

An Adaptive Threshold Energy Detection Technique with Noise Variance Estimation for Cognitive Radio Sensor Networks

Nixon Thuo Ng'ethe



This thesis is submitted in fulfilment of the academic requirements
for the degree of
Master of Science in Electrical Engineering
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As the candidate's supervisor, I have approved this dissertation for submission.

Name: Dr. Mqhele E. Dlodlo, Associate Professor

Signed by candidate

Signed: Signature Removed

Date: 12 October 2015

Declaration

I declare that this thesis is my own work. Where collaboration with other people has taken place, or material generated by other researchers is included, the parties and/or materials are indicated in the acknowledgements or are explicitly stated with references as appropriate.

This work is being submitted for the Master of Science in Electrical Engineering at the University of Cape Town. It has not been submitted to any other university for any other degree or examination.

Nixon Thuo, NG'ETHE

12/06/2015

Name _____

Date _____

Dedication

To Almighty God, my heavenly father

And

To my mother

Alice N. Mbutu

With so much love and deep gratitude.

To God be the glory!

Abstract

The paradigm of wireless sensor networks (WSNs) has gained a lot of popularity in the recent years due to the proliferation of wireless devices. This is evident as WSNs find numerous application areas in fields such as agriculture, infrastructure monitoring, transport, and security surveillance. Traditionally, most deployments of WSNs operate in the unlicensed industrial scientific and medical (ISM) band and more specifically, the globally available 2.4 GHz frequency band. This band is shared with several other wireless technologies such as Bluetooth, Wi-Fi, near field communication and other proprietary technologies thus leading to overcrowding and interference problems. The concept of dynamic spectrum access alongside cognitive radio technology can mitigate the coexistence issues by allowing WSNs to dynamically access new spectrum opportunities. Furthermore, cognitive radio technology addresses some of the inherent constraints of WSNs thus introducing a myriad of benefits. This justifies the emergence of cognitive radio sensor networks (CRSNs).

The selection of a spectrum sensing technique plays a vital role in the design and implementation of a CRSN. This dissertation sifts through the spectrum sensing techniques proposed in literature investigating their suitability for CRSN applications. We make amendments to the conventional energy detector particularly on the threshold selection technique. We propose an adaptive threshold energy detection model with noise variance estimation for implementation in CRSN systems. Experimental work on our adaptive threshold technique based on the recursive one-sided hypothesis test (ROHT) technique was carried out using MatLab. The results obtained indicate that our proposed technique is able to achieve adaptability of the threshold value based on the noise variance. We also employ the constant false alarm rate (CFAR) threshold to act as a defense mechanism against interference of the primary user at low signal to noise ratio (SNR). Our evaluations indicate that our adaptive threshold technique achieves double dynamicity of the threshold value based on the noise variance and the perceived SNR.

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Asanteni sana na Mungu awabariki nyote!

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Abbreviations

CFAR:	Constant False Alarm Rate
CR:	Cognitive Radio
CRSN:	Cognitive Radio Sensor Networks
DSA:	Dynamic Spectrum Access
FFT:	Fast Fourier Transform
ISM:	Industrial, Scientific and Medical (band)
MNF:	Maximum Normal Fit
PCA:	Principal Component Analysis
ROHT:	Recursive One-sided Hypothesis Test
SHM:	Structural Health Monitoring
SNR:	Signal to Noise Ratio
VHF:	Very High Frequency
WSN:	Wireless Sensor Network

Chapter 1

1 Introduction

1.1 Background Review

The modern world we live in is seemingly becoming smarter as we witness the proliferation of concepts such as smart homes, smart buildings and even smart cities. These smart spaces thrive on their ability to perceive and interpret sensory data from their immediate environment. Wireless sensors are needed to collect relevant information about the surroundings from distributed sources in order to sustain these smart environments. Wireless sensor networking has been the enabling technology supporting this paradigm of ambient intelligence. Wireless sensor networks (WSNs) are therefore a critical piece of infrastructure that supports the emergence of smart spaces and ubiquitous intelligence.

Wireless sensor networks find a wide array of applications in fields such as transport, agriculture, industrial processes among a myriad of military applications [1]. One of the key features of WSNs is their operation in the unlicensed Industrial, Scientific and Medical (ISM) frequency bands and more particularly, the 2.4 GHz ISM band. This band is shared with several other wireless technologies such as Wi-Fi, Bluetooth and other proprietary wireless technologies under stringent guidelines. This band employs an open sharing model where multiple unlicensed users can transmit at the same frequency as long as they adhere to a predefined set of regulations [2]. However, due to the world wide availability of the 2.4 GHz frequency band, the spectrum space is getting overcrowded. As a result, there are some coexistence issues between technologies operating in this band [3], [4]. The performance of WSNs deployed in this band could be suboptimal due to interference from other cohabiting systems.

Wireless sensor nodes also have some inherent challenges, such as single band communication, security and energy constraints that need to be addressed in order to enhance the applications of WSNs. The high cost of deployment is also a major point of concern in WSNs. To put this into perspective, let us consider an indoor deployment of a WSN. The communicating sensor nodes may encounter obstructed or completely blocked communication paths thus reducing the quality and range of reliable communication. This can be attributed to the undesirable indoor propagation characteristics of the 2.4 GHz frequency as shown in [5].

One way of solving this problem is to increase the number of sensing nodes and to make use of mesh networking repeater nodes. However, introducing mesh networking to WSNs increases the cost of deployment and complexity of implementation by introducing mesh routing and protocol design challenges.

On a positive note, some of these inherent challenges of WSNs can be mitigated by employing dynamic spectrum access (DSA). DSA is a new paradigm in spectrum management that allows for opportunistic access of the frequency spectrum. In this paradigm, a secondary user (unlicensed user) can opportunistically access the licensed spectrum in the absence of the primary user (licensed user) thus leading to higher spectral efficiency [2]. The severe underutilisation of the spectrum resource under 3 GHz and more particularly in the TV broadcast bands has been the main motivation to reconsider the current fixed spectrum assignment policy and design a more dynamic spectrum access model [6]. Cognitive radio technology has been cited as the key enabling technology to achieve dynamic spectrum access in [7].

The benefits of inculcating DSA in WSN are numerous and undeniable [8]. For instance, cognitive radio technology affords WSNs dynamic access to frequency bands with better propagation characteristics such as the ultra-high frequency (UHF) band used for TV broadcasting. The spectrum holes in the UHF band, otherwise referred to as TV white spaces, could be harnessed for operations of the cognitive radio based WSNs. The lower frequencies in this band would allow for a longer transmission range and energy efficiency. The marriage between cognitive radio technology and WSNs has led to the paradigm of cognitive radio sensor networks (CRSNs). The element of cognition introduced to WSNs by cognitive radio encapsulates the cognition cycle which includes; spectrum sensing, spectrum sharing, spectrum mobility and spectrum decision. These four processes form the core pillars of cognitive radio technology. This study investigates the subject of spectrum sensing in cognitive radio sensor networks.

1.2 Scope of Research

This study focuses specifically on the spectrum sensing aspect of CRSNs. We appraise the spectrum sensing techniques proposed in literature from the perspective of cognitive radio sensor networks seeking the most suitable technique. We challenge the fixed threshold energy detection technique as the most preferred spectrum sensing technique for CRSNs by proposing

the adoption of the adaptive threshold energy detection technique. This study does not seek to model a new spectrum sensing technique for CRSN but rather to redesign and propose a modified spectrum sensing technique that we recommend for CRSN. We propose an adaptive threshold energy detection technique with noise estimation which we have designed. A performance evaluation of our proposed technique is included in this report. The probabilities of detection, misdetection and false alarm, and the signal to noise ratio are used as metrics in the performance analysis. Test bed implementations and real-world deployments of our work are not considered in the scope of this study.

1.3 Problem Statement

A lot of studies have been conducted in realm of spectrum sensing for cognitive radio but very few works touch on subject of spectrum sensing for resource constrained cognitive radio sensor networks. An appraisal on the spectrum sensing techniques proposed in literature, (discussed in Section 3.3), reveals that the conventional energy detector is the most suitable sensing technique for CRSNs. Unfortunately the performance of the conventional energy detector is greatly affected by noise fluctuations which are typical in the radio environment [9]. This can be attributed to the fixed threshold selection technique that the conventional energy detector employs and lack of a priori knowledge of the noise variance. Therefore, the implementation of an adaptive threshold energy detector with noise estimation requires investigation.

1.4 Research Objectives

In a bid to enhance the performance of the conventional energy detector and optimize it for spectrum sensing in CRSNs, we must consider reinforcing the detector against volatility of the noise level. Knowledge of the noise variance is therefore key in this regard. Consequently, we must also seek to develop a technique that allows the energy detection threshold value to take into consideration the variation of the ambient noise so as to ensure accurate detection even at low SNR levels.

Therefore, with reference to the above, the objectives of this research are as follows;

- To formulate a technique that can estimate the noise variance in a radio channel without any a priori knowledge of the primary signal.

- To implement an adaptive threshold technique that varies dynamically with the noise variance.
- To create a robust spectrum sensing system model that can insulate the primary users against interference at low SNR.

1.5 Dissertation Organization

Chapter 1 has introduced the subject area stating the preliminary background of wireless sensor networks leading up to cognitive radio sensor networks. The problem statement, the scope of the work and the research objectives are also laid out here.

Chapter 2 discusses the back ground of wireless sensor networks and some of the application areas. The advantages of dynamic spectrum access in WSNs are also discussed. The chapter concludes by introducing the concept of CRSN and focusing attention on the subject of spectrum sensing.

Chapter 3 expounds on the topic of spectrum sensing from the perspective of CRSN. An appraisal of the spectrum sensing techniques proposed in literature is discussed here. The system model of the conventional energy detector is also presented.

Chapter 4 introduces the concept of adaptive thresholding and noise estimation. Both the fixed and adaptive thresholding techniques are discussed. An account of a conventional adaptive threshold energy detector is also included. Finally, our proposed adaptive threshold technique is presented.

Chapter 5 highlights the research methodology before presenting the results and analysis of our proposed adaptive threshold technique alongside the conventional energy detector. In this chapter we also highlight how double dynamicity of the threshold value is achieved.

Chapter 6 gives a chronological summary of our research and it concludes by highlighting the major contributions of this work. Finally, future works are recommended.

Chapter 2

2 Cognitive Radio Sensor Networks: A Background

2.1 Introduction

The act of gathering information about the occurrence of events, a process or even a physical object is referred to as sensing and the device that performs the sensing task is referred to as a sensor. However, in the realm of digital electronics, a sensor can be defined as a device that captures information about real world phenomena and converts this information into a form that can be processed, stored and acted upon. Sensors play a vital role in the modern day world as they can help us detect and avoid catastrophic infrastructural failures, increase productivity and efficiency of processes, protect and conserve natural resources and enhance security surveillance. Sensors have also contributed to the development of new applications and technologies that enhance the quality of human life.

Furthermore, the recent advances in technologies such as Very Large Scale Integration (VLSI), Micro-Electro-Mechanical Systems (MEMS) and wireless communication has led to the proliferation and widespread use of distributed sensor systems [10]. These advancements in technology have led to the development of smart sensors that are of low cost, small size, low power requirements, multifunctional and capable of untethered communication over short distances. Although most commercial deployments of sensors were dominated by the aerospace and defence industries, we are seeing more deployments in civil infrastructure, pipeline infrastructure and the national power grid [11]–[13]. These sensors are deployed in the hundreds forming networks used for the purposes of monitoring geographical areas to keep an eye on pollution, flooding or even security surveillance which can be beneficial for the agricultural sector. Sensor networks are also used to collect information about the structural health of civil infrastructure such as bridges, railways and tunnels. They can also be used to monitor the health of the national power grid. A network of such sensors connected wirelessly is known as a wireless sensor network.

2.2 Wireless Sensor Networks

A sensor is a special type of a transducer that converts energy collected from the physical world into electrical energy that can be passed into a controller or a computing system for processing, storage and transmission. Traditionally, sensors were connected to the controller and processing stations directly via wired local area networks. However, there is a need to deploy an increasing number of sensor nodes especially in remote and inaccessible areas. This has led to the development of wireless sensor nodes which have the capability of transmitting the collected information wirelessly to a central processing station. Therefore, in addition to their sensing capabilities, wireless sensor nodes also have the capability to process, store and transmit information. This means that a sensor node is responsible for in-network analysis, correlation and fusion of its own collected data as well as data from other sensor nodes [10].

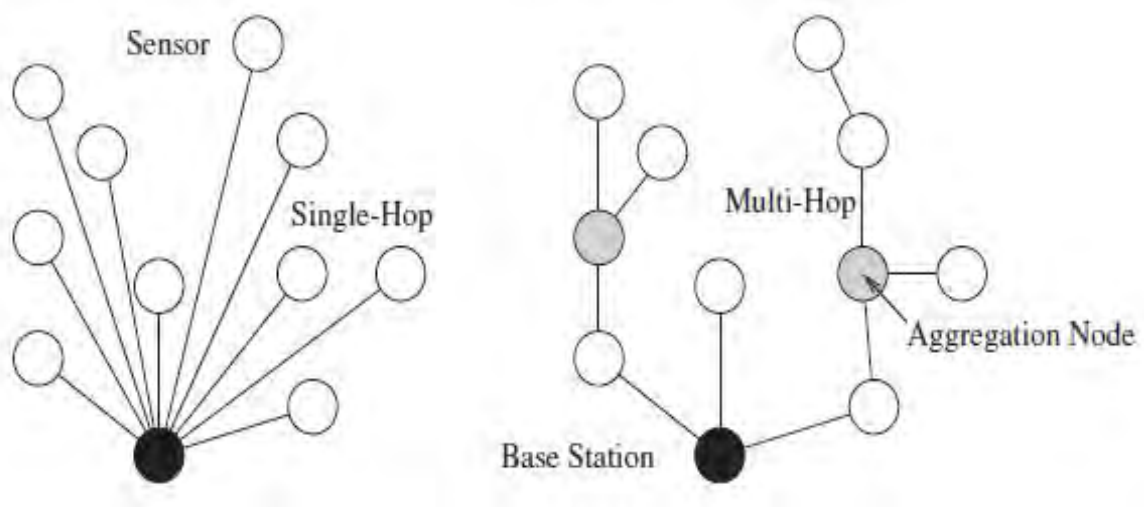


Figure 2.1 Single hop and Multi hop WSN communication

A network of such sensor nodes deployed cooperatively to monitor different physical phenomena forms a Wireless Sensor Network (WSN). Wireless sensor nodes vary greatly in terms of their processing capabilities and communication techniques. While simple sensors

only have sensing capabilities, more able WSN nodes may perform extensive processing and data aggregation functions [10], [14] . WSN communication techniques vary from either ultrasound, infrared or radio frequency technology all depending on the parameter to be measured and the environment of deployment. As shown in Figure 2.1, wireless sensors are capable of both single hop and multi hop communications between the nodes. However, since sensor nodes may be densely deployed in a certain geographical region, multi hop communications can be expected to lower the power consumption as compared to single hop communications. Multi hop communication uses mesh networking capabilities of the wireless sensor nodes to overcome the signal propagation issues over long distances. Figure 2.2 is a representation of a wireless sensor network with two sensing fields transmitting data to their respective base stations which are then connected to remote processing stations via the internet.

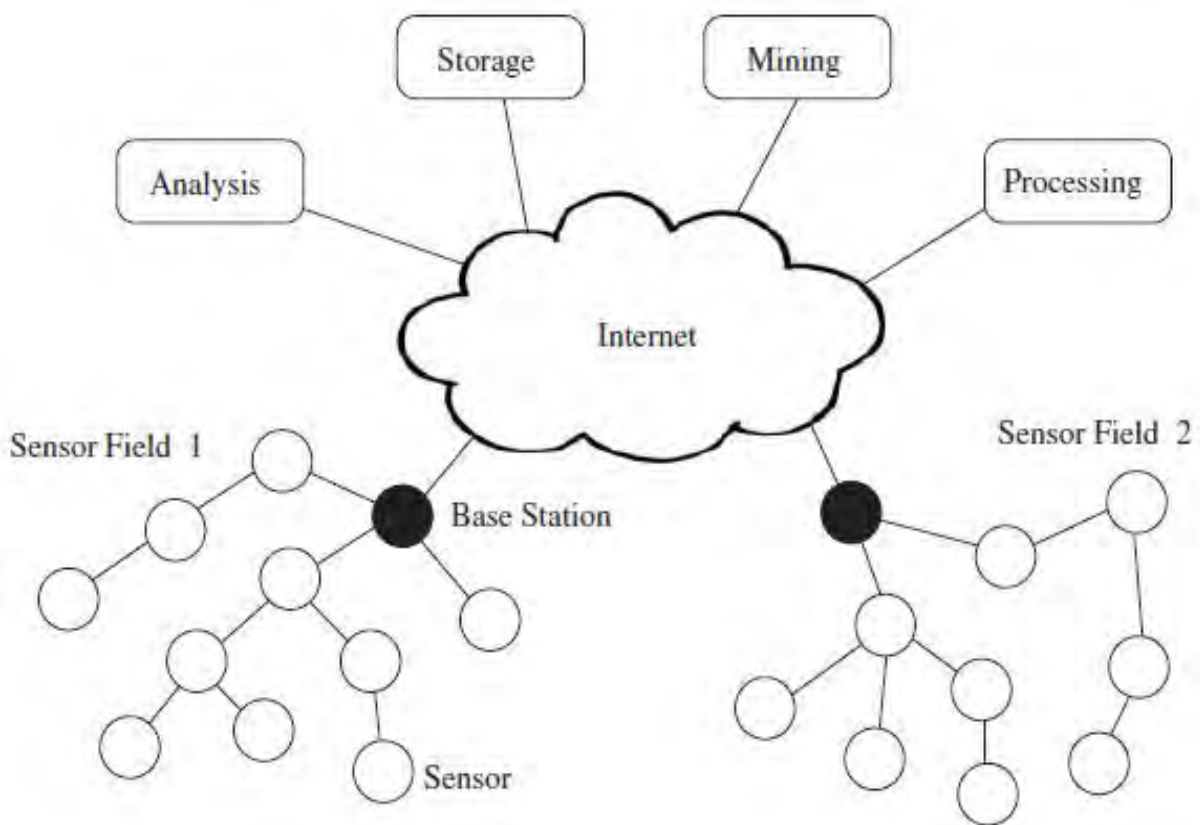


Figure 2.2 A representation of a Wireless Sensor Network [10]

Wireless Sensor Networks usually have little or no network infrastructure as they consist of several sensor nodes collaborating and communicating with each other in an ad hoc manner using mesh networking protocols. WSNs can be deployed in a structured or an unstructured fashion. In a structured deployments the position of all sensor nodes is pre-planned and carefully engineered. The advantage of such a structured network is that the coverage area can be maximized and the maintenance and deployment costs minimized as fewer nodes may be utilized. Sensor nodes may be placed at strategic places for maximum coverage while unstructured or ad hoc deployments may have uncovered regions [14]. On the other hand, we may have an unstructured deployment of wireless sensor nodes which may contain a dense deployment of nodes in an ad hoc manner [15]. The drawback of such an unstructured deployment is that troubleshooting and maintenance is difficult due to the large number of sensor nodes deployed in an unstructured manner.

2.3 Applications of Wireless Sensor Networks

Wireless Sensor Networks provide distributed sensing, computing and communication services concurrently and consequently, they find a broad array of applications across multiple fields. Due to the size and technical abilities of wireless sensor nodes, sensor networks can be deployed in areas that are out of human reach or in dangerous environments such as in battle fields, underneath bridges or even near an active volcano. Sensors can also be used to improve the provisioning of other services such as education and health care. Below we discuss some of the major application areas of Wireless Sensor Networks.

2.3.1 Military applications

It is crucial for military communications to be readily available on demand at any given time and area. Military communications must be robust and secure and not susceptible to jamming or attacks for obvious defence reasons. Wireless Sensor Networks provide a way to enhance military surveillance and communications and assist in operations other than war such as peacekeeping and disaster relief [16]. These sensors can be deployed to detect an impending chemical or biological attack, or to track the movement of people and objects.

PinPtr [17] is an example of an acoustic sensor network that detects the muzzle blasts and acoustic shock waves that emanate from gunfire. The system then calculates the position of the shooter based on the arrival of times of the various acoustic components on different sensor nodes. Another example mentioned in [18] is DARPA's self-healing minefield which is a distributed self-organizing network of anti-tank mines which communicate in a peer-to-peer fashion to respond to attacks and breaches. Moreover, a hierarchical organization of Wireless Sensor Networks can be used for military surveillance [19].

2.3.2 Structural Health Monitoring (SHM)

Wireless Sensor Networks can be deployed on civil infrastructure to collect information on the structural state of the infrastructure. They can also serve the purpose of detecting any physical changes that may negatively affect the performance of the structure. Wireless sensors can be used to thoroughly inspect civil infrastructure such as bridges and buildings. Their small sizes means that they can be deployed in areas that are inaccessible to larger inspection equipment. Sensors are a preferred tool for structural health monitoring because they do not disturb the routine operation of the infrastructure. Furthermore, they can be deployed in large numbers thus making it easier to find correlation between different measurements [10]. WSNs can also be used to detect the effect of seismic activity and natural frequencies on civil infrastructure.

Researchers from the University of California, Berkeley developed an SHM prototype that was deployed on the Golden Gate Bridge in San Francisco for structural monitoring [11]. The prototype was deployed to investigate the response of the bridge to the ambient and extreme conditions and compare the collected data to the design predictions. The WSN also measures the acceleration due to vibrations and shaking resulting from tremors or earthquakes. Figure 2.3 shows the deployment scenario of wireless sensor nodes on the Golden Gate Bridge.

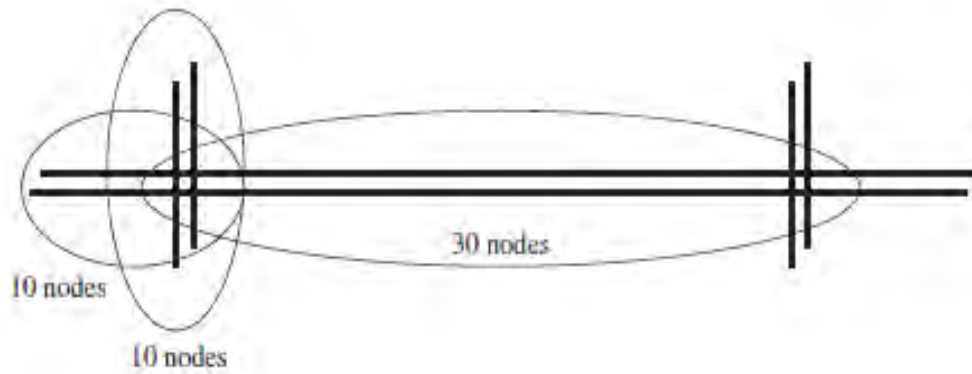


Figure 2.3 A representation of the layout of sensor nodes on the Golden Gate Bridge [10].

2.3.3 Pipeline Monitoring

Wireless Sensor Networks can be used to monitor gas, water and oil pipelines. Traditionally, wired networks were deployed to take internal and external measurements pertaining to the pipeline. Internal measurements include the pressure, flow and temperature while external measurements include fire detection, surveillance and leakage detection. Despite the advantages, wired networks have the following inherent problems: a damaged wire can compromise the entire pipeline network, faults in the wire are difficult to locate, unauthorized people may easily sabotage the pipeline network by cutting the wires and duplicate information may drown the networks ability to communicate more urgent information such as a fire report [12]. For these reasons, Wireless Sensor Networks have been adopted to monitor pipelines. With WSNs the cost and ease of deployment and maintenance is significantly reduced. Furthermore with WSNs, it is easy to install other redundant sensing and communication nodes, and additional security provisions. This increases the reliability, security, robustness and the availability of the network. A real-world example is the PipeNet prototype that was developed as a joint venture between the Imperial College of London, Intel Research, and MIT [20]. PipeNet was developed to monitor water pipelines in urban areas and more specifically to monitor the water quality and water levels in the sewer system.

2.3.4 Active Volcano Monitoring

Predicting a volcanic eruption is a task that has puzzled geoscientists for a very long time. Scientists have resorted to capturing, analysing and studying the nature of active volcanoes with the hope of predicting future eruptions. Seismic and acoustic sensors are employed to capture seismic and infrasonic signals that emanate from an active volcano. However, the equipment used for monitoring is bulky and very expensive and the biggest drawback is that they require an external supply of voltage. On the other hand, self-organizing and autonomous wireless sensors can be deployed in a volcanic environment at much lower costs. Sensor nodes can provide a high density and wide area coverage therefore enabling scientists the advantage of spatial diversity at a fraction of the cost [21].

2.3.5 Precision Agriculture

Wireless Sensor Networks have also found some applications in the field of precision agriculture. Precision agriculture is the art of using technologies such as Geographic Information Systems (GIS), Global Positioning System (GPS), radar and aerial images to monitor and improve the utilization of farm resources so as to increase the efficiency of production. This usually involves aspects such as micro-monitoring soil, crops and climate change in a field to provide a decision support system (DSS). This would not be possible without the use of wireless sensor networks. Wireless sensor nodes are required to perform tasks such as yield monitoring, yield mapping, weed mapping, variable spraying, salinity mapping and machinery guidance among many others [10]. For instance, farmers in British Columbia are using wireless sensor networks to monitor the temperature in wine farms so as to increase the efficiency of production [22]. Similarly, WSNs have also been used to automate the irrigation processes in Malawi and efficiently utilize the scarce water resources [23].

2.4 Node Architecture

At the heart of wireless sensor networks are the wireless sensor nodes. These nodes are responsible for the actual sensing, data processing and communication functionalities. Data processing algorithms and communication protocols are hosted and executed in the processing unit of the sensor node while a power supply provides the DC power requires to power all other subsystems. Therefore the sensing frequency and quality of data that can be extracted from the wireless sensor network is dependent on the physical resources that are available to the sensor nodes. Figure 2.4 shows a block diagram of the architecture of a single wireless sensor node.

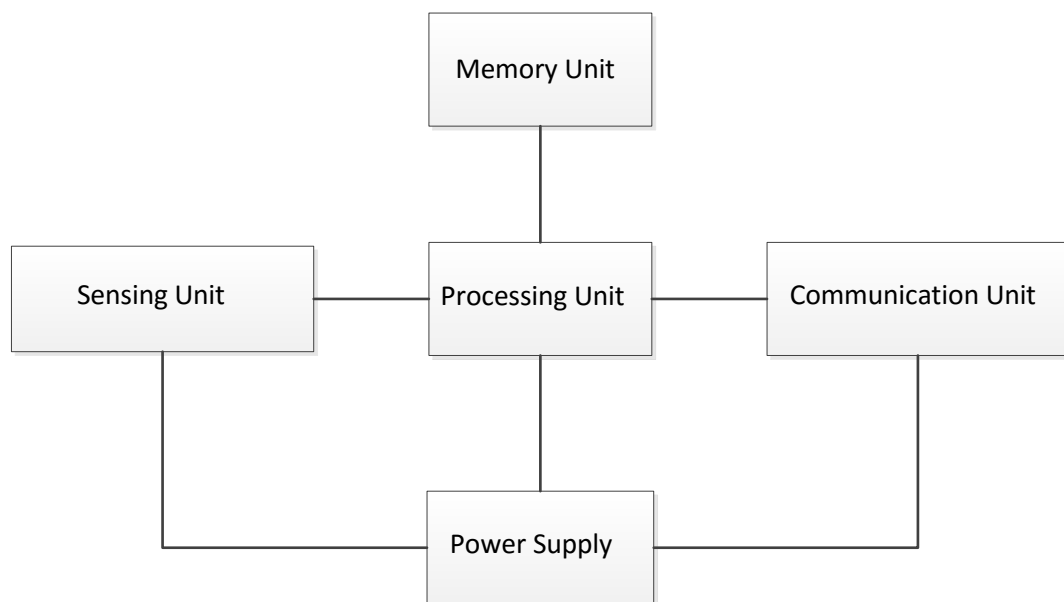


Figure 2.4: Block diagram of a wireless sensor node architecture

As shown in Figure 2.4, a wireless sensor node consists of sensing, processing, communication and power units. The sensing unit integrates one or more sensors to collect data pertaining to physical parameter under consideration. This could include heat sensors, acceleration monitors, pressure sensors and humidity sensors among many others. Also included in the sensing unit is an analog-to-digital converter (ADC) and a multiplexing mechanism to enable sharing of the ADC [10]. The processing unit usually consists of a processor chip and flash memory for storing the program instructions. The choice of the processing chip should be carefully determined as it has direct implications on the cost,

performance, efficiency, flexibility and energy consumption of the sensor node. The processing unit performs all the sensing and self-organization processing tasks. Collected data is also pre-processed and fused at the processing unit before transmission to the main processing stations by the communication unit. The main component of the communication unit is the transceiver which is interfaced with the processing unit via a data bus. In some cases the transceiver may perform low-level signal processing on the physical and data link layers. As a result, the communications unit consumes a lot of power and must be regulated to ensure efficient power resource utilization. Typically, the wireless sensor nodes are powered by energy constrained batteries which are usually expensive to replace once the nodes have been deployed. To circumnavigate this problem, the sensor nodes are equipped with sleep scheduling mechanisms to reduce the energy that is wasted when the transceiver is the idle and listening state [24]. Figure 2.5 shows the design architecture of the XYZ mobile sensing node prototype that was developed at Yale university [25], [26].

