SENSING AND DETECTION OF A PRIMARY RADIO SIGNAL IN A COGNITIVE RADIO ENVIRONMENT USING MODULATION IDENTIFICATION TECHNIQUE

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A thesis submitted to the Faculty of Engineering and the Built Environment, University of the Witwatersrand, Johannesburg, in fulfilment of the requirements for the degree of Doctor of Philosophy.

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DECLARATION

I declare that this thesis is my own unaided work. It is being submitted to the degree of Doctor of Philosophy to the University of the Witwatersrand, Johannesburg. It has not been submitted before for any degree or examination in any University.

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(Signature of the Candidate)

……9th……… day of …… May…………… 2012

ABSTRACT

In today's society, the need for the right information at the right time and the right place as well as increased number of high bandwidth wireless multimedia services and the explosive proliferation of smart phone and tablet devices has led to increase in demand for and use of radio spectrum, which is the primary enabler of wireless communications. With this increase, the principal engineering challenge in wireless communications domain is now on how to effectively manage the radio spectrum to ensure its sustainability for future emerging wireless devices, since virtually all usable radio frequencies for wireless communications have been licensed to commercial users and government agencies.

Traditionally, the approach to radio spectrum management has been based on a fixed allocation policy, whereby licenses are issued to users or operators for the usage of frequency bands. With a license, operators have the exclusive right to use the allocated frequency bands for assigned services on a long-term basis. However, over the last ten years, this strict allocation policy has been subjected to a lot of criticism because of its observed contribution to radio spectrum scarcity and underutilization.

In mitigating these negative effects of the current radio spectrum management policy, one of the suggested measures is to open up the licensed frequency bands to unlicensed users on a non-interference basis to licensed users. In this new spectrum access system, an unlicensed or secondary user can opportunistically operate in unused licensed spectrum bands without interfering with the licensed or primary user, thereby reducing radio spectrum scarcity and at the same time increasing the efficiency of the radio spectrum utilization.

In achieving this objective, there is a need to develop a radio engine that can sense its environment to determine the presence of primary users. Cognitive radio is seen as the enabling technology for opportunistic spectrum sharing. It is a radio with the capability to sense and understand its environment, and proactively alter its operational mode as needed to avoid interference with a primary user. To ensure interference-free use to the

primary user, spectrum sensing and detection has been observed as a key functionality of cognitive radio.

However, there is currently no single sensing method that can reliably sense and detect all forms of primary radios' signals in a cognitive radio environment. Therefore, in order to achieve this goal, this thesis addresses the problem of accurate and reliable sensing and detecting of a primary radio signal in a cognitive radio environment. The principal research issue addressed is the possibility of sensing and detecting all forms of primary radio signals in a cognitive radio environment. This objective was achieved by developing an adaptive cognitive radio engine that can automatically recognize different forms of modulation schemes in a cognitive radio environment.

The thesis pictures spectrum sensing as the combination of signal detection and modulation classification, and uses the term Automatic Modulation Classification (AMC) to denote this combined process. The hypothesis behind this detection method is that, since all transmitters using the radio spectrum make use of one modulation scheme or another, the ability to automatically recognize modulation schemes is sufficient to confirm the presence of a primary user signal while the opposite confirms absence of a primary user signal.

The research work methodology was divided into two stages. The first stage involves the development of an automatic modulation recognition (AMR) or AMC using an Artificial Neural Network (ANN). The second stage involves the development of the Cognitive Radio Engine (CRE), which has the developed AMR as its core component. The developed CRE was extensively evaluated to determine its performance. The overall numerical results obtained from the developed CRE's evaluation shows that the developed CRE can reliably and accurately detect all the modulation schemes considered without bias towards a particular Signal-to-Noise Ratio (SNR) value, as well as any modulation scheme. The research work also revealed that single spectrum sensing and detection method can only be achieved when a general feature common to all radio signals is employed in its development rather than using features that are limited to certain signal types.

DEDICATION

To my treasured and lovely wife,

Misitura Abiola Popoola

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LIST OF PUBLICATIONS

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Jide Julius Popoola and Rex van Olst. Performance evaluation of Spectrum sensing implementation using an automatic modulation classification detection method with universal software radio peripheral. *Submitted to "An International Journal on Performance Evaluation" Elsevier Publisher.*

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Conference Publications

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Jide Julius Popoola and Rex van Olst (2011): "Application of neural network for sensing primary radio signals in a cognitive radio environment," *in Proceedings of 10th IEEE AFRICON 2011*, The Falls Resort and Convention Centre, Livingstone, Zambia, 13 – 15 September 2011.

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Jide Julius Popoola and Rex van Olst (2009): "Detection of primary radio signals in cognitive radio environment," *in Proceedings of Southern Africa Telecommunication Networks and Applications Conference 2009 (SATNAC 2009)*, Royal Swazi Spa, Swaziland, pp. 469-470, 30 August – 2 September 2009.

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$x(t)$ = the received signal at the receiver

$s(t)$ = the transmitted signal from the primary transmitter

$n(t)$ = the additive white Gaussian noise

A_c = carrier amplitude

f_c = carrier frequency in Hertz (Hz)

ϕ = phase angle in radian or degree

$x_c(t)$ = sinusoidal carrier signal

$m(t)$ = message or modulating signal

f_s = sampling rate

N = sample in signal segment

N_{ip} = the total number of input

T_b = bit duration in seconds

E_i = symbol energy

T = time in seconds

B_T = bandwidth

W = weight

E_R = mean square error

LIST OF ABBREVIATIONS

AAMR	Analog Automatic Modulation Recognition
ADC	Analog-to-Digital Converter
ADAMR	Analog and Digital Automatic Modulation Recognition
ADMRA	Analog and Digital Modulation Recognition Algorithm
AI	Artificial Intelligence
AIT	Artificial Intelligence Technique
ALRT	Average Likelihood Ratio Test
AM	Amplitude Modulation
AMC	Automatic Modulation Classification
AMR	Analog Modulation Recognition
AMRA	Analog Modulation Recognition Algorithm
ANN	Artificial Neural Network
API	Application Programming Interface
ASK	Amplitude Shift Keying
AWGN	Additive White Gaussian Noise
BCW	Broadband Cellular Wireless
BER	Bit Error Rate
BFSK	Binary Frequency Shift Keying
BP	Back Propagation
BPA	Back Propagation Algorithm
BPSK	Binary Phase Shift Keying
CC	Cyclic Cumulants
CCK	Communications Commission of Kenya
CE	Cognitive Engine
CN	Cognitive Network
COMINT	Communication Intelligent
CONJGRAD	Conjugate Gradient
CPFSK	Continuous Phase Frequency Shift Keying
CQAM	Circular Quadrature Amplitude Modulation
C-QAM	Cross Quadrature Amplitude Modulation

CR	Cognitive Radio
CRE	Cognitive Radio Engine
DAC	Digital-to-Analog Converter
DARPA XG	Defense Advanced Research Projects Agency neXt Generation
DAMRA	Digital Automatic Modulation Recognition
DDC	Digital Down Converter
DFT	Discrete Fourier Transform
DMRA	Digital Modulation Recognition Algorithm
DSA	Dynamic Spectrum Access
DSB	Double Side Band
DSR	Dedicated Sensing Receiver
DT	Decision Theoretic
DUC	Digital Up Converter
FCC	Federal Communications Commission
FE	Front End
FFNN	Feed-Forward Neural Network
FFT	Fast Fourier Transform
FM	Frequency Modulation
FPGA	Field Programmable Gate Array
FSK	Frequency Shift Keying
GA	Genetic Algorithm
GLRT	Generalized Likelihood Ratio Test
GMLC	General Maximum Likelihood Classifier
GRC	GNU Radio Companion
HLRT	Hybrid Likelihood Ratio Test
HOS	Higher Order Statistics
IA	Interference Avoidance
ICASA	Independent Communications Authority of South Africa
IF	Intermediate Frequency
IP	Internet Protocol
ISM	Industrial, Scientific and Medical
ITU	International Telecommunication Union

