# ESTIMATION OF DETECTION THRESHOLD FOR SPECTRUM SENSING IN COGNITIVE RADIO USING ADAPTIVE NEUROFUZZY INFERENCE SYSTEM AND MONTE CARLO TECHNIQUES

BY

MOHAMMED MIFTAHABDULLAHI
B.Sc (NDA) 1992, M.Tech (OAU), 2006
PhD/ENG/01022/2008-2009
mmabdullahi2000@yahoo.co.uk

A THESIS SUBMITTED TO THE SCHOOL OF POSTGRADUATE STUDIES, AHMADU BELLO UNIVERSITY, ZARIA IN PARTIAL FULFILMENT OF THE REQUIREMENTS FOR THE AWARD OF DOCTOR OF PHILOSOPHY (Ph.D) DEGREE IN ELECTRICAL ENGINEERING

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FACULTY OF ENGINEERING,
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NIGERIA

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## DECLARATION

I hereby declare that this thesisentitled "**Estimation of Detection Threshold for Spectrum Sensing in Cognitive Radio using Adaptive NeuroFuzzy Inference System (ANFIS) and Monte Carlo Techniques**" has been carried out by me in the Department of Electrical and Computer Engineering. The information derived from the literature has been duly acknowledged in the text and a list of references provided. No part of this Dissertation was previously presented for another degree or diploma at this or any other institution.

MohammedMiftah**ABDULLAHI** _____ _____

Signature Date

## CERTIFICATION

This thesisentitled **"ESTIMATION OF DETECTION THRESHOLD FOR SPECTRUM SENSING IN COGNITIVE RADIO USING ADAPTIVE NEURO FUZZY INFERENCE SYSTEM AND MONTE CARLO TECHNIQUES"** by Mohammed Miftah**ABDULLAHI**meets the regulations governing the award of the degree of Doctor of Philosophy of the Ahmadu Bello University, and is approved for its contribution to knowledge and literary presentation.

| | | |
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| Chairman, Supervisory Committee<br>(Dr. S. M. Sani) | _____<br>Signature | _____<br>Date |
| Member, Supervisory Committee<br>(Prof. B. G. Bajoga) | _____<br>Signature | _____<br>Date |
| Member, Supervisory Committee<br>(Prof. M. B. Mu'azu) | _____<br>Signature | _____<br>Date |
| Head of Department<br>(Prof. M. B. Mu'azu) | _____<br>Signature | _____<br>Date |
| Dean, Post Graduate School<br>(Prof. A. Z. Hassan) | _____<br>Signature | _____<br>Date |

## DEDICATION

I dedicate this research work to Almighty Allah, my late parents and to my entire family, particularly my dear wife and children.

## ACKNOWLEDGEMENT

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My deep affection and love goes to my late parents for all their effort to make me a responsible person. May Allah have mercy on their souls and grant them paradise.

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Finally, I sincerely hope that this work will contribute immensely to knowledge and will lay a foundation for further research in the field of cognitive radio.

## ABSTRACT

An important component of cognitive radio is spectrum sensing to detect the presence or absence of primary (licensed) user in the spectrum band of interest. However, the traditional static spectrum allocation strategies cause temporal and geographical holes of spectrum usage in licensed bands. Spectrum occupancy was categorized into completely free (white hole), partially free (grey hole) and fully occupied (black hole) in spectrum usage. Cognitive radio has a potential to improve spectrum utilization by opportunistically identifying and exploiting the available spectrum holes without causing harmful interference. One such detection method is the energy detection, used for this research, which is capable of sensing primary user transmitted energy signal. Furthermore, due to signal degradation caused by multipath fading and path loss, a single secondary user running the cognitive software on-board cannot accurately detect the presence of primary user and thus leads to missed detections. This drawback in a single user demands a different approach to the sensing in terms of number of active sensors which lead to the introduction of multiple cognitive radios in a network called a cooperative spectrum sensing network. A major challenge in spectrum sensing is the uncertainty associated with the detection of the primary user by the secondary users.This uncertainty arisesfrom the effects of noise, multi-path effects like randomness of primary user's presence in radio spectrum. In order to reduce the impact associated with the uncertainty problem and improve detection performance, this research carried out a comprehensive study between the use of Adaptive NeuroFuzzy Inference System and Monte Carlo techniques with a view to estimating detection threshold value for both cooperative and non-cooperative sensing for efficient utilization of radio spectrum. The ANFIS estimation gave a threshold value of -39dBm while the Monte Carlo gave a simulated threshold value of -71dBm. A simulated threshold value of -71dBm was obtained for thenon-cooperative spectrum sensing using Monte Carlo technique. This was validated by conducting extensive indoor and outdoor measurements using a commercially available energy detector with an incorporated spectrum analyzer. A measured threshold value of -71.138dBm was obtained which was similar to the threshold value of -71dBm realized from the non-cooperative model. Measurements were also conducted at two GSM frequencies viz: 900MHz and 1800MHzwith a view to ascertaining existence of spectrum holes at those frequency bands and for noise level characterization. The measurements were twofold: Indoor measurements for the determination of benchmark for noise level and for calibration of the outdoor measurements. From the experiments and measurements made, a minimum noise level of -91dBm and maximum noise level of -69dBm were obtained for 1800MHz and Outdoor measurements gave the signal plus noise levels of -91dBm and -64dBmfor minimum and maximumsensed energy at 1800MHzrespectively. While at 900MHz -79dBm and -55dBm were obtained for the minimum and maximumrespectively.

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## LIST OF ABBREVIATIONS

| | |
|---|---|
| ADC | Analog-to-Digital Converter |
| AI | Artificial Intelligence |
| ANFIS | Adaptive Neuro Fuzzy Inference System |
| ANN | Artificial Neural Network |
| API | Application Programming Interface |
| AWGN | Additive White Gaussian Noise |
| BER | Bit Error Rate |
| CE | Cognitive Engine |
| CN | Cognitive Network |
| CR | Cognitive Radio |
| CRE | Cognitive Radio Engine |
| DAC | Digital-to-Analog Converter |
| DARPA XG | Defense Advanced Research Projects Agency neXt Generation |
| DSA | Dynamic Spectrum Access |
| DSB | Double Side Band |
| ETEP | Etisalat Telecommunication Engineering Programme |
| FCC | Federal Communications Commission |
| FE | Front End |
| FPGA | Field Programmable Gate Array |
| ISM | Industrial, Scientific and Medical |
| ITU | International Telecommunication Union |
| ITU-R | International Telecommunication Union-Radio Communication |
| MSE | Mean Square Error |
| NCC | Nigerian Communications Commission |
| NN | Neural Network |
| Ofcom | Office of Communications |
| OS | Operating System |
| OSA | Opportunistic Spectrum Access |
| PC | Personal Computer |
| PDF | Probability Density Function |

| | |
|---|---|
| PE | Processing Element |
| PR | Pattern Recognition |
| PSD | Power Spectral Density |
| PU | Primary User |
| QoS | Quality of Service |
| RF | Radio Frequency |
| Rx | Receiver |
| SDR | Software Defined Radio |
| SNR | Signal-to-Noise Ratio |
| SR | Software Radio |
| SSADA | Spectrum Sensing and Detection Algorithm |
| SSB | Single Side Band |
| SU | Secondary User |
| SUS | Secondary User Sensor |
| Tx | Transmitter |
| USB | Universal Serial Bus |
| USRP | Universal Software Radio Peripheral |
| UWB | Ultra-Wide-Band |
| W | Bandwidth |
| Wi-Fi | Wireless Fidelity |
| WiMAX | Worldwide Interoperability for Microwave Access |
| WLAN | Wireless Local Area Network |

# CHAPTER ONE

# INTRODUCTION

## 1.2 Background of Study

In recent years, wireless communication technologies have grown rapidly and more frequency spectrum resources are needed for the modern society to support numerous wireless services. It was established in a study that the current frequency spectrum resources are faced with two major challenges, namely, limited spectrum resources and inefficient spectrum utilization. Therefore, in order to address these challenges, cognitive radio was recently proposed to enhance efficient spectrum utilization(FCC, 2002; FCC, 2003). Additionally, spectrum is amongst the most heavily regulated and expensive natural resources around the world. Even though these facts are evident in almost all allocated spectrum available for wireless communications, studies indicate that many portions of the radio spectrum are grossly underutilized. An experimental analysis on shared spectrum shows that 62% of the white space below the 3GHz band even in the most densely populated areas such as Washington D.C., which host massive government and commercial activities (McHenry 2003). A band is considered as white space if it is wider than 1MHz and if it is unoccupied for 10 minutes or longer (McHenry 2003).

The existing regulatory polices ensure that license holder has exclusive rights to utilize the spectrum as no other parties may access it, hence protecting the licensee from interference. New wireless technologies aim to improve data rates, Quality of Services (QoS), robustness, latency, etc, and the bandwidth requirement for these technologies increases(3GPP, 2011). Consequent upon this, spectrum scarcity has become a major problem as network operators do not have access to large continuous blocks of spectrum. The increasingly large number of wireless devices also strains the capacity of wireless network and the accessible network spectrum such as the 2G

–GSM bands around 900MHz and 1800MHz, 3G-UMTS band in 2.1GHz and ISM band of 2.4GHz (Chiang, Rowe et al. 2007). Furthermore, the high cost of prime spectrum constitutes a significant overhead cost to network operators and this was compounded by the accepted norm that customers expect to get more while paying less. Moreover, frequency ranges specifically meant for a particular usage are not necessarily licensed for such applications; therefore, operators often have to resort to less efficient systems of using the spectrum that is available to them. In general, wireless technologies appear to be encountering a critical problem of inadequate spectrum availability and perhaps more disturbingly, the available spectrum is grossly underutilized.

Contrary to common knowledge, recent studies on spectrum occupancy have provided a different insight into the spectrum usage and the problem with spectrum scarcity. Studies conducted around the world measured the activities of wireless technology over various allocated spectra throughout day and night made some stunning discoveries (Chiang, et al., 2007;Weiss, et al., 2010). While certain spectral ranges such as mobile communications systems and ISM bands are cluttered (Wellens, et al., 2007), there are large band of spectra where average usage is below 10% (Chiang, et al., 2007).

## 1.2 Radio Spectrum Management

The radio spectrum is one of the most important resources for communication. Traditionally, spectrum governance throughout the world has tended towards exclusivity of its use in large geographical areas, allocating frequency bands for specific applications and assigning license to specific users or service providers. This policy has generated a shortage of frequencies available for emerging wireless products and services, as most frequencies are already assigned. (Hassan

and Boostanimehr, 2011).As a public resource, radio spectrum is being managed by governments to ensure that it is shared equitably to promote the public interest, convenience, or necessity (Nunno, 2002). It is being tightly regulated around the world by both the international and national regulators. At international level, the International Telecommunication Union (ITU) is managing spectrum. The International Telecommunication Union-Radio communication, Sector (ITU-R) maintains a table of frequency allocations which identifies spectrum bands for about fourty (40) categories of wireless services with the aim of avoiding interference among those services. Once the broad categories are established, each country may allocate spectrum for various services within its own borders in compliance with ITU's table of frequency allocations.

At the national level, the use of radio spectrum in most countries is currently being managed by government agencies rather than by market forces. For instance, in the United Kingdom, it is being regulated by the Office of Communications (OfCom) while the Federal Communications Commission (FCC) is responsible for radio spectrum regulation in the United States. The Nigerian Communications Commission (NCC) is responsible for radio spectrum regulation in Nigeria. In all of these countries, the primary tool of spectrum management by government is a licensing system through bidding. This involves spectrum being apportioned into blocks for specific uses, and assigned licenses for these blocks to specific users or companies. The main advantage of this licensing approach is that the licensee completely controls its assigned spectrum and can thus unilaterally manage interference between its users and their quality of service. However, one of the drawbacks of this policy is the impossibility of re-allocating spectrum to different technologies or other users who might have better use for the spectrum(Olafsson, et al., 2007). In addition, another demerit of this approach is that the

frequency allocation procedures were lengthy and bureaucratic, opening up the possibility that the decision-making process could be influenced by non-relevant factors(Olafsson, et al., 2007).

Furthermore, the once and for all allocation of radio spectrum that gives exclusive right of using the spectrum to the licensed owners has been observed as the main cause of both spectrum underutilization and spectrum artificial scarcity (Akyildiz, et al., 2006;Haykin, 2005). This is because allocation by fixed spectrum assignment policy encourages the sporadic usage of spectrum as shown. Figure 1.1 shows the signal strength distribution over a large portion of the radio spectrum, reveals that while the spectrum usage is concentrated on certain portions of the spectrum, a significant amount of the spectrum remains unutilized in some bands. This necessitates the need for a more flexible means of controlling radio spectrum usage and control.

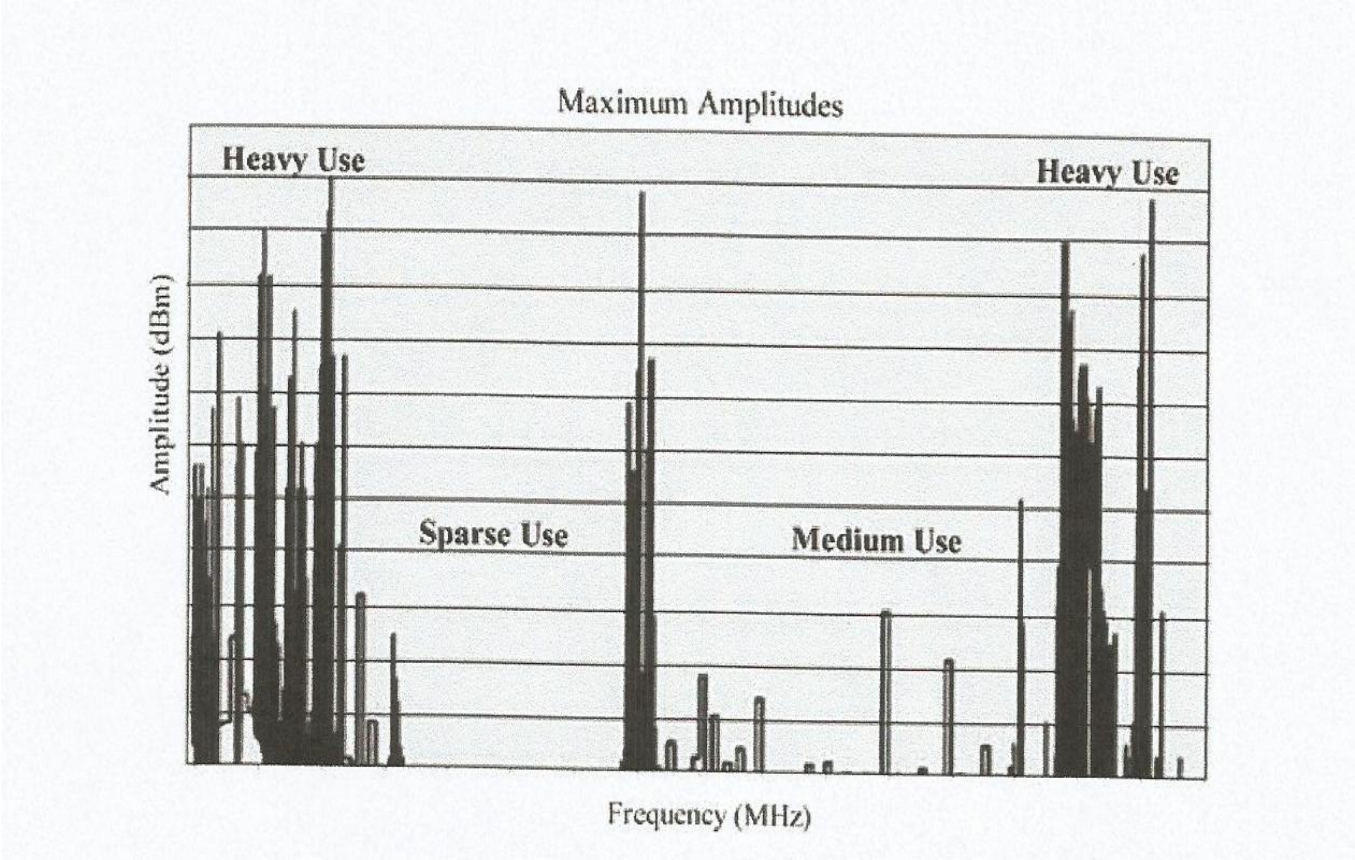



Figure 1.1: Spectrum Utilization (Akyildiz et al., 2006)

## 1.3 The Need for Flexibility in Spectrum Management

Based on the disadvantages of the current fixed or rigid spectrum assignment policy, as well as increase in demand for radio spectrum, coupled with the increase in deployment of new wireless applications and devices in the last decade, it is obvious that strict command-and-control management of the spectrum is not suitable for the increasingly dynamic nature of spectrum usage. This has geared the regulatory body, such as the FCC, to begin to consider more flexible and comprehensive uses of available spectrum (FCC, 2002). The essence of this flexibility in spectrum usage is to deal with the conflicts between spectrum scarcity and spectrum underutilization, as well as to provide spectrum for emerging wireless communication technologies. Flexible usage means that an unlicensed or secondary user can opportunistically operate in an unused licensed spectrum bands. According to (Song, et al., 2007)and(Chen, et al., 2008), this new scheme is termed Opportunistic Spectrum Access (OSA) or Dynamic Spectrum Access (DSA).

In this new scheme for spectrum access control and management, the secondary users must not cause any interference to the primary or licensed users, as well as the other unlicensed users sharing the same portion of the spectrum. As the primary user still holds exclusive right to the spectrum; it is not its responsibility to mitigate any additional interference caused by unlicensed or secondary user's operation. It is the secondary user that periodically has to sense the spectrum to detect both the primary and other secondary users' transmissions and should be able to adapt to the varying spectrum conditions for the avoidance of mutual interference. An approach, which can meet these goals according to(Čabrić, et al., 2005), is to develop a radio that is able to reliably sense the spectral environment over a wide bandwidth, detect the presence/absence of a legacy or primary user, and use the spectrum only if communications do not interfere with the

primary user. Radios that have such capability are termed cognitive radios (Chakravarthy, et al., 2005, Haykin, 2005 and Akyildiz, et al., 2006).

## 1.4 Enabler of Flexible Spectrum Management

In order to implement dynamic spectrum management and break the spectrum inflexibility policy, (Olafsson, et al., 2007)suggested that the following three close coupling elements: spectrum, ownership and applications needs to be broken. This is because the tight relationships, as shown in Figure 1.2, among these three elements support the present rigid regulatory policy. Hence, to break the interdependence of these three elements, a radio device that is neither application-bound nor licensed-bound will be the very viable solution (Olafsson, et al., 2007)

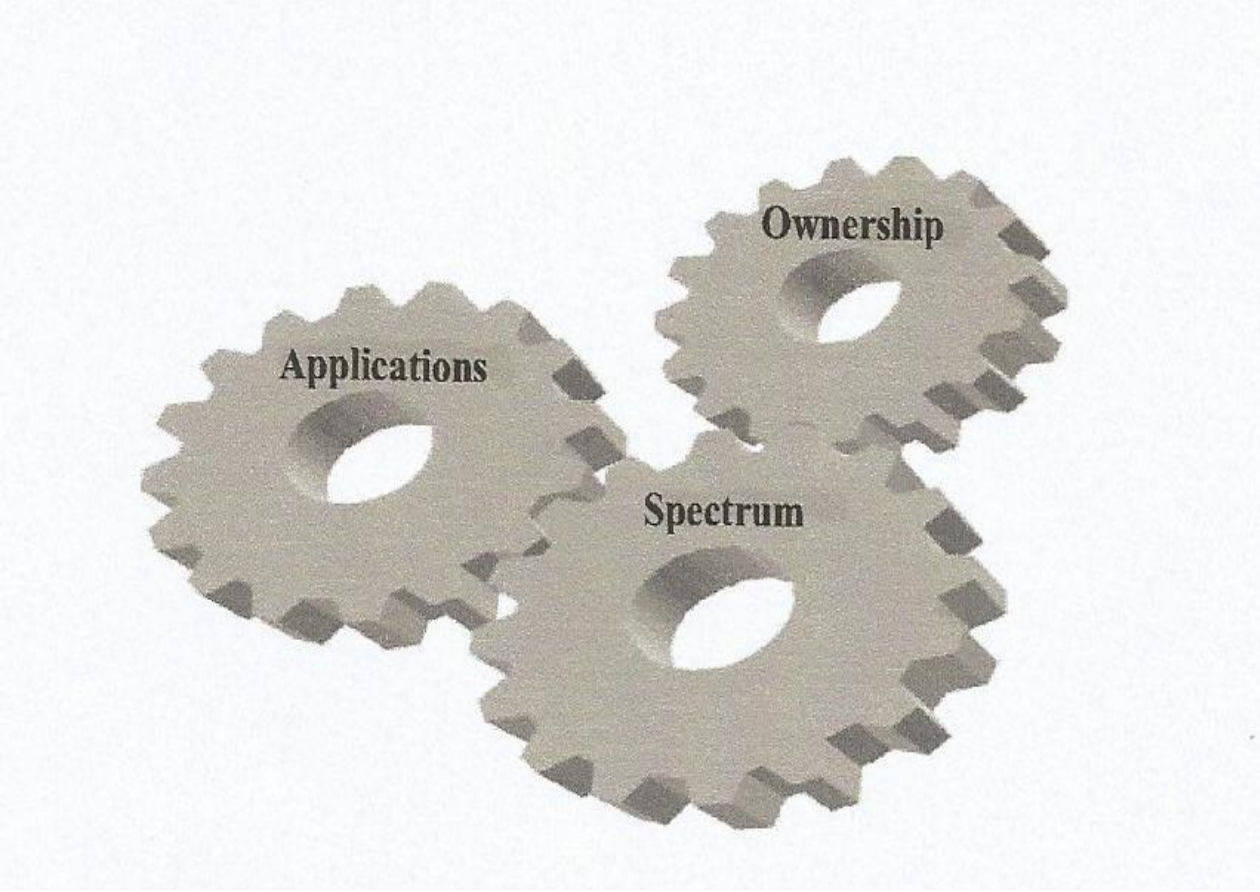



Figure 1.2: Relationship between Applications, Ownership and Spectrum (Olafsson et al., 2007)

## 1.5 Cognitive Radio and Spectrum Sensing

The term ‘cognitive radio’ is given to an emerging wireless access scheme that is ‘an intelligent wireless communication system that is aware of its surrounding environment to allow changes in certain operating parameters for the objective of providing reliable communications and efficient utilization of the radio spectrum’ (Haykin, 2005). Cognitive radio is based on the concept of dynamic spectrum access, whereby licensed holders known as the primary users grant permission for spectrum access to non-licensed secondary users as long as interference to Primary User (PU) activity is minimal and confined(Hossain and Bhargava, 2007). Since the first mentioning in 1999(Mitola III, et al., 2012), cognitive radio has become the focus of significant research from industry, research centers and universities alike (Bergman et al., 2008). In fact, the popularity and potential of cognitive radio is acknowledged by IEEE to promote and develop a standard based on cognitive radio technology, ‘IEEE 802.22 Wireless Region Area Networks, to deliver wireless broadband to regional area using UHF /VHF TV bands between 54-862 MHZ in America (Stevenson, et al., 2009).

The integrity of cognitive radio relies on the ability of the secondary users to restrict interference to primary users and maintain a reliable QoS for its own operations(Mitola III and Maguire Jr, 1999). To achieve this goal, secondary users must actively sense primary user’s spectrum to detect spectrum holes or spectrum opportunity. Spectrum opportunity is defined as a specific ‘dimension’ of wireless communication that is currently not in use by the primary users which can be utilized by the secondary users without causing interference to the primary users(Horne, 2004). The most common model of spectrum opportunity is the time-frequency-space relation: a spectral band not in use by the primary users of that band at a particular time within a particular geographical space can be utilized by secondary users for secondary access(Kolodzy, 2001).

Other possible dimensions for spectrum opportunity include coding, modulation, polarization, transmission direction/ angle, and possibly many more. All these dimensions collectively form the 'spectrum space' as the radio resource that can be shared among primary users and secondary users(Hoyhtya, et al., 2008). Spectrum sensing is the task where the secondary users identify possible spectrum opportunities and is one of the most crucial components of cognitive radio.

Spectrum sensing is performed by the secondary users to sense a spectrum of interest with the objective of detecting the presence of any primary user's signals to prevent interference and identify spectrum opportunity for secondary access (Haykin, 2005andLiang, et al., 2008). Spectrum sensing poses new challenges in both hardware and software: radio front end to operate over wide frequency ranges, high speed signal processors and efficient system and algorithms to process computation demands, to name a few (Song, et al., 2007). Primary user activity changes from time to time, hence spectrum sensing has to be performed in a periodic manner, thus, forming a sensing cycle(Ghasemi and Sousa, 2007).

A common model of sensing cycle adopted by various studies to focus on the physical layer sensing consists of a spectrum sensing period directly followed by a data transmission period(Pei et al., 2007).

The secondary user uses spectrum sensing detectors to analyze the signal captured or observed during the sensing period, and based on the detection results, decides whether or not to utilize the spectrum during the transmission period. Sensing can be performed using the same transceiver and radio chain as data transmission, or independent radio chains dedicated for spectrum sensing and transmission(Shankar, et al., 2005). Spectrum sensing results in one of two decisions: false alarm where the secondary user declares primary user is present when the spectrum is empty and

detection where the secondary user correctly declares a primary user is using the spectrum(Cabric et al., 2006). The performance of sensing detection is thus measured through the probability of these two events. Probability of false alarm is desired to be as low as possible, as false alarms results in the secondary user wasting spectrum opportunity by not transmitting. Probability of detection is desired to be as high as possible to minimize interference to primary user. These two metrics however, are conflicting parameters and the ideal case of perfect detection performance is rarely achievable. Therefore in practice, the primary user and secondary user specifies a set of detection requirements based on the maximum interference the primary user can tolerate and the minimum spectral efficiency required to operate the secondary user network (Cavalcanti et al. 2008).

It is inevitable for cognitive radio to find unutilized portion of the spectrum more accurately for successful deployment of dynamic spectrum sensing, usually cooperative spectrum sensing is employed but still there is a margin to improve local sensing overhead among cognitive radio users, which can be reduced by improving local spectrum sensing. Several signal processing techniques for primary user's detection have been proposed in literature but there is still room for researchers to explore more sophisticated approaches to enhance sensing efficiency. This research proposes a two stage local spectrum sensing approach. In the first stage each cognitive radio performs one of the existing spectrum sensing techniquesthat is energy detection, matched filter detection, or cyclostationary detection. While in the second stage output from the technique employed in step one is combined using fuzzy logic to ultimately decide about the presence or absence of primary user. Monte Carlo simulation technique would then be used to analyze the performance of the spectrum detection algorithms in cognitive radio networks.

## 1.6 Motivation for the study

Cognitive radio which forms the cornerstone of secondary user equipment in intelligent, dynamic spectrum sensing and usage has created the need for profound studies in recent literature of new methods to optimally harness the scarce resource described previously. The appeal for cognitive radio amongst spectrum users draws inspiration from different sources and for many reasons.

Some of the reasons for this study as highlighted in literature and based on current trends in cognitive radio research are as follows:

1. Limited spectrum availability due to saturated bands with simultaneous underutilization of spectrum by certain primary user , random or stochastic nature of primary user presence on allocated frequency spectrum which leads to opportunistic transmission on unused spectrum by secondary user(Ÿucek and Arslan, 2007). The uncertain nature of this exploitation leads to algorithms that are probability based.

2. Interference issues, presence of noise in the spectrum and false alarm rate due to imperfect sensing.
3. The above reasons create uncertainty in the spectrum sensing by cognitive radio which must be reduced sufficiently to allow more effective use of cognitive radio technology. This uncertainty reduction in the cognitive radio sensing operations has inspired the current research.

While in most of the literature, an underlying base scheme for solving the problem of spectrum sensing is made to consist of:

1. A spectrum estimation methodology or model for sensing the primary user parameters of interest which will be used to obtain PU utilization information on the spectrum. Such a parameter to be used for the estimation might be the frequency or RF transmission power, energy.

2. Which when combined with the sensed data and analyzed with a statistical measure or heuristic is used in decision making. This decision engine or algorithm must be able to reach a sufficiently accurate and timely assessment of the spectrum characteristics in terms of primary user presence or absence and availability of holes to be exploited by secondary user.

The motivation for this study is to attempt the implementation of a fuzzy logic and monte-carlo based cognitive radio model to solve the problem of detection in the presence of uncertainty and also build a prototype system to test our designed and simulated hypothesis.

## 1.7 Problem Definition

Spectrum sensing comes with its own attendant issues such as interference on the services of primary users caused by opportunistic probing of primary user spectrum bands by the secondary users, the non-availability of intelligent(accurate and timely) algorithms for detection, test and analysis of sensed data.These have a bearing on reducing the level of false alarm rate to a reasonable degree and making the sensing by the secondary user non-intrusive. These are the major challenges of the cognitive radio sensing process.

Furthermore, radio communications by licensed primary user within the spectrum band is a random process andits stochastic nature, makes for a certain degree of “uncertainty”; this is the chief culprit in efficient utilization of the cognitive radio. Analyzing this uncertainty using

relevant metric like probability of false-alarm ($P_{fa}$) and probability of detection ($P_d$) in addition to setting of the accurate detection threshold will be used to address the uncertainty problem in the sensing process of the cognitive radio.

## I.8 Aim and Objectives

The aim of this research is to estimate the detection thresholds for spectrum sensing in cognitive radio using Adaptive Fuzzy Inference System and MonteCarlo techniques to enhance spectrum sensing performance by reducing the uncertainty region caused by noise.

The objectives are to:

i. Estimate detection threshold for non-cooperative spectrum sensing;
ii. Estimate detection threshold for cooperative spectrum sensing
iii. Validate the estimated detection threshold values for the non-cooperative spectrum sensing system.

## 1.9 Research Methodology

The methodology set out shows the sequence of activities carried out in the implementation of the overall Research work. These are:

1) Developing a model for Non-Cooperative spectrum sensing
2) Simulating theNon-Cooperative model using (a) Monte-Carlo algorithm and (b) ANFIS algorithm for the determination of threshold value for spectrum sensing
3) Developing a model for Cooperative sensing
4) Simulating the Cooperative model in using (a) Monte-Carlo and (b) Fuzzy Logic algorithms with a view to determining threshold values for spectrum sensing.

5) Comparison of (2) and (4) above

6) Experimental validation of the threshold for non-cooperative sensing.

## 1.10 Significance of the Study

Despite the fact that a series of studies have been carried out on the spectrum sensing to detect different primary radio signals in a cognitive radio environment or network, none of these has been able to detect all forms of radio signals due to fundamental limitations of the central features employed in developing those detection methods. Preliminary investigations into a series of earlier-developed detection methods reveal that there are so many challenges associated with the determination of detection threshold due to uncertainty with regards to probabilities of miss detection and false alarm. Based on this observation, in order to improve the spectrum sensing performance this research made the following significant contributions:

i. Development of non-cooperative and cooperative simulation models in MATLAB'S Simulink from suitable algorithms employing energy detectors for the sensing block. These models could provide a platform for studying and understanding of operational principles of cognitive radio. A detection threshold of -64dB was obtained for non-cooperative sensing and a detection threshold value of -39dB was obtained for the cooperative sensing. This result shows the superiority of cooperative sensing over non-cooperative.

ii. The research explored the implementation of two estimation techniques namely; Adaptive Neural Fuzzy Inference System (ANFIS) and Monte Carlo for the detection of optimum detection threshold in both models. A detection threshold seed value of 25dB was improved to 12.875dB (51.5%) using Monte Carlo techniques. While the estimated

value of 14.3dB (57.2%) was obtained using ANFIS. Hence, ANFIS performed better than Monte Carlo technique.

iii. The research exploited the use of commercially acquired energy detection (SPECTRAN X) and the microwave link facilities at the ETEP laboratory to carry out the validation experiments. Indoor and outdoor measurements were conducted at 900MHz and 1800MHz. The detection threshold of -64dBm obtained from the non-cooperative simulation model was validated and a value of -71dBm was obtained using the hardware energy detector. Hence, the analytical and the simulation results obtained in this research provided significant improvement in the probability of detection of primary user signals.

## 1.11 Scope of Work

This research work covers the estimation of the detection thresholds for spectrum sensing using Adaptive Fuzzy Inference System (ANFIS) and Monte Carlo technique in cognitive radio to enhance efficient utilization of radio spectrum.

## 1.12 Thesis Outline

The report of the thesis is organized into five chapters. Chapter One is the introductory chapter which contains the aim and objective of the work, motivation, problem definition, methodology and scope of the work. Chapter Two contains the literature review. Chapter Three is on Materials and Methods. It contains the detailed design concept and working principles of cognitive radio networks including non-cooperative and cooperative spectrum sensing models. Chapter Four is on Results and Discussions. It contains details of the field tests to evaluate the performance of the prototype in terms primary user's detection and validation of the model developed. It also

contains the results and their discussions and analysis. Conclusion and recommendations are contained in Chapter Five. References and Appendices presented at the end of the report.

# CHAPTER TWO

# LITERATURE REVIEW

## 2.1 Introduction

This chapter covers thereview of fundamental concepts relevant to the research and the review of related works.

## 2.2 Review of Fundamental Concepts

Cognitive radio or system that senses its operational electromagnetic environment and autonomously adjusts its radio operating parameters to modify system operations, such as maximize throughput, mitigate interference, facilitate interoperability and access secondary markets(Federal Communication Commission, 2005). In other words,cognitive radio is a generic term used to describe a radio that is aware of the environment around it and can adapt its transmissions according to the interference it sees. Cognitive radios can recognize the available systems around them and adjust their frequencies, waveforms and protocols to access those systems efficiently. Conceptually, cognitive radios include multiple domains knowledge, model-based reasoning and negotiation(Jafar and Srinivasa, 2007). The knowledge and reasoning can include all aspects of any radio etiquette such as radio frequency bands, air interfaces, protocols, and spatial as well as temporal patterns that moderate the use of the radio spectrum.

### 2.2.1 Operation of Cognitive Radio

The network architecture of cognitive radio varies greatly depending on the desired applications(Hossain and Bhargava, 2007). Cognitive radio network can be centralized where a central node coordinates spectrum sensing, allocation and management of all serviced nodes

(Fig. 2.1a). On the other hand, nodes in a distributed cognitive radio network communicate with each other in an ad-hoc manner to coordinate cognitive tasks (Fig. 2.1b). Typically, a centralized network simplifies the communication and computation load of each end node, but requires more infrastructures and costs(Cavalcanti, et al., 2008). On the other hand, distributed network is more structurally flexible and requires little infrastructure at the expense of increased complexity(Hossain and Bhargava, 2007). Regardless of architecture, cognitive radio must be flexible in detecting changes in primary user activity, hence the cognitive tasks must be performed periodically(Yücek and Arslan, 2009). Collectively, the cognitive tasks form a 'cognitive cycle' to ensure the integrity of cognitive radio network and protection of primary user activities. The sensing cycle discussed in Chapter One is part of the cognitive cycle that focuses on the spectrum sensing and cognitive intelligence aspect of cognitive radio. While cognitive tasks may vary between implementation and applications, the cognitive cycle consists of four core operations: spectrum sensing, spectrum analysis, spectrum decision and data transmission. The research in this thesis focuses on:

i. Spectrum Centralized: end users communicate through the central node.

ii. Spectrum Distributed: end users communicate directly with each other.

Therefore, the following overview of these tasks will present the context of spectrum sensing within the whole operation of cognitive radio.

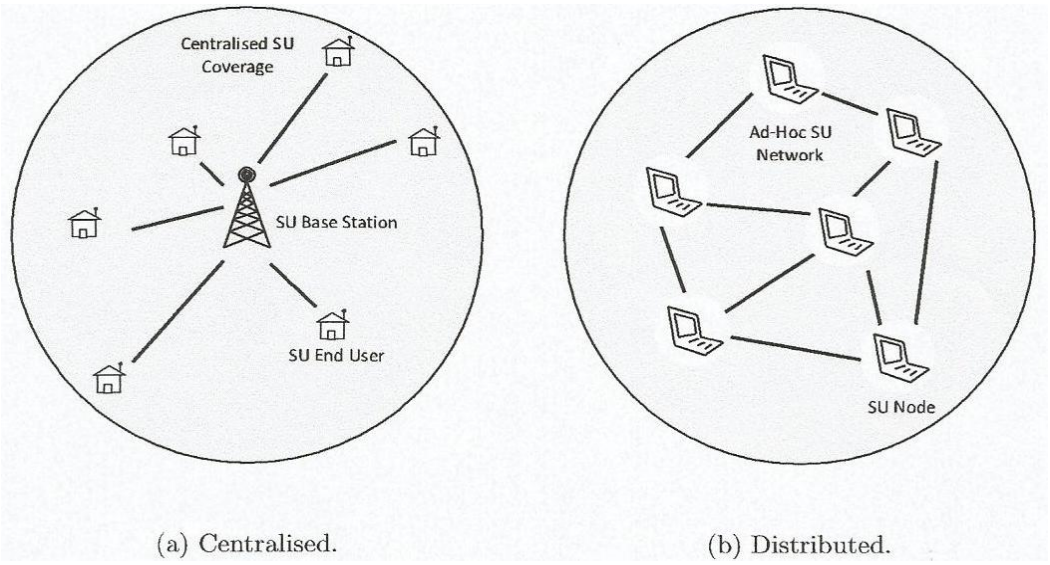



Figure 2.1: Architecture of Centralized vs. Distributed Cognitive Radio Network.

Spectrum sensing is the task where the secondary user senses the spectrum to detect the presence of primary user signals and identify empty spectrum spaces(Yücek and Arslan, 2009). Sensing can be performed in-band to detect primary user on the spectral channel currently used by the secondary user, or out-of-band to identify other possible spectrum spaces beside the channel currently in use(Ghasemi and Sousa, 2007). Out of band sensing is beneficial in locating possible back-up channels in case in band sensing failed, or assisting other secondary user in detecting a usable channel. Sequential search senses single channels iteratively while parallel search senses multiple channels simultaneously(Lee et al., 2009). Spectrum sensing is the main focus of this research, therefore an in-depth review will be presented in the following section. Once spectrum spaces are detected, the secondary user enters next task of spectrum analysis.

Spectrum analysis is the task where the secondary user analyses the detected spectrum space and determine whether these spaces are suitable for the desired secondary user operation(Hossain and Bhargava, 2007). Depending on the spectrum frequency, transmission and propagation

characteristics of certain channels may not be able to support the desired operation, such as unsatisfactory quality of service (QoS), insufficient coverage, etc.

Furthermore, if the primary user traffic model has been established, it is possible that primary user for particular spectrum spaces are more likely to return in the near future and is best avoided. Once the secondary user has analyzed which spectrum spaces are more suitable, it then must decide on a space to use.

Spectrum decision decides on which spectrum space to continue communication and will affect all nodes within the secondary user network (Hossain and Bhargava, 2007). The decision may instruct the nodes to remain on the current channel if primary user is not detected, or immediately relocate to the next backup channel if primary user is present. If the secondary user network is changing to a different channel, then all secondary user nodes must know which channel to change to. If particular nodes cannot be serviced after the channel change, they must also know which back-up service to switch to. Spectrum decision is best performed by combining spectrum analysis results from all nodes within the secondary user network, an example illustrated in Figure 2.3(Zhang et al., 2009). The decision collaboration can be either through decision fusion or data fusion. For decision fusion, secondary user nodes provide a hard decision on which channel they detected to be empty. For data fusion, secondary user nodes provide a soft metric, such as the test statistic of the sensing detector, to be collaboratively analyzed. Fusion and decision can be made at the coordinating node of a centralized network, or by individual nodes in a distributed network(Sarvanko et al., 2008). Once all nodes within the networks agree on an operating channel, they can then begin or continue data transmission.

Data transmission is where the secondary user transmits the communication data. The secondary user must adapt its transmission parameters such as radio hardware and software algorithms to suit the propagation characteristics of different primary user channels. Longer data transmission period increases the overall throughput of the secondary user network and the spectrum utilization is more efficient(Ghasemi and Sousa, 2007). Furthermore, achieving greater bandwidth can maintain higher QoS. Secondary user nodes are typically monetarily charged based on the duration or amount of data transfer. Therefore, as the network operator, it is important to maximize data transmission while maintaining the efficiency of secondary user network and protecting primary user activity.

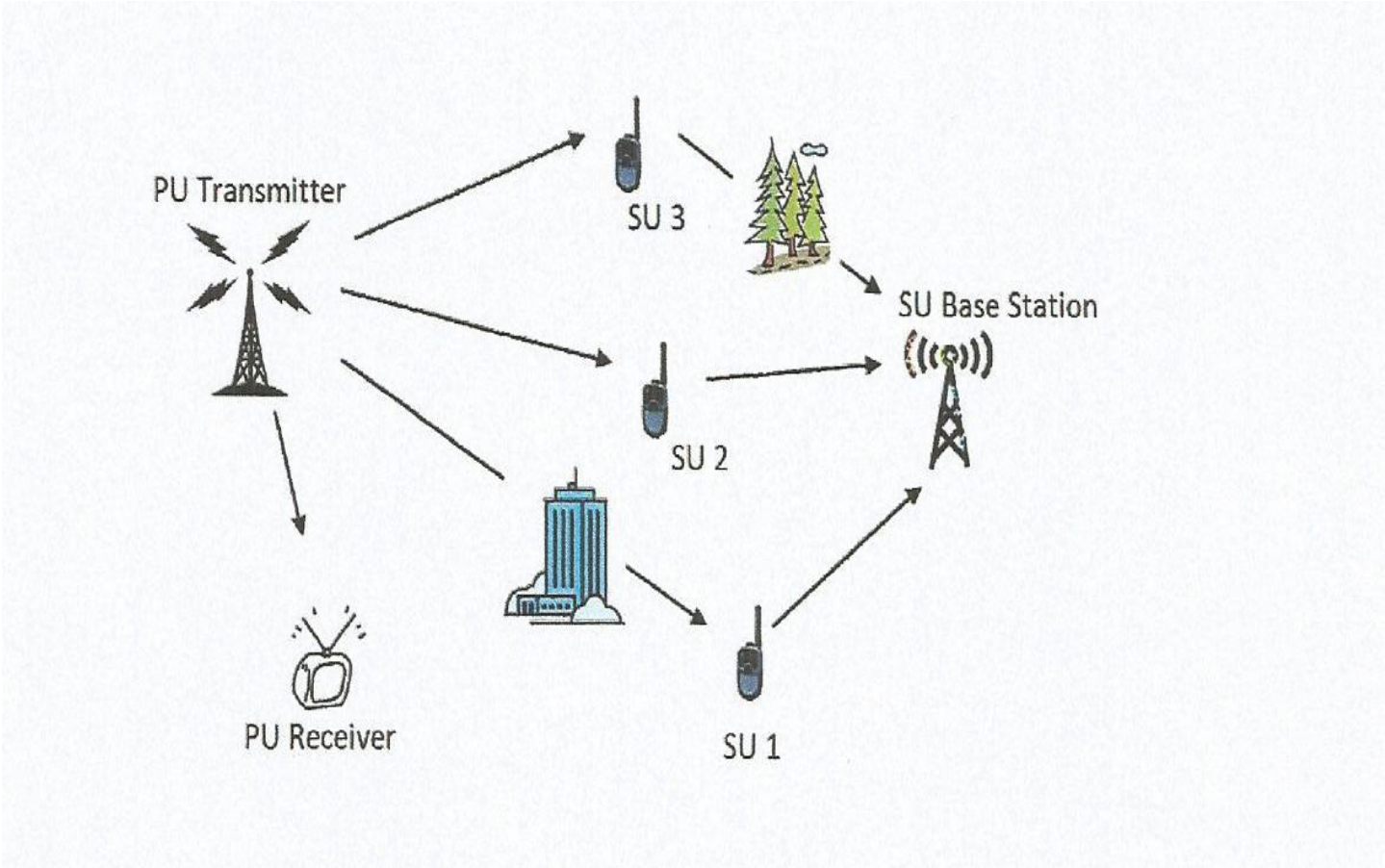



Figure 2.2: Cooperative Spectrum Sensing to Improve Global Sensing Performance (Zhang et al., 2009)

### 2.2.2 Area of Application of Cognitive Radio

Technology is futile without its application. Dynamic Spectrum Access (DSA) has been the most recognized application of cognitive radio. Dynamic spectrum access is a decentralized approach to spectrum allocation policy that allows a communication device to operate on any unused spectrum. In this new paradigm, unlicensed or secondary users can opportunistically operate in an unused licensed spectrum, as long it does not cause interference to the licensed or primary users, thereby increasing the efficiency of spectrum utilization.