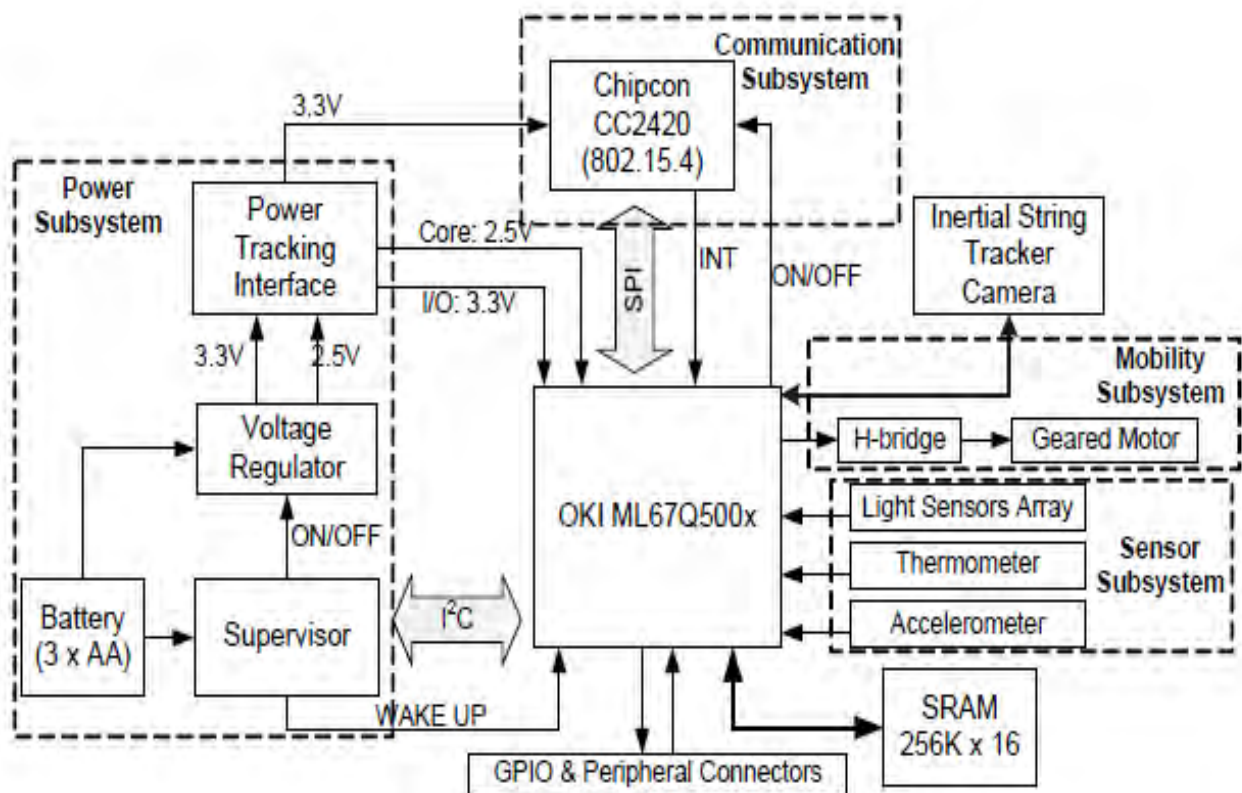


Figure 2.5: The XYZ sensor node architecture [26]

The XYZ prototype was developed at Yale University as an open source sensing platform that was designed in an attempt to investigate the paradigm of mobile sensor networks. As observed in the diagram, the XYZ architecture includes a mobility subsystem to facilitate the movement. Furthermore, like most other prototypes and commercial deployments of wireless sensor nodes such as TelosB [27] and MicaZ [28], the XYZ communication unit is based on the 2.4GHz Chipcon CC240 RF transceiver chip which is IEEE 802.15.4 compliant. The IEEE802.15.4 is an IEEE standard that specifies a data protocol for very low duty cycle wireless networks [29].

2.5 Challenges and Constraints of WSNs

Despite their myriad of application areas, wireless sensor networks are subject to very unique constraints and challenges based on their design and intended functionality. Therefore these constraints have to be considered in the design and deployment of wireless sensor nodes to achieve maximum efficiency. Protocols and algorithms dictating the operations of the wireless sensor node may have to be modified so as to cater for the constraints faced by wireless sensor nodes. In the following section we describe some of the design challenges and constraints that have plagued wireless sensor networks.

2.5.1 Energy Constraints

Wireless sensor nodes are micro-electronic devices with a limited power source and limited energy budgets. In most cases, sensor nodes are equipped with replaceable or rechargeable batteries depending on the type of application they serve. However, this is not a viable option for some applications and the nodes may be considered obsolete once their energy sources are depleted. Therefore the lifetime of a sensor node is most often dictated by the lifetime of the battery. Moreover, in the case of non-rechargeable batteries, it is adamant that a wireless sensor node remains operational until the completion of the mission or until replacement of the battery. For instance, some applications may require the sensor nodes to be operational for years, such as remote monitoring of glacial movements, while others, such as battlefield applications, may require functionality for a few hours or days.

Energy is therefore a key resource in the world of wireless sensor networks and efficient energy consumption strategies must be considered for optimizing power consumption. Therefore, to increase the robustness and lifetime of wireless sensor networks, energy efficiency must be at the heart of wireless sensor node design. Since decisions made at the physical layer have dire effects on the energy consumption of the entire node, a physical layer driven approach to designing protocols and algorithms should be considered for maximum energy efficiency [30].

The selection of medium access control (MAC) strategies also has a great effect on the energy consumption of sensor nodes. If a contention-based MAC strategy is employed, nodes may attempt to access the wireless medium at any time thus leading to multiple collisions in transmissions from different nodes. Furthermore, the nodes have to listen to the medium at all times to ensure no transmission opportunity is missed. This strategy will result in increased energy overheads, delays and recovery mechanisms which put a huge strain on the limited energy budgets of the sensor nodes. A contention-free MAC strategy may be preferred because access to the wireless medium is carefully regulated under strict conditions thus avoiding collisions. This also allows the node to power down in the event of idle periods thus minimizing energy consumption [10]. Energy efficiency must also be considered in the choice of operating system and processing unit design especially if pre-processing and aggregation of sensor data is required. The communication and processing units consume most of the node's power supply and this usually leads to a trade-off between communication and processing. However, studies have shown that this trade-off can be exploited and manipulated to obtain significant energy savings [31], [32].

2.5.2 Security

The threats faced by wireless networks are similar to those faced by wired networks. However, wireless networks are more susceptible to security vulnerabilities due to their unguided transmissions in the air interface. Furthermore, the broadcast nature of wireless communications makes it easy for an adversary to eavesdrop on transmissions. Ad hoc networks share some few similarities with wireless sensor networks and as a result they have some common security threats. Some of the attacks on wireless sensor networks include: denial

of service (DoS) attacks otherwise known as jamming attacks, sinkhole attacks, wormhole attacks, hello flood attacks and sybil attacks [33].

Several research efforts, [34], [35] address the security vulnerabilities in ad hoc networks however the proposed solutions cannot be directly adopted into wireless sensor networks due to the architectural differences of the two networks. Ad hoc networks are self-organizing peer to peer networks with dynamic topologies while wireless sensor networks have static topologies with a centralized command node known as a sink. The main obstacle encountered in adopting an efficient security scheme for wireless sensor networks is the size, processing power, memory and application of the wireless sensor nodes [33].

The conventional security schemes of wireless networks such as cryptography and steganography may have to be rethought in order for them to be feasible in wireless sensor networks. For instance the encryption and decryption of sensor data in cryptography will require the transmission of extra bits thus putting a strain on the processing, memory and energy resources of the resource constrained sensor nodes. However, access to the transmission medium at the physical layer can be secured by employing a technique known as frequency hopping. A wireless node may manipulate a dynamic set of parameters accessible to it to ensure secured physical access to the transmission medium. These parameters include; available frequencies for hopping, time interval per hop and hopping pattern. The main advantage of this technique is that secured access can be achieved at low processing, memory and energy costs [33]. Despite the obvious merits of the frequency hopping technique, the advantages may be barred by overcrowding in the industrial, scientific and medical (ISM) bands where wireless sensor networks operate.

2.5.3 Wireless Networking

Wireless sensor networks rely on suitable radio frequencies (RF) to achieve wireless communication. However, radio communication has some inherent challenges that should be considered when planning a wireless sensor network. These challenges include propagation distance, attenuation and susceptibility to interference. A suitable radio frequency has to be selected from the pool of available spectrum while carefully considering the spectrum regulations and the propagation characteristics. Furthermore, the chosen spectrum space must be available worldwide so as to enable the global operation of these networks. For this reason

most commercial deployments of wireless sensor networks are deployed on the ISM bands [15]. The ISM bands are unlicensed and offer free access in most countries in the world. This means that devices operating in these bands should be able to tolerate any interference that is caused by ISM equipment and other devices operating in the unlicensed bands. Table 2.1 below shows the international frequency allocations in the ISM band.

TABLE 2.1
Frequency allocations in the ISM bands

Frequency Range	Centre Frequency	Bandwidth
6765 – 6795 kHz	6780 kHz	30 kHz
13533 – 13567 kHz	13560 kHz	14 kHz
26957 – 27283 kHz	27120 kHz	326 kHz
40.66 – 40.70 MHz	40.68 MHz	40 kHz
433.05 – 434.79 MHz	433.92 MHz	1.74 MHz
902 – 928 MHz	915 MHz	26 MHz
2400 – 2500 MHz	2450 MHz	100 MHz
5725 – 5875 MHz	5800 MHz	150 MHz
24 – 24.5 GHz	24.125 GHz	250 MHz
61 – 61.5 GHz	61.25 GHz	500 MHz
122 – 123 GHz	122.5 GHz	1 GHz
244 – 246 GHz	245 GHz	2 GHz

The main advantage of using the ISM bands is free radio access and huge spectrum allocation. The 2.4 GHz frequency band is even more popular due to its worldwide availability and its desired signal propagation characteristics. For this reason, most commercial deployments of wireless sensor networks operate in this frequency band [20], [21], [26]. Furthermore, the IEEE 802.15.4 standard has been designed to operate on the 2.4 GHz frequency as a low data rate and low power consumption protocol for wireless sensor networks and has been adopted by the ZigBee Alliance [36]. However, the issue of reliable communication range and deployment costs has plagued wireless sensor networks operating in this frequency band. For example, most communication paths in indoor (home, office or industrial) environments are either completely obstructed or heavily shadowed. Repeaters may be used to solve this problem and increase the propagation distance but at a much higher deployment costs. The mesh networking capabilities of the repeaters may be leveraged to solve the problem but at a cost of added complexity to the routing protocols of wireless sensor networks.

Wireless sensor networks are rapidly gaining popularity as they are considered as the underlying infrastructure at the forefront of ubiquitous and embedded computing applications. This will lead to the deployment of hundreds of thousands of sensor networks across the globe with millions of sensor nodes. Consequently, this will lead to the overlapping and coexistence of multiple wireless sensor networks. Furthermore, most of the research and deployments of wireless sensor networks follows the single frequency deployment paradigm and would lead to significant performance degradation for overlapping sensor systems. To deal with this issue, Gang Zhou et. al. [37] proposes the use of multi-frequency systems. However, this rises the concerns of spectrum regulations and spectrum crowding on the ISM band.

The 2.4 GHz ISM frequency band also plays host to a myriad of other technologies due to its worldwide availability and desirable propagation characteristics. For instance, this band is used in applications such as cordless phones and microphones, remote controls, microwave ovens and other proprietary wireless technologies. Furthermore, this band also hosts several other IEEE 802 wireless standard technologies such as wireless local area networks (WLANs) via Wi-Fi (IEEE 802.11b), Bluetooth (IEEE 802.15.1) and ZigBee (IEEE 802.15.4). Therefore, due to the unexpected deployment dynamics of wireless sensor networks with coexisting networks and devices, the limited spectrum at the 2.4 GHz ISM band is getting extremely crowded [37]. The spectrum occupancy of this band could reach levels of 90% in some locations. Inevitably, this has led to some coexistence issues within this spectrum band. It is

also well known knowledge that wireless sensor networks operating in the 2.4 GHz band under the IEEE 802.15.4 standard suffer severe performance degradation when coexisting with IEEE 802.11 Wireless LANs (WLANs) [4]. Table 2.2 below shows some commercial deployments of wireless sensor network transceivers and the overlapping wireless systems.

TABLE 2.2

Operating spectrum bands of commercial WSN transceivers and overlapping wireless systems. (Adapted from, [8])

Sensor node platforms	Radio Chip	Operating Bands	Overlapping wireless systems
IMote, MicaZ, SenseNode, XYZ, Sentilla Mini, TelesB	Chipcon (TI Norway) CC2420	2.4 GHz	Fixed, mobile, armature radio as secondary, 802.11b/g/n, Bluetooth, Zigbee
ANT	Nordic nRF24AP1	2.4 GHz	Fixed, mobile, armature radio as secondary, telemetry, 802.11b/g/n, Bluetooth, Zigbee
Iris	Atmel AT86RF230	2.4 GHz	Fixed, mobile, armature radio as secondary, telemetry, 802.11b/g/n, Bluetooth, Zigbee
Bean, BTnode, Mica2, MANTIS Nymph	Chipcon (TI Norway) CC1000	315, 433, 868, 915 MHz	Fixed, mobile, armature, satellite, radiolocation, broadcasting, telemetry
EyesIFX v. 1 and v. 2	Atmel AT86RF230	868 – 870 MHz	Fixed, mobile, broadcasting, telemetry

2.6 Dynamic Spectrum Access in Wireless Sensor Networks

Wireless sensor networks often operate in the fixed and unlicensed ISM bands. However, as we have already discussed, there is increasing congestion and crowding in the ISM bands leading to interference and other coexistence issues. From a larger perspective, these problems arise because of the rigid spectrum regulation paradigms that are employed. Traditionally, communication regulation regimes work on a fixed spectrum assignment policy where usable frequencies are assigned to licensed users who then have full exclusivity of the radio resource. However, studies and reports indicate that the licenced spectrum is rarely utilized continuously thus leading to inefficiency and very poor spectrum utilization [6]. Furthermore, these spectrum portions are licensed in large chunks over large geographical areas leading to a situation of spectrum scarcity for new wireless services. Consequently, since spectrum is traded as a commodity, the laws of demand and supply dictate very high prices for vacant portions of usable spectrum space. This is the reason why most proprietary wireless technologies are deployed in the free and unlicensed ISM bands.

This has led to the development of the dynamic spectrum access (DSA) paradigm which seeks to exploit the existing wireless spectrum opportunistically. DSA seeks to solve the problem of spectrum scarcity and inefficiency by allowing for secondary access into the licensed frequency bands. Unlicensed secondary users can transmit in the licensed bands as long as their transmissions do not interfere with the primary users. The key technology that has been employed to achieve the goals of DSA is Cognitive Radio (CR) technology. This technology allows for secondary and opportunistic access into the licensed bands. CR achieves this by giving the users a mechanism to detect which portions of spectrum are vacant and also to detect the presence of a licensed user. CR also selects the best available channel for transmission, coordinates access to this channel with other users and vacates the channel once a licensed user is detected so as to avoid causing interference. In this way, cognitive radio technology meets the obligations of dynamic spectrum access.

Therefore, dynamic spectrum access is well positioned as a promising spectrum efficient communication paradigm for wireless sensor networks. The advantages introduced by cognitive radio such as, spectrum agility and opportunistic access, can help open up new spectrum space, improve spectrum utilization and improve communication quality. These features are a perfect match for the unique constraints and challenges faced by the resource constrained wireless sensor networks. Consequently, the agglomeration of cognitive radio

technology with wireless sensor networks has led to the birth of a new communication paradigm known as Cognitive Radio Sensor Networks (CRSN) [8]. Before we delve into the CRSN paradigm we further explore the concept of dynamic spectrum access and cognitive radio.

2.7 Dynamic Spectrum Access

With the progression in communication technology, consumers are increasingly interested in wireless services. This has led to the dramatic increase in the demand for usable radio spectrum space. Moreover, the ever evolving wireless services and devices enhances the great appetite for wireless broadband access thus fuelling the demand for the radio spectrum. However, due to the command and control nature of the conventional spectrum management techniques, there is a shortage of usable radio frequencies. The spectrum regulation regimes dictate that a licensed operator has full exclusivity to operate in a particular band. This leads to inefficiencies due to the rigidity of the spectrum management policies. Furthermore, since most of the useful spectrum is already licensed in huge chunks over large geographical areas, it is difficult to find vacant bands to deploy new services or to enhance old services. This has reinforced the belief that we are quickly running out of usable radio frequencies.

On the contrary, spectrum measurements published by the FCC's Spectrum Policy Task Force indicate that much of the licensed radio spectrum lies idle at any given time and location [38]. This report shows us that much of the perceived spectrum shortage results from the inflexible spectrum management policies and severe underutilization of the licensed spectrum rather than physical spectrum scarcity. Figure 2.6 below shows the average spectrum utilization measurements for the frequency bands ranging from 30 MHz to 3GHz from six different locations.

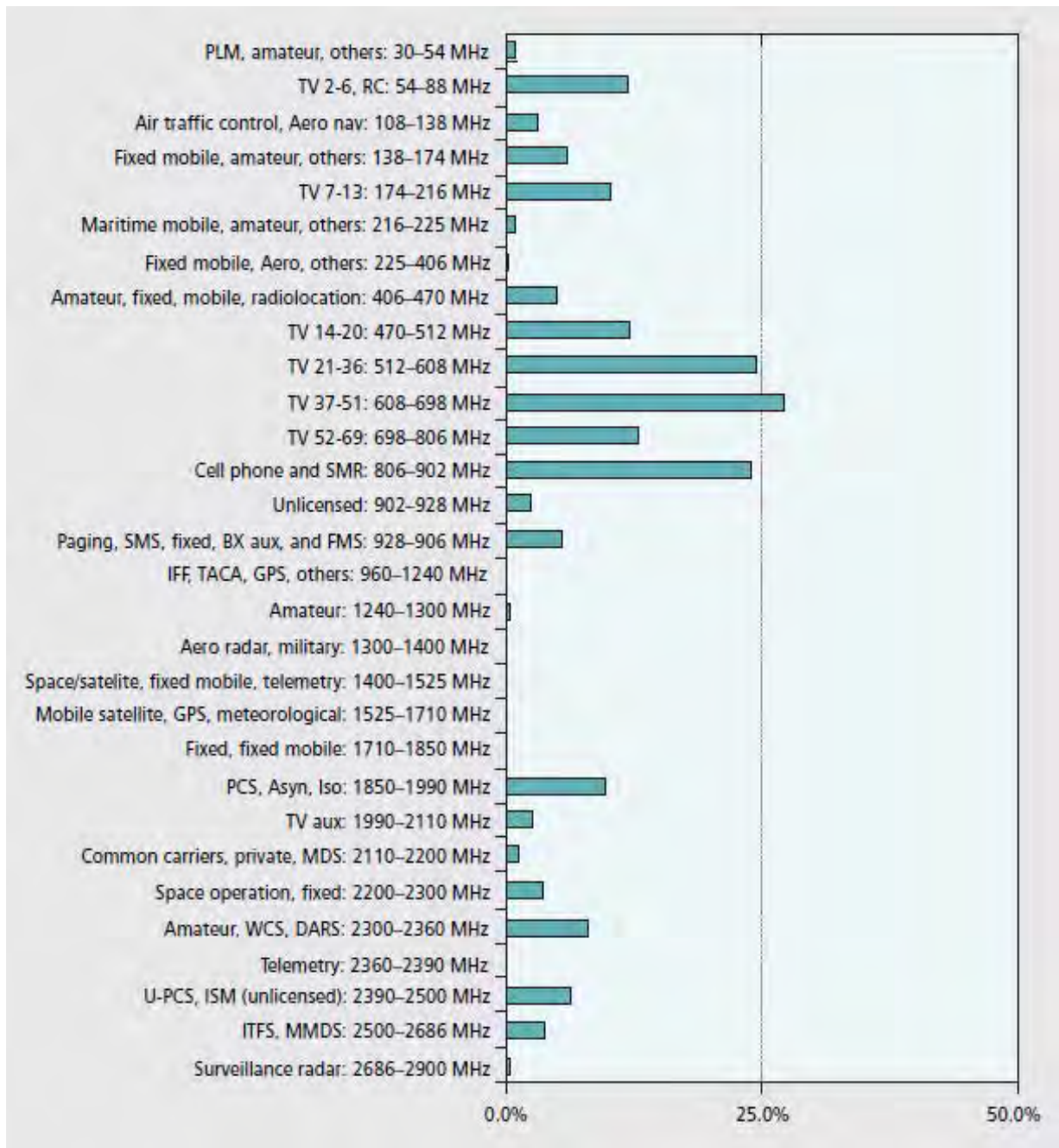


Figure 2.6: Spectrum utilization measurements between 30 MHz – 3 GHz [6]

Due to the significant underutilization of the radio spectrum, various communication regulatory authorities have been prompted to look into improved spectrum management and access techniques. This has led to the development of dynamic spectrum access (DSA) strategies where secondary (unlicensed) systems are permitted to coexist with the primary

(licensed) users and consequently improve the spectrum utilization. These DSA strategies can broadly be categorized into three major techniques as shown in Figure 2.7 below.

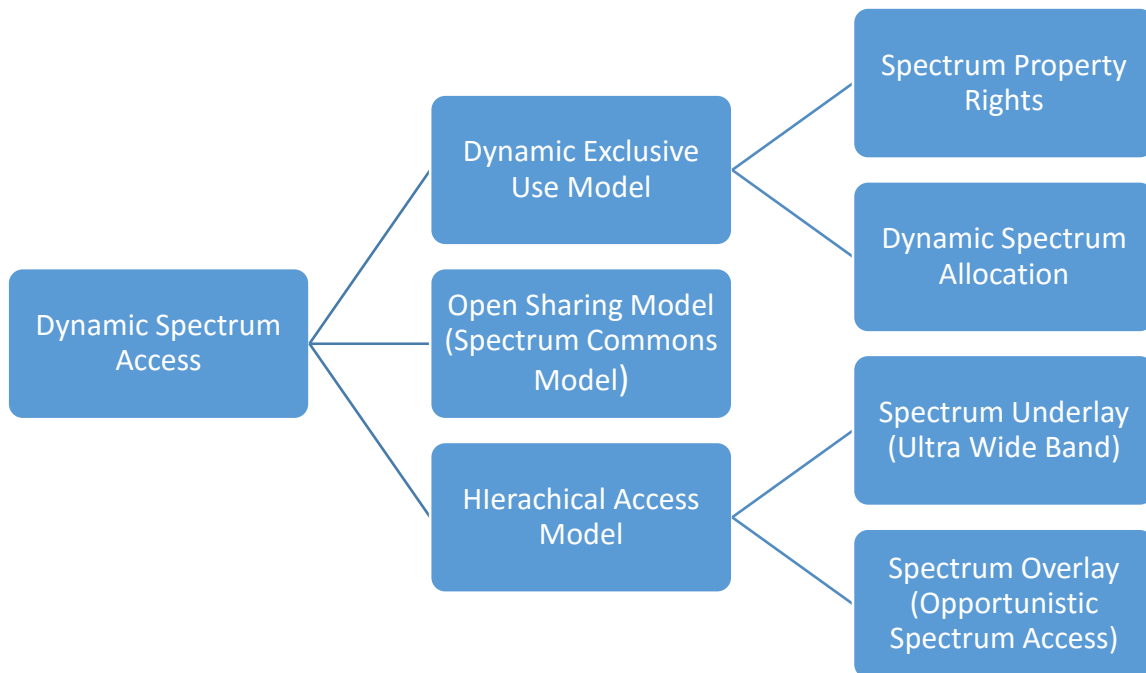


Figure 2.7: Taxonomy of dynamic spectrum access

2.7.1 Dynamic Exclusive Use Model

This DSA strategy maintains the basic command and control structure of the conventional spectrum regulation policies but with an added level of flexibility. In this technique, the spectrum exclusivity is still maintained but dynamicity is introduced by the following two approaches: Spectrum property rights and dynamic spectrum allocation. In the first approach, the licensed operators have the liberty to freely sell or lease the spectrum for an economic gain. In this case, the spectrum is treated as a commercial commodity and economic forces dictate the most profitable use.

The dynamic spectrum allocation technique introduces flexibility into spectrum assignment by leveraging the spatial and temporal traffic statistics of various services. Therefore, a portion of vacant spectrum may be licensed in different regions and at different

times. However, because these techniques still employ the exclusivity models, they do not solve the problem of poor spectrum utilization and spectrum holes [2].

2.7.2 Open Sharing Model

This technique, also known as the spectrum commons model, is primarily based on an open sharing policy among users in a given location. The spectrum management policies employed here are similar to those adhered to in the unlicensed industrial, scientific and medical (ISM) bands. This technique enforces stringent transmission characteristics such as controlled transmission power levels to allow for the coexistence of devices.

2.7.3 Hierarchical Access Model

This model employs a hierarchical structure of spectrum sharing so as to achieve dynamicity in spectrum access. The hierarchical access model allows for secondary (unlicensed) access into to the licensed bands as long as the secondary transmissions do not interfere with the primary users. The coexistence of the primary and secondary users in the same frequency band is achieved by employing the spectrum underlay or spectrum overlay technique.

The spectrum underlay approach allows for secondary access provided the secondary transmissions operate below the noise floor of the primary users. The technique works by spreading the secondary signal over a wide frequency band so as to achieve high data rates at a very low transmission power. Figure 2.8 below shows a graphical depiction of the spectrum underlay technique.

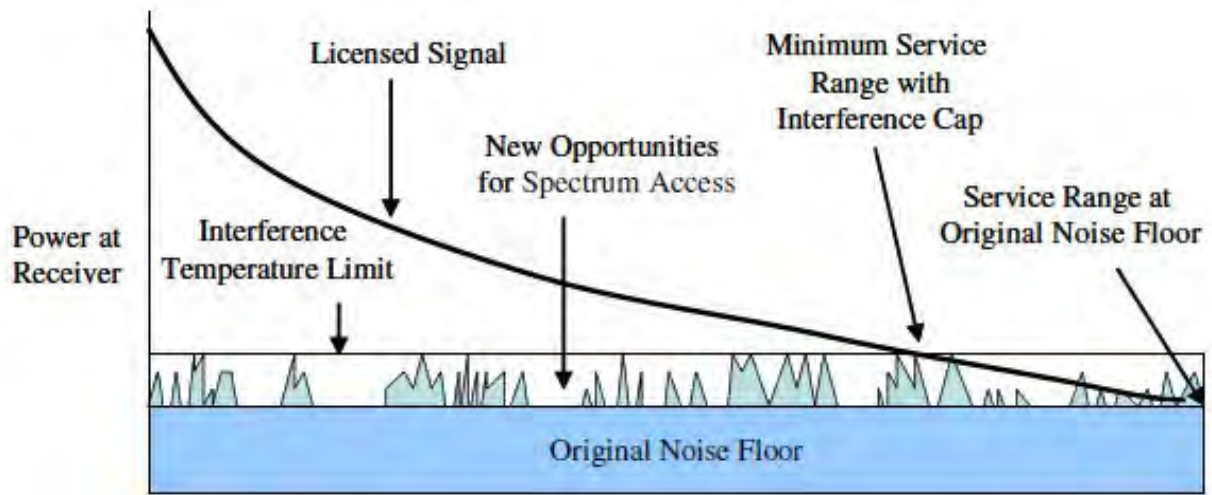


Figure 2.8: The spectrum underlay technique [39]

Secondary users may operate above the noise floor of the primary users and below the maximum tolerable interference permitted (interference temperature limit) through very strict constraints on the secondary user's transmission power. This is achieved by spreading the secondary transmissions in the frequency domain by using a technique known as ultra-wide band (UWB).

As opposed to the spectrum underlay technique that imposes stringent restrictions on the transmission power, the spectrum overlay technique only dictates when the secondary transmissions should occur [2]. This technique leverages the fact that the radio spectrum is not utilized continuously and contains idle moments referred to as spectrum holes or white spaces. Therefore, the spectrum overlay approach allows for opportunistic secondary transmissions in the spectrum holes as shown in Figure 2.9. This technique was first suggested by Joseph Mitola [7] as the key spectrum access strategy for cognitive radio technology.