ITU-R	International Telecommunication Union-Radiocommunication
LF	Likelihood Function
LLF	Log-Likelihood Function
LO	Local Oscillator
MCTT	Ministry of Communication Technology and Transport
ML	Maximum Likelihood
MLP	Multilayer Perceptron
MLPNN	Multilayer Perceptron Neural Network
MN	Master Node
MPSK	M-ary Phase Shift Keying
M-QAM	M-ary Quadrature Amplitude Modulation
MSDM	Modulation Scheme Detection Matrix
MSE	Mean Square Error
NCA	National Communications Authority
NCC	Nigerian Communications Commission
NN	Neural Network
Ofcom	Office of Communications
OFDM	Orthogonal Frequency Division Multiplexing
OQPSK	Orthogonal Quadrature Phase Shift Keying
OS	Operating System
OSA	Opportunistic Spectrum Access
PC	Personal Computer
PDF	Probability Density Function
PE	Processing Element
PM	Phase Modulation
PR	Pattern Recognition
PSD	Power Spectral Density
PSK	Phase Shift Keying
PU	Primary User
QoS	Quality of Service
QAM	Quadrature Amplitude Modulation
QPSK	Quadrature Phase Shift Keying

REM	Radio Environment Map
RF	Radio Frequency
RNN	Recurrent Neural Network
RQAM	Rectangular Quadrature Amplitude Modulation
Rx	Receiver
SCG	Scaled Conjugate Gradient
SDR	Software Defined Radio
SNR	Signal-to-Noise Ratio
SQAM	Square Quadrature Amplitude Modulation
SR	Software Radio
SSADA	Spectrum Sensing and Detection Algorithm
SSB	Single Side Band
SU	Secondary User
SU^{MNS}	Secondary User Master Node Sensor
SU^{S}	Secondary User Sensor
TQAM	Triangular Quadrature Amplitude Modulation
Tx	Transmitter
UHD	Universal Hardware Driver
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 1

1.0 INTRODUCTION AND BACKGROUND OF THE STUDY

This chapter provides the basic background of this thesis. It presents basic information on radio spectrum as an enabler of radio or wireless communication. The chapter also provides insight into the current radio spectrum regulatory policy on the worldwide level, and why the policy needs to be abolished. In addition, the aim and objectives of the research work, as well as its expected contributions to knowledge, are presented in this chapter. The last section of the chapter also provides detailed information on the organization of this thesis.

1.1 Introduction

Through the ages, people have devised different methods of communicating their messages, thoughts and needs to others. In the primitives days when human beings lived in small groups distributed over a relatively small geographical area, communication within the group took place through speech, gestures and graphical symbols. As these groups became larger and civilizations spread over large geographical areas, it was necessary to develop methods of long-distance communication (Popoola and Adeloye, 2007). Early attempts at long-distance communication included using signs, such as smoke signals, gun shots, and so forth.

With the beginning of the industrial revolution, the need for fast and accurate methods of long-distance communication became more pressing. Communications systems using electrical signals to convey information from one place to another over different transmission media provided an early solution to the problem of fast and accurate means of long-distance communication. In 1895, Marconi (Goldsmith, 2005) successfully demonstrated the first radio transmission from the Isle of Wight to a tugboat eighteen miles away, and gave birth to radio communication. Since this first employment of radio spectrum over one hundred years ago to transmit information, both the demand for radio spectrum and the utilization of radio spectrum have greatly increased (Olafsson *et al.*, 2007). This is because of an increase in both the benefits of wireless services and users of the radio spectrum over the years.

From its very beginning, radio or wireless communication has played a vital role in protecting lives and property and, subsequently, through the development of radio and television broadcasting, in delivering information and entertainment programming to the public at large. More recently, regions, countries, industries, and individuals around the world have realized that wireless communications and services are indispensable enablers of productivity and economic growth (Hatfield, 1993). This realization was as a result of the capability of wireless communications and services to deliver information services directly to individuals on the move, far from the office desk or factory floor, thereby increasing their personal productivity. In addition, there is an increasing realization that wireless communication has a critical role to play in the telecommunications and information sectors, as it can deliver information to fixed locations that cannot be economically served by hard-wired facilities because of physical infeasibility or prohibitively high costs. Thus, radio-based systems play increasingly important roles in rapidly and efficiently extending the benefits of modern telecommunications and information services.

In radio communication, radio spectrum availability is the most valuable resource. Spectrum refers to electromagnetic waves that travel through the space. These waves are used to convey information over a long distance without wires or other physical media. It consists of two major parts, namely radio waves and light waves. While measurements of radio waves are in terms of frequency or number of oscillations per second, hertz (Hz), the measurements of light waves are in terms of wavelength (meters) or energy (electron volts). The whole electromagnetic spectrum as shown in Table 1.1 consists of waves. The radio spectrum covers from 3 kHz to 300 GHz. This spectrum is divided into different bands. Table 1.2 shows the various frequency bands and their corresponding frequency ranges, as well as some applications of each of the bands.

Table 1.1: Electromagnetic Waves Components and their Ranges

Electromagnetic waves	Range
Radio waves	3 kHz - 300 GHz (Frequency)
Sub-millimeter waves	100 μm – 1 mm (Wavelength)
Infrared	780 nm – 100 μm (Wavelength)
Visible light	380 nm – 780 nm (Wavelength)
Ultraviolet	10 nm – 380 nm (Wavelength)
X-ray	120 eV – 120 keV (Energy)
Gamma rays	120 keV and above (Energy)

Source: Prasad (2003).

Table 1.2: Radio Frequency Bands and their Corresponding Applications

Frequency Band	Frequency Range	Applications
Very Low Frequency (VLF)	3 kHz – 30 kHz	Radio navigation, maritime mobile (communication on ships)
Low Frequency (LF)	30 kHz – 300 kHz	Radio navigation, maritime mobile
Medium Frequency (MF)	300 kHz – 3 MHz	AM radio broadcast, aeronautical mobile
High Frequency (HF)	3 MHz – 30 MHz	Maritime mobile, aeronautical mobile
Very High Frequency (VHF)	30 MHz – 300 MHz	Land mobile, FM broadcast, TV broadcast, aeronautical mobile, radio paging, trunked radio
Ultra High Frequency (UHF)	300 MHz – 1 GHz	TV broadcast, mobile satellite, land mobile, radio astronomy
L band	1 GHz – 2 GHz	Aeronautical radio navigation, radio astronomy, earth exploration satellites
S band	2 GHz – 4 GHz	Space research, fixed satellite communication
C band	4 GHz – 8 GHz	Fixed satellite communication, meteorological satellite communication
X band	8 GHz – 12 GHz	Fixed satellite broadcast, space research
Ku band	12 GHz – 18 GHz	Mobile and fixed satellite communication, satellite broadcast
K band	18 GHz – 27 GHz	Mobile and fixed satellite communication
Ka band	27 GHz – 40 GHz	Inter- satellite communication, mobile satellite communication
Millimeter	40 GHz – 300 GHz	Space research, Inter- satellite communications

Source: Prasad (2003).

Radio spectrum is a natural resource with some special characteristics (Hatfield, 1993). The key characteristics of the radio spectrum are the propagation features and the amount of information that signals can carry (Cave *et al*., 2006). In general, according to these authors, signals sent using the higher frequencies reach shorter distances, but have a higher information-carrying capacity. These physical characteristics of radio spectrum limit the currently identified range of applications for which any particular frequency band is suitable.

