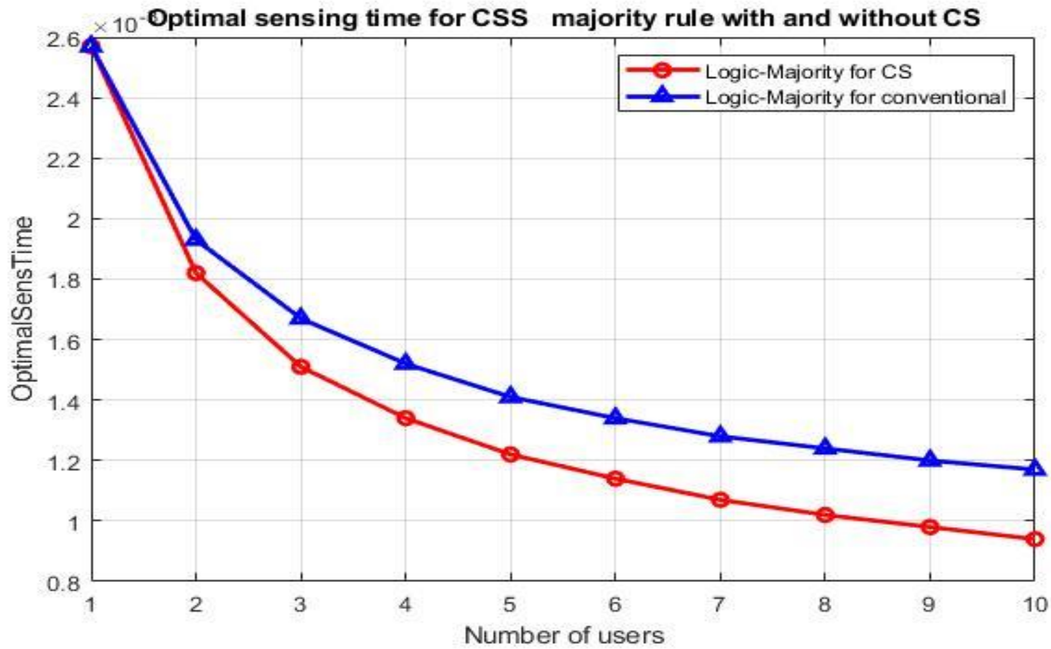

Figure 4-9 Optimal sensing time for CSS majority rule with and without CS

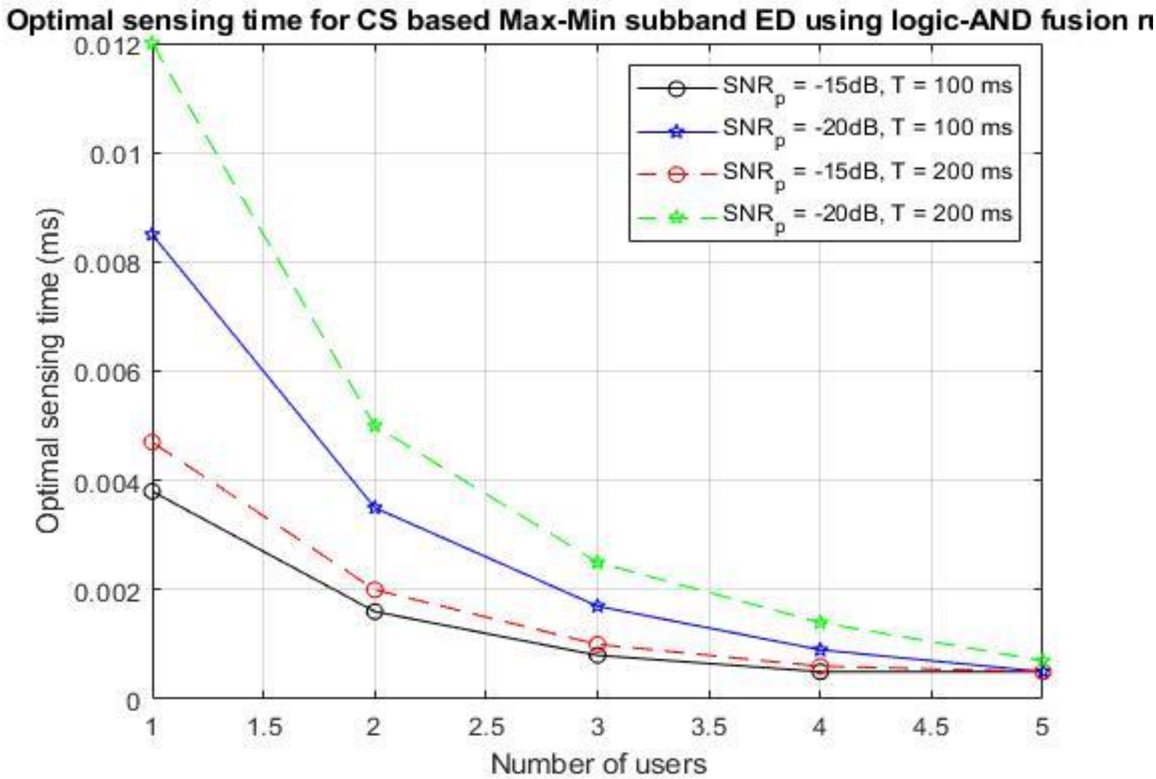

Figure 4-10 Optimal sensing time for CSS using logic AND decision fusion rule

Figure 4-10 shows If only one SU is used, the optimal sensing time increases from $4\mu s$ to $8.2\mu s$, as the $SNRp$ drops from $-15dB\ to\ -20dB$ at T=100ms. For the same value of sensing time 'T' if four SUs are used, the optimal sensing time increases from $1\mu s$ to $1.75\mu s$, as $SNRp$ drops from $-15dB\ to\ -20dB$.

Further, if the frame duration increases, the optimal sensing time also increases, for the given drops in the received SNR of PU at different number of SUs.

4.6 Result and Discussion for Max. Achievable Throughput Using Decision Rules

Figure 4-11 shows Max. normalized throughput with a different number of SUs for various decision rules. In this figure max normalized throughput is evaluated for different number of sensing users using OR, AND, and Majority fusion rules using the formula for the normalized throughput for all the three logics probability of false alarm. In order to find for three logics, the false alarm probability for those three logics is used which is shown in the hard fusion schemes.