2.8 Cognitive Radio

The concept of Cognitive Radio (CR) was first introduced by Joseph Mitola III in 1999 in his paper, [7]. A cognitive radio can be described as an intelligent radio that can be programmed and configured dynamically to adjust its transmitter parameters based on the interaction with the environment it operates in. The fundamental aim of cognitive radio is to allow users who do not have spectrum rights to temporarily operate in the unused portions of

the licensed spectrum as Secondary Users (SU). Cognitive radio employs the spectrum overlay technique to dynamically access the unused portions of the licenced spectrum that are otherwise known as spectrum holes or white spaces.

The main aim of cognitive radio is to obtain the best available spectrum band through cognitive ability and reconfigurability. Cognitive ability is the capacity of the secondary users to sense the radio conditions in its immediate environment such as the presence of a licensed user, transmission frequency and power, bandwidth and modulation scheme. However, this capability cannot solely depend on monitoring the power levels in selected frequency bands. Advanced techniques such as autonomous learning and action decision have to be employed to assess and capture the temporal and spatial variations in the radio environment so as to minimize interference to the licensed users. On the other hand, the secondary users are able to make decisions and adapt their operation parameters based on the conditions in the radio environment due to their reconfigurability. Furthermore, CRs can be programmed to operate in a number of frequency bands using a variety of access technologies as permitted by the hardware design [40].

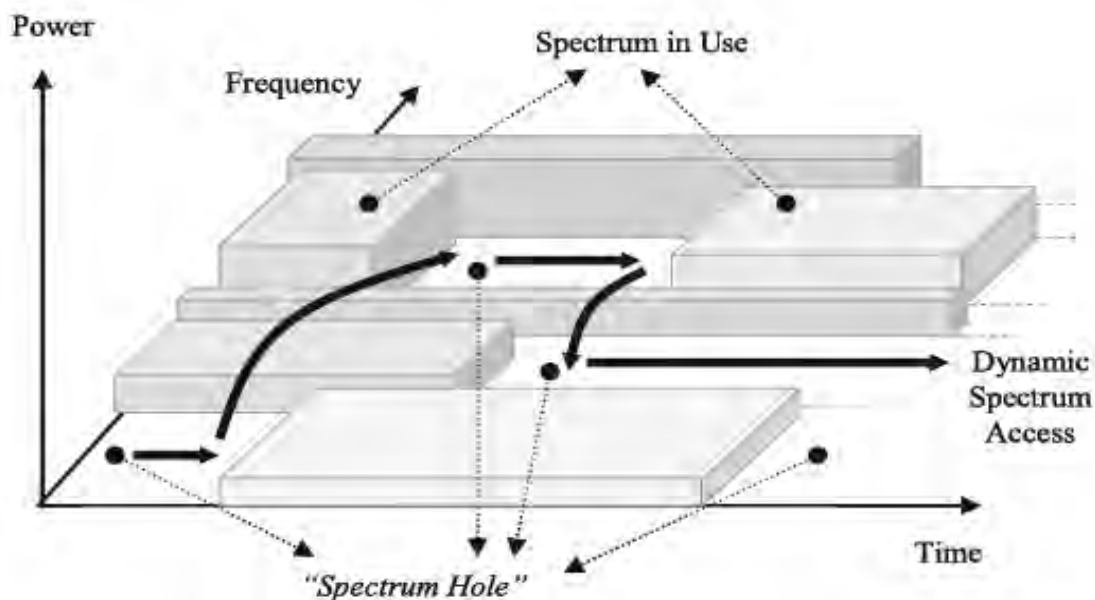


Figure 2.9: Spectrum Holes

Cognitive Radio technology significantly enhances spectrum utilization by fostering the coexistence of Primary Users (PU) and Secondary Users (SU). However, the PUs always have priority over the SUs and must be protected from any interference caused by the coexistence. Therefore, the SU is tasked with the responsibility of sensing the radio environment in real time for the PU's transmissions. If a PU is detected, the SU should vacate the spectrum hole for another or wait until the PU has finished transmitting in order to transmit. The SU may also lower its transmission power and adjust its modulation scheme so as to continue transmitting at the same time with the PU.

2.8.1 Cognitive Radio Tasks

The fundamental aim of Cognitive Radio is to foster the opportunistic usage of temporarily unused spectrum portions otherwise known as spectrum holes. In this way, CR differs from traditional radio due its cognitive ability and its reconfigurability. Therefore, following its interaction with the spectrum, the CR has to autonomously adapt to the dynamic radio conditions present in its operating environment. In order to achieve this, the CR device employs a set of spectrum aware operations consisting of several CR tasks that form the cognition cycle. Figure 2.10 below is a graphical depiction how of the various cognitive radio features interact with the radio environment.

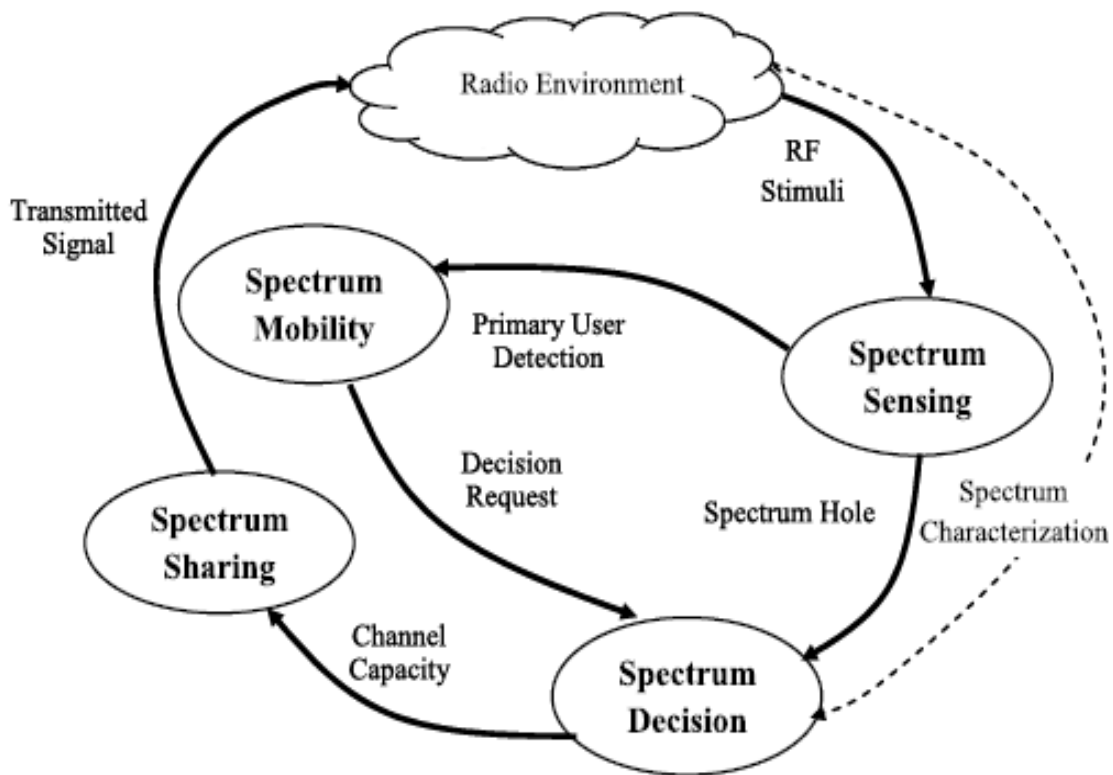


Figure 2.10: The Cognition Cycle [40]

The cognition cycle is continuously run by the CR device so as to observe the presence or absence of the primary user and detect spectral opportunities. It also enables the CR device to dynamically reconfigure itself autonomously based on the underlying conditions present in the radio environment. The cognition cycle is made of up of four defining cognitive radio tasks. They include; spectrum sensing, spectrum decision, spectrum mobility and spectrum sharing.

2.8.1.1 Spectrum Sensing

Spectrum sensing is the ability of a CR device to scan different spectrum bands and measure the electromagnetic activity present in order to determine the presence or absence of any ongoing radio transmissions. The intrinsic characteristics of the spectrum band such as cumulative power levels or modulation schemes can be captured and used in the determination of spectrum occupancy. Spectrum sensing is the most critical functionality of CRs and it is

related to all other spectrum management functions as it provides spectrum usage awareness in the radio environment. Also as important is the choice of which spectrum bands to sense, at what time and the sensing duration. These decision ultimately determine the accuracy of the cognitive radio detector.

Spectrum sensing may be classified as either out-band or in-band. Out-band sensing involves monitoring the spectrum band for spectrum holes, which are characterised as transmission opportunities for secondary users. In-band sensing involves monitoring the frequency band in which the CR is currently transmitting on for the return of the PU. Moreover, the existing spectrum sensing techniques in use depend solely on detecting the activities of primary transmitters. These techniques include energy detection, matched filter detection, cyclostationary feature detection and interference-temperature based detection.

2.8.1.2 Spectrum Decision

Once the spectrum has been characterised and the vacant portions of spectrum (white spaces) have been identified, the CR user must then select the most appropriate spectrum bands in accordance with their QoS requirements. The cognitive radio user parameters such as the required data rate, bandwidth, acceptable error rate, delay bound and mode of transmission are essential metrics used in the selection of the most suitable transmission band. This selection is based on a predetermined decision rule that may seek to ensure fairness and minimize communication costs. For instance, five spectrum decision rules are presented in [41] based on a device-centric spectrum management scheme and the assumption that all channels have equal throughput. Alternatively, a channel selection decision rule based on the SNR is also proposed in [42].

However, the CR user must always keep track of spectrum space because the radio environment is very dynamic with lots of changes over time and space. Moreover, since CR users operate as secondary users, the selected spectrum may become unavailable once the primary user is detected. As a result, the CR device will have to reconfigure itself by adapting its protocols at different layers of the network stack to the current channel parameters and operating frequency. Therefore, the spectrum mobility functionality will have to be executed to ensure seamless transmissions by the CR user.

2.8.1.3 Spectrum Mobility

The CR device usually selects the best available channel through the process known as spectrum decision. However, it is worth noting that CR devices usually operate as guests to the selected portion of spectrum. This means that if the primary user returns to the selected band, the CR user must vacate that band and continue its transmissions on another vacant portion of spectrum. As a result, a spectrum handoff is performed as the ongoing CR transmissions switch from one spectrum band to another. A handoff may also be performed when the current band in which the CR device operates cannot meet the desired QoS requirements. This notion is referred to as spectrum mobility.

A temporary break in communication maybe experienced during the spectrum handoff process because new spectrum holes must be discovered. Furthermore, the available spectrum bands are often not continuous but are dis-contiguous and distributed over a large spectrum range. For this reason, the CR device may have to perform a reconfiguration of its RF front end due to the different operating frequencies in order to maintain communication. Consequently, this may lead to longer switching times from one band to another. However, spectrum mobility may collaborate with spectrum decision so as to determine a list of vacant and available back-up channels on the desired route as is the case with the IEEE 802.22 Wireless Regional Area Networks (WRAN) protocol [43]. This technique ensures a high probability of finding available portions of vacant spectrum in a short period of time. Moreover, to reduce the delay introduced to the ongoing transmission due to spectrum handoff, upper layer protocols such as transmission control protocol (TCP) must collaborate with the connection manager to ensure seamless spectrum switching.

2.8.1.4 Spectrum Sharing

The notion of spectrum sharing is very similar to the medium access control (MAC) protocol in conventional systems. Given that the wireless channel is a shared resource and that all CR devices have equal spectrum access rights, transmissions by the secondary user should be coordinated so as to prevent collisions in overlapping bands. Furthermore, CR users have to share the frequency resource with the licensed user as they share it among themselves (intra-network spectrum sharing). Therefore, multiple access coordination and resource allocation

schemes have to be employed in order to maintain the desired QoS without causing interference to the primary user. Moreover, it is worth noting that the spectrum resource may also have to be shared among multiple coexisting CR networks. This is referred to as inter-network spectrum sharing.

Spectrum sharing techniques can be broken down into two major functionalities namely; resource allocation and spectrum access. In the former, the CR users select the best channels based on the QoS monitoring results. CR users also control their transmit power levels so as to meet their QoS requirements. Spectrum access is a functional block that regulates access to channel so as to avoid collisions in transmissions and interference to the primary user. However due to difficulties in synchronization between the multiple CR users, spectrum access may probably be a random process [40]. Moreover, spectrum sharing techniques can be classified into three categories based on their architecture assumption, spectrum allocation behaviour and spectrum access technique.

Spectrum sharing architecture may be classified as central or distributed. Under centralised spectrum sharing, a centralised node is responsible for spectrum allocation and access. Therefore, every CR node has the mandate to send its spectrum measurements and sensing results to the centralised node (usually a spectrum broker) for the purpose of constructing a spectrum allocation map. Contrary to that, distributed spectrum sensing involves every node being responsible for the spectrum allocation and access based on the spectrum policies. Spectrum access may be cooperative or non-cooperative. Thus, cooperative spectrum sharing solutions consider the effect of communication on other nodes while non-cooperative spectrum sharing solutions do not. Lastly, based on the access technology, spectrum sharing techniques can be considered as overlay or underlay. Overlay spectrum sharing involves transmitting in spectrum holes (white spaces) thereby minimizing interference to the primary user. On the other hand, underlay spectrum sharing utilizes the spread spectrum techniques to transmit below the noise floor of the primary users.

2.8.2 Cognitive Radio Network Architecture

Cognitive Radio Networks are made up of interconnected CR devices usually operating as secondary users in the licensed band. Ideally cognitive radio networks can be considered as heterogeneous networks. This is because such networks utilize various wireless access

technologies and are composed of different communication systems, networks and end devices. However, despite this nature of cognitive radio networks, three fundamental network architectures can be established .

2.8.2.1 Ad-hoc Architecture

In such topologies, there is no defined network infrastructure dedicated to coordinating the flow of communication between end devices. As a result, mobile stations form links with other compatible devices discovered in the vicinity thus forming an ad hoc network. Consequently, communication in such topologies assumes the multi-hop paradigm.

2.8.2.2 Infrastructure Architecture

In this architecture, the cognitive radio network is built around a set of base stations or access points. Therefore, a mobile station communicates with the nearest base station within transmission range in a single hop. Inter-cell communication (communication between the base stations) is routed through the core network. In this case there is dedicated network infrastructure [39], [44].

2.8.2.3 Mesh Architecture

A mesh architecture is a cocktail of both the ad hoc and infrastructure architectures. A mobile station operating in such an architecture can either communicate with the base station directly or use other mobile stations as multi-hop relay nodes. In such cases there is usually some wireless communication between the base stations.

2.9 Cognitive Radio Sensor Networks

The marriage between Cognitive radio technology and Wireless Sensor Networks has inevitably led to the development of cognitive radio based wireless sensor networks otherwise referred to as Cognitive Radio sensor Networks (CRSNs). Cognitive radio technology has not only helped wireless sensor networks to gain access new spectrum but also spectrum with better propagation characteristics. Furthermore, allowing WSNs networks to operate at lower frequency bands such as the UHF band, will result in an increase in the transmission range. As a result, fewer sensor nodes will be required for a given geographical area thus simpler topologies. Another worthwhile benefit accrued from employing CRSNs is lower power consumption and higher energy efficiency [45]. Although cognitive radio technology may introduce new constraints into the CRSN paradigm, such as algorithm and protocol design, WSNs may benefit from some of the salient features of dynamic spectrum access as discussed in the following subsection.

2.9.1 Advantages of Cognitive Radio Sensor Networks

The main advantage of cognition in WSNs is dynamic spectrum access. Traditionally, deployments of wireless sensor networks adhere to the fixed spectrum allocation regime. This means that usable frequencies were accessed either through spectrum leasing or through operations in the free unlicensed bands such as the ISM. Congestion in the ISM bands would degrade the performance of the WSNs and the high cost of spectrum acquisition would skyrocket the cost of deployment. However, dynamic spectrum access would lessen the overall cost of deployment of WSNs and maximize performance as it affords the sensor networks opportunistic access to licensed bands.

Cognitive radio technology has proved to be a worthy candidate to handle the bursty nature of sensor node communication. Communication in WSNs tends to be event driven and thus upon detection of the parameter in question, sensor nodes generate bursts of packets. Furthermore, in a densely deployed sensor network environment, a large number of nodes will be actively trying to access the same wireless channel when an event is triggered. Therefore as a result of this bursty communication, WSNs experience severe performance degradation due to a higher probability of collision, packet loss and delays. On the contrary, cognitive radio

affords the sensor nodes access to multiple alternative channels thus accommodating bursty traffic. Moreover, access to multiple channels also means that CRSNs are not bound by different spectrum regulations because of the spectrum agility of cognitive radio.

Lastly, cognitive radio also fosters the deployment of multiple overlaid sensor networks. There is an increasing usage and need for more sensor systems and it is not unusual to find multiple sensor networks operating in the same geographical location. However, due to the overcrowding in the ISM band, coexisting of multiple sensor networks and other systems on the same band may have adverse effects such as interference [46]. Cognitive radio allows for the coexistence of multiple concurrent sensor networks in the same region without interference nor performance degradation.

2.10 Chapter Summary

In this chapter, we have discussed the concept of wireless sensor networks (WSNs) and some of the application areas of this technology. WSNs find applications in a numerous fields such as structural health monitoring, pipeline monitoring, active volcano monitoring, precision agriculture among a myriad of military applications. We have also discussed the inherent challenges and constraints faced by WSNs and how they affect the performance and operations of the sensor networks.

This chapter introduces the concept of dynamic spectrum access (DSA) in wireless sensor networks as a solution to most of the constraints of WSNs. Cognitive radio technology has been proposed as the most promising candidate to fulfil the goals of DSA in wireless sensor networks. We further discuss the paradigm of DSA and we show how agglomeration of cognitive radio technology with WSNs has led to the development of Cognitive Radio Sensor Networks (CRSN).

In the next chapter we further explore the concept of Cognitive Radio Sensor Networks. However, as discussed earlier in section 1.8.1, spectrum sensing forms one of the integral functional blocks of cognitive radio. This has led us to further explore the paradigm of spectrum sensing in cognitive radio sensor networks, which forms the basis of this research. We will discuss the different spectrum sensing techniques suggested in literature and their suitability for cognitive radio sensor networks thereby laying the foundation for our proposal in Chapter 4.

Chapter 3

3 Spectrum Sensing in Cognitive Radio Sensor Networks

3.1 Introduction

It is evident that the element of cognition and dynamic spectrum access introduce a myriad of benefits to wireless sensor networks (WSNs) as was shown in section 2.9.1 of the previous chapter. Furthermore, some of the inherent constraints of wireless sensor networks have been solved by incorporating cognitive radio technology. However, before we make our contribution to the paradigm of cognitive radio sensor networks (CRSNs), we must first explore and seek to understand the fundamental blocks that constitute the cognition cycle. Specifically, we focus our attention on the aspect of spectrum sensing as this is the general direction of this research. In this chapter, we discuss the spectrum sensing techniques that have been proposed in literature and we also analyse their suitability for use by cognitive radio sensor networks.

3.2 Spectrum Sensing

The wireless spectrum is a naturally occurring resource and as is the case with such resources, their use has to be regulated. Currently, communications regulatory bodies have adopted the fixed spectrum allocation regime where frequency bands are licenced in large portions over large geographical areas. Furthermore, the licensed users have full exclusivity over their frequency bands due to the command and control nature of these spectrum regulatory regime. Moreover, with technological advancements, the demand for wireless bands is ever increasing and there is a notion that we are running out of usable spectrum space [2]. To this effect, the cost of spectrum acquisition has shot up thus relegating the deployment of wireless sensor networks to the unlicensed bands and more particularly, the 2.4 GHz ISM band. However, this band is shared with several other technologies such as Wi-Fi, Bluetooth and other proprietary wireless technologies. Consequently, the performance of the WSNs is degraded because of the

coexistence. The CRSN paradigm offers a way around this problem by incorporating cognitive radio technology.

In retrospect, the looming spectrum shortage seems to be more of a human creation rather than a natural phenomenon. This is because of the severe spectrum underutilization and static allocation of the licensed wireless channels as revealed by a number of spectrum utilization surveys [47]. Therefore, the major advantage that CRSNs have over their conventional counterparts is their ability to sense their immediate radio environment for spectrum holes and transmission opportunities. This opportunistic spectrum access opens up new spectral opportunities which can be accessed dynamically by the cognitive radio sensor nodes provided they do not cause any interruption to the licensed user. The cognitive radio sensor nodes thus operate as secondary users or guests within the licensed bands. To that end, it is adamant that the cognitive radio sensor nodes detect white spaces accurately and reliably to avoid causing interference to the primary user. However, there lies one obstacle to this realisation. The fading, shadowing and the time dependence of wireless channels results in lower signal to noise ratios (SNR) thus reducing the probability of accurate detection of spectrum holes. As a result, the spectrum sensing techniques for CRSNs should be able to perform accurate detection in low SNR environments.

There are several spectrum sensing techniques that have been proposed in literature but they can be broadly categorized into three major techniques; transmitter detection, interference based detection and cooperative detection. The major spectrum sensing techniques based on transmitter detection methods include; energy detection, matched filter detection and cyclostationary feature detection. Other techniques include hybrid sensing which incorporates two different sensing methods. However, it is worth noting that wireless sensor nodes are resource constrained low power devices. This means that they are physically small devices with weight restrictions and limited power sources. Therefore, the aforementioned spectrum sensing techniques to be considered for CRSNs also ought to consider energy efficiency at the heart of their design. Figure 3.1 shows the hierarchical classification of the spectrum sensing techniques.

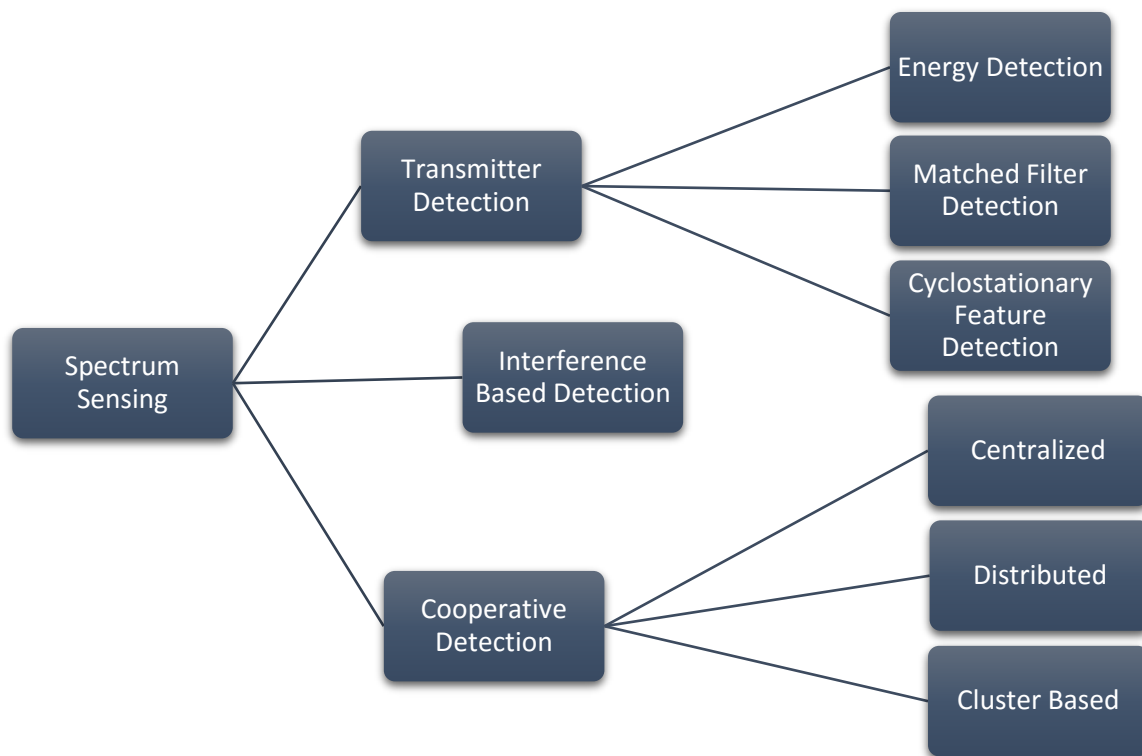


Figure 3.1: A classification of spectrum sensing techniques.

The most critical parameters that are used to judge the performance of any spectrum sensing technique include the probability of detection (P_d) and the probability of false alarm (P_{fa}). The probability of detection refers to the probability of accurately detecting the presence of the primary (licensed) user. Therefore, a high P_d is desirable as this will ensure less interference to the primary user. The probability of false alarm is the likelihood of declaring the primary user to be present falsely. For high channel throughput values, lower values of P_{fa} are desirable.

3.2.1 Transmitter Detection

The transmitter detection methods may also be classified as non-cooperative sensing techniques. This means that there is no cooperation between the spectrum sensing nodes due to lack of communication between the sensing terminals or only one terminal is available for spectrum sensing. Therefore, the spectrum decision is made based on the local observations of

the cognitive radio user. The signal detection process can be expressed as a simple identification process that can be modelled analytically as a binary hypothesis test [48].

$$\begin{aligned} H_0 : Y(n) &= w(n) \\ H_1 : Y(n) &= s(n) + w(n) \end{aligned} \tag{3.1}$$

Equation 3.1 describes the two hypotheses that are under consideration in the signal detection problem. $Y(n)$ represents the signal received by the cognitive radio sensing terminal, $s(n)$ represents the transmitted primary signal and $w(n)$ represents the additive white Gaussian noise which has a variance of σ_n^2 . The absence of the primary signal is represented by null hypothesis that is denoted by H_0 . In this sensing state, only the additive white Gaussian noise is present on the spectrum band under consideration. The alternative hypothesis, H_1 , indicates the presence of the primary user. In this case, both the white noise and primary signal are detected in the band.

Given the binary hypothesis we can have four possible outcome scenarios. The first is declaring H_1 under the hypothesis H_1 which then defines the probability of detection (P_d). Another situation is declaring H_1 under the hypothesis H_0 which leads to the probability of false alarm (P_{fa}). Moreover, H_0 can be declared falsely under hypothesis H_1 leading to the probability of miss detection (P_{md}). This is the probability of declaring the primary signal absent while it is actually present. Lastly, the hypothesis H_0 can be declared correctly thus indicating the absence of the primary signal.

Due to the statistical properties of the wireless channel, correct signal detection is not always guaranteed. Therefore, the spectrum sensing techniques are optimized to operate within certain error levels. In the following subsection, we show how it is possible to implement transmitter detection using three different techniques while maintaining the binary hypothesis model. The three techniques include energy detection, matched filter detection and cyclostationary feature detection.

3.2.1.1 Energy Detection

Energy detection is the most preferred spectrum sensing technique when no a priori knowledge of the primary user is known [48]. The energy detector determines spectrum occupancy by measuring the energy of the received signal over a period of time and comparing it against a certain threshold. Its main operating principle is that the energy of the received signal should be greater than the ambient noise energy. Furthermore, the energy detector does not take into consideration the characteristics of the received signal. Therefore, in this regard, the energy detector may also be referred to as a blind detector.

In the energy detection process, the spectrum occupancy decision is based solely on the threshold value. Therefore, threshold selection is a very critical factor on which the success of the energy detector hangs. If the perceived energy at the secondary receiver is higher than the threshold energy, it can be concluded that the primary user is present and hypothesis H_1 stands. Consequently, the secondary users are not allowed to transmit. On the contrary, the spectrum space will be declared vacant if the perceived energy is lower than the threshold value thus declaring the null hypothesis (hypothesis H_0). This indicates the presence of a spectrum hole in which secondary users can opportunistically transmit. Equation 3.2 depicts the binary hypothesis problem referred to above.

$$\begin{aligned} H_0 : Y(n) &= w(n) && : \text{Primary user absent} \\ H_1 : Y(n) &= s(n) + w(n) && : \text{Primary user present} \end{aligned} \tag{3.2}$$

The energy detection process can be conducted in both the frequency and time domain using Fast Fourier Transform (FFT). For signal detection in the time domain, the received signal is first passed through a band pass filter. The output of the filter is then squared and integrated over a predefined time interval. The resultant signal is used to formulate a test static which is compared against a decision threshold (λ) so as to determine spectrum occupancy. For detection in the frequency domain, the time domain signal has to be transformed using the FFT and the combined signal power over all the frequency bins is compared against the decision threshold. Figure 3.2 shows a block diagram of the energy detection process.