On the other hand, unlike most natural resources, such as oil, coal, iron or other mineral resources, radio spectrum's unique characteristics is that it is not consumed by use. This means that the resource is infinitely renewable. Since it is renewable, radio spectrum cannot be accumulated for later use but must be properly managed. These factors therefore necessitate an efficient process for making radio spectrum available for purposes which are useful to society (Cave *et al.*, 2006).

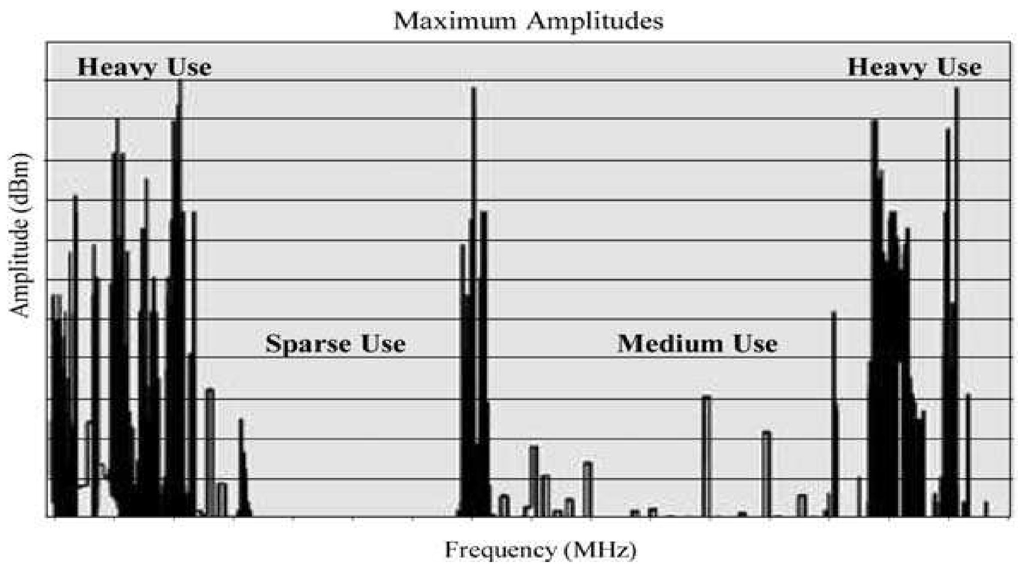
1.2 Radio Spectrum Management

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-Radiocommunication (ITU-R) Sector maintains a table of frequency allocations which identifies spectrum bands for about forty (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. The table divides the world into three regions. Region 1 includes Africa and Europe, region 2 includes North and South America, and region 3 includes Australia and Asia.

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 Independent Communications Authority of South Africa (ICASA), the Nigerian Communications Commission (NCC), the Ministry of Communication Technology and Transport (MCTT), the Communications Commission of Kenya (CCK) and the National Communications Authority (NCA) to mention but a few, are responsible for radio spectrum regulation in South Africa, Nigeria, Tunisia, Kenya and Ghana respectively. In most of these countries, the primary tool of spectrum management by government is a licensing system. This involves spectrum being apportioned into blocks for specific uses, and assigned licenses for these blocks to specific users or companies. This divide and set aside policy grants exclusive right to use the assigned spectrum to licensed users on a long-term basis.

The main advantage of the 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, there has recently been numbers of identifying disadvantages of traditional "once and for all" means of allocation of radio spectrum. One of the disadvantages 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). Another observed disadvantage of the approach according to Olafsson *et al.* (2007) is that the allocation procedures were lengthy and bureaucratic, opening up the possibility that the decision-making process could be influenced by non-relevant factors.

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 in Figure 1.1. The figure, which 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.



Sources: Akyildiz et al. (2006).

Figure 1.1: Spectrum Utilization

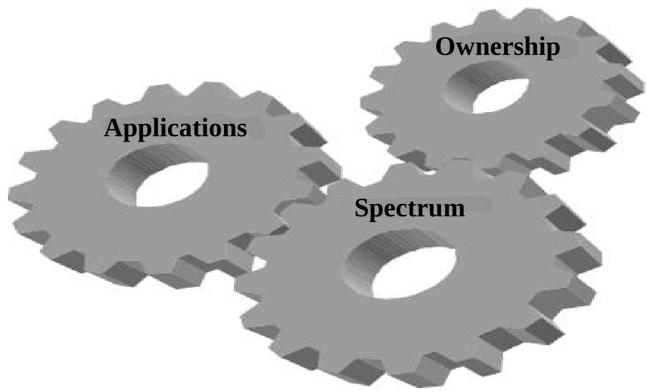
1.3 The Need for Flexibility in Spectrum Management

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 mutual interference avoidance. 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 communication does not interfere with the legacy user. Radios that have such capability are termed cognitive radios (Chakravarthy *et al.*, 2005; Haykin, 2005; Akyildiz *et al.*, 2006).

1.4 Enabler of Flexibility 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 only solution.



Source: Olafsson et al. (2007)

Figure 1.2: Relationship between Applications, Ownership and Spectrum

Cognitive radio has been observed as the only radio that has such capability. It is such a radio that changes its transmitter parameters based on interaction with the environment in which it operates (Akyildiz *et al*., 2006). Cognitive radio is a promising technology for overcoming the apparent spectrum scarcity problem, as well as improving communications efficiency. It has been described as an intelligent wireless communication device capable of adapting and reconfiguring itself to achieve the goal of satisfying the needs of the end-user. The idea of cognitive radio is that spectrum licensed to primary users may be used in an unlicensed fashion by secondary users, if these secondary users do not create harmful interference for the primary users. Therefore, a cognitive radio needs to continuously observe and learn the environmental parameters, identify the primary requirements and objectives of the user, and appropriately decide upon the transmission parameters in order to improve the overall efficiency of the radio communications.

Historically, Mitola and Maguire (1999) first coined the term cognitive radio, and it has recently become a topic of great research interests. Cognitive radio is a spectrum sharing technology like Ultra-Wide-Band (UWB) (FCC, 2002). The key differences between them is the fact that while the UWB signal spectrum overlaps with the primary user signal spectrum, a cognitive radio's signal spectrum resides solely in the unused spectrum segments or “spectrum hole” (Tang, 2005). Though cognitive radios can coexist with the primary user or owner of the spectrum, they are considered the lower priority or secondary users. Hence, their fundamental requirement is to ensure interference-free to communication for the potential primary owner or user in their vicinity. Therefore, to ensure interference-free communication, the cognitive radio must frequently sense all degrees of freedom, which include time, frequency and space, Čabrić and Brodersen (2005) while minimizing the time in sensing (Čabrić *et al.*, 2006)

Spectrum sensing has been observed as a key enabling functionality to ensure that cognitive radios do not interfere with primary users (Haykin, 2005; Akyildiz *et al*., 2006; Gandetto and Regazzoni, 2007; Čabrić *et al.*, 2006; Larsson and Regnoli, 2007). One way to sense the spectrum is by scanning the corresponding band for sometime and detect whether any primary signal is present. If no signal is detected, which is a condition known as *vacant frequency* or *spectrum hole*, it may be concluded safe to begin transmission at a small-predetermined power (Larsson and Regnoli, 2007).

There are two spectrum-sensing techniques proposed and theoretically analyzed in the literature using different detection methods. These detection methods can be categorized into different classes. Two of such classes are coherent and non-coherent detection methods. The different between them is that, while a coherent detection method is used when the cognitive radio has *a priori* knowledge of the primary user signal’s characteristic, the non-coherent detection method is used for radio environment where the cognitive radio has *no a priori* knowledge of the characteristic of the primary user’s signal. Other classes of detection methods are narrow band and wide band detection methods. However, with these two spectrum sensing techniques and different detection schemes in place, the fundamental problem remains is how to detect the presence of weak primary user’s signal in a cognitive radio environment or network (Larsson and Regnoli, 2007).

