

Multi-Slot Cooperative Spectrum Sensing for Cognitive Radio Networks



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- ii. Ideas and material generated from other researchers are explicitly stated with appropriate references.
- iii. This work is submitted for the Master of Engineering specializing in Telecommunication at the University of Cape Town. It has not been submitted to any other university for any other degree or examination.
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ABSTRACT

A key challenge with current radio access technologies and a consideration in the implementation of next generation radio access networks is limited spectrum availability. Current mobile technologies have been standardized to operate within reserved, dedicated frequency bands. Network operators are granted exclusive access to the allocated frequency bands, which are reserved regardless of users' activity. Research in spectrum utilization patterns has revealed significant occurrences of inactivity and sparse usage patterns within these reserved spectrum bands. This dissertation investigates spectrum sensing cognitive radio with the aim of identifying an efficient model to effectively utilize the available spectrum.

A cooperative spectrum sensing cognitive radio model is presented based on energy detection sensing and multi-slot spectrum allocation. The model is evaluated based on two decision strategies namely, 'Square Law Combining' soft fusion sensing and 'Majority Rule' hard fusion sensing, and the two decision strategies are investigated under the same channel conditions. The model is implemented using MATLAB considering probability of detection as the main performance metric. Simulations results show that the soft fusion decision scheme performs better than the hard fusion decision scheme, with respect to detection accuracy. This finding shows that an energy detection scheme incorporating soft fusion sensing can improved spectrum usage in cognitive radio networks.

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ABBREVIATIONS

5G	5th Generation
CR	Cognitive Radio
CSD	Cyclostationary Signal Detection
CSS	Cooperative Spectrum Sensing
D2D	Device-to-Device
ED	Energy Detection
FFT	Fast Fourier Transform
GSM	Global System for Mobile Communication
ITU	International Telecommunication Union
IMT	International Mobile Telecommunications
LTE	Long Term Evolution
M2M	Machine-to-Machine
MFD	Matched Filter Detection
mmWave	Millimeter Wave
MNO	Mobile Network Operator
PU	Primary User
RSSI	Received Signal Strength Indication
SCF	Spectral Correlation Function
SU	Secondary User
SDR	Software Defined Radio
TVWS	Television White Space
UMTS	Universal Mobile Telecommunications System

NOMENCLATURE

φ_e	Detection Error Rate
σ_w^2	Noise Variance
σ_x^2	Signal Variance
$\alpha_t(\mathbf{i})$	Baum-Welch Algorithm Forward Variable
λ_{opt}	Optimised Detection Threshold
\mathbf{w}_n	Noise Component (AWGN)
P_d	Probability of Detection
Γ	Estimation Threshold
$\mathbf{R}_x^\alpha(\boldsymbol{\tau})$	Cycle Autocorrelation
$\mathbf{Q}(\mathbf{x})$	Gaussian Q-Function
λ_D	Energy Detection Threshold
P_f	Probability of False Detection
P_{md}	Probability of Missed Detection
$\mathbb{T}_i(y_I)$	Test Statistic for Energy Detection
τ_s	Sensing Period
$(\cdot)^H$	Conjugate Transpose Operator

CHAPTER 1: INTRODUCTION

1.1. Background

A key requirement in the implementation of radio access technologies is efficient management of the spectrum available for data transmission. Globally, allocation of spectrum is governed by the International Telecommunication Union (ITU) -Radio Communication Sector. Countries regulate the use of radio frequency spectrum within their geographic bounds in-line with the ITU defined standards [1]. The union maintains a database of all frequency assignments in the form of the Master International Frequency Register (MIFR) [2]. Spectrum allocation has traditionally been through a static approach in which specific frequency bands are defined for implementation of specific radio technologies and standards. Network operators are assigned licences for specific frequency band(s) within the available frequency bands [3].

The radio spectrum is a finite resource and the spectrum challenge in telecommunications has become a key research area due to the continued exponential increase in the number of connected devices and evolving broadband needs [4]. In South Africa, as an example, the operating frequency bands allocated by the Independent Communications Authority (ICASA) for LTE use include 1800MHz, 2100MHz and 2300MHz [5],[6]. This fixed frequency allocation approach is implemented globally, restricting transmission to specific frequency band(s) assigned to licence holders. The rapidly growing bandwidth demands on the available spectrum has led to the need for different approaches in spectrum allocation. The growing

research trend has been centred on efficient utilization of the spectrum by extending the technologies that can be implemented within the same spectrum space.

Efficient spectrum utilization techniques can enable reserved frequency bands to also be utilized for other enhanced broadband use cases and emerging technologies such as the 5G network. The spectrum required for the 5G network is expected to be obtained from both the millimetre wave range of frequencies above 24 GHz and frequency bands below 6 GHz. This would include some of the bands currently being used by traditional access technologies and mobile satellite communication systems. Adopting cognitive radio (CR) techniques with the ability to detect and allocate free channels within the primary frequency band would enable effective spectrum utilization and provide additional spectrum for implementation of 5G and other broadband use cases.

In recent times, computational intelligence (CI) techniques have been applied to cognitive radio networks. CI is an emerging science concept involving the development of nature-inspired computational paradigms for building intelligent systems [7]. The main application methods for computational intelligence include Fuzzy Logic, Neural Networks, and Evolutionary Computation. These technologies are defined by their sources of inspiration. Fuzzy Logic as an example is inspired by human reasoning and attempts to mimic a human thinking approach in decision making [7],[8]. In the context of radio communications, cognitive systems can be modelled based on these CI techniques to create a self-aware radio network.

The concept of a self-aware radio is centred on developing an intelligent radio system that is conscious of and can learn from its environment [9]. In the context of cognitive radio, full-cognitive radio refers to a completely self-aware network while spectrum

sensing cognitive radio centres on intelligent spectrum management [10]. This dissertation focuses on spectrum sensing cognitive radio, and it is aimed at implementing energy detection-based sensing algorithms for comparing the performance of soft fusion sensing and hard fusion sensing.

1.2. Problem Statement

There has been widespread research and a growing interest in the application of cognitive radio systems in wireless radio networks. Research in the field is increasingly gravitating towards dynamic spectrum access applications, driven by the exponential increase in the demand for bandwidth and increase in the number of subscribers on radio access networks [11]. This high bandwidth demand has necessitated the development of different approaches for spectrum assignment and development of new adaptive communication technologies. While there has been significant research on use of the millimeter wave band of frequencies above 24GHz, current radio access technologies depend mostly on the sub-6 GHz microwave frequency bands. New technologies such as the 5G network also share this sub-6 GHz spectrum [12]. Cognitive radio networks provide a viable solution to the rising spectrum challenge within the sub-6 GHz frequency band.

Research in cognitive radio has been predominantly based on dynamic spectrum allocation strategies that are centred on classification of users as primary users (PUs) and secondary users (SUs). Primary users are the default licenced spectrum subscribers while secondary users are the cognitive radio users that are given limited and controlled access to the spectrum. The principle of operation within the cognitive radio system is to allow the secondary users access to the spectrum when the primary users are inactive or idle. A major problem area identified in research on this cognitive

radio approach is the management of channel interference. Channel interference in cognitive radio networks is predominantly linked to the hidden-terminal problem, inaccurate primary user detection algorithms, and transmission delays [12],[13].

The hidden-terminal problem arises when a single node is unable to accurately detect the presence of other nodes communicating with a shared access point due to shadowing or multipath fading [13]. Shadowing and multipath fading are common sources of signal degradation in wireless communication. The collaborative approach of cooperative spectrum sensing has largely been presented as a solution to managing the hidden-terminal problem in cognitive radio networks [13]. Detection accuracy and transmission delay are directly linked to the algorithms designed for local sensing within the cognitive radio model. Developing an efficient detection algorithm is a critical aspect in managing channel interference within cognitive radio networks.

Increased transmission delay is an issue in cooperative spectrum sensing due to the overheads introduced by local spectrum sensing and channel reporting. Managing transmission delay is critical in avoiding interference because reducing sensing and reporting times can ensure secondary users can maximize the use of available timeslot for data transmission [14]. There has been growing research on reducing transmission delay by optimising channel frame structures in cognitive radio networks. This is achieved by segmenting the transmission frame into a multi-slot frame structure to reduce transmission delay by enabling sensing over multiple sub-slots [14],[15]. The multi-slot frame structure is a time-division based framework that allocates specific slots for multiple functions. In the cognitive radio context, these slots can be used for both spectrum sensing and data transmission functions.

Existing works on cognitive radio networks have shown energy detection as the predominant sensing scheme applied for cooperative spectrum sensing due to its low complexity and ease of implementation. The technique however displays low detection accuracy challenges particularly in low-SNR (Signal-to-Noise Ratio) channels [16]. This dissertation focuses on implementing and evaluating the performance of energy detection-based sensing under two decision schemes, namely, soft fusion and hard fusion sensing.

1.3. Research Objectives

The aim of this research is to investigate energy detection sensing based on two major decision strategies applied in spectrum sensing, namely, soft fusion and hard fusion sensing. The following are the specific objectives of the research:

1. Review relevant literature on cognitive radio and spectrum sensing techniques, with a major focus on energy detection-based models.
2. Implement an energy detection algorithm using cooperative spectrum sensing.
3. Evaluate the performance of the energy detection scheme and evaluate its performance for soft fusion and hard fusion sensing strategies.

1.4. Research Contributions

The proposed research focuses on cooperative spectrum sensing implemented using energy detection. It provides a comparative analysis of energy detection using soft fusion and hard fusion sensing strategies. The research contributes to the field of cognitive radio by investigating two cooperative spectrum sensing strategies and evaluating their effectiveness through simulations. A detailed literature review

provides an analysis of how cognitive radio and spectrum sensing address the greater challenge of limited spectrum availability through efficient spectrum sharing.

1.5. Research Methodology

This research is centred on evaluating detection accuracy for the two main fusion strategies for cognitive radio networks, namely, soft fusion and hard fusion sensing. An in-depth literature review on the local sensing techniques and decision strategies for cognitive radio is conducted to enable the design of spectrum sensing algorithms. Energy detection-based cooperative sensing is applied for the sensing.

The performance of the energy detection scheme is evaluated by designing and simulating soft fusion and hard fusion spectrum sensing strategies using MATLAB. The simulation environment is modelled to mimic a radio access network with signal generators producing user data, and noise models producing varying channel conditions. The performance evaluation is centred on simulating the same network conditions for the soft fusion and hard fusion sensing strategies. The metric used to evaluate the detection accuracy of the two sensing strategies is the probability of detection. The probability of detection for each fusion strategy is evaluated with respect to three varying metrics, namely, signal to noise ratio, number of cognitive radio users, and probability of false alarm.

1.6. Research Scope and Limitations

This research is restricted to energy detection spectrum sensing scheme. Energy detection is chosen due to its ease of implementation and low memory requirements in simulation. The focal point in the research is to evaluate the soft fusion and hard fusion strategies in cooperative sensing through MATLAB simulations. Signal-to-noise ratio is a key metric used in the simulations of the varying channel conditions. Ideally,

a comprehensively wide range of SNR values should be used for the performance evaluations. However, the simulations generated in this research show poor performance in terms of probability of detection when the SNR values are below -10dB. This is expected because energy detection performance degrades under low SNR conditions. Further research aimed at optimizing the performance of energy detection schemes operating in very low SNR conditions is required.

1.7. Dissertation Outline

This dissertation is structured into six chapters. Chapter 1 outlines the broad problem, which is the spectrum challenge in radio access networks, and introduces cooperative spectrum sensing cognitive radio as a solution. The chapter highlights the research focus which is a comparative analysis of soft fusion and hard fusion strategies in energy detection spectrum sensing. The chapter also states the research objectives as well as the scope and limitations of the research.

Chapter 2 provides a literature review on the cognitive radio concept and highlights the standardization aspects linked to cognitive radio. The chapter also gives a review on spectrum management, covering spectrum sensing and spectrum mobility. Moreover, the chapter outlines the mathematical models used for channel state prediction in cognitive radio spectrum sensing.

Chapter 3 provides an in-depth literature review on cooperative spectrum sensing. The chapter provides an analysis of some schemes that have been designed for implementation of cooperative sensing, which include the application of dynamic detection thresholds and the application of a multi-slot frame structures. The chapter highlights the advantages and limitations associated with the reviewed techniques.

Chapter 4 presents the cognitive radio model with algorithms for a comparative analysis of soft fusion and hard fusion energy detection. The soft fusion algorithm applies a Square Law Combining (SLC) technique while the hard fusion algorithm applies the Majority rule technique for decision making.

Chapter 5 contains a performance evaluation of the designed cooperative spectrum sensing scheme. The chapter also presents the results and analysis of the sensing algorithms simulated.

Chapter 6 provides a summary of the dissertation and draws conclusions based on the simulation results. The chapter also outlines recommendations for future research.

CHAPTER 2: COGNITIVE RADIO NETWORKS

2.1. Introduction

Extensive research on wireless communication networks has led to the development of cognitive radio as a pioneering technology that can address the limited spectrum challenge. This literature review provides a comprehensive overview of cognitive radio, focusing on its fundamental concepts and the key techniques employed to enhance spectrum efficiency. Specifically, it delves into spectrum sharing, where cognitive users coexist with primary users without causing interference; spectrum sensing, the process by which cognitive radios detect the presence of primary users to avoid collisions; and spectrum handoff, a mechanism through which cognitive radios can seamlessly switch to alternative frequencies when the current channel becomes unavailable. This chapter aims to provide a detailed insight into the current state and direction of cognitive radio networks as a foundation for the research carried out.

2.2. Cognitive Radio Overview

Joseph Mitola originally presented the idea of cognitive radio (CR) in his research work on software defined radio (SDR) and its applications in wireless networks [17]. The concept is centred on building an intelligent network that can learn its surrounding radio conditions and execute optimization changes without any human intervention. Traditionally, mobile network users have access to the mobile network resources within their geographic location.

Cognitive radios can be described through two main operational features, namely, self-awareness and adaptiveness. Self-awareness in CR networks implies that cognitive

radios can scan and learn their environment without any human intervention. While standard radios also perform background scans on the environment to measure network conditions at certain frequency bands, they do not track transmission patterns of other users. Self-aware cognitive radios monitor parameters of the radio environment including user activity and transmission patterns of other users operating on the same network. The cognitive radios are therefore aware of the activity patterns on the operating spectrum bands [9].

The adaptive aspect of CR networks describes how the cognitive radios continually self-adjust to changing conditions. Cognitive radios must be able to adjust to dynamic wireless network conditions such as channel interference and signal power. The self-aware and adaptive functions of cognitive radio networks are driven through software based intelligent algorithms running through a cognitive engine. The cognitive engine applies computational intelligence to re-configure radio parameters and improve network efficiency [18].