As shown in Figure 2.4, dynamic spectrum access strategies can be classified into three basic models: The dynamic exclusive-use model, Open sharing model, which is also known as the spectrum common model and Hierarchical access model.

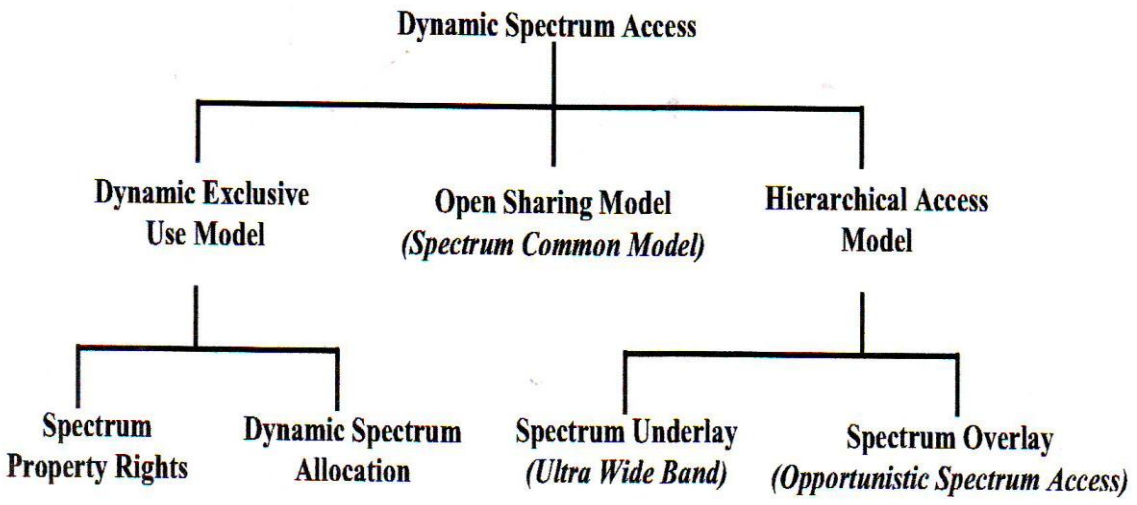



Figure 2.3: Taxonomy of Dynamic Spectrum Access (Zhao and Swami, 2007)

### 2.2.3 Dynamic Exclusive Use Model

This model maintains the basic structure of the current spectrum allocation policy, whereby spectrum bands are licensed to users for exclusive use. This method of spectrum allocation policy has led to many successful applications, like broadcasting and cellular, which can be cited as evidence by the proponents of spectrum property rights (Ileri and Mandayam, 2008). However, the method has also been criticized as inefficient in the overall use of spectrum. For instance, a report presenting statistics regarding spectrum utilization show that only about 13% of the allocated spectrums were utilized(McHenry et al., 2004). In addition to the problem of underutilization characterizing the current fixed spectrum allocation policy, the inherent political inefficiency of government controllers also plays a role in the poor effectiveness of the current allocation policy. To correct this problem, the proposed idea is to introduce flexibility to spectrum access. Two approaches have been proposed under this model. The first approach is spectrum property rights (Hatfield and Weiser, 2005). As reported by(Zhao and Swami, 2007), this approach allows licensees to sell and trade spectrum, and to freely choose technology.

The second approach is dynamic spectrum allocation (Xu et al., 2009), which was brought about by the European Drive project. Its aim, as reported by(Zhao and Swami, 2007), was to improve spectrum efficiency through dynamic spectrum assignment by exploiting the spatial and temporal traffic statistics of different services. Similar to the current fixed spectrum allocation policy, this strategy allocates, at a given time and region, a portion of the spectrum to a radio access network for its exclusive use. Based on an exclusive-use model, it has been established that both spectrum property rights and dynamic spectrum allocation cannot eliminate the current problem of spectrum underutilization with increasing wireless traffic(Zhao and Swami, 2007).

### 2.2.4 Open Sharing Model

The open sharing model, which is also referred to as spectrum commons model (Lehr and Crowcroft, 2005), puts all users on equal footing(Zhao and Swami, 2007), provided that users obey specific rules similar to current unlicensed Industrial, Scientific and Medical (ISM) radio bands. According to(Zhao and Swami, 2007), advocates of this model draw support from the phenomenal success of wireless services operating in the current unlicensed ISM radio band, like Wireless Fidelity (Wi-Fi).

### 2.2.5 Hierarchical Access Model

Under this radio spectrum access model, the radio spectrum is viewed as having a primary or licensed user, as well as a secondary or unlicensed user. The model is considered a hybrid of the other two models previously discussed. It is fundamentally different from the other two models in both technical and regulatory aspects. The fundamental idea of the model is to open licensed spectrum to unlicensed users, but with Interference Avoidance (IA) to the licensed users. Based on this concept, two different approaches to radio spectrum sharing between licensed and unlicensed users have been considered, namely spectrum underlay and spectrum overlay.

#### a. Spectrum Underlay

The spectrum underlay technique is a spectrum access system whereby signals with a very low spectral power density can coexist as secondary users with the primary users of the frequency bands. The technique imposes severe restraints on the transmission power of secondary users so that they operate below the noise floor of primary users. An Ultra Wide Band (UWB) transmitter that uses this technology usually spreads its transmitted signal over a wide frequency band in order to achieve short-range high data rate with extremely low transmission power. The detection

component for primary users is not required in spectrum underlay, since the energy of the transmission signals by the secondary users are spread over a very wide frequency range, thus only negligibly increasing the interference temperature(Berthold et al., 2008).

However, according to Khoshkholgh*et al*., (2010), satisfying the interference constraint is technically challenging, since the interference power constraints associated with underlay access strategy only allows short-range communications. In addition, in underlay spectrum sharing, the secondary user must satisfy the interference threshold condition even when the primary user is idle. During this idle period, fulfilling the interference constraint limits the transmission power of the secondary user, hence reducing its achievable transmission capability. More so, in underlay access strategy, the achievable capability of the secondary user is further reduced during the busy periods of the primary user because of the interference imposed by the primary user's activity at the secondary user's receiver. In order to tackle these aforementioned issues, overlay spectrum sharing was proposed.

**b. Spectrum Overlay**

The spectrum overlay technique is a spectrum access system whereby a secondary user uses a spectrum band from a primary user only when it is free. Unlike the underlay system, which hides the transmission signal under the noise level of the primary user, overlay system must have the capability of dynamic spectrum access, as they must work dynamically around the licensed system's allocation. This technique is based on a detection and interference avoidance mechanism. This mechanism requires the secondary user to sense the frequency spectrum and thus, if a primary user is active, the channel will not be used.

The spectrum overlay access strategy was first envisioned by (Mitola III and Maguire Jr, 1999)under the term spectrum pooling. It was later investigated by the Defense Advanced ResearchProjects Agency next Generation (DARPA XG) program under the term OSA(Zhao and Swami, 2007). Unlike the spectrum underlay, this radio spectrum access strategy does not impose severe restrictions on the transmission power of secondary users, but rather there are restrictions on when and where secondary users can transmit.

Spectrum overlay, according to Fuji and Suzuki (2005), can be applied in either temporal or spatial domain. When using the radio spectrum in temporal domain, secondary users aim to exploit temporal spectrum opportunities resulting from the busy traffic of primary users. On the other hand, when the radio spectrum is used in spatial domain, secondary users aim to exploit frequency bands that are not used by primary users in a particular geographic area. This unused portion of the licensed spectrum is known as 'white space' or 'spectrum hole'. (Haykin, 2005) defined it as, "a band of frequencies assigned to a primary user but at a particulartime and specific geographic location the band is not being utilized by that user". The special radios that are enablers of Opportunistic Spectrum Access (OSA) or dynamic spectrum access that can use spectrum holes in an opportunistic fashion are known as cognitive radios.

### 2.2.6 Spectrum Sensing Techniques

Spectrum sensing is a key element in cognitive radio communications, as it should be firstly performed before allowing unlicensed users to access an unused licensed spectrum. The essence of spectrum sensing are two-fold: one to ensure cognitive radio or secondary user does not cause interference to a primary user and two, to assist cognitive radio or secondary user to identify and exploit the spectrum holes for the required quality of service(Popoola and Van Olst, 2011). This

sensing operation is a binary hypothesis-testing problem. The goal of spectrum sensing is to decide between the following two hypotheses:

$$H_0: x(t) = n(t) \quad (2.1)$$

$$H_1: x(t) = s(t) + n(t) \quad (2.2)$$

where, $H_0$denotes the absence of the primary user, $H_1$denotes the presence of the primary user, $x(t)$ is the received signal at the cognitive radio, $s(t)$ is the transmitted signal from the primary transmitter and $n(t)$ is the Additive White Gaussian Noise (AWGN). The determination of the two hypotheses is called spectrum sensing.

Generally speaking, spectrum sensing techniques are classified into either non-cooperative or cooperative. However, from the perspective of signal detection, sensing techniques are classified into four broad categories(Akyildiz et al., 2011). The first two broad categories are coherent and non-coherent detection techniques. In coherent detection, *a priori* knowledge of the primary users' signals is required, which will be compared with the received signal to coherently detect the primary signal. In non-coherent detection, no *apriori* knowledge of primary users' signals is required for coherent detection. The last two broad categories, which are based on the bandwidth of the spectrum of interest for sensing, are narrowband and wideband detection techniques. The classification of sensing techniques is shown in Figure 2.4.

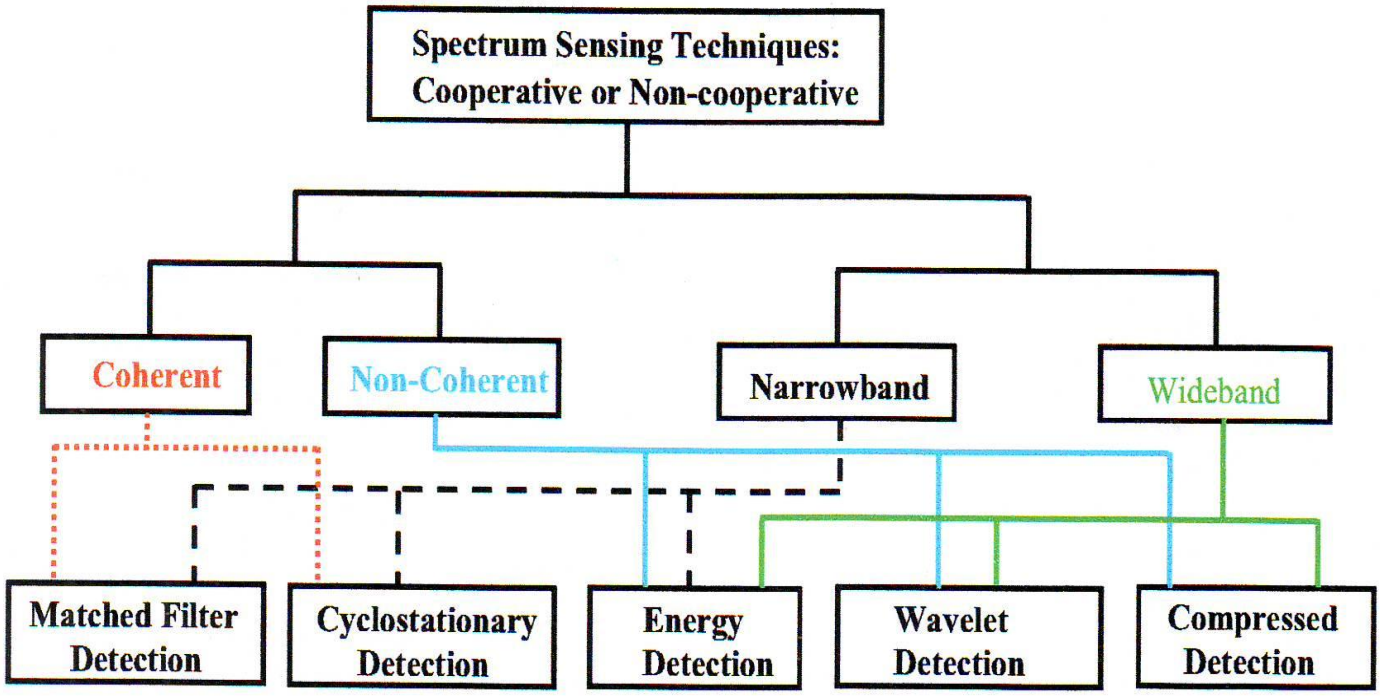



Figure 2.4: Classification of Spectrum Sensing Techniques (Akyildz et al., 2011)

**Parameter Definition for Spectrum Sensing:**

H0: hypothesis that PU is absent and only noise present

$H_1$: hypothesis that PU is present plus noise present

Y[n]: the received signal

W[n]: the received noise energy

X[n]: received energy of primary user

$P_{md}$: probability of missed detection

$P_d$: probability of detection

$P_{fa}$: probability of false alarm

$T_i$: test statistic

$\Lambda$: threshold setting

$\sigma_w^2$: noise covariance

$\sigma_x^2$: $signalcovariance$

From first principles, the spectrum sensing problem can be formulated mathematically as a Binary hypothesis test (BHT) problem with the following two hypotheses

$$H_0 : y[n] = w[n] n = 1,2, \dots, N \quad (2.3)$$

$$H_1 : y[n] = x[n] + w[n] n = 1,2, \dots, N \quad (2.4)$$

Where $H_0$ is a null hypothesis which states that the received signal y[n] corresponds to noise samples w[n] only; meaning no PU signal in the sensed spectrum band.

$H_1$indicates the contrary; that a licensed user is present, making the received signal

$$y[n] = x[n] + w[n] \quad (2.5)$$

Ideally spectrum detection would mean hypothesis H1 for PU present and hypothesis H0 otherwise. But due to mistakes in spectrum sensing and the stochastic nature of spectrum utilization in practice, some new terms will now be defined to handle this drawback in mistaken detection. The terms are missed detection (md) and false alarms(fa)

Based on these definitions, the performance of any spectrum algorithms can be summarized by means of 2 probabilities:

Probability of missed detection given by

$$P_{md} = \mathrm{P}(H_0|H_1) \tag{2.6}$$

or complimentarily, the probability of detection

$$P_d = \mathrm{P}(H_0|H_1) = 1 - P_{md} \tag{2.7}$$

And probability of false alarm

$$P_{fa} = \mathrm{P}(H_0|H_1) \tag{2.8}$$

In practice, large Pd and low Pfa values are desirable with some tradeoff necessary.

**Spectrum Sensing**

There are two techniques for spectrum sensing such as:

a. Non-cooperative Spectrum Sensing Method
b. Cooperative Spectrum Sensing Method

In non-cooperative spectrum sensing method, an individual cognitive radio device or secondary user does the non-cooperative spectrum sensing method locally. Each secondary user will sense the spectrum channel to detect the presence or absence of a primary user. Since the sensing method does not involve spectrum sensing results' sharing, as well as final decision making, energy consumption is very low compared to cooperative spectrum sensing where users consume significant energy because of heavy communication. However, the detection accuracy of the

method is very low compared to the cooperative method. This is because poor channel conditions do affect single user spectrum sensing results (Lee and Wolf).

Unlike non-cooperative spectrum sensing methods, where an individual cognitive radio surveys the spectrum to gather information, the cooperative spectrum sensing method usually involves two or more cognitive radios working together. In this spectrum sensing method, an individual cognitive radio or secondary user will perform local spectrum sensing independently and then makes a decision. Thereafter, all the cognitive users will forward their decisions to a common receiver or Master Node (MN). The common receiver will combine these decisions and makes a final decision to infer the presence or absence of the primary user in the observed frequency band.

In general, activities in cooperative spectrum sensing can be summarized in three basic steps as follows:

1) **Step I:** Each cognitive radio performs its own local spectrum sensing measurement independently and then makes a binary decision on whether the primary user is present or not.
2) **Step II:** All the cognitive radios forward their decisions to the master node (also called the common receiver).
3) **Step III:** The master node aggregates the cognitive radios binary decisions received using an "OR" logic and finally makes a decision as to either infer the presence or absence of the primary user.

The primary idea of cooperative spectrum sensing is to enhance the spectrum sensing performance by exploiting the spatial diversity in the observations of spatially located secondary

users. Since it is unlikely that all spatially distributed secondary users in a cognitive radio environment will concurrently experience the fading or receiver uncertainty problem. Hence, when users collaborate and share the spectrum sensing results among themselves, the combined cooperative decision derived from the spatially collected observations can overcome the deficiency of individual observation of each secondary user. This is why the cooperative spectrum sensing method has been observed as an effective method to combat fading and shadowing, as well as mitigating the receiver-uncertainty problem in a cognitive radio environment (Akyildiz et al., 2011, Mishra et al., 2006).

Architecturally, cooperative spectrum sensing is categorized into three classes based on how cooperating cognitive radio users share the sensing information or data in the network (Akyildiz et al., 2011, Popoola and Van Olst, 2011). The classes are namely centralized, distributed and relay-assisted. The three classes of cooperative spectrum sensing illustrated in Figure 2.5 are briefly discussed in the following subsections.

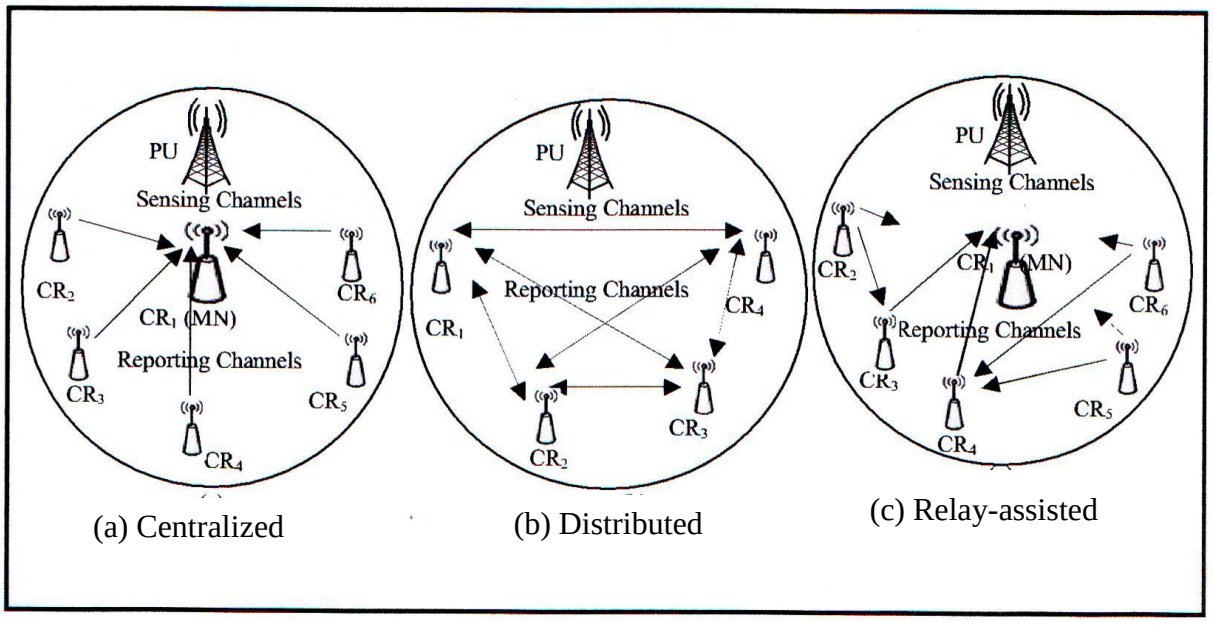



Figure 2.5: Classification of Cooperative Sensing (Popoola and Van Olst 2011)

### a. Centralized Cooperative Spectrum Sensing

In centralized cooperative spectrum sensing, a central identity called the master node or fusion centre controls the three steps involved in cooperative sensing described above. In Figure 2.5(a), CR1 is the master node and CR2-CR6 are the cooperative cognitive radio users performing local sensing and reporting the results back to CR1. CR1 or master node collects sensing information from CR2-CR6, identifies unused spectrum and broadcasts the information to CR2-CR6.

### b. Distributed Cooperative Spectrum Sensing

Unlike centralized cooperative sensing, distributed cooperative sensing, as shown in Figure 2.5(b), does not rely on a master node for making the final cooperative decision. In this cooperative sensing, after local sensing, the cognitive nodes CR1-CR4 share the local sensing results amongst each other, but they make their own decisions as to which part of the spectrum they can use. If there is no clear decision after this initial process, cognitive radio users send their combined results to other users and repeat the sensing process until the algorithm is converged and a decision is reached (Akyildiz et al., 2011). The disadvantage of distributed cooperative sensing is a decision delay possibility because several iterations may be involved to reach a unanimous cooperative decision.

### c. Relay-Assisted Cooperative Spectrum Sensing

The third cooperative spectrum-sensing scheme is relay-assisted. It was proposed to overcome the imperfection in both sensing and reporting channels, so that a CR user which experiences a weak sensing channel and a strong reporting channel and a CR which experiences a strong sensing channel and a weak reporting channel, can complement and collaborate with each other to improve the overall performance of the cooperative sensing. For instance in Figure 2.5(c),

CR2, CR5 and CR6 that observe strong primary users' signals will observe a weak reporting channel. CR3 and CR4 that have strong reporting channels can serve as relays to the prior CRs and assist them in forwarding their sensing results to master node. In Figure 2.5(c), reporting channels from CR3 and CR4 report to master node and are known as relay channels (Akyildiz et al., 2011).

Cooperative spectrum sensing draws inspiration from the inability of a single secondary user to correctly infer the presence or absence of primary user on the channel. The inference is parameterized by two metrics: probability of false alarm, which denotes the probability of a cognitive radio user declaring that a primary user is present when the spectrum is actually free, and probability of missed detection, which denotes the probability of a cognitive radio user declaring that a primary user is absent when the spectrum is actually occupied by the primary user. Since a miss in the detection will cause the interference with the primary user and a false alarm will reduce the spectral efficiency, it is usually required for optimal detection performance that the probability of detection is maximized subject to the constraint of the probability of false alarm. These metrics which will be used in characterizing the detection uncertainty are made the more important as critical measures of the cooperative spectrum sensing scheme when we include the nature and effect of the radio operating environment such as multipath, shadowing and fading as depicted in Figure 2.6.

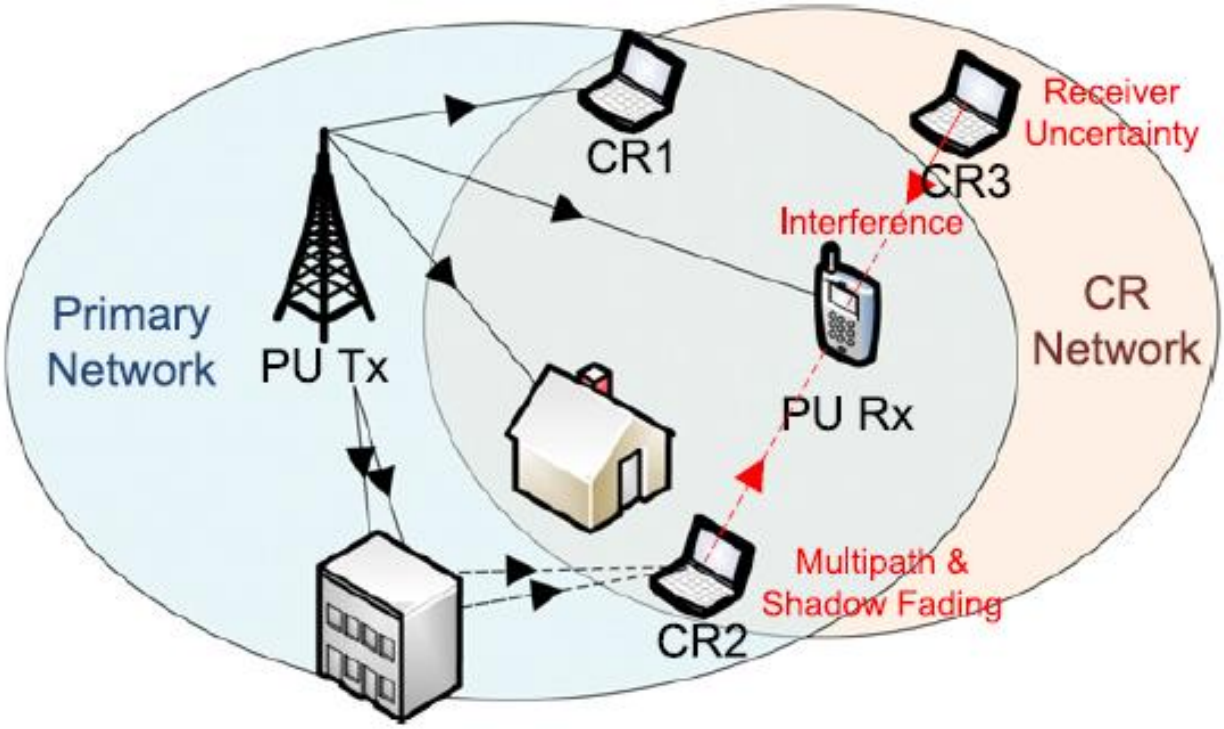



Figure 2.6: Receiver Uncertainty and Multipath/Shadow Fading (Akyildiz, 2011)

Many factors in practice such as multipath fading, shadowing, and the receiver uncertainty problem may significantly compromise the detection performance in spectrum sensing, Akyildiz et al., (2011). An illustration of multipath fading, shadowing and receiver uncertainty is given in Figure 2.6. In the figure, CR1 and CR2 are located inside the transmission range of primary transmitter (PU TX) while CR3 is outside the range. Due to multiple attenuated copies of the Primary User signal and the blocking of a house, CR2 experiences multipath and shadow fading such that the PU's signal may not be correctly detected. Moreover, CR3 suffers from the receiver uncertainty problem because it is unaware of the Primary User's transmission and the existence of primary receiver (PU RX). As a result, the transmission from CR3 may interfere with the reception at PU RX. However, due to spatial diversity, it is unlikely for all spatially distributed Cognitive Radio users in a Cognitive Radio network to concurrently experience the fading or

receiver uncertainty problem, Akyildiz et al., (2011). If Cognitive Radio users, most of which observe a strong Primary User signal like CR1 in the figure, can cooperate and share the sensing results with other users, the combined cooperative decision derived from the spatially collected observations can overcome the deficiency of individual observations at each Cognitive Radio user. Thus, the overall detection performance can be greatly improved. This is why cooperativespectrum sensing (simply called cooperative sensing thereafter) is an attractive and effective approach to combat multipath fading and shadowing and mitigate the receiver uncertainty problem. The main idea of cooperative sensing is to enhance the sensing performance by exploiting the spatial diversity in the observations of spatially located Cognitive Radio users. By cooperation, Cognitive Radio users can share their sensing information for making a combined decision more accurate than the individual decisions.

This sharing is coordinated in a fusion center which employs any of several chosen methods to combine local sensing data for hypothesis testing. In general, the sensing results reported to the fusion center can be combined in three different ways, arranged here in descending order of demanding control channel bandwidth (Akyildiz, 2011)

1. Soft combining: cognitive radio users can transmit the entire local sensing samples or the complete local test statistics for soft decision
2. Quantized soft combining: cognitive radio users can quantize the local results and send only the quantized data for onward soft computing to alleviate control overhead
3. Hard combining: cognitive radio users make a local decision and transmit the one-bit decision for hard combining. The third method was explored in this work for its least overhead demands even though this happens at the expense of some degraded performance such as noise uncertainty.

### 2.2.7 Background to Fusion Center Operation

A discussion of the role of the fusion center is necessary to understand the decision making mechanism of the cooperative cognitive radio scheme.

The fusion center collects from all the cooperating cognitive radios their individual sensing decisions and analyzes them. The analysis is based on the laid down decision rule algorithm implemented for the fusion of all the secondary user binary local decisions. The established rules for decision combination are

(i) "AND" rule

(ii) "OR" rule

(iii) Majority rule

(i) The "AND" rule works by analyzing the crisp input decisions and deciding on a global decision by everyone ("ALL") of the cognitive radios registering the same local decision. The implication of this for secondary spectrum users will involve better efficiency in primary user detection with an accompanying reduction in the possibility of interference due to improper sensing. Improper sensing could result from a premature de-allocation of a secondary user when primary users is still absent from its original channel slot. The "AND" rule is a strict condition for deciding primary user behavior. However this rule does not come without its drawback. From the utilization of the "AND" rule, issues were observed such as the computation overhead attached to verifying through repeated checking (in the algorithm and code this is represented by a "for-loop" or compound "IF" condition which is a major

speed impediment in code execution) by the fusion center of the satisfying condition for “ALL” being met by each cognitive user. The algorithm for implementation of the “AND” rule is given by:

(ii) The “IF” rule works by analyzing the crisp input decisions and deciding on a global decision by anyone (“ANY”) of the cognitive radios registering the presence of the primary user. The implication of this for secondary spectrum users will involve reaching a “quicker” global decision and fast allocation or de-allocation based on the results reached. The speed efficiency in primary user detection with an accompanying reduction in computation overhead comes with its own cost. This is the possibility of making a false decision of primary user absence thus creating opportunity for interference due to improper sensing. Improper sensing here meaning the “OR” rule is a loose rule and can’t be as trusted as in the case of the “AND” rule. The implication here could mean, missing out on potential returning primary users thereby causing interference from continuous transmissions by secondary users. The implication here is late detection and missed opportunities or false alarm. This report and the experiments performed did not use this technique as it was found to be insufficient and prone to the most error in primary user detection decision even though it required least computation resources.

(iii) The majority rule is based on the result of individual cognitive radio collated at the fusion center. The resulting vote works by certain laid down rules which do a selection of a certain number of users from the total cognitive users voting at the fusion center. Some schemes implementing the majority rule use loose conditions such as detecting primary user presence by voting that if more than half of the

cognitive users report primary user present then the spectrum is occupied. Another scheme also uses a combinational "k out of N majority rule" to set the number of votes that count as sufficient for determining the decision status of the primary user. This counting is implemented in the software which makes a quick count and reporting of the local results at each cognitive user to generate a global result for use in final decision making.

### 2.2.8 Decision Analysis at the Fusion Center in Cooperative Spectrum sensing

When binary local decisions are reported to the Fusion Center, it is convenient to apply linear fusion rules to obtain the cooperative decision. The commonly used fusion rules are AND, OR, and majority rules. (Akyildiz, 2011)

Let $u_i$ be the local decision of cognitive radio user i and u be the cooperative decision made by the Fusion Center,

$u_i, u \in \{0, 1\}$

Where ''1'' and ''0'' indicate a PU's presence ($H_1$) and absence ($H_0$), respectively.

The AND rule refers to the Fusion Center determining that

$u = 1$ if $u_i = 1, \forall i$.

Similarly, the OR rule refers to

u = 1 if ui= 1, for any i.

The majority rule requires at least a half of the cognitive radio users to report ''1''.

These simple fusion rules can be generalized to the k out of the N rule. Under this rule, the Fusion Center declares $H_1$ ($H_1$) if k out of N cognitive radio users report ‘‘1’’. The false alarm and detection probabilities for cooperative sensing under this rule for data fusion are given by, (Akyildiz, 2011):

$$\mathrm{Q_f} = \sum_{l=k}^{N} \binom{N}{l} P_{\mathrm{f}}^{l} \left(1 - P_f\right)^{\mathrm{N-l}} \tag{2.9}$$

$$\mathrm{Q_d} = \sum_{l=k}^{N} \binom{N}{l} P_{\mathrm{d}}^{l} (1 - P_d)^{\mathrm{N-l}} \tag{2.10}$$

The equations (2.25) and (2.26) express a combinatorial relationship of selecting k out of N cognitive radios in estimating the probability of false alarm and missed detection in a cooperative cognitive radio setting. These two parameters are also used for characterizing the radio operation in terms of the optimum numbers of cognitive radios for achieving a minimum possible error tolerance while choosing the optimal detection threshold.

In effect the statistic $H_0$ means allowing the secondary users to transmit on the white space while $H_1$ means continuous transmission by primary user indicating non-existence of white space.

### 2.2.9 Detection Methods for Spectrum Sensing

Irrespective of the type of spectrum sensing technique or method used, either non-cooperative or cooperative, every secondary user needs to first detect the spectrum status using one specific detection method. Five of most commonly used detection methods in spectrum sensing in a cognitive radio environment or network were considered. Each detection method is briefly reviewed with emphasis on their merit and demerit, as follows:

### a. Matched Filter Detection

Matched filter detection is an optimal detection method (Cabric et al., 2004) normally used in a situation where a secondary user has *a* prioriknowledge of the primary user's signal. The matched filter is achieved by correlating a known signal or template with an unknown signal in order to detect the presence of the template in the unknown signal.

The primary advantage of the matched filter detection is that it requires less time to achieve high processing gain due to coherent detection. However, the use of matched filter detection is currently limited because no pre-knowledge of the primary user's signal is expected to be known by the cognitive radios or secondary users. This disadvantage and the need for cognitive radios or secondary users to have receivers for all signal types make matched filter detection method uneconomical to implement(Letaief and Zhang 2007).

### b. Energy Detection

The energy detector based approach, also called radiometry or periodogram, is more generic as the receiver does not need any pre-knowledge of the primary user's signal. In the absence of *a* prioriknowledge concerning the primary signal, it has been proved to be appropriate to use an energy detector in determining the presence of unknown signal (Hamdi et al., 2007andLetaief and Zhang, 2007).

It is suitable for wideband spectrum sensing, where simultaneous sensing of a number of sub-bands can be realized by simply sensing the power spectral density of the received wideband

signal. It works by measuring the RF energy in the channel or the received signal strength indicator to determine whether the channel is idle or not.

Although an energy detection technique can be implemented in an environment where there is no *a* prioriknowledge about the primary user signal characteristics, it still has some limitations. Its first limitation is that it has poor performance under low SNR conditions. This is because energy detection does not accurately determine the noise variance at low SNR, causing noise uncertainty to render the energy detection useless. The second limitation of energy detection is its inability to distinguish between interference from other secondary users sharing the same channel as that of the primary user(Shankar et al., 2005). The third observed limitation of this detection method is the high sensing time required to achieve a given probability of detection(Shankar et al., 2005).

In spite of these limitations, the energy detection method remains the most common detection mechanism currently in use in cooperative spectrum sensing(Akyildiz et al., 2011). This is because some of its performance degradation, due to noise uncertainty, can be mitigated by the diversity gain resulting from cooperation.

### c. Cyclostationary Feature Detection

Radio signals are generally non-stationary with statistical characteristics that exhibit periodicity. Since the periodicity varies periodically with time, radio signals and other related signals that exhibit periodicity, are referred to as cyclostationary signals. In telecommunications, periodicity may be caused by modulation, sampling, multiplexing and coding operations (Gardner *et al*., 2006, Ma and Tsang, 2009), or even be intentionally produced to aid channel estimation and synchronization(Ma and Tsang, 2009). A detection technique where such periodicity is utilized for detection of random signal with a particular modulation type in a background of noise and

other modulated signals is known as cyclostationary detection. The cyclostationary feature detection technique is a method for detecting a primary user's signal by exploiting the cyclostationary features of the received signals(Shankar et al., 2005).

The cyclostationary detection method, as reported in(Akyildiz et al., 2011), exploits the periodicity in the received primary user's signal to identify the presence of primary signals. It is an optimized technique that can easily isolate the noise from the primary user's signal(Malik et al., 2010). This is because noise is a stationary signal with no correlation, while modulated signals are cyclostationary signals with spectral correlation due to the embedded redundancy of signal periodicity (Cabric and Brodersen, 2005, Akyildiz et al., 2006). This makes cyclostationary feature detection outperform energy detection when discriminating against noise due to its robustness to the uncertainty in noise power (Akyildiz et al., 2006, Akyildiz et al., 2011).

However, the drawbacks of cyclostationary feature detection, when compared with energy detection, are the need for *a priori* knowledge of the primary user's signal such as the modulation scheme and its implementation complexity. Another disadvantage of theCyclostationary detection method is its poor performance when a user experiences shadowing or fading effects. This is because the method cannot distinguish between an unused band and a deep fade in such cases (Hamdi et al., 2007).

### d. Wavelet Detection

The wavelet detection method uses the principle of wavelet transformation where multi resolution analysis mechanisms decompose the input signal into different frequency components. Each component is then studied with resolutions matched to its scales.

Wavelet transform uses irregularly-shaped wavelets as basic functions and thus offers better tools to represent sharp changes (Wornell, 1996, Laneman and Wornell, 2005). In order to identify the locations of idle frequency bands, the entire wideband is modeled as a train of consecutive frequency sub-bands where the power spectral characteristic is smooth within each subband, but changes abruptly on the border of two neighboring sub-bands (Letaief and Zhang, 2007). By analyzing the irregularities in the power spectral density characteristic with wavelet transform, the spectrum hole is located. Its advantage is that it can perform optimally without *a* prioriknowledge information about the primary user's signal.

**e. Compressed Sensing**

In energy or cyclostationary detection, detection is based on a set of observations sampled by an analog-digital converter at a Nyquist rate in the interested frequency band.

In either of the two detection techniques, the spectrum sensing approach is to sense one band at a time because of their hardware limitations on the sampling speed. In order to sense multiple frequency bands using either technique, the cognitive radio or the secondary user needs to use multiple radio frequency front-ends for sensing multiple bands. Hence, using these techniques for wideband sensing will either cause a long sensing delay or incur higher computational complexity and hardware cost.

On the other hand, sampling of the wideband signals at a sub-Nyquist rate to relax the analog-digital converter is now possible through compressed sensing (Candès et al., 2006, Donoho, 2006). Its operation is based on the assumption that radio spectrum is currently underutilized. Based on this assumption, compressed sensing can be utilized to approximate and recover the sensed radio spectrum, which facilitates the detection of sparse primary users' signals in

wideband spectrum (Akyildiz et al., 2011). This makes compressed sensing a valid sensing technique, which currently provides promising solutions to prompt recovery of wideband signals and facilitates wideband sensing at reasonable computational complexity.

### 2.2.10 Spectrum Sensing Detection Methods Analyses

Analyses of the above five spectrum sensing detection methods in literature show that no single detection method can detect all forms of radio signals. This necessitates the advent of another sensing/detection method that can overcome these shortcomings identified in the spectrum sensing detection method currently in the literature. In addition, since the cognitive radio is expected to be unaware of the transmission scheme used by the primary user of the spectrum and not be synchronized to the primary user's signal, it means that the cognitive radio is constrained to use a non-coherent detection method, which has poor performances compared to the coherent method under low or weak SNR.

Coupled with this issue of low SNR is the hidden terminal problem that arises because of shadowing. This occurs because of topographical elements, such as tall buildings, trees and other structures in the transmission path. As a result of this shadowing effect, the cognitive radio or secondary user may be shadowed away from the primary transmitter, but there may be a primary receiver closer to the cognitive radio or secondary user that is not shadowed from the primary transmitter. In such a situation, if the cognitive radio transmits, it may interfere with the primary receiver's reception. Another challenge is the signal fading problem, which can be as a result of radio signal diffraction when it incidents on tall buildings, trees and other structures in the transmission path. The negative effect of signal fading is that, it will reduce the signal strength and impairs the sensitivity of the secondary user. In such fading environment, the cognitive radio

transmission can interfere with the primary user signal as a result of weak signal strength at the cognitive radio terminal. Hence, for the general acceptability of application of cognitive radio technology, the issues of accurate detection of all forms of primary radio signals, coupled with the probability of hidden terminals as well as signal fading, need to be addressed in order to guarantee the general deployment of cognitive radio by both the spectrum regulatory bodies and the spectrum-licensed owners.

### 2.2.11 Fuzzy Logic

Ahmad et al., (2010), gave a good review of fuzzy logic workings. Here the benefit of fuzzy logic in dealing with uncertainties and ambiguities in a way that mimics human reasoning is highlighted. Fuzzy logic based systems are easy to understand and the mathematical concepts behind their reasoning are very simple with an accompanying reduction in time management, data management and algorithm computation overhead compared to most other signal classification techniques. Furthermore, since the truth of a statement in a fuzzy based system is a matter of degree, rule based decision making is at the heart of a fuzzy logic system. This rule based system is usually implemented with the use of if-then rules. The basic advantage underlying the if-then rule principle is its flexibility and ease of adding additional rules in order to extend the functionality of the system.

With respect to this work, fuzzy logic could either be used for classification of signal or model analysis. By model analysis is meant the realization of a working model through algorithm implementation. Depending on the sensing technique (matched filter, energy detector, cyclostationary) chosen, the presence or absence of knowledge concerning primary user is made more difficult by the presence of uncertainties. These uncertainties (noise, multipath, Doppler

spread, coexisting effects) make it difficult to categorically identify primary user signals. Fuzzy logic thus becomes an easy way to implement a radio classifier since it provides a human-like inference machine based upon the already mentioned vague, noisy or even missing input information.