The problem of weak signal detection for cognitive radio has previously been studied in Larsson and Regnoli (2007), Čabrić and Brodersen (2005), Hoven (2005), Wild and Ramachandran (2005), Haartsen *et al.* (2005) and Čabrić *et al.* (2005). Hoven (2005) for instance, in his Master's Thesis, as reported by Reddy (2008) showed that signal detection is very difficult if there is uncertainty in the receiver noise variance. Wild and Ramachandran (2005) in detecting weak primary signals, took the advantage of Local Oscillator (LO) leakage power emitted by the Radio Frequency (RF) front end to locate the primary receivers and guaranteed that cognitive radio will not interfere with primary receivers once their locations are known. Haartsen *et al.*, (2005) after establishing the fact that it will be very hard for cognitive radio to detect weak signals without *a priori* knowledge of the existing service signal signature, then suggested a new methodology to identify weak signals based on studying signal characteristics. This suggestion supports the suggestions of Čabrić *et al.* (2005) and Le *et al.* (2005) that had also suggested that the perfect identification of a primary user signal would be based upon the signal characteristics or signatures and signal classification system respectively.

Based on these suggestions, Artificial Intelligence (AI) techniques using rule-based systems, neural networks and stochastic models, are various approaches for the detection of a signal with known signature. However, these methods may have problems in detecting signals deviating from known signature, since most of the wireless signatures have either static, which are previously known signatures or dynamic, which are those deviating from the known signatures.

Judging from this number of recent research works on radio spectrum sensing and detection, it is clear that primary radios' signals sensing and detection is important for the successful adoption of a cognitive radio in a licensed spectrum. However, with the limitations observed in virtually all the sensing and detection methods proposed and analyzed in the literature, it is also clear that there is not a single sensing and detection method that can currently detect all forms of primary radios' signals in a cognitive radio environment or network. Hence, for general acceptability of cognitive radio operation, it has become a matter of urgency to devise an effective sensing and detection method that can sense and detect the presence of all forms of primary radio signals, irrespective of their natures, whether they are weak or strong, pre-known or unknown. This is the motivation behind this research work, because being able to reliably detect and sense different radio environments will definitely enhance the general acceptability of cognitive radio technology. In addition, it will indeed enhance spectrum usage efficiency and reduce both spectrum scarcity and underutilization.

1.5 Problem Statement/Motivation

In sensing and detecting the presence of a primary user signal, numerous detection schemes have been employed. However, the challenges being presently researched are devising the effective technique(s) that can detect all forms of primary radios signals present in the cognitive radio environment. In this research work, therefore, an automatic modulation identification technique using an Artificial Neural Network (ANN) is proposed since all signal transmitting in the spectrum bands are modulated using one form of modulation technique or another. The main motivation behind using Automatic Modulation Recognition (AMR) in this research work is based on the inherent potential of AMR in accurate recognition of modulation communication signals without fore-knowledge of its feature. The AMR for the study is developed using ANN, which has ability to learn from past data and generalize its past experience when responding to new input data (Kasabov, 1998). In addition, ANN was considered as the best choice for this study because of its following advantages.

- The network can make fast decisions due to its massively parallel and decentralized computing system, being an analogy of the human brain; and
- It gives results or outcomes that are very reliable and robust to interference from noise (Kasabov, 1998).

The approach used in this thesis, assumed exclusive use of the channel by the primary user. Hence, once the cognitive radio or secondary user identifies any modulation scheme on a channel, the presence of a primary user is automatically inferred. Similarly, when it is safe to transmit on the licensed spectrum by a secondary user or cognitive radio to avoid interference to the primary user, the secondary user or cognitive radio can easily determine when it does identify or recognize any modulation scheme on the channel.

1.6 Research Aim and Objectives

From the discussions in the previous sections it is evident that the development of a reliable and accurate spectrum-detection method is fundamental to adoption of a DSA, which obviously can mitigate the current inefficient usage of radio spectrum, as well as enhance the availability of radio spectrum for emerging wireless devices as both the users and applications of wireless communication is increasing. In light of this, this research work is conceived to develop a cognitive radio engine that can detect all forms of radio signals in a cognitive radio environment. This aim of the research work will be achieved through the following objectives:

(i) *By developing an automatic modulation recognition that can automatically detect both analog and digital modulation schemes without any pre-knowledge about the modulation scheme;*

(ii) *By developing a sensing time algorithm that can improve cooperative spectrum sensing reliability among secondary users collaborating together to detect a primary radio signal in a cognitive radio environment; and.*

(iii) *By developing a cognitive radio engine that is self-sufficient for automatic recognition/identification of all forms of modulation schemes.*

1.7 The Relevance of this Research Work

Despite the fact that a series of studies have been carried out on the development of a cognitive radio engine that can 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 most of their central detection features are based on specific characteristic of radio signals, instead of on general features common to all radio signals.

Based on this observation, a novel detection method is proposed in this research work using the only best-known feature common to all radio transmitting signals in the radio spectrum. The common feature employed as the core detection feature in this research work is an Automatic Modulation Recognition (AMR) classifier that can recognize all forms of modulation signals without any pre-knowledge of the signals.

In this research work, spectrum sensing and detection is defined as a combination of signal detection and modulation recognition. Hence, automatic modulation recognition or classification was used as the general term to denote this combined process. The numerical results of performance from the developed cognitive radio engine for this research work proves the suitability and practicability of using automatic modulation identification or recognition as means of detecting the presence of all forms of communication signals in the cognitive radio environment, which is the major contribution of this research work to knowledge.

1.8 The Thesis Outline

This thesis contains seven chapters, as illustrated in Figure 1.3. This chapter, which is the first chapter, contains the introduction, the study background, motivation for the study and the problem statement. Other information presented in this chapter includes the aim and objectives of the study, as well as the relevance of the research work.

The second chapter provides a literature survey on software-defined radio and cognitive radio technology. The chapter also provides in-depth reviews on different sensing and detection methods in the literature. Reviews on different automatic modulation recognition techniques for different modulation schemes, such as analog and digital, are also presented in the chapter. It also presents a literature review on Artificial Neural Networks (ANNs). Various extraction keys for both analog and digital modulation schemes classifiers are equally reviewed in the chapter.

The third chapter focuses on the development of the three automatic modulation recognition classifiers, namely analog, digital, and combined analog and digital, for the research work. The methodology employed in extracting the feature keys used as input data sets for the three classifiers is fully discussed in this chapter. The chapter highlights the training and testing of the three classifiers, as well as the classifiers' architectures. The performances of the three developed classifiers are presented also in the chapter.

The fourth chapter of this thesis focuses on cooperative spectrum sensing optimization. The sensing time algorithm used in chapter five for the development of the cognitive radio engine for the research work is developed in this chapter. This chapter also provides detailed information on how to improve cooperative spectrum sensing gain without incurring cooperative overhead.

The fifth chapter of this thesis focuses on the development of the Cognitive Radio Engine (CRE) for the research work. Details on the CRE's development are described in the chapter. The sixth chapter contains details on analysis carried out on the developed CRE. The results obtained in the course of testing the developed CRE is presented and discussed in line with the aim and objectives of the study. The seventh chapter, which is the final chapter of this thesis, summarizes the study output based on the analysis carried out in chapter six. Conclusions and recommendations based on the findings from the research work are also presented in this chapter.