$$B(\tau) = (1 - \frac{\tau}{T})(1 - P_f)$$

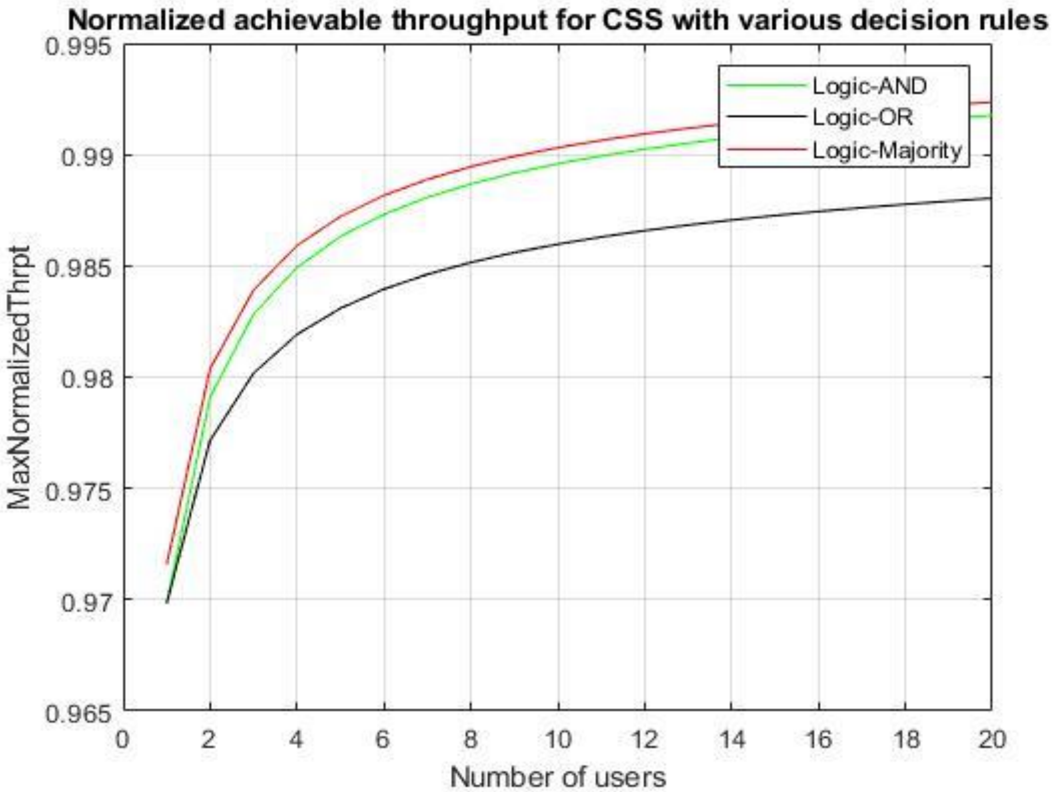

Figure 4-11 Normalized Max. Achievable throughput using decision rules

It is also seen that this normalized throughput increases with the increase of the number of SUs, and we can conclude from the results as the SUs increase the normalized throughput increases for Majority logic and can be chosen as the preferable method to compute max. throughput.

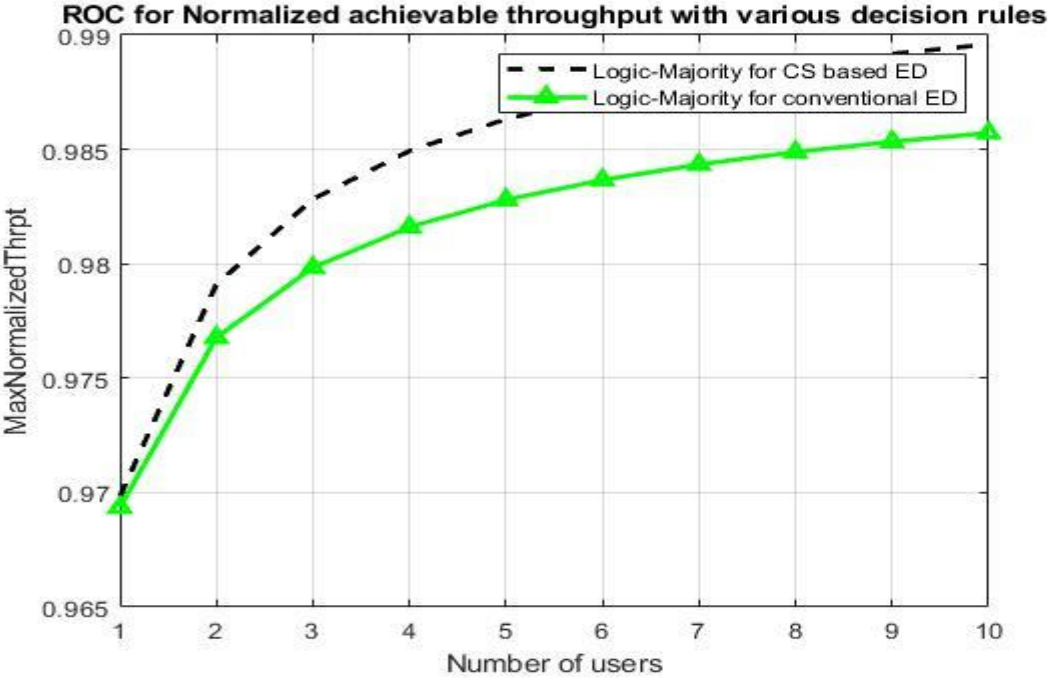

Figure 4-12 Normalized Max. Achievable throughput using Majority rule with and without CS

4.7 Result and Discussion for Energy efficiency Vs D/t values Sensing Time and SUs

Figure 4-13 shows the energy efficiency versus sensing time for the different number of SUs. we have evaluated at 5 different number of sensing users as shown in the paper from 5 to 25.