Before continuing, some definitions prevalent in fuzzy logic literature will be in order:

i. Fuzzy set: a fuzzy set is a collection of ordered pairs as follows A={(x,u(x))} where item x belongs to the universe of discourse and u(x) is the degree or grade of membership. Since frequency is the central resource in radio environment and all electromagnetic activities revolve around it and this can be replacedby frequency to define our fuzzy radio set (FRS) as follows: F={(x,u(x))}

ii. Universe of discourse: the input space, where elements of a fuzzy set are taken from, is called universe of discourse or simply universe and is often represented by u or U. the entire radio frequency is the universe of the fuzzy radio model (FRM)

iii. Membership function(MF): a membership functionis a curve that defines how each point in the input space is mapped to a membership value(or degree of membership) between 0 and 1. It is conveniently denoted as μ(x) or equivalently as μ(f) in FRM. The set of elements that have a non-zero membership is called the support of the fuzzy set

iv. Standard fuzzy operators: Boolean operators AND,OR and NOT are interpreted as intersection or min(n), union or max(u), and fuzzy complement (1-A) respectively

v. Similarity measure(SM): Similarity measureis used in fuzzy mathematics to measure the grade of similarity between two fuzzy sets. Several definitions of similarity measure have been presented

### 2.2.12 Monte-Carlo Method

Monte Carlo (MC) methods provide approximate solutions to a variety of mathematicalproblems by performing statistical sampling experiments. They can be loosely definedas statistical simulation methods, where statistical simulation is defined inquite general terms to be any method that utilizes sequences of random numbers to perform the simulation. Thus Monte Carlo methods are a collection of differentmethods that all basically perform the same process. This process involvesperforming many simulations using random numbers and probability to get an approximationof the answer to the problem. The defining characteristic of MonteCarlo methods is its use of random numbers in its simulations. The fact that MonteCarlo is well suited to random number computations makes it very suitable to the primary user detection problem which is very stochastic in nature.

Note that these methods only provide a approximation of the answer. Thusthe analysis of the approximation error is a major factor to take into account whenevaluating answers from these methods. The attempt to minimise this error is thereason there are so many different Monte Carlo methods. The various methods canhave different levels of accuracy for their answers, although often this can dependon certain circumstances of the question and so some method's level of accuracyvaries depending on the problem. The common Monte Carlo techniques include:

i. Crude Monte-Carlo
ii. Acceptance - Rejection Monte Carlo
iii. Stratified Sampling
iv. Importance Sampling

The acceptance-rejection MonteCarlo technique is preferred for this work as the ultimate goal of the spectrum sensing operation is to make a decision of primary user presence or absence based on comparison with a pre–specified detection threshold.

### 2.2.13 Probability versus Energy Curve Characteristics

The transmission characteristics of the channel can be explained as the relationship between the energy of the transmitted signal and the various probabilities computed as a probability distribution function (PDF). It is well captured in the plot of probabilities vs. energy shown in Figure 2.7 and which is described by a chi-squared distribution.

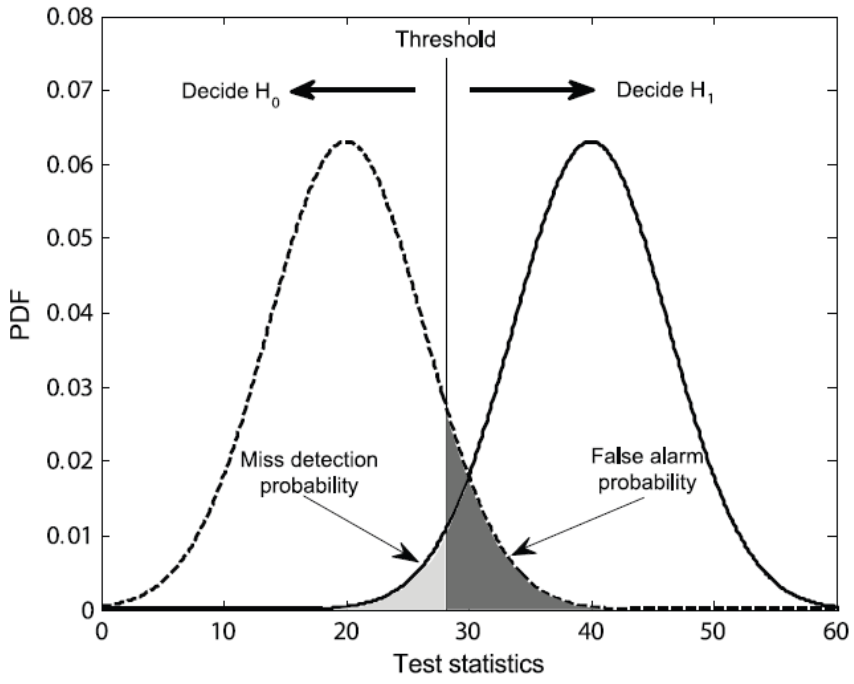



Figure 2.7: Probability vs. Energy Plot Showing Chi-square Distribution (Wang, 2010)

From the distribution being described relates the probabilities to signal energy for the case when;

i. **Primary User is absent** and only noise energy is being sensed (H0 hypothesis) and

ii. **Primary User is present** and transmission is of both the noise and signal energy (H1 hypothesis)

These two cases are clearly shown Figure 2.8

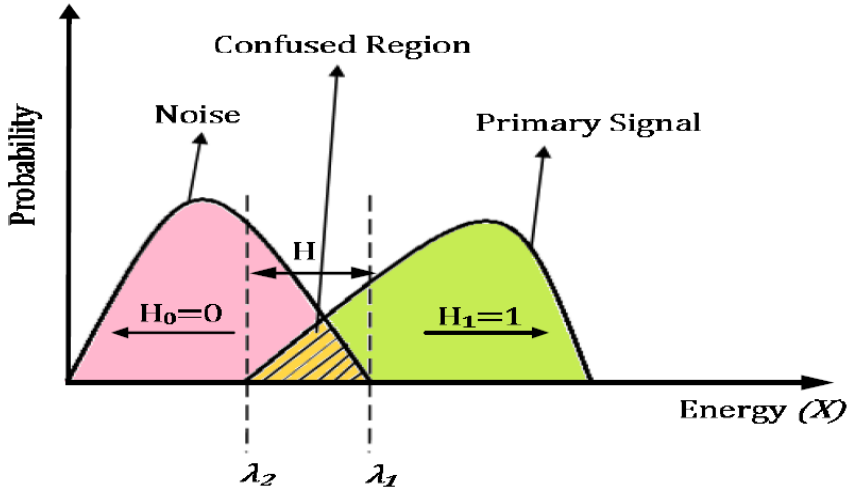



Figure 2.8: Probability vs. Energy Plot Showing Chi-square Distribution (Bagwari, 2010)

The left hand side curve describes the case when no Primary User signal is on the spectrum while the right hand side curve describes the case of Primary User transmitting or the presence of signal. The area of the curve which we must bring into focus is the region of intersection of the two curves (between λ1 and λ2) which is called the uncertainty region because within this region the sensing action of the Cognitive Radio is not decisive. To highlight further this uncertainty region, it is the region in which the Cognitive Radio has the highest probability of either missing a detection opportunity because the threshold was set too high or in which the Cognitive Radio has a higher probability of false alarm because the threshold is set too low. What these two probabilities describe in the case of missed detection is a tendency to miss the presence of a Primary User by the Cognitive Radio sensing subsystem thereby allowing the Secondary User to transmit simultaneously (a state that causes interference and this is unwanted in the Cognitive

Radio). This further means that the Secondary User is allocated a still occupied spectrum slot which is not an allowed state of operation of the Cognitive Radio. On the contrary, the false alarm case arises where the threshold is set too low, and there is the tendency to misrepresent noise energy as being that of a Primary User signal, thereby missing a chance to allocate an actually empty spectrum slot to a Secondary User on standby.

A very striking observation from the analysis show that when the probability of missed detection is the parameter chosen to make the threshold analysis, the threshold usually falls more in the region of the noise plus signal curve and it is represented by the H1 hypothesis while when the probability of false alarm is used to make the threshold analysis, the threshold usually falls more towards the noise only curve region. (Clarify missed detection as either too high in the noise only curve while simultaneously too low in the noise and signal curve and vice versa for false alarm)

Therefore choosing the right threshold is a compromise between allowing a high level of probability of false alarm certainty and having a high level of probability of missed detection certainty but not both of them simultaneously.

## 2.3 Review of Similar Research Works

The following are some of the relevant research works critically reviewed for the implementation of the working cognitive radio techniques for spectrum sensing.

**Sarvanko*et al.*, (2008)**proposed cooperative and non-cooperative spectrum sensing techniques using Welch's periodogram in cognitive radios. An analysis of radio spectrum deployment for detecting utilized frequency channels and isolate unoccupied parts of radio spectrum was carried out. However, the work did not address the issue of uncertainty in the detection process of white space.

**Quan *et al.*,(2008)** introduced a novel wideband spectrum sensing technique called multiband joint detection. In this work a bank of multiple narrowband detectors were jointly detected in order to improve the opportunistic throughput capacity in cognitive Radios. They considered a primary communication system over a wideband channel that is divided into K non-overlapping narrowband sub-channels in which some of the sub-channels may not be utilized by primary users and are therefore available for opportunistic spectrum access. They assumed that during detection, the only spectral power in the air is emitted by the primary users and noise. They modeled the threshold, probability of miss detection and probability of false detection as vector products. While the results attempted to show that more efficient use of the RF spectrum was done and interference reduced, it lacked clarity on the computation of the threshold, probability of miss detection and probability of false alarm.

**Chen *et al.*, (2008),** addressed the channel fading suffered by the single radio, by applying cooperative spectrum, to associate the detection of multiple radios. The optimization problem of detection efficiency under the constraint of detection probability was addressed and an algorithm to evaluate the required radio number and sensing time for maximal detection efficiency was developed. However, with Monte Carlo and Fuzzy logic estimation techniques the result can be improved upon.

**Weidong*et al.*, (2009),** proposed a method to achieve excellent detection performance through application of cooperative spectrum. Additionally, a novel cooperative spectrum sensing scheme based on fuzzy integral theory and optimization method was proposed, in which the reliability of local spectrum sensing is taken into account in the final decision whether the primary user (PU) is present or not and the optimization method is used to find the optimal fuzzy measures.

Obtained results showed the scheme performed better than other fusion strategies implementing cooperative spectrum sensing.

**Wei*et al.*,(2009)** worked on improving the optimality of cooperative spectrum sensing with an aim to optimize the detection performance in an efficient and implementable way. An optimal voting rule was derived for any detector type applied to cooperative spectrum sensing. However, the work only investigated energy detector type spectrum sensing for use in cooperative spectrum sensing scheme but did not optimize the detection threshold which is the focus of this research work.

**Raut and Kulat (2009**)proposed a new autocorrelation-based method (CurrSum method) for spectrum sensing and compared its performance with energy detection. The benefit of the new method was in its ability to exploit the difference between the signal spectrum and noise spectrum over sensing bandwidth, which arose due to the higher autocorrelation of the signal. It was discovered that the use of practical modulation schemes and the existence of RF channel guard bands tended to increase signal correlation. The result of the work showed that the currSum method performed better than the energy detection method. The method was not robust enough to address other spectrum sensing challenges, such as detection of false alarm and noise.

**Haykin *et al.*,(2009)**researched into the utility of the multi-taper method and cyclostationarity for sensing the radio spectrum including the digital TV spectrum. The methodology used involved a spectrum sensing approach that was used to detect spectrum holes and provided high spectral resolution capability as well as estimated power in each subband of the spectrum. They also made use of cyclostationarity method for signal detection and classification. The multi-taper

method was used for non-parametric spectral estimation. The method could not accomplish the task accurately, and was not robust enough to tackle the uncertainty due to noise interference.

**Matinmiko*et al.*, (2010)** focused on the cooperative spectrum occupancy measurement in the 2.4 GHZ ISM band. The methodology involved in this work was the combination of the spectrum occupancy information obtained from the different antennas and the measurement devices using techniques known from the cooperative spectrum sensing. The results found out that the spectrum occupancy is heavily dependent on the measurement location particularly in the ISM bands where transmission power levels are low. The spectrum occupancy values can differ even in the same office area due to the locations of the transmitters and the radio propagation environment. This approach is very limited as it cannot be relied upon for mobile network systems.

**Tevfik and Hüseyin (2010)**centered their work on a survey of spectrum sensing algorithms for cognitive radio applications. The methodology used was cooperative sensing where various aspects of spectrum sensing problem were highlighted and multi-dimensional spectrum sensing concept was introduced.From there, the spectrum opportunity and spectrum sensing were re-evaluated by considering different dimensions of the spectrum space. The result revealed that, the new interpretation of spectrum space creates new opportunities and challenges for spectrum sensing, while solving some of the traditional problems. They also considered collaborative sensing as a solution to some common problem in spectrum sensing. The method can only be effective if estimation of spectrum usage in multiple dimension of time, frequency, spaces, angle or code could be determined.

**Wang *et al.*, (2010)** looked at advanced sensing techniques of energy detection in cognitive radios. The aim of this study was to provide a macroscopic view of spectrum sensing, especially with energy detection, in the cognitive radio. In order to do so, a generalized sensing performance evaluation is given first, which allows for greater understanding of the multi-antenna and the cooperative sensing performances. For multi-antenna sensing techniques, the performances were analyzed and compared in consideration to practical problems. This work does not address uncertainty reduction in the implementation of the energy detector and makes an in-depth study of the working of the cooperative spectrum scheme especially as it concerns sensing and voting rule.

**Bajaj and Gong (2011)** focused on licensed spectrum sensing and empty spectrum used while protecting licensed band primary users. In their work, they proposed a new mobile user protocol for dynamic channel selection via channel working estimation. The mobile node senses channel usage in unlicensed ISM band and select the maximum residual capacity channel for its own packet transmission. The new protocol was implemented on Microsoft SORA software defined radio system that enabled fast prototyping. They evaluated the performance using a campus deployed SORA test bed. Experimental results showed the efficiency of the approach in avoiding external interference. From study, it was apparent that development of intelligent channel sensing using received energy level measurements and workload calculation in an SDR system was feasible. However, it was limited to the ISM band. This work limits the spectrum sensing to only frequencies within the ISM band and does not attempt to sense outside this band.

**Atapattu*et al.*,(2011)** considered Energy Detection Based Cooperative Spectrum Sensing in Cognitive Radio Networks over channels with both multipath fading and shadowing. The analysis focused on two fusion strategies: data fusion and decision fusion. Under data fusion,

upper bounds for average detection probabilities are derived for four scenarios: 1) single cognitive relay; 2) multiple cognitive relays; 3) multiple cognitive relays with direct link; and 4) multi-hop cognitive relays. Under decision fusion, the exact detection and false alarm probabilities are derived under the generalized "k-out-of-n" fusion rule at the fusion center with consideration of errors in the reporting channel due to fading. The results are extended to a multi-hop network as well. Validation is done by numerical and simulation results. Although, this research focused on the effects of Rayleigh multipath fading and lognormal shadowing in detecting the presence of white space. However, their work did not address static network allocation.

**Akyildiz*et al.*,(2011)** studied optimal spectrum utilization for mitigating effects such as multipath fading, shadowing and receiver uncertainty issues. To mitigate the impact of these issues, cooperative spectrum sensing was shown to be an effective method to improve the detection performance by exploiting spatial diversity. Moreover, the impacting factors of achievable cooperative gain and incurred cooperation overhead are presented. Key factors considered include sensing time and delay, channel impairments, energy efficiency, cooperation efficiency, mobility, security, and wideband sensing issues. The related research challenges related to each issue in cooperative sensing processes were also addressed but optimal detection threshold selection was not addressed.

**Zhao*et al.*, (2011)**, described an improved spectrum utilization scheme employing a weighted cooperative spectrum sensing framework for infrastructure-based cognitive radio networks, to increase the spectrum sensing accuracy. The framework contains two modules. In the first module, each cognitive radio performs local spectrum sensing and computes the total error probability, which combines the false alarm probability and the miss detection probability. The

total error probability and the energy signal from the primary user are then sent to the base station. In the second module, the base station makes a final decision after combining the weighted energy signals from all cognitive radios. The final decision is then broadcasted back to all cognitive radios. To reduce the computation complexity and communication overhead, the base station also instructs the cognitive radios that have large total error probabilities not to report their local sensing results. While their work is mainly a theoretical model for the proposed framework, and derived the optimal detection threshold, as well as the minimum number of cognitive radios required to participate in cooperative sensing, subject to a given total error probability. However, in contrast, this work explored the modeling and simulation approach of all aspects of the cognitive radio model.

**Yu *et al.*,(2012)**investigated the relationship between energy detection performance and detection sensitivity with average noise power fluctuation. They found out that detection performance and detection sensitivity dropped quickly with increasing average noise power fluctuation and became worse with low signal-to-noise ratio. They proposed an energy detection algorithm based on dynamic threshold. In this work, the researchers set a value for the threshold which they referred to as the dynamic threshold and were able to mathematically demonstrate that at that point, (dynamic threshold value), the noise average power fluctuation is reduced without increasing the detection duration. Theoretical results and simulations showed that the proposed scheme removed the falling proportion of performance and detection sensitivity caused by the average noise power fluctuation with a choice threshold, and also improved the antagonism of the average noise power fluctuation in short time and obtained a good performance. Increasing the dynamic threshold factor increased the detection sensitivity and the performance improved as well.

**Qin *et al.*, (2012)** proposed an adaptive threshold for energy detector based on discrete wavelet packet transform. In their work, they first performed n levels discrete wavelet packet transform on the received signals, then calculated the energy of each sub-channels, and compared it with a fixed threshold so as to classify the sub-channels as occupied or unoccupied. The sub-bands denoted as occupied are further subjected to another test based on a threshold adapter given the term, α. α was found to work best within a certain limit of 0.55 and was used as the control in their mathematical model. The model which demonstrated better reliability than the conventional energy detector is complex and led to an increased cost. Moreover, the value of 5dB was set for the fixed threshold. This was considered to be too high and will increase considerably, the probability of false alarm.

**Lopez-Benitez and Casadevall (2013)**investigated the signal uncertainty in spectrum sensing for cognitive radio. It was argued that the inability of cognitive radio users to perfectly know beforehand the primary signals that might be present in the sensed band and their properties, referred to as signal uncertainty, also resulted in additional detection degradation. In the analysis of this work, the spectrum sensing algorithms, such as energy detection, were not taken into account in the final analysis performance evaluation of spectrum sensing in cognitive networks. However, the researcher developed a mathematical model for signal uncertainty and, based on this model, analyzed the impact of signal uncertainty on the resulting detection performance of spectrum sensing. The limitation of this work was in the aspect of sensing and detection of weak signals. This work was purely analytical with no numerical or experimental results to validate the work.

**Nautiyal and Kumar (2013)** looked at implementation of cognitive radio in MATLAB. Their implementation employs energy detection sensing technique. The reason for choosing this

detection technique comes from its suitability to situations where sufficient information about the primary user signal cannot be gathered. The energy detector is also called a radiometer. This paper does not address the problem of uncertainty associated with spectrum sensing and detection.

**Lavudiya*et al.*, (2013)** implemented a cognitive radio in MATLAB with the aim to simulate its behavior and analyze the results. The primary goal was to investigate methods of increasing spectrum capacity or use through sensing for holes and allocating same to ready secondary users. Two types of cognitive radio are defined thus; full cognitive radio and spectrum sensing cognitive radio. The main characteristics (cognitive capability and reconfigurability) and functions (sensing, management, sharing and mobility) of cognitive radio are also listed.

**Nautiyal and Kumar (2013)** looked at implementation of cognitive radio in MATLAB. Their implementation employs energy detection sensing technique. The reason for choosing this detection technique comes from its suitability to situations where sufficient information about the primary user signal cannot be gathered. This paper did not address the problem of uncertainty associated with spectrum sensing and detection but only attempts to implement the energy detector in MATLAB.

**Mohammadi*et al.*, (2013)** considered the problem of cooperative spectrum sensing in the presence of the noise power uncertainty. Their work proposed a new spectrum sensing method based on the fuzzy hypothesis test (FHT) that utilizes membership functions as hypotheses for the modeling and analyzing such uncertainty. Application was made of the Neyman–Pearson lemma on the FHT and the work proposed a threshold-based local detector at each secondary user (SU) in which the threshold depends on the noise power uncertainty. In the proposed

scheme, a centralized manner in the cooperative spectrum sensing is deployed in which each SU sends its one bit decision to a fusion center. The fusion center makes a final decision about the absence/presence of a primary user (PU). The performance of the PU's signal detection is evaluated by the probability of signal detection for a specific signal to noise ratio when the probability of false alarm is set to a fixed value. The performance of the proposed algorithm is compared numerically with two classical threshold-based energy detectors. Simulation results show that the proposed algorithm considerably outperforms the methods with a bi-thresholds energy detector and a simple energy detector in the presence of the noise power uncertainty.Similar method will aim to be followed during this work but with extra verification

**Kieu-Xuanand Koo (2013)** Presented a new design of Cognitive radio for the next-generation of wireless networks that can enhance utilization of the scarce spectrum available. It allows dynamic spectrum access over temporarily unused spectrum holes that are identified by spectrum sensing. In order to enhance the sensing accuracy it took advantage of the spatial diversity in multiple cognitive radio user networks, cooperative spectrum sensing has been proposed in the literature. However, most existing cooperative spectrum sensing schemes require knowledge of the noise variance and signal-to-noise ratio of primary signal at each node, which can add a significant transmission overhead. This paper proposed an adaptive fuzzy system-based scheme for cooperative spectrum sensing without the need for a priori network information such as the noise variance, channel state information, and characteristics of existing primary signals. Energy observations at nodes are used for online learning from the environment to make a reliable global sensing decision at a central node without further information. Simulation results show that the proposed scheme outperforms the equal-gain combination based scheme, and matches the optimal soft combination scheme in terms of sensing accuracy.

**Ejaz*et al.*, (2013)** addressed Cognitive radio for ad hoc network. These radios are dynamic in nature and have no central point for data fusion. In their paper, gradient-based fully distributed cooperative spectrum sensing in cognitive radio was proposed for ad hoc networks. The licensed band used for TV transmission is considered the primary user. The gradient field changes with the energy sensed by cognitive radios, and the gradient was calculated based on the components, which include energy sensed by secondary users and received from neighbors. The proposed scheme was evaluated from the perspective of reliable sensing, convergence time, and energy consumption. Simulation results demonstrated the effectiveness of the proposed scheme. This work however uses a cooperative scheme in which a central fusion center takes the final decision based on a vote count.

From the review of literature, it is evident that a lot of work has been done in the area of spectrumsensing in an effort to provide means to detect primary presence. It is, however, clear that the majority of the works focused on detection performance whereas this research effort focuses on estimation of detection threshold to improve quality of spectrum sensing using Monte Carlo and ANFIS techniques.

# CHAPTER THREE

# MATERIALS AND METHODS

## 3.1 Introduction

The system considerations for the Non-cooperative and cooperative spectrum sensing techniques comprise combination of different elements working together to produce a cognitive radio network.

## 3.2 Research Materials

The materials used in this research work are MATLAB/Simulink, Microwave-link and Cognitive radio system.

### 3.2.1 MATLAB/Simulink

MATLAB is a proprietary software simulation and prototyping tool for designing, modelling and simulation of dynamic systems. ItsSimulink is a graphical tool comprising specialized toolboxes for use by different engineering and science disciplines. Specifically, the ANFIS and Monte Carlo spectrum sensing processes in cognitive radio are implemented using the MATLAB v 7.12.0.635 (R2011a).

### 3.2.2 Cognitive Radio System

The cognitive radio system is divided into three modules, namely; spectrum sensing, spectrum predicting and spectrum management modules. The focus of this work is on the spectrum sensing and spectrum predicting functions of the cognitive radio. The system block diagram shown in Figure 3.1 depicts a cognitive radio system. The functional components of the

Cognitive Radio system comprises Primary User generator, transmission channel for signal propagation, spectrum sensing subsystem, Secondary User Generator and allocation or spectrum management subsystem.

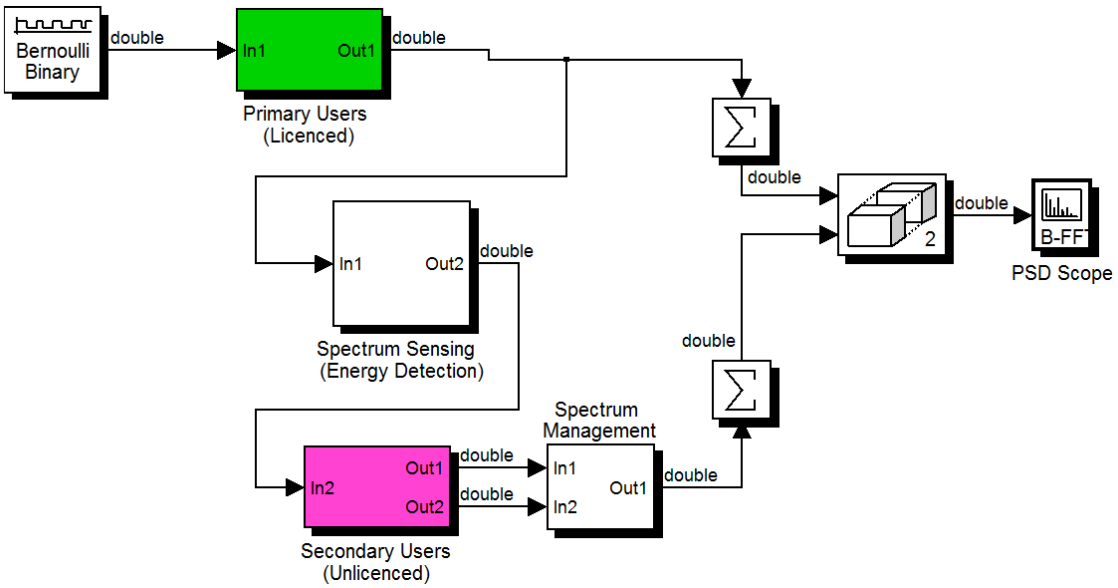



Figure 3.1 Cognitive Radio Systems

The spectrum sensing module of the cognitive radio uses energy detector algorithm. The block diagram shown in Figure 3.2 depicts the system process of the energy detector. The functional subsystems in this block diagram include a prefilter for the input signal, a squarer and an integrator which gives the magnitude of the sensed energy signal.

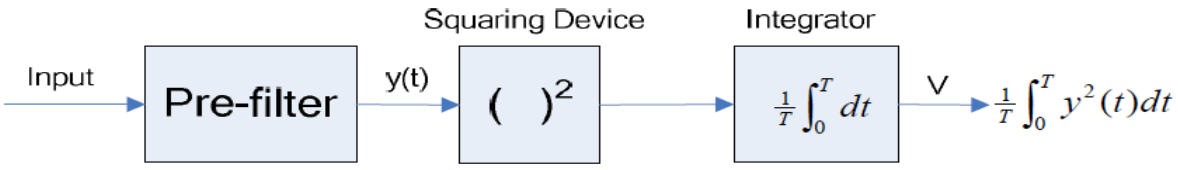



Figure 3.2: Block Diagram of the Energy Detector

The energy detector was used to achieve the following:

i. Sampling via Analog to Digital Converter (ADC) converter and filtering
ii. Computation of covariance or magnitude squared of the energy signal i.e. power spectral density.
iii. Comparing this energy output against a test statistic in the form of a threshold to ascertain the presence or absence of Primary User signal

For the spectrum predicting function, there must exist a detection threshold which is dependent on noise. The maximum noise energy value is usually set as the initial detection threshold. However, due to the fact that the noise is random in nature and there is existence of uncertainty region (combinations of noise and signals) during spectrum sensing process. Therefore, the detection threshold will always fall within the uncertainty region.

### 3.3 Research Methodology

The methodologies adopted in this work are as follows:

1. Estimation of detection thresholds in non-Cooperative spectrum sensing using Monte-Carlo and ANFIS algorithms;
2. Estimation of detection threshold in cooperative spectrum sensing using Monte-Carlo and ANFIS algorithms;
3. Spectrum management for the allocation and de-allocation of Secondary Users;
4. Performance analysis of Monte Carlo and ANFIS based on estimated threshold values
5. Validation of estimated threshold value for non-cooperative spectrum sensing processes.

### 3.3.1 Non-cooperative System Development

In non-cooperative spectrum sensing method, an individual cognitive radio device or secondary user does the non-cooperative spectrum sensing process locally. Each secondary user sensed the spectrum channel to detect the presence or absence of a primary user. Since the sensing method does not involve spectrum sensing results' sharing, as well as final decision making, energy consumption is very low compared to cooperative spectrum sensing where users consume significant energy because of heavy communication. However, the detection accuracy of the method is very low compared to the cooperative method. This is because poor channel conditions do affect single user spectrum sensing results. Figure 3.3 shows the program flowchart for non-cooperative spectrum sensing process.

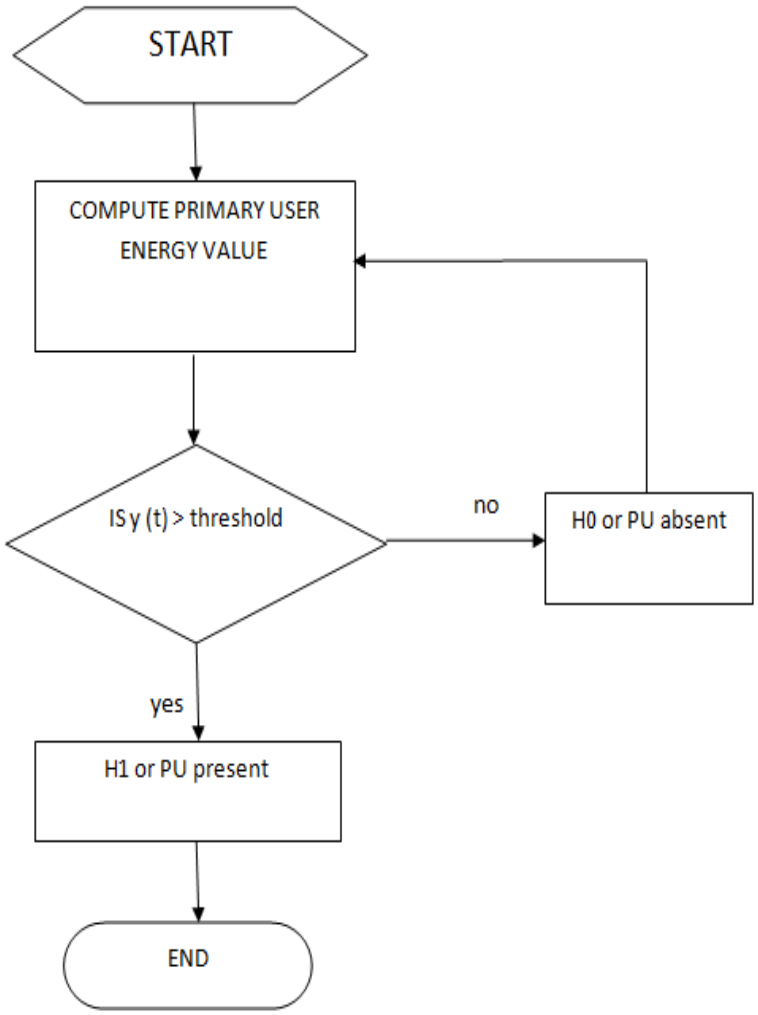



Figure 3.3: Program Flow chart for Non-cooperative spectrum sensing

### 3.3.2 Cooperative System Development

Cooperative spectrum sensing model requires a model which involves sharing of information and decision among individual cognitive users and a central fusion decision center as shown in Figure 3.4. The five subsystems that comprise a basic cognitive radio system are:

1. Cognitive Radio Network of N Secondary Users consisting of Primary User Generator, Transmission channel, Spectrum sensing subsystem or energy detector system, Secondary User Generator etc.

2. Fusion Center Subsystem system.
3. Voting subsystem system.
4. Allocation or spectrum management subsystem.

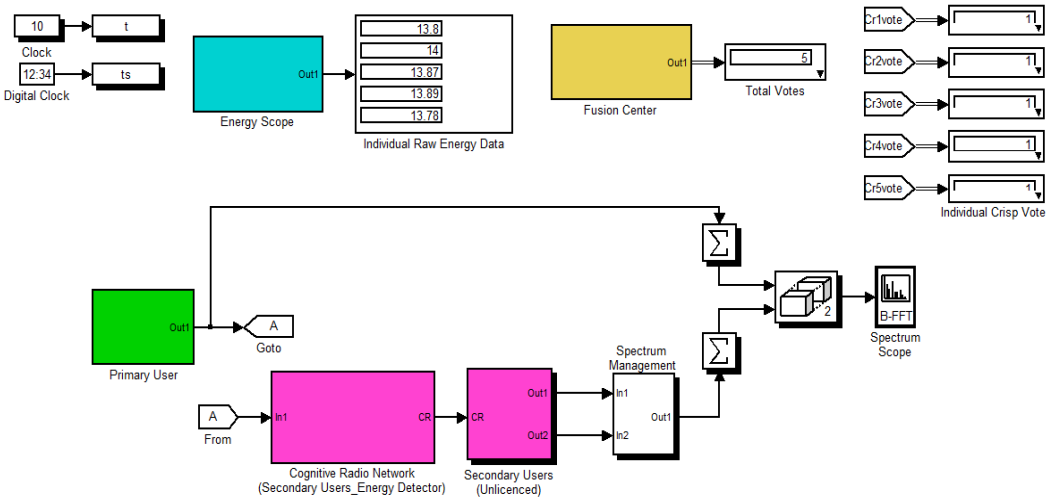



Figure 3.4: Cooperative Sensing Spectrum Model

These four subsystems come together to create a functional cooperative spectrum sensing model. The primary user behavior subsystem is the same as that for the non-cooperative model. This is because the cooperative spectrum sensing scheme differs only in the multiplicity of secondary users and the manner in which decision on primary user presence is reached. The sub-system comprises Bernouli Binary Generator, Sine Wave Generator, Gaussian Noise Generator and Modulated Sine Wave Signal Product.

A working flowchart of the cooperative spectrum sensing model is first presented as shown in Figure (3.5). It details the cooperative spectrum sensing (CSS) algorithm in use for this model.

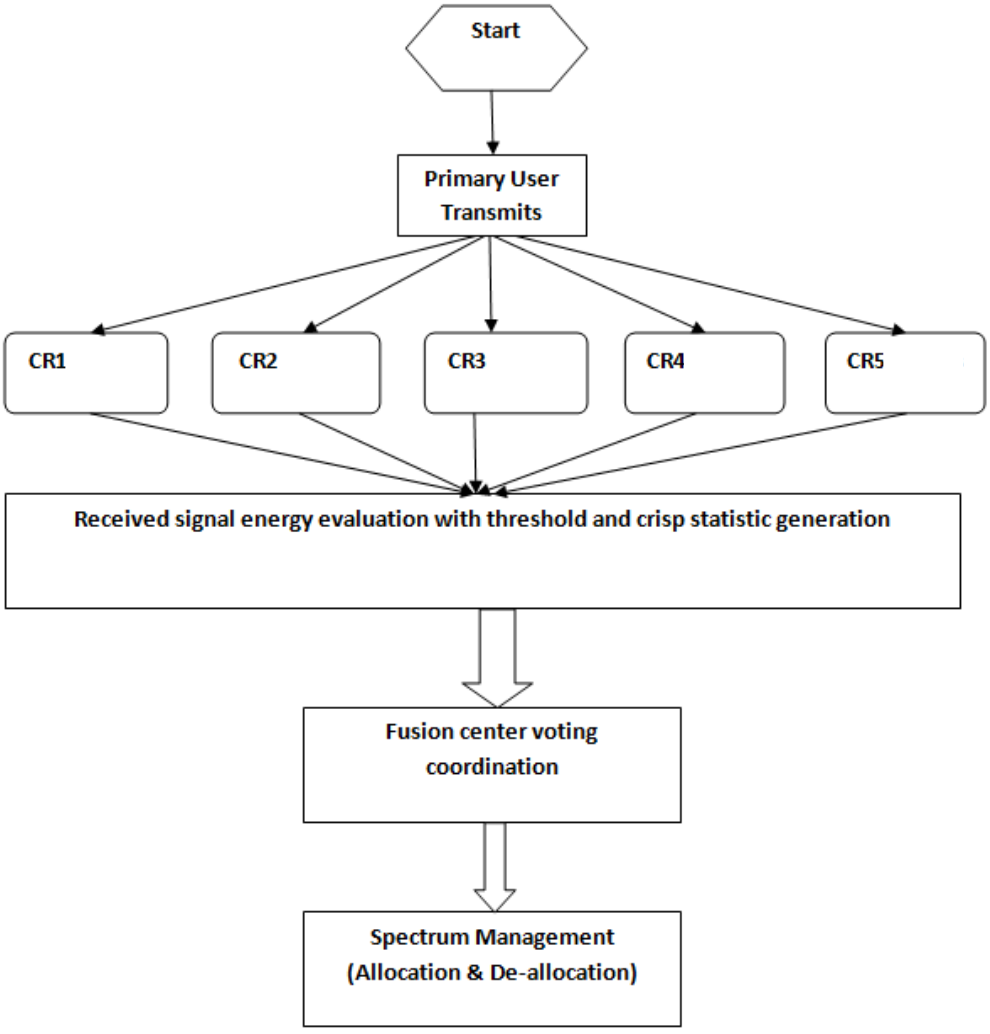



Figure 3.5: Cooperative Spectrum Sensing Flowchart

While we have a single primary user, the secondary users can be generalized to greater than two and up to N users. Energy evaluation and statistic determination is made possible by the energy threshold comparison. The fusion center plays the role of collecting all the individual cognitive radio results and counting the votes based on presence or absence of primary user. It is the most important aspect of the cooperative spectrum sensing Cognitive radio model as this functionality is what handles the cooperation in the cooperative cognitive radio.

The operation of the cooperative cognitive radio network follows from the flow of information as seen in Figure (3.5). With a single primary user being the broadcast source for each cognitive radio, the modulated primary user energy is sensed at each cognitive radio and evaluated for its strength. The evaluation follows the comparison of the sensed energy against a predetermined threshold value. The result of this evaluation is then used to generate a binary statistic for primary user present (1, when the sensed energy is greater than the threshold) and for primary user absent (0, when the sensed energy is less that the threshold). Each decision reached at the cognitive radios is a local decision and must be broadcast to a fusion center which plays the role of collecting all local decisions and generating a global statistic via a voting process to establish the presence or otherwise of the primary user signal on the channel. The counting of the number of votes will determine if the secondary users can begin transmission or not on the licensed primary user channel. This leads to the final part of the model which is the spectrum management subsystem that handles the scheduling of transmission priority and interference avoidance between primary and secondary users on the channel.

From the aforementioned described process, the generated binary (crisp) values are absolute and the reality could be quite different as there is always a probability that with an improperly set threshold, a statistic of 1 might not truly mean the primary user is present or conversely a statistic of 0, might not mean the primary user is absent. Getting the true state of the sensing and detection might therefore have to be enhanced with some statistical and estimation tools such as Monte Carlo and ANFIS. The precise characterization and subsequent reduction in the sensing uncertainty is the major part of the work achieved by the cooperative spectrum sensing methodology implemented.

#### 3.3.2.1 *Determination of Detection Threshold*

Setting a correct threshold value in real time is very crucial. The solution method applied employs two estimation methods: Monte Carlo (Monte Carlo) and ANFIS for detection of primary user through estimated threshold selection. The selection of the threshold value for each cognitive radio was made for the purpose of local sensing and detection decision. This has to be the case considering all radios do not see the same type and magnitude of interference from noise sources.

The need for proper threshold selection and the cooperative spectrum sensing solution comes to the fore considering the Cognitive Radio Network's inherent drawbacks such as;

i. Noisy channel
ii. Fading effect or varying signal strength at receiver compared to that on transmitter
iii. Different radio operating environment

All these factors come together to make a single threshold value unsuitable for sensing in a Cooperative Cognitive Radio model employing Energy Detector as the sensing technique. To counteract this drawback, threshold determination is performed from knowledge of the received signal energies and their probability distribution in real time, while the cognitive radio is operational.

Furthermore, the susceptibility of the Energy Detector to noise level plays a big role in the requirement for properly choosing the threshold. It is well established that very low SNR diminishes the suitability of choosing an Energy Detector for the sensing part of a Cognitive Radio.

### 3.3.3 Performance Indicators

Identification of spectrum holes by cognitive radios (secondary users) is the main task of spectrum sensing and the ultimate goal of any spectrum sensing scheme. Efficiency in any cognitive radio process is tied to;

i. It's performance, which means the frequency of successful and correct detection or identification of spectrum holes and
ii. Operational optimization which entails the Timely identification of spectrum holes and allocation of white spaces which is desired in any cognitive radio scheme.

These two identified characteristics can be hampered by the presence of uncertainty in the sensing process, uncertainty in the cooperative spectrum sensing scheme coming from the effect of signal fading, shadowing and hidden primary user. For the cooperative spectrum sensing scheme, since the decision for identification is given by the results from the fusion center, verifying this result is necessary to achieving an interference free cognitive radio scheme which is a desired quality for use in measuring the performance and optimality of the cognitive radio process entailing; spectrum sensing, detection, correct identification and allocation process. Interference free operation being a most needed requirement for correct operation of the cognitive radio device. This efficiency and optimality is implemented into the cooperative spectrum sensing process through the use of soft computing tools such as Monte Carlo and Fuzzy logic algorithm.

This work has aimed to utilize both methods as a comparative tool to decide correct identification of spectrum opportunities. Though their implementation and operational methodologies differ, the aim is the same for this work.

### 3.3.4 Spectrum Management System

The spectrum management model in Figure 3.5 concerns itself with the allocation task of a Secondary User on the licensed Primary User spectrum. It helps in visualization of the signal behaviors of the Primary User and Secondary User as the CR is operational. It serves to implement the logic for turning ON and OFF, for either the Primary User or Secondary User depending on the functional behavior of either user at any time. In essence, it is the allocation block doing the coordination of spectrum assignment to the Secondary User and also allowing for de-allocation whenever the Primary User is back to transmit as the original user of the spectrum. The algorithm for spectrum management is depicted in the flow chart of Figure 3.6.