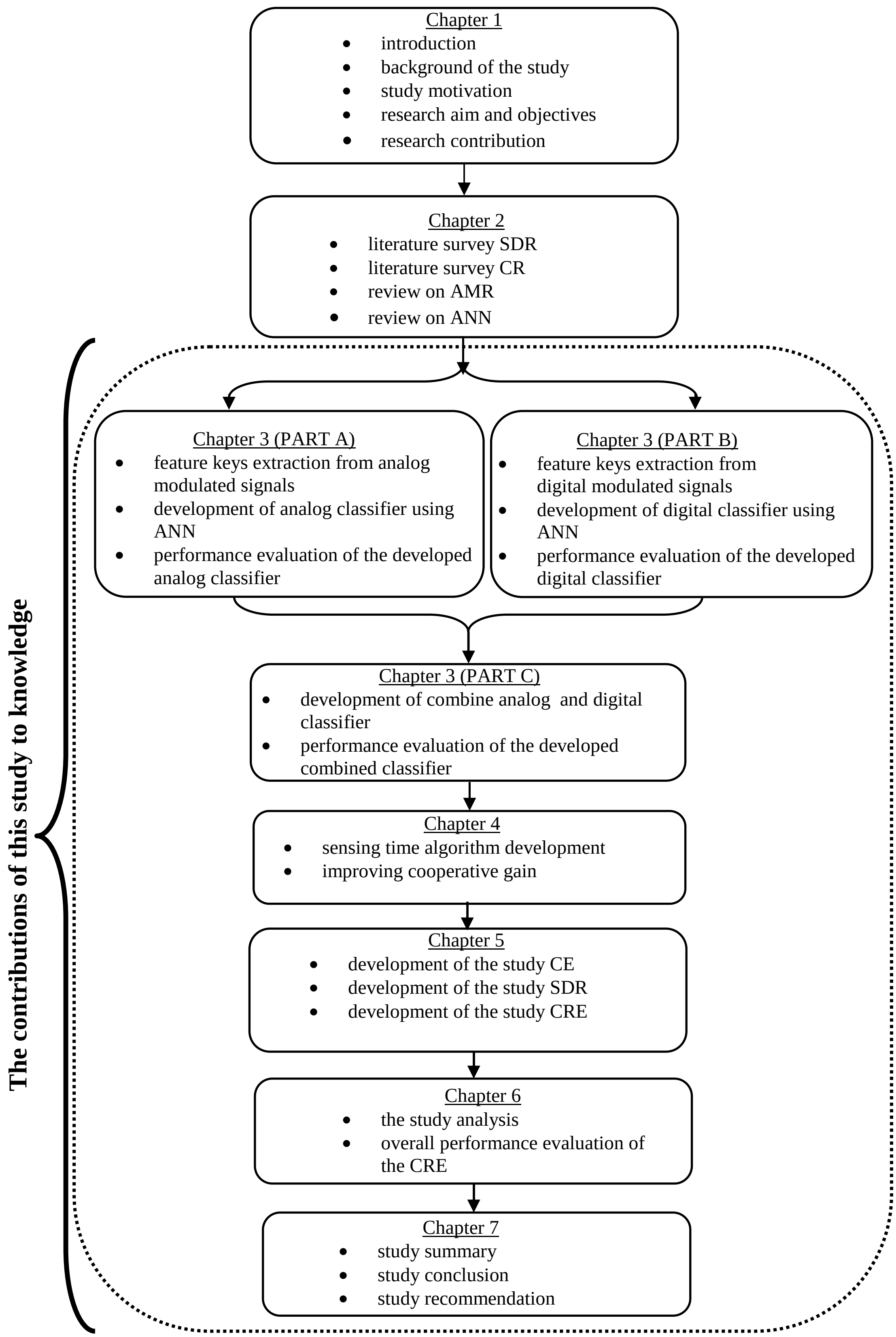


Figure 1.3: The Dissertation Outline Flowchart

CHAPTER 2

2.0 LITERATURE REVIEW

This chapter provides an in-depth literature survey on radio evolution, Software Defined Radio (SDR), Cognitive Radio (CR), automatic modulation classification using various methods and artificial neural network. In addition, the chapter reviews the principle of operation of CR as well as different sensing and detection methods in the literature. The goal of the chapter is to enlighten readers on some of the developmental history in radio technology and terms that will be later employed.

2.1 Radio Evolution Technology

Historically, radios have been fixed-point designs (Fette, 2006). However, over the last decade, the design and implementation of wireless devices has undergone a substantial transition from pure hardware-based radios to radios that involve a combination of hardware and software. The functions that were formerly carried out by hardware can now be performed by software, and the new functionality can easily be deployed on a radio by simply updating the software running on it. Part of this change has ushered in the advent of SDR, which is currently standard radio in the military arena and is gaining favour in academic and commercial environments because of its ability to support wireless communication research and implementation of real-world radio system.

Unlike the traditional radio devices that had fixed design and configuration, emerging designs are allowing for much more flexibility in these areas. The culmination of this additional flexibility produced the software capable radio, which later transitioned into the software programmable radios that gave birth to SDR (Polson, 2004). The next step along this path yielded the aware radio and the adaptive radio (Polson, 2004). In the same vein, a more recent development has been the advent of CR. The transition in the radio technology is illustrated in Figure 2.1.

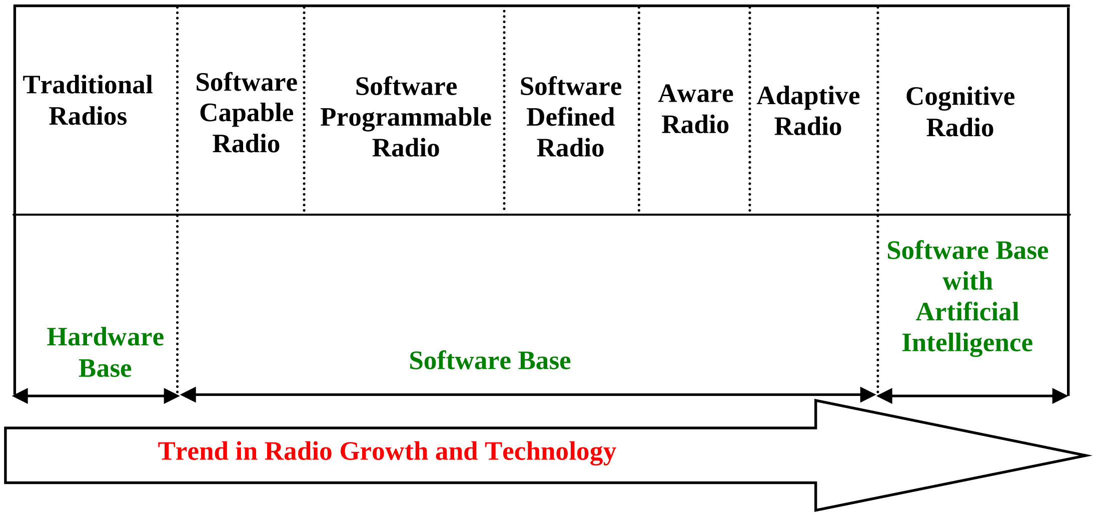


Figure 2.1: The Evolution of Radio Technology

CR is a form of radio in which a transceiver can intelligently detect which communication channels are in use and which are not, and thus instantly move into vacant channels while avoiding occupied ones. This optimizes the use of the available radio spectrum while minimizing interference to other users. It is an extension of modern SDR with AI technology. The radio encompasses all the re-configurability attributes of a conventional SDR, while possessing the intelligence to automatically adapt operating parameters, based on learning from previous events and current inputs to the system (Newman *et al.*, 2007). The two components of the CR, the SDR and AI, will be briefly overviewed before reviewing the CR technology.

2.2 Software Defined Radio

The term Software Defined Radio (SDR) was coined in 1991 by Joseph Mitola, who published the first paper on the topic in 1992 (Mitola, 1992). Although the concept was first proposed in 1991, according to the Free Encyclopedia (2009), SDR has its origin in the defense sector since the late 1970s in both the United States (US) and Europe. One of the first public software defined radios' initiatives was a US military project named SpeakEasy (Lackey and Upmal, 1995). As reported by these authors, the primary aim of the SpeakEasy project was to use programmable processing to emulate more than ten existing military radios, operating in frequency bands between 2 and 2000 MHz. Another designed goal of the radio, as reported, was to easily be able to incorporate new coding and modulation standards in the future, so that military communications can keep pace with advances in coding and modulation techniques.