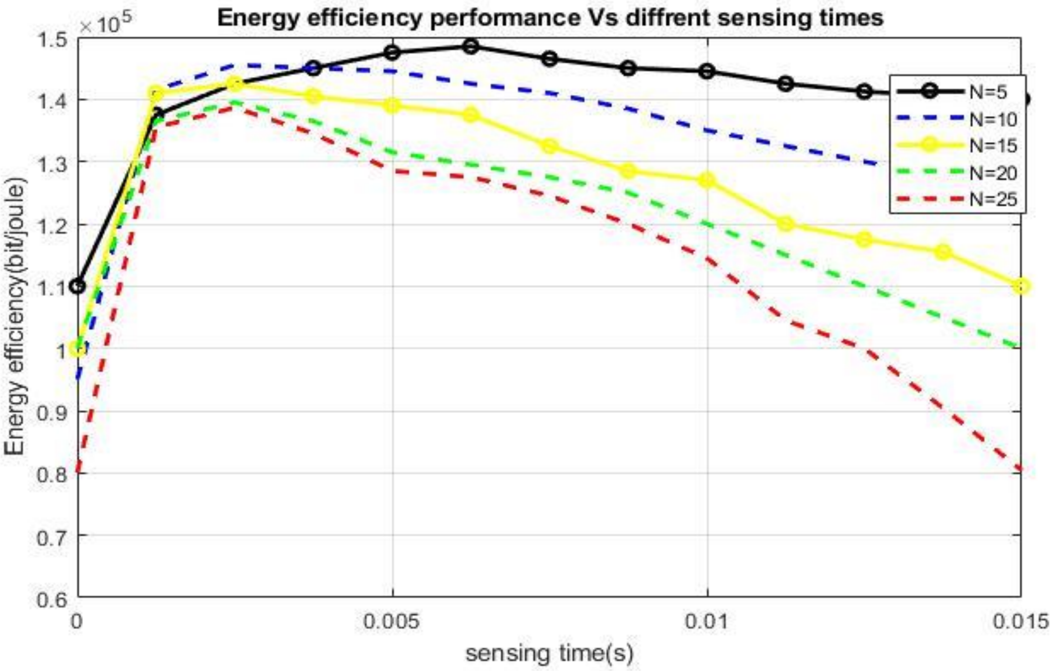

Figure 4-13 Energy efficiency performance Vs different sensing time

If N increases, P_f diminishes, as shown in Equation (3.41), which expands the energy consumed during transmission, as demonstrated in Equations (3.71) and (3.72), however the good throughput increases also. In any case, bigger N infers more reporting energy and less transmission time which diminishes good throughput. At less amount of sensing time, for any number of users, the EE is similar without drastic changes. But as the sensing time is increasing, it shows a great deal of variation in the energy efficiency for the increasing order of the number of users. And the EE is showing a drastic decrement even if the number of users is maintained similarly for increasing sensing time. As the number of sensing time increases the EE increases for all number of users that's why they overlap in the graph.

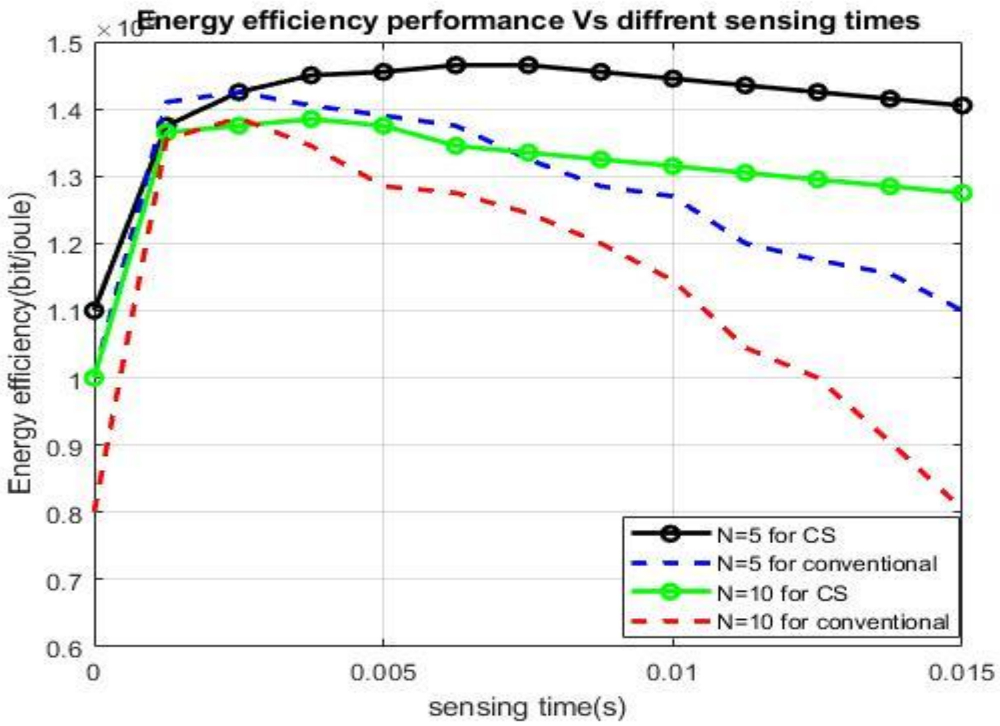

Figure 4-14 Energy efficiency performance Vs different sensing time with and without CS

For the further comparison we have selected randomly two different number of sensing users we have evaluated energy efficiency vs sensing time for CS based max-min subband ED and for conventional ED. As we can see from the results our proposed system performs better that that of the conventional ED. Furthermore, more time consumption is reduced in SS duration depend on signal strength due to the introduction of CS in maximum-minimum subband ED.