In the initial CR research by Mitola [17], a full cognitive radio concept is explored. The full cognitive radio network would have complete control of all network parameters through an integrated software defined radio system. Research is increasingly gravitating towards spectrum sensing cognitive radio which is primarily centred on identification and re-allocation of spectrum holes on specific frequency bands [19]. The functions of a cognitive radio system are represented through the cognitive radio cycle [20]. Figure 1 shows the cognitive radio cycle for spectrum management in cognitive radio networks.

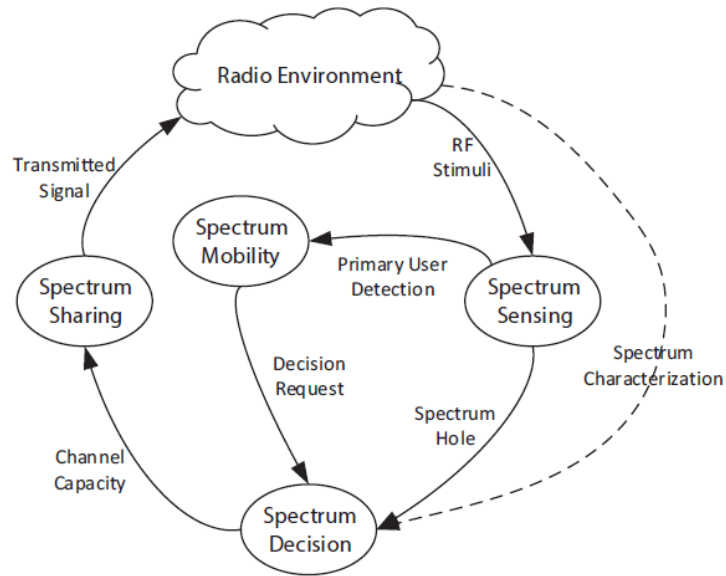


Figure 1:Cognitive Cycle [20]

2.3. Spectrum Sharing

2.3.1. Spectrum Access Techniques

Spectrum access defines the models through which different classes of users can have shared access to the spectrum. There are three models through which dynamic spectrum access is implemented namely, open sharing, dynamic exclusive access, and hierarchical access [21]. First, the open sharing model allows for shared access with equal opportunity for users to access the spectrum region. Second, the dynamic exclusive use model is the spectrum allocation models where frequency bands are licensed for exclusive use. In the dynamic spectrum access under this exclusive model, the licensed owners of the spectrum bands are allowed to re-distribute their allocated spectrum. License owners can sell or lease out their allocated spectrum through a process of spectrum auction. Koutroumpis *et al* [22] gives some insight on the spectrum auction processes.

A third model for spectrum sharing is the hierarchical access model. Hierarchical access is based on the user group classification as primary and secondary users. An exclusive access approach applies to the primary users while a restricted access approach applies to secondary users on the same spectrum. Figure 2 provides an illustration of the sharing techniques applied for spectrum access between the primary and secondary users. In spectrum overlay, secondary users can only transmit when there are no transmissions from primary users. In spectrum underlay, primary and secondary users can concurrently transmit on the same spectrum band within that same time interval. The interference control is implemented by regulating the transmit power for the secondary users. The transmit power limit on secondary users is applied based on the acceptable tolerance levels of the primary user [23].

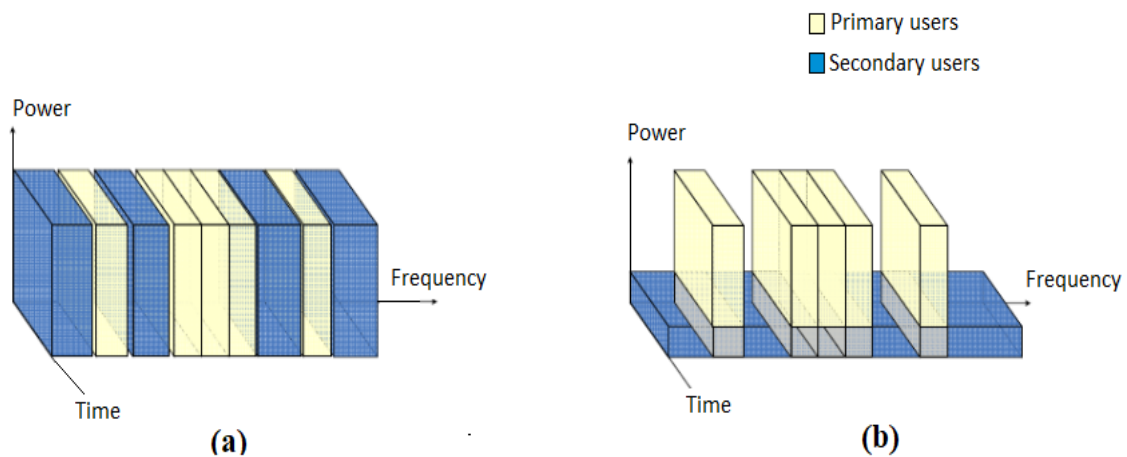


Figure 2: Spectrum Access Techniques: (a) Spectrum Overlay, (b) Spectrum Underlay [24]

2.3.2. Standardization

Cognitive radio has gained widespread acceptance as the standard technology that will allow dynamic spectrum access in wireless communication systems. To create standards that will allow spectrum sharing in wireless regional area networks, the Institute of Electrical and Electronics Engineers (IEEE) Standards Association formed

the IEEE 802.22 Standard. The standard consists of several working group's whose objective is to advance the study of dynamic spectrum access and create a universal air interface structure for cognitive radio-based systems [25].

IEEE 802.22-2011 Standard is one of the finished IEEE 802.22 projects that has offered important insight on cognitive radio implementation. The standard's primary goal is to allow unlicensed operators to use underutilized TV spectrum bands on licensed networks without causing interference. The 54 MHz to 862 MHz spectrum band is primarily designated for television (TV) broadcasts [26]. The VHF and UHF bands in the TV spectrum have the benefit of having extensive transmission coverage. Based on a fixed point-to-multipoint cellular network topology, the 802.22 architecture consists of managed nodes and a network control system.

The IEEE Project 1900 (P1900) is a standards committee that was established to create the framework for spectrum sharing and interoperability among next generation radio networks. The P1900 committee has evolved into the Dynamic Spectrum Access Networks Standards Committee (DySPAN-SC), centred on developing the standards for dynamic spectrum access. The standards are established through working groups (WG), with members affiliated to research institutions, telecommunication operators and equipment manufacturers. The DySPAN standards committee oversees six working groups, the functions of which are enumerated below [27]:

IEEE 1900.1

The IEEE1900.1 WG explains the fundamental ideas behind dynamic spectrum access and its associated technologies under the following four categories: advanced

radio system concepts, functional capabilities of the radio system, network technologies, and management of spectrum [27].

IEEE 1900.2

The technical standards for how radio systems operating on the same or different frequency bands can cooperate and manage interference are defined by the IEEE 1900.2 WG [27].

IEEE 1900.4

IEEE 1900.4 WG provides the baseline standard for cognitive radio systems' configuration-related elements. The goal of the working group is to lay the groundwork for the creation of an intelligent management system that can optimize spectrum utilization across various radio access technologies and frequency bands [27].

IEEE 1900.5

IEEE 1900.5 WG describes related control architectures and the vendor-neutral policy language for controlling the behaviour and functions of dynamic spectrum allocation in wireless networks. Also, the working group establishes how the policy's architecture and wording relate to the requirements of the regulator, the equipment manufacturer, and/or the operator [27].

IEEE 1900.6

IEEE 1900.6 WG defines the industry standard for data structures and interfaces for spectrum sensing in advanced radio communication systems implementing dynamic spectrum access. This working group establishes data structures and logical interfaces for information exchange between spectrum sensors and user clients [27].

IEEE 1900.7

IEEE 1900.7 is the working group centred on developing the standard for the radio interface for white space dynamic spectrum access systems. The interface, which is made up of the media access control (MAC) sub-layer and the physical layer (PHY), supports both fixed and mobile network operations in the white space spectrum bands. In these frequency bands, the interface also manages the primary users' avoidance of interference [27].

2.4. Spectrum Sensing

Cognitive radios need to employ spectrum sensing algorithms that precisely identify spectrum gaps in frequency space and time in order to utilise the available spectrum. To identify and forecast usage patterns, cognitive radio must acquire and evaluate the transmission characteristics of a radio access network's principal users. There are two approaches for spectrum sensing implementation: cooperative and non-cooperative sensing. The concept of cooperative spectrum sensing involves secondary users working together to share their sensing and transmission information and make decisions based on the shared information. In non-cooperative sensing, each cognitive radio engages in independent sensing and decision-making, disregarding the sensing information from other cognitive users [28], [29].

Signal detection, which is centred on determining the primary user activity on a frequency channel, is the crucial process in the spectrum sensing. A statistical hypothesis test can be used to model signal detection through statistical probability. The null hypothesis, represented by H_0 , indicates that a primary user signal is absent on a channel, whereas the alternate hypothesis, H_1 , denotes the presence of a primary

user signal. The probability of false detection is represented as P_f , while the probability of detection is represented by P_d [30].

$$P_d = Prob [signal\ detected|H_1] \quad (1)$$

$$P_f = Prob [signal\ detected|H_0] \quad (2)$$

Probability of false detection indicates the degree of missed opportunities by implying that a primary user signal is detected as present while the channel is free. The probability of missed detection, or P_{md} , is the opposite of the detection probability and it reflects the degree of interference that will be introduced if secondary users are unable to detect signals from primary users.

$$P_{md} = Prob [signal\ not\ detected|H_1] = [1 - P_d] \quad (3)$$

Assuming that y represents the received signal that the secondary users detected during a specific observation interval t , sample $y(t)$ can be expressed as follows [30]:

$$y(t) = \begin{cases} n(t); & H_0 \\ h * x(t) + n(t); & H_1 \end{cases} \quad (4)$$

where the noise on the sensed channel is represented by $n(t)$. The primary user-transmitted signal is denoted by the symbol $x(t)$, and the channel gain is denoted by the symbol h .

2.4.1. Local Spectrum Sensing Techniques

By applying cognitive radio in heterogeneous networks, secondary users can access primary users' licensed spectrum. To facilitate effective spectrum sharing, secondary users need to apply local spectrum sensing algorithms that allow them to identify signals from primary users (PU) without having to communicate with them directly [1]. The term local denotes spectrum sensing at a user level. Spectrum sensing principle

is based on modelling a signal detector that compares a test statistic to a sensing threshold and chooses between the two hypotheses (H_0 or H_1) previously explained. The comparison determines the decision outcome regarding the availability of a channel. The three most common and extensively studied local spectrum sensing methods are energy detection, cyclostationary detection, and matched filter detection [31],[32].

2.4.1.1. Matched Filter Detection (MFD)

One method of spectrum sensing that depends on prior knowledge of the main characteristics of the primary user signal is matched filtering. A time-shifted version of the known PU signal is cross-correlated with the unknown signal using the matched filter to find any patterns of the primary user signal. The application of convolution on the unknown sensed signal and the known PU signal is the fundamental working principle. The coefficients of the matched filter, which are derived from the known reference signal, are examined alongside the sensed signal to detect shared points. [31].

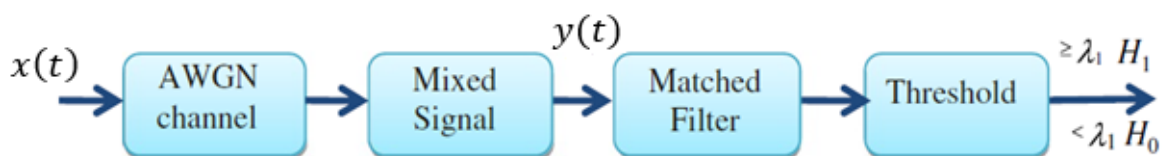


Figure 3: MFD Block Diagram [31]

The matched filter block diagram is shown in Figure 3. The signal transmitted by the primary user, represented by $x(t)$, combined with the noise component is directed into the matched filter as the input signal represented by $y(t)$. To determine PU signal presence on a channel, the matched filter output (T) is compared to the estimation

threshold. Given an estimation threshold of λ_1 , the decision regarding the matched filter can be expressed as follows [31]:

$$\begin{cases} T \geq \lambda_1 ; & H_1 \text{ (Primary user signal present)} \\ T < \lambda_1 ; & H_0 \text{ (Primary user signal absent)} \end{cases} \quad (5)$$

2.4.1.2. Cyclostationary Signal Detection (CSD)

Wireless transmission signals exhibit cyclostationary characteristics, which implies that the signals' statistical properties change with time depending on the carrier and modulation types implemented. By examining the cyclostationary correlation in the received signal's spectrum features, cyclostationary signal detection can be applied to confirm the presence of a primary user signal. Figure 4 shows a block diagram for implementation of cyclostationary signal detection. A cyclostationary detector can be modelled by utilizing likelihood analysis to extract periodic features from the modulated signals' autocorrelation [32],[33]. A cycle frequency domain profile (CDP) scans all the cyclic frequencies to detect and preprocess signals. Primary user transmission on the spectrum channel is represented by a peak in the cycle frequency domain profile. The degree of correlation in cyclostationary signals is quantified using the Spectral Correlation Density Function (SCD), which is obtained by applying Fourier transformation on the cyclic autocorrelation function [33],[34]. The expression for the autocorrelation function, over a period t , is as follows [33]:

$$R_x(t, \tau) = R_x(t + T, \tau) \quad (6)$$

where the time instance and cycle period of a signal correlation process are denoted as τ and T , respectively. The Fourier coefficients of the autocorrelation function are represented by the cycle autocorrelation function (CAF), which can be written as [34]:

$$R_x^{k\alpha}(\tau) = \lim_{T \rightarrow \infty} \frac{1}{T} \int_{-\frac{T}{2}}^{\frac{T}{2}} R_x(t, \tau) e^{-j2\pi kat} dt \quad (7)$$

$$R_x^\alpha(\tau) = \lim_{T \rightarrow \infty} \frac{1}{T} \int_{-\frac{T}{2}}^{\frac{T}{2}} \int x(t + \frac{\tau}{2}) x^*(t - \frac{\tau}{2}) e^{-j2\pi\alpha t} dt \quad (8)$$

After the cyclic autocorrelations' Fast Fourier transform, the Spectral Correlation Density Function that is produced is given as [34]:

$$S_x^\alpha(f) = \int_{-\infty}^{\infty} R_x^\alpha(\tau) e^{-j2\pi f\tau} d\tau \quad (9)$$

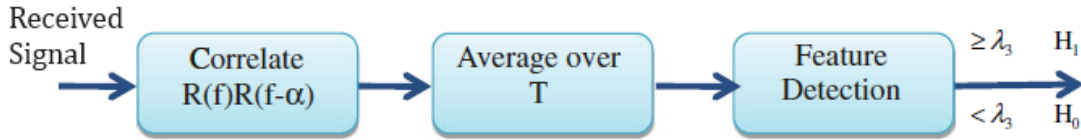


Figure 4: CSD Block Diagram [31]

2.4.1.3. Energy Detection (ED)

A primary user signal transmitted on a frequency channel can be identified using energy detection. Energy detection is a spectrum sensing technique that is based on extracting energy samples from the received signals. The technique is one of the most studied spectrum detection models with the highest level of implementation ease because it does not require any prior knowledge of the primary user signal [35]. Figure 5 illustrates an energy detector block diagram which comprises of a bandpass filter, signal squarer, integrator, and threshold blocks.