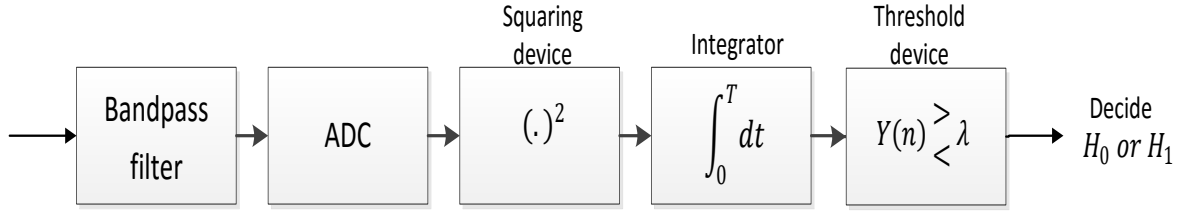


Figure 3.2: The energy detection process.

The test statistic is also considered while making the spectrum occupancy decision and it can be defined as the numerical summary of the received signal data set. The presence or absence of the primary user is made by comparing the test statistic to the decision threshold (λ). The test statistic can be formulated as shown in equation 3.3, where N is the size of the observation vector.

$$M = \frac{1}{N} \sum_{n=1}^N |Y(n)|^2 \quad (3.3)$$

The probability of detection (P_d) and probability of false alarm (P_{fa}) are the two metrics used to evaluate the performance of the energy detector. Both the P_d and the P_{fa} are associated with a particular threshold that is tested against the test statistic. Therefore, given a situation where the test statistic is greater than the threshold, ($M > \lambda$), the primary signal will be declared present. Contrary to that, if the test statistic is less than the threshold, ($M < \lambda$), the primary signal is declared absent. Moreover, given that the signal is declared to be present correctly, hypothesis H_1 will be declared. Thus the probability of detection can be represented shown in Equation 3.4;

$$P_d = (M > \lambda | H_1) = Q_u(\sqrt{2\gamma}, \sqrt{\lambda}) \quad (3.4)$$

Where $Q_u(x, y)$ is the generalised Marcum Q -function which can be expressed as shown in Equation 3.5 below [49];

$$Q = \frac{1}{\sqrt{2\pi}} \int_x^{\infty} e^{-t^2/2} dt \quad (3.5)$$

The variable γ represents the signal-to-noise-ratio (SNR) which can be expressed as a ratio of the signal variance to the noise variance as shown below. The SNR is also expressed as $\gamma = \lambda/2$ or $\gamma = \sigma_s^2 / \sigma_n^2$ in [48].

However, given that the primary signal is declared to be present falsely, hypothesis H_0 is declared. Therefore, the likelihood of falsely declaring the presence of a primary signal is referred to as the probability of false alarm and it is represented by Equation 3.6 below;

$$P_{fa} = (M > \lambda | H_0) = \frac{\Gamma(u, \lambda/2)}{\Gamma(u)} \quad (3.6)$$

Where $\Gamma(.,.)$ is the incomplete gamma function, $\Gamma(.)$ is the complete gamma function and u is the time bandwidth product.

3.2.1.2 Matched Filter Detection

In the event that the receiver has a priori knowledge of the primary user, the matched filter detector is the optimal detector to determine spectrum occupancy [50]. The matched filter works by correlating a known signal template to the received signal. In this way, the detector is able to determine the presence or absence of the signal template in the received waveform. The test statistic of the matched filter is derived based on a principle known as the inner product which can be used to determine the correlation coefficient of the template and the received signal. Therefore, the detector can make spectrum occupancy decisions by comparing the output of the matched filter to a certain threshold value as shown in Equation 3.7 below.

$$M = \sum_{n=0}^{N-1} y(n)s(n) \begin{matrix} > \\ < \end{matrix} \lambda \quad (3.7)$$

The matched filter stores information on the primary user's signal such as the modulation type, pulse shape and packet format may be stored in the memory of the cognitive radio device. This a priori knowledge makes signal detection faster and even more accurate as compared to the conventional energy detector. However, the implication of this is that the cognitive radio receiver would need a dedicated receiver for every different primary signal. Consequently, the performance of the detector is based solely on the accuracy of the a priori information.

Moreover, the matched filter maximizes the SNR by amplifying the signal components of the received waveform as it concurrently suppresses the noise components. This means that the detector only requires only $O(1/SNR)$ samples to achieve the target performance metrics [51]. However, the success of the matched filter is pegged on the availability and quality of the a priori knowledge of the primary signal. Figure 3.3 below shows a block diagram of the matched filter detection process.

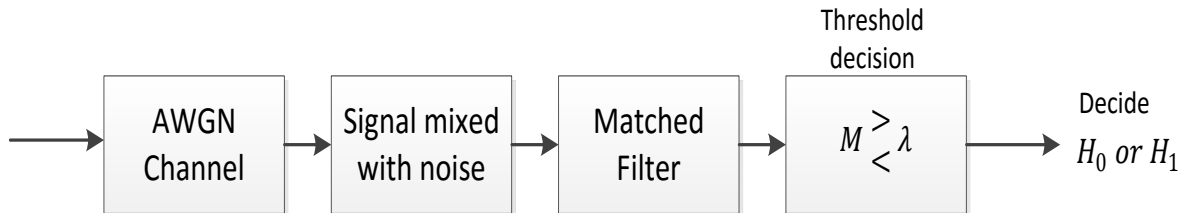


Figure 3.3: Matched Filter detection

3.2.1.3 Cyclostationary Feature Detection

The cyclostationary feature detector is an alternative technique used for signal detection based on the cyclostationary features of the received signal [52]. Some signals can be described as cyclostationary due to the interaction of a linear or nonlinear system with some periodically

varying parameter. The modulated signals are usually integrated with the sine wave carriers, pulse trains, hopping sequences and cyclic prefixes which introduce an element of periodicity into the signal [53]. Consequently, a cyclostationary feature detector is able to detect and extract these features in the received waveform by analysing a spectral correlation function. In this way, the detector is able to accurately distinguish between the primary user and noise signal. This is because noise is a stationary signal with no correlation while modulated signals are generally cyclostationary with spectral correlation as a result of the in-built periodicity [54]. Figure 3.4 shows a block diagram of the cyclostationary feature detection process.

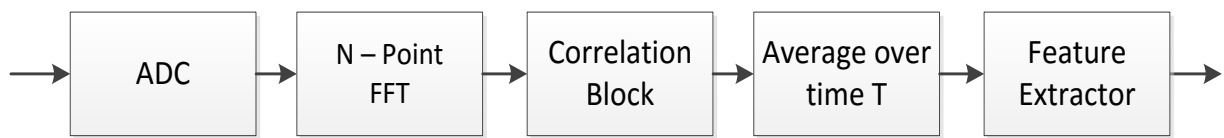


Figure 3.4: Cyclostationary Feature Detection

The cyclostationary feature detection problem may also be classified as a binary hypothesis problem. Given that the received signal, $y(t)$, has no periodicity, the spectrum band is declared vacant under the null hypothesis (H_0). On the contrary, if the received signal is cyclostationary then the band under consideration is declared occupied under the alternative hypothesis (H_1). The received signal, $y(t)$, is considered to be cyclostationary when the mean and autocorrelation are periodic as follows in Equation 3.8 [55], [56];

$$\begin{aligned}
 E_x(t) &= \mu(t + mT_0) \\
 R_x(t, \tau) &= R_x(t + mT_0, \tau + mT_0)
 \end{aligned}
 \tag{3.8}$$

where T_0 is the period of mean and autocorrelation, τ is the lag associated with the autocorrelation function, t is the time index and m is an integer.

Moreover, the periodic autocorrelation function can be expressed in a Fourier series as in Equation 3.9.

$$R_x(t, \tau) = \sum_{\alpha=-\infty}^{\infty} R_x^\alpha(\tau) e^{-2j\pi\alpha t} \quad (3.9)$$

The term R_x^α represents the Cyclic Autocorrelation (CA) function and α represents the cyclic frequency which is assumed to be known by the receiver. The cyclic autocorrelation function is obtained from the Fourier coefficients and it is given by Equation 3.10 below.

$$R_x^\alpha(\tau) = \frac{1}{T} \int_{-1/T}^{1/T} R_x(t, \tau) e^{-2j\pi\alpha t} dt \quad (3.10)$$

The Cyclic Spectral Density (CSD) is defined as the Fourier transform of the cyclic correlation function and it is expressed as show in Equation 3.11;

$$S_x^\alpha(f) = \int_{-\infty}^{\infty} R_x^\alpha(\tau) e^{-2j\pi\alpha\tau} d\tau \quad (3.11)$$

The CPS as defined in the expression above is also known as the Spectral Correlation Function (SCF) and it is a function of the frequency f and the cyclic frequency α . Moreover, the SCF can be measured over an interval of Δt by the normalized correlation between two spectral components of the received signal at frequencies $(f - \alpha/2)$ and $(f + \alpha/2)$. Therefore, for the ease of computation, an alternative expression for the SCF is expressed in Equation 3.12.

$$S_x^\alpha(f) = \lim_{T \rightarrow \infty} \left[\lim_{\Delta t \rightarrow \infty} \frac{1}{\Delta t} \int_{-\Delta t}^{\Delta t} \frac{1}{T} X_T(t, f + \alpha/2) X_T^*(t, f - \alpha/2) dt \right] \quad (3.12)$$

The finite time Fourier transform of $x(t)$ is expressed in Equation 3.13 as follows;

$$X_T(t, u) = \int_{t-T/2}^{t+T/2} x(u) e^{-2j\pi u} du \quad (3.13)$$

The spectral correlation function allows the cyclostationary feature detector to accurately distinguish the noise from the cyclostationary signals with embedded periodicity. This is because noise is a stationary signal and its SCF will always return a zero for any value of the cyclic frequency [55]. However, the cyclostationary signals will always have peaks in the SCF graphs thus making spectral occupancy decisions very accurate.

3.2.2 Interference Based Detection

The energy that may cause interference to the primary user is ever present at the receiver at any given time due to ambient transmissions and imminent noise in the radio environment. For this reason, most interference happens at the primary receiver [57]. As a result, the primary transmissions are designed to operate above a prescribed noise floor at a certain distance from the transmitter. However, the noise floor may vary due to the unpredictable nature of noise in the radio environment thus causing further interference to the primary user. The FCC Spectrum Policy Task Force [58] has addressed this issue by introducing an adaptive technique to assess the real-time interaction between transmitter and the receiver. The weight of their recommendation rests on the proposed *interference temperature* metric that enforces the interference limit perceived by receivers. The interference temperature measurements from distributed receivers are gathered and fused then used to estimate the real-time conditions of the ambient radio environment [59]. Therefore, the interference temperature limit is the maximum allowable interference in a spectral band.

The interference temperature limit sits above the original noise floor and it is considered as an upper bound of the maximum allowable interference. Therefore, secondary devices can access the spectrum provided they transmit above the noise floor and below the interference temperature limit. Any secondary transmissions that occur above this limit are considered to be harmful because they raise the noise floor beyond the upper bound thus causing interference to the primary users. The interference temperature is measured in degrees kelvin and it can also be defined as the temperature equivalent to the radio frequency (RF) power available at a receiving antenna per bandwidth. This is given by Equation 3.14 as;

$$T_I(f_c, B) = \frac{P_I(f_c, B)}{kB} \quad (3.14)$$

Where $P_I(f_c, B)$ is the average interference power in Watts centred on the carrier frequency f_c . The variable B represents the bandwidth in Hertz and k represents the Boltzmann's constant which equals to $1.38 * 10^{23}$ Joules per degree Kelvin. The interference limit acts as a cap on the secondary transmissions and is set as T_L for a frequency band with a bandwidth of B . Therefore, the secondary users must keep their interference level below kBT_L . In the event that the estimated interference temperature is lower than the predetermined interference threshold in a given period of time, the secondary user assumes the presence of a spectrum hole. Therefore, the secondary user may opportunistically access the vacant band by adjusting its transmission power and modulation type thus achieving dynamic spectrum access.

3.2.3 Cooperative Detection

In the transmitter detection techniques, each cognitive radio (CR) user operates in isolation and determines spectrum occupancy based on its own individual local observations. The location of the primary receiver is unknown to the CR users due to the absence of signalling between the primary users and the secondary users. This is because in most cases the CR network and the primary network are separated and there is no interaction between the two contending users. Furthermore, the observation range of the CR user in the transmitter detection mode is small and typically less than its transmission range. Thus for this reason, the CR user cannot completely avoid causing interference to primary receivers within its transmission range due to the lack of the primary receivers' information. Moreover, a CR user may not be able to detect the presence of a primary user if it receives a weak signal with a low signal to noise ratio (SNR) due to the effects of shadowing and multi-path fading propagation. Therefore, the transmitter detection techniques are not well equipped to deal with the hidden node problem due to their non-cooperative nature [39].

For accurate detection of a primary user signal, the CR users need to collaborate and share sensing information amongst themselves. This can be achieved when all individual CR nodes send their sensing data to a central node for fusion and thus a spectrum occupancy decision is made based on the combined results [60], [61]. This is referred to as centralised cooperative

spectrum sensing. This technique is plagued by poor fault tolerance, redundant reporting costs and poor scalability [62]. On the other hand, cooperative sensing can also be implemented in a distributed manner. In this case, there is no need for a centralised fusion centre. The CR users share sensing information amongst themselves and thus make spectrum occupancy decisions based on their local observation. These cooperative schemes are able to alleviate the undesirable effects of multi-path propagation and can improve the detection of a PU in heavily shadowed environments [63]. However, there is a need to have a dedicated control channel among the CR users so as to achieve the accuracy collaborative sensing. This introduces additional operational and overhead traffic to the resource-constrained networks [40].

3.3 An appraisal of the spectrum sensing techniques for CRSN

While making a selection on the spectrum sensing techniques for CRSNs, we must consider some of the inherent constraints of wireless sensor networks. Some of these limitations include memory and energy constraints, restricted physical size and limited computational power. Furthermore, the principles of wireless sensor networking suggest that wireless sensor nodes ought to consume extremely low power, operate in highly dense topologies and have very low production costs. In addition, they ought to be autonomous, unmanned and adaptive to the environment [15]. Therefore, any spectrum sensing technique for cognitive radio based sensor networks has to consider the aforementioned constraints and principles. Moreover, other factors to consider in the choice of a spectrum sensing technique include desired accuracy, sensing duration, network requirements and the computational complexity. In this section, we discuss the suitability of the transmitter detection and interference based detection techniques for sensing applications in CRSNs. A summary of the spectrum sensing techniques is presented in Table 3.1.

The main advantage of the energy detection technique is that no prior knowledge of the primary signal is required. Spectrum occupancy decisions are based solely on the received signal strength. However, the conventional energy detector works on the assumption that the noise is stationary and its variance is known [64]. Some of the issues that are encountered in the implementation of the energy detector include poor detection of narrowband signals, unwanted pulse shaping by the baseband filter and the undesired effects of spurious tones [65]. Furthermore, the energy detector suffers from poor detection in low SNR regimes. There is a

minimum SNR value, referred to as the SNR wall, below which signals cannot be detected [66]. The success of the energy detection technique rests on the selection of a proper decision threshold. Therefore, threshold selection is one of the main challenges faced in the realisation of the energy detector. However, despite all the challenges, the energy detection technique ranks high in simplicity and has very low signal processing requirements. For this reason, the energy detector is very attractive for CRSN applications.

TABLE 3.1

A Summary of the Spectrum Sensing Techniques

Spectrum Sensing Technique	Advantages	Disadvantages
<i>Energy Detection</i>	Very low computational power requirements. Low complexity. Ease of deployment.	Highly dependent on the noise variance. Poor performance in low SNR environments. Longer sensing duration.
<i>Matched Filter Detection</i>	Best in white Gaussian noise. Shorter sensing durations.	Requires a priori information on the PU signal. Requires extra hardware for synchronization with the PU.
<i>Cyclostationary Feature Detection</i>	Resilient to variations in the noise levels.	Highly complex and requires high computational ability on the nodes.
<i>Interference Temperature Detection</i>	Protects PU's from interference by setting a predetermined interference limit.	Requires the knowledge of PU's location. Requires nodes with a high computational power.

The main advantage of the matched filter detector is the short time it takes to achieve the target probabilities of misdetection and false alarm. Moreover, if a priori knowledge on the primary users' signal is available, the matched filter is the most preferred detection technique due to its accuracy. This is because the detector works by isolating the signal components of the received

signal and averaging the noise. As a result, this detector manages to achieve high accuracy in low SNR regimes and even in noise uncertainty [66]. In order to achieve high levels of accuracy, the matched filter requires specific knowledge of the primary signal such as the bandwidth, operating frequency, modulation type and order, pulse shaping and frame format. However, such knowledge may not be readily available especially when there is no interaction between the primary and the secondary system. In addition, the matched filter detector needs to demodulate the received signal before performing the correlation with the signal template stored in its memory. This would mean that a dedicated receiver would be needed for each different primary signal type and thus increasing the complexity of implementation. Furthermore, this would result in large sensing units which would defy the size constraints of the wireless sensor nodes [52]. Another disadvantage of this detector is its large power consumption due to the execution of various receiver algorithms. For these reasons, the matched filter may not be a suitable detection technique for the resource constrained cognitive radio sensor nodes.

The main advantage of the cyclostationary feature detector technique is its ability to discriminate against noise and its robustness to noise uncertainty. This is due to the fact that noise is generally a stationary signal with no correlation while cyclostationary signals exhibit correlation between spectral components because of inbuilt periodicity. To that end, the cyclostationary feature detector outperforms the energy detector in noise uncertainty and low SNR environments [54]. However, the robustness of this detector comes at a cost of increased complexity. According to Qiwei Zhang *et al*, the cyclostationary feature detector can be implemented as a combination of an FFT and spectral correlation with a computational complexity of $O(N^2 + \frac{N}{2} \log_2 N)$ where N represents the size of the FFT. In the event that a large N is used, the detector would require large computational power and performance may be compromised [67]. This has huge cost implications when it comes to the implementation of this particular detector. Furthermore, the cognitive radio sensor nodes are constrained in terms of computational power thus disqualifying the cyclostationary feature detector as the preferred sensing technique.

The interference based detection technique is based on the interference temperature metric that was proposed by the FCC to quantify the interference at the receiver [58]. The basic operating principle suggests that opportunistic access is permitted only if the estimated interference temperature is lower than the set interference temperature limit. However, the main drawback of this technique is the difficulty associated with accurately setting the interference temperature

threshold. In this regard, it is difficult to mitigate interference to the primary system [68]. Furthermore, the interference based detector requires nodes with high computational power and knowledge of the location of the primary receiver. This makes this detection technique unsuitable for cognitive radio sensor network applications.

In retrospect, the energy detector is the most suitable detection technique for spectrum sensing in cognitive radio sensor networks due to its simplicity and low computational power requirements. However, threshold selection, noise uncertainty and poor performance in low SNR environments have to be addressed for optimum performance. In the subsequent section, we discuss the energy detector system model in spectrum sensing for cognitive radio sensor networks.

3.4 Energy Detection System Model

The energy detector works on the principle of radiometry. This is where the electromagnetic energy present in a particular spectrum band is sampled and compared against a predefined threshold in order to determine spectrum occupancy. For the sake of simplicity, the primary signal and the noise signal are assumed to be independent and identically distributed random processes with a zero mean and variance σ_s^2 and σ_n^2 respectively. It is also assumed that the primary signal is independent of noise and fading. In this case the received SNR (γ) can be computed as shown in Equation 3.15 below.

$$\gamma = \frac{\sigma_s^2}{\sigma_n^2} \quad (3.15)$$

As was mentioned in section 3.2.1.1, a spectrum hole can be identified by comparing the test statistic (M) against a specified decision threshold (λ) as shown in Equation 3.16. For a large number of samples (N) the central limit theorem (CLT) would be invoked and thus we could assume that the sample mean and standard deviation represents the true mean and standard deviation for the entire spectrum band.

$$M = \frac{1}{N} \sum_{n=1}^N |Y(n)|^2 \begin{matrix} > \\ < \end{matrix} \lambda \quad (3.16)$$

The variable N is also defined as the minimum integer value that is not greater than τf_s , where τ represents the available sensing time and f_s represents the frequency of the spectrum band under consideration. For the sake of simplicity, we equate the number of samples to the product of the available sensing time and frequency as shown in Equation 3.17. We also assume that the test statistic follows a normal Gaussian distribution with mean μ_i and variance σ_i under a hypothesis H_i ($i = 0,1$) [48]. It then follows that the mean and the variance of the test statistic could be represented as shown below in Equation 3.18 to Equation 3.21 [69], [70].

$$N = \tau f_s \quad (3.17)$$

$$\mu_0 = \sigma_n^2 \quad (3.18)$$

$$\sigma_0 = \frac{\sigma_n^2}{\sqrt{\tau f_s}} \quad (3.19)$$

$$\mu_1 = \sigma_n^2 * (1 + \gamma) \quad (3.20)$$

$$\sigma_1 = \sigma_0 * \sqrt{(2\gamma + 1)} \quad (3.21)$$

The Equation 3.21 can further be simplified into Equation 3.22 as follows;

$$\sigma_1 = \frac{1}{N} (2\gamma + 1) \sigma_n^4 \quad (3.22)$$

When the number of samples is sufficiently large, the probability of detection given by Equations 3.4 can be rewritten as shown in Equation 3.23 as follows.

$$P_d = Q \left(\frac{\lambda - \mu_1}{\sigma_1} \right) \quad (3.23)$$

The Q -function represented by $Q(x)$ is defined as the complementary distribution function of the Gaussian function and is represented by Equation 3.5. The expression for the probability of detection can further be simplified into Equation 3.24 as shown.

$$P_d = Q \left(\left(\frac{\lambda}{\sigma_n^2} - \gamma - 1 \right) \sqrt{\frac{\tau f_s}{2\gamma + 1}} \right) \quad (3.24)$$

The probability of false alarm given by Equation 3.6 can also be rewritten as shown.

$$P_{fa} = Q \left(\frac{\lambda - \mu_0}{\sigma_0} \right) \quad (3.25)$$

Equation 3.25 can further be simplified into Equation 3.26 as shown below.

$$P_{fa} = Q \left(\left(\frac{\lambda}{\sigma_n^2} - 1 \right) \sqrt{\tau f_s} \right) \quad (3.26)$$

The theoretical threshold (λ) associated with a predefined probability of detection or false alarm can be obtained from the equations described above. For instance, the threshold associated with the given a target probability of detection, (λ_d), can be derived from the expression below.

$$Q^{-1}(P_d) = \left(\left(\frac{\lambda_d}{\sigma_n^2} - \gamma - 1 \right) \sqrt{\frac{N}{2\gamma + 1}} \right) \quad (3.27)$$

The threshold associated with a predefined probability of false alarm, (λ_{fa}) , can also be derived from Equation 3.28 below.

$$Q^{-1}(P_{fa}) = \left(\left(\frac{\lambda_{fa}}{\sigma_n^2} - 1 \right) \sqrt{N} \right) \quad (3.28)$$

Since the target probabilities are known variables, we can derive the critical number of samples (N) that are required to achieve the desired target metrics. By comparing Equation 3.27 and Equation 3.28 and cancelling the common terms, the value of N can be calculated as shown in Equation 3.29 below.

$$N_c = \frac{1}{\gamma^2} \left[Q^{-1}(P_{fa}) - Q^{-1}(P_d) \sqrt{2\gamma + 1} \right]^2 \quad (3.29)$$

Moreover, the critical SNR required to meet the target probability of detection and false alarm can be derived from Equation 3.29 and it is represented by Equation 3.30 as follows;

$$\gamma_c = \left[\frac{Q^{-1}(P_{fa}) - Q^{-1}(P_d)}{Q^{-1}(P_d) + \sqrt{N}} \right] \quad (3.30)$$

3.5 Implementation Challenges of the Energy Detector

Some of the challenges encountered in the implementation of the energy detector include threshold selection and poor performance in low SNR environments. R. Tandra and A. Sahai have shown that there is a minimum SNR below which the energy detector cannot perform spectrum sensing reliably regardless of the number of samples taken [71]. We have also shown in Figure 3.5 that the performance of the energy detector deteriorates with decreasing SNR. In our simulation of the energy detector, 1000 samples and 10000 Monte Carlo simulations were done to calculate the P_{fa} and P_d under different SNR regimes.

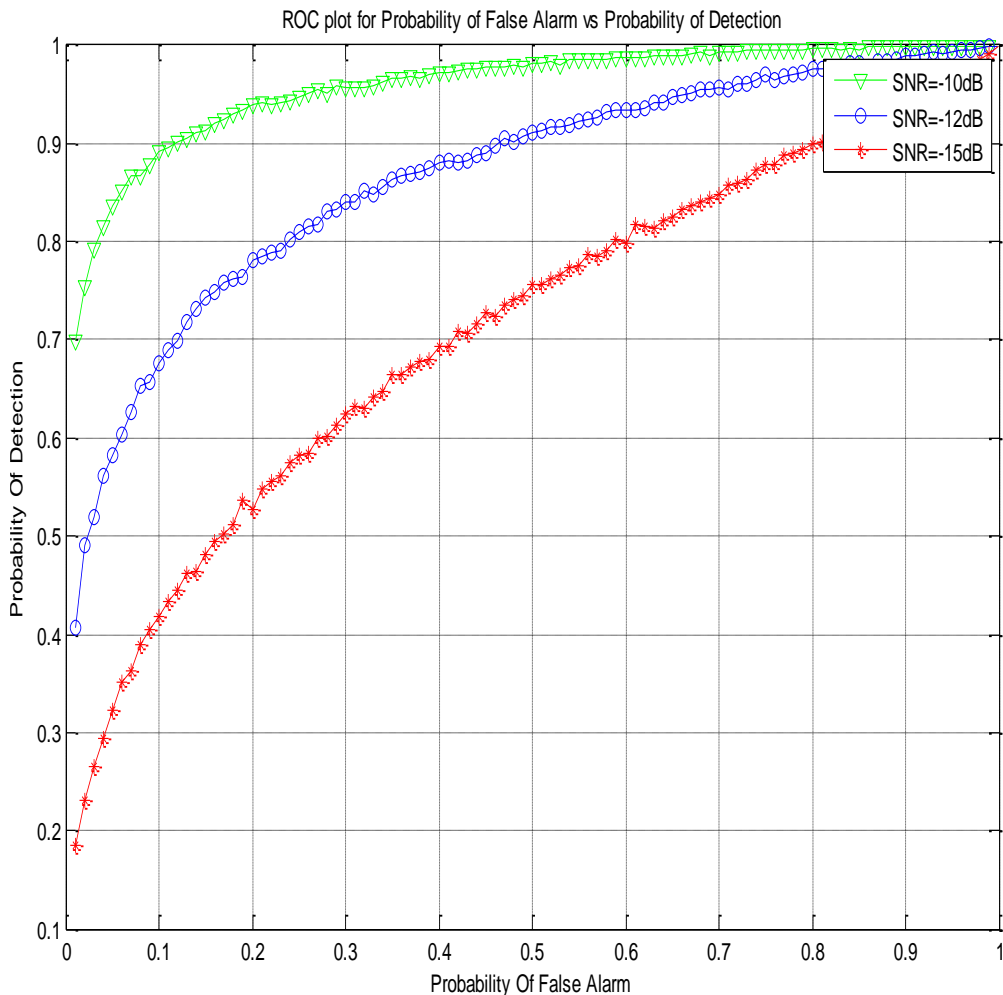


Figure 3.5: Receiver Operating Characteristics Curve at different SNR values

Another major point of concern in the implementation of the energy detector is the SNR estimation and threshold setting. The performance of the energy detection technique solely depends on the ability to select a proper decision threshold. The threshold value could either be fixed or adaptive. In the former, the threshold value does not vary with the noise variance however in the latter, the threshold value varies adaptively. The fixed threshold techniques are prone to a higher probability of false alarm because they do not consider the fluctuating nature of noise signals. On the contrary, the adaptive threshold techniques are validated by the fact that they can be more robust towards noise fluctuations.

3.6 Chapter Summary

In this chapter we have discussed the various spectrum sensing techniques that can be employed in cognitive radio. Transmitter detection, interference based detection and cooperative detection are three major classifications of the detection techniques. We have also discussed the three major implementations of the transmitter detection techniques namely; energy detection, matched filter detection and cyclostationary feature detection. Furthermore, an appraisal of the mentioned spectrum sensing techniques revealed that energy detection is the most preferred technique for spectrum sensing in cognitive radio sensor networks.

This chapter sets the pace for our proposal in Chapter 4 by presenting the system model for the energy detector. This leads to the concept of optimum thresholding which forms the core of this research. In the next chapter, we build up to our proposal by discussing some threshold selection and noise estimation techniques before presenting our threshold selection technique and our energy detection technique for CRSNs.

Chapter 4

4 Threshold Selection for Energy Detection in CRSN

4.1 Introduction

The energy detection technique as used in spectrum sensing uses a radiometer to detect the presence or absence of a primary user in the frequency band under consideration. This technique works by measuring the electromagnetic energy present in a particular frequency band and comparing it against a certain threshold. The frequency band under question is declared to be occupied when the received signal strength is found to be above the threshold and vacancy is declared when the received signal strength falls below the same decision threshold. Therefore, there is no doubt that the accuracy of the energy detection technique solely depends on the ability to select a proper decision threshold.