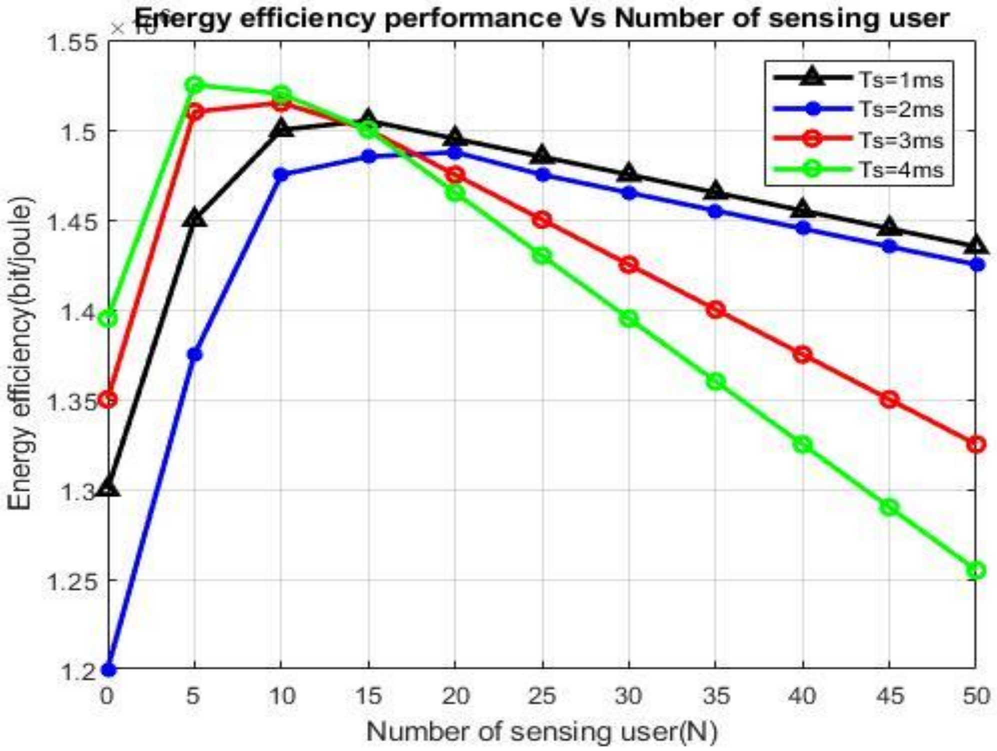

Figure 4-15 Energy efficiency performance Vs the number of SU

If T_s increases, number of samples increases, P_f decreases, which increases the probability of transmitting data and consumed energy during the transmission time, but also, good throughput increases. However, as τ decreases, P_f decreases, which increases transmission energy without good throughput. Therefore, selected values of N and τ affect energy consumption, which in turn affects energy efficiency. The above graph shows the energy efficiency versus the number of SUs presented for multiple values of τ. Notice that the maximum EE is achieved at a low value of τ and it is increasing even with the increment of the number of users. But for the larger values of τ, as the number of users is increasing the maximum EE shows very small variations in the increment.