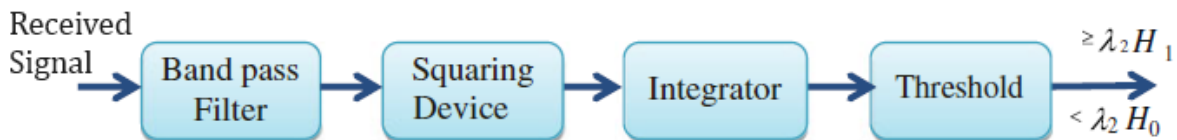


Figure 5: ED Block Diagram [31]

The bandpass filter reduces noise in the received signal and chooses the desired bandwidth channel. The signal squarer determines the squared values of the signals it receives in order to yield the signal energy measurements. To ascertain the channel

availability, the integrator block output, which is the test statistic, is compared with a predetermined threshold. If the test statistic's energy level is higher than the predetermined threshold, a primary user is assumed to be present; if it is lower, the channel is taken to be free [35],[36].

The hypothesis model for signal detection, where H_0 represents no signal detected and H_1 represents a primary user signal detected, is applied to energy detection spectrum sensing. Taking a primary user signal $x(t)$ transmitted on a channel with gain h and a noise component $n(t)$, the hypothesis test for signal detection can be expressed as follows [36]:

$$\begin{cases} H_0: y(t) = n(t) \\ H_1: y(t) = hx(t) + n(t) \end{cases} \quad (10)$$

The measured input signals are used to compute the energy detector test statistic (T). The energy detector determines the average energy of the observed samples to obtain the test statistic. With respect to a collection of N signal samples, the test statistic is represented as follows [36]:

$$T = \frac{1}{N} \sum_{t=1}^N |y(t)|^2 \quad (11)$$

Determining the detection threshold (λ) in energy detection is essential for assessing the likelihood of both missed and signal detection. The detection accuracy linked to the energy detection model is reflected through the attained probability of detection (P_d) and probability of false alarm (P_f) [36]:

$$\begin{cases} P_d = \Pr[T > \lambda | H_1] \\ P_f = \Pr[T > \lambda | H_0] \end{cases} \quad (12)$$

P_d is the probability of the energy detector accurately identifying a primary user signal while P_f denotes the probability of incorrectly detecting a signal when the channel is unoccupied. The probability that the energy detector will correctly detect a primary

user signal is represented by P_d , whereas the probability that a signal will be incorrectly detected when the channel is empty is represented by P_f .

2.4.2. Cooperative Spectrum Sensing

There has been significant research on cooperative sensing techniques that can curb some challenges encountered in radio systems like the hidden terminal problem [37]. The hidden terminal problem arises when channel effects like multipath fading and shadowing prevent a user transmitting to a node from detecting transmission from another terminal. Consequently, there is a chance that both terminals will transmit to the same node at the same time, leading to the possibility of interference and packet collisions [37]. Interaction and information sharing among secondary user terminals form the foundation of the cooperative sensing approach. The key objective of cooperative spectrum sensing is to make sure every participating user in the cognitive radio network is in synchrony and has the most up-to-date information about the traffic pattern on the frequency of interest. A distributed or centralized sensing architecture is applied to model cooperative sensing. The distinction between the two sensing architectures is in the way cognitive radio users gather data to establish whether a primary user signal is present on a chosen frequency channel.

In centralized cooperative sensing, all the information from the individual cognitive radios is forwarded to a single centralized fusion centre. The fusion centre uses a multi-step spectrum sensing sequence to make a global decision on presence of a primary user. First, the fusion centre selects a frequency channel of interest and gives each cognitive radio a specific frequency band to perform spectrum sensing on. After sensing, cognitive radios report back to the fusion centre with their findings. Following the integration of all the sensing data, the fusion centre determines if a primary user

signal is present and relays the information back to the cognitive radios. In the centralized cooperative sensing process, two types of channels, namely, reporting and sensing, are used for transmission. To perform spectrum sensing, cognitive radios are tuned into sensing channels where the primary user signals are observed. The reporting channels are control channels used to transmit and receive decisions between the fusion centre and CR users. [38].

Distributed cooperative sensing eliminates the need for a centralized fusion centre by allowing users of the CR to communicate directly and share information. Based on the aggregated data that is directly gathered from other users, each cognitive user independently senses the state of the channel. To mitigate potential overhead in communication messages among CR users, shared sensing data is broadcast as control messages over a shared control channel. Time slots on the shared control channel can then be assigned to cognitive radio users to prevent interference. Mukherjee [19] explores a cooperative sensing model that integrates spectrum sensing with game theory based interactive decision making.

2.4.3. Decision Strategies

The two primary strategies used in spectrum sensing decision-making are Hard Fusion and Soft Fusion. The distinguishing factors between these strategies are in the type of data transmitted to the fusion centre and the rule applied by the fusion centre for decision-making [39].

2.4.3.1. Hard Fusion

Hard fusion involves making decisions at an individual user level and then forwarding them to a central fusion centre. Every cognitive radio identifies whether a primary

user's signal is present by using local sensing techniques. The cognitive users use a threshold to compare the sensed signal test statistic with a set threshold and then convert their sensing decisions into a binary result. Subsequently, the fusion centre receives the one-bit binary decision outcome from each cognitive radio, where one represents the presence of a primary user signal and zero represents the absence of a primary user signal. Using logic operation rules, the fusion centre then makes a final decision regarding the presence of a primary user's signal. Three logic operator models can be applied in Hard Fusion decision making namely OR-logic, AND-logic, and Majority-logic. If at least one cognitive radio transmits a decision of one, OR-logic provides a centralized decision of one. In AND-logic, for the final decision to be one, all cognitive radios must send logic one decisions. Majority-logic applies a voting rule where a decision of logic one can only be made if at least half of the sent decisions are logic one [39].

2.4.3.2. Soft Fusion

Without making any local decisions, cognitive radios that use soft fusion forward their sensing data to the fusion centre. At the fusion centre, the received signal statistics from every cognitive radio are combined using combining rules to create a global test statistic that is used to make the final decision. Square Law Combining (SLC), Maximum Ratio Combining (MRC), Selection Combining (SC), and Equal Gain Combining (EGC), are examples of common soft combining rules. Square Law Combining is the simplest soft fusion method, in which the fusion centre receives the signal energy estimate transmitted directly from each cognitive radio. To determine whether there is a PU signal, the fusion centre adds the energy samples it has received and compares the total to a detection threshold. In Maximum Ratio Combining, a weight factor is applied to each received signal that is inversely proportional to the

mean square signal-to-noise ratio and proportional to the signal's root mean square amplitude. As a result of this weighting, weaker sample signals are attenuated while stronger energy levels are amplified further when they are received. The signals are then summed up and used as the test statistics. The test statistic with the highest diversity gain is determined. Selection Combining is based on the received signal with the highest SNR readings. It is a simpler fusion rule than Maximal Ratio Combining. In Equal Gain Combining, all received signals, regardless of their characteristics, are co-phased before being summed to produce a stronger signal. To determine the decision outcome, the weighted signals are added together and compared to a detection threshold [39],[40].

2.5. Spectrum Mobility

Spectrum mobility refers to the technique by which a radio user switches its channel of operation while ensuring uninterrupted data transfer. Combining spectrum handoff with connection management allows for spectrum mobility. Spectrum mobility, in the cognitive radio context specifies the channel occupancy and handover sequence that CR users apply to move to a different channel when a primary user is present [38].

2.5.1. Spectrum Handoff

When a user needs to switch channels because another user is transmitting or when the occupied spectrum cannot meet their quality-of-service demands, spectrum handoff is initiated. Spectrum handoff is executed in one of two ways: reactively or proactively. In reactive handoff, a secondary user leaves the frequency channel upon the appearance of a primary user and finds another free channel. This process occurs on a demand basis. As soon as the primary user signal appears, spectrum sensing and handover take place [38]. The disadvantage of this concurrent operation is that it

introduces a delay after the handover trigger due to spectrum sensing, which results in reduced accuracy in spectrum mobility. Proactive handoff involves the secondary user locating an alternate transmission channel prior to handover being triggered. The cognitive radio users monitor every spectrum channel and compile data on channel usage to determine backup channels. Before the handoff process takes place, candidate channels are reserved from the spectrum observations [38]. Because spectrum sensing is done ahead of time, this approach has the benefit of a reduced handoff delay. Proactive handoff has the drawback that a backup channel that was previously reserved might be occupied by a primary user just before handoff. In this scenario the scheduled sequence would potentially cause interference.

2.6. Channel State Prediction

An essential component of cognitive radio network design is modelling spectrum occupancy for channel state prediction. Using mathematical and statistical modelling and simulation, traffic patterns and channel states can be evaluated. Among the most popular models used to simulate spectrum occupancy are those based on game theory and hidden Markov models [41],[42].

2.6.1. Game Theory

Game theory is mathematical framework that examines the interactions between a group of players to aid in decision-making. Decision results for interference avoidance and channel allocation in dynamic spectrum access can be obtained using the mathematical model. There are three primary parts to a game: the players (N), the strategies (S_i), and the utility functions (u_i). A game's intended goal is to reach an equilibrium state where every player is conscious of the others' strategy and lacks motivation to alter their own state. This is because every player's actions have an

impact on the results of every participant. The term Nash Equilibrium is used to refer to this target steady state [42].

In the context of cognitive radio, game theory has been used to model dynamic spectrum allocation where channel allocation is set as the output of a game. The cognitive radio users are the players while their independent choice of transmission channels are the game strategies. The utility functions are linked to the quality of the transmission channels. In the game, each user updates its strategy to a strategy that will maximise its utility. The target Nash equilibrium state of the utility functions therefore matches the best point for the cognitive radio users. In [42], a game-based spectrum allocation algorithm is modelled where the utility function is designed with the system signal-to-interference ratio (SIR) as the reference point.

2.6.2. Markov Chain Modelling

A Markov chain is a stochastic process where the likelihood of going from one state to another depends on the state at hand. The characteristic of Markov chains is that only the most recent event influences the subsequent state and previous events are ignored. The idea originated with Andrey Markov's research on stochastic processes and finds extensive use in communication models, genetics, and economics. The use of Markov based models for channel state prediction is a subject of growing research. Sadeghi *et al.* [43] explores finite state Markov modelling of fading channels in wireless communication systems.

2.6.2.1. Hidden-Markov Models for Cognitive Radio

In cognitive radio, hidden-markov chain models (HMM) are convenient as they allow future state prediction and concurrent referencing of underlying (hidden) states. When

applied to CR networks, HMM define the transition sequence for channel state estimation for dynamic spectrum access. The transitions are centred on the two possible channel conditions of busy and idle. The accuracy of the spectrum detection sequence is reflected through the two possible likelihood outcomes which are probability of detection (P_d) and probability of false detection (P_{fa}). Figure 6 illustrates the state transition patterns in a hidden markov model applied for spectrum sensing. Two transition probabilities represented as β and α are used to characterize the channel state transition pattern. β represents the likelihood of a transition from an occupied channel to free while α represents the likelihood of a state transition from free to occupied [44], [45].

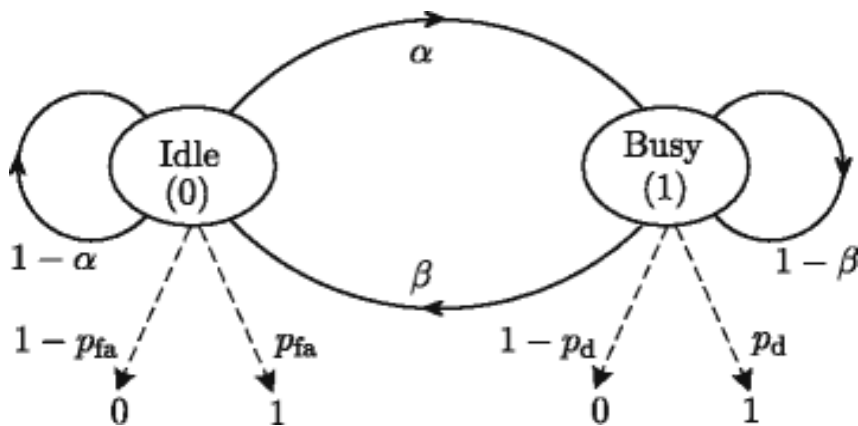


Figure 6: HMM Channel State Transitions [45]

2.7. Summary

This chapter has explained in detail the concept of cognitive radio (CR) networks with emphasis on the application of their self-learning and adaptive capabilities for efficient spectrum management. A historical background on the emergence of cognitive radio is presented followed by discussions on spectrum sharing and spectrum sensing. Additionally, the chapter explores spectrum mobility and channel state prediction models applied in CR networks. An insight is presented on mathematical models that

can be applied in spectrum sensing, such as the Hidden Markov Model. This detailed background on the various aspects of cognitive radio provides the foundation for some of the spectrum access models that have been proposed for cognitive radio networks. In the following chapter, an in-depth analysis of some spectrum access models is presented.

CHAPTER 3: COGNITIVE RADIO SENSING MODELS

3.1. Introduction

A review of cooperative spectrum sensing (CSS) models from literature is presented in this chapter. By reviewing existing research papers, the chapter aims to highlight advancements and challenges with the cognitive radio concepts introduced in the previous chapter, with a greater emphasis on cooperative spectrum sensing. The main objectives of cooperative spectrum sensing models are to enhance spectrum usage and address specific challenges identified on local spectrum detection algorithms. Previous research on cooperative sensing schemes has illustrated an increase in sensing accuracy that is linked with this collaborative approach. Existing CSS cognitive radio models still have some shortcomings, which include high energy consumption patterns, delayed transmission times, and channel interference.

A channel state estimation model, a decision-making scheme, and a local sensing technique are the key components of a CSS cognitive radio network design. As stated in the objectives, a comparative study of hard and soft fusion decision-making strategies applied in an energy detection-based scheme is the key goal of this research. This chapter also discusses energy detection, and the channel frame structures involved in time slot allocations in cognitive radio networks. Additionally, it discusses the advantages, drawbacks, and viability of various aspects linked to detection accuracy in spectrum sensing. The chapter provides an important foundation for the research carried out.