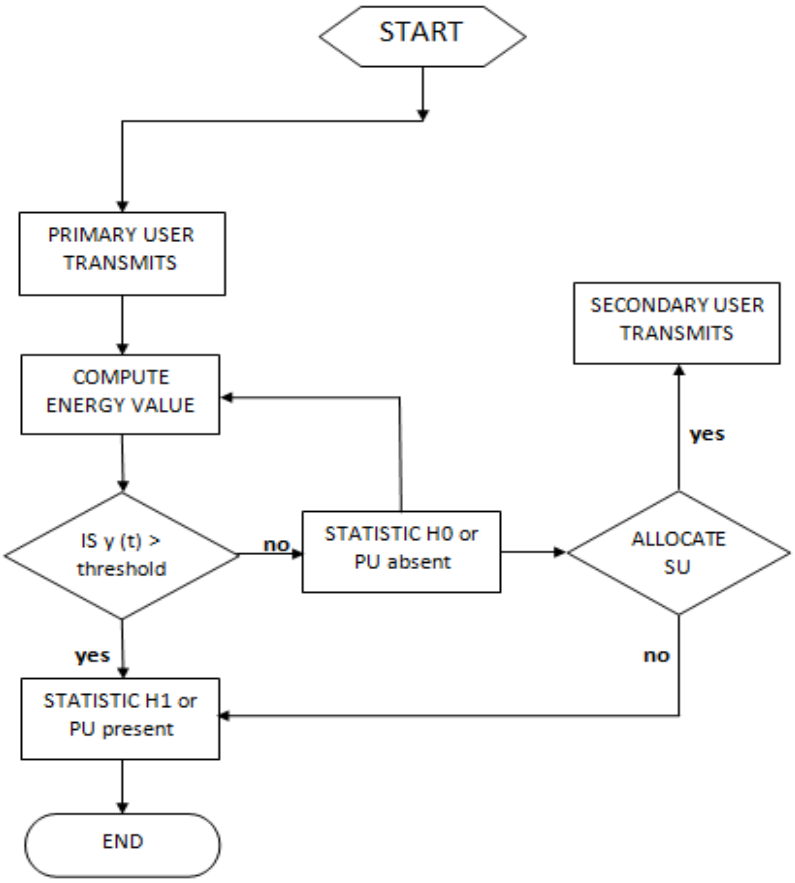



Figure 3.6: Spectrum Management Flowchart

### 3.3.5 Sensing Uncertainty and Threshold Selection

The sensing is negatively impacted by the region of uncertainty formed by the intersection of the noise and signal curves. The implication of this intersection on the operation of the Cognitive Radio is that the sensing is sometimes compromised by the fact that it might not always be possible to tell with accuracy that there are absolutely no Primary User presently transmitting or otherwise. The inability to conclusively tell the state of the spectrum by the sensing algorithm by employing only the crisp analysis led to the introduction of a Monte Carlo and Fuzzy logic model to enhance the sensing and detection of Primary User on the spectrum. This requires that a suitable detection threshold is set and must be dependent on the Receiver Operating Characteristics such as SNR which plays a major role in the probabilities of detection and false alarm.

The uncertainty plot in Figure 2.9 is a theoretical result depicting the Probability distribution function of the sensed energies of Primary User plotted against energy. The plot which is described in detail may be used here to describe the various parts of the experimental result of the Monte Carlo model as shown in Figure 3.7. This will give a good insight into the various parts of the plot in Figure 3.7 obtained from our simulation experiments and also to help readers make inference.

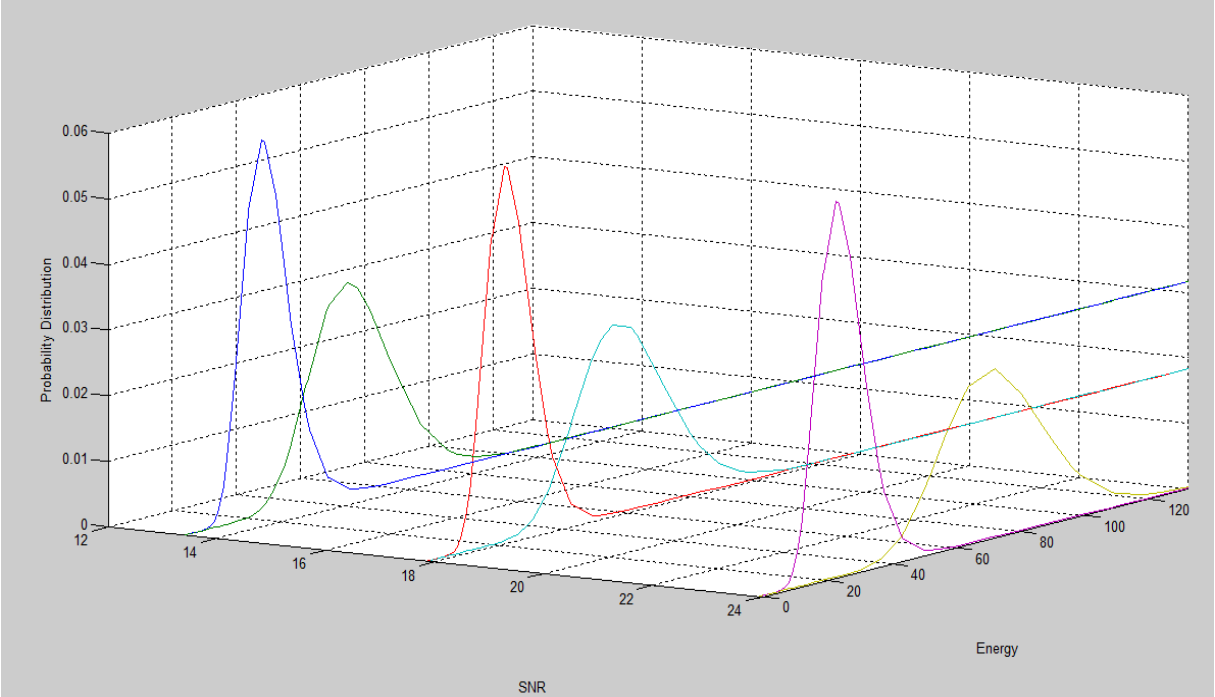



Figure 3.7: 3D Chi-Square Probability Distribution Curve (Pdf vs. SNR vs. Energy)

Figure 3.7 is a chi-square probability distribution curve of the sensed energies during transmission by the cognitive radio. This distribution is used to infer the level of sensing efficiency by computation of probabilities of Missed detection and false alarm in the system.

### 3.3.6. Monte Carlo Analysis

The Monte Carlo analysis used in threshold estimation serves as a statistical tool to estimate the optimal threshold for energy detection based on the SNR which is used as a random variable for the estimation process. Figure 3.8 is a flow chart of the Monte Carlo Algorithm

The input to the Monte Carlo estimator is a random variable, the cognitive radio model possesses two possible candidates for this random variable in the signal to noise ratio (SNR) or degree of freedom (DOF), which will be impacting on the PDF curve of the Primary User signal as seen in

the uncertainty plot of PDF vs. energy. The output will be the computed Probabilities of detection and false alarm.

The operation of Monte Carlo analysis requires that to get a good estimate from the run of the simulation, we use as many samples as possible so as to have a large data set to work with. In a nutshell, the more the data, the better the convergence to an optimal value.

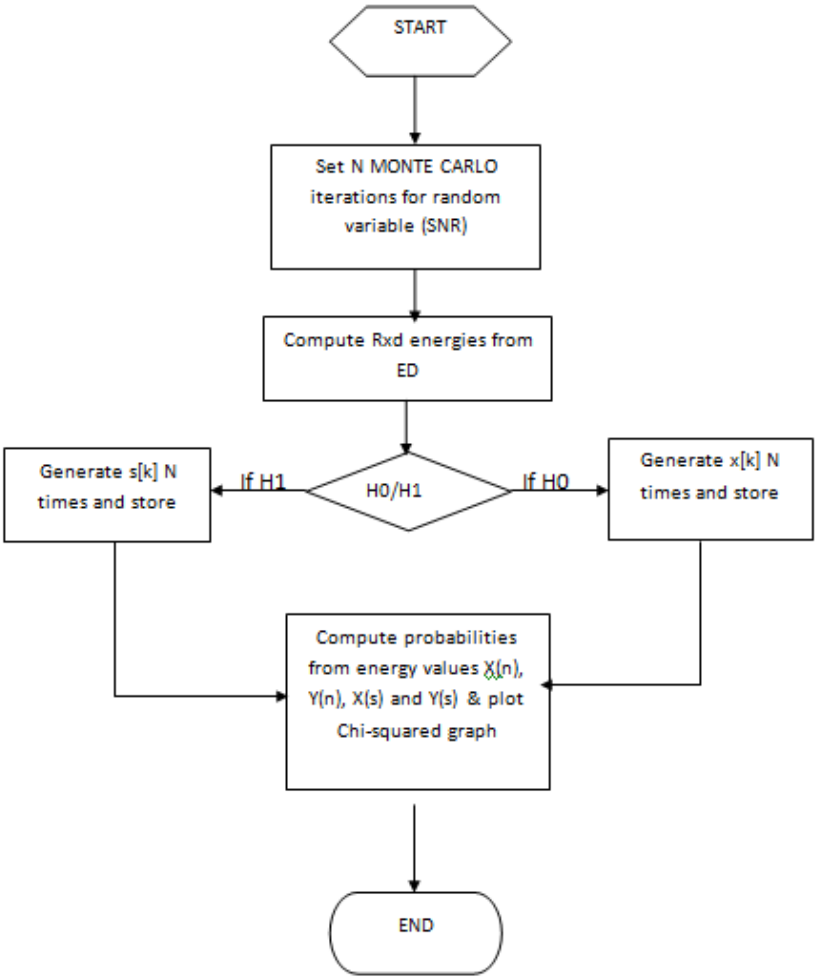



Figure 3.8: Flowchart of Monte-Carlo Estimation

However it must be mentioned that as data points increase, this will be at the expense of longer simulation run times and in most cases, the regular processors on our laptops is too slow in carrying out these data intensive computations.

The Monte Carlo model is implemented within a subset of the Cognitive Radio model as will be seen in the script listings of Appendix A2. Since the Monte Carlo analysis is meant to choose a suitable threshold value for efficient detection, the algorithm for the Monte Carlopart is run inside the sensing part of the model. It works by recalculating the SNR foreach iteration of the Cognitive Radio model and uses the recalculated SNR to capture the changing radio characteristics experienced by the Primary User signal. This is in turn used to calculate a suitable threshold based on the SNR observed in the transmission channel.

The Monte Carlo model takes the energy detected as input. Where it must be borne in mind that the energy detected is also a function of the SNR, thus in a nutshell, the SNR is a changing random variable.

### 3.3.7. ANFIS Analysis

The ANFIS analysis performed is meant to compute the probabilities whose expressions were previously given by the probability distribution function (PDF) describing the $P_d$, Pm and $P_{fa}$. The flowchart depicting the algorithm used is given in Figure 3.9. These PDFs will serve as output while known inputs are the SNR and the energy of the signal. The ranges of the inputs and outputs are chosen based on experience gained from running several simulations and iterations in the Monte Carlo analysis done in the previous section. From literature a SNR value of around 15dB has been employed in experimental work using a Matlab/Simulink system for cognitive radio implementation; thus informing our choice of a starting SNR range of between

10 and 15dB. This value was considered safe for the work at hand a suitable range for the "universe of discourse" of the SNR input variable. The universe of discourse of a fuzzy variable represents the possible range of values realistically assumed by that variable. Since the energy is never negative, we choose an energy range spanning from 0 to 100 which is quite representative of energy values obtained during the Monte Carlo run. This method of setting variable values is a unique feature of fuzzy analysis and setting representative values is important to get a good fuzzy estimate.

Using these two inputs and with a probability density function (PDF) as output, all possible universes of discourse are set based on some prior knowledge of the Cognitive Radio behavior gained from experience in simulations run. The numerical universes of discourse are now correlated with linguistic variables describing their degree of belonging to each of the variables involved. We then proceed to form a rules table which gives the fuzzy rules to be used to generate the PDF values after defuzzification is done on the output PDF. The said rules are in the form of if-then statements, the "if" part representing the precedent or condition to be met while the "then" part represents the consequent or action to be taken.

#### **3.3.7.1** *Fuzzy Variables*

The variables used in the fuzzy decision engine are:

i. Inputs: SNR and Energy

ii. Output: PDF

#### 3.3.7.2 *Universe of Discourse*

The universe of discourse for the variables chosen have the following ranges which are carefully chosen from prior knowledge of the value space taken by these variables. Below is the universe of discourse

i. SNR will be between 10 to 15dB

ii. Energy will be between 0 and 130dB

iii. Probabilities will be naturally between 0 and 1.

#### 3.3.7.3 *Linguistic Terms*

These variable values will now be mapped to linguistic terms to describe their degree of belonging within the ranges given. The linguistic terms used are called fuzzy sets and in this work takes the form:

i. Low(L) or Very Low(VL)

ii. Medium (M)

iii. High (H) or Very High(VH)

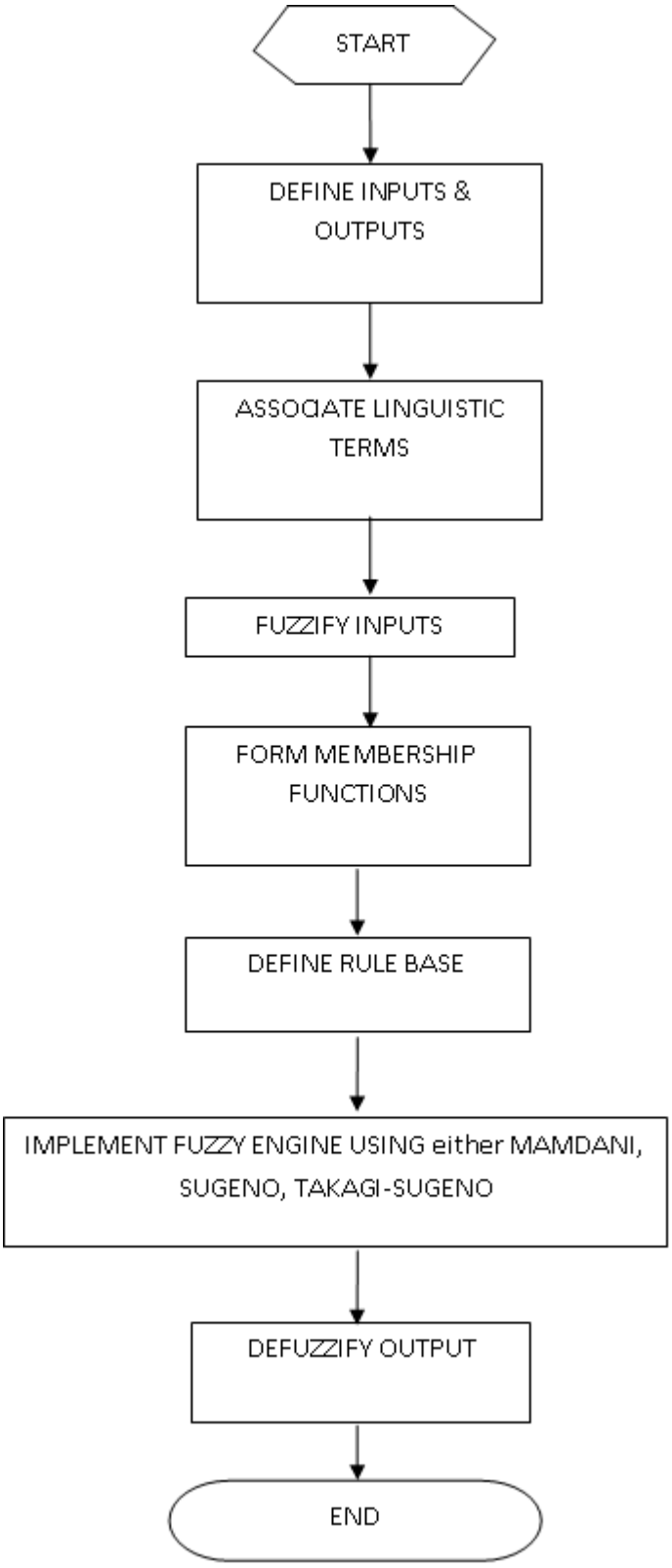
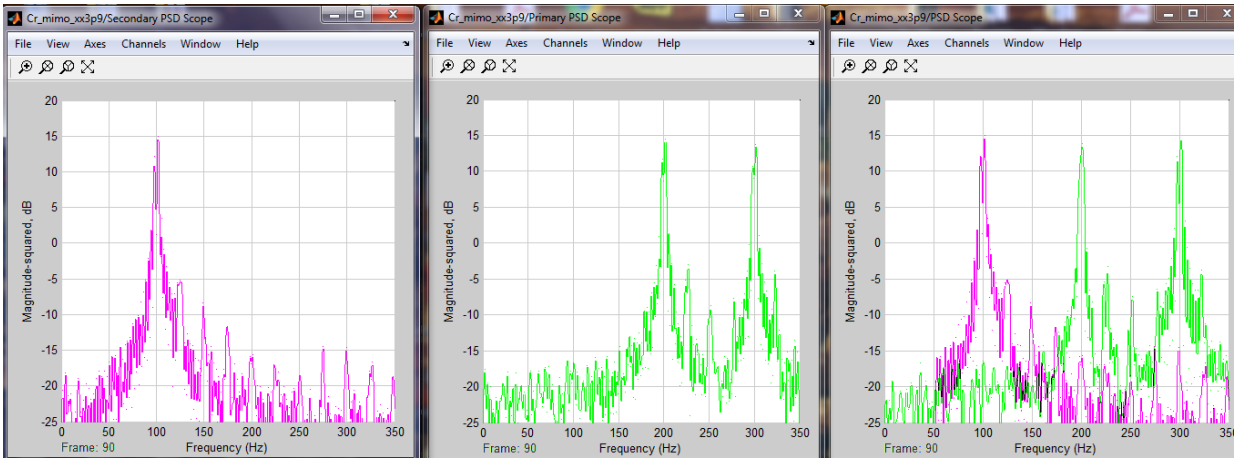



Figure 3.9: Flowchart for ANFIS Algorithm

### 3.3.8. Management of Allocation and De-allocation of Radio Spectrum

Figure 3.10 a, b, c shows a Cognitive Radio system where spectrum sensing and allocation is taking place in real time from our simulation. The Primary User shown in Figure 3.10b and the Secondary User is shown in Figure 3.10a. In the above result, it can be seen that while the Primary User is actively transmitting on the center frequency of 100Hz, the Secondary User is allowed to occupy the other free bands at 200 and 300Hz respectively. The third plot is just a combined plot showing the spectrum occupancy at that particular time. Having explained the plot in Figure 3.10, other results of the simulation; Figures3.10 (a, b & c) show that the Cognitive Radio model developed has been able to demonstrate satisfactorily Primary User behavior, Secondary User behavior, sensing, allocation and de-allocation etc.




(a) Secondary Users (b) Primary Users (c) Combined PUs & SU

Figure 3.10: Results Showing Different Real Time Allocation between Primary User and Secondary User

Figure 3.10b shows the spectrum allocation with Primary User 2 and 3 active. Allocating the free spectrum band requires that only Secondary User 1 (Figure 3.10a) can transmit simultaneously. This is clearly depicted in Figure 3.10c.

### 3.3.9 Validation of Estimated Thresholds for Non-cooperative Spectrum Sensing

The estimated detection threshold for non-cooperative sensing was validated through series of measurements.The noise level in the channel was used as a benchmark for setting a suitable detection threshold value for the energy detector. Measurements were conducted in at two GSM frequencies: 900MHz and 1800MHz.The Spectral sensing was achieved through the aid of an energy detector (Aaronia AG HF – 6060 V4 Spectrum Analyzer from Aaronia Company, Germany) with an incorporated spectrum analyzer for experimental validation as shown in Figure 3.11.

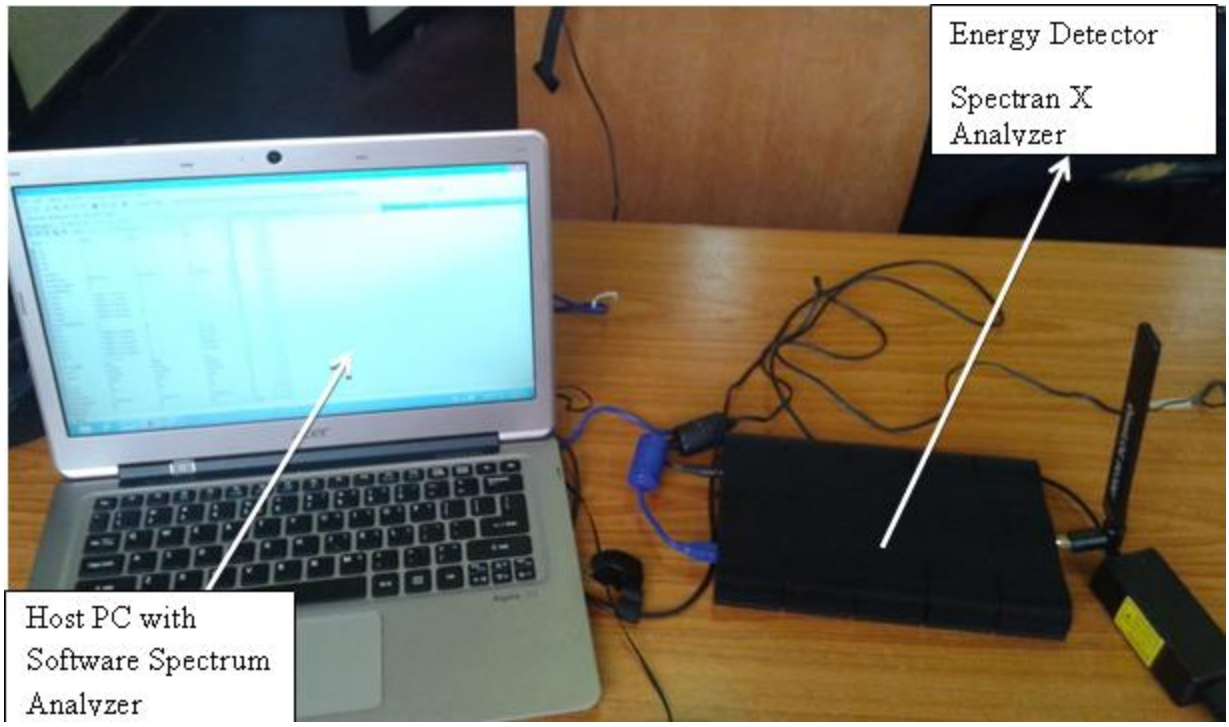



Figure 3.11: Energy Detector Type Spectrum Sensor Integrated with Spectrum Analyzer

The main focus of this section is to carry out the experimental validation of the threshold values obtained by simulation using Monte Carlo and Adaptive Neural Fuzzy Inference System (ANFIS).

The measurements which were conducted at the GSM frequencies of 900MHz and 1800MHz were twofold:

i. Indoor measurement: this was laboratory based using the microwave link equipment in the EtisalatTelecommunication Engineering Programme (ETEP) Laboratory at Electrical and Computer Engineering Department of AhmaduBello University, Zaria. The purpose was to determine base values of (a) detected noise in the absence of any transmissions (b) detected signal and noise

ii. Outdoor measurements: these were conducted in the open between the prototype energy detector and any available transmissions at the tuned frequencies. In particular, experiments were conducted outside of the Electrical and Computer Engineering Department in AhmaduBello University, Zaria. The energy detector was tuned to the two frequencies in turn with a view to detecting any transmitted signal at these frequencies. The purpose being to validate the simulated threshold value and identify existing spectrum holes if any.

Spectral sensing was achieved in this report through the aid of an energy detector (Aaronia AG HF – 6060 V4 Spectrum Analyzer from Aaronia Company, Germany) with an incorporated spectrum analyzer for experimental validation as shown in Figure 3.11.

The measurements were conducted to validate the results from the software models. The detection threshold which is the main parameter of interest in this work was used to detect

presence or absence of primary user. Specifically, the noise level in the channel was used as a benchmark for setting a suitable detection threshold value for the energy detector. This is important as noise is a principal impediment to the utilization of the energy detector sensing algorithm.

The measurements were conducted in two stages:

a. Indoor measurements
b. Outdoor measurements

**3.3.9.1** *Experimental Setup*

The experimental setup for the validation of non-cooperative sensing model is shown in Figure 3.12

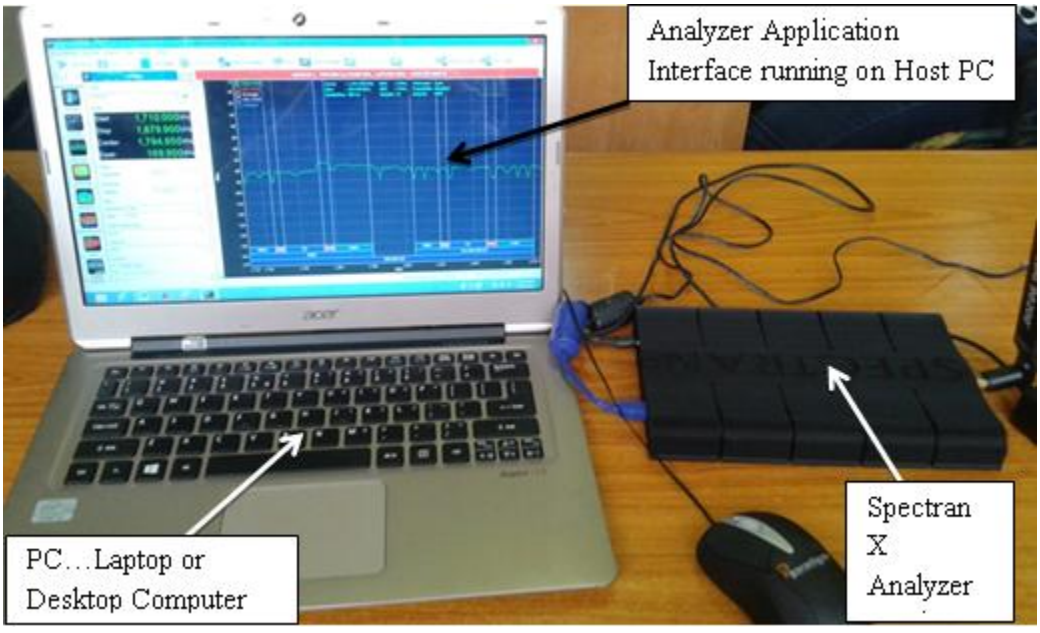



Figure 3.12: Experimental Setup for Validation of Non-Cooperative Model

The energy detector is equipped with its own proprietary software which runs the application programming interface (API) for the incorporated Spectran analyzer. From this interface, the spectrum bands for GSM networks at 900MHz and 1800MHz can be selected for investigation of primary user behavior. The available bands included in the spectrum analyzer software are mainly commercial spectrum bands ranging from 1Hz to 9.4GHz. However, it is also possible to select an arbitrary band of interest to suit a particular kind of investigation.

The frequency bands being investigated for primary user behavior are the GSM bands of 900MHz and 1800MHz. Since comparison of the detection performance of both the prototype and software non-cooperative model of the energy detector has to be made, energy capture has to be limited to these frequency bands of interest i.e. 900MHz and 1800MHz for GSM 2G and 3G respectively.

The reasons for choosing these two bands is because the 900MHz and 1800 MHz bands are well known commercial GSM bands used in Nigeria by the major telecommunications operators. This means there is a high chance of measuring this signal from most locations. It is also used in validation experiments with the non-cooperative model implemented previously using Matlab.

Two experiments were conducted: (i) Laboratory based indoor experiments and (ii) Outdoor field measurements.

#### **3.3.9.2** *Indoor Measurements*

These were measurements conducted in order to firstly; define noise level benchmarks for the outside measurements. The microwave link test bench at the ETEP Laboratory in Electrical and Computer Engineering Department was used in conjunction with acquired energy detector. The noise signal value was measured by (i) replacing the antenna with terminating 50 Ohm matching

impedance and (ii) measuring the energy signals when the signal generator was turned OFF. This second method which has been employed for noise level measurement is as shown in Figure 3.13.

Secondly signals generated by the microwave generator were detected by the energy detector which comprises of the useful signal as well as the corrupting noise signal. This was why a base knowledge of the noise level was necessary for an accurate interpretation of both indoor and outdoor measurements for investigating primary user behavior. Consequently noise measurements were conducted at 1800MHz in the ETEP lab by using the microwave link experimental kit. The experimental setup is as shown in Figure 3.13

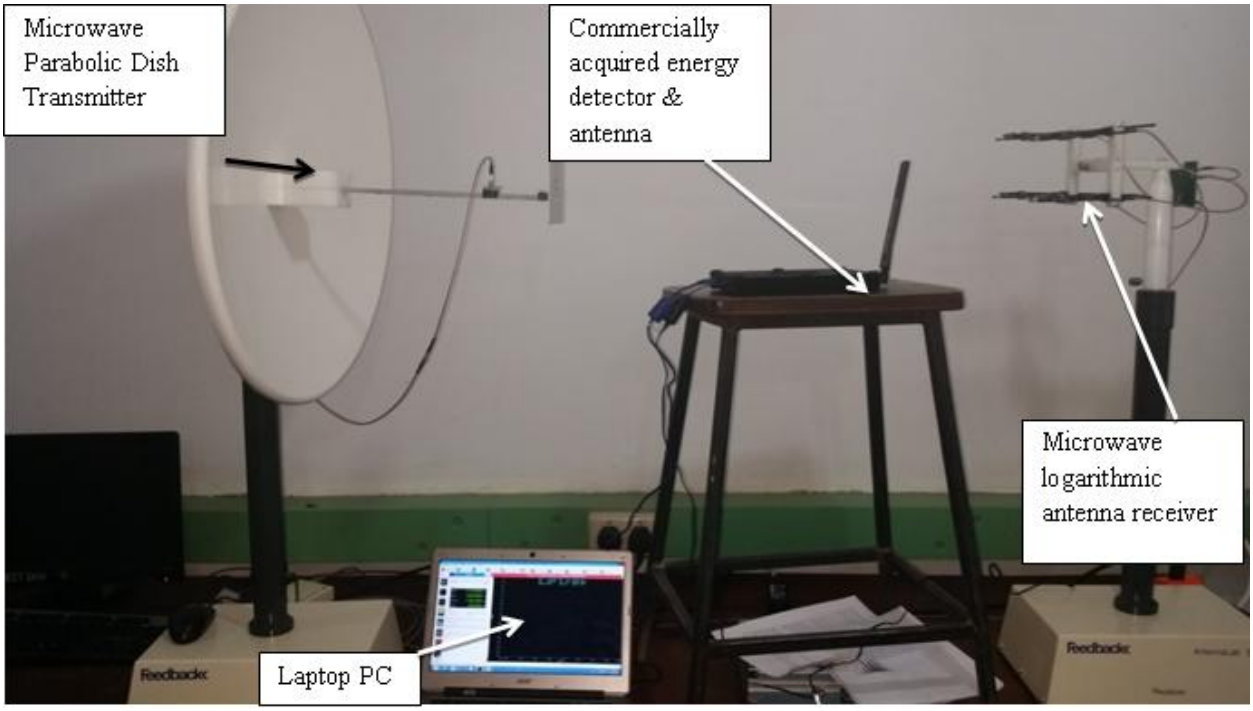



Figure 3.13: Indoor Experimental Setup at the ETEP Laboratory

The noise signal value was also measured by replacing the antenna with a terminating 50Ω resistor for noise measurements. For a suitable baseline noise value, the noise measurements

obtained were averaged over the entire set of values and the resulting value used for thresholding experiment and generation of crisp values as given by Table 3.13.

**3.3.9.3** *Outdoor Measurements*

Figure 3.14 shows the setup of the energy detector in an outdoor scenario as against the previous measurements which were measured indoors. The outdoor experiments depend on only the energy detector sensing at the tuned frequencies. The sources are not known precisely but the captured data is meant to give insight into the available transmission spectral energy components.

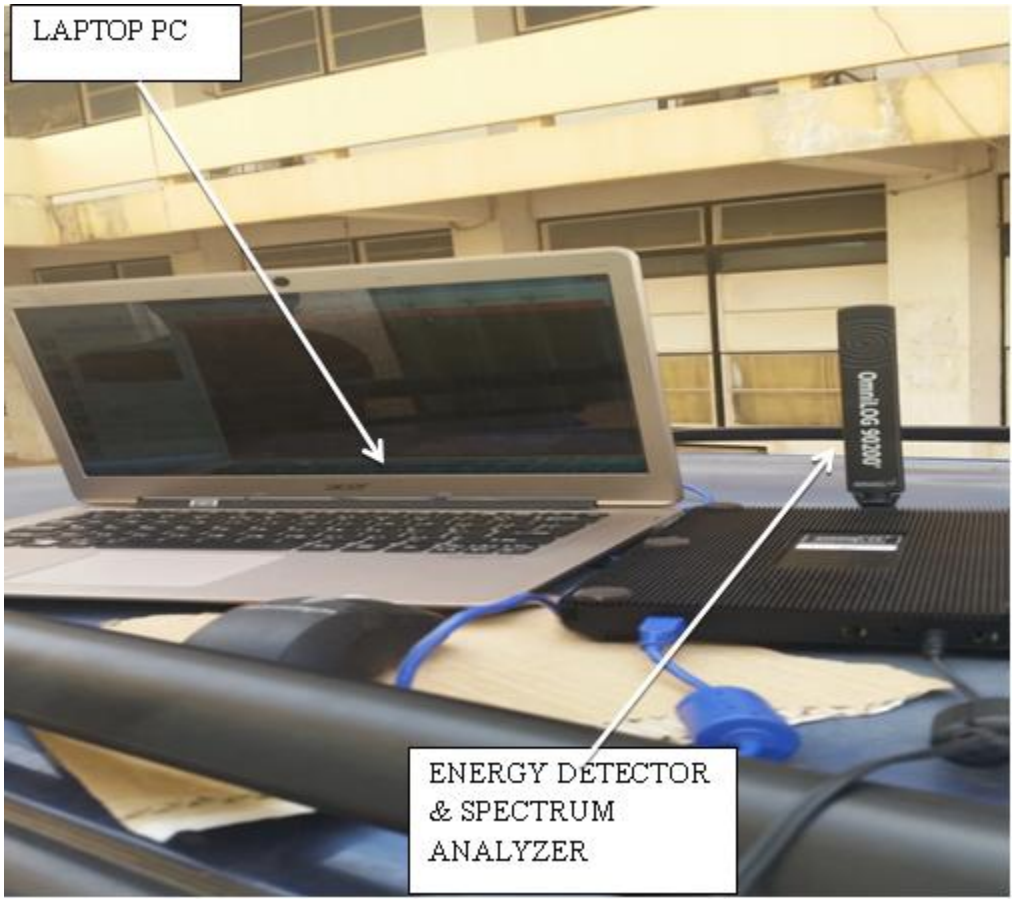



Figure 3.14: Outdoor Measurement Setup for Investigating Transmissions at 900 and 1800 MHz

This experiment was carried out outside the Faculty of Engineering at ABU Zaria. The laptop and energy detector were placed at a reception height of two experiments were performed at each of the investigated frequencies to acquire confidence in the measurements made.

# CHAPTER FOUR

# RESULTS AND DISCUSSIONS

## 4.1 Introduction

The results of the various experimental analyses carried out in this work include the results of various Monte Carlo and Adaptive Neural Fuzzy Inference Systems simulations obtained from the developed spectrum sensing models, the comparative analyses on the performance of the techniques were highlighted and the results of the experimental validation for the detection threshold using the commercially acquired hardware energy detector were presented.

## 4.2 Monte CarloExperiments and Analyses

250 iterations of the Monte Carlo were made in this experiment. The parameter values used for the plot of Figure 4.1 are for 3 different points within the total Monte Carlo iterations. The results for only three simulations is here shown because of the computational power involved in plotting more and also for clarity sake in rendering the uncertainty region to be analyzed. The three samples used for the plots shown in Figure 4.1 are at 80,160 and 240 extracted from the total of 250 iterations. The uncertainty regions are represented by approximate triangles called delta1, delta2 and delta3.

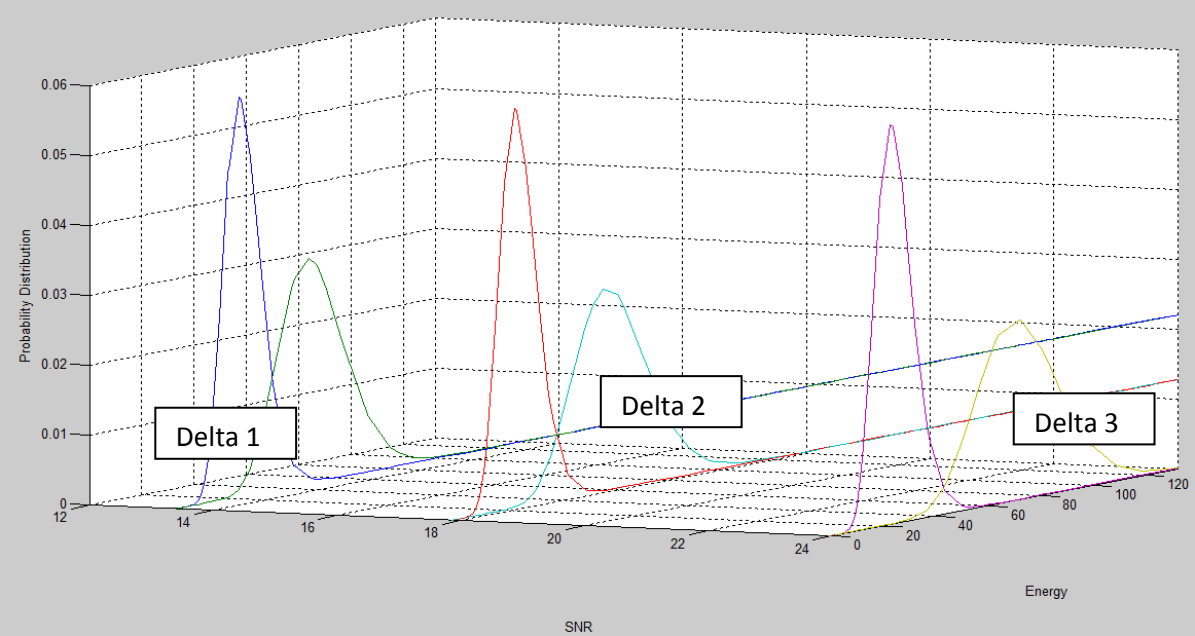
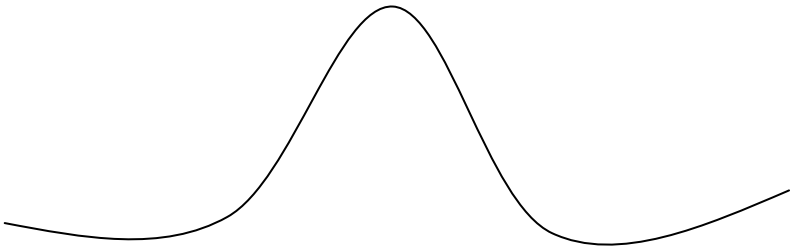



Figure 4.1: Chi-square Plot Showing Uncertainty Region as Triangles

Coordinates of the triangles are given in Figure 4.2 with the following notation;

Peak



Left Right

Figure 4.2: Extract of Uncertainty Triangle

Each of the points of the triangle is described using a coordinate triple i.e. (x, y, and z)

Delta1: peak(13.4,37.15,0.01508),left(13.4,23.43,0.00095),right(13.4,51.42,0.00059)

Delta2: peak(17.86,38.8,0.01115),left(17.86,27.85,0.0006334),right(17.86,52.93,0.0003958)

Delta3:peak(23.94,44.53,0.003317),left(23.94,37.76,0.000996),right(23.94,52.89,0.0003998)

The areas are now computed for each of the triangles using the parameters highlighted

Delta1 area: ½ *27.99*0.01449=0.202

Delta 2 area: ½ *25.08*0.01075=0.1348

Delta 3 area: 1/2 *15.13*0.00292=0.022

Reduction in uncertainty is given by

$$\%\, reduction = \frac{\text{area difference}}{\text{original area}} * 100 \qquad (4.1)$$

1. delta1 & delta 2: (0.202-0.1348)/0.202 *100 =33.27%
2. delta2 & delta 3: (0.1348-0.022)/0.1348 *100 =83.7%
3. delta1 & delta 3: (0.202-0.022)/0.202 *100 =89.1%

A look at the values obtained for the areas of the uncertainty triangles shows that there is a remarkable reduction in the uncertainty region as SNR increases; which is a very significant result considering the fact that a good SNR value enhances the detection capability of the energy detector.

The results shown in Figures 4.3-4.7 show some of the deductions already referred to above:

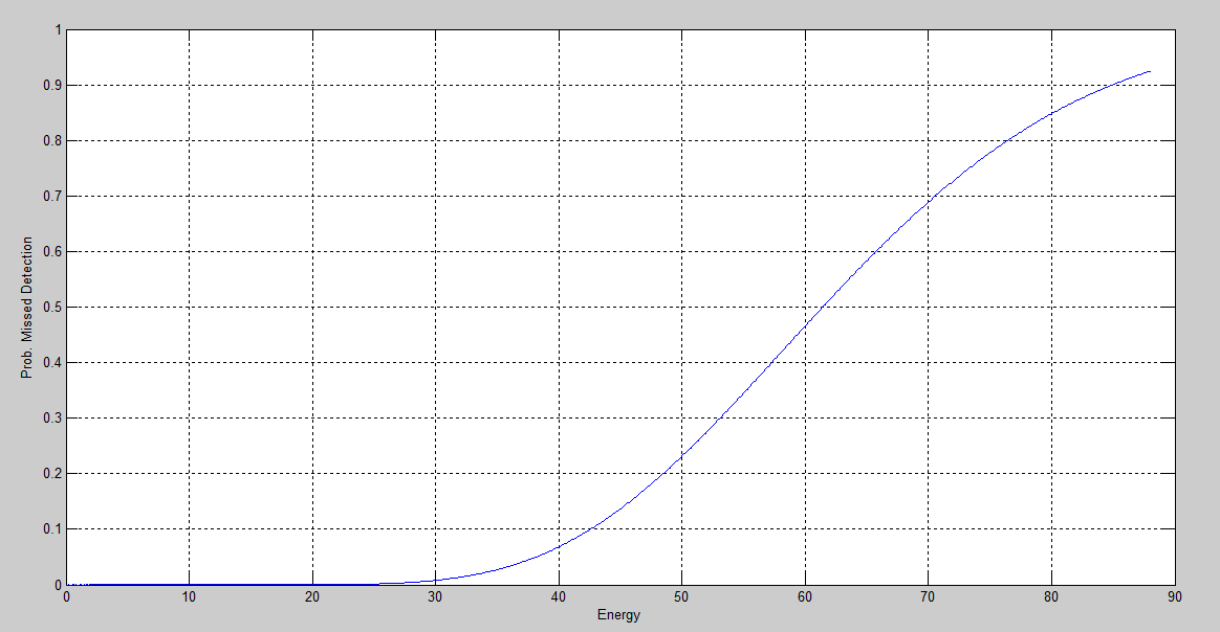



Figure 4.3: Pmd vs. Energy Plot

From a single iteration of the Monte Carlo model, an array of values is obtained for the Pd, Pm, Pfa. The average of these values is computed and this value is subsequently mapped to the energy axis of the PDF vs. Energy plot to obtain an optimal threshold value. For an average probability of Missed detection of about 0.395 computed by the Monte Carlo model, have an equivalent energy threshold value of about 51dB/Watt from the plot above. Looking at the equivalent plot as shown in Figure 4.3, the PDF value can be traced at 0.395 on the first set of plots to obtain a close result to what is obtained here. Subsequent simulations done showed that a large $P_d$ value and a small $P_{fa}$ value to meaning that a good detection threshold is feasible.