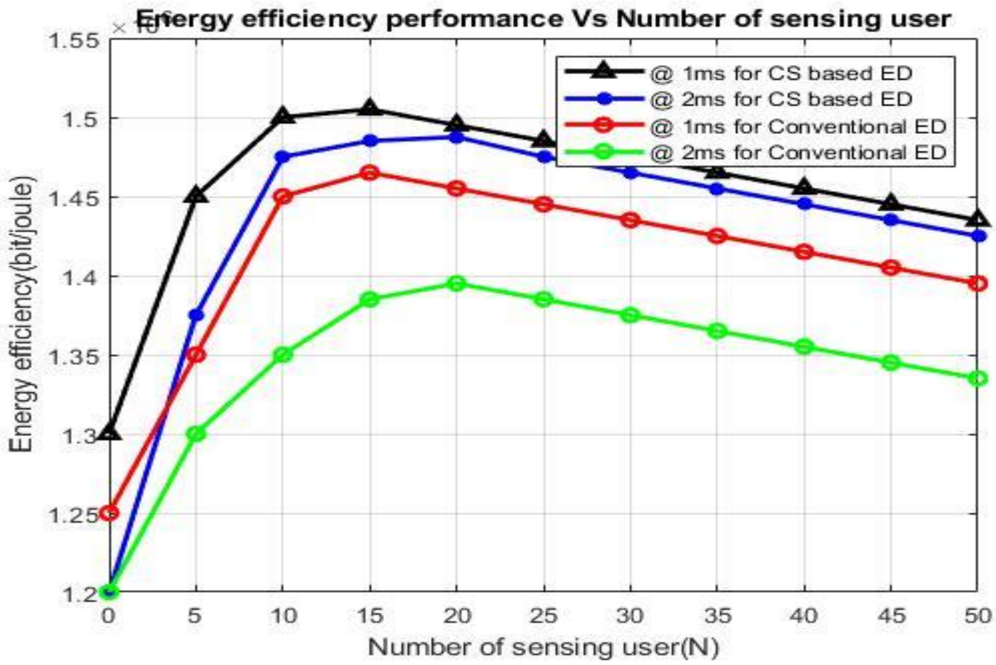

Figure 4-16 Energy efficiency performance Vs the number of SU

The simulation result shows that CS based max-min subband ED has good energy efficiency when compared with conventional method. As the number of users increases the energy efficiency also increases because the throughput increases as N increases.

4.8 Result and Discussion for EE Performance with Fusion Threshold Optimization

In **Figure 4-17** we compare the energy efficiency when fusion threshold is optimized using CS subband ED with conventional ED.

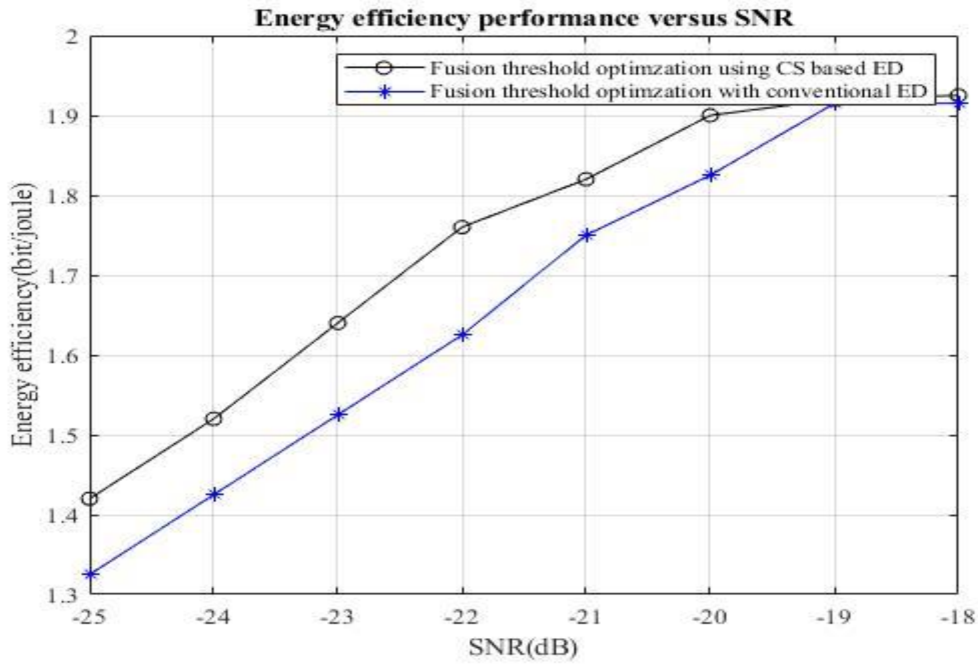

Figure 4-17 Energy efficiency of CRN using fusion threshold optimization

It can be seen that at low γ location, optimization by utilizing CS is about 0.1bits/Hz/joule higher than simply enhancing conventional ED strategy. At high γ location, there is not really any increase. Accordingly, we can reason that having a criticism or feedback channel to input the ideal λ may not be vital if k is advanced, particularly at high γ district. At the point when the quantity of sensing nodes N or detecting time τ builds, it improves the detecting execution however diminishes the transmission time and expands the amount of detecting energy.