3.2. Energy Detection Spectrum Sensing

The most studied local spectrum sensing methods, as previously mentioned, are Matched Filter detection, Cyclostationary detection, and Energy detection. Due to its low design complexity and minimal sensing time requirements, this research is centred on energy detection as the local spectrum sensing method. An additional benefit of energy detection is that it is independent of past information of the detected signal, allowing for quicker detection [46]. Shortfalls associated with energy detection are linked to difficulties in accurately differentiating the transmitted signal and noise components. Energy detection has a drawback in that its performance degrades at very low SNR ranges.

The likelihood of detection (P_d) indicates the accuracy of spectrum sensing, while the probability of false alarm (P_{fa}) and the probability of missed detection (P_{md}) indicate the inaccuracy of the detection process. In energy detection spectrum sensing, the detection threshold used affects the performance of the sensing scheme. The test statistic that is employed for energy detection in [47] is stated below:

$$\mathbb{T}_i(y_i) = \sum_{n=1}^N |y_i[n]|^2 \begin{matrix} H_1 \\ \geq \lambda \\ H_0 \end{matrix} \quad (13)$$

Whereas $\mathbb{T}_i(y_i)$ indicates the calculated test statistic compared with a detection threshold λ . H_0 and H_1 represents the hypothesis testing conditions for signal detection. y_i is the input signal observed by the energy detector at the i^{th} sensing cycle. A Gaussian distribution based on central limit theory can be used to estimate the test statistic, where N denotes the number of samples, provided that N is large enough [47]:

$$\mathbb{T}_i(y_i) \sim \begin{cases} \mathcal{N}(N\sigma_w^2, 2N\sigma_w^4), & H_0 \\ \mathcal{N}(N(\sigma_x^2 + \sigma_w^2), 2N(\sigma_x^2 + \sigma_w^2)^2), & H_1 \end{cases} \quad (14)$$

The received signal variance is denoted as σ_x^2 while noise variance is denoted as σ_w^2 . The energy detection algorithm's probability of false alarm (P_{fa}) can be derived from the approximation of $\mathbb{T}_i(y_i)$ [47]:

$$P_{fa} = P\{\mathbb{T}_i(y_i) > \lambda\}_{H_0} = Q\left(\frac{\lambda - N\sigma_w^2}{\sqrt{2N\sigma_w^4}}\right) \quad (15)$$

The Gaussian probability Q-function is represented as $Q(\cdot)$. The typical method for determining the detection threshold in recent energy detection research is based on noise variance estimations, which produces a dynamic detection threshold [48].

3.2.1. Dynamic Energy Detection Threshold

Static detection thresholds are used as benchmarks for determining whether a primary user signal is present in energy detection models for cognitive radio. There has been more research drawing on an adjustable detection threshold that can accommodate the real-time variations in channel conditions that are observed in wireless networks. In [49] and [50], improved methods for energy detection based on an enhanced detection threshold have been explored. Depending on the measured noise variance in the received signal, the method employs a dynamic detection threshold factoring the varying conditions. The noise fluctuation and uncertainty present in real-world radio environments are accommodated by the dynamic threshold approach.

The idea behind the dynamic threshold is to update the threshold-estimation algorithm's by continuously utilizing previous knowledge of the noise component within the observed received signals. While it may be difficult to predict the signal power pattern, noise variance will normally follow a pattern that can be estimated. In [50] and [51], algorithms designed for obtaining an optimal detection threshold (λ_{opt}) have been

explored where the threshold is modelled around the detection error. The algorithms aim to determine the best threshold that minimizes the error rate in signal detection.

The optimization expression is given as follows:

$$\lambda_{opt} = \arg \min_{\lambda} (\varphi_e) \quad (16)$$

where detection error rate is represented by φ_e , which is the result of a linear combination of the probability of missed detection P_{md} and the probability of false alarm P_{fa} [51].

$$\varphi_e = P(H_0)P_{fa} + P(H_1)P_{md} \quad (17)$$

The probability of the primary user's presence and absence are respectively denoted by $P(H_1)$ and $P(H_0)$. An optimal detection threshold would be the threshold that reduces detection error rate (φ_e) to the lowest point. At this lowest error rate point, the detection error rate derivative would be equal to zero. The threshold can therefore be obtained by solving the derivative expression below [51]:

$$\left. \frac{\partial \varphi_e(\lambda)}{\partial \lambda} \right|_{\lambda=\lambda_{opt}} = P(H_0) \frac{\partial P_{fa}}{\partial \lambda} + P(H_1) \frac{\partial P_{md}}{\partial \lambda} = 0 \quad (18)$$

Probability of missed detection (P_{md}) is obtained from probability of detection (P_d), where $P_{md} = 1 - P_d$. P_{md} can be substituted with P_d in (18) such that $\frac{\partial P_{md}}{\partial \lambda} = -\frac{\partial P_d}{\partial \lambda}$. The derivative expression for the optimal detection threshold that gives the lowest probability of error is therefore expressed as [51]:

$$\left. \frac{\partial \varphi_e(\lambda)}{\partial \lambda} \right|_{\lambda=\lambda_{opt}} = P(H_0) \frac{\partial P_{fa}}{\partial \lambda} - P(H_1) \frac{\partial P_d}{\partial \lambda} = 0 \quad (19)$$

In [51], an optimal detection threshold is computed by solving the derivative expression for the minimum error rate for a cooperative spectrum sensing system.

$$\left. \frac{\partial \varphi_e(\lambda)}{\partial \lambda} \right|_{\lambda=\lambda_{opt}} = P(H_0) \frac{\partial Q_f(\lambda)}{\partial \lambda} - P(H_1) \frac{\partial Q_d(\lambda)}{\partial \lambda} = 0 \quad (20)$$

Q_d is the cooperative probability of detection while Q_f is probability of false alarm.

In previous works, the performance metrics predominantly used to assess the energy detection performance are probability of detection (P_d) and probability of false alarm (P_{fa}). The control parameters applied to evaluate these metrics include the SNR and CR user count. In [49], the energy detection scheme is evaluated by simulating the probability of detection obtained at varying SNR values. Higher probability of detection values closer to 1 illustrate good detection performance. In [50], an additional metric is used to evaluate energy detection which is detection error probability (P_e). In terms of detection performance, the detection error probability is required to be as low as possible as it is derived from a linear combination of the likelihood of false detection and missed detection in the spectrum sensing scheme.

The performance of an energy detection scheme is evaluated with respect to signal to noise ratio. To ensure that primary users encounter the least amount of interference, an energy detection scheme should function over a broad range of varying channel conditions. It is anticipated that next-generation network services, like Machine-to-Machine (M2M) communications, will also utilize low power transmission bands with low-signal-to-noise ratio channels [50]. To guarantee quality of service, cognitive radios need to be interoperable with next-generation networks and flexible enough to adjust to high noise environments.

3.3. Cooperative Sensing: Timeslot Management

In cooperative spectrum sensing, the effective management of channel interference is heavily dependent on the criteria employed for scheduling sensing windows. The sensing sequence in cooperative sensing is modelled from the channel frame structure that is based on time and frequency division multiple access schemes. Figure 7

illustrates the fundamental structure of a cognitive radio (CR) frame, having a frame duration T , which is divided into the transmission time ($T-\tau$) and sensing time (τ).

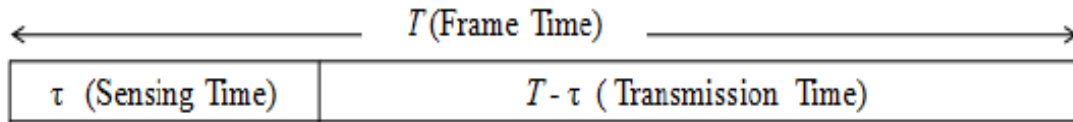


Figure 7: Standard CR Frame Structure [52]

The fixed sensing time slot is when spectrum sensing takes place. Data transmission and channel assignment are only possible after the sensing duration. One of the challenges with this fixed frame structure is that it limits the amount of time that CR users can sense. Figure 8 illustrates how the likelihood of channel interference would rise with a brief and fixed sensing time.

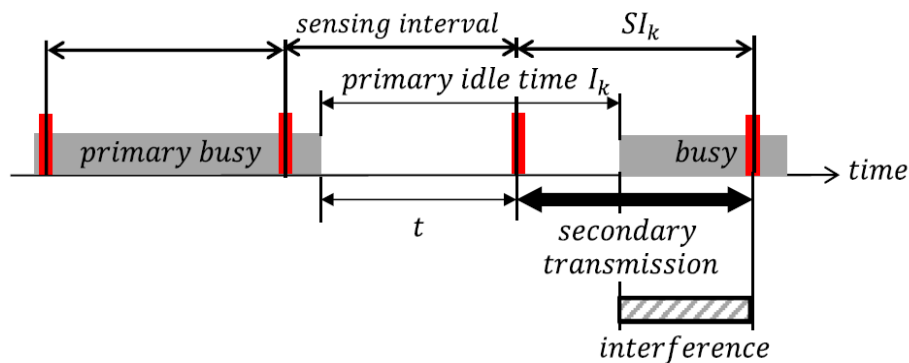


Figure 8: Interference Scenario in Spectrum Sensing [53]

Figure 8 illustrates three fixed sensing intervals. A primary signal is detected in the first interval. The primary signal becomes idle in the second sensing interval triggering secondary user transmission in the third interval (SI_k). A primary user reappears within the same fixed sensing interval (SI_k) resulting in channel interference.

3.3.1. Multi-Slot Spectrum Sensing

Recent cognitive radio research has explored the optimizing of the standard TDM-based frame structures. One of the algorithms proposed in the literature uses multi-slot frame structures for channel sensing and transmission. By allowing cognitive radios to conduct channel sensing and reporting simultaneously, the multi-slot frame structure in spectrum sensing aims to provide the best sensing accuracy while minimizing transmission delay.

A multi-slot model intended for mobile communication applications is reviewed in [15]. The proposed model allows secondary users based on satellites and terrestrial platforms to dynamically receive spectrum on the L/S bands (1-4GHz) from low earth orbit satellites. Using a hard-fusion technique, the multi-slot scheme forwards the binary decision outcomes to the fusion centre after secondary users' complete local spectrum sensing. Several secondary users perform spectrum sensing on a designated channel during the sensing slot's multiple mini slots, and each secondary user reports the results of its sensing to the fusion centre. A typical frame structure of frame duration T in a cognitive radio system of M secondary users would include a transmission time (τ_t), a reporting time (τ_r), and a sensing period (τ_s) as shown in Figure 9. Using the frame structure, the available transmission is as follows:

$$\tau_t = T - \tau_s - M * \tau_r \quad (21)$$

where $M * \tau_r$ is the product of the number of CR users involved in channel sensing and the reporting duration per user.

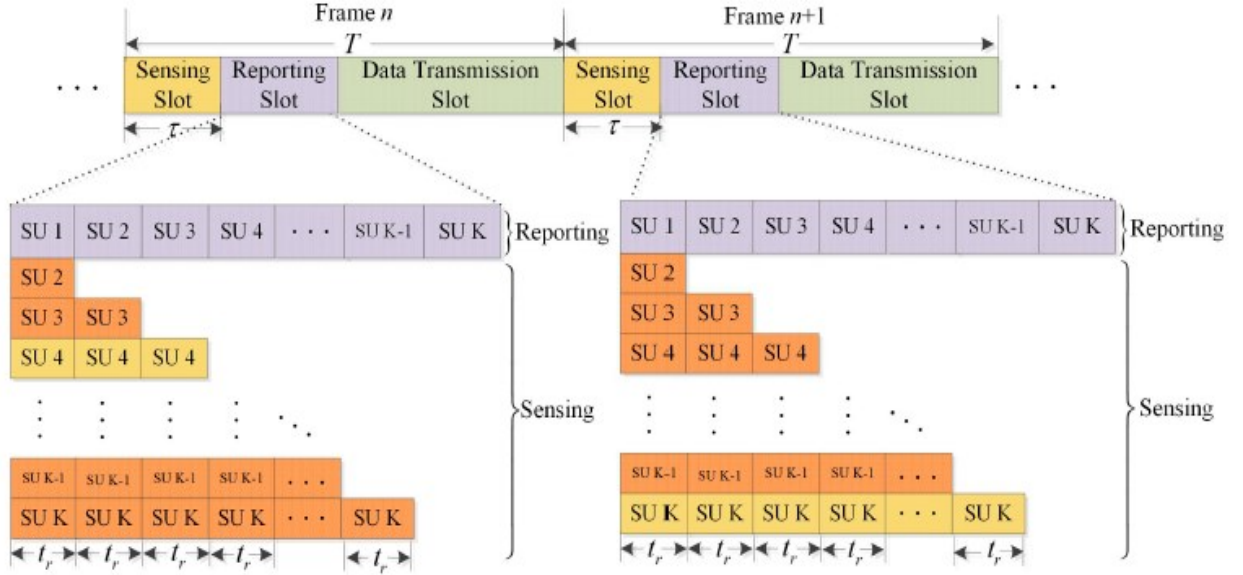


Figure 9: Optimised Frame Structure for Cooperative Sensing [15]

Hu H. *et al.* [14] proposed a model for determining the ideal sensing duration needed to guarantee efficient spectrum sensing. They derived a mathematical expression for calculating the probability of detection (P_d) for a cognitive radio system with SNR (γ), Gaussian noise variance (σ^2) and a detection threshold (λ_D).

$$P_d = Q\left(\left(\frac{\lambda_D}{\sigma^2} - \gamma - 1\right) \sqrt{\frac{\tau f_s}{2(2\gamma + 1)}}\right) \quad (22)$$

$Q(\cdot)$ denotes the Gaussian Q-function. τ represents the sensing time while f_s denotes the sampling frequency. Primary users are deemed to be insignificantly impacted by channel interference to yield a target probability of detection (P_d^t). The resultant probability of false detection is expressed as follows [14]:

$$P_f = Q\left(\sqrt{2\gamma + 1} \cdot Q^{-1}(P_d^t) + \gamma \sqrt{\frac{\tau f_s}{2}}\right) \quad (23)$$

3.4. Cooperative Sensing: Decision Strategies

In cooperative spectrum sensing, the decision strategy outlines how the ultimate determination of channel state is made in relation to primary user signal presence. Cooperative spectrum sensing models predominantly apply soft combining or hard combining approaches to decision making, and these schemes have been discussed in the previous chapter.

3.5. Summary

In this chapter, an energy detection scheme has been identified as the scheme of choice for implementing spectrum sensing for cognitive radio due to its reduced complexity and quicker implementation. The concept of a multi-slot spectrum management approach for cooperative sensing is presented in the chapter. The chapter analyses specific energy detection and cooperative sensing models proposed in previous research papers. Based on the reviewed research papers, a motivation for the application of energy detection with a dynamic detection threshold is given. This approach is significant in that it considers existing real-time variations in the wireless environment which would enhance detection accuracy. Decision-making schemes are also highlighted as a key factor in ensuring successful implementation of cooperative sensing. The review given in this chapter forms the basis for the design and simulation of the proposed spectrum sensing scheme presented in the following chapter.