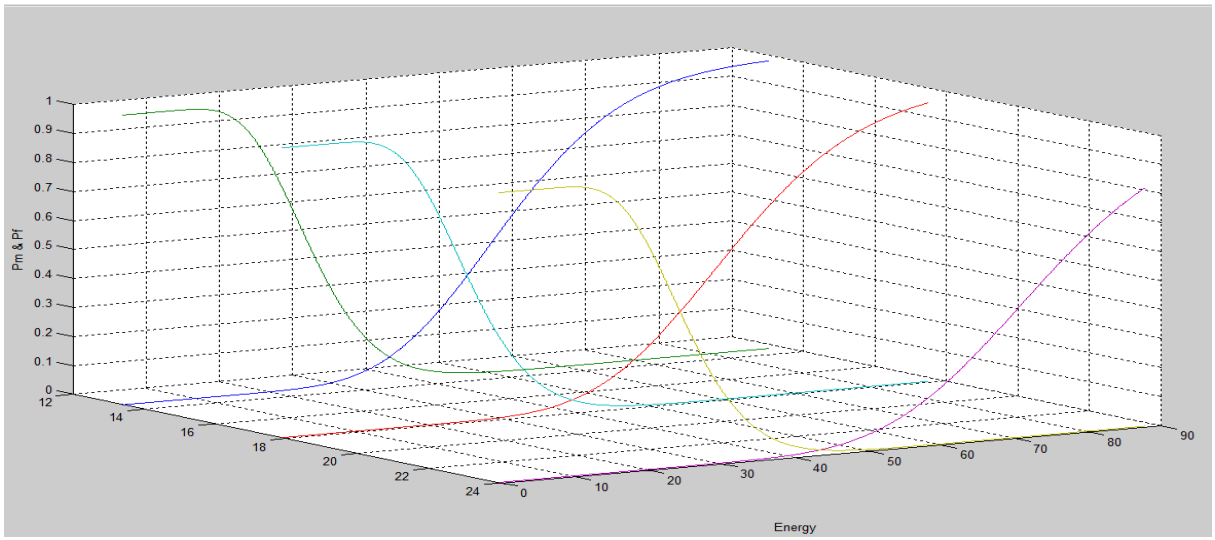



Figure 4.4: $P_{md}$&$P_{fa}$ vs. Energy Plot

Figure 4.4 show the result from plotting probabilities of false alarm and missed detection against SNR and energy. This plot is used to obtain a threshold on the energy axis corresponding to an optimal value of either probability of false alarm or probability of missed detection but not both simultaneously. This is because optimization of one item means sacrificing optimality in the other. The method used in this work to determine the threshold also employed the convergence point of the two plots to decide the optimal threshold by computing the values of probabilities at the index at which the two plots intersect and further reading the corresponding energy value.

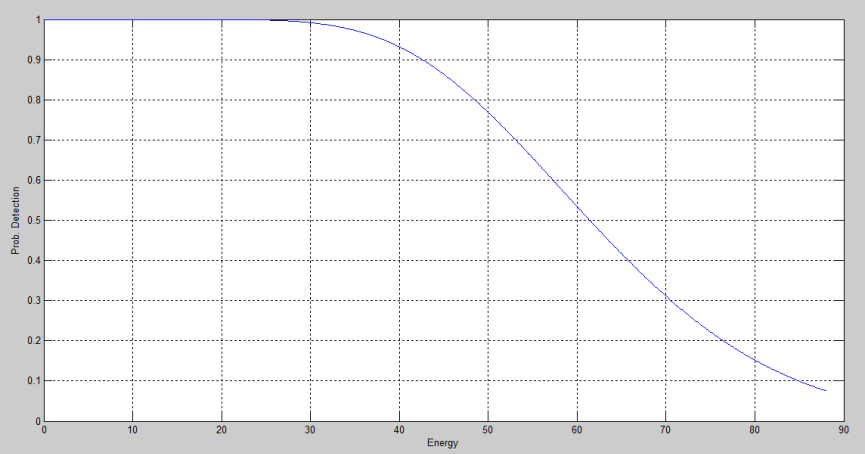



Figure 4.5: Pd vs. Energy

Figure 4.5 extracts the individual curve of detection vs. energy from Figure 3.20 to show more clearly the relationship between the probabilities of detection on the y axis and the energy on the x axis

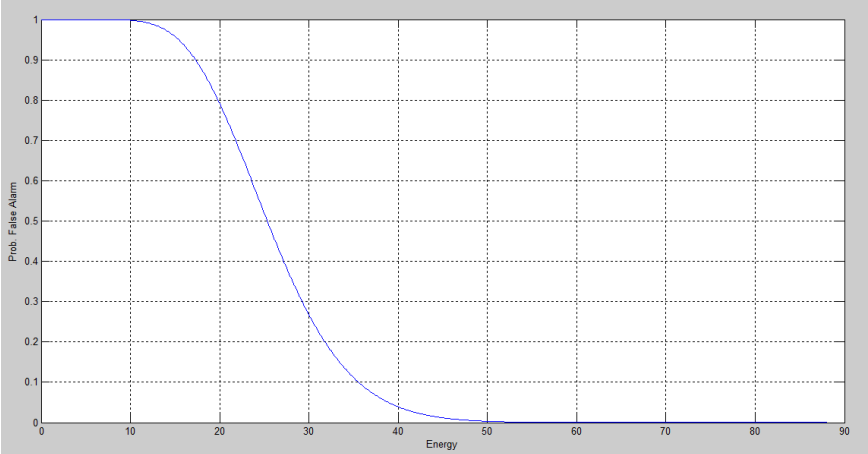



Figure 4.6: Pfa vs. Energy

Figure 4.6 extracts the curve of false alarm vs. energy from Figure 3.40 to show more clearly the relationship between the probabilities of false alarm on the y axis and the energy on the x axis

The Monte Carlo analyses show an estimated energy detection system. This estimation is dependent on the number of iterations made. More iterations result in a quicker convergence to the optimal value and a corresponding reduction in the uncertainty region which is a major objective of this work. Figure 4.6 to 4.8are results that show the changing uncertainty region for 250 Monte Carlo iterations. It can be seen that as the number of iterations increase and with corresponding increase in SNR, the size of the uncertainty region diminishes. Further estimation studies are performed using ANFIS as discussed in section 3.3.7.

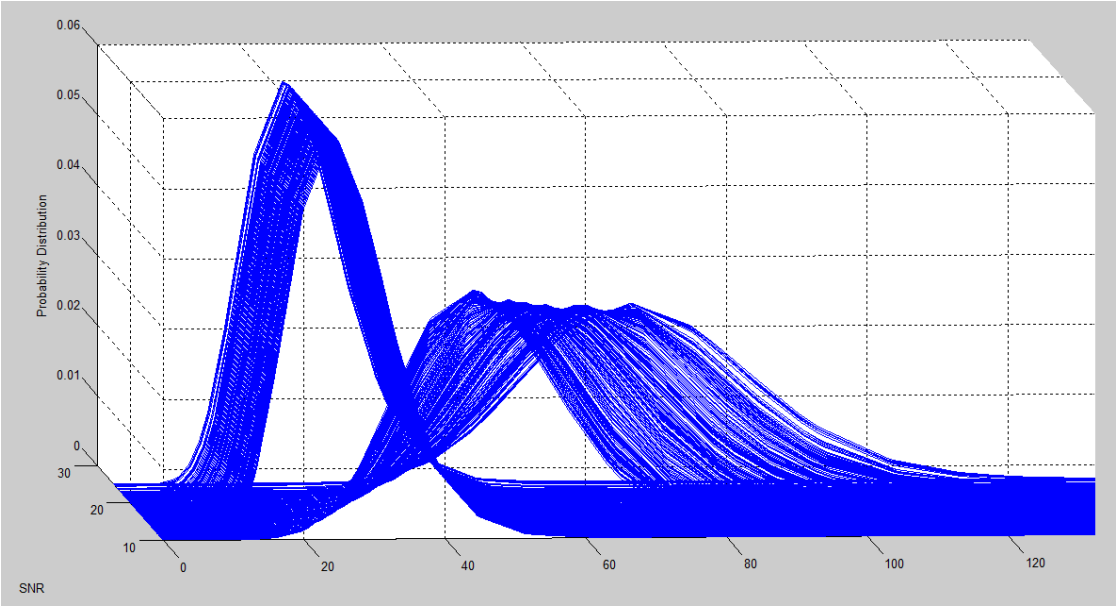



Figure 4.7: PDF vs. Energy for 250 Monte Carlo Iterations

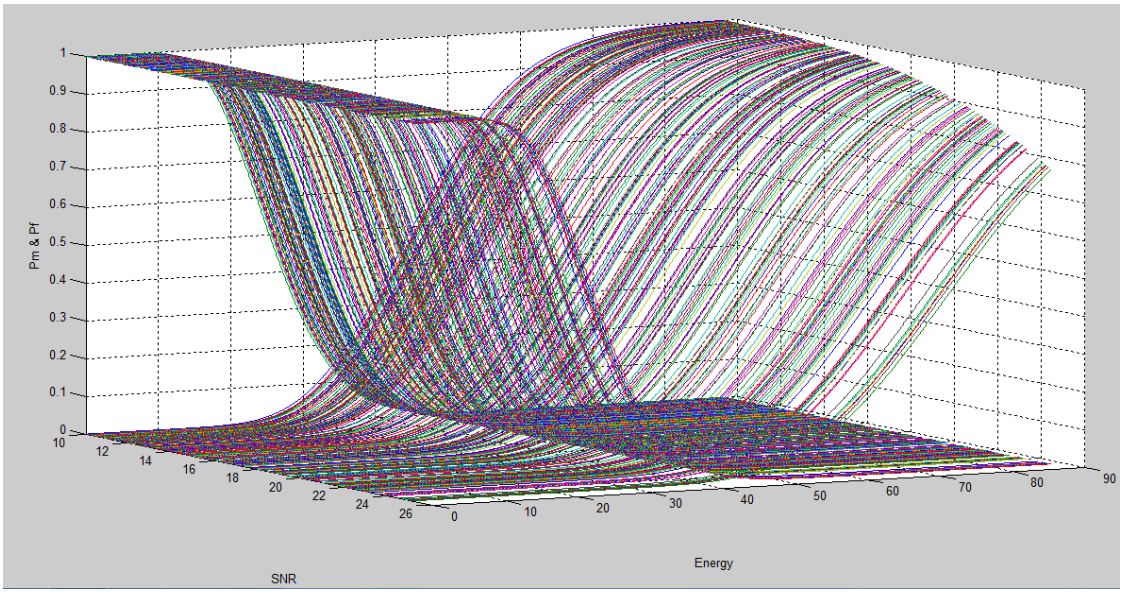



Figure 4.8: Pm & Pf vs. Energy for 250 Monte Carlo Iterations

**Threshold Estimation using Monte Carlo (MC) Statistical analysis**

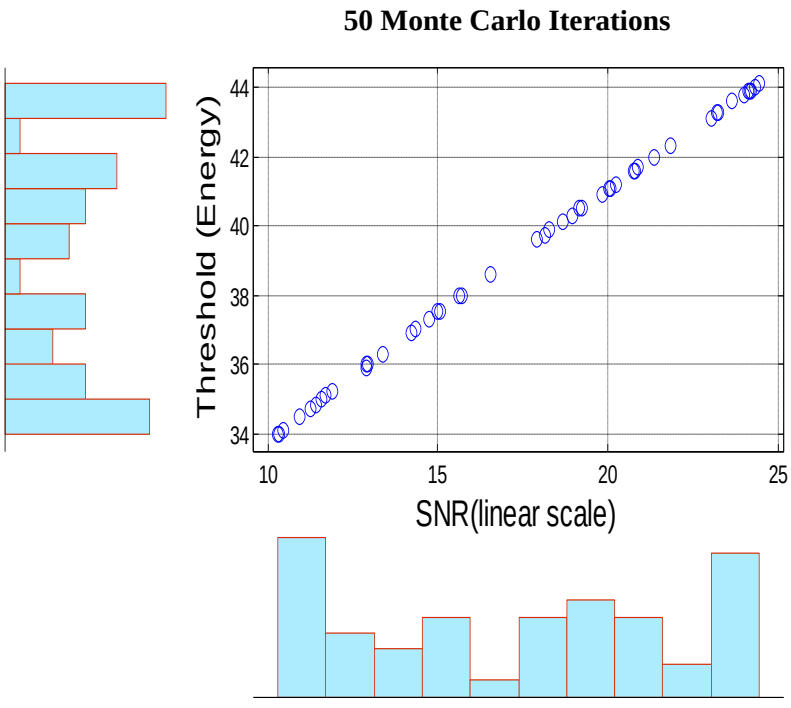



Figure 4.9: 50 Monte Carlo Iterations

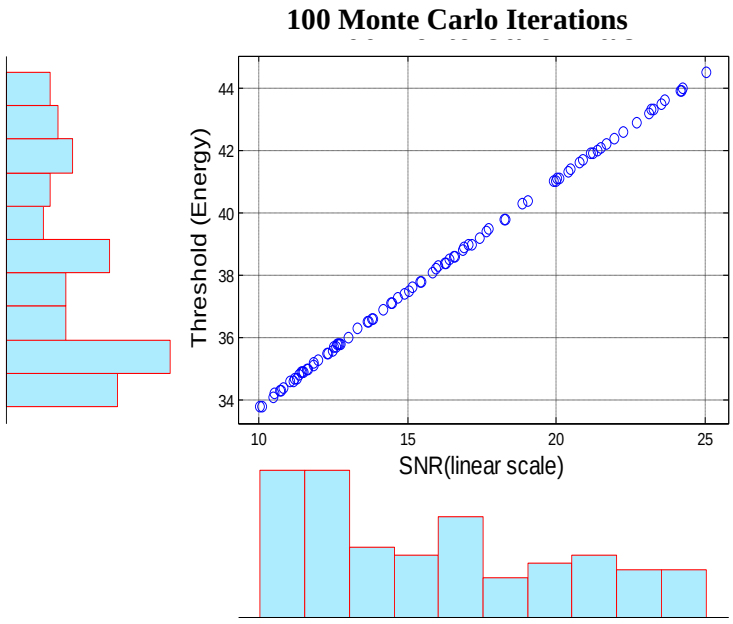



Figure 4.10: 100 Monte Carlo Iterations

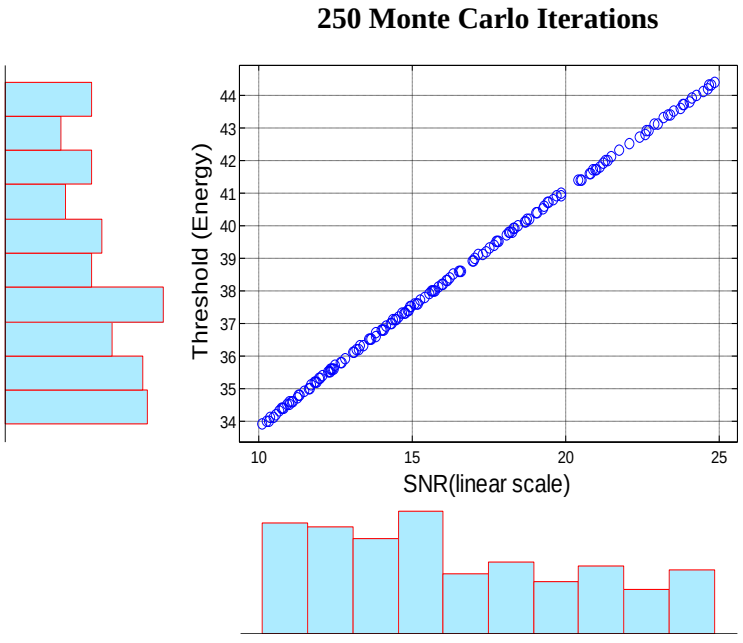



Figure 4.11: 250 Monte Carlo Iterations

Different iterations were made in the Monte Carlo experiment to study the convergence rate to an optimal energy threshold value and the magnitude of deviation between the starting seed threshold and the final computed optimal value. In particular, the Monte Carlo simulation were iterated for 50,100,150,200,500 & 1000 times for the optimization of the detection threshold and all results obtained are logged and displayed for analyses. The increasing number of iterations made is necessary because the Monte Carlo technique which simulates random or chance occurrence of events will perform better with a large sample space. Larger number of iterations bringing correct convergence to a single optimal value. Simultaneously bringing about a corresponding reduction in the uncertainty attached to primary user detection by the secondary users. Some probabilities computed from the sensed energy values are given below in for of a probability vs. Energy plot in Figures 4.12-4.14.

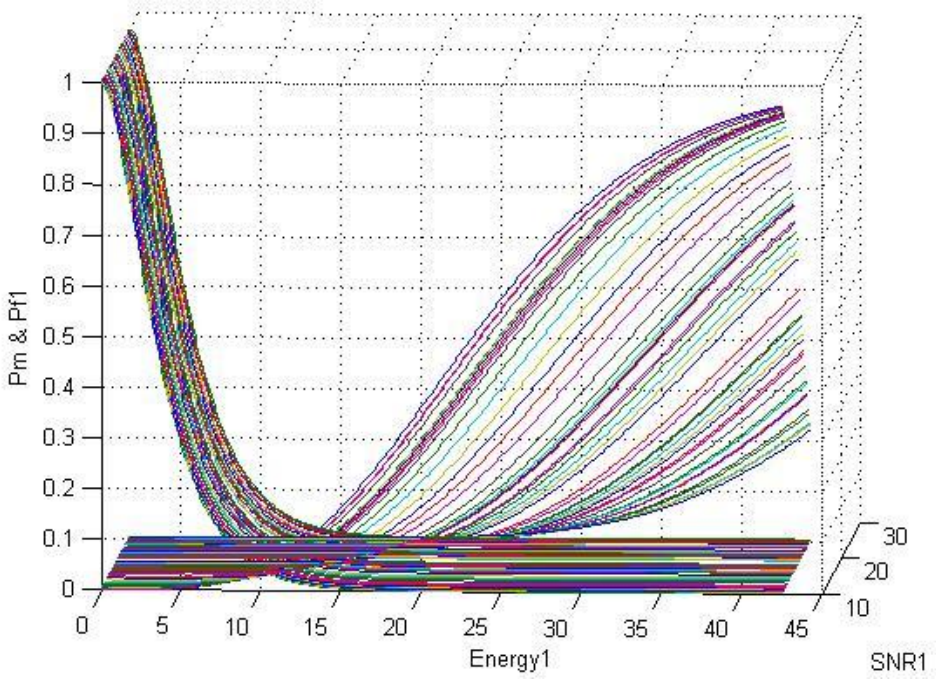



Figure 4.12: Pf,Pm vs. Energy Plot for 50 Iterations

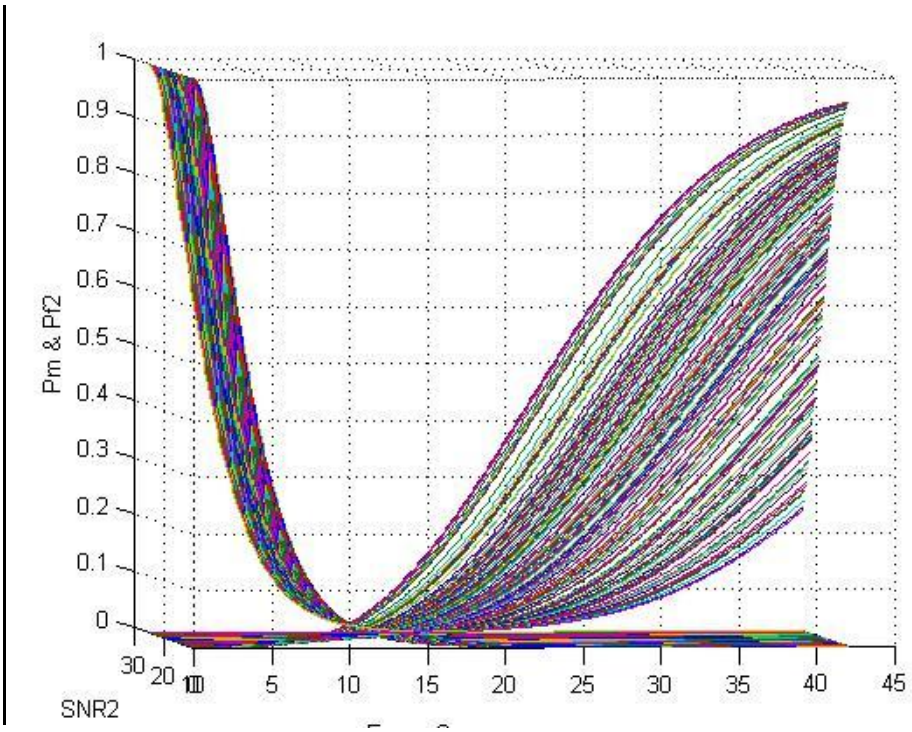



Figure 3.13: Pf,Pm vs. Energy Plot for 150 Iterations

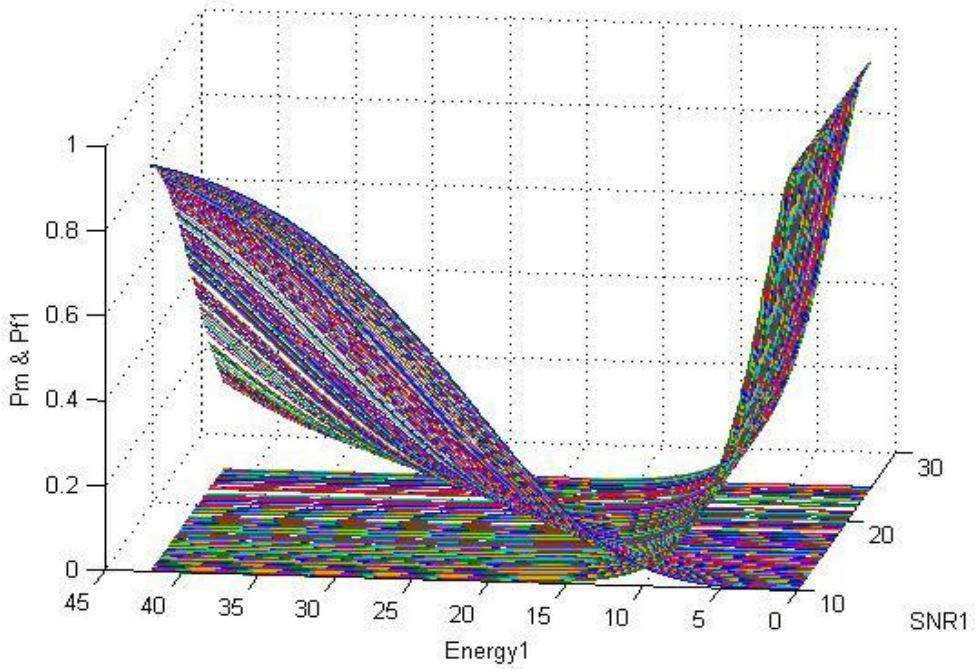



Figure 4.14: Pf,Pm vs. Energy Plot for 200 Iterations

### 4.2.1 Simulation Results

The simulation results show the Threshold estimation using Monte Carlo (MC) Statistical analysis. The estimated threshold value can be read-off the vertical axis of the threshold vs. Monte Carlo plot and the signal to noise ratio (SNR) vs. Threshold plot. The estimated value is represented by the highest magnitude (bar) of the Histogram. All experiments carried out here made use of only two cognitive radios due to computational overhead.

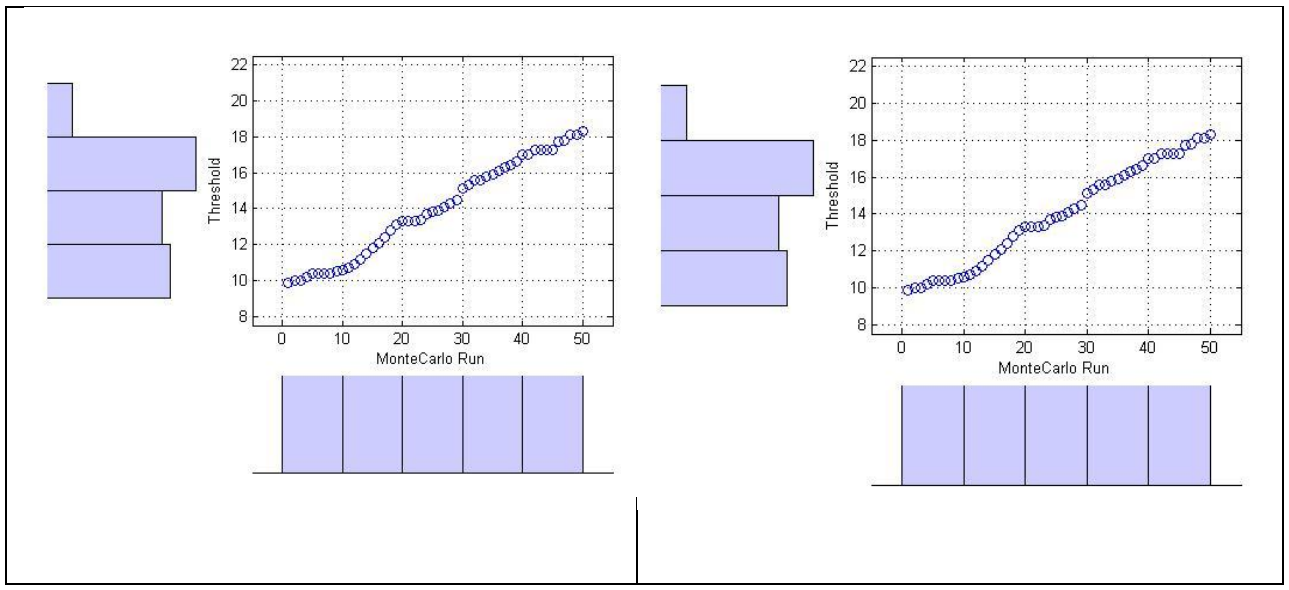



Figure 4.15: Monte Carlo Run for 50 Iterations on CR1 & CR2

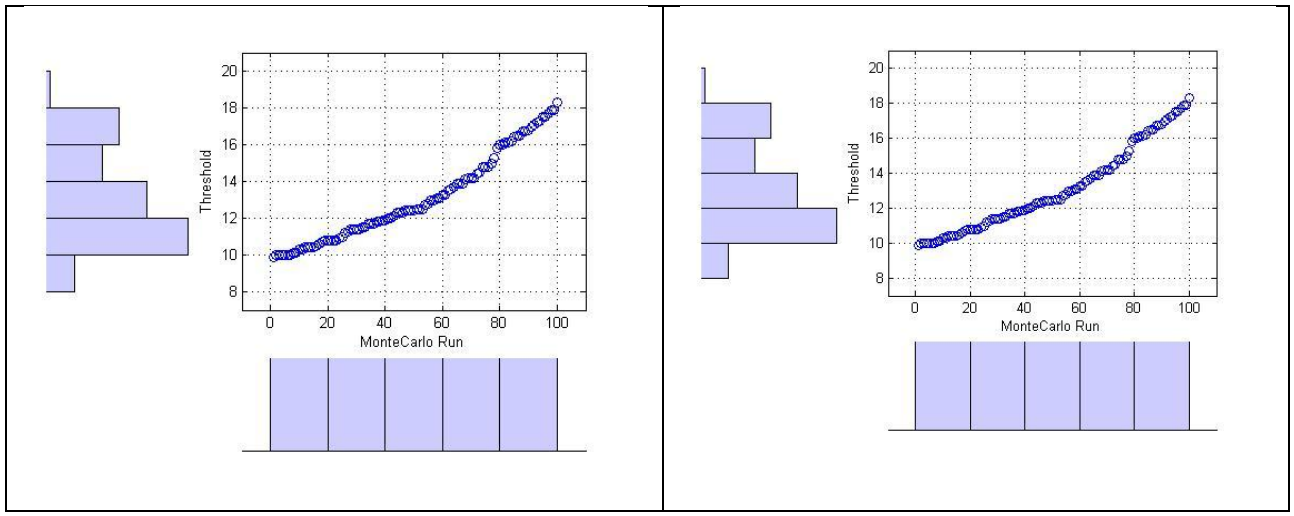



Figure 4.16: Monte Carlo Run for 100 Iterations on CR1 & CR2

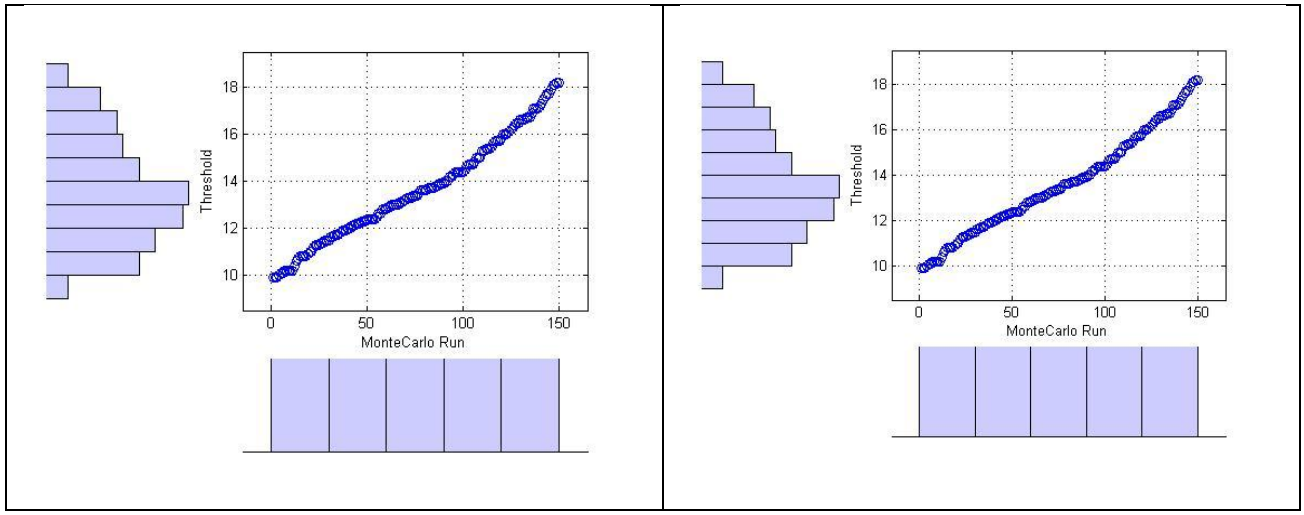



Figure 4.17: Monte Carlo Run for 150 Iterations on CR1 & CR2

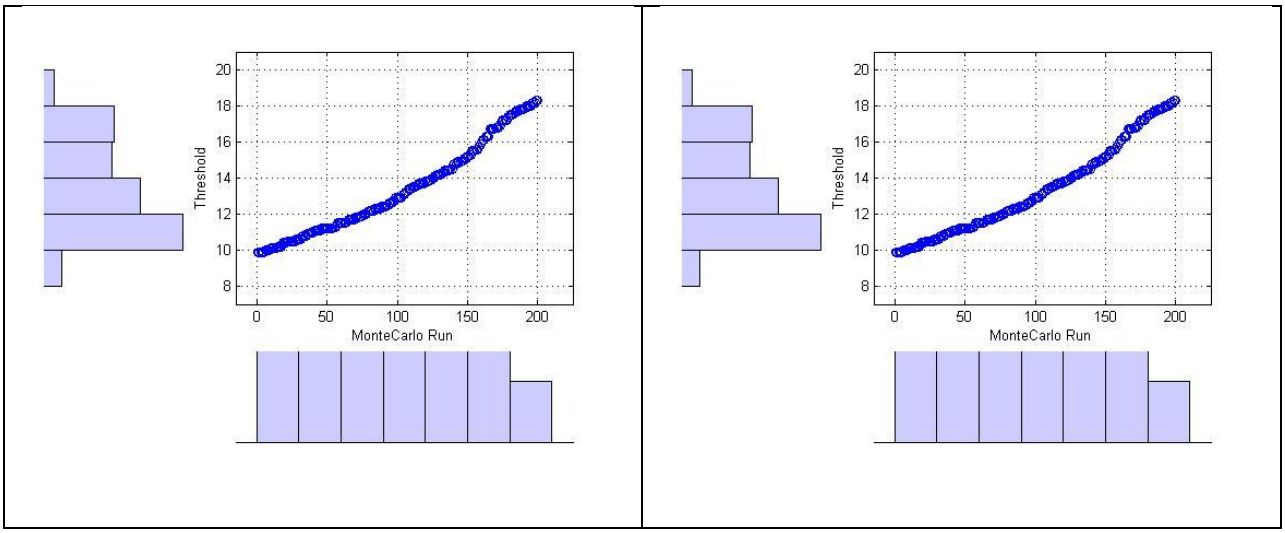



Figure 4.18: Monte Carlo vs. Threshold Plot for 200 Iterations on CR1 & CR2

The Monte Carlo iterations showed a noticeable variation in detection threshold estimated value with change in iteration numbers. An obvious correlation exists between the threshold value and the number of iterations made. Though not conclusive, it is seen that the estimated threshold derived always lies within the region of uncertainty. With estimation being done at the cost of sacrificing accuracy in false alarm or missed detection, the plots of the probabilities (Pf & Pm) vs threshold will give a good measure of which one of these parameters has been considered critical for detection.

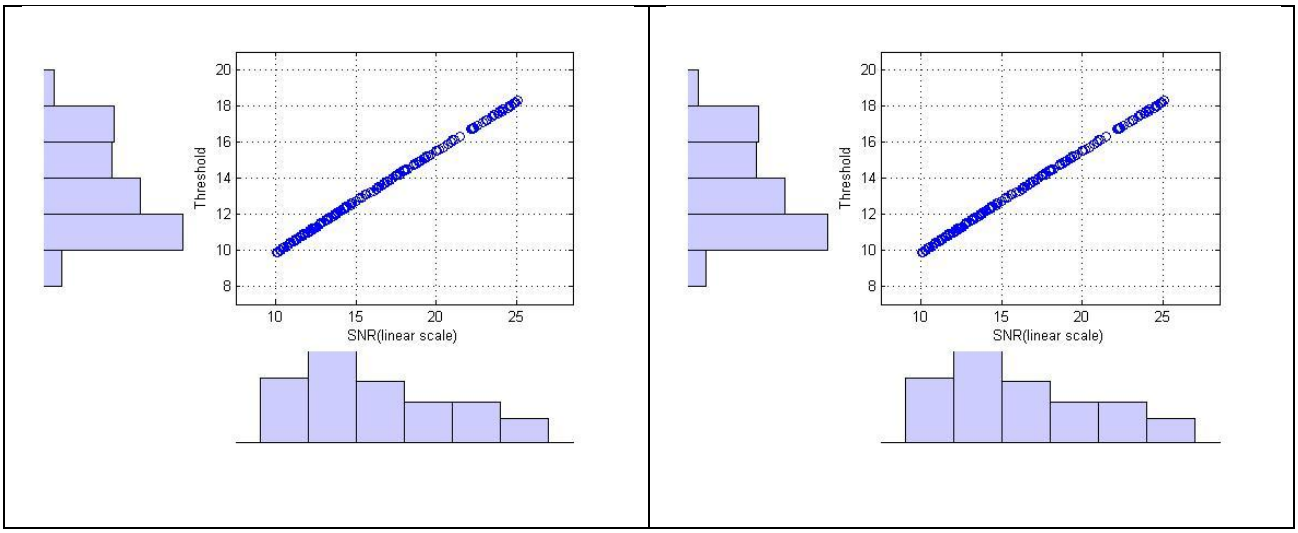



Figure 4.19: SNR vs. Threshold Plot for 200 Iterations on CR1 & CR2

## 4.3 Presentation of Results from Monte Carlo and ANFISEstimation Experiments

Plots from the Monte Carlo and ANFIS Experiments are shown in Figures 4.20-4.25. Using similar experimental parameters for reason of visualization and setting a good basis for comparison. The parameters used for the experiments include the same threshold value for individual cognitive radio sensing, the same number of iterations and same set of input energy values sensed by secondary users.