Conventionally, software defined radio is a radio communication system where components that have typically been implemented in hardware, like mixers, filters, amplifiers, modulators/demodulators, detectors and so forth, are instead implemented using software on a personal computer (PC) or other embedded computing devices (Free Encyclopedia, 2009).

According to Lackey and Upmal (1995), a SDR consists of the same basic functional blocks as any digital communication systems. However, SDR lays new demands on many of these blocks in order to provide multiple bands, multiple service operation and re-configurability needed for supporting various air interface standards. In order to achieve this flexibility, the boundary of digital processing should be moved as closely as possible to antenna, while specific integrated circuits that are used for baseband signal processing, need to be replaced with programmable implementations (Salcic and Mecklenbrauker, 2002). The idea behind SDR is to do all the modulation and demodulation with software, instead of using dedicated circuitry.

In SDR, like the traditional radio, the signal is still being received by an antenna. However, in SDR, the signal is digitally converted to a sequence of numbers representing the value of the signal at regular time intervals (Katz and Flynn, 2009). These digital values are then processed in software, while the resulting output can then be converted back into audio, video or remaining data. The waveforms in SDR are therefore generated as sampled digital signals, converted from digital to analog via a wideband Digital-to-Analog Converter (DAC). The receiver similarly employs a wideband Analog-to-Digital Converter (ADC) that extracts, down-converts, and demodulates the receive waveform or signal using software built into a general-purpose processor or PC (Bedell, 2005). The radio employs a combination of techniques that include multiband antennas and RF conversion; wideband ADC and DAC conversion and the implementation of Intermediate

Frequency (IF), baseband and bit stream-processing functions in general-purpose programmable processors, as shown in Figure 2.2.

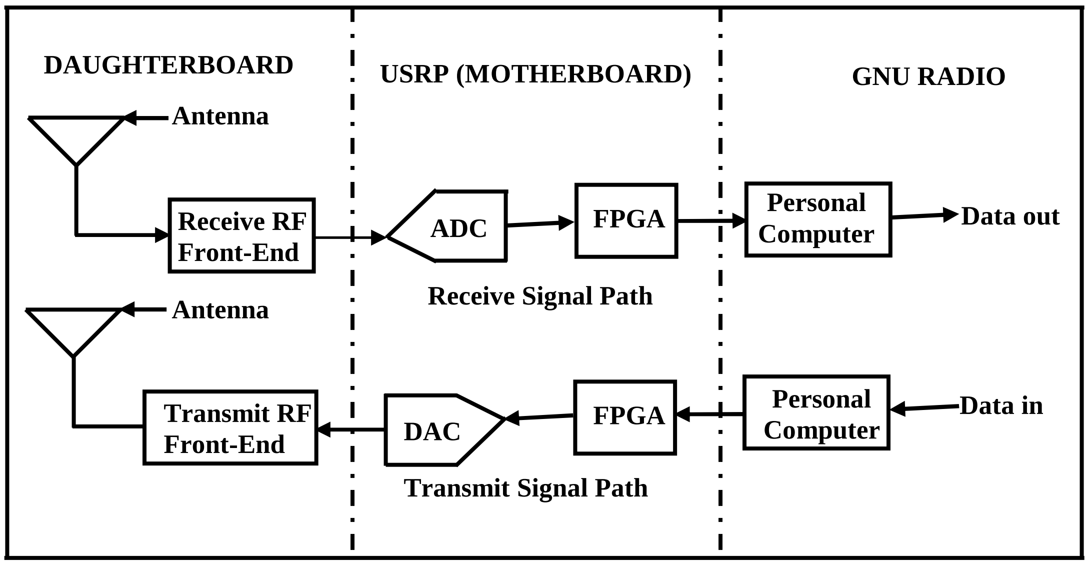


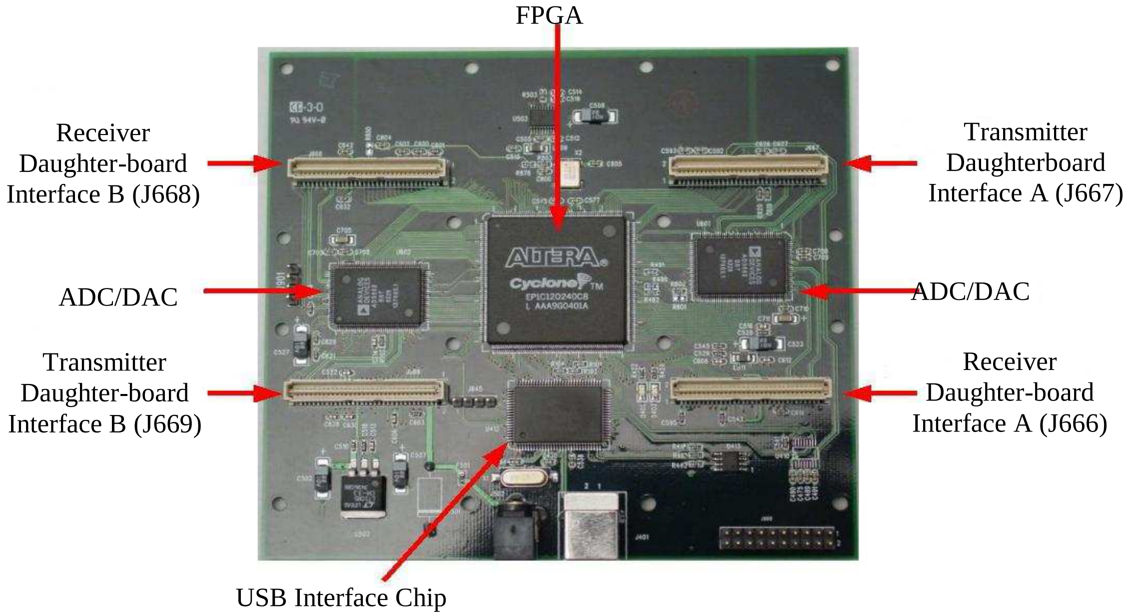
Figure 2.2: Software Defined Radio Communication System

2.3 Implementation of Software Defined Radio

Figure 2.2 shows a typical block diagram for a software-defined radio. It implementation involves using GNU Radio and the Universal Software Radio Peripheral's (USRP) motherboard and its associated daughterboard. The USRP motherboard provides the ADC/DAC and Field Programmable Gate Array (FPGA) functionality, while daughterboard attached to the USRP motherboard provides the frequency translation functionality of the RF front-end (FE). The picture of a USRP motherboard with the basic daughterboard's slots is shown in Figure 2.3. The daughterboard's slots are labeled J66X (where X = 6, 7, 8 and 9).

There are number of experimental SDR platforms that have been developed to support individual research projects. A selection of these platforms included (Minden *et al*., 2007; Polydoros *et al.*, 2003; Mishra *et al*., 2005; Adachi *et al.*, 2007). These experimental

SDRs were developed using GNU Radio and USRP. This involves writing code to process signals and control the USRP.



Source: Patton (2007)

Figure 2.3: USRP Motherboard without Daughterboard

2.3.1 GNU Radio

GNU Radio is a free software development toolkit that provides the signal processing runtime and processing block to implement software radios (SRs) or SDRs using readily available RF hardware and commodity processors. Its applications are primarily written using the Python Programming language (Blossom, 2010), while its performance critical signal path is implemented in C++ using floating point extensions (Katz and Flynn, 2009). It is empowered with a rapid development environment capable of implementing real-time, high-throughput radio systems.