4.9 Result and Discussion for Energy Efficiency by Different Comparing Algorithms

Figure 4-18 shows energy efficiency versus the number of available users. In these section three algorithms are compared. The first two are optimization of basic parameters which are sensing time, number of sensing node, and fusion threshold based on CS based subband ED and conventional ED. The last one is only SUs optimization based on conventional ED.

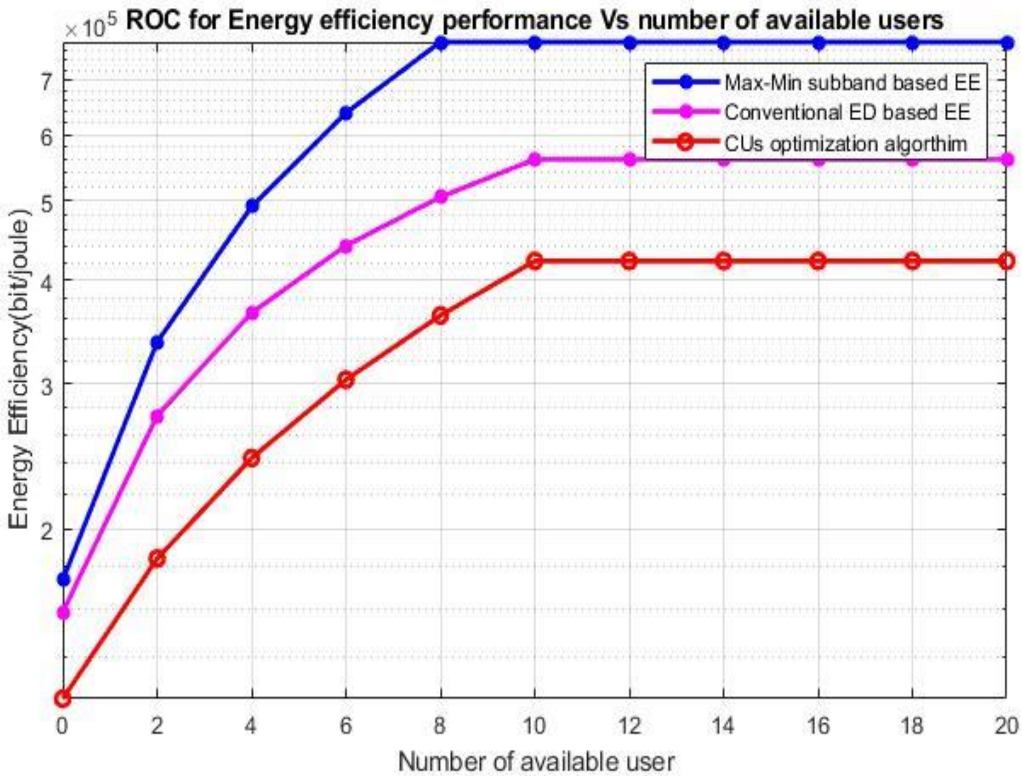

Figure 4-18 Energy efficiency performance versus the number of available users

The conventional Ed based joint optimization energy efficiency algorithm achieves good energy efficiency results compared with the case only CUs optimization approach of conventional ED, our proposed algorithm gives better results than the two because we had optimized the sensing time along with the number of sensing users and fusion threshold using CS based Max-Min subband ED spectrum sensing to reduce the effect of noise uncertainty.

Chapter 5 : Conclusion and Future Work

5.1 Conclusion

The proficient utilization of free RF band and limited interference with the licensed users can depend on the use of the spectrum sensing method. Most of the challenges raised by cognitive radios can be erased by using suitable spectrum sensing techniques. The technique used in detecting the interference and/or sensing the spectrum must be more reliable. Hence, the primary user will not face any problem from the cognitive radio system to use their allocated spectrum. Since the following coming period of communications systems requires high data rates and consequently high transmission capacity these regular or conventional SS methods are impractical. accordingly, ED, MFD, and CFD are illogical, since they are planned for narrowband detecting. From this viewpoint, the SUs needs to scan large dynamic ranges of the frequency spectrum to find the best available channels. Wideband spectrum sensing scans multiple channels over a wide RF band to discover more spectral opportunities to improve the spectrum and energy efficiency in comparison to narrowband SS.

Therefore, in this work, the SS is done to sense multiple band (wideband) in one sensing period in CR by using CS. We showed by simulation that there is an optimal sensing time, number of cooperating nodes and fusion threshold that maximizes energy efficiency.

Finally, we have compared our proposed method which is CS based max-min subband ED based cooperative spectrum sensing with different methods and the proposed system shows 74.6% efficiency increment compared with that of conventional ED based method.