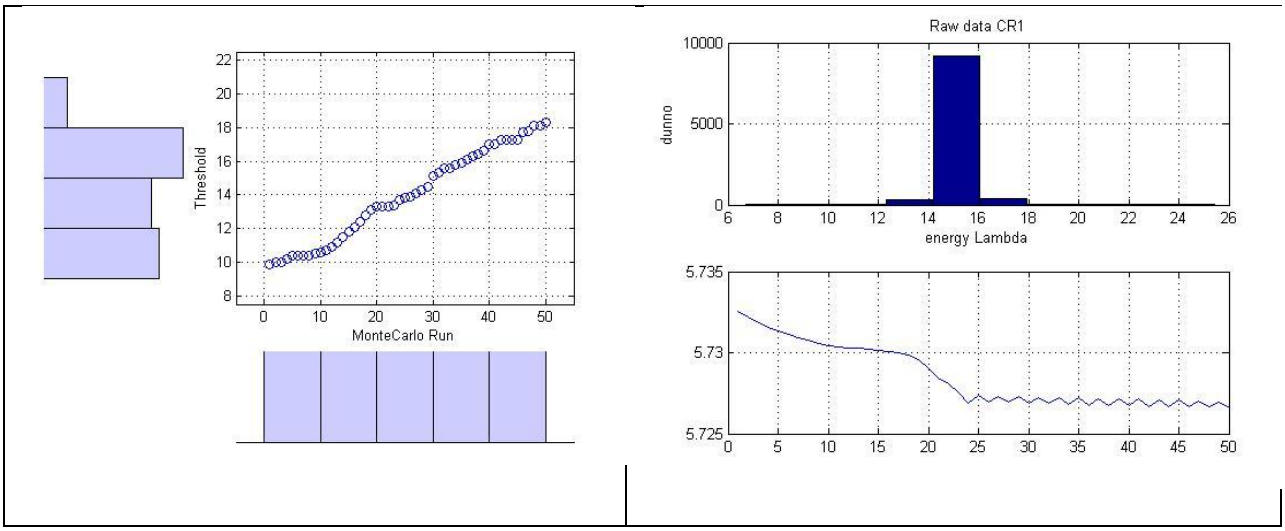



Figure 4.20: Monte Carlo and Fuzzy Results for 50 Iterations on CR1

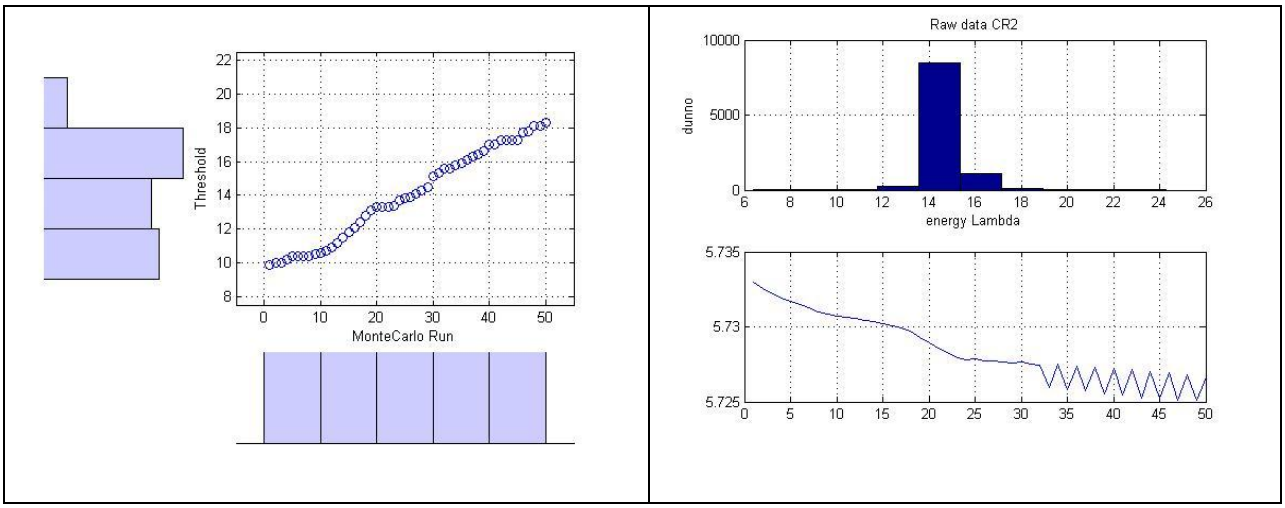



Figure 4.21: Monte Carlo and Fuzzy Results for 50 Iterations on CR2

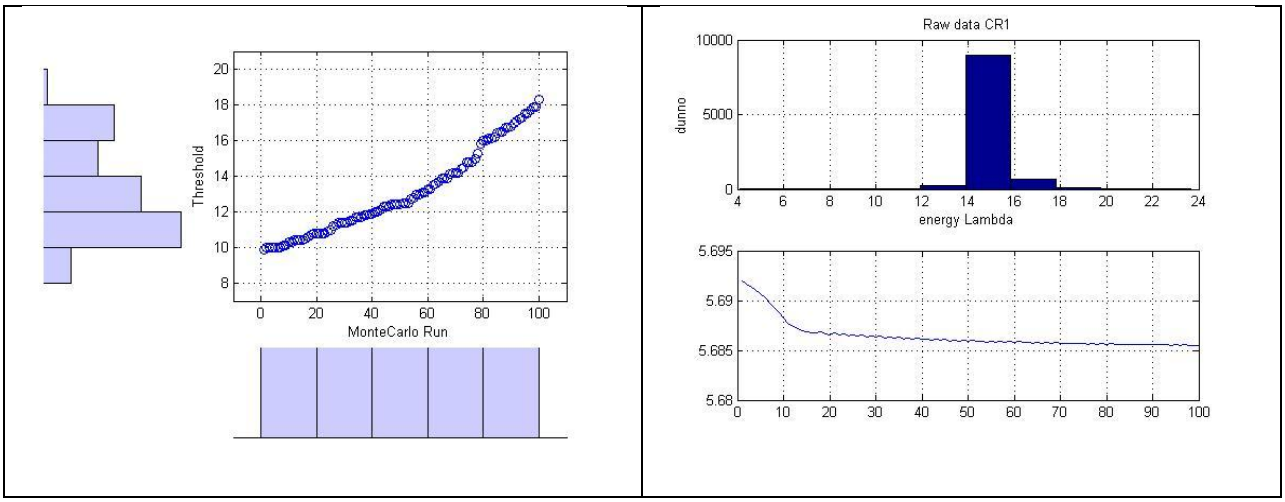



Figure 4.22: Monte Carlo and Fuzzy Results for 100 Iterations on CR1

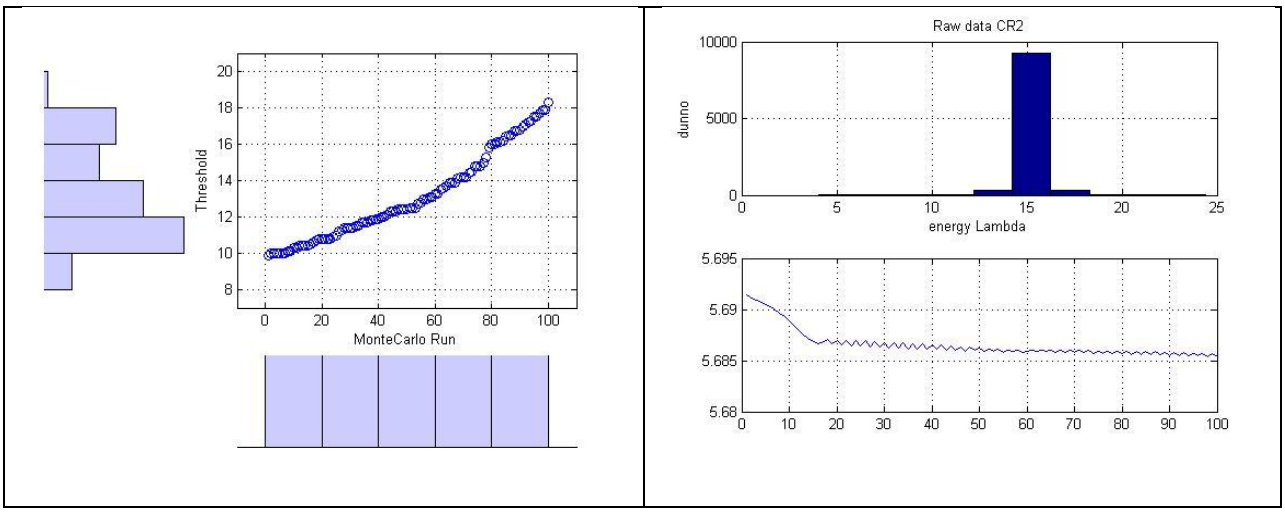



Figure 4.23: Monte Carlo and Fuzzy Results for 100 Iterations on CR2

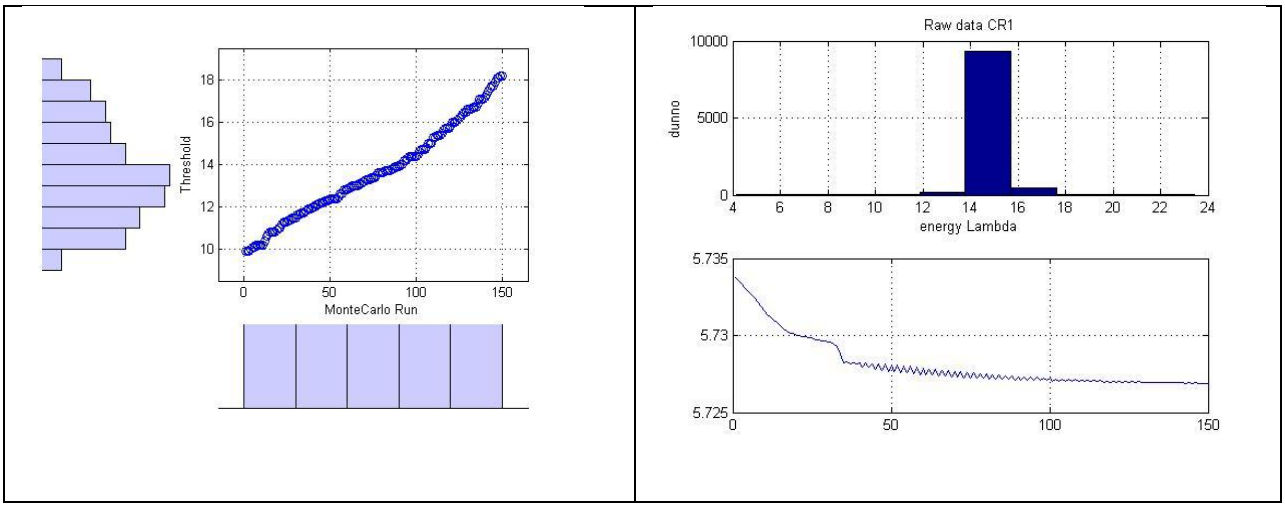



Figure 4.24: Monte Carlo and Fuzzy Results for 150 Iterations on CR1

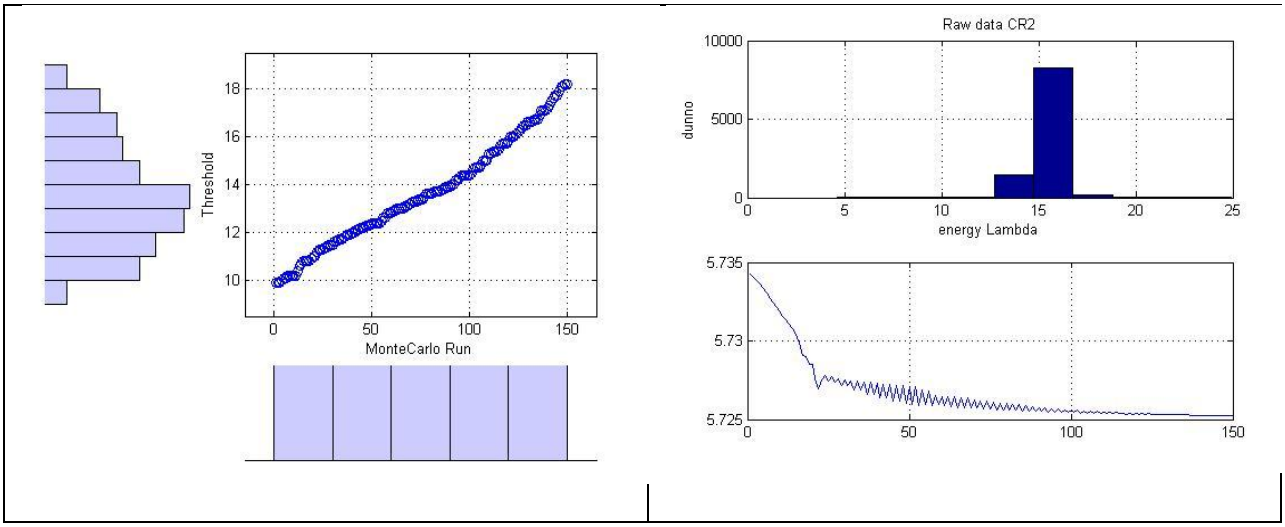



Figure 4.25: Monte Carlo and Fuzzy Results for 150 Iterations on CR2

Observing the results from the Monte Carlo and ANFIS experiments show a very close concurrence in the detection output threshold value obtained. The basis for the comparison rests on the selection of similar parameters for both experiments. It is also of note that both estimation methods employ the model directly in their analysis. Table 4.1 shows some relevant parameters used in the experiments. The start threshold parameter is carefully selected to have a value approximately equal to the signal to noise ratio value used for the simulation. This is because

using this value is a good estimate of the energy to be sensed. This experiment uses two variants of the start threshold value; firstly a fixed threshold value is used and later the same experiment is performed with a randomly generated threshold.

Table 4.1: Performance Comparison between Monte Carlo and Fuzzy Logic

| **Experiment type** | | **No. of Iterations** | **Seed threshold/SNR** | **Estimated threshold** | **% Estimation** | **Elapsed time(s)** |
|---|---|---|---|---|---|---|
| **Monte Carlo** | | 50 | 25, | 15 | 60 | 333.649 |
| | | 100 | 25, | 11.5 | 46 | 626.445 |
| | | 150 | 25, | 13 | 52 | 945.2198 |
| | | 200 | 25, | 12 | 48 | 1284.56 |
| | | | | | | |
| **ANFIS** | | 50 | 25, | 14.5 | 58 | 587.9206 |
| | | 100 | 25, | 14 | 56 | 1171.0 |
| | | 150 | 25, | 13.7 | 54.5 | 1807.1 |
| | | 200 | 25, | 15 | 60 | 2360.99 |

## 4.4 Comparative Analysis of Monte Carlo and ANFIS Estimation Results

Comparative analysis of results from Monte Carlo and ANFIS simulations showed that the estimated threshold in all iterations remained within the observed uncertainty region. Comparison include:

i. Monte Carlo simulations showed a dependence on the number of iterations used unlike the ANFIS simulations which do not depend on the number of iterations.

ii. The computation time for the Monte Carlo analysis as compared to ANFIS was shorter. This can be explained by the type of fuzzy inference engine used which is adaptive and requires continuous recalculations.

iii. Monte Carlo analysis is suitable in non-cooperative cognitive sensing where static allocation is being used. This is so as user diversity is not an issue in the static case. On the hand ANFIS will work better in cooperative spectrum sensing scheme as against non-cooperative.

iv. The role of ANFIS is found to be more useful in cooperative sensing as against non-cooperative spectrum sensing. Especially as it is used to overcome the presence of noise power uncertainty which is the major drawback in cooperative spectrum sensing.

It is worthy of mention that this stage of the work faced many computing constraints in form of slow processing power of the laptops used. Some experiments could not be performed satisfactorily as a result of memory insufficiency issues and so recourse was made to break up some experiments such as the adaptive fuzzy inference iterations which could not take as input all five energy signals of each cognitive user. The data training done here and the subsequent optimization had to be performed for each cognitive user independently.

## 4.5 Experimental Results

Table 4.2 shows the snapshot of energy values sensed at 900MHz while making use of the commercially acquired energy detector set up as shown in Figure 3.13. This setup is preferred for experiments at 900MHz inside the lab because the available microwave generator at the lab is limited to a minimum frequency of 1.2GHz. Therefore in carrying out this experiment, the

microwave link was switched off, while the GSM frequency band of 900MHz was selected as the target band of interest.

Table 4.2: Snapshot of Raw measured data for Signal Measurement at 900MHz (dBm)

| | A | B | C | D | E | F |
|---|---|---|---|---|---|---|
| 1 | Timestamp | Measure Unit | 876100000 | 877600000 | 879100000 | 880600000 |
| 2 | 2014-11-24T12:07:25.331 | dBm | -72.598 | -72.851 | -69.984 | -69.83 |
| 3 | 2014-11-24T12:07:25.488 | dBm | -71.833 | -72.273 | -69.403 | -69.621 |
| 4 | 2014-11-24T12:07:25.644 | dBm | -70.202 | -71.411 | -69.372 | -67.657 |
| 5 | 2014-11-24T12:07:25.785 | dBm | -71.622 | -72.084 | -69.642 | -69.104 |
| 6 | 2014-11-24T12:07:25.926 | dBm | -72.12 | -71.091 | -70.184 | -68.597 |
| 7 | 2014-11-24T12:07:26.051 | dBm | -72.04 | -71.841 | -70.262 | -69.201 |
| 8 | 2014-11-24T12:07:26.176 | dBm | -72.791 | -71.811 | -69.761 | -68.615 |
| 9 | 2014-11-24T12:07:26.317 | dBm | -72.079 | -72.005 | -69.467 | -69.282 |
| 10 | 2014-11-24T12:07:26.457 | dBm | -72.733 | -73.274 | -69.369 | -68.372 |

**Legend**

Location: Etisalat Lab., ABU Zaria

Time: 12:07:25

Date: 24/11/2014

Tables 4.3 and 4.4 show the experimental values for sensed energy recorded when making use of the microwave link at 1800MHz. Data shown in Table 4.2 are values recorded by the energy detector when the experimental setup used is as shown in Figure 4.26, with the microwave generator aligned with the antenna of the energy detector for maximum reception effect.

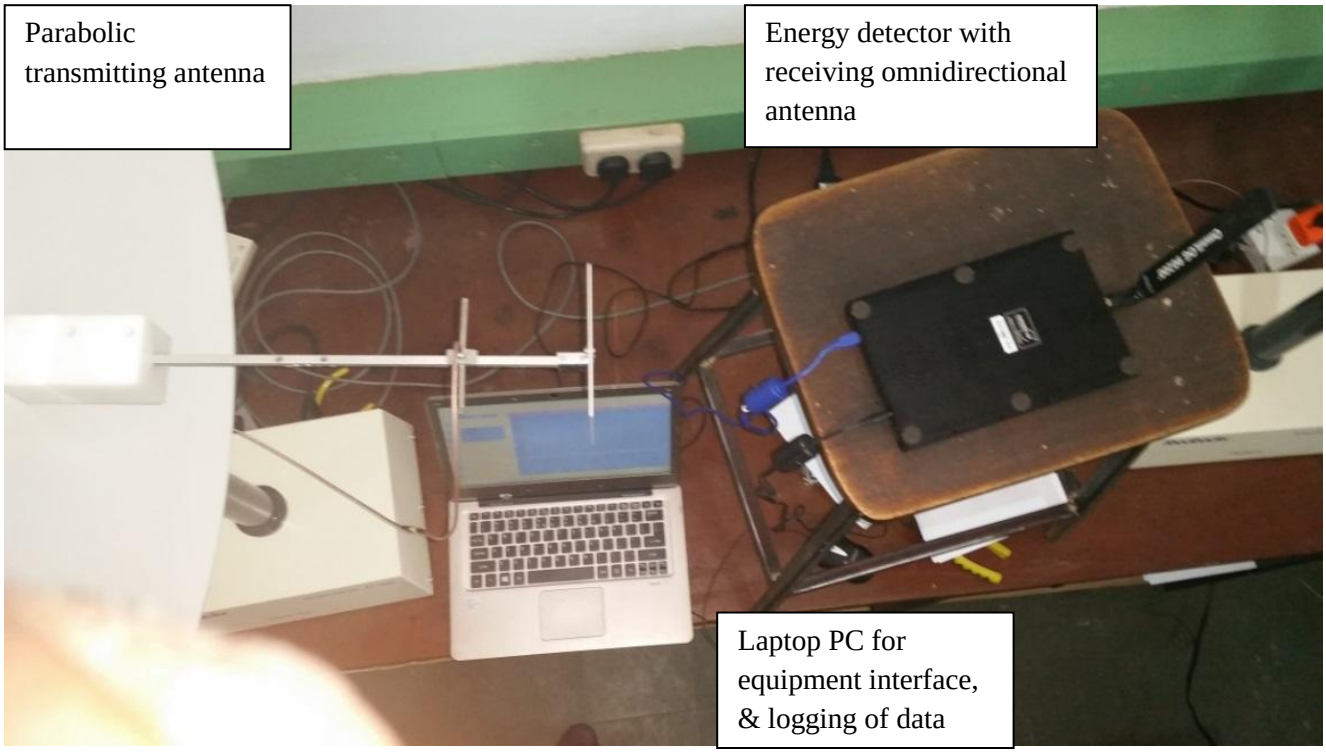



Figure 4.26: A View of Indoor Experimental Setup used at ETEP Lab. of ABU, Zaria

Figure 4.26 shows a view of the experimental setup used for detection and recorded measurements and is depicted here to show the alignment of the transmitting and receiving antennas. It is worthy of note that the microwave link kit had no feature for continuous recording of the sensed energy even though it is also an energy detector.The commercially acquired energy detector on the other hand possessed this recording feature which aided the collection and storing of working data from captures and measurements made. This is the reason why the receiver for the microwave link is subsequently replaced by the commercially acquired energy detector in all the experiments.

Table 4.3: Snapshot of Measured Data for Signal Measurement at 1800MHz (dBm).

| | A | B | C | D | E | F | G | H | I |
|---|---|---|---|---|---|---|---|---|---|
| 1 | Timestamp | Measure Unit | 1710000000 | 1711500000 | 1713000000 | 1714500000 | 1716000000 | 1717500000 | 1719000000 |
| 2 | 2014-11-24T12:09:29.120 | dBm | -79.443 | -90.128 | -79.728 | -79.918 | -79.703 | -79.852 | -84.396 |
| 3 | 2014-11-24T12:09:30.809 | dBm | -78.803 | -90.135 | -79.836 | -79.997 | -79.898 | -79.488 | -82.771 |
| 4 | 2014-11-24T12:09:32.554 | dBm | -77.483 | -80.159 | -77.711 | -77.884 | -77.425 | -78.161 | -78.592 |
| 5 | 2014-11-24T12:09:34.254 | dBm | -77.478 | -80.19 | -77.961 | -77.917 | -77.608 | -77.793 | -78.448 |
| 6 | 2014-11-24T12:09:35.927 | dBm | -77.086 | -80.465 | -77.654 | -77.892 | -77.412 | -77.77 | -79.754 |

**Legend**

Location: Etisalat Lab., ABU Zaria

Time:12:07:25

Date:24/11/2014

On the other hand, Table 4.4represents the noise measurements recorded when the energy detector was tuned to 1800MHz while the microwave link has been switched off. This was done with the knowledge that when the microwave link is switched ON and generating, the measured and recorded signals will be both signal and noise.While when it is switched OFF, mostly noise will be sensed at that frequency considering the experimental setup used,taking note of the short separation distance between the transmitter and the receiver.

Table 4.4: Measured Data for Noise Measurement at 1800MHz (dBm).

| | A | B | C | D | E | F | G | H |
|---|---|---|---|---|---|---|---|---|
| 1 | Timestamp | Measure Unit | 1710000000 | 1711500000 | 1713000000 | 1714500000 | 1716000000 | 1717500000 |
| 2 | 2014-11-24T12:24:35.659 | dBm | -82.345 | -82.6 | -82.953 | -82.899 | -82.369 | -82.325 |
| 3 | 2014-11-24T12:24:37.219 | dBm | -82.233 | -82.996 | -83.106 | -82.883 | -82.52 | -82.716 |
| 4 | 2014-11-24T12:24:38.933 | dBm | -82.337 | -82.854 | -83.072 | -82.815 | -82.543 | -82.498 |
| 5 | 2014-11-24T12:24:40.713 | dBm | -81.637 | -82.137 | -82.093 | -81.747 | -81.654 | -81.748 |
| 6 | 2014-11-24T12:24:42.277 | dBm | -81.619 | -81.823 | -82.088 | -81.888 | -81.701 | -81.772 |
| 7 | 2014-11-24T12:24:43.839 | dBm | -80.664 | -81.698 | -82.007 | -82.039 | -81.535 | -81.713 |
| 8 | 2014-11-24T12:24:45.449 | dBm | -81.413 | -81.67 | -81.856 | -81.836 | -81.854 | -81.659 |
| 9 | 2014-11-24T12:24:47.199 | dBm | -80.971 | -82.043 | -81.915 | -81.699 | -81.701 | -81.632 |

**Legend**

Location: Etisalat Lab., ABU Zaria

Time:12:07:25

Date:24/11/2014

### 4.5.1 Data Capture of Primary User Energy

From theory of energy sensing using the energy detector algorithm, it is known that the following mathematical expressions hold for the hypothesis test (Digham et al., 2003)

$$Y(t) = N(t); \text{ where noise only is present} \quad (4.2)$$

$$Y(t) = N(t) + S(t); \text{ received signal and noise together} \quad (4.3)$$

The results depicted by the spectral plots shown in Figures 3.4-3.11 show graphically the validity of the equations (4.2) and (4.3) for experiments in which signal or noisewas measured. The axes of the histogram has energy signal in decibel miliwatts (dBm) on the vertical axis and frequency distribution on the horizontal axis. The plots were obtained from the following experiments:

i. Captured energy from **indoor** experiment using the energy detector hardware for sensing within the ABU Zaria, (Etisalat laboratory). Where the word captured means the utilization of the energy detector device only for measurements without the microwave signal generator

ii. Measured energy from indoor experiment generated by microwave generator link and sensed by energy detector in the Etisalat laboratory. Where the word measured means the microwave generator was utilized in the experiments.

iii. Captured energy from outdoors at Faculty of Engineering, ABU Zaria

Figures 3.13 and 4.26,show the experimental setup arrangement as was used indoors of the Etisalat communication lab. The main components of this setup include

i. A microwave signal generator covering frequency range of 1.2GHz to 1.8GHz.

ii. A microwave signal receiver with the logarithmic antenna on the far right of the picture.

iii. A desktop PC which hosts the application interface for the microwave link described by i& ii.

iv. In between the microwave link is a laptop PC and a commercially acquired energy detector with receiving range of 1Hz to 9.4GHz.

## 4.6 Further Quantitative Analysis and Collation of Relevant Results

Other analyses made were the comparison of the energy minimums and maximums for both the signal and the noise captures and measurements. The utility of this is to show the change in value or contribution of the signal and/or noise in the captured and measured data. This analysis follows from the data used in generating the histogram plots for the various experiments described in the indoor and outdoor experiments.

Table 4.5, shows that with the effect of the signal added to the noise brings about a considerable increase in the energy value as reflected in the computed percentage maximum in the last column of the table. It is noteworthy that the percentage minimums do not change much as the component making up the minimum measured signal in both the signal measurements and noise measurements is predominantly the noise which is noticeable in both types of captured data.

Table 4.5: Experiment for Energy Capture at 900MHz

| Exp | Signal minimum dBm | Signal maximum dBm | Noise minimum dBm | Noise maximum dBm | Difference minimum dBm | Difference maximum dBm |
|---|---|---|---|---|---|---|
| 1 | -75.053 | -52.707 | -75.355 | -66.503 | 0.302(0.401%) | 13.796(20.74%) |
| 2 | -79.175 | -53.35 | -80.893 | -66.535 | 1.718(5.1%) | 13.185(19.78%) |

Table 4.6, can be explained similarly. It represents the summary and comparison of results obtained from outdoor measurements at 1.8GHz. The 50Ω impedance was employed here to obtain noise level measurements for both experiments done at this frequency.

Table 4.6: Experiment for Energy Capture at 1800MHz

| Exp | Signal minimum dBm | Signal maximum dBm | Noise minimum dBm | Noise maximum dBm | Percentage difference minimum dBm | Percentage difference maximum dBm |
|---|---|---|---|---|---|---|
| 1 | -90.135 | -63.879 | -92.061 | -72.331 | 1.926(2.09%) | 8.452(11.69%) |
| 2 | -90.588 | -62.795 | -93.268 | -71.329 | 2.68(1.6%) | 8.534(13.18%) |

## 4.7 Experiments for 1800MHz Generated from the Microwave Parabolic Dish Antenna

Indoor measurements also showed a remarkable difference in the measured signal and noise values. The difference was more evident here due to limitations in impediments which are not as pronounced when compared to that of outdoor measurements. The results show a significantly higher signal measure as against those obtained outdoors. The arrangement of the experimental setup is given as the reason for the higher magnitude recorded signals. Reduced interference

from fading and multipath effects is also another reason why the indoor measurements can be seen to have stronger deviation between the noise and signal measurements. These results are summarized in Table 4.7

Table 4.7: Generated Signal at 1800MHz from the Microwave Parabolic Dish Reflector and Antenna

| **Exp** | **Signal minimum (generator ON) dBm** | **Signal maximum (generator ON) dBm** | **Noise minimum (generator OFF) dBm** | **Noise maximum (generator OFF) dBm** | **difference & % difference for minimum (dBm)** | **difference & % difference for maximum (dBm)** |
|---|---|---|---|---|---|---|
| 1 | -89.071 | -38.225 | -91.91 | -66.62 | 2.839 (3.1%) | 28.395 (42.6%) |
| 2 | -89.960 | -55.95 | -92.27 | -69.96 | 2.31 (2.5%) | 14.01 (20%) |

## 4.8 Summary of Results

In summary, results for all three action items from the research methodology are presented as follows:

a. Measurement of pertinent parameters from the energy detector. The values which were obtained from the measurement are the primary users signal energy, noise measurements, detection threshold values and working frequencies which can be seen in Figures

Table 4.8 shows the different experimental results for the detection threshold. The final detection threshold is computed from the average value at the particular frequency.

Table 4.8: Measured Pertinent Parameters using the Hardware Experiments

| Serial number | Experiment Type | Detection threshold | Mean detection threshold |
|---|---|---|---|
| 1 | 1st set Noise energy capture at 900MHz | -71.1388dBm | -70.944dB |
| 2 | 2nd set Noise energy capture at 900MHz | -70.7483dBm | |
| 3 | 1st set Noise energy capture at 1800MHz | -81.3657dBm | -81.326dB |
| 4 | 2nd set Noise energy capture at 1800MHz | -81.2865dBm | |

b. Lastly the validation is made, which is a repetition of experiments from the prototype on the simulation model of the non-cooperative cognitive radio model utilizing the same system parameters as in the prototype. The obtained primary user energy values wererecorded and thresholding was performed on the sensed energies utilizing the computed noise threshold from the prototype experiments. The validation experiment was performed with an operating frequency of 1.8GHz similar to that used at the ETEP lab indoor experiments.

Table 4.9: Summary of Results

| Experiment | Investigated Frequency | Nominal Sample Time (prototype) | Sample Time (Simulation Model) | Noise threshold (prototype) | Noise threshold (Model) |
|---|---|---|---|---|---|
| 1 | 900MHz | 1ms | 1ms | -71.1388dBm | -67dBm |
| 2 | 900MHz | 1ms | 1ms | -70.7483dBm | |
| 3 | 1800MHz | 500ms | 500ms | -81.3657dBm | -80.1dBm |
| 4 | 1800MHz | 500ms | 500ms | -81.2865dBm | |

Table 4.9 gives the spectrum occupancy at the two frequencies of interest and for the various experiments made. The detection using a dynamic or computed threshold is presented and that

with the fixed computed mean threshold is also made. Table 4.10 gives an indication of the number of primary users present or absent.

Table 4.10: Spectrum Occupancy Results for Dynamic and Mean Threshold Settings of Prototype

| **Dynamic Threshold** | | | | |
|---|---|---|---|---|
| | | Threshold | PU present | PU absent |
| 1 | 900MHz | -71.1388dBm | 1576 | 3352 |
| 2 | 900MHz | -70.7483 dBm | 6034 | 5166 |
| 3 | 1800MHz | -81.3657 dBm | 170 | 334 |
| 4 | 1800MHz | -81.2865 dBm | 275 | 341 |
| **Mean Threshold** | | | | |
| 1 | 900MHz | -70.944 dBm | 1868 | 3060 |
| 2 | 900MHz | -70.944 dBm | 5454 | 5746 |
| 3 | 1800MHz | -81.326 dBm | 174 | 330 |
| 4 | 1800MHz | -81.326 dBm | 268 | 348 |

## 4.9 Interpretation of Results

Two frequency bands have been investigated in this work, from the captured data and knowledge of the GSM operating conditions at the Electrical and Computer Engineering Department of ABU, Zaria where the data was collected, it is observed that higher spectrum occupancy was obtained at the 900MHz or 2G band. This agrees with the prevailing GSM operating standards, which sees most of the operators still having a 2G back bone for their networks. Compared to the 3G or 1800MHz standard in which fewer occupants are observed. This is borne out by the fact that similar times for data capture were recorded with a considerable reduction in the number of captures for the 1800MHz case as against the 900MHz.

For the threshold selection, using the 50Ω matched impedance, the average or mean noise value recorded and used for the detection experiments was -70.944dBm in the 900MHz case and -

81.326dBm in the 1800MHz experiment. These values were recorded, for use in simulation verification exercise on the non-cooperative cognitive radio model developed in the first part of this research work. The recorded noise values have been described to be mean values of the noise measurement recorded at the test frequency of either 900MHz or 1800MHz. On transferring the measured parameters to the simulation model of the non-cooperative system, the simulated results for primary user energy was obtained and used in carrying out comparison with the sensed energy values from the prototype detector. In doing this, it was made sure that same threshold was set and same test parameters were used.

The simulation model which runs an energy detector generated magnitude squared values as its final output. These values which were generated as a single column array have been converted to their decibel equivalent so as to get the output from the simulation model in same units as the sensed energy from the prototype detector. It is on this transformed magnitude to decibel values that threshold operation is performed using the earlier computed noise average. Furthermore the threshold setting and comparison enabled the generation of crisp statistic values and evaluation of overall spectrum occupancy by primary users. Utilizing the Matlab version of the non-cooperative CR system with similar experimental parameters as set on the prototype system, the results yielded values that were close to that recorded on the prototype.

Some further notes on the threshold obtained from the prototype must be made considering the fact that the sensed energy is a function of free-space noise and other impairments which impair the sensed primary user signal. On the other hand, the signal to noise ratio value set in the simulation model is not subject to these spurious noise and external disturbances. Consequently, the behavior of the sensed signal by the energy detector prototype and the energy detector for the simulation experiments will be somewhat different.

Finally the spectrum occupancy has been evaluated in terms of primary user present and numbers of primary users absent. This result is shown in Table 4.10. From the table of results it was deducted that at the mean threshold values, the overall statistic for the spectrum occupancy revealed that there were more PUs absent than present. The inference from this was that the holes can be allocated to intending secondary users.

At the dynamic threshold setting, the same statistic applied and same inference can be made save for experiment 2 at 900MHz which showed a higher spectrum occupancy number.

## 4.10 Discussion of Results

The results of the experimental validations and the histogram plots of all the indoor and outdoor measurements carried out and the interpretations were discussed in the following sections.

### 4.10.1 Further Explanation of Experiments

Where two spectral plots depict the same frequency in the title, it means either

1. The experiment was repeated twice so as to gain confidence in the observed measurements i.e. for the same frequency, signal capture and recording was done twice or
2. At the same investigated frequency, signal measurements were taken and then noise measurements proceeded to be taken at the same frequency was also taken. The difference here is the use of the energy detector omnidirectional antenna for signal measurements and the use of the 50Ω matching impedance for the noise level measurementsonly.

3. A third type of experiment was carried out with the microwave link in which noise measurement at the investigated frequency of 1800MHz were carried out by simply switching off the microwave link before commencing measurements.
4. Where the caption for the figures says Capture, the microwave generator has not been used. While when the caption says Measurement, the microwave generator was deployed and used.

### 4.10.2 Capture Experiments at 900MHz and 1.8GHz

The following histogram plots of the energy vs. frequency distribution have been chosen as the preferred choice of rendering graphically the sensed energy by the energy detector. The energy shown on the vertical axis represents the various spectral energy components as measured and earlier shown as the values in Table 4.3 consisting of processed results. The horizontal axis labeled as frequency distribution is a dimensionless quantity and just shows the number of times a particular spectral energy component or energy value occurs.

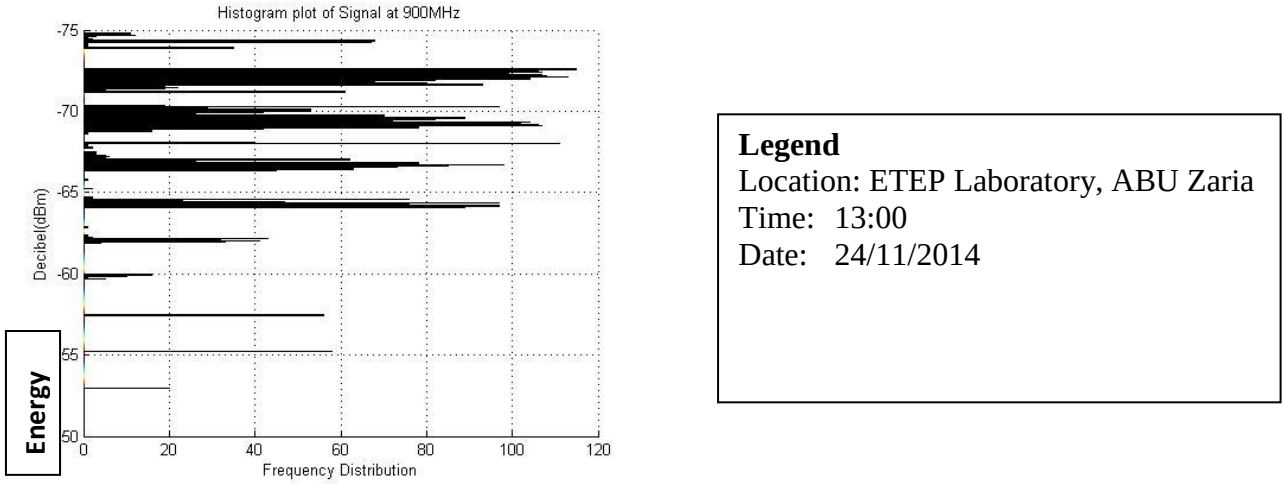
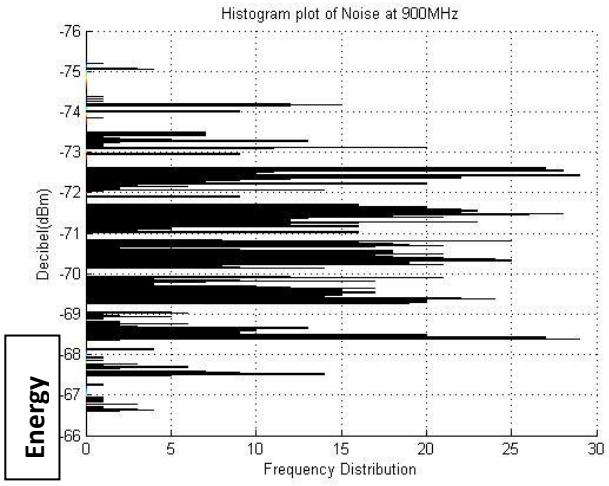



Figure 4.27: Signal plus Noise Capture at 900MHz

Recalling the equations for the hypothesis test (equations (4.2) and (4.3)) describing the value of sensed energy for noise only present and signal plus noise present, it is observed that the spectral plot of Figure 4.27 gives a good insight into the availability or presence of primary user energy through the higher recorded energy values in dBm shown on the vertical axis of Figure 4.27. It is observed that the largest magnitude component of the recorded signal is at -53dBm of Figure 4.27.




**Legend**
Location: ETEP Laboratory, ABU Zaria
Time: 13:00
Date: 24/11/2014

Figure 4.28: Noise only Capture at 900MHz

Furthermore Figure 4.28 represents energy of signal plus noise captured within the ETEP Labat a transmission frequency of 900MHz without utilizing the microwave generator which is ineffective at this frequency due to its being limited to a lower frequency limit of 1.2GHz. A higher frequency distribution for the signal plus noise as against the noise only was observed. This explains the fact that most GSM network operators in Nigeria are operating at this frequency, making it to have a high incidence of occurrence unlike the noise plot at the same frequency which is having a lower incidence.

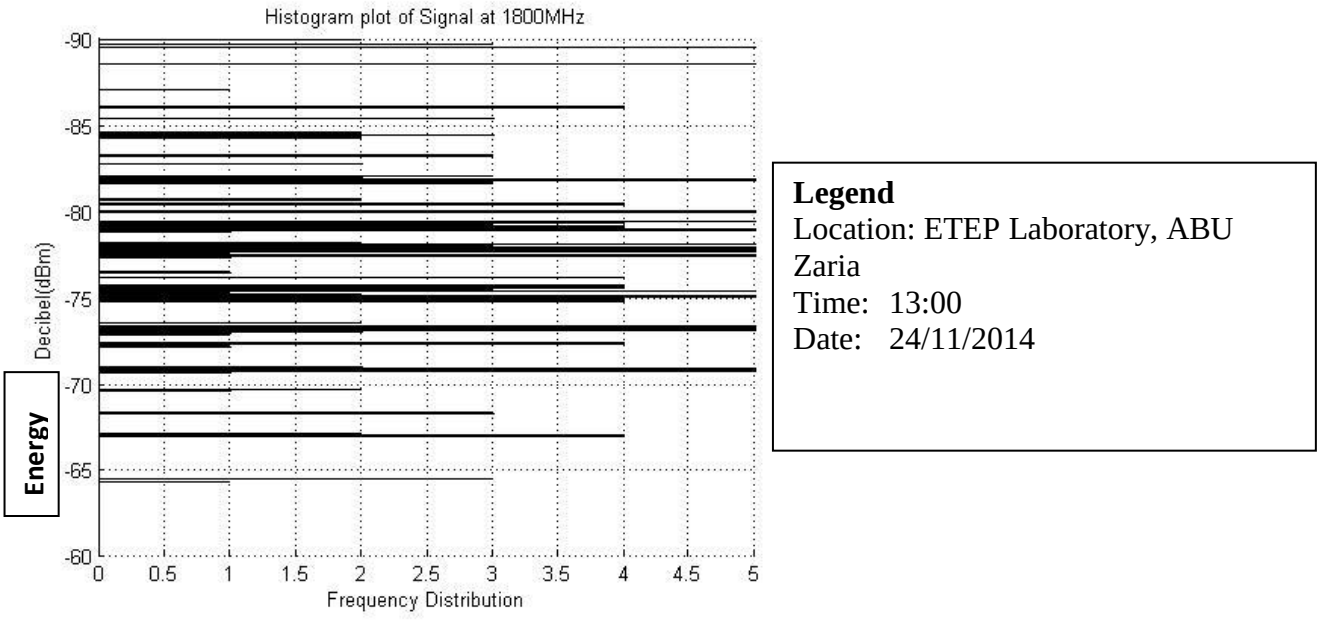



Figure 4.29: Captured Signal plus Noise at 1800MHz

Figure 4.29 shows a weak or sparse energy spectral plot for signal plus noise measurements at 1800MHz. This capture was made with the omnidirectional antenna of the energy detector fixed. The plot in Figure 4.30 shows the result from noise measurements using the 50Ω matching impedance.

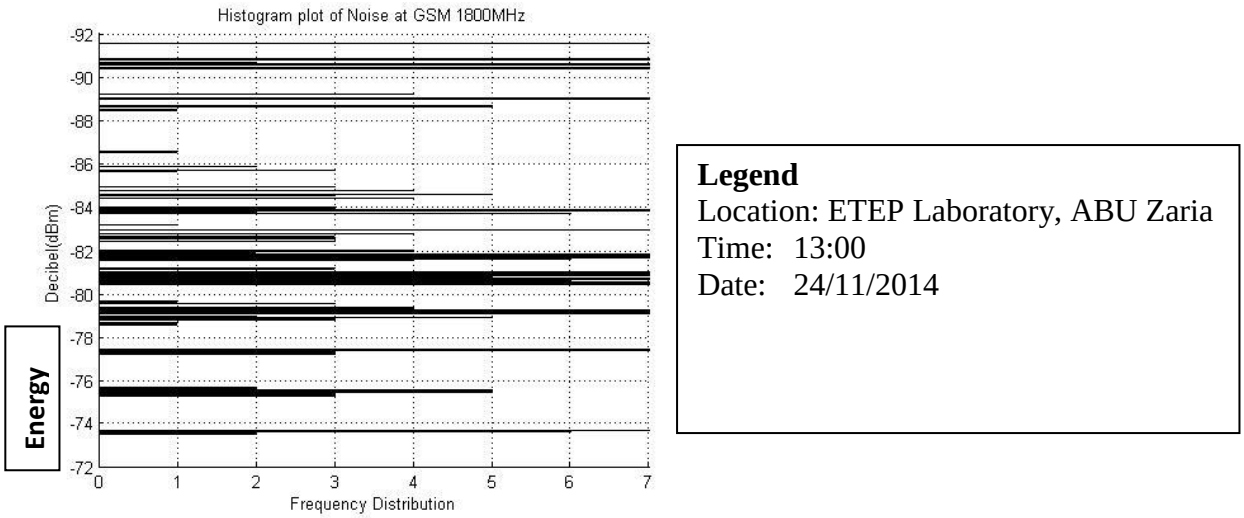



Figure 4.30: Captured noise only at 1800MHz

Again from Figures4.29 and 4.30, it is seen that captured energy of signal and noise was displayed at 1800MHz operating frequency. Informative here is the lower frequency distribution of signal at 1800MHz because very few operators are operating at this frequency. The noise component captured at this frequency is seen to have a higher frequency distribution as noise predominates at this frequency.

### 4.10.3 Microwave Generator Experimentsat 1.8GHz

Experiments using microwave generator at 1800MHz will now be described in detail. Figure 4.31 shows the first result obtained from transmissions by the microwave generator and parabolic dish transmitting antenna. From the plots observed so far, this spectral plot shows the strongest magnitude of signal at about -40dBm. This is useful to note when it is compared to the plot at1.8GHz displayed in Figure 4.32 for a simple capture experiment which had its strongest spectral component at about -64dBm. Reasons for this will be the directivity of the transmitter and receiver in the measurement experiment as against the capture experimental data.

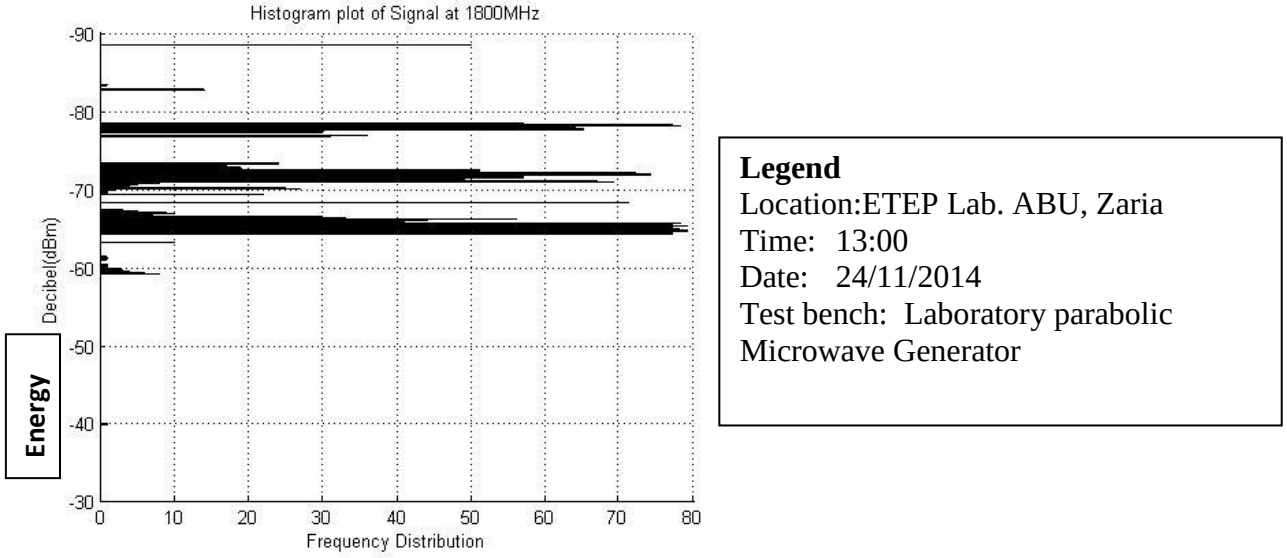



Figure 4.31: Measured Signal at 1800MHz

Very interestingly, while this is the energy captured and rendered by the prototype energy detector, the application interface that comes with the microwave link also recorded the same peak value. This will explain the other spectral components to either be more of noise contributions as for this experiment, the transmitter and receiver were placed close to each other and along a common line of sight so as to reduce incidence of spurious signal measurement.