CHAPTER 4: DESIGN AND IMPLEMENTATION OF COOPERATIVE SPECTRUM SENSING SCHEME

4.1. Introduction

In this chapter, an energy-detection spectrum sensing cognitive radio scheme is designed and implemented based on soft fusion and hard fusion sensing strategies. The key objective of the chapter is to design a scheme through which the performance of soft fusion and hard fusion sensing strategies can be evaluated. First, a system model is presented to give a contextual representation on the network environment in which the cognitive radio system would operate. The algorithms for soft fusion and hard fusion sensing are then presented. The chapter then details the approach applied for simulation of the proposed cognitive radio scheme.

4.2. System Model

The system model considered consists of a radio access network and a cognitive radio network, as shown in Figure 10. The radio access network uses licenced frequency bands accessible to both primary and secondary users. The primary users are connected to the radio access network while the cognitive radio network consists of multiple secondary users linked to a centralized fusion centre. The fusion centre is responsible for making global sensing decisions and controlling access to the licenced spectrum on the radio access network. Communication between the secondary users and the fusion centre occurs through control channels that operate at frequencies within the unlicensed band. This reduces the chances of interference on the primary user channels by allowing SUs to continually transmit control messages on separate channels. The multi-slot frame structure also allows for dynamic allocation of sub

channels within the licenced spectrum for control messages if the control channels using unlicensed bands become unavailable.

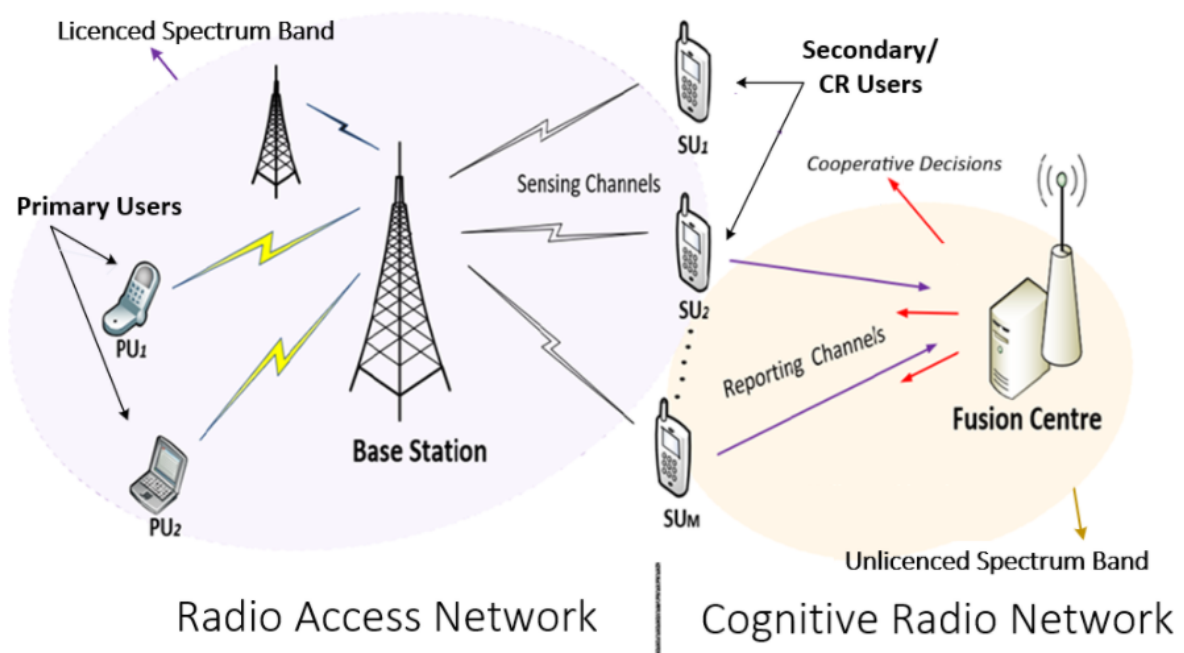


Figure 10: CSS Cognitive Radio Network Diagram

The reporting channels indicated in Figure 10 are control channels only used for dedicated information exchange relating to channel availability and sensing decision updates. This limited scope allows for flexible use of unlicensed frequency bands for the control channels within the cognitive radio network. This would enable rapid and adaptive use of cognitive radios in different wireless networks and ensures the objective of efficiently utilizing the licenced spectrum is maintained.

Spectrum sensing and data transmission occurs on the licensed channels on the radio access network. A time division approach is applied where the available spectrum is segmented into discrete time slots for sensing and data transmission. Time slots for data transmission have greater priority and duration. Cognitive radios use the sensing

time slots to perform channel sensing and send the results to the fusion centre through the control channels. If a transmission slot is deemed to be free, the fusion centre automatically assigns it to a cognitive radio user based on predefined scheduling criteria. The scheduling criteria are based on a multifaceted approach that include metrics such as signal quality and user application type.

4.3. Decision Strategies for Energy Detection

4.3.1. Soft Fusion Sensing

When the cooperative energy-detection scheme applies the soft fusion sensing algorithm, each CR user sends their local sensing information directly to the fusion centre. The fusion centre combines the CR users sensing data, and a single decision is made on the channel state regarding primary user signal presence. As previously explained in chapter 2, the received signal $y(t)$ observed by the CR users can be represented as:

$$y(t) = \begin{cases} n(t); & H_0 : \text{Signal Absent} \\ h * x(t) + n(t); & H_1 : \text{Signal Present} \end{cases} \quad (24)$$

where $x(t)$ is the primary user transmitted signal and $n(t)$ represents the channel noise. The received signal is taken to have been sampled at the i^{th} secondary user for a finite number of secondary users (N). Energy detection is applied as the local spectrum sensing technique by each CR user. A global test statistic is derived from the collated energy measurements of each CR user and is applied for the decision-making process. Figure 11 illustrates the cooperative sensing model for soft fusion sensing.

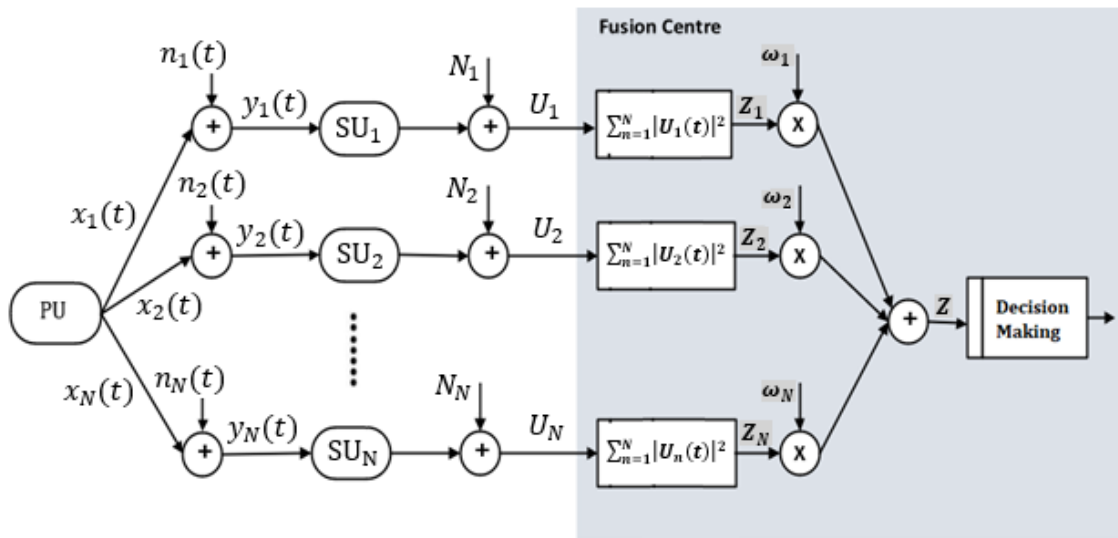


Figure 11: Cooperative Spectrum Sensing Model [54]

Figure 12 is the flowchart for the soft fusion sensing algorithm. Each CR user performs energy detection sensing on a single channel. It senses the next channel once the centralized fusion centre sends the decision outcome of the current channel. For each channel, the fusion centre waits to obtain the sensing information from all the participating CR users on the network before making the final decision.

While the approach of combining sensing information from all the CR users can enhance detection accuracy, the high data volumes would also increase computational and communication overheads. The number of CR users is varied in simulating the soft fusion sensing scheme, with the objective of obtaining the optimum number of CR users that would provide the best sensing performance. A cluster based soft fusion sensing approach can then be applied where the CR network is grouped into clusters based on the optimum number of CR users that will be identified in the simulations.

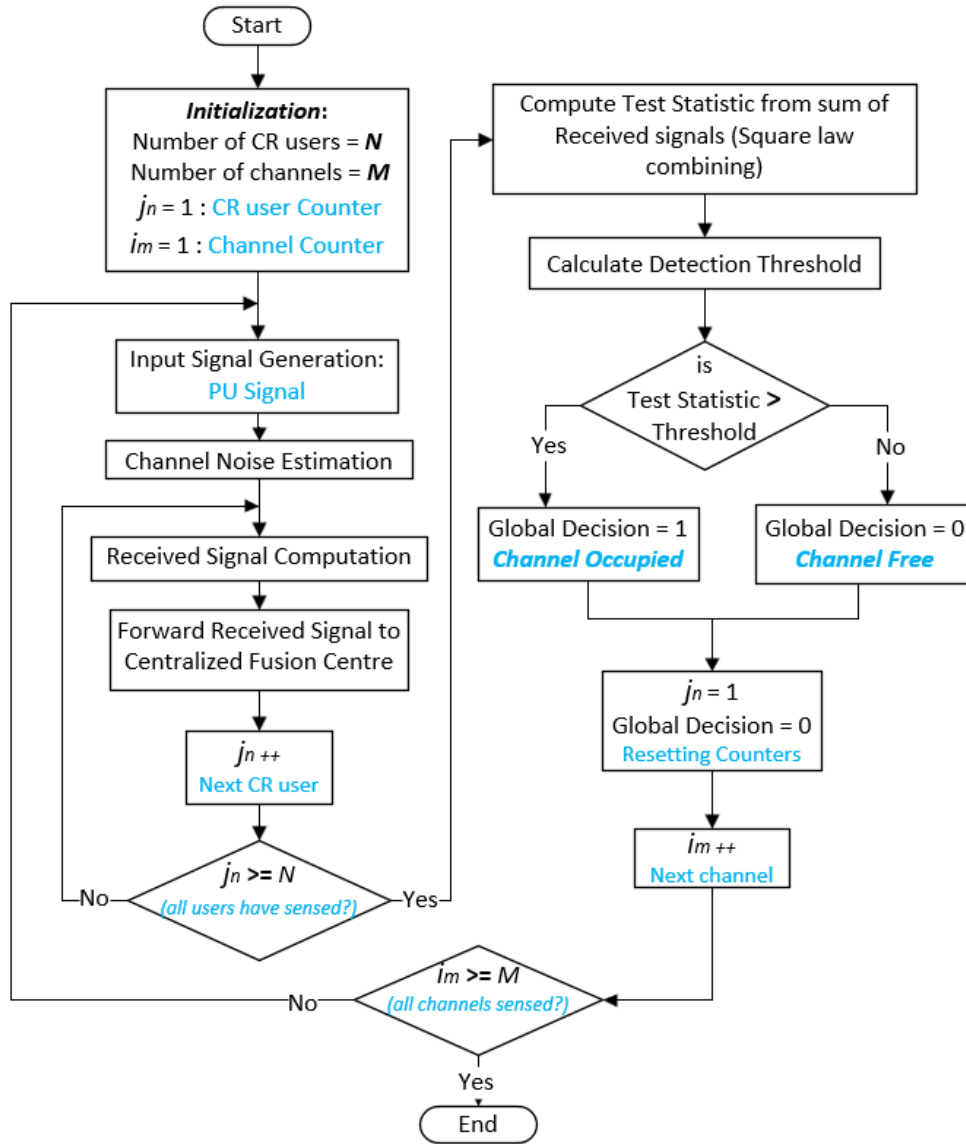


Figure 12: Flowchart for the Soft Fusion Sensing Algorithm.

4.3.2. Hard Fusion Sensing

When the cooperative energy-detection scheme applies the hard fusion sensing algorithm, local sensing is performed by each CR user to obtain local decisions. The local decision outcomes are then forwarded to the fusion centre which generates the global decision outcome. The proposed hard fusion scheme applies the m out of N majority rule where in a system of N CR users, a global decision on channel availability is made if at least m users report PU signal presence or absence. Figure 13 is the flowchart for the hard fusion sensing algorithm.