There are quite a number of techniques that can be used for noise estimation and threshold selection. For instance, Dinesh Datla *et al.* cites empirical analysis, computational methods, histogram analysis, cumulative density function analysis and statistical methods as threshold estimation techniques [72]. However, these threshold estimation techniques can broadly be classified as either fixed threshold techniques (FTT) or adaptive and autonomous threshold techniques (AATT).

4.1.1 Fixed Threshold Techniques

The conventional energy detector uses a static threshold value that is set just above the noise floor to judge spectrum occupancy. In this case the threshold value is fixed and it does not change based on the perceived SNR. This is referred to as fixed thresholding. The downfall of this approach is that the system requires a priori knowledge of the noise power and spectrum activity. Some examples of fixed threshold techniques are; empirical analysis of spectrum measurements [73], receiver noise characteristics thresholding [74], P-tile based thresholding technique [75] and histogram analysis (Laplacian Threshold) technique [76].

The fixed threshold techniques in their elementary form require that the spectrum measurement data be inspected by an operator who then proceeds to set the decision threshold as per the observations made. In the case of p-tile thresholding, an empirical analysis of the spectrum measurements is performed followed by a Cumulative Distribution Function (CDF) analysis to obtain the optimum threshold [72]. The Histogram technique assumes that the spectrum measurements are bimodal. Therefore, a bimodal histogram constructed from the received spectrum measurements will have two peaks belonging to the signal and noise samples respectively. The value of the local minimum or the centre point that resides between the two peaks is chosen as the decision threshold [72], [76]. However, in the case of a sparsely occupied frequency band, the constructed histogram cannot be bimodal. In this case a Laplacian operator is applied to the spectrum measurements and that aids in determining the slope of the generated histogram. The Laplacian threshold technique can then be used to pick out the Laplacian values of large magnitude which are then used in the setting of the threshold [72].

Although the fixed threshold techniques are relatively easy to implement, they are susceptible to erroneous decision making due to the fluctuating nature of noise signals. This leads to higher rates of false alarm and miss detection. A false alarm refers to a situation where the noise signal is falsely identified as the primary signal. Moreover, a false alarm can be more accurately be defined a false positive result. Consequently, this results in the underutilization of the spectrum resource due to the missed transmission opportunities. On the other hand, miss detection refers to a situation where the primary signal is wrongly identified as a noise signal. This is a highly undesirable situation as it results in interference of the primary user's transmission. A miss detection is also referred to as a false negative result.

Another drawback of the fixed threshold techniques (FTT) comes about when the decision threshold is fixed at a static level above the noise floor. Weak primary signals would go undetected if they fall below the threshold and the secondary transmission may cause harmful interference to the primary user. Moreover, some FTT techniques require empirical analysis of the spectrum measurement data thus making it quite difficult to automate the threshold selection process. This is highly impractical especially in the case of cognitive radio sensor networks (CRSNs) as the nodes are required to be completely autonomous without any human intervention. Furthermore, a priori knowledge on the noise variance and spectrum may not always be available. For this reason, Adaptive and Autonomous Threshold Techniques are more desirable for CRSN applications.

4.2 Adaptive and Autonomous Threshold Techniques

Adaptive and autonomous threshold setting techniques can estimate the value of the decision threshold from a given set of spectrum measurements without any need for priori knowledge of the noise level or spectrum occupancy. Furthermore, the value of the decision threshold varies adaptively based exclusively on the interaction with the time varying radio environment. No human intervention is required in order to shift the threshold value dynamically. The adaptive threshold techniques have the advantage of being able to dynamically adjust the threshold value thus enhancing the reliability of the energy detector. These techniques help reduce the performance of the energy detector by reducing the probability of false alarm and miss detection. Furthermore, these techniques are more robust towards noise uncertainty as compared to fixed threshold techniques.

Adaptability can be achieved through analysing the statistical properties of the received spectrum measurements in that the standard deviation gives the dispersion level of spectral measurement data around a mean value. Therefore, if the data varies widely the dispersion of the received signal will change more rapidly and the opposite is also true. Consequently, computing the mean and standard deviation at each point of the time varying signal and changing the threshold accordingly will provide some robustness against fluctuations in the signal [77]. Some examples of the adaptive and autonomous threshold techniques include;

- Maximum Normal Fit (MNF) [78]
- Principal Component Analysis (PCA) [79]
- Otsu's algorithm [80]
- Recursive One-Sided Hypothesis Testing (ROHT) [72], [81]

4.2.1 Maximum Normal Fit (MNF)

The MNF technique is a statistical method of separating the noise components of the received signal from the signal components based on distribution estimates. The technique assumes that the noise components are represented by the lowest set of components in the distribution. The MNF algorithm initiates by computing probability density function of the received signal, $Y(x)$, is represented as shown in equation (4.1).

$$f_Y(x, \alpha, \mu, \sigma) = f_{Y_w}(x, \alpha_w, \mu_w, \sigma_w) + f_{Y_s}(x, \alpha_s, \mu_s, \sigma_s) \quad (4.1)$$

The probability density functions of the signal and noise components are represented by f_{Y_s} and f_{Y_w} respectively. In the same breath, the variables α, μ, σ represent the amplitude, mean and standard deviation of the received data set, inclusive of both the noise and signal components. It also assumes that the distribution of samples follows a Gaussian distribution. Moving forward, the MNF algorithm attempts to isolate the peak values of the combined distribution. The assumption is that the data set will have two peaks with the first representing the noise component (P_w) and the second representing the signal component (P_s). Further, the algorithm isolates the noise component of equation (4.1) by considering the lowest sample in the set to the sample that has P_w . Thereafter, a randomly estimated noise set (based on randomly guessed number within minimum bounds) is compared against the isolated noise set as shown in equation (4.2).

$$\Delta f(x, \alpha, \mu, \sigma) = f_{Y_w}(x, \alpha_w, \mu_w, \sigma_w) - f_w(x, \hat{\alpha}_w, \hat{\mu}_w, \hat{\sigma}_w) \quad (4.2)$$

The variables $\hat{\alpha}_w, \hat{\mu}_w, \hat{\sigma}_w$ represent the initial amplitude, mean and standard deviation of the estimated noise distribution.

Moreover, the distribution of the estimated noise set f_w can be described as follows;

$$f_{Y_w}(x, \widehat{\alpha}_w, \widehat{\mu}_w, \widehat{\sigma}_w) = \frac{\widehat{\alpha}_w}{\sqrt{(2\pi\widehat{\alpha}_w^2)}} e^{-\frac{1}{2}\left(\frac{x-\widehat{\mu}_w}{\widehat{\sigma}_w}\right)^2} \quad (4.3)$$

The MNF algorithm terminates once the difference in equation (4.2) is less than a specified arbitrary value that is explained in elaborate detail in [78]. Upon termination, the signal component can be isolated as follows;

$$f_{Y_s}(x, \alpha_s, \mu_s, \sigma_s) = f_Y(x, \alpha, \mu, \sigma) - f_w(x, \widehat{\alpha}_w, \widehat{\mu}_w, \widehat{\sigma}_w) \quad (4.4)$$

The MNF technique uses a best-fit approach to calculate the decision threshold. The threshold value is identified as the point where the estimated noise and signal PDFs (f_w and f_Y) intersect [78].

4.2.2 Principal Component Analysis (PCA)

The PCA technique is a mathematical technique that can be used to reduce the dimensionality of data [79]. This technique first represents the received spectral measurements in terms of an orthogonal set of principle components. It then proceeds to use Eigen-decomposition to compute the eigenvalues of the Covariance matrix. At this point, the principle components are uncorrelated and orthogonal and can be processed independently. The signal components will then be along the dimension with the largest covariance values, while the noise components will be along the dimension with the smallest covariance values. The decision threshold can then be estimated to be between the two points. The main advantage of the PCA technique is that it can be used to decompose/whiten signals that are non-Gaussian [82]. Figure 4.1 shows a block diagram of the PCA technique.

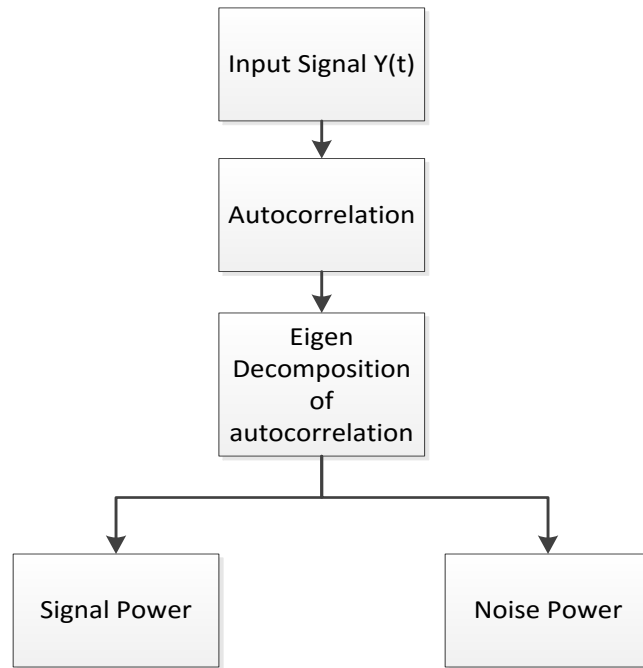


Figure 4.1: The PCA technique

4.2.3 Otsu's Algorithm

Otsu's algorithm was originally used in the field of picture processing for image thresholding [83]. The technique can however be used in signal processing to obtain the optimum threshold value to distinguish between signal and noise components [80]. This technique assumes that an image contains two classes of pixels namely the foreground and the background pixels. These can be compared to the two classes of the spectral measurement components; the noise components and the signal components. A bimodal histogram with two peaks can be generated out of the data. These two peaks represent the object and the background respectively. The optimum threshold can be calculated by separating the two classes of components and minimizing the intra-class variance. The threshold is then determined as the lowest point between the two peaks [83].

4.2.4 Recursive One-sided Hypothesis Testing (ROHT)

The Recursive one-sided hypothesis testing (ROHT) was first proposed by Weidling *et al.* [81] and it is a statistical threshold selection technique based on the mathematical technique for analysing random noise referred to as one-sided hypothesis testing [84]. The one-sided hypothesis testing usually seeks to disprove a null hypothesis by testing the data set against a defined test statistic at a certain level of statistical significance. The ROHT algorithm has been optimized to work for varying levels of the statistical significance. The ROHT algorithm as applied in the context of energy detection tries to identify the signal components from the noise components of the received signal and subsequently set the decision threshold. The algorithm first begins by assuming that there are more noise components in the received energy as compared to the signal components and that the noise distribution follows a normal Gaussian distribution as shown in Figure 4.2. It also assumes that there are a sufficient number of samples in the received spectrum measurements such that the sample mean and standard deviation can be considered to be the actual mean and standard deviation throughout the entire channel under consideration [80].

The ROHT algorithm runs over a number of iterations and each time the signal components at the right hand tail of the Gaussian curve are identified, clipped off and discarded. These components are identified by comparing the unknown components against a test statistic and a certain p-value. The test statistic in this application of the ROHT algorithm is usually a function of the decision threshold and the p-value is the number of standard deviations away from the mean and it could also represent the confidence level. Elements of the unclassified measurements that are equal to or greater than the decision threshold are identified as the signal components and those below the threshold are classified as noise components. To represent this mathematically, let us consider the following notations;

- M - represents the data set from initial spectrum measurements (received energy measurements)
- S - represents the set of signal components that reside within M
- S_i – this is a subset of S representing the i^{th} iteration of the algorithm
- N – represents the set of noise components that reside within M
- N_i – this is a subset of N representing the i^{th} iteration of the algorithm
- μ_i, σ_i – represent the mean and standard deviation of elements of N_i respectively

- λ_i – represents the decision threshold that is used to identify the signal component of the i^{th} iteration

The following pseudo code elaborately explains the flow of the algorithm for the initialization to termination.

- I. **Initialize** $S = \emptyset, S_0 = \emptyset, N_0 = M, i = 0$
- II. **Do**
 - 1) $\lambda_{i+1} = \text{p-value} * \sigma_i + \mu_i$
 - 2) $S_{i+1} = \{n_i | n_i \in N_i \text{ and } n_i \geq \theta_i\}$
 - 3) $N_{i+1} = N_i - S_{i+1}$
 - 4) $S = S \cup S_{i+1}$
 - 5) $i = i + 1$
- III. **Until**

$$(\sigma_{i+1} - \sigma_i) \leq \beta$$

The algorithm, first begins by initializing the set of signal components within the received measurements and should not be a null set. At the start of the algorithm, it is assumed that the received measurements contain more noise components than signal components and thus the purpose of the recursive one side hypothesis testing is to disprove this null hypothesis. The algorithm then proceeds to set the initial decision threshold which is given as a function of the p-value and the standard deviation and the mean of the components in the i^{th} iteration. Based on the p-value and the decision initial threshold, the algorithm then views a given percentage of measurements on the right hand side of the normal Gaussian distribution as signal components and considers everything to the left hand side as noise components.

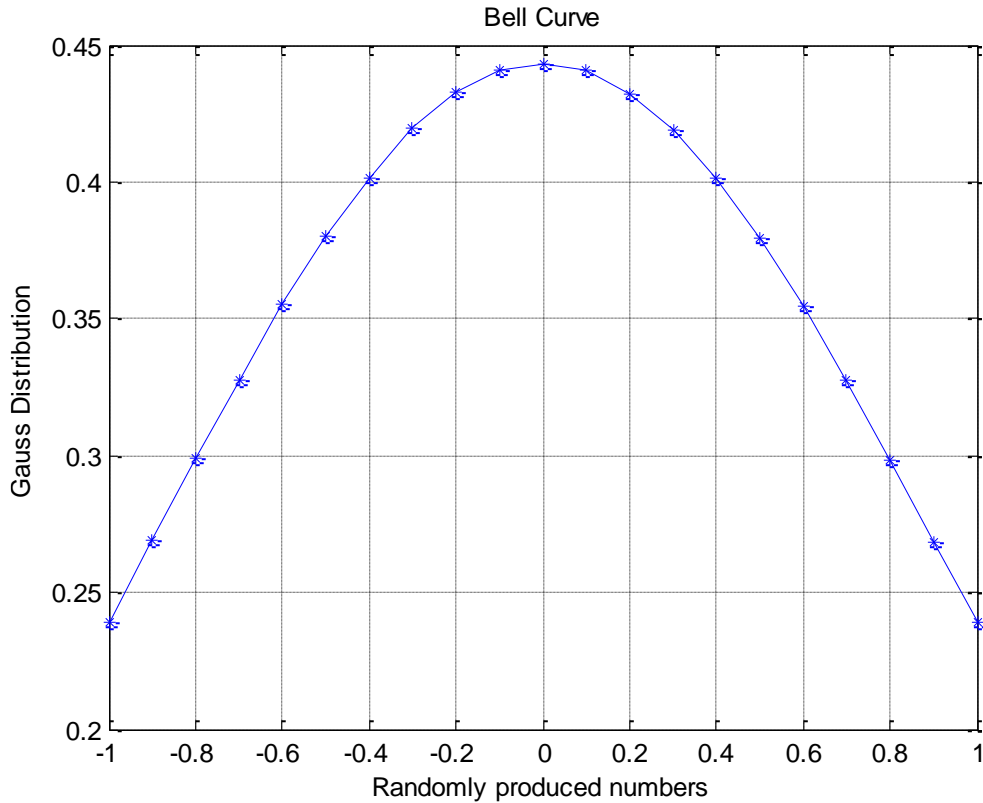


Figure 4.2: A bell shaped Gaussian distribution assumed by the ROHT

However, since the main aim of running this algorithm is to find the final and most accurate decision threshold, the identified signal portions are discarded and the process repeats. With every iteration of the algorithm the Gaussian curve gets tighter and tighter as the standard deviation is reduced. The algorithm comes to a halt once the difference in standard deviation between two consecutive iterations is less than a specified random positive value given as β . At this point the, the Gaussian curve represents estimates of the noise power in the frequency band under consideration. The generated threshold, mean and standard deviation are considered to be the optimal and accurate for the entire frequency band under consideration. The ease of computation of this algorithm coupled with its low level of complexity make it the most desirable candidate for threshold setting in energy detection in the context of resource constrained cognitive radio sensor nodes. In [72] and [81] the ROHT algorithm has been shown to operate optimally at a 95% confidence level in the digital television broadcast bands with 100% probability of detection. Figure 4.5 show the flow chart of the ROHT algorithm from initialization to termination.

4.3 A Conventional Adaptive Threshold Technique for Cognitive Radio

Although many adaptive threshold techniques have been proposed in literature, only a handful are able to meet the stringent requirements of the resource constrained cognitive radio sensor nodes. Consequently, (in our knowledge), there are no implementations of the adaptive threshold energy detector specifically for cognitive radio sensor networks. The work of Prashob Nair and Anoop Kumar, [85] has contributed to the world of cognitive radio by proposing a technique to achieve dynamicity in the threshold value for the energy detector. Their proposed technique reduces the complexity of achieving an adaptive threshold and this makes it attractive for use by the resource constrained cognitive radio sensor nodes. Moreover, their proposed technique is able to perform accurate detection in low SNR conditions that typically plague cognitive radio sensor nodes. Figure 4.3 below shows a block diagram of the implementation of the conventional adaptive threshold energy detector.

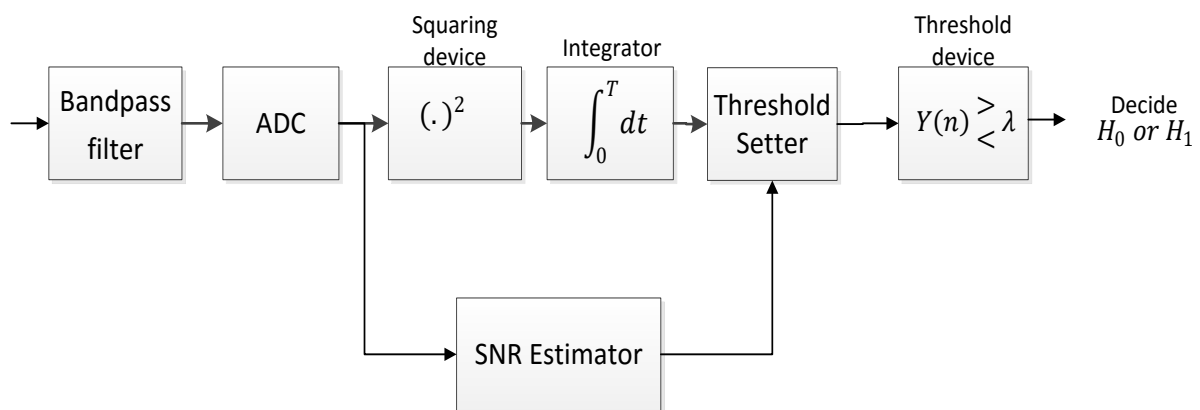


Figure 4.3: A block diagram of the conventional adaptive threshold energy detector

The conventional adaptive threshold technique proposed by Nair and Kumar [85] first begins by setting the target performance metrics; the probability of false alarm and detection. The thresholds associated with the probabilities of detection (λ_d) and false alarm (λ_{fa}), are calculated. Secondly, the number of samples, N , is set based on the sampling rate of the analog-to-digital converter (ADC). The critical SNR is also calculated at this point. Thereafter, the SNR of the channel under consideration is estimated. Fourthly, the threshold is varied between

λ_d and λ_{fa} based on the critical SNR and the perceived SNR. Finally, the test static is compared against the threshold value and a spectrum occupancy decision is made. Figure 4.4 shows the flow chart of the conventional adaptive threshold technique for energy detection.

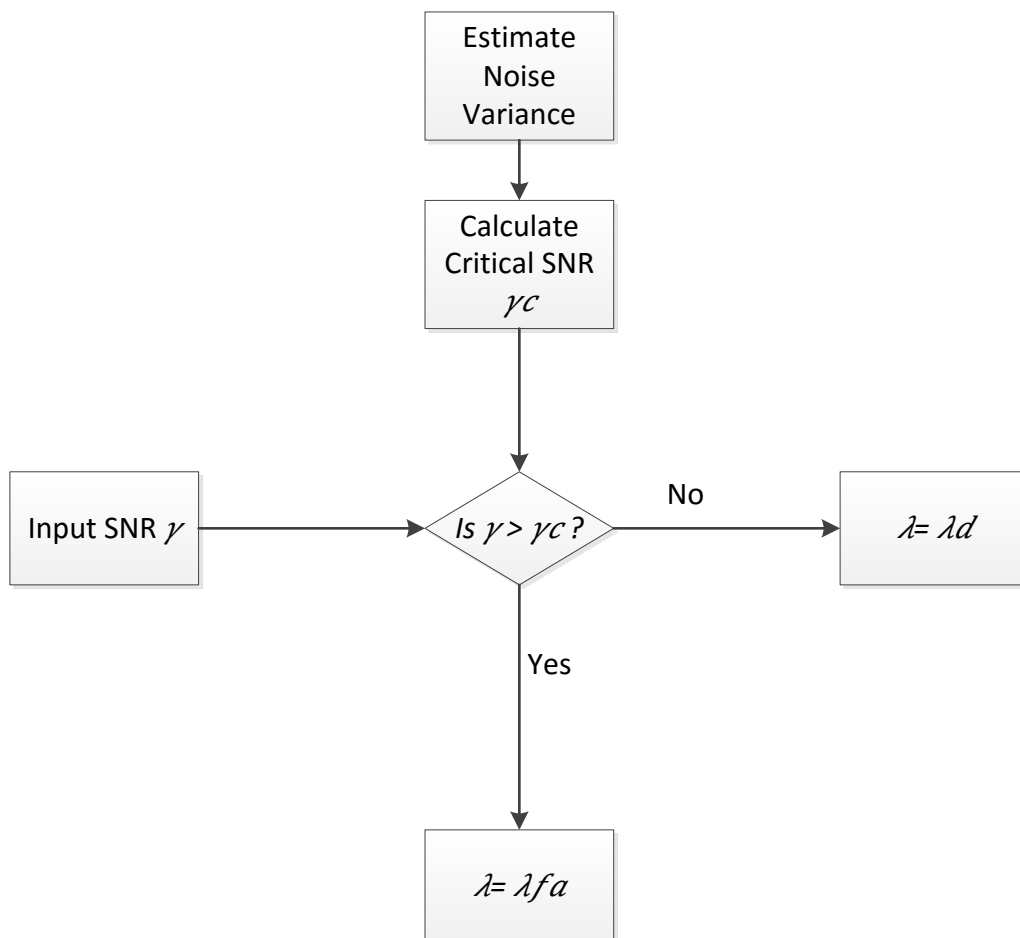


Figure 4.4: An adaptive threshold technique based on the SNR [70].

In the event that the perceived SNR is greater than the critical SNR, the threshold is set based on the target probability of false alarm. This can also be referred to as the constant false alarm rate (CFAR) principle. On the contrary, the threshold of probability of detection, (λ_d), will be used. However, as shown in Figure 4.3, the threshold value varies fuzzily from λ_d to λ_{fa} based on the signal to noise ratio in the radio environment.

Despite the computational simplicity and implementation ease of the aforementioned technique, Nair and Kumar [85] make the assumption that the noise variance and SNR ratio of the channels under consideration are known. This is not always the case in the real world as noise uncertainty is one of the major problems faced by the typical energy detectors. In the following section, we propose an adaptive threshold technique based on [85], with noise variance estimation that can be implemented in cognitive radio sensor networks.

4.4 An Adaptive Threshold Technique with Noise Variance Estimation

The uncertainty or lack of knowledge of the noise power levels at the cognitive radio sensor node can limit or even paralyse the sensing capability of the energy detector. This is because in real systems, the energy detector does not have any prior knowledge on the noise power or the primary user's signal. Moreover, majority of the implementations and performance investigations of the energy detector presented in literature assume a perfect knowledge of the noise variance which is not the case in the real world [48], [86], [87]. Furthermore, the energy detection system model presented in section 3.4 requires an estimate of the noise and signal variance in order to calculate the SNR and to set the decision threshold. As a result, noise variance estimation is very essential for the real world operation of the energy detector.

Our proposal seeks to build on the work of Nair and Kumar [85] by proposing a noise estimation technique that adaptively gives the noise variance level based on the statistical properties of the received signal. We propose the use of the recursive one-sided hypothesis test (ROHT) algorithm in the estimation of the noise variance and the SNR of the channel under consideration. The main advantage of this technique is its computational simplicity in computing the SNR and thus, the decision threshold value. This feature makes it very ideal for noise estimation in cognitive radio sensor nodes as compared to the other aforementioned adaptive threshold techniques. Furthermore, the ROHT algorithm computes the threshold value adaptively based on the estimated noise variance. For this reason, the ROHT is also classified as an adaptive threshold technique and not merely a noise estimation technique. Figure 4.5 below shows the flow chart of the ROHT algorithm from initialization to termination.

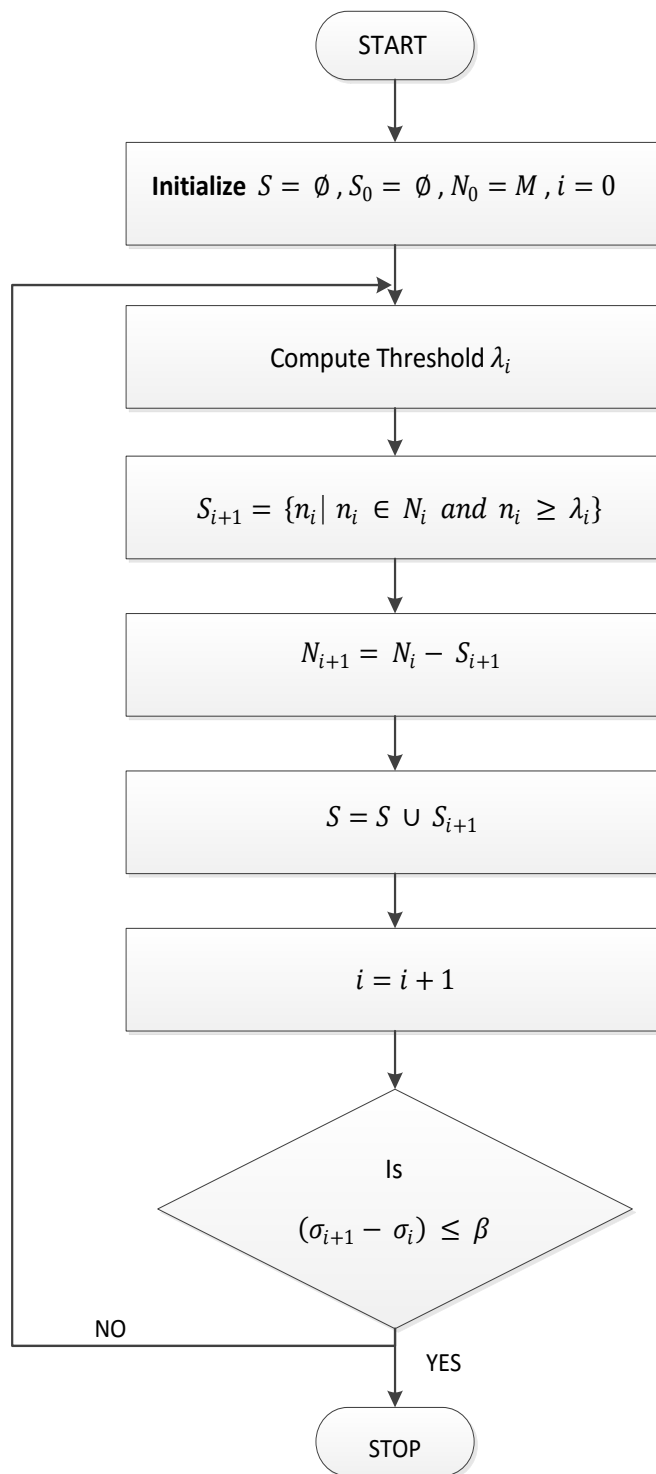


Figure 4.5: The Recursive One-sided Hypothesis Testing (ROHT) algorithm

The ROHT algorithm terminates once the difference in standard deviation between two successive iterations is less than or equal to an integer value described as β and specified as 0.05 in our case. Upon completion, the ROHT algorithm gives us the estimated noise variance and the threshold value of the channel under consideration. Using this technique, our research seeks to set the foundation for the real world implementation of the adaptive threshold energy detector proposed in [85] by filling in the gaps left in their work. We seek not to nullify the work of Nair and Kumar but to advance it and apply it to the field of cognitive radio sensor networks. The flow chart shown in Figure 4.6 below shows our proposed model of the adaptive threshold energy detector with noise estimation.