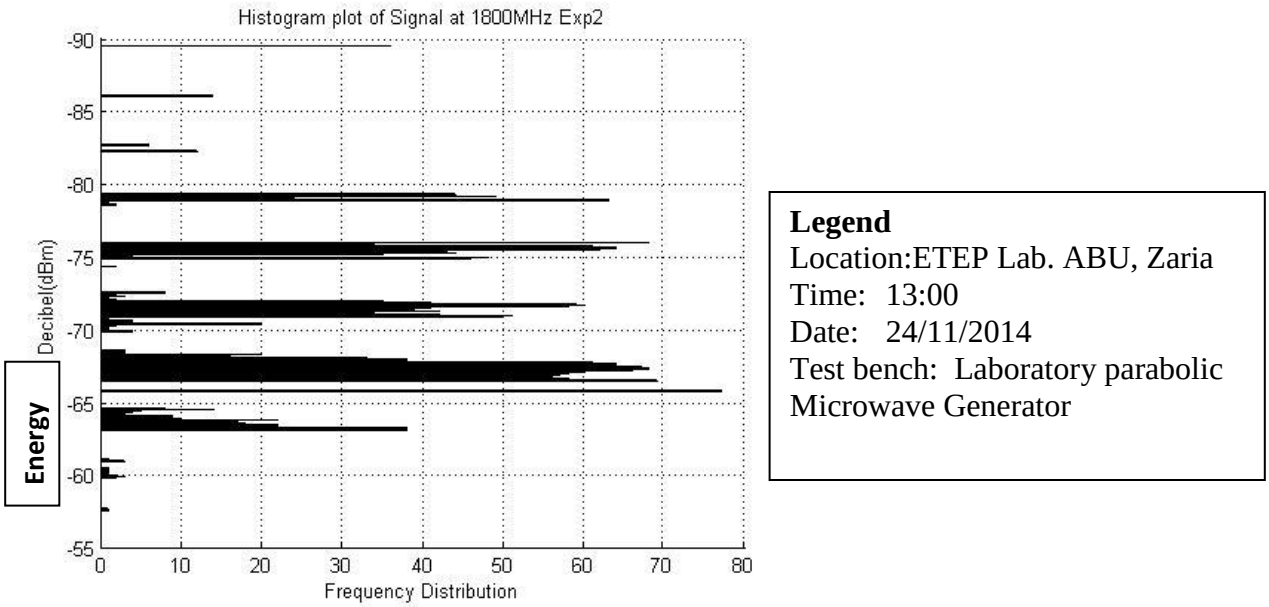



Figure 4.32: Measured Signal at 1800MHz

Furthermore Figures 4.29 and 4.31have shown measurement of signals generated within the Etisalat lab. At the working frequency of 1.8GHz using the parabolic reflector which forms part of the microwave link equipment in the ETEP lab. The microwave link generated the signal while the energy detector was used to measure the incoming energy. It is pertinent to repeat that the signal generator has a constraint as to the minimum and maximum frequency it can generate. The minimum frequency achievable is 1.2GHz while the maximum frequency is 1.8GHz. Consequently, laboratory measurements at 900MHz could not be carried out.

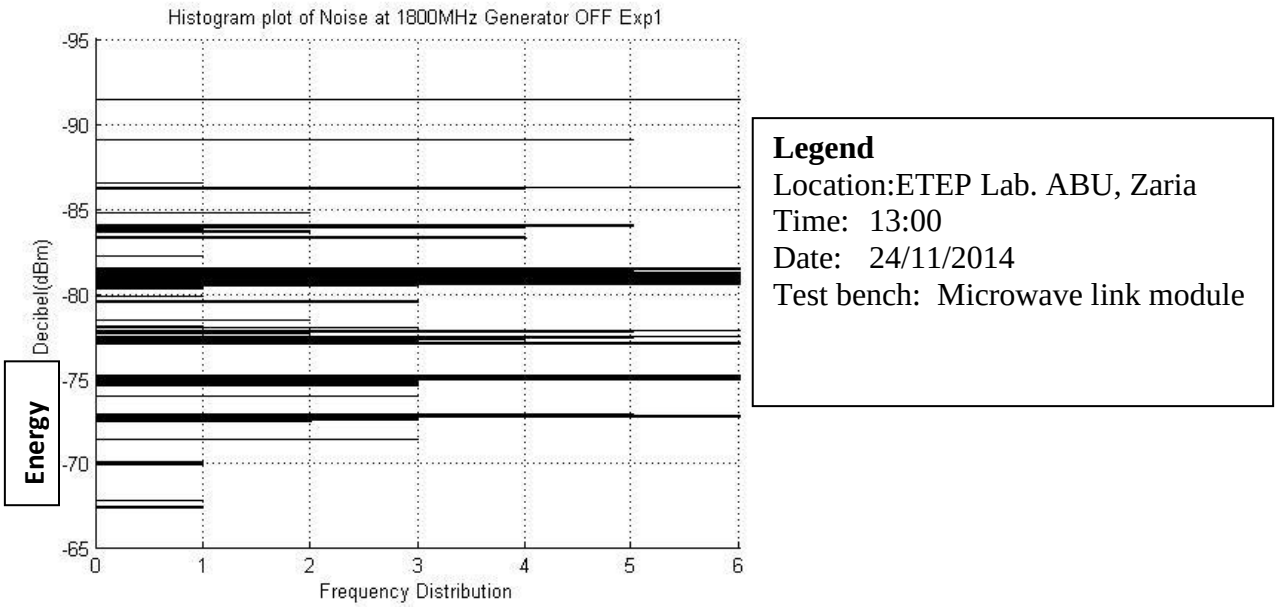



Figure 4.33: Experiment 1 of Noise Measurements with Signal Generator OFF from 1800MHz

The next experiment had the signal generator switched OFF, while the energy detector remains ON to measure incoming energy signals. The aim was to study the effect of noise right after the signal energy transmissions ceases. This scenario is represented by the spectral plots of Figures 4.33 and 4.34

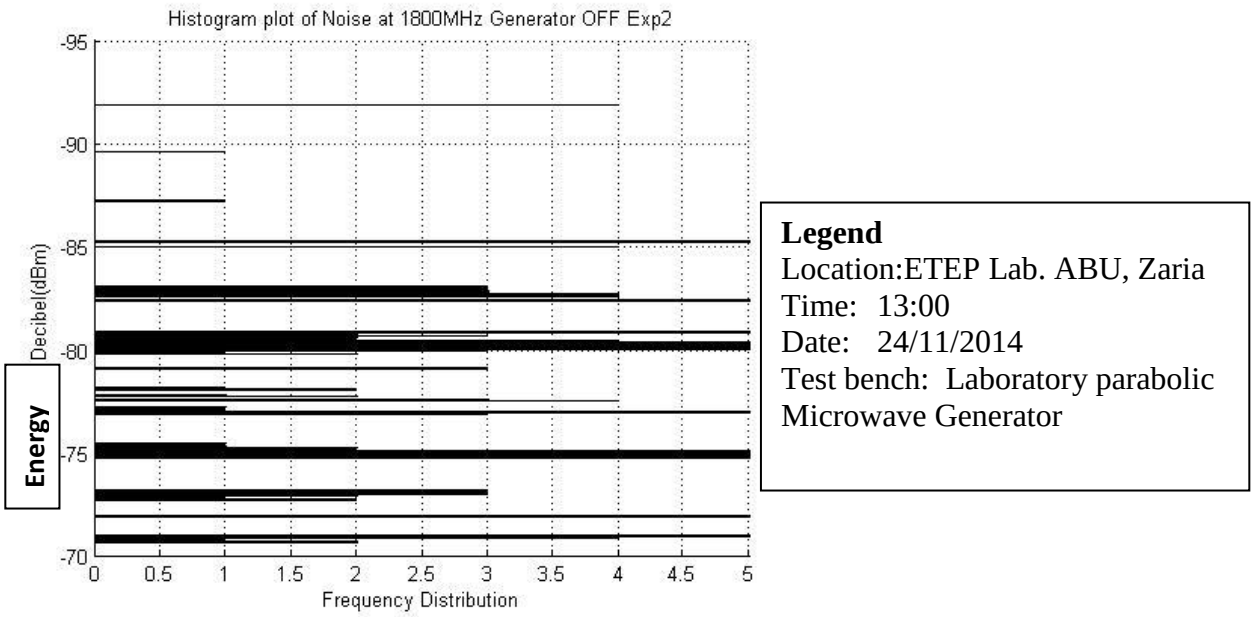



Figure 4.34: Experiment 2 of Noise Measurements when Generator is switched OFF at 1800MHz

While the signal generator is switched off, we can clearly see the change in the maximum spectral component measured now dropping from what was observed with the signal generator transmitting. This drop which is summarized by Table 4.10 shows that for the two experiments there was a 42% and 20% drop in signal strength respectively when the signal generator was switched off. This drop representing the predominant influence of noise on the measurement. This means even though the energy detector was set to capture signals at 1800MHz, with the generator off, it should measure more of noise than any available signal at this frequency.

Figure 5.9 showed the signal capture at 900 MHz when the energy detector was placed outdoors. What was observed was that the energy strength is weaker than any of those measured indoors from transmissions generated by the microwave generator.

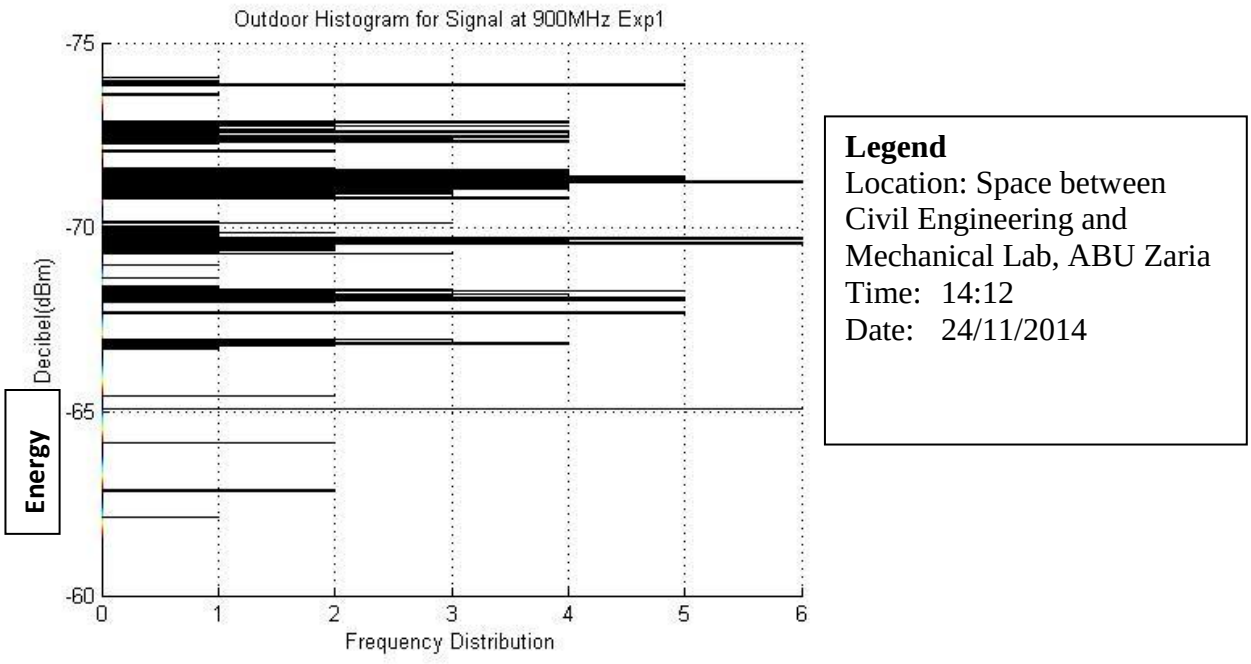



Figure 4.35: Captured Energy Spectral Plot at 900MHz

This is expected as the received signal is not a directed signal like those of the indoor experiments carried out in the lab and whose setup was depicted in Figures 3.43 and4.26. Those results showed strongest spectral component at -38.9dBm and -56dBm for the first and second experiments respectively at 1800 MHz

Figure 5.10 shows a similar experiment to that shown in the spectral plot of Figure 5.9.This second experiment is only shown to reinforce the credibility of the measurements made at 900MHz.

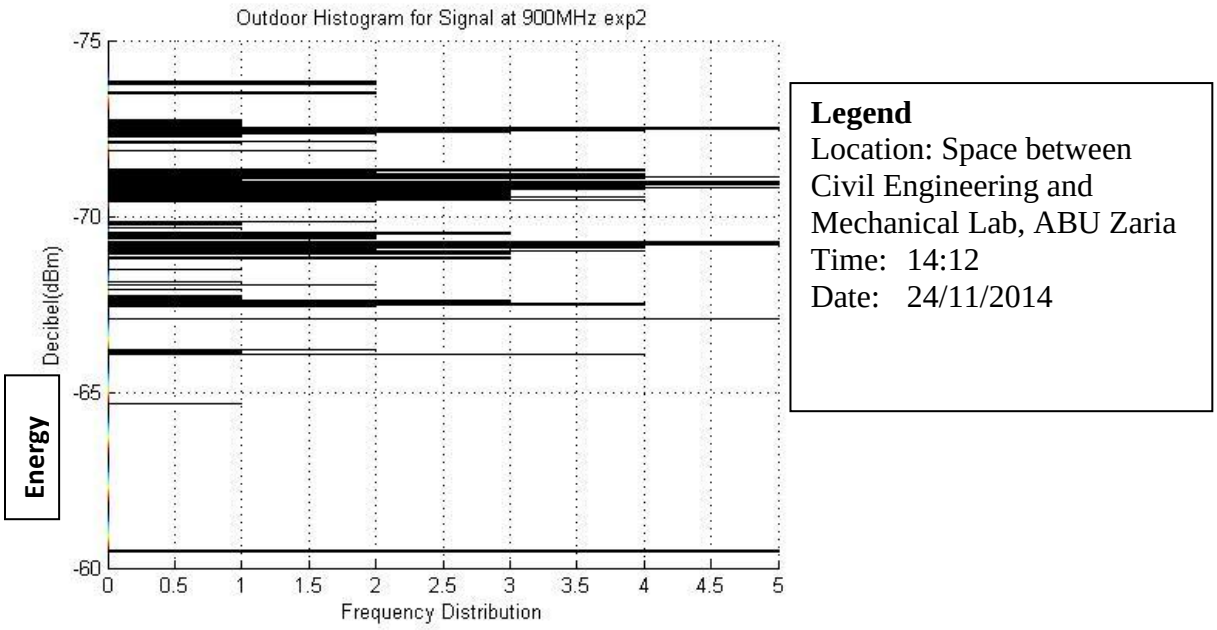



Figure 4.36: Captured Signal Outdoors at 900MHz

Figure 4.36is the first outdoor measurement at 1800MHz. Seen here is the spectral plot showing a maximum received signal strength of about -68dB. What can be inferred from this received signal seems to be making certain the overall weakness of the energy transmissions at 1800MHz compared to those of 900MHz.

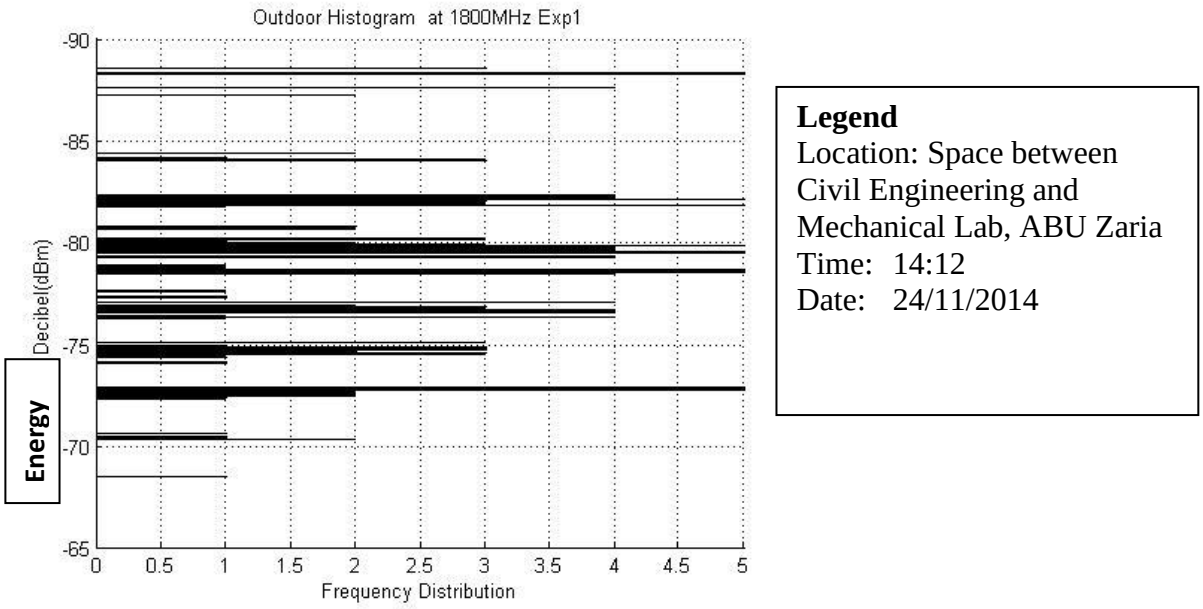



Figure 4.37: Histogram of Measured Signal at 1800MHz

This second plot shown in Figure 4.37represents another measurement made outdoors at 1800MHz and reconfirms the earlier assertion that weaker maximum energy was obtained for all transmissions at 1800MHz outdoors compared to those at 900MHz. It is only in the case of indoor transmissions from the signal generator at 1800MHz that stronger energy values were recorded in all experiments made. The experimental setup for the indoor experiment assures this stronger response and can partly be explained by the fact that indoor signals measured previously do not suffer from impairments as outdoor because they are insulated from atmospheric and terrain effects such as gaseous absorption and fading due to multipath components. Another reason adduced for the stronger energy signal measured indoors is also the closeness and directivity ensured by the experimental setup where a small separation was maintained between transmitter and receiver unlike the case where the transmitters for outdoor energy captured are assumed to be from distant sources.

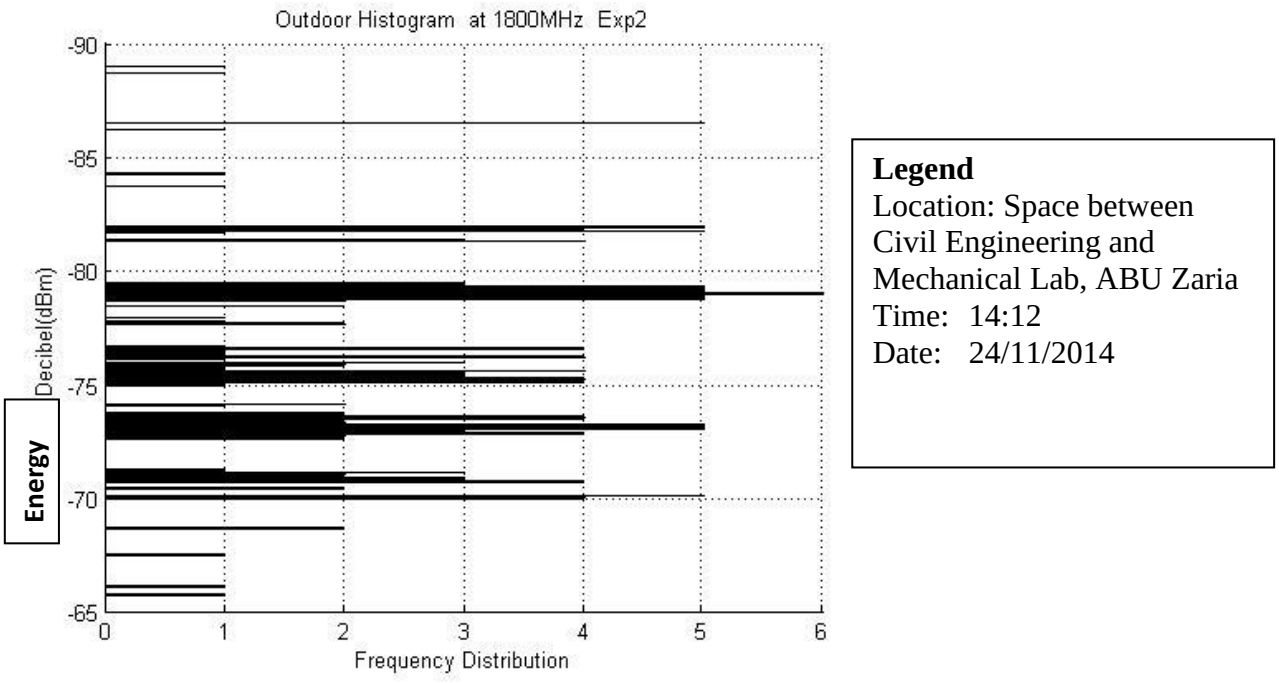



Figure 4.38: Captured Signal Outdoors at 1800MHz

Figures 4.38and4.39shows capture of energy at 1800MHz done outside of the lab at the Faculty of Engineering. These experiments were performed to study the behavior oftransmissions at the investigated frequency of 1800MHz outdoors of the laboratory. The source of these transmissions was not controlled and received signal was randomly located in free space. There was no measureable line of sight separation between the transmitter and receiver but the energy detector's omnidirectional antenna receives any transmissions at the selected frequency of 1800MHz. What was observed is that the strongest component of detected signal was around -65dBm and -68dBm which is quite less than those measured inside the lab from transmissions obtained through utilization of the microwave generator.

### 4.10.4 Outdoor Captured Channel Noise Signals at 900 and 1800MHZ

As has previously been mentioned, the importance of knowing the noise on the transmission channel is useful if any correct primary user detection is to be done. Therefore the channel noise was measured and recorded at the operating frequencies of investigation as stated earlier. These measurements are also location specific and are displayed in the following Figures 4.39to 4.40. What the information from the spectral plots of noise provides is an intuitive idea for the selection of a suitable noise threshold to be set as our signal detection threshold in subsequent experiments for validation. This is important as the detection of primary user is dependent upon the proper selection of a suitable detection threshold. Threshold being understood to be impacted upon negatively by the noise component in the medium and for an energy detector it is well known that good signal to noise ratio is important for proper functioning of the energy detector.

Figures 4.35 to 4.39is the decibel spectral energy plots of the noise measured at 900MHz when the 50Ω matched impedance was connected to the input of the spectrum analyzer. This character was used for outdoor noise level characterization. It was necessary to characterize the noise this way for 900MHz because the indoor noise experiment did not permit the noise level measurement at 900 MHz as the signal generator wasn't designed to accommodate this frequency range. Therefore in other to aid thresholding experiments for primary user signal detection at 900MHz, the 50Ω matching impedance was used for noise measurements at this frequency.

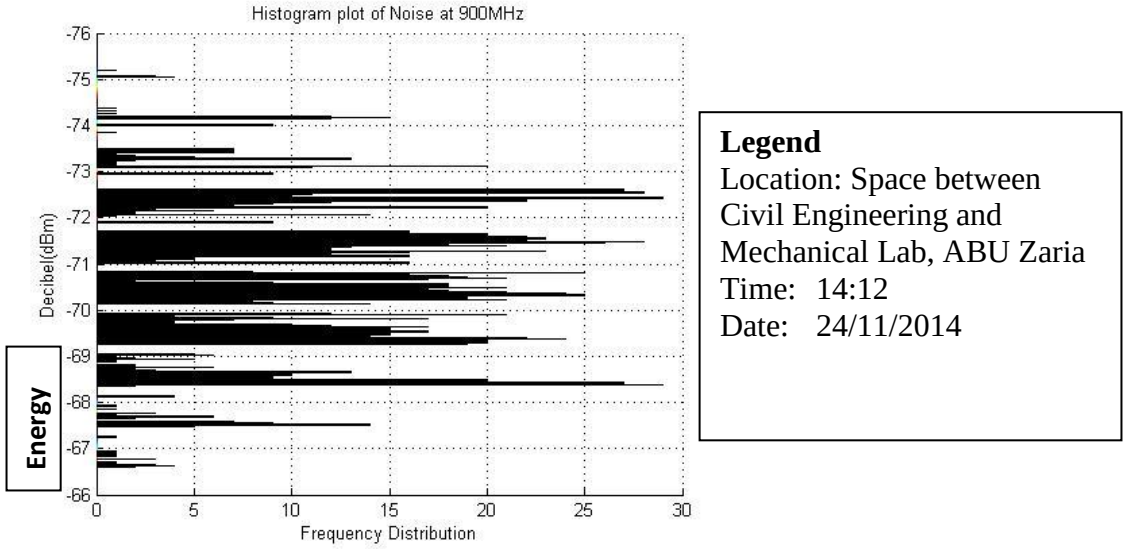



Figure 4.39: Spectral Display of Sensed Noise Signal in dBm at GSM 900MHz

Figure 4.40shows the display of noise measurement at 900MHz. The computed average noise value was obtained as -70.693dBm which falls between the noise minimum and maximum of -75.355dBm and -66.503dBm respectively.

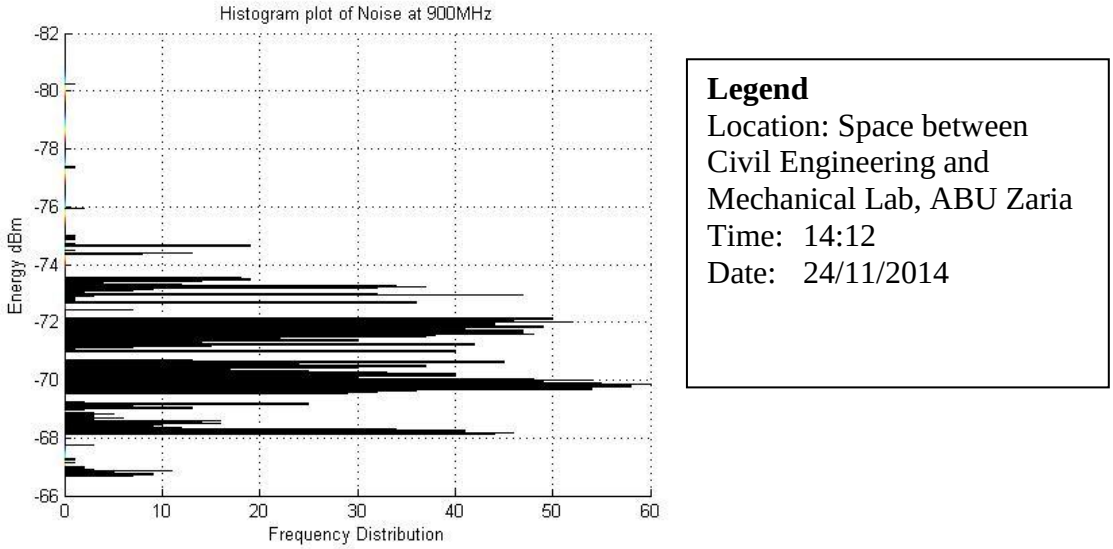



Figure 4.40: Histogram of Noise Signal in dBm at GSM 900MHz

The computation of the noise value in the channel which was used for thresholding experiments is as follows:

1) The captured values in the noise matrix were averaged over every column first
2) The individual averages from each column were then averaged to get the mean noise value on the channel at 900MHz

Through the stated process, the computed mean noise was found to be -71.1388dBm. Also, from the noise histogram at 900MHz in Figure 4.40, it was seen that this value of-71.1388dBm falls in a densely packed area of the histogram plot having the greatest occurrence. Performing a second experiment for the mean noise value at 900MHz yielded a value of -70.7483dBm which is close to the first mean result obtained.

Figure 4.41 is the decibel plot of the noise measured at 1800MHz when the 50Ω matched impedance is connected to the input of the spectrum analyzer.

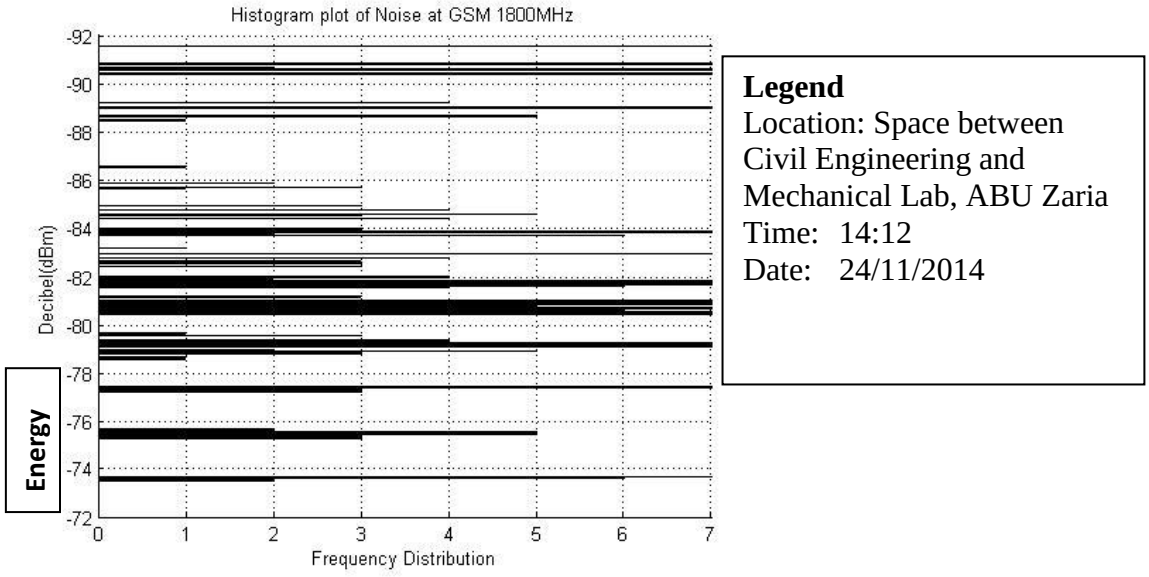



Figure 4.41: Sensed Noise Signal in dBm at 1800MHz from Capture experiment

Figure 4.42gives the noise capture histogram plot at 1800MHz. The average computed noise value was obtained as -81.025dBm. This is between the noise minimum and maximum values of -92.061dBm and -72.33dBm.

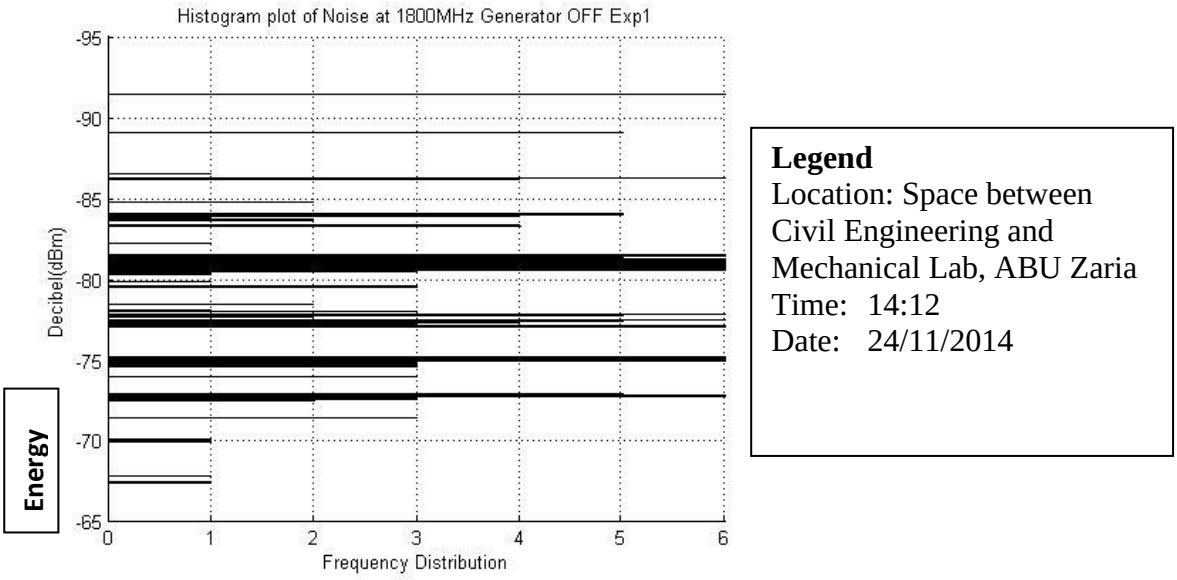



Figure 4.42: Spectral Display of Sensed Noise Signal dBm at GSM 1800MHz

Figure 4.43gives a noise threshold from computations of the average of all the noise values for this experiment of -79.003dBm. This noise measurement is taken with the signal generator switched off. The minimum and maximum ranges for the measured noise are -91.91dBm and

-66.62dBm.

Table 3.4 gives a noise threshold from computations of the average of all the noise values for this experiment of -78.342dBm. This noise measurement is also taken with the signal generator switched off but with the energy detector tuned to receive energy signals at the stated frequency. The minimum and maximum ranges for the measured noise are -92.27dBm and -69.96dBm.

The computation of the noise value in the 1800MHz channel which was used for thresholding experiments is as follows:

1) The captured values in the noise matrix are averaged over every column first
2) The individual averages from each column are then averaged to get the mean noise value on the channel at 1800MHz

Through the stated process, the computed mean noise was found to be -81.3657dBm. From the noise histogram at 1800MHz in Figure 4.43, it is seen that this value of -81.3657dBm falls in a densely packed area of the histogram plot having the greatest occurrence. A second experiment for the mean noise value at 1800MHz yielded a value of -81.2865dBm which is similar or close to the first result.

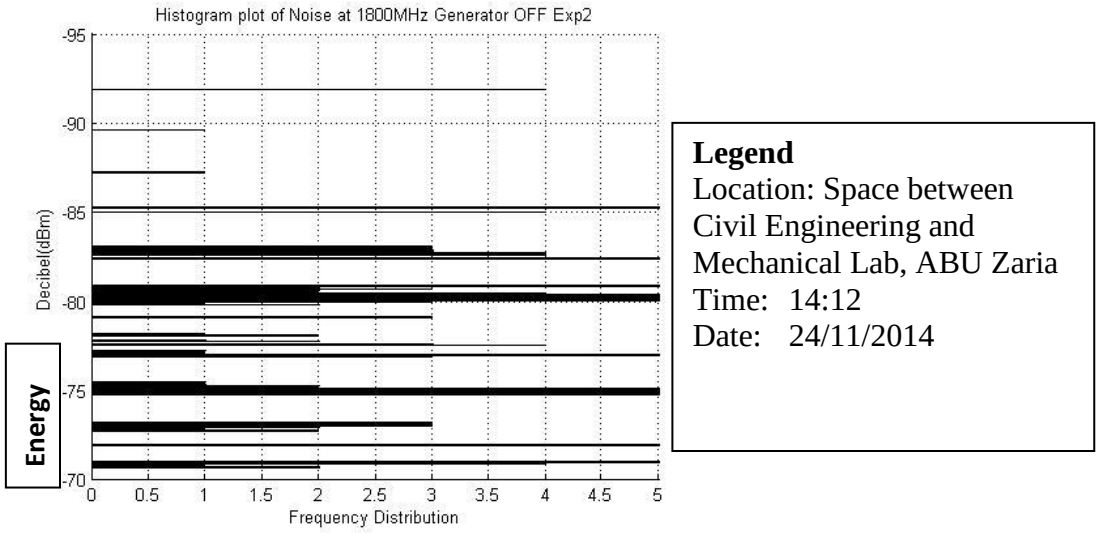



Figure 4.43: Spectral Display of Sensed Noise Signal dBm at GSM 1800MHz

### 4.10.5 Validation Experiment for Comparison between Non-Cooperative Model and Prototype Results

For the experiments that have been carried out, the method used has assumed that from analysis of the spectrum analyzers output, the recorded data can be separately investigated using the analysis tools of the non-cooperative cognitive radio model developed earlier. This, however, is not the case here as unlike in the software model of the cognitive radio developed, there was control over the frequency of switching ON/OFF the primary user transmissions using the aid of the Bernoulli Random number generator. This switching randomness is not possible in the use of the prototype as there is no specific way to isolate and identify a particular or unique individual primary user from amongst all the transmissions at a certain frequency.

### 4.10.6 Parameter Values for Non-Cooperative Cognitive Radio Model in MATLAB

The following parameters discussed have been set for the software model of the non-cooperative cognitive radio. It is to be noted that for any comparison made, uniform benchmarks must be set for these parameters. A firm basis for comparison being the choice of uniform parameter values such as career frequency, message frequency, simulation time, threshold value and sample time.

Replicating this experiment in the non-cooperative software model was achieved here. Table 4.11 shows the experimental parameters as set in the Spectran X energy detector and spectrum analyzer Prototype and were used for the experiment with the non-cooperative cognitive radio model.

Table 4.11: Commercially Acquired Energy Detector Operating Parameters

| **Investigated Frequency** | **Start frequency** | **Stop frequency** | **Center frequency** | **Bandwidth** | **Sample time** |
|---|---|---|---|---|---|
| 900MHz | 876.1MHz | 959.9MHz | 918.0MHz | 83.8MHz | 1e-3s |
| 1800MHz | 1710.0MHz | 1879.9MHz | 1794.95MHz | 169.9MHz | 500e-3s |

The inference to be drawn from the experiments on the simulation model is revealing in the results produced. Although there is no complete agreement between both software and hardware systems, the results nonetheless reinforced the output of prototype experiments made. This is so because sensing on the prototype at 900MHz, the energy values were always in the range of -52dBm to -79dBm. While at 1800MHz, lesser energy values were recorded in the range of -74dBm to -91dBm. Similar values can be observed in the records of received decibel energy values on the simulated model. At 900MHz the energy values were between-45dB to -79dB ranges while at 1800MHz the detected energy values spanbetween -54dB to-93dB.

It should be noted that differences still exist in the output from the two experiments which must not be ignored. These differences were analyzed and their effect is characterized. While the prototype detector does not work in isolation from the immediate radio environment and whatever measurement are taken from it must consider the input from other sources of inference, other than the selected frequency of the primary user. On the other hand the simulated experiment is not interacting with the noise in its environment in any way except for the randomly induced noise function used by the Additive White Gaussian noise parameter in the energy detector model. This practically accounts for the difference in values between the prototype outcome and the outcome from the simulated model.

## 4.11 Contribution to Academic Knowledge

The significant contributions of this work include:

i. The development of a Monte Carlo algorithm and ANFIS algorithm for efficient threshold detection is spectrum sensing.

ii. The experimental confirmation of cooperative spectrum sensing as a better sensing scheme than the non-cooperative sensing based on a lower detection threshold of -64dBm obtained for non-cooperative sensing and a detection threshold of -39dBm for cooperative sensing;

iii. The analytical confirmation that at a threshold of -71.1388 dBm on 900MHz frequency, 69% of available spectrum was unutilized and this spectrum could be profitably allocated.

# CHAPTER FIVE

# CONCLUSION AND SUMMARY

## 5.1 Conclusion

Inthis research work, an improved spectrum sensing and detection threshold for efficient utilization of radio spectrum was achieved. The innovative approach employed the use of Monte Carlo and ANFIS algorithms for the estimation of detection threshold. Furthermore, non-cooperative and cooperative spectrum sensing subsystems of cognitive radio were implemented in MATLAB environment. The spectrum sensing system developed from this work sufficiently yielded a lot of insight into the operational behavior of the various elements making up the cognitive radio cycle.

In summary, this work successfully implemented the following:

1. A complete non-cooperative and cooperative systems for spectrum sensing system.
2. The spectrum sensing system properly detectedPrimary User signals.
3. An energy detectionmodel to sense the incoming signal from the primary user transmitter.
4. The secondary user process was also modeled.
5. A working fusion center was developed to make the cooperative sensing decision.
6. Determination of detection threshold value of - 64dBm was obtained using ANFIS and verified by Monte Carlo algorithms.
7. Spectrum management system to enhance spectrum utilization by allocating idle channels to secondary users.

Finally, an experimental prototype energy detector was setup and used to make measurements of both signal and noise values. The validation was conductedthrough extensive indoor and outdoor

measurements using a commercially available energy detector with an incorporated spectrum analyzer. These measurements were made indoors in the ETEP lab at the Electrical and Computer Engineering Department ABU, Zaria and other measurements made outside the laboratory for two working frequencies of 900MHz and 1800MHz. Some pertinent parameters from the prototype were then fed into the non-cooperative model in order to obtain an optimum detection threshold via Monte Carlo simulations.

A measured threshold value of -71.138dBm was obtainedat 900MHz which was similar to the threshold value of -64dBm realized from the non-cooperative system. Similarly a working threshold of -81dBm was obtained at 1800MHz. Validation experiments with the non-cooperative model yielded an estimated threshold value of -80.1dBm after Monte Carlo analysis. In view of the threshold results from the different analytical experiments, a degree of validation was achieved.

Theresulting validated threshold valueallows for some error tolerances coming from the different experimental setup and operating environment. While experimental analyses were executed on computers in a closed and controlled environment, the practical experiment for energy detection was subject to various impairments coming from the sensing environment. The experimental analysis also had the advantage of a controlled primary user as against the prototype detection whose primary users could not be controlled.

Validation of simulated threshold of -39dBm for cooperative sensing presented could not be carried out because of constraint due to non-availability of needed devices.

## 5.2 Limitation of the Work

This work, estimation of detection threshold for spectrum sensing in cognitive radio using Adaptive Neural Fuzzy Inference System and Monte Carlo techniqueshas many significances as outlined earlier and at the same time has some limitations to its performance. The basic limitations of this work include:

i. Computing constraints in form of slow processing power as the computation speed required could not be achieved by the available laptops.
ii. Some experiments could not be performed satisfactorily due to insufficient memory capacity.
iii. Validation of cooperative spectrum sensing model could not be achieved due to lack of available test bench for cooperative spectrum sensing experiments.
iv. The commercially acquired energy detector used for the spectrum sensing had no means of identifying the source of the captured signals. Hence, the exact service provider transmitting at the investigated frequencies could not be ascertained.

## 5.3 Recommendations for Further Work

Recommended for further research works are the development of:

i. Innovative spectrum sensing algorithms that will reduce interference from secondary users;
ii. Efficient resource allocation systems based on the spectrum occupancy of the primary users.
iii. Optimization of detection threshold for spectrum sensing in cognitive radio.