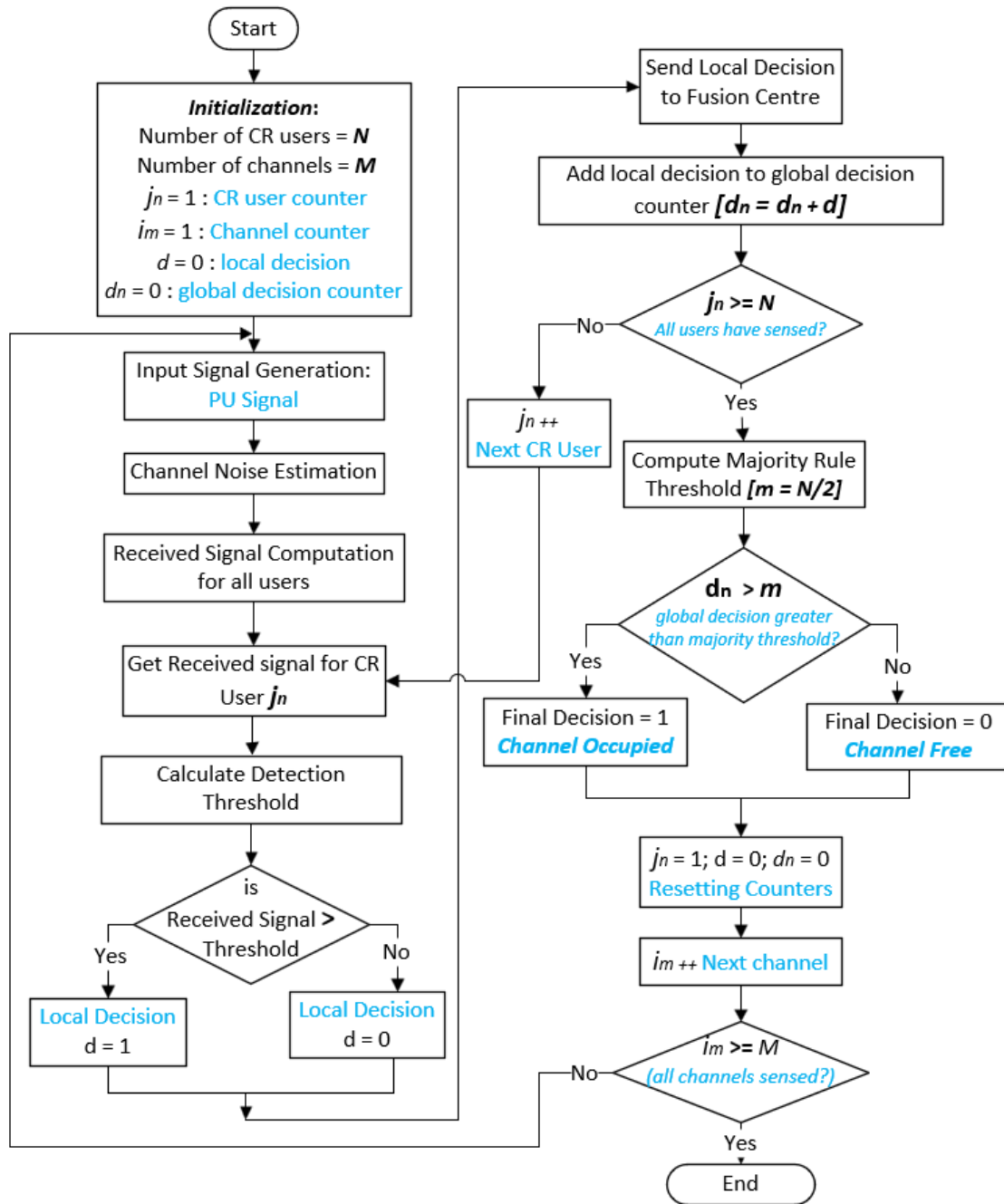


Figure 13: Flowchart of the Hard Fusion Sensing Algorithm (Based on Majority Rule)

While the hard fusion algorithm has additional steps associated with the individual CR user sensing, the approach has lower computational complexity due to the resultant transmission of only binary decisions (0 or 1) to the fusion centre. The binary decisions also result in lower data transmission requirements, which would result in higher energy efficiency when compared to the soft fusion scheme.

4.4. Implementation and Simulation

Using MATLAB, the designed energy detection-based soft fusion and hard fusion sensing schemes have been implemented based on the algorithms shown in Figure 12 and Figure 13. The hard fusion algorithm in Figure 13 has been chosen based on the cluster model in [51], where the majority rule was identified as the most effective hard fusion scheme for cooperative spectrum sensing. To accurately compare the two decision strategies, the fusion algorithms have been simulated for the same input signals and channel conditions. The cognitive radio network is considered to have a fixed number of cognitive radio users (N). Each CR user participating in the sensing process collects received signal samples from the primary user spectrum bands. The overall objective of the spectrum sensing algorithm is to identify free channels not being used by the primary users.

The performance metrics used in the simulation are the probability of detection, and probability of error. Probability of detection is measured at different Signal-to-Noise Ratios (SNR). A wide SNR range is used in the simulation of the varying channel conditions of the cognitive radio network with low SNR values representing noisy channel conditions. The MATLAB code written for the model simulations is segmented into three parts, namely, received signal generation, threshold computation and sensing sequence.

4.4.1. Received Signal Generation

To simulate the signals observed by the CR users within the cognitive radio network, received signal samples are generated using the MATLAB random number generator function. The main objective is to model general signal behaviour at any given time with less emphasis on the underlying probability distribution of the signal. In this

scenario, random number generators provide more flexibility and less computational complexity for repeated random sampling and probability outcome predictions. The received signal $y(t)$ is obtained based on the hypothesis testing problem model for spectrum sensing where H_0 hypothesis represents PU signal absence, and H_1 represents a PU signal presence [36]:

$$y(t) = \begin{cases} n(t); & H_0 \\ h * x(t) + n(t); & H_1 \end{cases} \quad (25)$$

The primary user input signal is represented by $x(t)$ while $n(t)$ represents the noise component. The channel gain h is set to 1 to maintain the input signal power. In the MATLAB code, the noise component and the input signal representing primary user transmission are both generated as a range of random integer values following a uniform distribution pattern. This approach is based on spectrum sensing algorithms applied in [55] and [56]. To ensure received signal samples are generated for each CR user, the digital input signal is simulated as an $S \times N$ matrix vector where S represents the number of samples generated for each CR user while N represents the number of users. The resultant MATLAB expression for generating the input signal matrix is:

$$inputSignal = randi ([0 \ 1], S, N) \quad (26)$$

The received signal samples (y) observed by the CR users are generated by adding a noise component to the input signals generated. The noise is generated as a random number sequence with a Gaussian distribution. The energy of the generated received signals is then computed based on the energy detection expression in [47]. The energy is obtained by linearly combining the squared values of received signal samples.

$$Energy = \sum_{s=1}^S |y_i[s]|^2 \quad (27)$$

y_i represents the received signal samples obtained from the $S \times N$ received signal matrix. S represents the total number of signal samples for each CR user. The resultant

energy values obtained from (27) are in the form of a $1 \times N$ matrix vector, with an energy value for each CR user. The test statistic applied for energy detection is obtained from these energy values depending on the fusion scheme. For soft fusion sensing, the energy values obtained from each CR user are added together and the test statistic is calculated from the average value of the energy sum. For the hard fusion algorithm, the energy value for each CR users is taken as its test statistic for local sensing.

4.4.2. Threshold Computation

A dynamic approach is applied in computing the detection threshold for energy sensing. The objective is to increase detection accuracy by computing a detection threshold that factors and adjusts to real-time changes in channel condition. In the simulated MATLAB code, changes in channel conditions are reflected through varying signal-to-noise ratio values. The detection threshold applied for energy detection is derived from the expression used to calculate probability of false alarm in [47].

$$P_f = Q \left(\frac{\lambda - N\sigma_w^2}{\sqrt{2N\sigma_w^4}} \right) \quad (28)$$

$$Q^{-1}(P_f)\sqrt{2N\sigma_w^4} = \lambda - N\sigma_w^2 \quad (29)$$

$$\lambda = Q^{-1}(P_f)\sqrt{2N\sigma_w^4} + N\sigma_w^2 \quad (30)$$

λ represents the detection threshold while P_f is probability of false alarm. The number of samples is represented by N while σ_w^2 denotes the noise variance. For the threshold computation, the number of samples is determined by the number of CR users as signal samples are simulated for each CR user. This approach applied for computing the detection threshold is based on the energy detection code outlined in [55]. The noise variance (σ_w^2) is calculated from the simulated signal-to-noise ratio (SNR) and signal variance (σ_x^2), based on the SNR expression in [47]:

$$SNR = \sigma_x^2 / \sigma_w^2 \quad (31)$$

4.4.3. Spectrum Sensing Sequence

In the simulation of the received signal, an array of random digital values is generated as an $S \times N$ matrix where S signal samples are generated for each of the N CR users. Once the received signal has been generated, the MATLAB code computes the energy of the received signals and applies a detection algorithm for spectrum sensing for the CR users. The spectrum sensing sequence involves computing the test statistic and detection threshold and applying two separate algorithms for soft fusion detection and hard fusion detection. The sensing sequence is repeated for a range of SNR values from -18dB to 18dB which is used to reflect varying channel conditions. Ideally, a wider range of SNR values would provide a broader set of simulation results for evaluating the performance of the spectrum sensing scheme. However, the previously reviewed energy detection model in [46] shows poor performance in terms of low probabilities of detection as the value of SNR drops to -20dB. Therefore, SNR values ranging from -18dB to 18dB are considered in this dissertation.

4.4.3.1. Soft Fusion algorithm

The soft fusion algorithm is modelled based on Figure 11 where the input signal energy measurement by each CR user is forwarded directly to the fusion centre. A global test statistic for energy detection is formulated at the fusion centre based on the received energy samples. A Square Law Combining (SLC) approach is applied where a global test statistic is computed by adding the outputs of the received signal energies captured by each secondary user. The average value of the squared sum of the energy samples is then computed to obtain the test statistic based on (11). The spectrum sensing process is completed by evaluating the global test statistic against the set

detection threshold. When the test statistic is greater than the detection threshold the soft fusion algorithm produces a decision outcome of 1 which denotes PU signal presence. Otherwise, it produces a decision outcome 0 which represents PU signal absence.

4.4.3.2. Hard Fusion algorithm

The hard fusion algorithm is modelled based on the sensing sequence outlined in Figure 13. Spectrum sensing for each CR user on a channel is completed by generating a local decision outcome of binary 1 or 0 based on the comparison of the local test statistic and detection threshold. The binary local decision outcomes are forwarded to the fusion centre to compute the global decision outcome based on the m out of N majority rule for hard fusion. The majority threshold is selected to match any value above half of the total CR users participating in spectrum sensing ($m \geq \frac{N}{2}$).

4.4.4. Performance Metrics

Probability of detection is the main performance metric used in the model simulations as it gives a reflection of the detection accuracy. In the MATLAB code, the probability of detection is obtained by simulating multiple iterations of the energy detection schemes and calculating the average value for the number of positive detection outcomes obtained over the total number of simulations. This approach is based on the sensing sequence used in [55] and [56]. The number of iterations applied in the MATLAB code is denoted as L . A sufficiently large number of iterations of $L = 100000$ is used to improve the accuracy of the probability of detection values obtained. Simulations of the soft fusion and hard fusion spectrum sensing algorithms have been carried out using the following performance metrics:

- a) Probability of detection against SNR (dB),
- b) Probability of detection against number of CR users,
- c) Probability of detection against probability of false alarm,
- d) Error probability against SNR (dB).

To simulate the probability of detection at varying probabilities of false alarm (P_f), a range of P_f values are generated from 0.00 to 1 and a dynamic detection threshold influenced by the probability of false alarm is applied. To simulate the probability of error, the detection error rate expression obtained from [50] is applied in the sensing algorithm. The probability of error (P_e) shows the likelihood of getting a false decision outcome in the spectrum sensing process. As previously outlined in the literature review, the likelihood of false detection is influenced by a linear combination of probability of false alarm (P_f) and the probability of missed detection (P_{md}) [50].

$$P_e = P(H_0)P_f + P(H_1)P_{md} \quad (32)$$

$P(H_1)$ represents the initial probability of a primary user signal presence before sensing and $P(H_0)$ represents initial probability of a primary user being absent. In the model simulations equal probability is assumed for a primary user signal being present or absent on a channel at the initial sensing such that $P(H_1) = P(H_0) = 0.5$. The resultant probability of error is simulated over the chosen range of SNR values from -18 dB to 18 dB. Appendix A.1 to A.4 contain the MATLAB codes used for evaluating the performance metrics for the implemented spectrum sensing algorithms.

4.5. Summary

This chapter explains the design and implementation of an energy detection-based cooperative spectrum sensing scheme. First, a system overview is presented which includes a radio access network with primary users and a group of secondary users operating within a cognitive radio network. The chapter then describes the soft fusion and hard fusion strategies applied by the secondary users to perform spectrum sensing on the radio access network. The system design is implemented using MATLAB, and the chapter describes the methodology used for simulating the signals, network environment, and fusion strategies. The parameters and metrics used to develop and simulate the sensing model are also explained. Simulation results of the designed sensing models are evaluated in the next chapter.

CHAPTER 5: PERFORMANCE ANALYSIS

5.1. Introduction

Detection accuracy is a key metric used in evaluating the performance of a spectrum sensing schemes developed for cognitive radio networks. While spectrum sharing is well defined as a viable approach to efficient spectrum management, avoiding interference remains crucial and is largely achieved by maximizing detection accuracy in the sensing process. In this chapter, simulation results of the designed cooperative spectrum sensing schemes are discussed. The results discussion is focused on determining the detection accuracy achieved through the designed soft fusion and hard fusion models. The detection accuracy is measured through the achieved probability of detection. Four different sets of simulations were conducted with varying metrics which are discussed in the below sections.

5.2. Effects of SNR on Probability of Detection

The performance analysis is carried out by evaluating the detection accuracy achieved by the soft fusion and hard fusion schemes under different channel conditions. The varying channel conditions are simulated using signal-to-noise ratio while the detection accuracy is simulated using probability of detection.

Figure 14 shows the probability of detection (P_d), obtained at varying signal-to-noise ratio (SNR) values over a range of -18dB to 18dB . The number of cognitive radio users is kept constant at $N = 20$, while the SNR value is incremented by 1 dB at each sensing cycle. The number of samples generated for each CR user is kept constant at $S = 8$. A constant probability of false alarm value of $P_f = 0.01$ is also applied in the simulation. A detection threshold influenced by the noise variance is applied in the energy detection sequence based on the expression stated in (30). The noise variance

is directly influenced by the signal to noise ratio as stated in (31). The range of SNR values used is chosen to obtain a wide range of sensing outcomes based on varying channel conditions. SNR values below 0dB are taken to represent noisy channel conditions since negative SNR occurs when the noise power is greater than the signal power. The sensing performance is measured through the probability of detection, where P_d values closer to 1.0 translate to better detection accuracy while values closer to 0.0 translate to poor detection performance. The best performance in the simulation results is therefore denoted by the algorithm that achieves a probability of detection (P_d) closest to 1.0 at lower SNR values.

From the results obtained in Figure 14, the hard fusion algorithm achieves the probability of detection (P_d) of 1.0 at a SNR value of 2dB. The soft fusion algorithm however achieves the P_d of 1.0 when the SNR value is 0dB. At an SNR value of -1dB, the probability of detection in the hard fusion scheme is 0.753 while the probability of detection in the soft fusion scheme is 0.966. Based on these simulation results, the soft fusion algorithm shows better performance in terms of detection accuracy when compared to the hard fusion scheme. The MATLAB code used to generate Figure 14 is contained in Appendix A.1.