5.2 Future Work

Further, the performance and optimization of CSS can be improved by considering the clusters. In cluster-based CSS cluster head plays a major role in the CR system. A SU who is having the maximum gain for reporting the channel in a cluster will lead the group. The primary task of the leader is to gather the detected signals from each SU in the same cluster and this collected result will be transferred to the common receiver i.e., FC. Later on, the common receiver sends back the global decision after deciding the occupation of the spectrum to the respective CHs.

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Appendix-1: For proof for Probability of Detection and False Alarm

The probability density function can be written as the number of samples are more$(N \geq 250)$ $f_Y(y)$ follows a Gaussian density function

$$i.e\ \ f_Y(y) = \begin{cases} N\left({\sigma_n}^2, \frac{{\sigma_n}^4}{N}\right) & : H_0 \\ N\left({\sigma_n}^2(1+\gamma),\ \frac{{\sigma_n}^4(1+\gamma)^2}{N}\right) & : H_1 \end{cases} \quad (1)$$

Where N normal density function

The general form of Gaussian density is given by

$$f_X(x) = \frac{1}{\sqrt{2\pi\sigma^2}} \int \frac{-(x-\alpha)^2}{2\sigma^2}\, dx \quad (2)$$

Where σ^2 - variance and α - mean

$$P_d = \int_{\gamma}^{\infty} f_Y(y)\, dy \quad (3)$$

From the above equation (2) we will use the one with H_1 because we are talking about probability of detection that means correct decision.

Let $\alpha = {\sigma_n}^2(1+\gamma)\ and\ \sigma^2 = \frac{{\sigma_n}^4(1+\gamma)^2}{N}$

$$P_d = \int_{\gamma}^{\infty} \frac{1}{\sqrt{2\pi\sigma^2}} \int e^{\frac{-(x-\alpha)^2}{2\sigma^2}}\, dx \quad (4)$$

The general form of Q function is given by

$$Q(x) = \frac{1}{\sqrt{2\pi}} \int_{x}^{\infty} e^{\frac{-u^2}{2}} \quad (5)$$

Let $\frac{x-\alpha}{\sigma} = u$

From this $x - \alpha = u\sigma \Longrightarrow x = u\sigma + \alpha$ let's say $x = \sigma$, $u = \frac{\Gamma - \alpha}{\sigma}$

$$dx = du\sigma \qquad x = \infty\ , u = \infty$$

$$P_d = \int_{\frac{\Gamma-\alpha}{\sigma}}^{\infty} \frac{1}{\sqrt{2\pi\sigma^2}} e^{\frac{-u^2}{2}} du\sigma$$

$$P_d = \frac{1}{\sqrt{2\pi}} \int_{\frac{\Gamma-\alpha}{\sigma}}^{\infty} e^{\frac{-u^2}{2}} du = Q\left(\frac{\Gamma-\alpha}{\sigma}\right)$$

(6)

The probability of detection and false alarm probability over AWGN channel is given as below:

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

$$P_d = Q\left(\left(\frac{\lambda}{\sigma_n{}^2(1+\gamma)} - 1\right)\sqrt{N}\right) \tag{7}$$

Here also we are going to use the same formula in order to find the P_F the only difference between finding probability of detection and probability of false alarm is only using H_1 and H_0 respectively. So, going through the same procedures as P_D to find P_F and is given below:

$$P_f = Q\left(\left(\frac{\lambda}{\sigma_n{}^2} - 1\right)\sqrt{N}\right) \tag{8}$$

Where $Q(x) = \frac{1}{\sqrt{2\pi}}\int_x^\infty e^{\left(\frac{-t^2}{2}\right)}dt$ and N is the number of the signal samples $N = \tau f_s$

Let us assume that the threshold value is chosen in order to guarantee a given detection probability$P_D{}^{th}$. If P_D is given, λ can be determined from (7)

$$\lambda = \sigma_n{}^2(1+\gamma)\left(\frac{Q^{-1}\tilde{P}_D}{\sqrt{N}} + 1\right) \tag{9}$$

The constraint $\tilde{P}_D$ is employed in order to limit the resulting interference at the primary users, caused when a missed detection occurs. If P_F is given, λ can be determined from (8)

$$\lambda = \sigma_n{}^2\left(\frac{Q^{-1}\tilde{P}_f}{\sqrt{N}} + 1\right) \tag{10}$$