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# APPENDIX I

## A1.1 code listing for Cognitive Radio

```
clearall; close all; clc

load_system('CogRad_SimTWO_05')

simTime = 10;
Ts = 1/10000;    % Sampling Time
N = simTime/Ts;

DecimationVal = 1;

% Message Signal Wave Generator
MSG_amp_A   = 30;
MSG_bias    = 0;
MSG_freq    = 1e2;
MSG_phase   = 0;
MSG_Fr_s    = 1;
sampleT_MSG = Ts;

% Bernoulli Generator
BERN_zero_Pr = 0.5;
% BERN_zero_Pr = rand();
BERN_seedVal = 81;
% BERN_seedVal = round( 100*rand());
sampleT_BERN = 0.25*simTime;
Ns_Fr = sampleT_BERN/Ts; % SU: Total Number of sample per unit frame Duration
n_sample = round(0.001*Ns_Fr); % Number of sample per sensing period

% IID Gaussian Noise (GN) @ source
GN_mean   = 0;
GN_var    = 0.1*MSG_amp_A;
GN_seed   = 60;
GN_sampleT  =Ts;

% AWGN Channel Primary
% AWGN_seed   = 84;
AWGN_seed = round( 100*rand());
AWGN_InputSigPowerRef_1ohm   = 5; % Input signal power, referenced to 1 ohm (watts)

samplingFreq = 1/Ts;
zoTs = (1/samplingFreq);

% Bandpass Filter
BW = 5; bwOffset = 0.1*BW;
Fs = (1/zoTs);
Astop1 = 60; Astop2 = Astop1; Apass = 1;
Fstop1 = (MSG_freq-BW); Fstop2 = (MSG_freq+BW);
Fpass1 = (MSG_freq-bwOffset); Fpass2 = (MSG_freq+bwOffset);

% SS-ED
```

```
buffSize = n_sample;
buffOverlap = 0;
CalibVal = 10;

% Spectrum Scope Ranges
Pri_minYlimit = -4*mag2db(MSG_amp_A);
Pri_maxYlimit = 2*mag2db(MSG_amp_A);
ScopeFreqRange_min = MSG_freq-(1*MSG_freq);
ScopeFreqRange_max = MSG_freq+(1*MSG_freq)-0;

% Spectrum Scope Parameters
BufferSize = 256; BufferOverlap = 0; numAvg = 2;
FFTlength = 4096; KaiserWin_beta = 0.005;

u = round(n_sample/2);  % Time-Bandwidth Product
DoF = 2*u;              % Degrees of Freedom
```

## A1.2 code Listing for Monte Carlo analysis

```
clearall; close all; clc

loadMyDataFile03.mat

figure(1);hold all

forll = 1:MonteCarlo
   plot3(SNR(:,ll),Xn(1:end-1,ll),Yn(1:end-1,ll));
   plot3(SNR(:,ll),Xs(:,ll),Ys(:,ll));



end
holdoff; grid on
ylim([0 3*Xs(max(find(Ys(:,1) == max(Ys(:,1)))),1)])
xlabel('SNR')
ylabel('Energy')
zlabel('Probability Distribution')

Lamda = (0:0.1:2*Xs(find(Ys(:,1) == max(Ys(:,1)), 1, 'last' ),1))';

Threshold = []; PD = []; PF = []; PM = []; Pm_opt = [];
C = []; ;Pf_opt = [];

figure(2);hold all
for mm = 1:MonteCarlo

   a=sqrt(Gamma(mm));
   b=sqrt(Lamda);

Pd = marcumq(a,b,u );
   Pf = gammainc((Lamda./2),u,'upper');
   Pm = 1-Pd;
```

```
%     c = Pf-Pm;
%     d = find(c>0);
%     indVal = find(0 < c & c <= min(c(d)));
%
%     PD = [PD Pd]; PF = [PF Pf]; PM = [PM Pm];
%     c = Pf-Pm;
%     indVal = find(0 < c & c <= min(c(find(c>0))));
%     lamdaOpt = Lamda(indVal);

%     Threshold = []; PD = [PD Pd]; PF = [PF Pf]; PM = [PM Pm];

    c = Pf-Pm;
lamdaOpt = Lamda(find(0 < c & c <= min(c(find(c>0)))));

pfopt = Pf(find(0 < c & c <= min(c(find(c>0)))));
pmopt = Pm(find(0 < c & c <= min(c(find(c>0)))));

    Threshold = [Threshold lamdaOpt];
    PD = [PD Pd]; PF = [PF Pf]; PM = [PM Pm];
Pm_opt = [Pm_optpmopt]; Pf_opt = [Pf_optpfopt];C = [C c];


plot3(ones(size(Lamda,1),1)*(Gamma(mm)/2),Lamda,Pm);
plot3(ones(size(Lamda,1),1)*(Gamma(mm)/2),Lamda,Pf);

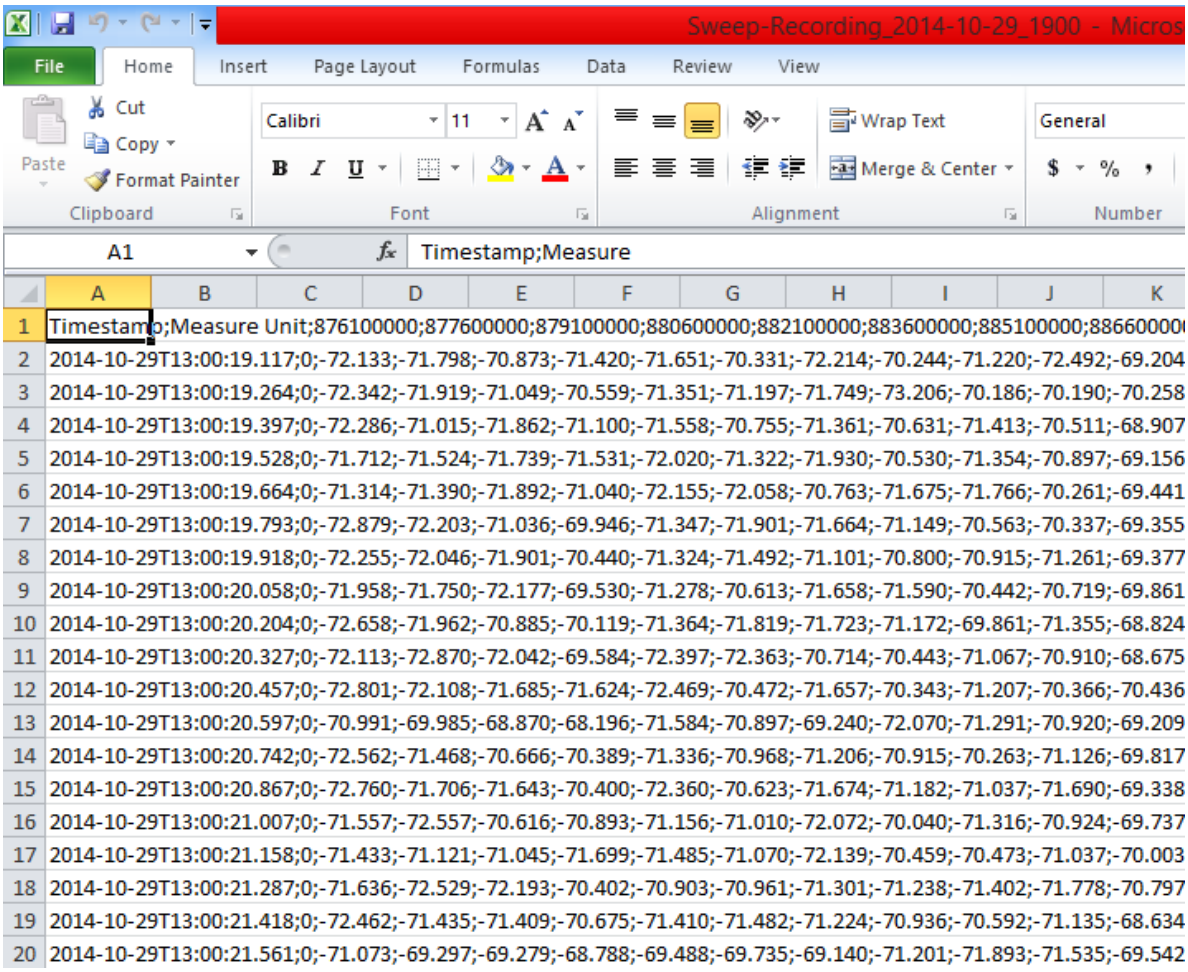

end

holdoff; grid on
xlabel('SNR'); ylabel('Energy'); zlabel('Pm & Pf');
```

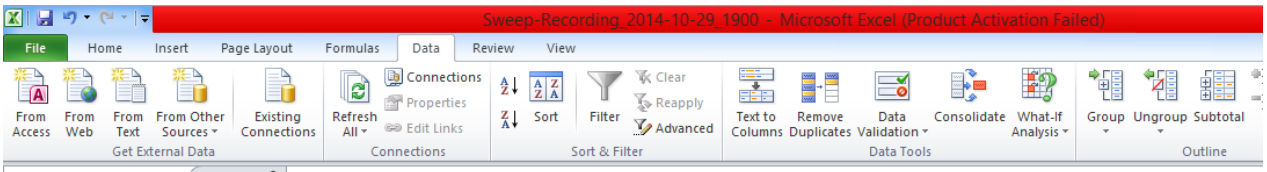
A1.3

## APPENDIX II

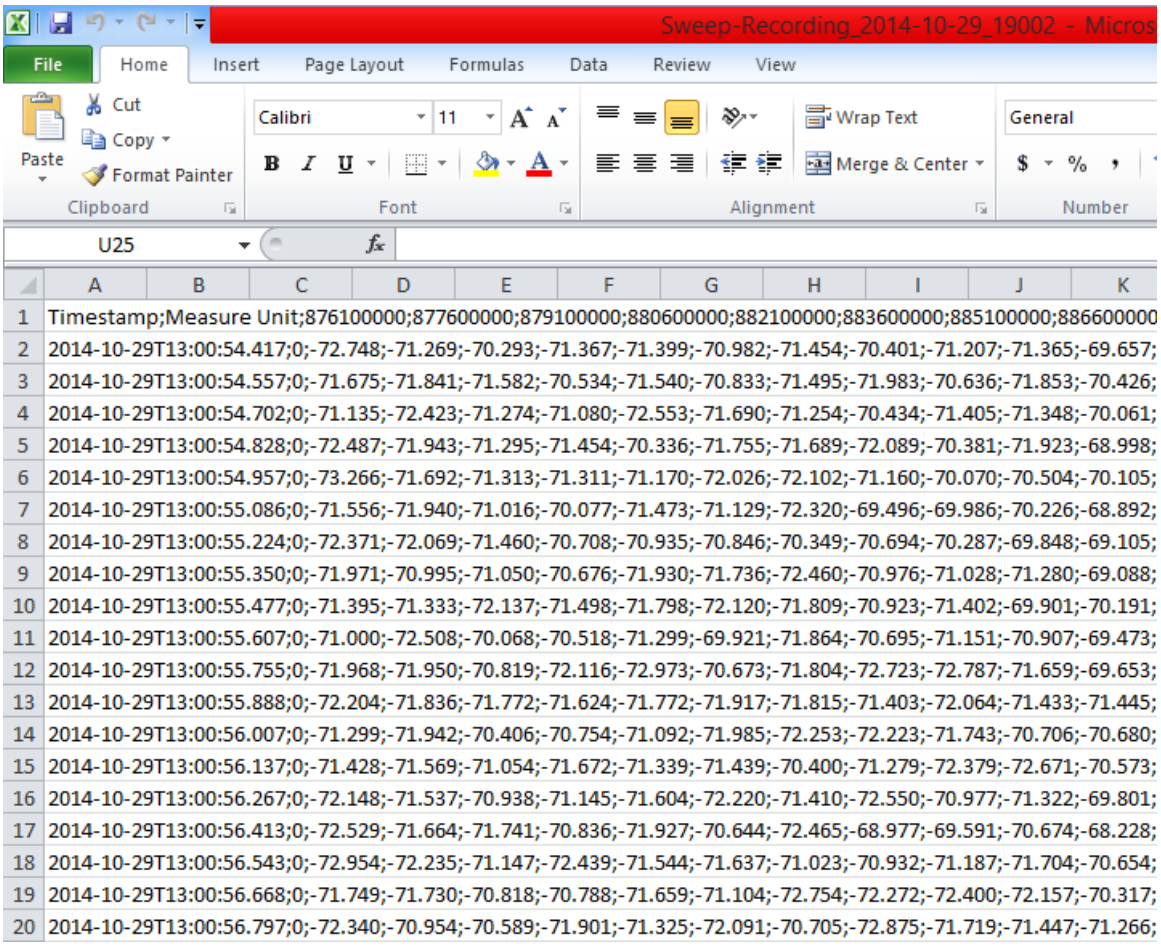
1. Data from the spectrum analyzer collected at GSM bands 900MHz and 1800MHz (for 2G and 3G respectively).



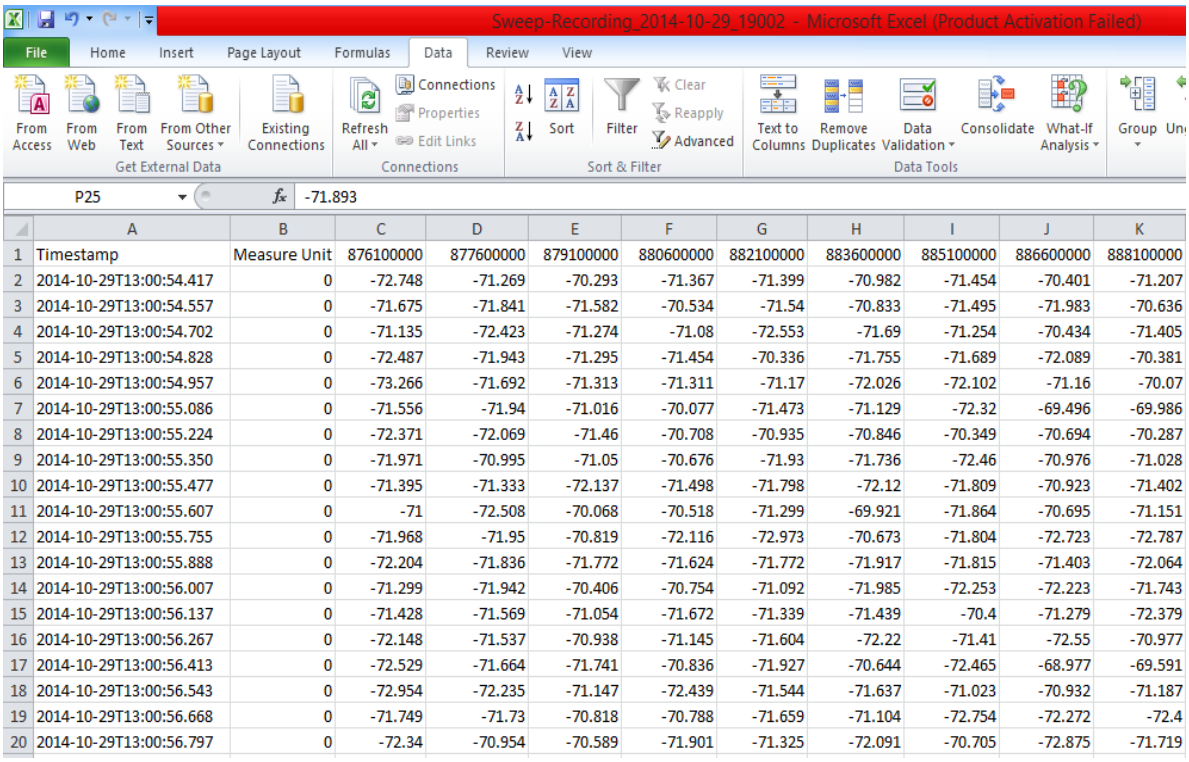

| | A | B | C | D | E | F | G | H | I | J | K |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | Timestamp;Measure Unit;876100000;877600000;879100000;880600000;882100000;883600000;885100000;886600000 | | | | | | | | | | |
| 2 | 2014-10-29T13:00:19.117;0;-72.133;-71.798;-70.873;-71.420;-71.651;-70.331;-72.214;-70.244;-71.220;-72.492;-69.204 | | | | | | | | | | |
| 3 | 2014-10-29T13:00:19.264;0;-72.342;-71.919;-71.049;-70.559;-71.351;-71.197;-71.749;-73.206;-70.186;-70.190;-70.258 | | | | | | | | | | |
| 4 | 2014-10-29T13:00:19.397;0;-72.286;-71.015;-71.862;-71.100;-71.558;-70.755;-71.361;-70.631;-71.413;-70.511;-68.907 | | | | | | | | | | |
| 5 | 2014-10-29T13:00:19.528;0;-71.712;-71.524;-71.739;-71.531;-72.020;-71.322;-71.930;-70.530;-71.354;-70.897;-69.156 | | | | | | | | | | |
| 6 | 2014-10-29T13:00:19.664;0;-71.314;-71.390;-71.892;-71.040;-72.155;-72.058;-70.763;-71.675;-71.766;-70.261;-69.441 | | | | | | | | | | |
| 7 | 2014-10-29T13:00:19.793;0;-72.879;-72.203;-71.036;-69.946;-71.347;-71.901;-71.664;-71.149;-70.563;-70.337;-69.355 | | | | | | | | | | |
| 8 | 2014-10-29T13:00:19.918;0;-72.255;-72.046;-71.901;-70.440;-71.324;-71.492;-71.101;-70.800;-70.915;-71.261;-69.377 | | | | | | | | | | |
| 9 | 2014-10-29T13:00:20.058;0;-71.958;-71.750;-72.177;-69.530;-71.278;-70.613;-71.658;-71.590;-70.442;-70.719;-69.861 | | | | | | | | | | |
| 10 | 2014-10-29T13:00:20.204;0;-72.658;-71.962;-70.885;-70.119;-71.364;-71.819;-71.723;-71.172;-69.861;-71.355;-68.824 | | | | | | | | | | |
| 11 | 2014-10-29T13:00:20.327;0;-72.113;-72.870;-72.042;-69.584;-72.397;-72.363;-70.714;-70.443;-71.067;-70.910;-68.675 | | | | | | | | | | |
| 12 | 2014-10-29T13:00:20.457;0;-72.801;-72.108;-71.685;-71.624;-72.469;-70.472;-71.657;-70.343;-71.207;-70.366;-70.436 | | | | | | | | | | |
| 13 | 2014-10-29T13:00:20.597;0;-70.991;-69.985;-68.870;-68.196;-71.584;-70.897;-69.240;-72.070;-71.291;-70.920;-69.209 | | | | | | | | | | |
| 14 | 2014-10-29T13:00:20.742;0;-72.562;-71.468;-70.666;-70.389;-71.336;-70.968;-71.206;-70.915;-70.263;-71.126;-69.817 | | | | | | | | | | |
| 15 | 2014-10-29T13:00:20.867;0;-72.760;-71.706;-71.643;-70.400;-72.360;-70.623;-71.674;-71.182;-71.037;-71.690;-69.338 | | | | | | | | | | |
| 16 | 2014-10-29T13:00:21.007;0;-71.557;-72.557;-70.616;-70.893;-71.156;-71.010;-72.072;-70.040;-71.316;-70.924;-69.737 | | | | | | | | | | |
| 17 | 2014-10-29T13:00:21.158;0;-71.433;-71.121;-71.045;-71.699;-71.485;-71.070;-72.139;-70.459;-70.473;-71.037;-70.003 | | | | | | | | | | |
| 18 | 2014-10-29T13:00:21.287;0;-71.636;-72.529;-72.193;-70.402;-70.903;-70.961;-71.301;-71.238;-71.402;-71.778;-70.797 | | | | | | | | | | |
| 19 | 2014-10-29T13:00:21.418;0;-72.462;-71.435;-71.409;-70.675;-71.410;-71.482;-71.224;-70.936;-70.592;-71.135;-68.634 | | | | | | | | | | |
| 20 | 2014-10-29T13:00:21.561;0;-71.073;-69.297;-69.279;-68.788;-69.488;-69.735;-69.140;-71.201;-71.893;-71.535;-69.542 | | | | | | | | | | |



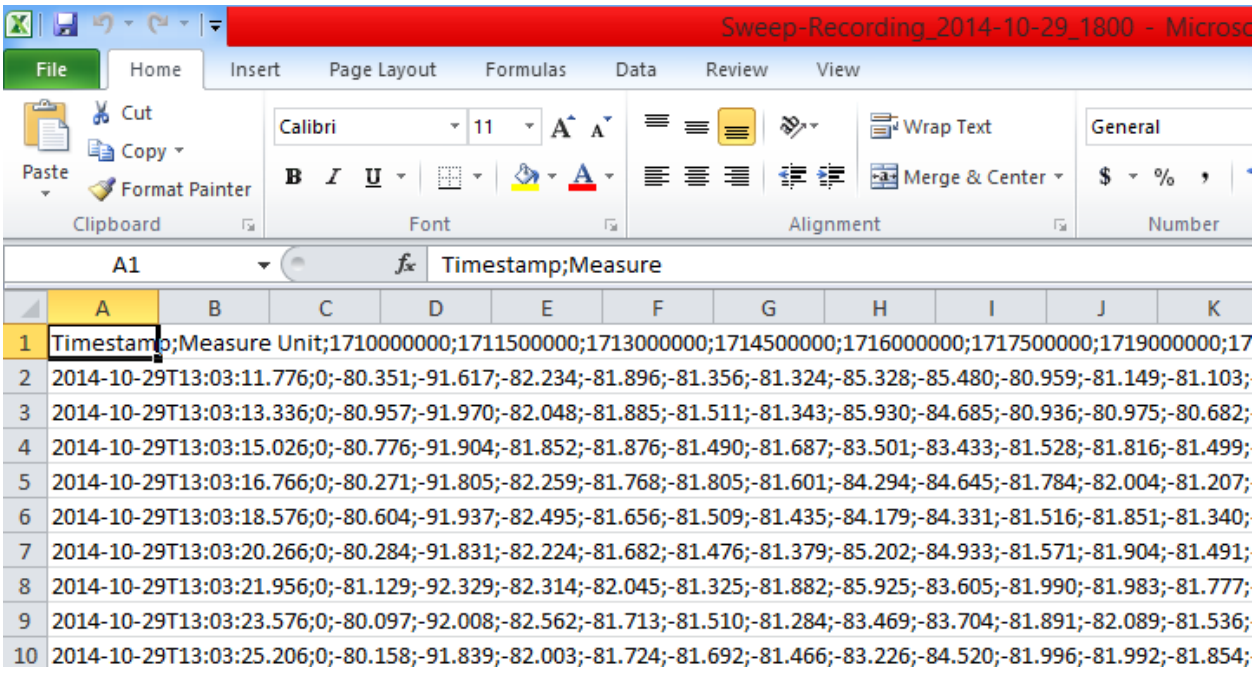

| | A | B | C | D | E | F | G | H | I | J | K |
|---|---|---|---|---|---|---|---|---|---|---|---|
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| 3 | 2014-10-29T13:00:19.264 | 0 | -72.342 | -71.919 | -71.049 | -70.559 | -71.351 | -71.197 | -71.749 | -73.206 | -70.186 |
| 4 | 2014-10-29T13:00:19.397 | 0 | -72.286 | -71.015 | -71.862 | -71.1 | -71.558 | -70.755 | -71.361 | -70.631 | -71.413 |
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| 6 | 2014-10-29T13:00:19.664 | 0 | -71.314 | -71.39 | -71.892 | -71.04 | -72.155 | -72.058 | -70.763 | -71.675 | -71.766 |
| 7 | 2014-10-29T13:00:19.793 | 0 | -72.879 | -72.203 | -71.036 | -69.946 | -71.347 | -71.901 | -71.664 | -71.149 | -70.563 |
| 8 | 2014-10-29T13:00:19.918 | 0 | -72.255 | -72.046 | -71.901 | -70.44 | -71.324 | -71.492 | -71.101 | -70.8 | -70.915 |
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| 10 | 2014-10-29T13:00:20.204 | 0 | -72.658 | -71.962 | -70.885 | -70.119 | -71.364 | -71.819 | -71.723 | -71.172 | -69.861 |
| 11 | 2014-10-29T13:00:20.327 | 0 | -72.113 | -72.87 | -72.042 | -69.584 | -72.397 | -72.363 | -70.714 | -70.443 | -71.067 |
| 12 | 2014-10-29T13:00:20.457 | 0 | -72.801 | -72.108 | -71.685 | -71.624 | -72.469 | -70.472 | -71.657 | -70.343 | -71.207 |
| 13 | 2014-10-29T13:00:20.597 | 0 | -70.991 | -69.985 | -68.87 | -68.196 | -71.584 | -70.897 | -69.24 | -72.07 | -71.291 |
| 14 | 2014-10-29T13:00:20.742 | 0 | -72.562 | -71.468 | -70.666 | -70.389 | -71.336 | -70.968 | -71.206 | -70.915 | -70.263 |
| 15 | 2014-10-29T13:00:20.867 | 0 | -72.76 | -71.706 | -71.643 | -70.4 | -72.36 | -70.623 | -71.674 | -71.182 | -71.037 |
| 16 | 2014-10-29T13:00:21.007 | 0 | -71.557 | -72.557 | -70.616 | -70.893 | -71.156 | -71.01 | -72.072 | -70.04 | -71.316 |
| 17 | 2014-10-29T13:00:21.158 | 0 | -71.433 | -71.121 | -71.045 | -71.699 | -71.485 | -71.07 | -72.139 | -70.459 | -70.473 |
| 18 | 2014-10-29T13:00:21.287 | 0 | -71.636 | -72.529 | -72.193 | -70.402 | -70.903 | -70.961 | -71.301 | -71.238 | -71.402 |
| 19 | 2014-10-29T13:00:21.418 | 0 | -72.462 | -71.435 | -71.409 | -70.675 | -71.41 | -71.482 | -71.224 | -70.936 | -70.592 |
| 20 | 2014-10-29T13:00:21.561 | 0 | -71.073 | -69.297 | -69.279 | -68.788 | -69.488 | -69.735 | -69.14 | -71.201 | -71.893 |

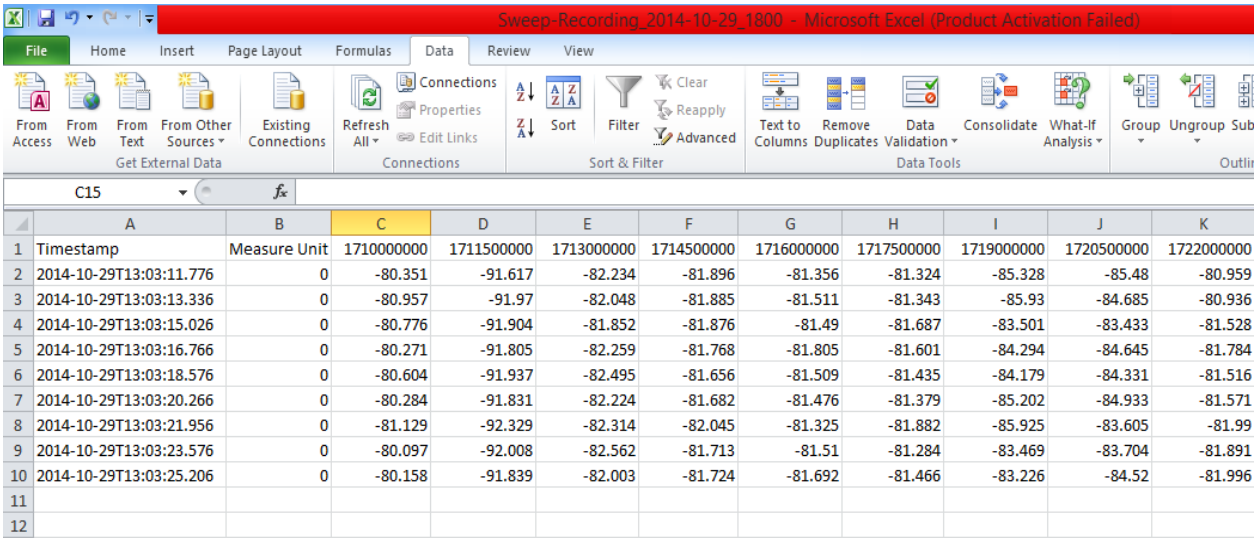


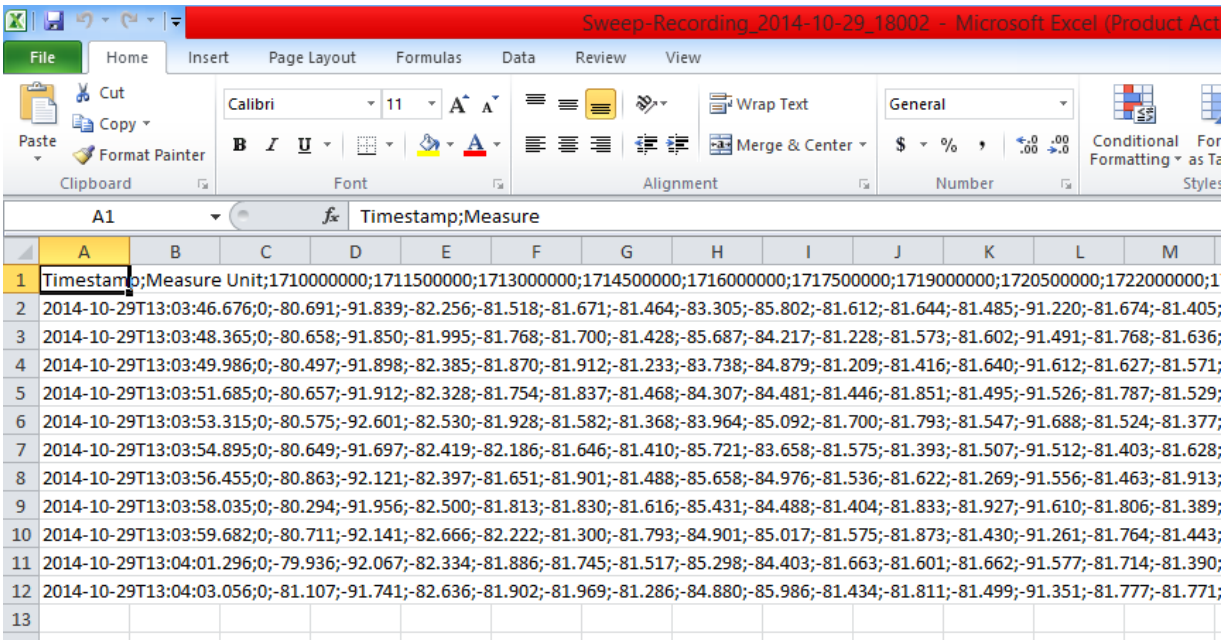

| | A | B | C | D | E | F | G | H | I | J | K |
|---|---|---|---|---|---|---|---|---|---|---|---|
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| 3 | 2014-10-29T13:00:54.557;0;-71.675;-71.841;-71.582;-70.534;-71.540;-70.833;-71.495;-71.983;-70.636;-71.853;-70.426; | | | | | | | | | | |
| 4 | 2014-10-29T13:00:54.702;0;-71.135;-72.423;-71.274;-71.080;-72.553;-71.690;-71.254;-70.434;-71.405;-71.348;-70.061; | | | | | | | | | | |
| 5 | 2014-10-29T13:00:54.828;0;-72.487;-71.943;-71.295;-71.454;-70.336;-71.755;-71.689;-72.089;-70.381;-71.923;-68.998; | | | | | | | | | | |
| 6 | 2014-10-29T13:00:54.957;0;-73.266;-71.692;-71.313;-71.311;-71.170;-72.026;-72.102;-71.160;-70.070;-70.504;-70.105; | | | | | | | | | | |
| 7 | 2014-10-29T13:00:55.086;0;-71.556;-71.940;-71.016;-70.077;-71.473;-71.129;-72.320;-69.496;-69.986;-70.226;-68.892; | | | | | | | | | | |
| 8 | 2014-10-29T13:00:55.224;0;-72.371;-72.069;-71.460;-70.708;-70.935;-70.846;-70.349;-70.694;-70.287;-69.848;-69.105; | | | | | | | | | | |
| 9 | 2014-10-29T13:00:55.350;0;-71.971;-70.995;-71.050;-70.676;-71.930;-71.736;-72.460;-70.976;-71.028;-71.280;-69.088; | | | | | | | | | | |
| 10 | 2014-10-29T13:00:55.477;0;-71.395;-71.333;-72.137;-71.498;-71.798;-72.120;-71.809;-70.923;-71.402;-69.901;-70.191; | | | | | | | | | | |
| 11 | 2014-10-29T13:00:55.607;0;-71.000;-72.508;-70.068;-70.518;-71.299;-69.921;-71.864;-70.695;-71.151;-70.907;-69.473; | | | | | | | | | | |
| 12 | 2014-10-29T13:00:55.755;0;-71.968;-71.950;-70.819;-72.116;-72.973;-70.673;-71.804;-72.723;-72.787;-71.659;-69.653; | | | | | | | | | | |
| 13 | 2014-10-29T13:00:55.888;0;-72.204;-71.836;-71.772;-71.624;-71.772;-71.917;-71.815;-71.403;-72.064;-71.433;-71.445; | | | | | | | | | | |
| 14 | 2014-10-29T13:00:56.007;0;-71.299;-71.942;-70.406;-70.754;-71.092;-71.985;-72.253;-72.223;-71.743;-70.706;-70.680; | | | | | | | | | | |
| 15 | 2014-10-29T13:00:56.137;0;-71.428;-71.569;-71.054;-71.672;-71.339;-71.439;-70.400;-71.279;-72.379;-72.671;-70.573; | | | | | | | | | | |
| 16 | 2014-10-29T13:00:56.267;0;-72.148;-71.537;-70.938;-71.145;-71.604;-72.220;-71.410;-72.550;-70.977;-71.322;-69.801; | | | | | | | | | | |
| 17 | 2014-10-29T13:00:56.413;0;-72.529;-71.664;-71.741;-70.836;-71.927;-70.644;-72.465;-68.977;-69.591;-70.674;-68.228; | | | | | | | | | | |
| 18 | 2014-10-29T13:00:56.543;0;-72.954;-72.235;-71.147;-72.439;-71.544;-71.637;-71.023;-70.932;-71.187;-71.704;-70.654; | | | | | | | | | | |
| 19 | 2014-10-29T13:00:56.668;0;-71.749;-71.730;-70.818;-70.788;-71.659;-71.104;-72.754;-72.272;-72.400;-72.157;-70.317; | | | | | | | | | | |
| 20 | 2014-10-29T13:00:56.797;0;-72.340;-70.954;-70.589;-71.901;-71.325;-72.091;-70.705;-72.875;-71.719;-71.447;-71.266; | | | | | | | | | | |

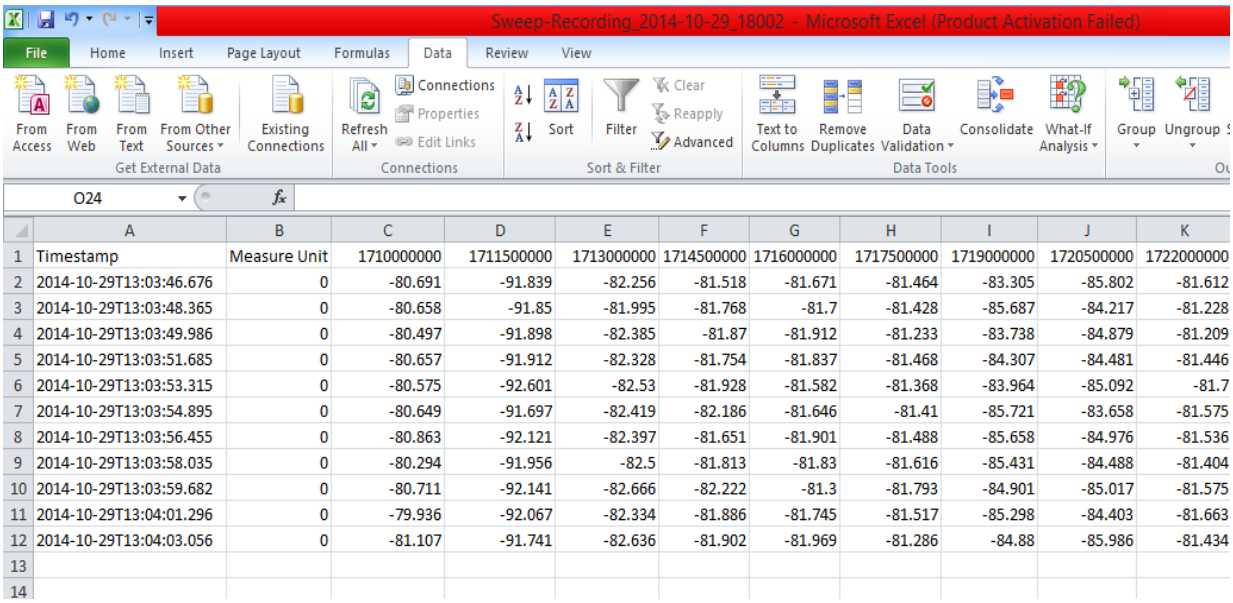



| | A | B | C | D | E | F | G | H | I | J | K |
|---|---|---|---|---|---|---|---|---|---|---|---|
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| 2 | 2014-10-29T13:00:54.417 | 0 | -72.748 | -71.269 | -70.293 | -71.367 | -71.399 | -70.982 | -71.454 | -70.401 | -71.207 |
| 3 | 2014-10-29T13:00:54.557 | 0 | -71.675 | -71.841 | -71.582 | -70.534 | -71.54 | -70.833 | -71.495 | -71.983 | -70.636 |
| 4 | 2014-10-29T13:00:54.702 | 0 | -71.135 | -72.423 | -71.274 | -71.08 | -72.553 | -71.69 | -71.254 | -70.434 | -71.405 |
| 5 | 2014-10-29T13:00:54.828 | 0 | -72.487 | -71.943 | -71.295 | -71.454 | -70.336 | -71.755 | -71.689 | -72.089 | -70.381 |
| 6 | 2014-10-29T13:00:54.957 | 0 | -73.266 | -71.692 | -71.313 | -71.311 | -71.17 | -72.026 | -72.102 | -71.16 | -70.07 |
| 7 | 2014-10-29T13:00:55.086 | 0 | -71.556 | -71.94 | -71.016 | -70.077 | -71.473 | -71.129 | -72.32 | -69.496 | -69.986 |
| 8 | 2014-10-29T13:00:55.224 | 0 | -72.371 | -72.069 | -71.46 | -70.708 | -70.935 | -70.846 | -70.349 | -70.694 | -70.287 |
| 9 | 2014-10-29T13:00:55.350 | 0 | -71.971 | -70.995 | -71.05 | -70.676 | -71.93 | -71.736 | -72.46 | -70.976 | -71.028 |
| 10 | 2014-10-29T13:00:55.477 | 0 | -71.395 | -71.333 | -72.137 | -71.498 | -71.798 | -72.12 | -71.809 | -70.923 | -71.402 |
| 11 | 2014-10-29T13:00:55.607 | 0 | -71 | -72.508 | -70.068 | -70.518 | -71.299 | -69.921 | -71.864 | -70.695 | -71.151 |
| 12 | 2014-10-29T13:00:55.755 | 0 | -71.968 | -71.95 | -70.819 | -72.116 | -72.973 | -70.673 | -71.804 | -72.723 | -72.787 |
| 13 | 2014-10-29T13:00:55.888 | 0 | -72.204 | -71.836 | -71.772 | -71.624 | -71.772 | -71.917 | -71.815 | -71.403 | -72.064 |
| 14 | 2014-10-29T13:00:56.007 | 0 | -71.299 | -71.942 | -70.406 | -70.754 | -71.092 | -71.985 | -72.253 | -72.223 | -71.743 |
| 15 | 2014-10-29T13:00:56.137 | 0 | -71.428 | -71.569 | -71.054 | -71.672 | -71.339 | -71.439 | -70.4 | -71.279 | -72.379 |
| 16 | 2014-10-29T13:00:56.267 | 0 | -72.148 | -71.537 | -70.938 | -71.145 | -71.604 | -72.22 | -71.41 | -72.55 | -70.977 |
| 17 | 2014-10-29T13:00:56.413 | 0 | -72.529 | -71.664 | -71.741 | -70.836 | -71.927 | -70.644 | -72.465 | -68.977 | -69.591 |
| 18 | 2014-10-29T13:00:56.543 | 0 | -72.954 | -72.235 | -71.147 | -72.439 | -71.544 | -71.637 | -71.023 | -70.932 | -71.187 |
| 19 | 2014-10-29T13:00:56.668 | 0 | -71.749 | -71.73 | -70.818 | -70.788 | -71.659 | -71.104 | -72.754 | -72.272 | -72.4 |
| 20 | 2014-10-29T13:00:56.797 | 0 | -72.34 | -70.954 | -70.589 | -71.901 | -71.325 | -72.091 | -70.705 | -72.875 | -71.719 |


Sweep-Recording_2014-10-29_1800 - Microsc
File
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Calibri
11
Font
Wrap Text
Merge & Center
Alignment
General
Number
A1
Timestamp;Measure
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4 2014-10-29T13:03:15.026;0;-80.776;-91.904;-81.852;-81.876;-81.490;-81.687;-83.501;-83.433;-81.528;-81.816;-81.499;
5 2014-10-29T13:03:16.766;0;-80.271;-91.805;-82.259;-81.768;-81.805;-81.601;-84.294;-84.645;-81.784;-82.004;-81.207;
6 2014-10-29T13:03:18.576;0;-80.604;-91.937;-82.495;-81.656;-81.509;-81.435;-84.179;-84.331;-81.516;-81.851;-81.340;
7 2014-10-29T13:03:20.266;0;-80.284;-91.831;-82.224;-81.682;-81.476;-81.379;-85.202;-84.933;-81.571;-81.904;-81.491;
8 2014-10-29T13:03:21.956;0;-81.129;-92.329;-82.314;-82.045;-81.325;-81.882;-85.925;-83.605;-81.990;-81.983;-81.777;
9 2014-10-29T13:03:23.576;0;-80.097;-92.008;-82.562;-81.713;-81.510;-81.284;-83.469;-83.704;-81.891;-82.089;-81.536;
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Remove Duplicates
Data Validation
Consolidate
What-If Analysis
Data Tools
Group
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C15
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3 2014-10-29T13:03:13.336 0 -80.957 -91.97 -82.048 -81.885 -81.511 -81.343 -85.93 -84.685 -80.936
4 2014-10-29T13:03:15.026 0 -80.776 -91.904 -81.852 -81.876 -81.49 -81.687 -83.501 -83.433 -81.528
5 2014-10-29T13:03:16.766 0 -80.271 -91.805 -82.259 -81.768 -81.805 -81.601 -84.294 -84.645 -81.784
6 2014-10-29T13:03:18.576 0 -80.604 -91.937 -82.495 -81.656 -81.509 -81.435 -84.179 -84.331 -81.516
7 2014-10-29T13:03:20.266 0 -80.284 -91.831 -82.224 -81.682 -81.476 -81.379 -85.202 -84.933 -81.571
8 2014-10-29T13:03:21.956 0 -81.129 -92.329 -82.314 -82.045 -81.325 -81.882 -85.925 -83.605 -81.99
9 2014-10-29T13:03:23.576 0 -80.097 -92.008 -82.562 -81.713 -81.51 -81.284 -83.469 -83.704 -81.891
10 2014-10-29T13:03:25.206 0 -80.158 -91.839 -82.003 -81.724 -81.692 -81.466 -83.226 -84.52 -81.996
11
12


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11
Font
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Number
Conditional Formatting
A1
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What-If Analysis
Data Tools
Group
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