GNU Radio framework incorporates software that supports the easy integration of a number of hardware modules so that radio signals may be received from, transmitted to, or exchanged with other GNU Radio-based SRs or conventional radio systems. As mentioned above, GNU Radio uses a modular block-based architecture with a hybrid Python/C++ programming model. This combination of Python and C++ provides a convenient and high performance platform for developers to use in the development of SR systems (Troxel *et al*., 2008). According to these authors, one of the features of the GNU Radio framework is an extensive library of pre-defined and tested functional blocks. The essence of these blocks is to provide signal processing functionality, encapsulate sources and sinks of data, as well as providing simple type conversions. According to them, the blocks are written in C++ with an automatic generated Python wrapper or interface that allows them to be manipulated, connected and utilized in Python.

GNU Radio software typically consists of four different elements: Sources, Sinks, Flow graphs and Schedulers.

2.3.1.1 Gnu Radio Sources

Normally, typical GNU Radio sources usually have at least one source. Each source forms the head of a processing chain or flow graph. A good example of a GNU Radio source is USRP radio. The USRP radio is a radio FE that can be connected to a computer via a USB 2.0 or Gigabit Ethernet. USB 2.0 is used for connecting USRP version 1 or USRP1 to PC while Gigabit Ethernet is used for USRP version 2 or USRP2.

2.3.1.2 Gnu Radio Sinks

Like GNU Radio sources, typical GNU Radio will normally have a least one sink. Each sink is the tail of a flow graph. An example of a sink is a sound card.

2.3.1.3 Gnu Radio Flow Graphs

A GNU Radio also has a flow graph. The flow graph links together each source and sink pair as well as any intermediate blocks. The intermediate block(s) is or are required to transform the data stream from a source into a format that is understandable by the sink. A good example of such conversion is the conversion of an FM radio signal that is received by a USRP into an audio signal that can be played through a sound card.

2.3.1.4 Gnu Radio Schedulers

A scheduler of a GNU Radio is associated with each active flow graph. The essence of each scheduler is to move data through its flow graph. A scheduler iterates through the blocks in the flow graph in order to identify blocks' conditions per time. In its iteration process, it will discover blocks that have sufficient data on their input(s) and sufficient data on their output(s), it will then trigger the processing function for those blocks to enable it to process data. Figure 5.4 shows a typical example of GNU Radio application with these four components.

2.3.2 Universal Software Radio Peripheral

The common hardware platform to run GNU Radio on is the USRP. USRP is a device that enables the creation of a SDR (Gahadza *et al*., 2009), using any computer with either a USB 2.0 port or Gigabit Ethernet port depending on the version of USRP. With different plug-on daughterboards nowadays, it is now possible to use USRP on different radio frequency bands. A good example of USRP is Ettus' USRP that allows general-purpose computers to function as a high bandwidth SRs.

The USRP1 motherboard for instance, contains four 12-bits 64M samples/sec ADCs, four 14-bit 128M samples/sec DACs, an FPGA for IF up/down conversion, and a programmable USB 2.0 controller to transfer control signals and baseband data sequences between the host and the hardware. The motherboard can support up to two pairs of transmitter/receiver (Tx/Rx) radio front ends in the form of daughterboards. Figure 2.4 shows a simple block diagram of USRP1.

There are multiple daughterboards options for different frequency bands. XCVR2450 transceiver daughterboards in junction with USRP2 are employed in this research work. The USRP2 full description and mode of operation are presented in Appendix B of this thesis.

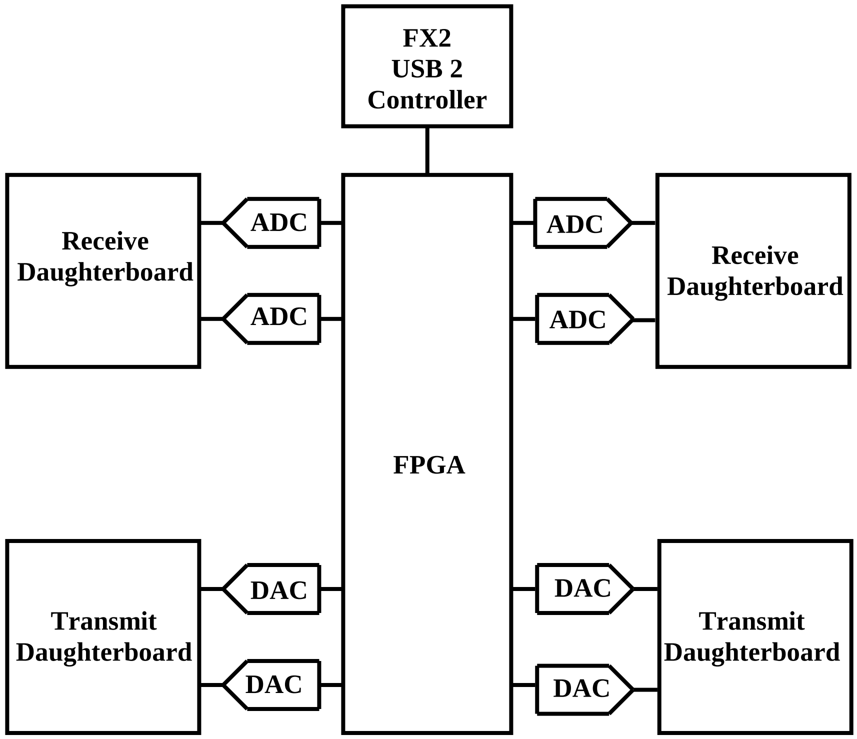


Figure 2.4: USRP1 Block Diagram

2.4 Artificial Intelligence Techniques in Cognitive Radio

The heart of a CR's application is in its ability to improve performance through learning. This behavioral capability is achieved by the Artificial Intelligence Technique (AIT) associated with CR. Artificial Intelligence is a field that is concerned with the design and development of an algorithm that enables computer to learn. It is suitable for situations based on experience, as they learn by example and act by analogy.

In CR, the integration of a learning engine has been established as very important (Tsagkaris, *et al*., 2008; Katidiotis, *et al*., 2010). This has led to the proposal of different intelligence algorithms for CR in literature. For instance, a cognitive engine developed at Virginia Tech was developed using a Genetic Algorithm (GA). Their simulation results validate that their GA implementation does change the transmission parameters to different settings (Maldonado *et al*., 2005; Rondeau *et al*., 2004). In a similar research conducted by Newman *et al.* (2007), GA was equally employed. Their work goes beyond only demonstrating GA output selection, but also provides the numerical analysis of the relationships between the environmental parameters and the transmission parameters.