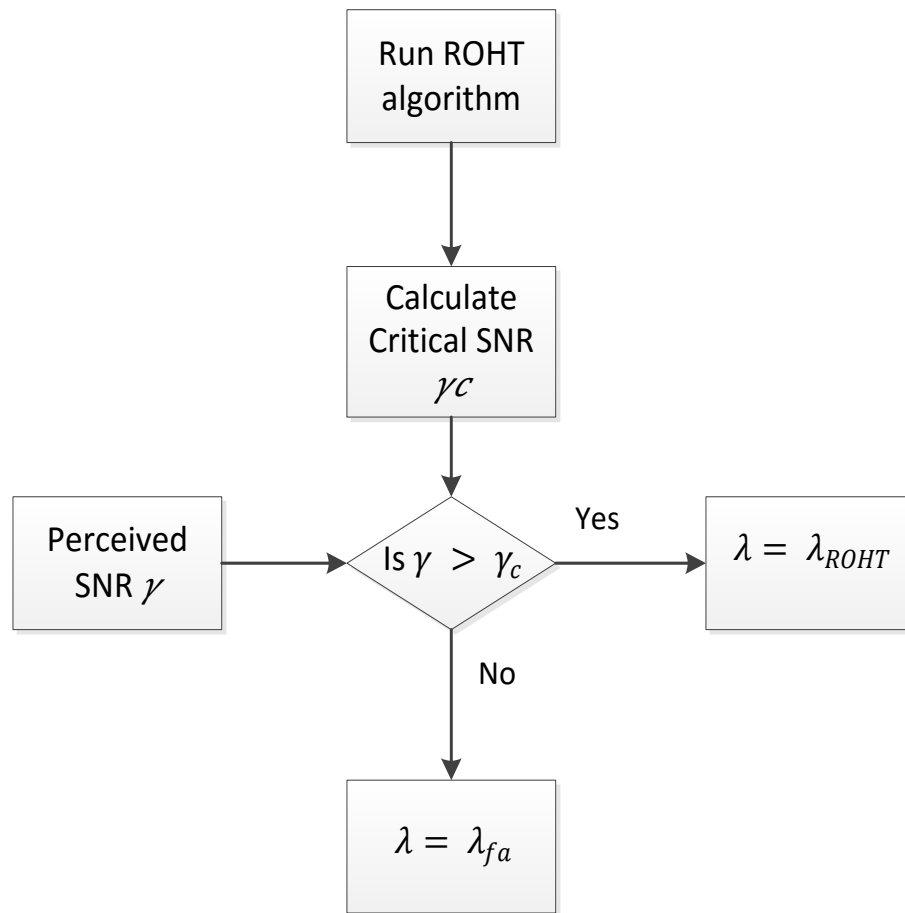


Figure 4.6: Proposed Adaptive threshold technique using ROHT

Our proposed technique initializes by running the ROHT algorithm to calculate the decision threshold and the signal to noise ratio that is herein referred to as the perceived SNR. We make the assumption that the decision threshold computed by the ROHT algorithm is the threshold for optimum detection. The critical signal to noise ratio is then calculated based on the number of samples achieved by the ADC and the target probabilities of detection and false alarm. Therefore, if the SNR is greater than or equals to the critical SNR then the threshold value from the ROHT algorithm will be used as the decision threshold. However, if the perceived SNR is less than the critical SNR, the probability of accurately detecting the primary signal is compromised. This introduces a high probability of interfering with the primary signal. As a defence mechanism, our system employs the constant false alarm rate (CFAR) principle so as to maintain a low and predictable probability of false alarm. For this reason, if the critical SNR is not met, the decision threshold is set to the CFAR threshold (λ_{fa}) based on a predefined target probability of false alarm. The CFAR threshold is computed from equation 4.5 where we use 1000 samples and assume a noise variance of unity. In this way, an adaptive threshold is achieved based on the SNR of the immediate radio environment.

$$Q^{-1}(P_{fa}) = \left(\left(\frac{\lambda}{\sigma_n^2} - 1 \right) \sqrt{N} \right) \quad (4.5)$$

4.5 Chapter Summary

In this chapter we have presented our adaptive threshold technique against the back drop of the conventional adaptive threshold energy detector presented in [77]. We have also highlighted the benefits of noise estimation in the real world applications of the energy detector thereby by validating our proposal. We introduce the ROHT algorithm as a noise estimation and threshold selection technique and thereby filling the gaps we identified in [85]. Our adaptive threshold technique also employs the CFAR principles as a defence mechanism in the case where inadequate samples are obtained from the ADC. Therefore, the threshold value varies adaptively between the ROHT threshold and the threshold associated with the target probability of detection based on the perceived SNR.

In the next chapter, we present the methodology to which this research has adhered to followed by the performance analysis of our proposed technique as well as the conventional energy detector. It is worth noting that it is not possible to compare our technique against the conventional adaptive threshold technique because the experiment parameters are not explicitly stated. However, we do show the receiver operating characteristics curves for both the conventional energy detector as well as our proposed technique. We also show how the probability detection varies as the SNR changes.

Chapter 5

5 Results and Analysis

5.1 Introduction

The knowledge of the noise variance is vital for the real world operation of cognitive radio wireless networks. Such knowledge is critical in setting the decision threshold to determine spectrum occupancy. For this reason, we are able to validate our proposal of an adaptive threshold energy detector with noise estimation. In order to analyse the performance of our proposed technique, as well as the conventional energy detector, we use key performance indicators such as the probability of detection, probability of false alarm and the probability of miss detection. These are the widely accepted metrics used in the performance analysis of spectrum sensing techniques. In this chapter we present the results of the spectrum sensing experiments obtained by employing the conventional energy detector as well as our proposed technique. We also present our analysis on the results obtained.

5.2 Research Methodology

Both the conventional energy detector and our adaptive threshold energy detector with noise estimation were built and simulated using the MATLAB (R2009b) software. MATLAB, which is short for MATrix LABoratory, was developed by Mathworks as a high-level programming language used for technical computing and numerical analysis. In Appendix A and B, we present the MATLAB codes that were used in the simulation of the conventional energy detector as well as our proposed technique. We use metrics such as the probability of detection and the probability of misdetection to quantify the performance of both techniques. In the following sections we present the experimental results alongside the experimental parameters employed.

5.3 Experimental Results and Analysis

Our experimental results are presented in a two tier layout that commences with the conventional energy detector followed by our adaptive threshold energy detector. We seek to highlight how double dynamicity of the threshold value can be achieved by employing our proposed technique.

5.3.1 Results of the Conventional Energy Detector

There have been several implementation and performance analysis of the energy detector in literature as shown in [48], [86], [87] to mention a few. Nevertheless, we proceed to simulate and analyse the conventional energy detection technique for further clarity. In this simulation, we consider a SNR range from -20 dB to 0 dB and a probability of false alarm of 0.1 and 0.01. Furthermore, 1000 samples of the received signal and 10000 Monte Carlo simulations are considered. The received signal is a function of the primary signal and Additive white Gaussian Noise (AWGN). We consider two scenarios in our implementation, the theoretical scenario and the simulated scenario. The theoretical scenarios show the ROC curves based on theoretical calculations as shown in [69], [70], [77]. The simulated scenarios show the ROC curves based on the actual sensing simulation. In Figure 5.1 we present the ROC curve for the probability of detection against the SNR when the probability of false alarm is set at 0.1.

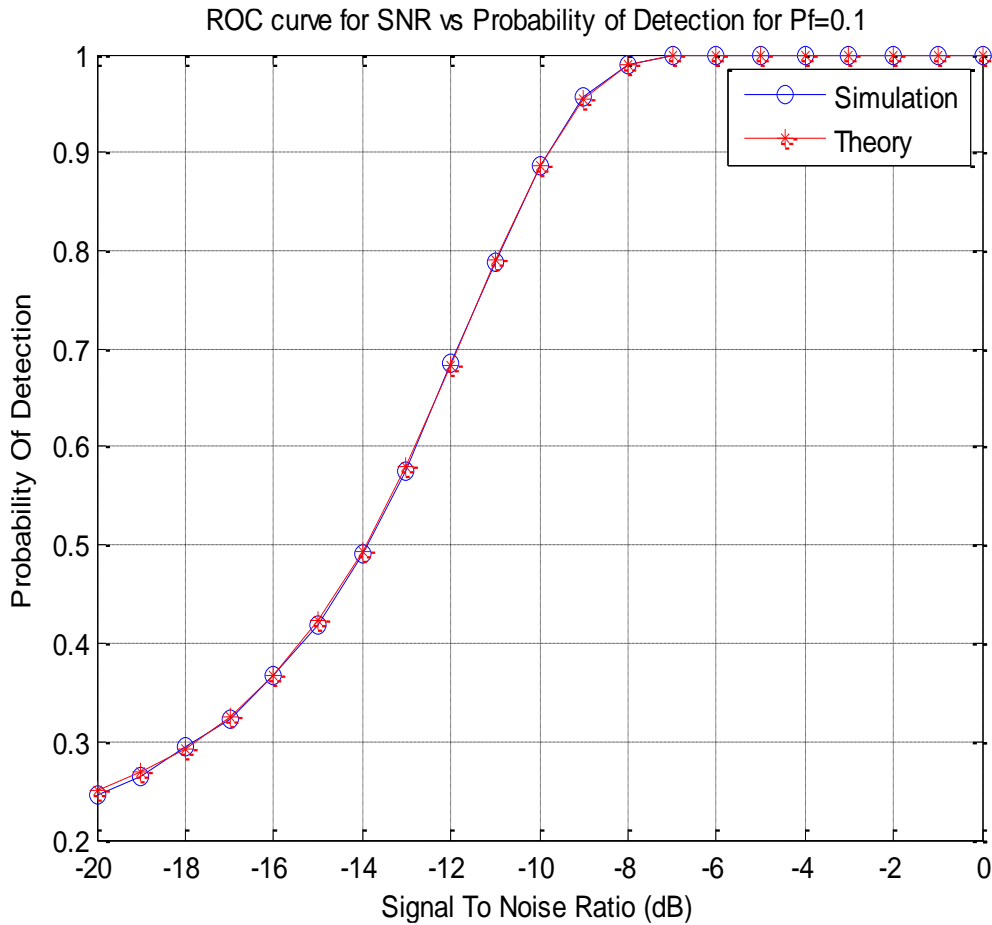


Figure 5.1: Signal to Noise Ratio vs Probability of Detection ($P_{fa} = 0.1$)

Figure 5.1 shows the variance of the probability of detection with the signal to noise ratio. There is a strong correlation between the theoretical and the simulation results as they are seen to be following the same trend. The results indicate that the performance of the energy detector deteriorates as the SNR value decreases. It can be observed that at SNR values greater than -8 dB, the energy detector has no problem distinguishing between the primary signal and the noise signals. At SNR values lower than -20 dB there is significant deterioration in the performance of the energy detector with a probability of detection value of 0.35. Tandra and Sahai have shown there is an SNR value, referred to as the SNR wall, below which the energy detector cannot be able to detect the primary signal [71]. Figure 5.2 shows the same plot at a probability of false alarm of 0.01. In this case, the probability of detection is lowest at 0.09 at -20 dB and -6 dB, the probability of detection levels at 1.

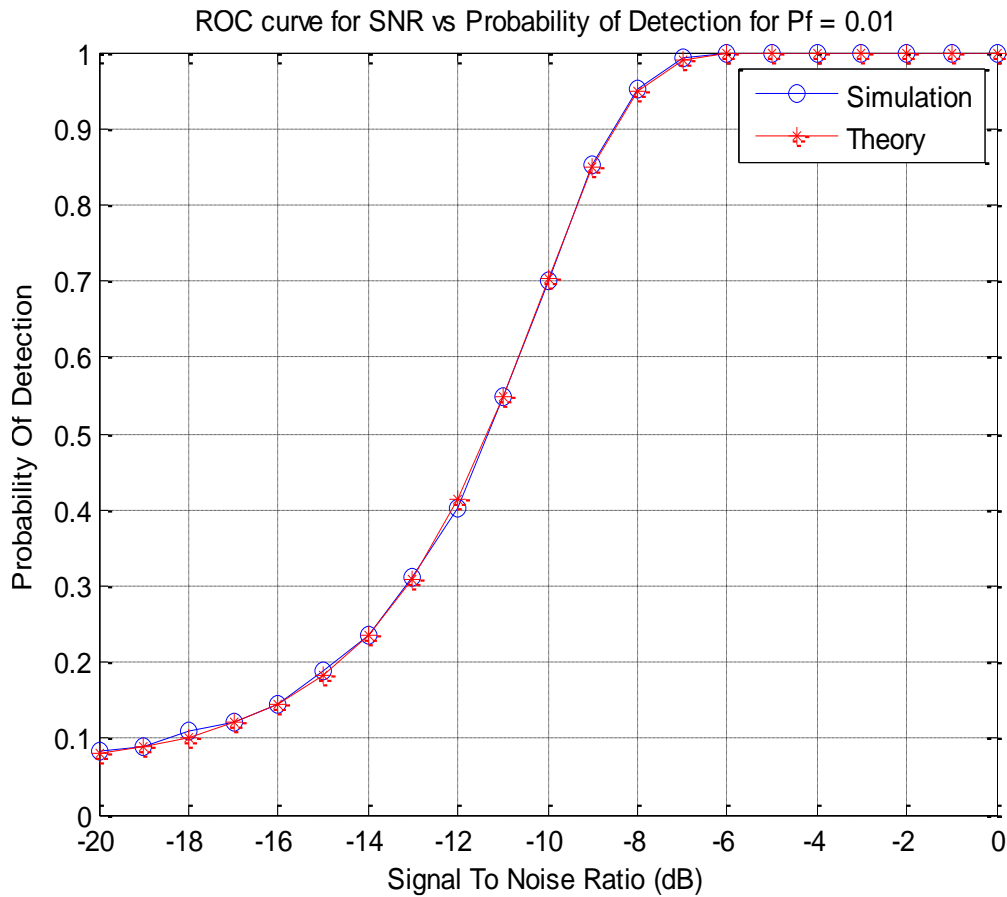


Figure 5.2: Signal to Noise Ratio vs Probability of Detection ($P_{fa} = 0.01$)

Figure 5.3 shows the simulation results of the same plot of the probability of detection against the signal to noise ratio. The graph below visibly shows the trade-off in choosing different values for the probability of false alarm. With a higher probability of false alarm, the probability of detection is higher and with a lower probability of false alarm, the probability of detection is lower. This is the trade-off between the probability of detection and the probability of false alarm.

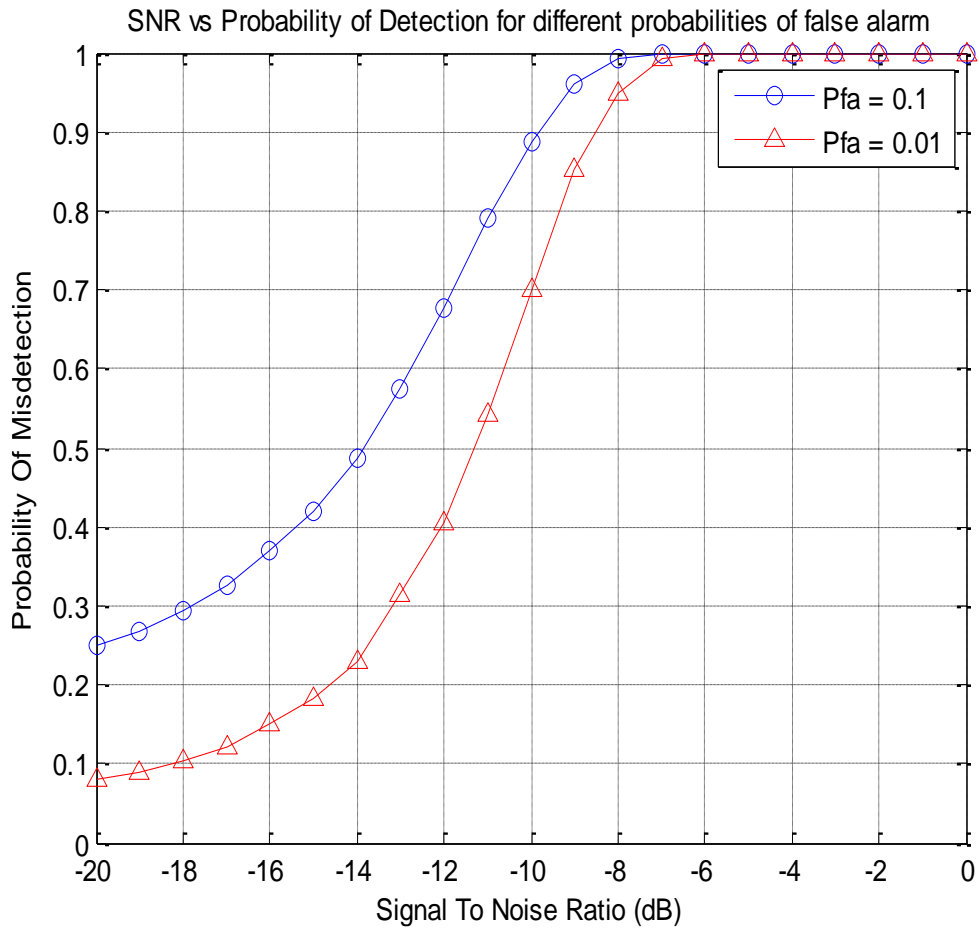


Figure 5.3: Signal to Noise Ratio vs Probability of Detection at different Probabilities of false alarm.

The trade-off between the probability of detection and the probability of false alarm can also be seen by examining the ROC curve shown in Figure 5.4. For the sake of simplicity we have used a single SNR value of -10 dB. An increase in the false alarm will have a corresponding increase in the probability of detection. The probability of detection will decrease with any decrease in the probability of false alarm.

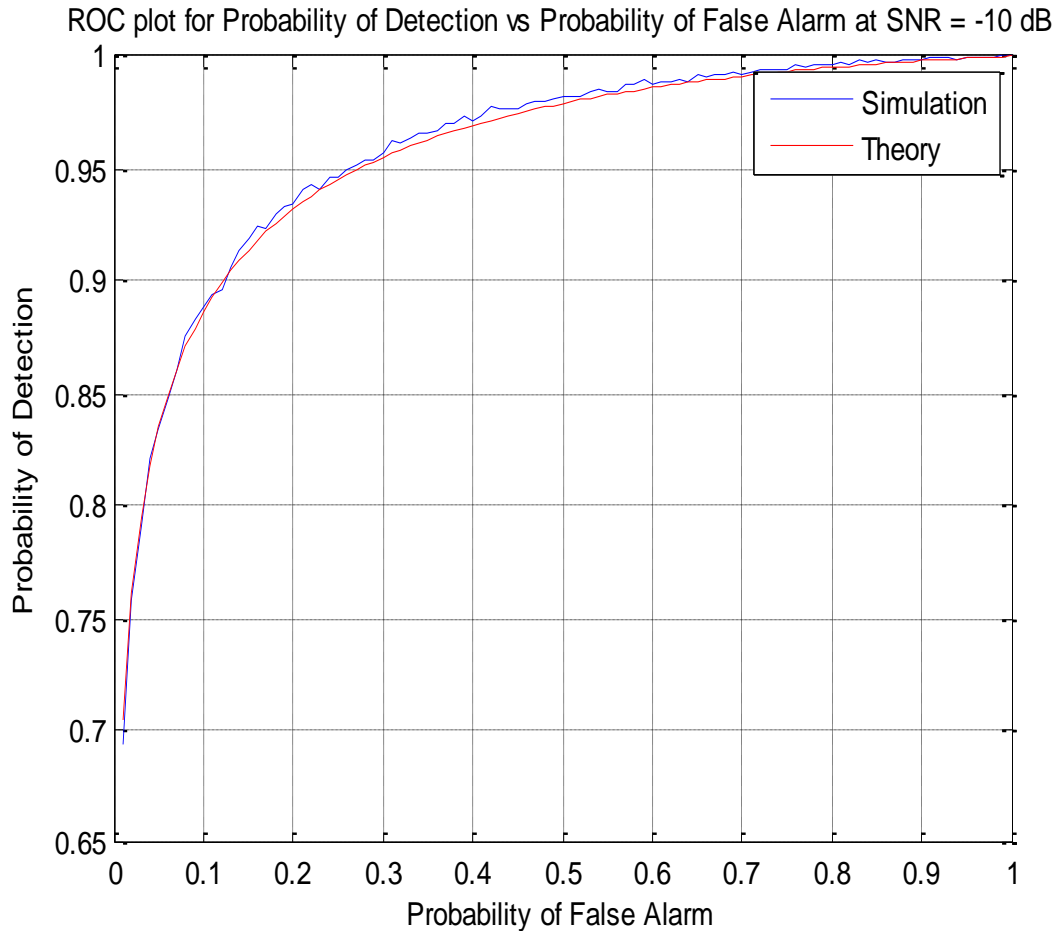


Figure 5.4: Probability detection of vs of detection false alarm

The performance of the energy detector can also be analysed in terms of the probability of misdetection as shown in Figure 5.5. The graph shows the ROC curve for the probability of misdetection against the SNR ranging from 0 dB to -20 dB and with the probability of false alarm set at 0.1. As the SNR value decreases, the possibility of falsely identifying a noise signal as the primary signal also decreases. Both the simulation and theoretical results show the same trend. The probability of misdetection is highest at -20 dB and it falls to zero at -8 dB. This is because at -8 dB, the signal to noise ratio is sufficiently large to avoid misdetection. Figure 5.6 shows the same plot but with the probability of false alarm set at 0.01. We observe that the probability of misdetection is at high of 0.91 at -20 dB. In this case, the probability of misdetection falls to zero at -6 dB.

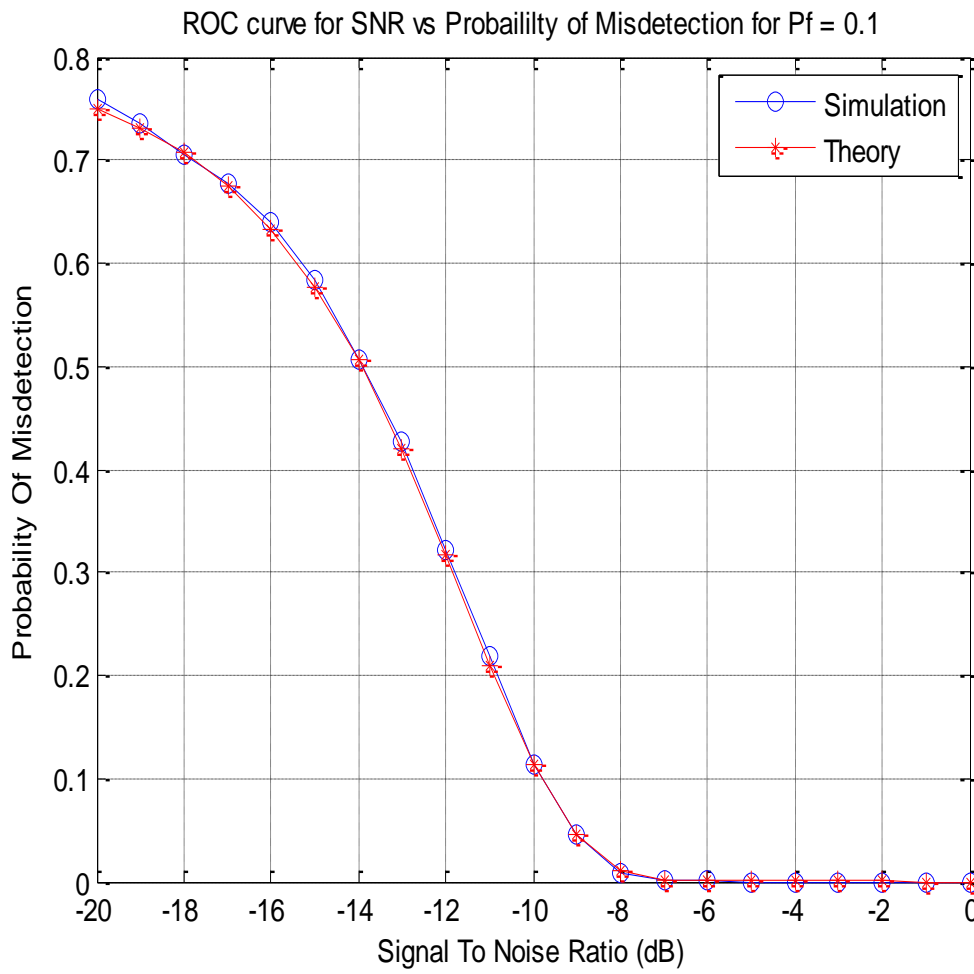


Figure 5.5: Signal to Noise Ratio vs Probability of Misdetection ($P_{fa} = 0.1$)

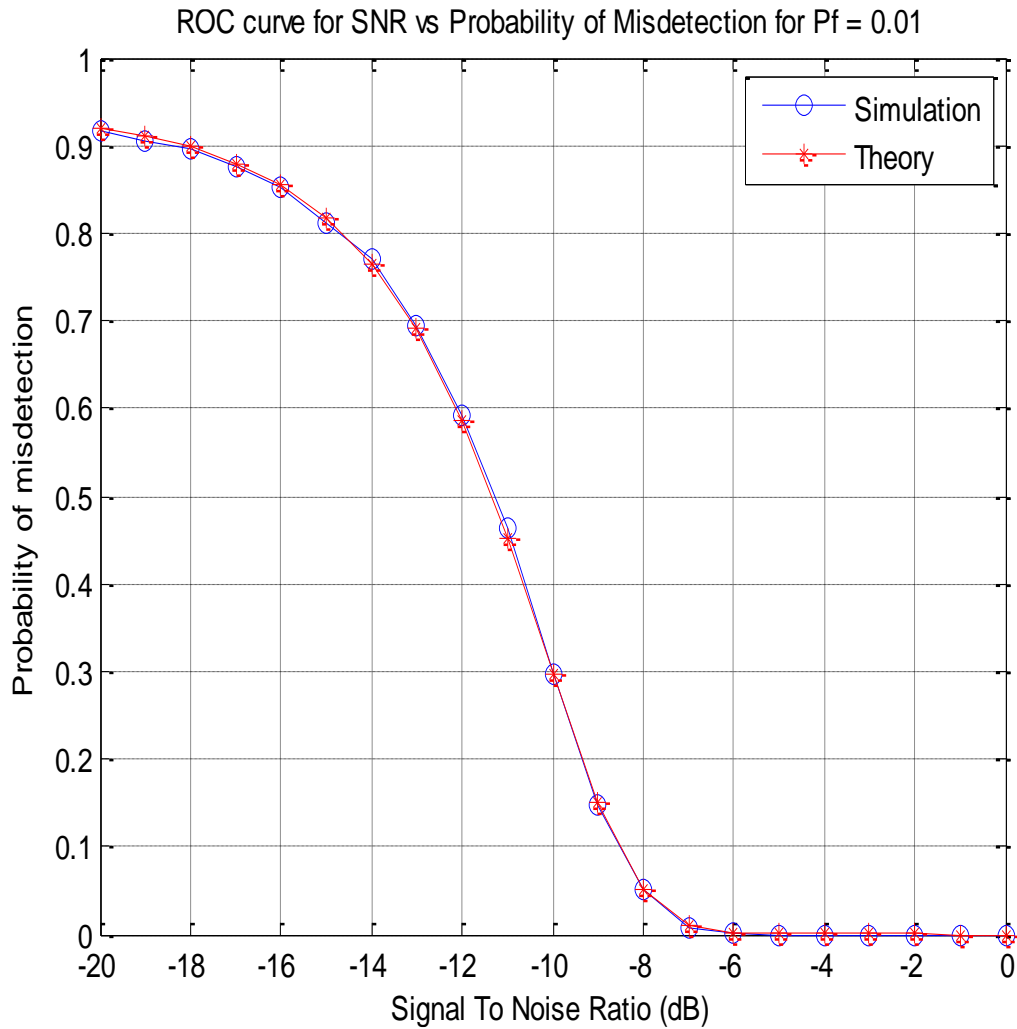


Figure 5.6: Signal to Noise Ratio vs Probability of Misdetection ($P_{fa} = 0.01$)

Figure 5.7 shows the plot of the probability of misdetection against the SNR at different values of the probability of false alarm. Just like Figure 5.3, this plot also serves as an indicator of the variance of the probability of misdetection with the probability of false alarm. The probability of misdetection will be increases as the probability of false alarm decreases. Similarly, the probability of misdetection decreases as the probability of false alarm increases. This is because if we reduce the likelihood of falsely identifying a signal, we increase the likelihood of incorrectly declaring a signal to be present.