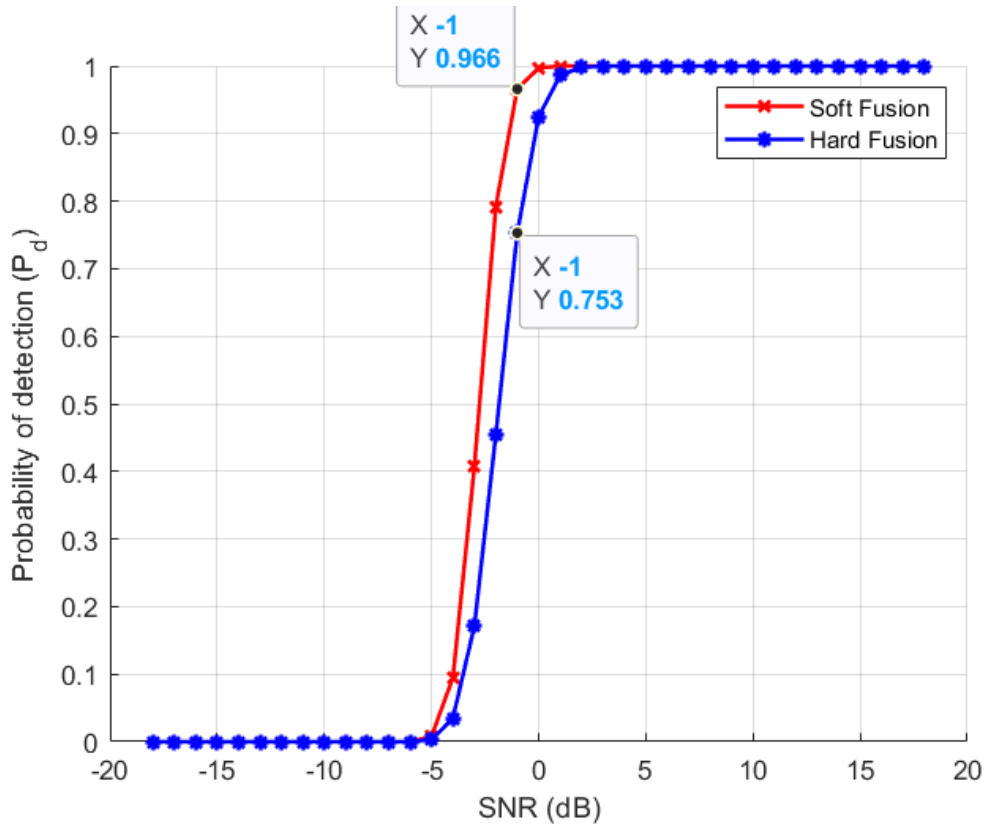


Figure 14: Probability of Detection versus SNR

5.3. Effects of the Number of CR Users on Probability of Detection

A second set of simulations is carried out to evaluate the impact of the collaborative approach of cooperative spectrum sensing on the soft fusion and hard fusion models. The cooperative aspect is reflected through the number of cognitive radio (CR) users participating in the sensing process.

In Figure 15, probability of detection is simulated at varying numbers of CR users (N). The number of CR users is incremented by 10 at each sensing cycle starting from 20 to 200. The probability of false alarm (P_f) is kept constant at 0.01. The code is also simulated at a constant SNR value of -1dB based on the previous simulation results in Figure 14 to establish an optimal reference point. The number of CR users is varied

to analyse the cooperative sensing effect on each fusion strategy. In both fusion schemes, the probability of detection increases with increasing number of CR users. At $N = 20$, a probability of detection of 0.753 is achieved for the hard fusion algorithm while the soft fusion algorithm achieves a probability of detection of 0.966. The soft fusion scheme achieves the desired probability of detection of 1.000 when $N = 60$ while the hard fusion algorithm achieves a maximum probability of detection of 0.998 at $N = 200$. These results illustrate that increasing the number of cooperative users has a positive effect on detection accuracy and the effect is more pronounced in the soft fusion algorithm. The soft fusion algorithm shows significantly better performance in terms of probability of detection obtained from the system when the number of CR users is below 160. The MATLAB code used to generate Figure 15 is contained in Appendix A.2.

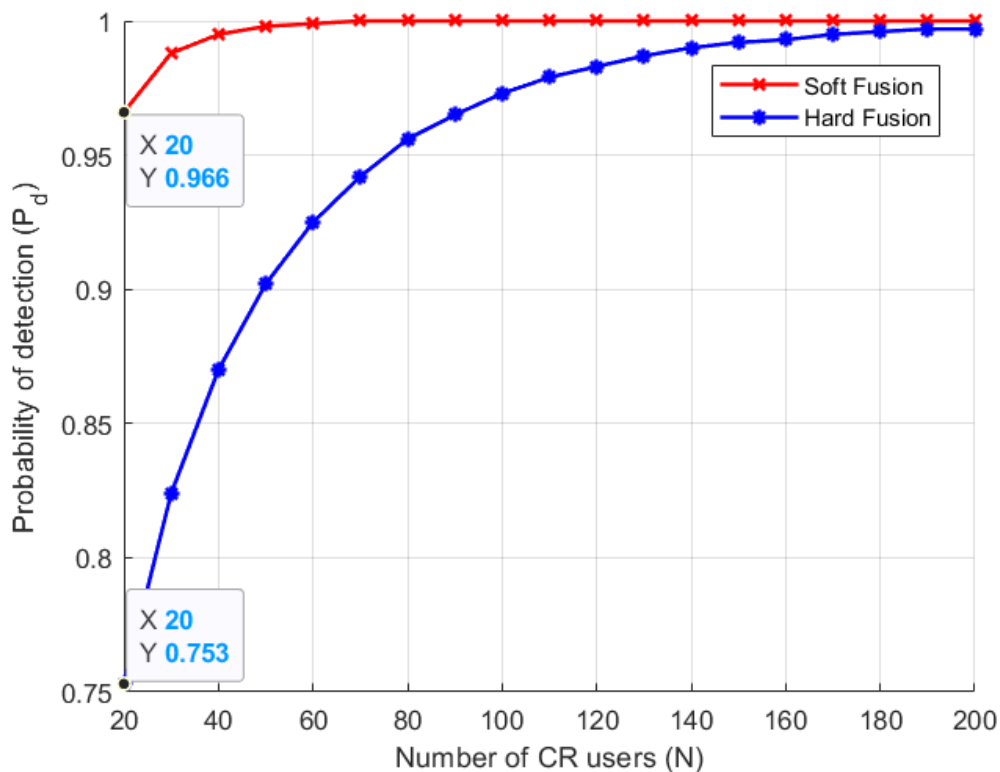


Figure 15: Probability of detection versus number of CR users (N)

5.4. Effects of Probability of False Alarm on Probability of Detection

The third set of simulations is centred on analysing reliability of the scheme by introducing distortions in the spectrum sensing models and analysing the detection accuracy achieved. In spectrum sensing, probability of false alarm represents the likelihood of the scheme incorrectly identifying a signal as present when it is not. Ideally, probability of false alarm should be a fixed predefined metric set to zero. System distortions can be introduced by increasing the probability of false alarm.

Figure 16 shows the simulation results for the probability of detection obtained at different probabilities of false alarm. A predefined range of probability of false alarm (P_f) values is applied starting from 0.00 to 1.00, incremented by 0.05 at each sensing cycle. The number of CR users is kept constant at $N = 20$ while the signal to noise ratio is also kept constant at $SNR = -5dB$. The constant SNR value is selected based on previous simulations in Figure 14 which show that non-zero probability of detection values start being observed at $-5dB$. A probability of detection value is simulated for each P_f value by calculating the average detection outcomes obtained over the total number of samples simulated at that P_f value. A theoretic detection threshold influenced by the probability of false alarm is applied in the energy detection sequence based on the expression stated in (30).

The simulation results in Figure 16 show a proportional increase in probability of detection as probability of false alarm increases with both fusion schemes. The maximum probability of detection of 1.00 is obtained for both soft fusion and hard fusion algorithms once the probability of false alarm exceeds 0.7. While a high probability of detection is desirable, in the instance simulated in Figure 16, the increase in the probability of detection is a result of the distortion introduced by false alarms. A

high probability of false alarm is undesirable as it would result in false detection and channel interference. At $P_f = 0.2$, the hard fusion algorithm has a P_d of 0.373 while the soft fusion scheme has a P_d of 0.707. The MATLAB code used to generate Figure 16 is contained in Appendix A.3.

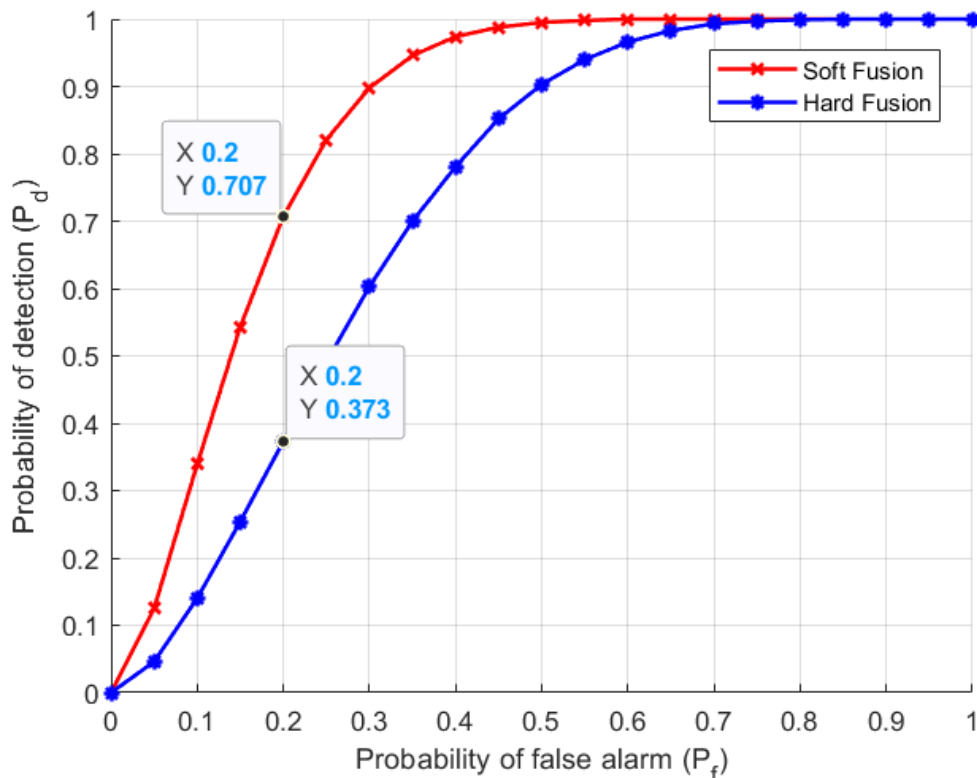


Figure 16: Probability of detection versus Probability of false alarm.

5.5. Effects of SNR on Probability of Error

The final set of simulations is centred on evaluating detection accuracy in the soft fusion and hard fusion models in terms of the error probability. The probability of error in spectrum sensing reflects the overall likelihood of making an incorrect sensing decision and it is influenced by a combination of the probability of false alarm and the probability of missed detection.

Figure 17 shows the probability of error obtained at varying SNR values over the range of -15dB to 15dB . The probability of error is calculated from the mathematical expression previously outlined in (32). A pre-defined target probability of false alarm of 0.01 is applied in the model simulation while the probability of missed detection varies at each sensing cycle as probability of detection changes. The number of CR users is kept constant at $N = 20$. In Figure 17, the soft fusion and hard fusion graphs both show a probability of error of 0.5 at $\text{SNR} = -5\text{dB}$. As the SNR values increase above -5dB , the soft fusion algorithm achieves lower error probabilities compared to the hard fusion algorithm. A probability of error of 0.126 is observed from the hard fusion algorithm at $\text{SNR} = -1\text{dB}$ while a probability of error of 0.022 is observed for the hard fusion algorithm at same SNR. This shows that at low SNR, a cooperative sensing scheme based on soft fusion technique achieves a lower error rate than a cooperative sensing scheme based on hard fusion technique. The MATLAB code used to generate Figure 17 is contained in Appendix A.4.

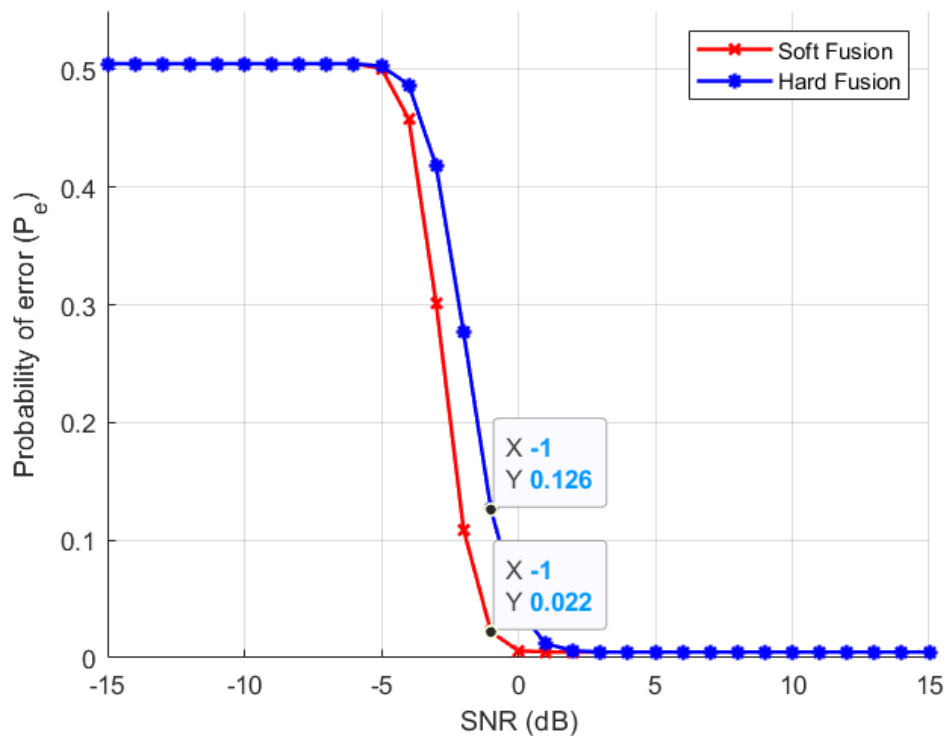


Figure 17: Probability of error versus SNR.

5.6. Summary

This chapter has presented the simulation results of the energy detection based cooperative spectrum sensing scheme for soft fusion sensing and hard fusion sensing strategies implemented using MATLAB. The simulation results are presented using four figures. The first three figures illustrate how the probability of detection varies with signal-to-noise ratio, number of CR users, and probability of false alarm, respectively. The fourth figure shows how the probability of error varies with signal-to-noise ratio. From the results presented, the soft fusion sensing strategy has superior detection accuracy compared to the hard fusion sensing strategy.

CHAPTER 6: CONCLUSION AND FUTURE WORK

6.1. Conclusion

In this dissertation, the application of cognitive radio for dynamic spectrum sharing in radio access networks has been investigated. The research has focused on cooperative spectrum sensing using energy detection and a comparative analysis of the two main decision strategies, namely, soft fusion and hard fusion sensing. The research has been driven by the need to explore solutions for the rising increase in bandwidth demands on the current spectrum bands used in radio access networks. Cognitive radio spectrum sensing enables users to share the available spectrum by allowing secondary users to access the spectrum during idle periods. The major issues identified with existing spectrum sensing techniques revolve around detection accuracy and interference management. The successful implementation of cognitive radio is centred on ensuring the secondary users can access the spectrum without causing any interference to the primary users or amongst themselves. An energy detection-based cooperative sensing scheme has been designed and evaluated based on soft fusion and hard fusion sensing.