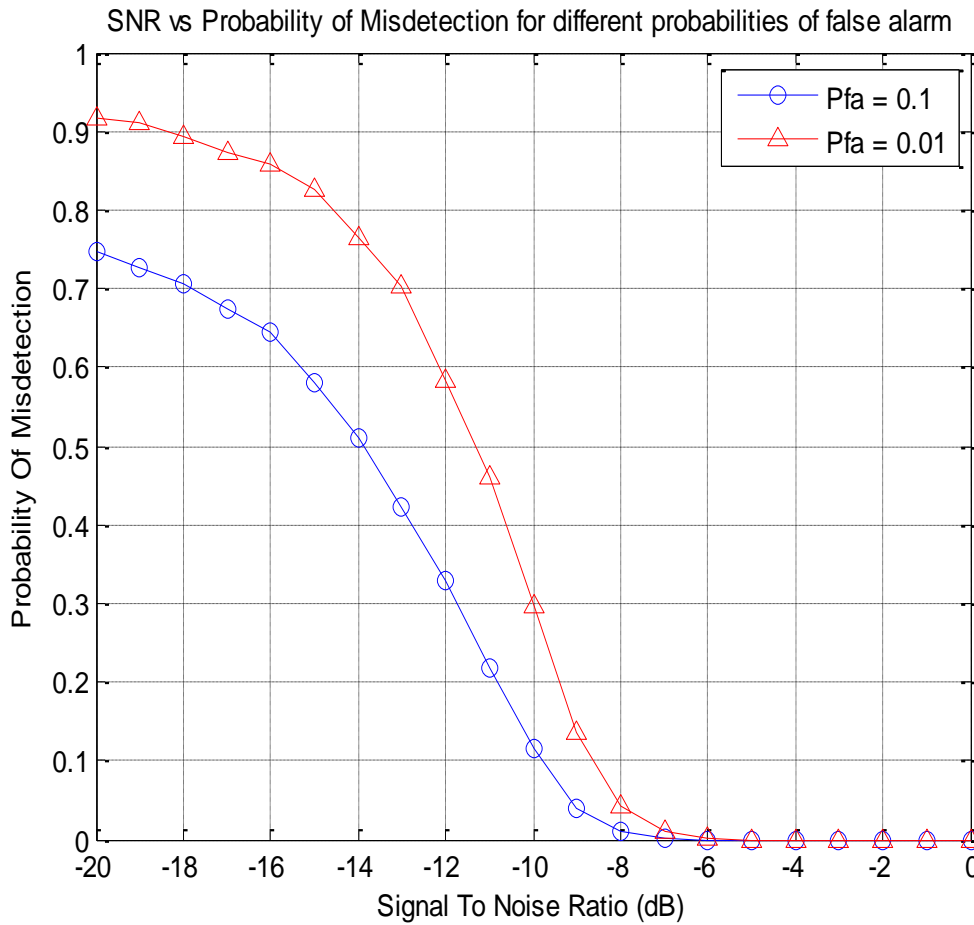


Figure 5.7: Signal to Noise Ratio vs Probability of Misdetection at different Probabilities of false alarm.

The relationship between the probability of misdetection and the probability of false alarm can also be represented as shown in Figure 5.8. It can be observed that the probability of misdetection decreases as the probability of false alarm increases and vice versa. This is the trade-off that exists between these two metrics in the performance of the conventional energy detector.

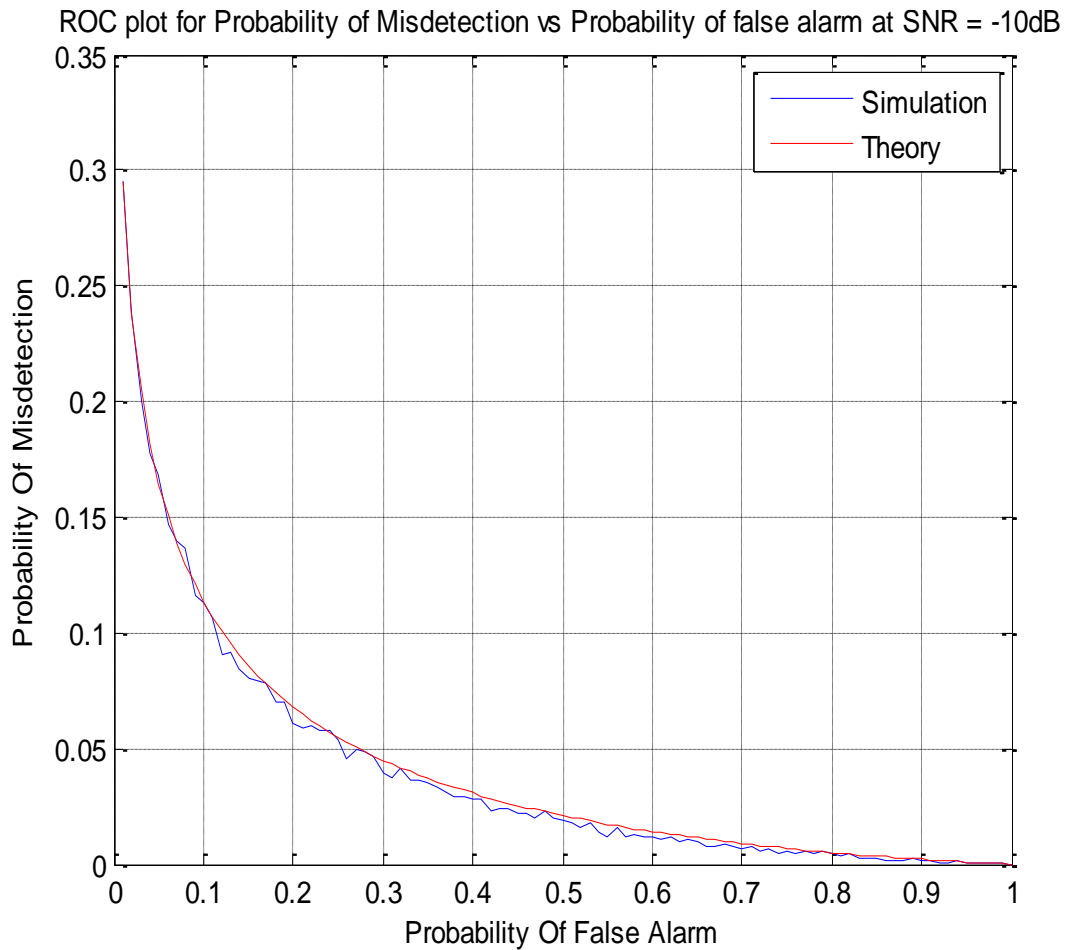


Figure 5.8: Probability misdetection of vs of detection false alarm

In conclusion, the performance of the energy detector is greatly affected by varying SNR levels. It has been shown that there is significant performance degradation at low SNR levels. This can be attributed to the fact that the conventional energy detector employs the fixed threshold technique. This means that the threshold value is static and cannot vary adaptively depending on activity in the radio environment. In high SNR environments, a fixed threshold may suffice however this is not the case in low SNR environments. A fixed threshold may discriminate against weak primary signals if the received signal strength is below the threshold value. This may lead to interference of the primary user's signal and an increased probability of misdetection. Similarly, if the threshold value is fixed at a low value, noise signals higher than the threshold value may wrongly be classified as signal components thus increasing the

probability of false alarm. Based on these achieved results, we recommend that the performance of the energy detector will be improved by using adaptive threshold techniques. In the next section we present the results of our adaptive threshold energy detection technique based on the recursive one-sided hypothesis testing algorithm.

5.3.2 Results of our Proposed Adaptive Threshold Energy Detector

As discussed in the preceding chapter, we employ the ROHT algorithm in order to achieve dynamicity in the threshold value. The experiment was conducted using the same experimental parameters as in the previous experiment. The set of input data, herein referred to as the received signal is a function of the primary signal and random white noise. We consider an SNR range of -20 dB to 0 dB. We use 1000 samples of the received signal and 10000 Monte Carlo simulations in this experiment.

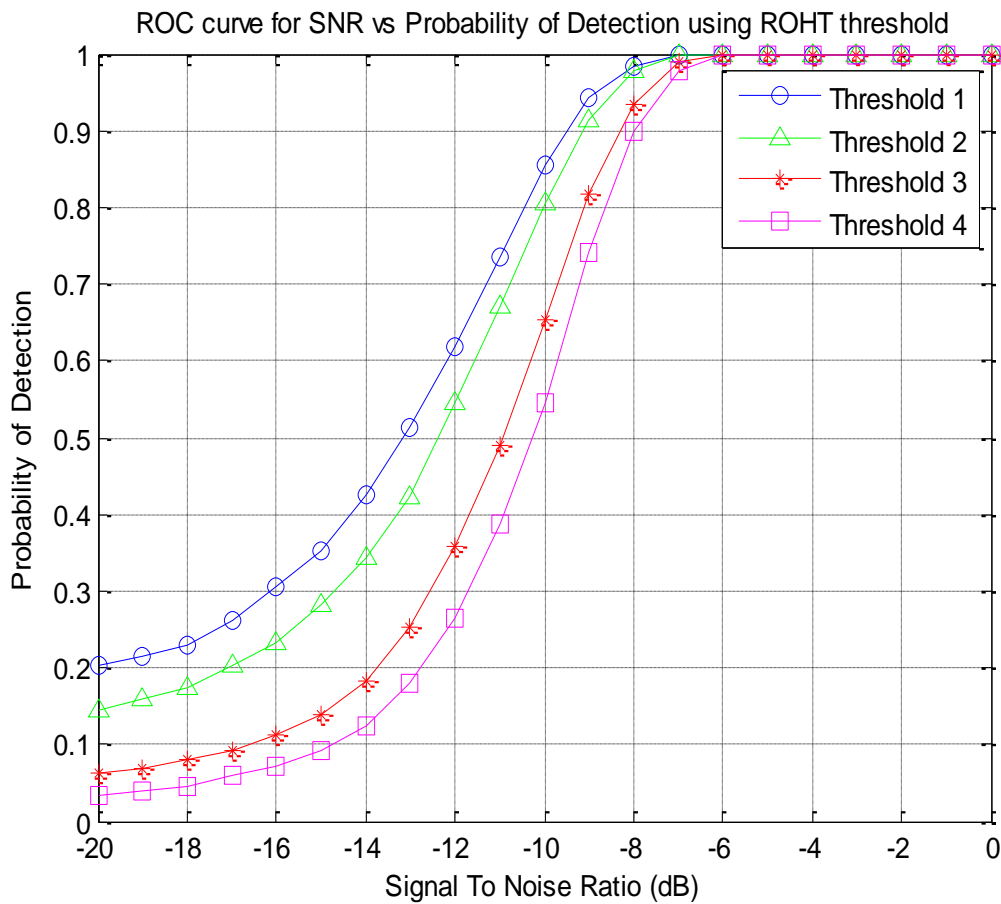
In the beginning, the ROHT algorithm assumes that the received signal is purely noise and it is the aim of the algorithm to disprove this hypothesis. The ROHT algorithm sorts through the received signal components iteratively thus identifying the primary signal components from the pool of unclassified components based on the statistical properties of the received signal. Upon termination of the algorithm, the identified signal components are all combined. It is noted that at each iteration of the ROHT algorithm, there are some components that appear unclassified (not classified as signal components). These components are combined and are thereby classified as noise components. The decision threshold value that we refer to as the ROHT threshold (λ_{ROHT}) is given as the mean of the noise components. However, it should be noted that the ROHT technique is an adaptive threshold technique meaning that the threshold value will change adaptively based on conditions in the radio environment. Therefore, we observe that at each run of the ROHT algorithm, the threshold value differs as a response to the random nature of the noise signals generated. Table 5.1 shows the threshold values derived from four runs of the ROHT algorithm.

TABLE 5.1

Variation in the ROHT threshold value

Run number	Threshold Value
Threshold 1	1.0482
Threshold 2	1.0576
Threshold 3	1.0806
Threshold 4	1.0931

Table 1.1 shows the variation in the ROHT threshold value with every run thus proving that indeed the threshold value is adaptive to the conditions in the radio environment. Figure 5.9 shows the variance of the probability of detection with the SNR at different runs of the ROHT algorithm.

**Figure 5.9:** Signal to noise ratio vs Probability of Detection using ROHT thresholds

It was observed that the performance of the energy detector varies due to the use of different threshold values. However, the use of different decision thresholds means that the energy detector can adapt itself to the conditions in the radio environment. Figure 5.10, similar to the preceding, shows how the adaptive threshold ROHT technique differs from the fixed threshold conventional energy detector. The conventional energy detector is denoted as CED in Figure 5.10 below.

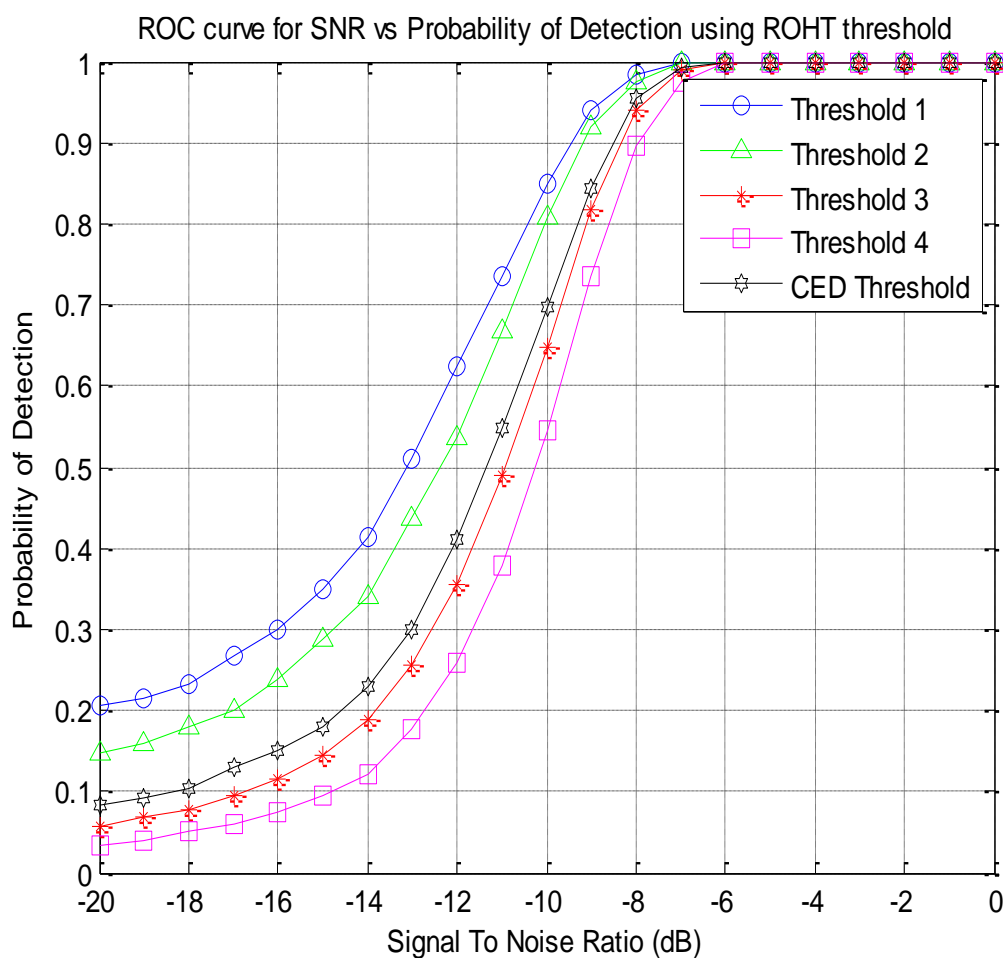


Figure 5.10: Signal to noise ratio vs Probability of Detection using ROHT thresholds in comparison to the fixed threshold conventional energy detector

The conventional energy detector produces a single ROC curve due to the single and fixed decision threshold it uses. On the contrary, our adaptive threshold technique produces

several ROC curves based on the varying threshold values at every run of the ROHT algorithm. This implies that our proposed technique is able to choose the most suitable threshold value in response to the conditions of the radio spectrum based on the statistical properties of the received signal. A dynamic threshold value ensures that weak primary signals are not discriminated against as is the case with the fixed threshold technique. The performance of the ROHT based adaptive threshold energy detector can also be expressed in terms of the probability of misdetection as shown in Figure 5.11. Similar to the previous results, the plot below shows the probability of misdetection against the SNR at different values of the decision threshold. Due to the random nature of noise signals, the resultant noise variance differs at every run of the ROHT algorithm. Consequently, the threshold value also varies with every run because it is a function of the noise variance. For the sake of consistency in our results, the same threshold values used in the previous experiment are replicated for this experiment.

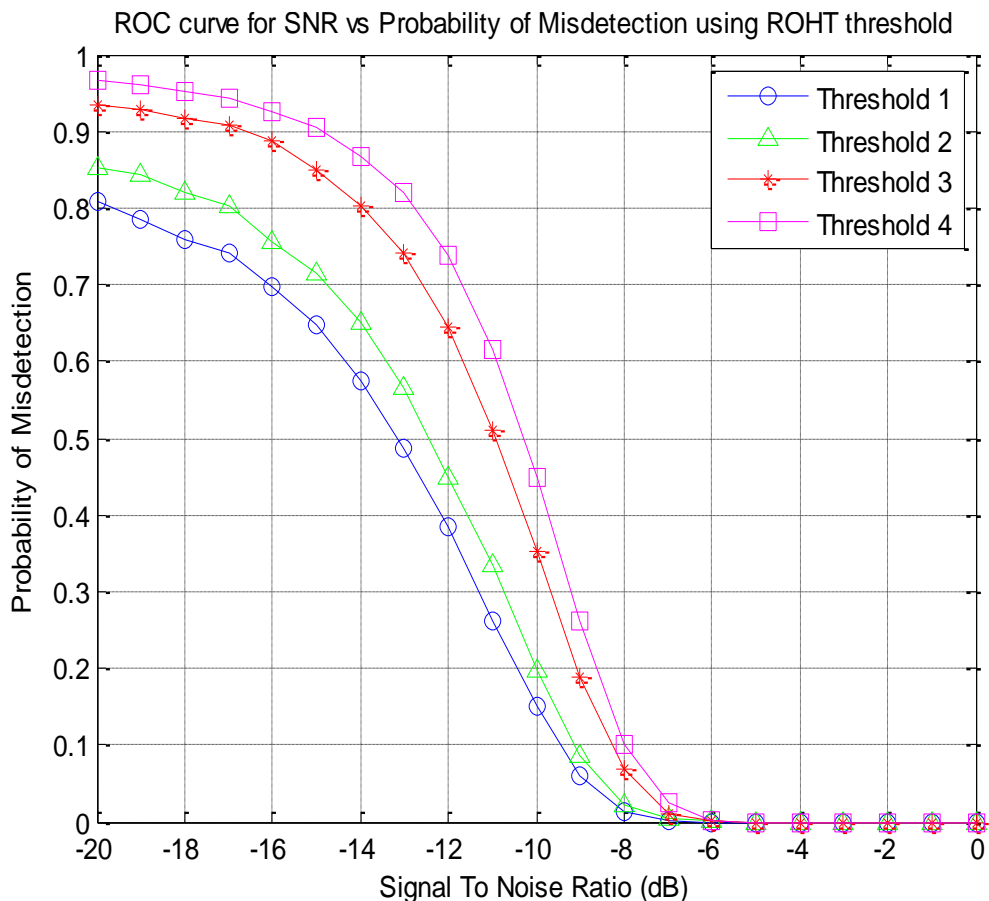


Figure 5.11: Signal to noise ratio vs Probability of Misdetection using the ROHT threshold

The above plot indicates that the selection of the threshold value has a corresponding effect on the performance of the energy detector. The plot in Figure 5.12 clearly shows the difference between the fixed threshold and the adaptive threshold. The adaptive threshold technique is capable of handling variations in the received signal and adjusting its threshold accordingly.

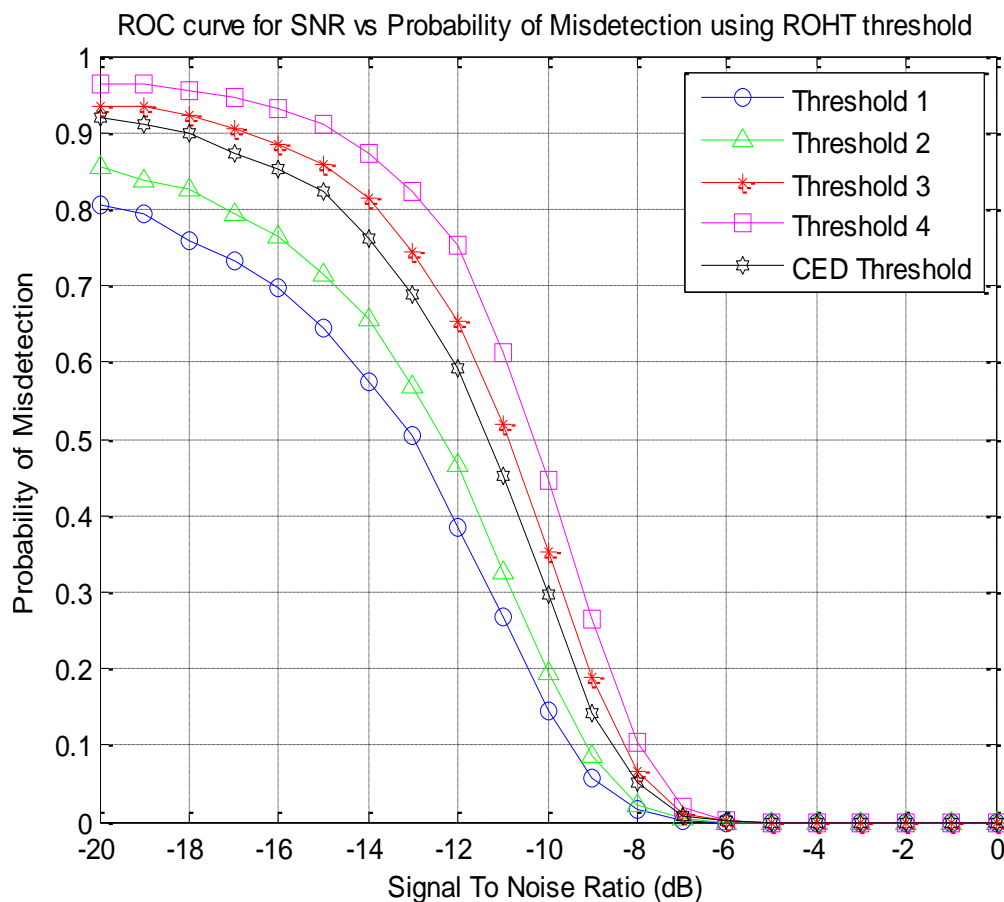


Figure 5.12: Signal to noise ratio vs Probability of Misdetction using ROHT thresholds in comparison to the fixed threshold conventional energy detector

Figure 5.12 indicates that the probability of misdetection varies as a function of the SNR. At higher SNR values, greater than -7 dB, the energy detector has its highest probability of detection and its lowest probability of false alarm. This means that as the SNR reduces, the probability of misdetecting a signal increases. This is the general trend that can be observed in

both the adaptive threshold energy detector as well as the conventional energy detector. However, due to the dynamicity of the ROHT threshold, our technique is able to achieve a wider range of performance. These results indicate that the adaptive ROHT threshold will lead to a higher sensitivity of the energy detector as opposed to a fixed threshold which may hinder the performance of the energy detector especially where there is great variation in the noise signal.

The advantage that our technique has over the conventional energy detector is the dynamicity in the threshold values. Furthermore, our technique serves as an improvement of the conventional adaptive threshold energy detector discussed in section 4.3 by providing a noise estimation technique on which the threshold selection technique is based. An adaptive threshold is essential especially in the noisy environments in which cognitive radio sensor nodes operate in. Figure 5.13 shows the variation of the ROHT threshold with the noise variance for 100 runs of the algorithm.

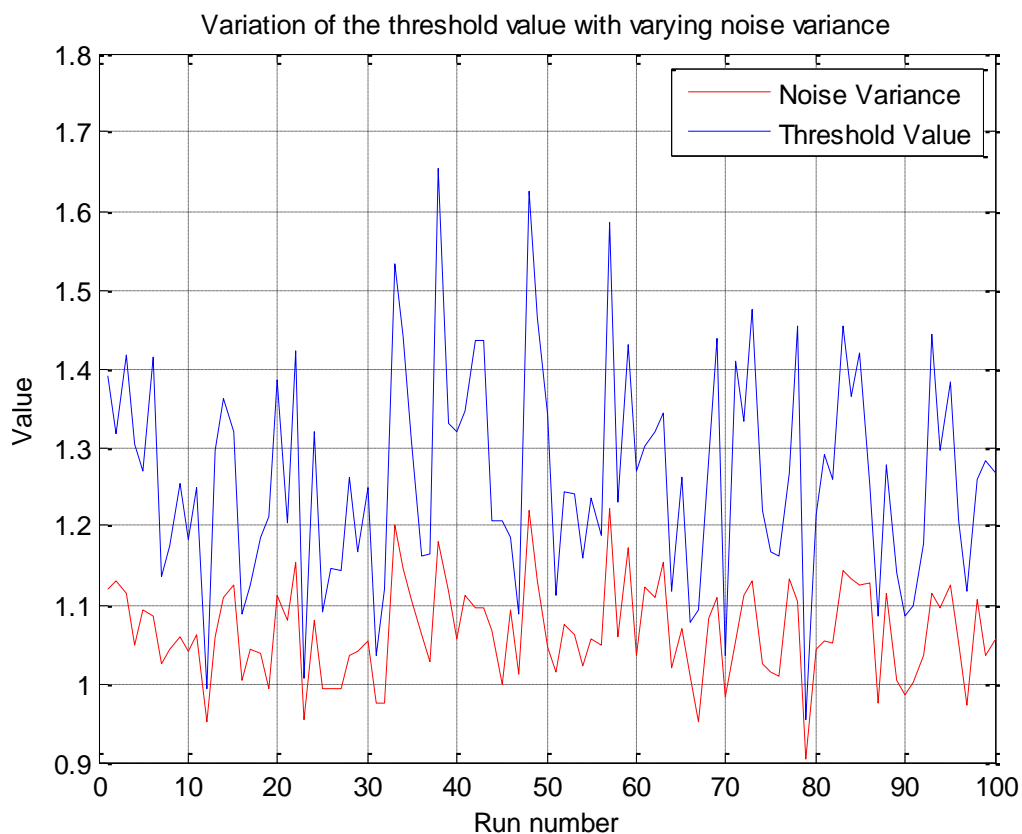


Figure 5.13: Threshold value adapting to the noise variance.

Since cognitive radio sensor networks operate as secondary devices in the licensed spectrum, it is adamant that primary user signals are sufficiently protected against resulting interference. A fixed threshold may be favoured for its simplicity but it is intolerant to fluctuation in the noise. This may result in discrimination against weak primary signals and consequently, interference on the primary user's transmission. However, a dynamic threshold that adapts itself based on the noise variance can greatly diminish the probability of interfering with weak primary signals in low SNR regimes. This is because the threshold value adapts based on the noise variance as shown in Figure 5.13. Figure 5.14 (similar to the preceding) shows an excel plot of the adaptability of the threshold value with the noise variance.

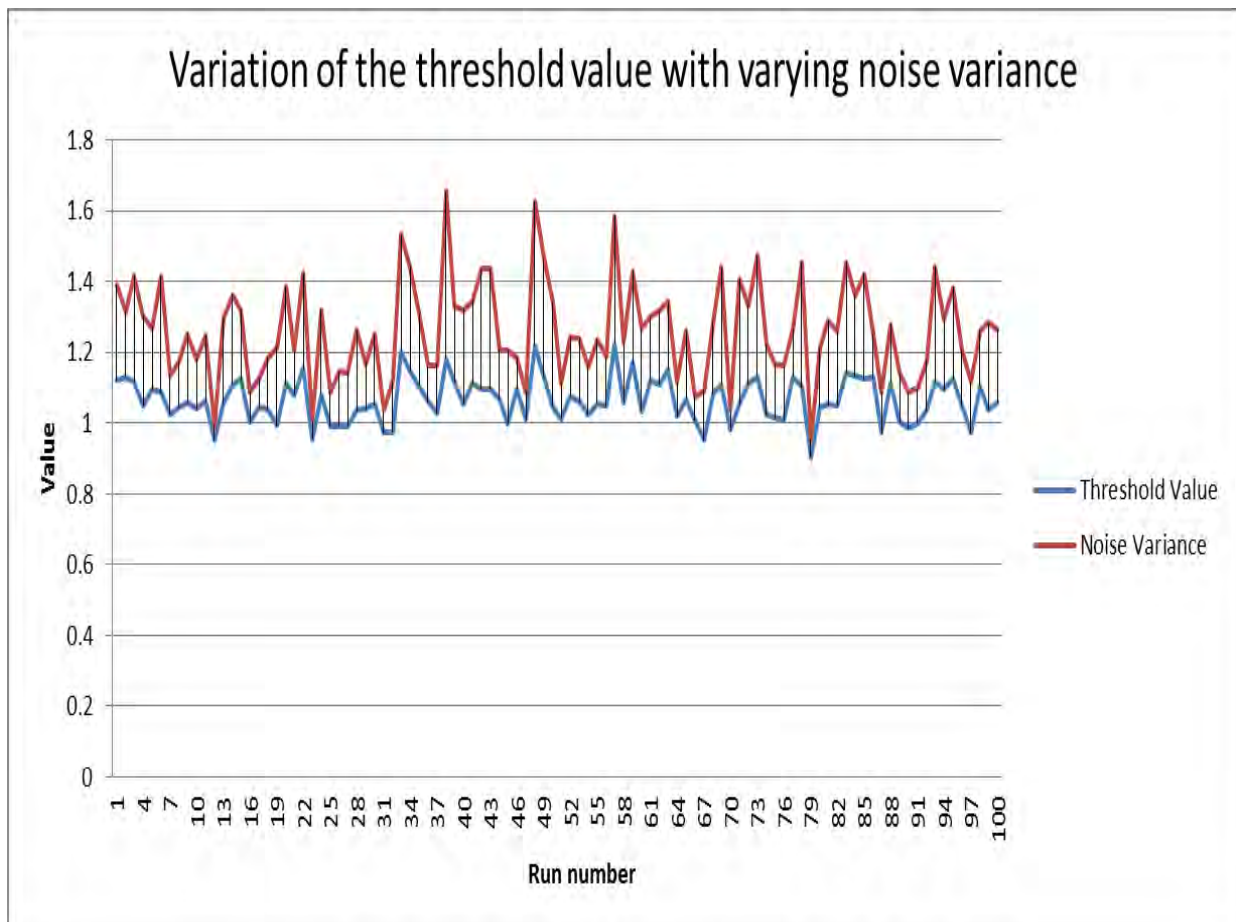


Figure 5.14: Excel plot showing the relationship between the noise variance and the threshold

Figure 5.14 shows the how the threshold value varies as the noise variance varies. It is clear that when the noise variance is high the threshold value will also be high in response. The advantage of this is that likelihood of noise components wrongly identified as signal components is reduced. When the noise variance is low then the threshold value is also low. A statistical analysis of the noise variance and the threshold value revealed a correlation coefficient of 0.9985 thus indicating a strong linear relationship between the data two sets. This proves that the threshold value does vary in response to the noise variance. Figure 5.15 below shows the effect on the probability of detection as a result of the varying threshold.

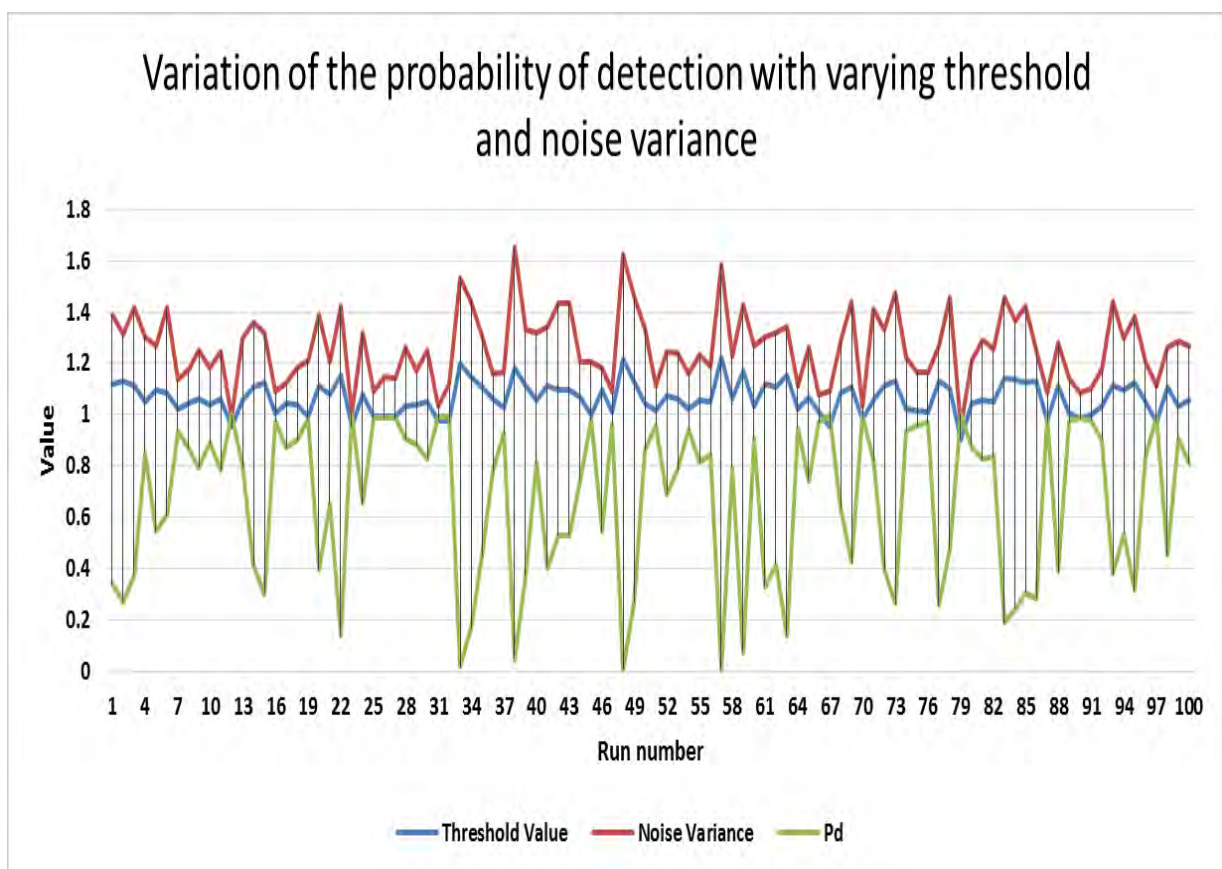


Figure 5.15: Variation of the probability of detection with a varying threshold and noise variance

A correlation analysis of the threshold values and the value of probability of detection resulted in a correlation coefficient of -0.9085. The statistical analysis revealed a strong inverse correlation between the threshold and the probability of detection thus suggesting a negative

linear relationship between the two variables. The results suggest that a high threshold may result in a low probability of detection and a low threshold leads to a higher probability of detection. These results further expound on the trade-off that exists between the probability of detection and the probability of false alarm that exists in detection systems. Furthermore, the results also indicate that our adaptive threshold technique is robustness to noise.

In the case where the perceived SNR is less than the critical SNR, the ROHT threshold may not be suitable. As a defence mechanism to avoid interference to the primary user, our system ceases to use the ROHT threshold (λ_{ROHT}) and instead adopts the CFAR threshold (λ_{fa}). The drafts of the functional requirements of the IEEE 802.22 standard specify a maximum probability of false alarm of 0.1 [88]. Therefore, for this experiment, the CFAR threshold ensures that a constant probability of false alarm of 0.1 is maintained if the critical SNR is not attained. The CFAR threshold is a fixed threshold value (of 1.0405 in this experiment) and it may be used as the last line of defence to guard against interference to the primary user at very low SNR. Figure 5.16 shows how the ROHT threshold and the CFAR threshold compare against each other over 100 runs of the algorithm.

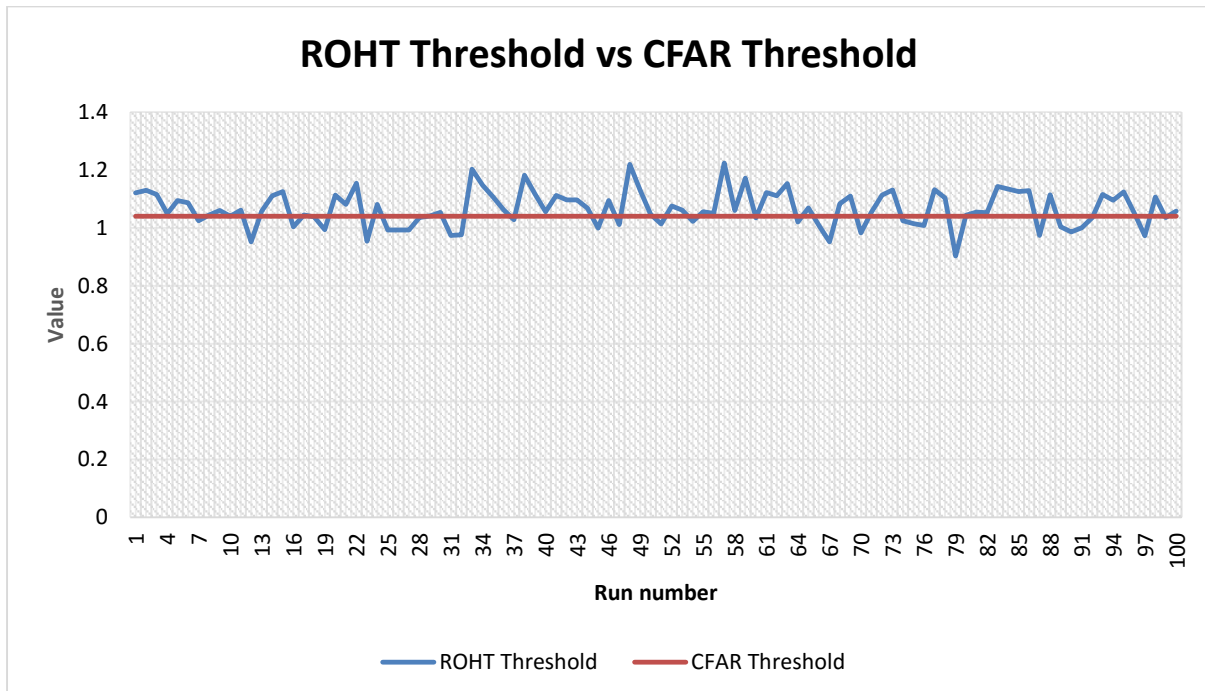


Figure 5.16: A comparison between the ROHT and the CFAR threshold

Figure 5.17 shows a comparison between the noise variance, the ROHT threshold and the CFAR threshold. It is noted that the ROHT threshold is adaptive in nature and it responds to the fluctuation in the noise variance. The secondary threshold which is the CFAR threshold is fixed and it is only employed in the case of very low SNR where the perceived SNR is less than the critical SNR.

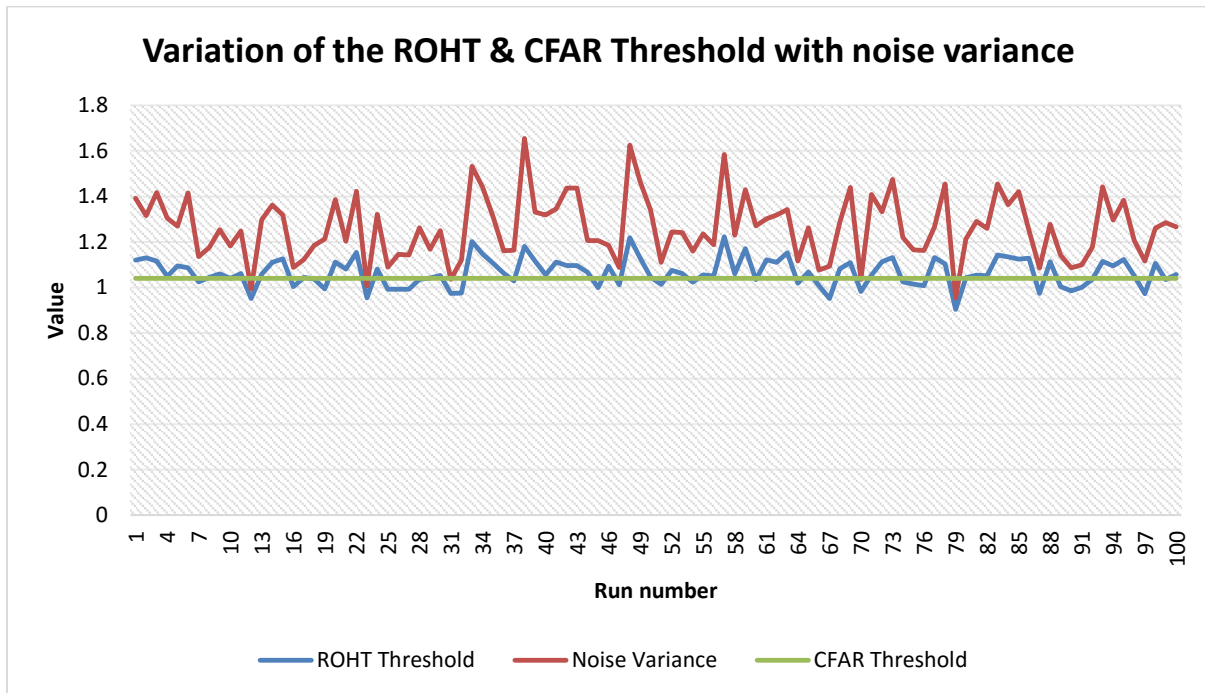


Figure 5.17: Variation of the ROHT and CFAR threshold with the noise variance.

5.4 Chapter Summary

A priori knowledge of the noise variance is essential in setting the signal detection threshold to determine spectrum occupancy for cognitive radio applications. Some of the adaptive threshold energy detection techniques laid out in literature assume a perfect knowledge of the noise variance which is not always the case in the real world. We have proposed an adaptive threshold energy detector that employs the ROHT algorithm to estimate the level of the noise variance.

In this chapter we have presented the results of our adaptive threshold technique against the backdrop of the results of the conventional energy detector. We have also provided an in-depth analysis of the accrued results. We have shown how dynamicity of the threshold value is achieved by employing the ROHT algorithm. We have also shown how the CFAR threshold can be used in the event where the perceived SNR is lower than the critical SNR thus making our system more robust. In the next chapter we present a summary of our research work alongside the major contributions of this dissertation. We also shed light on future work that may enhance or expand the scope of this work.

Chapter 6

6 Summary, Conclusion and Future Work

6.1 Summary

In Chapter 2, a thorough review of the concept of wireless sensor networks (WSNs) is given alongside the applications and challenges of this paradigm. The modern world we live in has seen a dense proliferation of WSNs and numerous applications areas have been developed. In Section 2.3, we have discussed some of the application areas such as structural health monitoring, pipeline monitoring, precision agriculture as well as a myriad of military applications. However, despite the many applications, WSNs are faced with some inherent constraints that limit their performance as shown in Section 2.5. We have discussed the energy, security and wireless communication constraints faced by wireless sensor nodes and how dynamic spectrum access (DSA) offers a viable solution. We also discuss the emergence of cognitive radio technology as the most suitable candidate for DSA. The chapter concludes by introducing the paradigm of cognitive radio sensor networks (CRSN) and discussing its advantages over the conventional wireless sensor networks.

Our interest in the CRSN paradigm led us to investigate the aspect of spectrum sensing which forms the foundation of cognitive radio technology. Chapter 3 kicks off by discussing the some of the spectrum sensing methods that have been proposed in literature such as transmitter detection, interference based detection and cooperative detection. In Section 3.2.1, transmitter detection was identified as the most common method of spectrum sensing and it includes techniques such as energy detection, matched filter detection and cyclostationary feature detection. An appraisal of the spectrum sensing techniques from the perspective of CRSNs revealed that the energy detector is the most suitable spectrum sensing technique for cognitive radio sensor nodes. This is because the energy detection technique favours the inherent constraints of wireless sensor nodes such as limited energy, small size and limited computational power. Despite its advantages, the conventional energy detector is not suitable for CRSN applications because of its non-robustness in noisy environments and its rigidity in the computation of the threshold value. The chapter concludes by laying out the system model for the conventional energy detector thus preparing the ground for our proposal in chapter 4.

The energy detector uses a predefined threshold value to distinguish between signal and noise components in a received signal. Spectrum occupancy decisions are then made based on the threshold value. Knowledge of the noise variance is paramount for setting the decision threshold. Chapter 4 begins by discussing the concept of fixed threshold techniques and adaptive threshold techniques. Adaptive threshold techniques are preferred over the fixed threshold techniques due to their robustness to noise fluctuation and superior performance. A conventional adaptive threshold technique is presented and discussed prior to our proposal. At the climax of the chapter (Section 4.4), we propose our adaptive threshold energy detection technique with noise variance estimation. Our proposed technique is based on the recursive one-sided hypothesis test (ROHT) algorithm which analyses the statistical properties of the received signal to estimate the noise variance and set a decision threshold.

Finally in chapter 5, we present the results of our adaptive threshold energy detection technique against the backdrop of the conventional energy detector. An in-depth analysis of our results revealed that the ROHT algorithm results in a dynamic threshold which varies adaptively with the noise variance. We also show through our results that our system has an inbuilt defence mechanism that protects the primary user against interference in low SNR regimes. In so doing we also show how our system achieves double dynamicity in the threshold value based on the noise variance and the perceived signal to noise ratio respectively.

6.2 Conclusion

This report has revealed that the benefits accrued by employing dynamic spectrum access in wireless sensor networks are undeniable. Moreover, this report supports the notion of cognitive radio technology as the most suitable candidate for dynamic spectrum access and by extension, the emergence of the CRSN paradigm. Delving deeper into the realm of cognitive radio, we discovered that the conventional energy detector is the most preferred technique for spectrum sensing in CRSNs. Further digging revealed that the conventional energy detector pegs its operations on a fixed threshold techniques that use a static threshold value to determine spectrum occupancy. Despite their simplicity and appeal, the fixed threshold techniques are more prone to performance impairment due to noise fluctuations and rigidity in the threshold selection. Consequently, this report favours the adaptive threshold techniques over the fixed

threshold technique due to their robustness in combating noise fluctuations and superior performance.

We make our contribution to the world of CRSNs by employing the ROHT algorithm to estimate the noise variance and thus set a decision threshold. The ROHT technique finds its origins in the world of statistics where it is first expressed as the one-sided hypothesis test. Our proposed algorithm is able to distinguish between the signal and noise components of a received signal based on its statistical properties. We refer to the threshold obtained by this technique as the ROHT threshold, denoted as, λ_{ROHT} . We also make a contribution to the conventional adaptive energy detection system by inculcating the concept of the constant false alarm rate (CFAR) threshold and thus achieving double dynamicity in the threshold selection. The ROHT threshold varies adaptively based on the noise variance experienced in the channel. Furthermore, the threshold selection also ranges dynamically between the ROHT threshold and the CFAR threshold based on the perceived SNR. The CFAR threshold acts as a defence mechanism to protect the primary user against interference at low SNR. Our proposed system also offers increased robustness against noise fluctuation.

6.3 Future Work

Although the scope of this work has been covered a lot more work can still be done in future to form the basis of a Master or PhD thesis. This work is still at its infancy and a lot more time and energy can go into make it finer and implementing it in the real world. The performance of our system was reviewed under simulated conditions and it would be interesting to see how our system performs in the real world conditions. Also of much interest is the performance of the proposed system while subjected to the spectrum sensing task in the TV broadcast bands under the IEEE 802.22 WRAN standard. Lastly, this work could be advanced to further the development of CRSNs applications such as precision agriculture, structural health monitoring among a myriad of military applications.

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Appendix A

In this appendix we present the MATLAB codes used in implementing the ROHT algorithm for the purpose of spectral elements classification. The systematic flow of the algorithm is discussed in section 4.2.4 of Chapter four.

```
clc
close all
clear all

L = 1000; % Number of Samples considered

snr_dB=-20:1:0;
snr= 10.^(snr_dB./10);

for i=1:length(snr_dB)

Noise = randn(1,L);
Signal = sqrt(snr(i)).*randn(1,L);
Recv_Sig = Signal + Noise; % Received signal at secondary user
Energy = abs(Recv_Sig).^2; % Energy of received signal over N samples

Test_Statistic =(1/L).*sum(Energy);

End
%% The iterations were done manually until the terminating condition was met.
Decreasing P-value is due to declining probability of finding signal components in
every iteration

%% Iteration 1
p_value = 0.8;

Threshold1 = p_value * std(Energy) + mean(Energy);
x_sig_find = find(Energy >= Threshold1);
signal_set1 = Energy(x_sig_find);
x_sig_find = find(Energy < Threshold1);
noise1 = Energy(x_sig_find);
std_diff1 = abs(std(noise1) - abs(std(Energy)));

%% Iteration 2
p_value = 0.5;

Threshold2 = p_value * std(noise1) + mean(noise1);
x_sig_find = find(noise1 >= Threshold2);
signal_set2 = noise1(x_sig_find);
x_sig_find = find(noise1 < Threshold2);
noise2 = noise1(x_sig_find);
std_diff2 = abs(std(noise2) - abs(std(noise1)));

%% Iteration 3
p_value = 0.1;

Threshold3 = p_value * std(noise2) + mean(noise2);
x_sig_find = find(noise2 >= Threshold3);
signal_set3 = noise2(x_sig_find);
x_sig_find = find(noise2 < Threshold3);
noise3 = noise2(x_sig_find);
std_diff3 = abs(std(noise3) - abs(std(noise2)));

%% Combine all components identified as signal components

SIGNAL = union(signal_set1,signal_set2);
```

```

FINAL SIGNAL = union (SIGNAL, signal_set3);

%% Combine all components identified as noise components

NOISE = union(noise1, noise2);
FINALNOISE = union (NOISE, noise3);

%%

FinalThreshold = mean(FINALNOISE) %ROHT threshold value

NV = var(FINALNOISE) %Estimate of the Noise Variance

```

Appendix B

We also present the MATLAB codes used in comparing the four selected ROHT thresholds against the CFAR threshold for the purpose of generating the ROC curves.

```

%% INITIALIZATION

clc
close all
clear all
L = 1000;

snr_dB=-20:1:0;
snr= 10.^(snr_dB./10);
% Pf=0.01:0.1:1;

%% START OF FOR LOOP (THRESHOLD 1)

for i=1:length(snr_dB)
    Detect=0;

    for kk=1:10000 % Number of Monte Carlo Simulations

        %-----AWGN noise with mean 0 and variance 1-----%
        Noise = randn(1,L);
        %-----Real valued Gaussian Primary User Signal-----%
        Signal = sqrt(snr(i)).*randn(1,L);
        Recv_Sig = Signal + Noise; % Received signal at SU
        Energy = abs(Recv_Sig).^2; % Energy of received signal over N samples

        %-----Computation of Test statistic for energy detection-----%
        Test_Statistic =(1/L).*sum(Energy);

        %-----Theoretical value of Threshold-----%
        % Threshold = (qfuncinv(Pf)./sqrt(L))+ 1

        if(Test_Statistic >= 1.0482) % Check whether the received energy is
            greater than threshold, if so, (Probability of detection) counter by 1
            Detect = Detect+1;
        end
    end

    Pd(i) = Detect/kk;
    Pm(i)=1-Pd(i);

    % Pd_the(i) = qfunc(((Threshold - (snr(i) +
    1)).*sqrt(L))./(sqrt(2).*(snr(i) + 1)));
    % Pm_the(i)=1-Pd_the(i);

```

```

end

semilogx(snr_dB,Pm,'-bo');
hold on;
% loglog(Pf, Pm);
% hold on
%% START OF FOR LOOP (THRESHOLD 2)

for i=1:length(snr_dB)
    Detect=0;
    Pf=0.01;
    for kk=1:10000 % Number of Monte Carlo Simulations

        %-----AWGN noise with mean 0 and variance 1-----%
        Noise = randn(1,L);
        %-----Real valued Gaussian Primary User Signal-----%
        Signal = sqrt(snr(i)).*randn(1,L);
        Recv_Sig = Signal + Noise; % Received signal at SU
        Energy = abs(Recv_Sig).^2; % Energy of received signal over N samples

        %-----Computation of Test statistic for energy detection-----%
        Test_Statistic =(1/L).*sum(Energy);

        %-----Theoretical value of Threshold-----%
        Threshold = (qfuncinv(Pf)./sqrt(L))+ 1

        if(Test_Statistic >= 1.0576) % Check whether the received energy is
greater than threshold, if so,(Probability of detection) counter by 1
            Detect = Detect+1;
        end
    end

    Pd1(i) = Detect/kk;
    Pm1(i)=1-Pd1(i);
    % Pd_the1(i) = qfunc(((Threshold - (snr(i) +
1)).*sqrt(L))./(sqrt(2).*(snr(i) + 1)));
    % Pm_the1(i)=1-Pd_the(i);

end

semilogx(snr_dB,Pm1,'-g^');
hold on

%% START OF FOR LOOP (THRESHOLD 3)

for i=1:length(snr_dB)
    Detect=0;
    Pf=0.01;
    for kk=1:10000 % Number of Monte Carlo Simulations

        %-----AWGN noise with mean 0 and variance 1-----%
        Noise = randn(1,L);
        %-----Real valued Gaussian Primary User Signal-----%
        Signal = sqrt(snr(i)).*randn(1,L);
        Recv_Sig = Signal + Noise; % Received signal at SU
        Energy = abs(Recv_Sig).^2; % Energy of received signal over N samples

        %-----Computation of Test statistic for energy detection-----%
        Test_Statistic =(1/L).*sum(Energy);

        %-----Theoretical value of Threshold-----%
        Threshold = (qfuncinv(Pf)./sqrt(L))+ 1

        if(Test_Statistic >= 1.0806) % Check whether the received energy is
greater than threshold, if so,(Probability of detection) counter by 1
            Detect = Detect+1;
        end
    end
end

```

```

        end
    end

    Pd2(i) = Detect/kk;
    Pm2(i)=1-Pd2(i);
    % Pd_the2(i) = qfunc(((Threshold - (snr(i) +
1)).*sqrt(L))./(sqrt(2).*(snr(i) + 1)));
    % Pm_the2(i)=1-Pd_the(i);

end

semilogx(snr_dB,Pm2,'-r*')
hold on

%% START OF FOR LOOP (THRESHOLD 4)

for i=1:length(snr_dB)
    Detect=0;
    Pf=0.01;
    for kk=1:10000 % Number of Monte Carlo Simulations

        %----AWGN noise with mean 0 and variance 1----%
        Noise = randn(1,L);
        %----Real valued Gaussian Primary User Signal-----%
        Signal = sqrt(snr(i)).*randn(1,L);
        Recv_Sig = Signal + Noise; % Received signal at SU
        Energy = abs(Recv_Sig).^2; % Energy of received signal over N samples

        %----Computation of Test statistic for energy detection-----%
        Test_Statistic =(1/L).*sum(Energy);

        %----Theoretical value of Threshold-----%
        Threshold = (qfuncinv(Pf)./sqrt(L))+ 1

        if(Test_Statistic >= 1.0931) % Check whether the received energy is
greater than threshold, if so, (Probability of detection) counter by 1
            Detect = Detect+1;
        end
    end

    Pd3(i) = Detect/kk;
    Pm3(i)=1-Pd3(i);
    % Pd_the3(i) = qfunc(((Threshold - (snr(i) +
1)).*sqrt(L))./(sqrt(2).*(snr(i) + 1)));
    % Pm_the3(i)=1-Pd_the(i);

end

semilogx(snr_dB,Pm3,'-ms')
hold on

%% CFAR THRESHOLD

for i=1:length(snr_dB)
    Detect=0;
    Pf=0.01;
    for kk=1:10000 % Number of Monte Carlo Simulations

        %----AWGN noise with mean 0 and variance 1----%
        Noise = randn(1,L);
        %----Real valued Gaussian Primary User Signal-----%
        Signal = sqrt(snr(i)).*randn(1,L);
        Recv_Sig = Signal + Noise; % Received signal at SU
        Energy = abs(Recv_Sig).^2; % Energy of received signal over N samples

        %----Computation of Test statistic for energy detection-----%
        Test_Statistic =(1/L).*sum(Energy);

```

```

%-----Theoretical value of Threshold-----%
Threshold = (qfuncinv(Pf)./sqrt(L))+ 1

if(Test_Statistic >= Threshold) % Check whether the received energy is
greater than threshold, if so,(Probability of detection) counter by 1
    Detect = Detect+1;
end
end

Pd4(i) = Detect/kk;
Pm4(i)=1-Pd4(i);
% Pd_the4(i) = qfunc(((Threshold - (snr(i) +
1)).*sqrt(L))./(sqrt(2).*(snr(i) + 1)));
% Pm_the4(i)=1-Pd_the(i);

end

semilogx(snr_dB,Pm4,'-kh')
hold on
%plot(snr_dB,Pm4,'-bo')
%% PLOTS
%plot(snr_dB,Pd_the,'-r*');
grid on
title('ROC curve for SNR vs Probability of Misdetection using ROHT and PFA
threshold')
xlabel('Signal To Noise Ratio (dB)');
ylabel('Probability of Misdetection');
legend('Threshold 1','Threshold 2','Threshold 3','Threshold 4','PFA threshold');

```