The main conclusion drawn from the simulation results presented in the dissertation is that the soft fusion sensing strategy outperforms the hard fusion sensing strategy in terms of detection accuracy. Higher probabilities of detection and lower error probabilities, which translate to better detection accuracy, have been observed for the soft fusion sensing strategy. Based on the results, the dissertation has achieved the required objectives in evaluating an energy detection-based cooperative spectrum sensing scheme for soft fusion and hard fusion sensing strategies.

6.2. Future Work

The simulations conducted illustrate that the energy detection model has poor performance in terms of detection accuracy at low SNR ranges below -5dB for both the hard and soft fusion sensing schemes. A key spectrum band in consideration for cognitive radio is the television white space (TVWS) band that generally has a higher occurrence of noise with a SNR tolerance of up to -20dB . Further research is therefore required for energy detection based cooperative sensing schemes to achieve high detection accuracy at low SNR (-10dB to -20dB). Exploring the use of particle swarm optimization for cluster formation and dynamic threshold adaptation is a promising research area that could improve detection accuracy in low SNR scenarios. Particle swarm optimization is a computational method that can be used to optimise sensing parameters such as power control and threshold adaptation to enhance detection accuracy [54]. Another research area that can be explored to enhance detection accuracy, as an extension to this research, is the application of hybrid fusion techniques. The hybrid fusion approach entails leveraging the advantages of both soft fusion and hard fusion approaches to enhance detection accuracy and robustness.

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APPENDIX

APPENDIX A: MATLAB codes for Energy Detection Spectrum Sensing

A.1. Probability of detection versus Signal to Noise ratio (SNR)

```
%% Initialization
clearvars;
N = 20; %number of CR users
S = 8; %number of samples for each CR user
Pf = 0.01; %probability of false alarm
snr_db = -18:1:18; %SNR range(dB)
L = 100000; %number of iterations

for i = 1:length(snr_db) %number of simulations (for each SNR value)
d = 0; %decision outcome
ds = 0; dh = 0; %detection counters
snr = 10.^(snr_db(i)/20); %linear value of SNR

%% SOFT FUSION SEQUENCE
for j = 1:L %number of iterations
inputSignal = randi([0 1],S,N); %input signal
noise = randn(S,N); %noise
y = inputSignal + noise; %received signal observed by CR users
energy = sum(abs(y).^2); %energy of received signals over S samples (35)

svar = var(inputSignal,0,"all"); %signal variance
nvar = svar/snr; %noise variance [based on (39)]
thresh = (qfuncinv(Pf)*sqrt(2*N)+ N)*nvar; %detection threshold (38)

for n = 1:N
energy_sum(n) = sum(energy); % energy sum for all CR users
end
test =(1/N)*energy_sum;% average energy of all CR users

if test > thresh
d(j) = 1; %global decision: PU signal present
ds = ds + 1; %increment detection counter
else
d(j) = 0; %global decision: PU signal absent
end
end
Pd_SF(i) = ds/L; %avg. probability of detection for ith SNR value
Pd_SF(i) = round(Pd_SF(i),3); %round Pd to 3 decimal places

%% Hard FUSION SEQUENCE
maj = N/2; %majority rule threshold
outcome = 0; %global decision outcome

for jj = 1:L %number of iterations
inputSignal = randi([0 1],S,N); %input signal
noise = randn(S,N); %noise
```

```

y = inputSignal + noise; %received signal observed by CR users
energy = sum(abs(y).^2); %energy of received signals (35)
svar = var(inputSignal,0,"all"); %signal variance
nvar = svar/snr; %noise variance [based on (39)]
thresh = (qfuncinv(Pf)*sqrt(2*N)+ N)*nvar; %detection threshold (38)

local_test = energy; %local test statistic from energy samples
for n = 1:N %for each CR user
if local_test(n) > thresh %local sensing for CR user n
d(n) = 1; %local decision outcome: Signal present
else
d(n) = 0; %local decision outcome: Signal absent
end
outcome = outcome + d(n); %add local decision results
end
if outcome > maj % total decisions above majority threshold
d(j) = 1; %global decision: PU signal present
dh = dh + 1; %increment detection counter
else
d(j) = 0; %global decision: PU signal absent
end
outcome = 0; %clear counter
end
Pd_HF(i) = dh/L; %avg. probability of detection over L simulations
Pd_SF(i) = round(Pd_HF(i),3); %round Pd to 3 decimal places

end
%% ROC PLOTS %%
figure(1)
xlabel('SNR (dB)');
ylabel('Probability of detection (P_d)');
axis([-20 20 0 1]);
grid on;
hold on;
plot(snr_db,Pd_SF,'-x','LineWidth',1.5,'color','red')
plot(snr_db,Pd_HF,'-*','LineWidth',1.5,'color','blue')
legend('Soft Fusion','Hard Fusion');
hold on;

```

A.2. Probability of detection versus Number of CR users (N)

```
%% Initialization
clearvars;
N = 20:10:200; %number of CR users
S = 8; %number of samples for each CR user
Pf = 0.01; %probability of false alarm
snr_db = -1; %SNR (dB)
L = 100000; %number of iterations

for i = 1:length(N) %number of simulations (for each number of CR users)
d = 0; %decision outcome
ds = 0; dh = 0; %detection counters
snr = 10.^(snr_db/20); %linear value of SNR
P = N(i); %number of CR users

%% SOFT FUSION SEQUENCE
for j = 1:L %number of iterations
inputSignal = randi([0 1],S,P); %input signal
noise = randn(S,P); %noise
y = inputSignal + noise; %received signal observed by CR users
energy = sum(abs(y).^2); %energy of received signals over S samples (35)

svar = var(inputSignal,0,"all"); %signal variance
nvar = svar/snr; %noise variance [based on (39)]
thresh = (qfuncinv(Pf)*sqrt(2*N(1)+ N(1))*nvar; %detection threshold (38)

for n = 1:P
energy_sum(n) = sum(energy); % energy sum for all CR users
end
test =(1/P)*energy_sum;% average energy of all CR users

if test > thresh
d(j) = 1; %global decision: PU signal present
ds = ds + 1; %increment detection counter
else
d(j) = 0; %global decision: PU signal absent
end
end
Pd_SF(i) = ds/L; %avg. probability of detection for ith SNR value
Pd_SF(i) = round(Pd_SF(i),3); %round Pd to 3 decimal places

%% Hard FUSION SEQUENCE
maj = P/2; %majority rule threshold
outcome = 0; %global decision outcome

for jj = 1:L %number of iterations
inputSignal = randi([0 1],S,P); %input signal
noise = randn(S,P); %noise
y = inputSignal + noise; %received signal observed by CR users
energy = sum(abs(y).^2); %energy of received signals (35)

svar = var(inputSignal,0,"all"); %signal variance
nvar = svar/snr; %noise variance [based on (39)]
thresh = (qfuncinv(Pf)*sqrt(2*N(1)+ N(1))*nvar; %detection threshold (38)

local_test = energy;%local test statistic from energy samples
for n = 1:P %for each CR user
if local_test(n) > thresh %local sensing for CR user n
```

```

d(n) = 1; %local decision outcome: Signal present
else
d(n) = 0; %local decision outcome: Signal absent
end
outcome = outcome + d(n); %add local decision results
end
if outcome > maj % total decisions above majority threshold
d(j) = 1; %global decision: PU signal present
dh = dh + 1; %increment detection counter
else
d(j) = 0; %global decision: PU signal absent
end
outcome = 0; %clear counter
end
Pd_HF(i) = dh/L; %avg. probability of detection over L simulations
Pd_SF(i) = round(Pd_HF(i),3); %round Pd to 3 decimal places

end
%% ROC PLOTS %%
figure(1)
xlabel('Number of CR users (N)');
ylabel('Probability of detection (P_d)');
grid on;
hold on;
plot(N,Pd_SF,'-x','LineWidth',1.5,'color','red')
plot(N,Pd_HF,'-*','LineWidth',1.5,'color','blue')
legend('Soft Fusion','Hard Fusion');
hold on;

```

A.3. Probability of detection versus Probability of false alarm (Pf)

```
%% Initialization
clearvars;
N = 20; %number of CR users
S = 8; %number of samples for each CR user
Pf = 0.00:0.05:1.00; %probability of false alarm range
snr_db = -5; %SNR (dB)
L = 100000; %number of iterations

for i = 1:length(Pf) %number of simulations (for each Pf value)
d = 0; %decision outcome
ds = 0; dh = 0; %detection counters
snr = 10.^(snr_db/20); %linear value of SNR

%% SOFT FUSION SEQUENCE
for j = 1:L %number of iterations
inputSignal = randi([0 1],S,N); %input signal
noise = randn(S,N); %noise
y = inputSignal + noise; %received signal observed by CR users
energy = sum(abs(y).^2); %energy of received signals over S samples (35)

svar = var(inputSignal,0,"all"); %signal variance
nvar = svar/snr; %noise variance [based on (39)]
thresh = (qfuncinv(Pf(i))*sqrt(2*N)+ N)*nvar; %detection threshold (38)

for n = 1:N
energy_sum(n) = sum(energy); %energy sum for all CR users
end
test =(1/N)*energy_sum;% average energy of all CR users

if test > thresh
d(j) = 1; %global decision: PU signal present
ds = ds + 1; %increment detection counter
else
d(j) = 0; %global decision: PU signal absent
end
end
Pd_SF(i) = ds/L; %avg. probability of detection for ith SNR value
Pd_SF(i) = round(Pd_SF(i),3); %round Pd to 3 decimal places

%% Hard FUSION SEQUENCE
maj = N/2; %majority rule threshold
outcome = 0; %global decision outcome

for jj = 1:L %number of iterations
inputSignal = randi([0 1],S,N); %input signal
noise = randn(S,N); %noise
y = inputSignal + noise; %received signal observed by CR users
energy = sum(abs(y).^2); %energy of received signals (35)

svar = var(inputSignal,0,"all"); %signal variance
nvar = svar/snr; %noise variance [based on (39)]
thresh = (qfuncinv(Pf(i))*sqrt(2*N)+ N)*nvar; %detection threshold (38)

local_test = energy; %local test statistic from energy samples
for n = 1:N %for each CR user
if local_test(n) > thresh %local sensing for CR user n
d(n) = 1; %local decision outcome: Signal present
```

```

else
d(n) = 0; %local decision outcome: Signal absent
end
outcome = outcome + d(n); %add local decision results
end
if outcome > maj % total decisions above majority threshold
d(j) = 1; %global decision: PU signal present
dh = dh + 1; %increment detection counter
else
d(j) = 0; %global decision: PU signal absent
end
outcome = 0; %clear counter
end
Pd_HF(i) = dh/L; %avg. probability of detection over L simulations
Pd_HF(i) = round(Pd_HF(i),3); %round Pd to 3 decimal places

end
%%% ROC PLOTS %%%
figure(1)
xlabel('Probability of false alarm (P_f)');
ylabel('Probability of detection (P_d)');
grid on;
hold on;
plot(Pf,Pd_SF,'-x','LineWidth',1.5,'color','red')
plot(Pf,Pd_HF,'-*','LineWidth',1.5,'color','blue')
legend('Soft Fusion','Hard Fusion');
hold on;

```

A.4. Probability of error versus Signal to Noise ratio (SNR)

```
%% Initialization
clearvars;
N = 20; %number of CR users
S = 8; %number of samples for each CR user
Pf = 0.01; %probability of false alarm
H1 = 0.5; %Initial probability of PU signal presence
H0 = 0.5; %Initial probability of PU signal absence
snr_db = -18:1:18; %SNR range(dB)
L = 100000; %number of iterations

for i = 1:length(snr_db) %number of simulations (for each SNR value)
d = 0; %decision outcome
ds = 0; dh = 0; %detection counters
snr = 10.^(snr_db(i)/20); %linear value of SNR

%% SOFT FUSION SEQUENCE
for j = 1:L %number of iterations
inputSignal = randi([0 1],S,N); %input signal
noise = randn(S,N); %noise
y = inputSignal + noise; %received signal observed by CR users
energy = sum(abs(y).^2); %energy of received signals over S samples (35)

svar = var(inputSignal,0,"all"); %signal variance
nvar = svar/snr; %noise variance (39)
thresh = (qfuncinv(Pf)*sqrt(2*N)+ N)*nvar; %detection threshold (38)

for n = 1:N
energy_sum(n) = sum(energy); % energy sum for all CR users
end
test =(1/N)*energy_sum; %average energy of all CR users

if test > thresh
d(j) = 1; %global decision: PU signal present
ds = ds + 1; %increment detection counter
else
d(j) = 0; %global decision: PU signal absent
end
end
Pd_SF(i) = ds/L; %avg. probability of detection for ith SNR value
Pm_SF(i) = 1 - Pd_SF(i); %probability of missed detection (3)
Pe_SF(i) = H0*(Pf) + H1*Pm_SF(i); %probability of error from (3)
Pe_SF(i) = round(Pe_SF(i),3); %round Pe to 3 decimal places

%% Hard FUSION SEQUENCE
maj = N/2; %majority rule threshold
outcome = 0; %global decision outcome

for jj = 1:L %number of iterations
inputSignal = randi([0 1],S,N); %input signal
noise = randn(S,N); %noise
y = inputSignal + noise; %received signal observed by CR users
energy = sum(abs(y).^2); %energy of received signals (3)

svar = var(inputSignal,0,"all"); %signal variance
nvar = svar/snr; %noise variance (39)
thresh = (qfuncinv(Pf)*sqrt(2*N)+ N)*nvar; %detection threshold (38)
```

```

local_test = energy;%local test statistic from energy samples
for n = 1:N %for each CR user
if local_test(n) > thresh %local sensing for CR user n
d(n) = 1; %local decision outcome: Signal present
else
d(n) = 0; %local decision outcome: Signal absent
end
outcome = outcome + d(n); %add local decision results
end
if outcome > maj % total decisions above majority threshold
d(j) = 1; %global decision: PU signal present
dh = dh + 1; %increment detection counter
else
d(j) = 0; %global decision: PU signal absent
end
outcome = 0; %clear counter
end
Pd_HF(i) = dh/L; %avg. probability of detection over L simulations
Pm_HF(i) = 1 - Pd_HF(i); %probability of missed detection (3)
Pe_HF(i) = H0*(Pf) + H1*Pm_HF(i); %probability of error from (17)
Pe_HF(i) = round(Pe_HF(i),3); %round Pe to 3 decimal places

end
%%% ROC PLOTS %%%
figure(1)
xlabel('SNR (dB)');
ylabel('Probability of error (P_e)');
axis([-15 15 0 1]);
ylim([0 0.55])
grid on;
hold on;
plot(snr_db,Pe_SF,'-x','LineWidth',1.5,'color','red')
plot(snr_db,Pe_HF,'-*','LineWidth',1.5,'color','blue')
legend('Soft Fusion','Hard Fusion');
hold on;

```