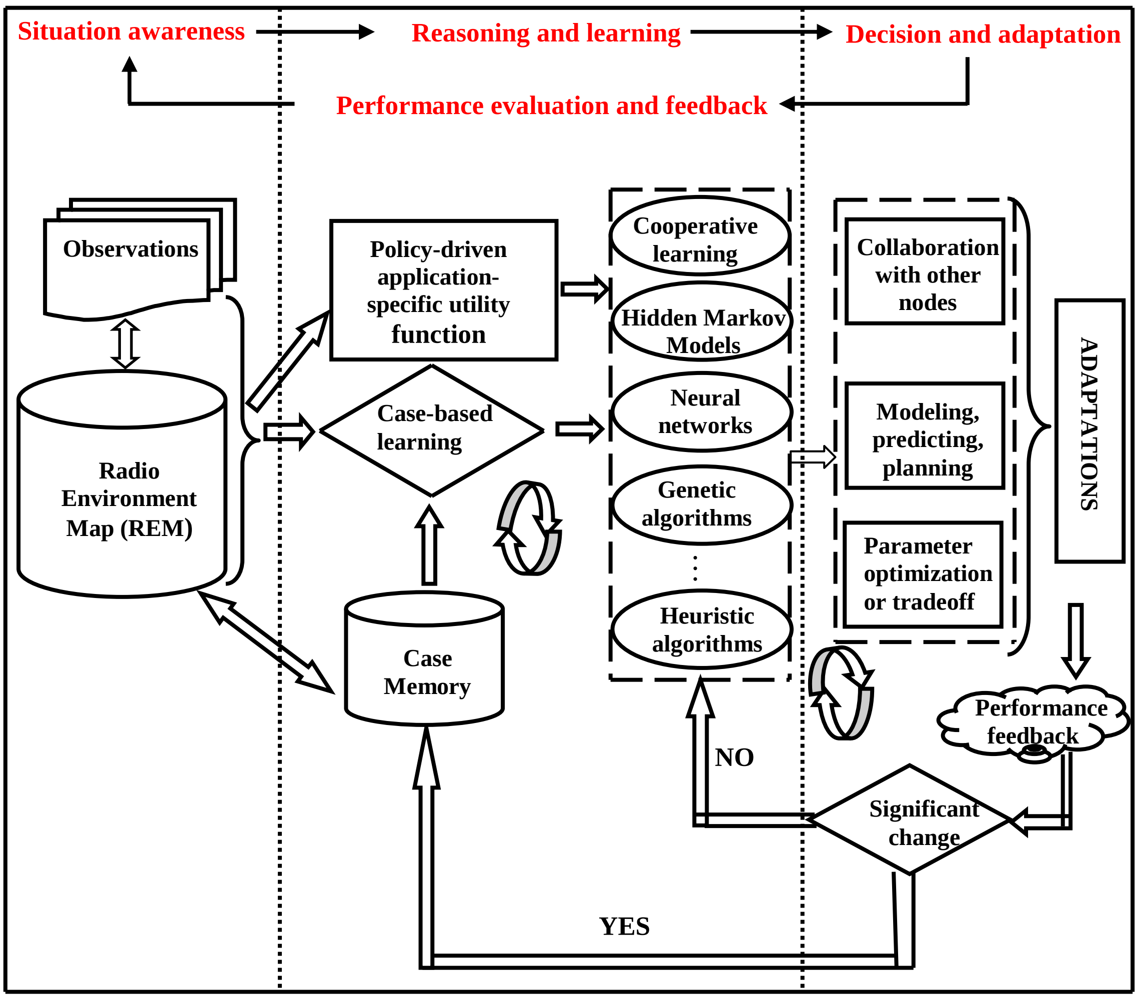
Several other AI methods have been employed in the implementation of a cognitive radio engine. A few of such methods are rule-based systems (Newman, 2008), case-based reasoning (He *et al*., 2009), fuzzy logic (Shatila *et al*., 2009), and neural networks (Tsagkaris, *et al*., 2008). A schematic diagram of the AI cognitive radio-learning algorithm employed by Zhao *et al.* (2006) is shown in Figure 2.5. The AI cognitive radio-learning algorithm is referred to as a Radio Environment Map (REM) enabled situation-aware learning algorithm. It comprises both a high-level and low-level learning loop. The high-level loop is based on case-based learning/reasoning, which leverages various learning algorithms to select the most appropriate learning method for the current radio scenario. The low-level loop is responsible for optimizing the corresponding parameters used in the specific learning algorithm.

2.5 Cognitive Engine

The Cognitive Engine (CE) is the intelligence system behind a CR or a node in a Cognitive Network (CN). The CE combines sensing, learning and optimization to control the CR or CN. A distinctive feature of CRs is their capability of making decisions and adaptations based on past experience, on current operational conditions and possibly also on future behaviour predictions (Mackenzie *et al.*, 2009). According to these authors, an underlying aspect of this concept is that CRs must efficiently represent and store environmental and operational information in databases. These resulting databases, which can be individual or shared, enable different functionalities of the CE. A possible embodiment of such databases is discussed in form of REMs.

The application of REMs to CR systems was first proposed in the context of unlicensed wireless wide area networks in Batra *et al*. (2004) and Krenik and Batra (2005). A detailed study of the use of REMs by different CEs is discussed in (Zhao *et al*., 2006;

Zhao, *et al*. 2007a; Zhao, *et al*. 2007b). In REMs, the database contains information that characterizes the environment in a given geographical area such as spectral regulations, geographical features and the locations and activities of radios (Zhao, *et al*., 2006; Zhao, *et al*., 2007a; Zhao, *et al*., 2007b).



Source: Zhao, et al., (2006)

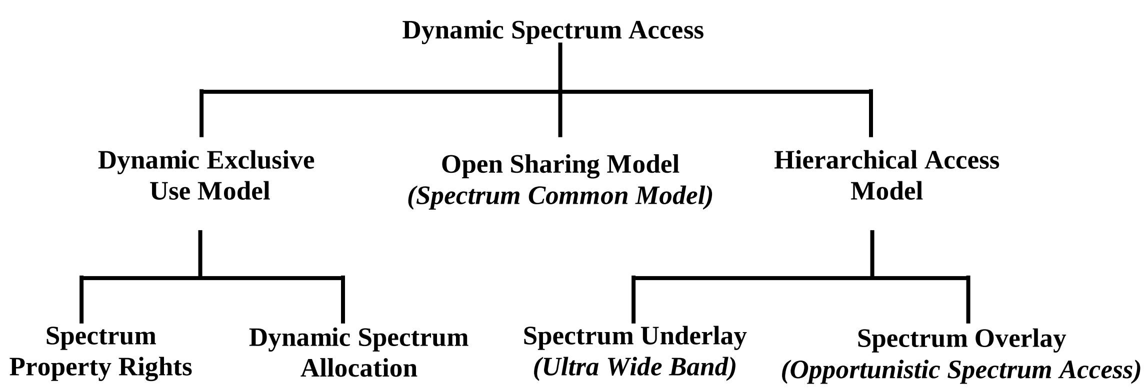
Figure 2.5: System Flow and Framework of REM-Enabled Situation-Aware Learning Algorithms

According to Mackenzie *et al.* (2009), REMs can be divided into two classes, namely global REMs and local REMs. While global REMs present a global view of the environment around the CR, the local REMs present a local view of the environment around the CR. A source of global REM is usually the network infrastructure, while a local REM is usually obtained, for example, by each radio from its own spectrum sensing and by monitoring transmissions of nearby CRs and Primary Users (PUs). The information in REMs is vital, as CRs uses it to optimize their transmit waveforms and other parameters across the protocol stack.

2.6 Area of Application of Cognitive Radio

Technology is futile without its application. Out of many applications of CR, DSA has been the most recognized application of CR. DSA 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 2.6, DSA 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.



Source: Zhao and Swami (2007)

Figure 2.6: Taxonomy of Dynamic Spectrum Access

2.6.1 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 recent report presenting statistics regarding spectrum utilization show that only about 13% of the allocated spectrums were utilized (McHenry and McCloskey, 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 (Coase, 1959; Hatfield and Wieser, 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*., 2000), 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).

2.6.2 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).

2.6.3 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, which are further discussed below.

2.6.3.1 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 (SUs) with the PUs of the frequency bands. The technique imposes severe restraints on the transmission power of SUs so that they operate below the noise floor of PUs. An 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 PUs is not required in spectrum underlay, since the energy of the transmission signals by the SUs are spread over a very wide frequency range, thus only negligibly increasing the interference temperature (Berthold *et al*., 2007).

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 (Srinivasa and Jafar, 2007). 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.

2.6.3.2 Spectrum Overlay

The spectrum overlay technique is a spectrum access system whereby a SU uses a spectrum band from a PU only when it is free. Unlike the underlay system, which hides the transmission signal under the noise level of the PU, 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 SU to sense the frequency spectrum and thus, if a PU is active, the channel will not be used.

The spectrum overlay access strategy was first envisioned by Mitola (1999) under the term spectrum pooling. It was later investigated by the Defense Advance Research Projects 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 SUs, but rather there are restrictions on when and where SUs can transmit.

Spectrum overlay, according to Fujii and Suzuki (2005), can be applied in either temporal or spatial domain. When using the radio spectrum in temporal domain, SUs 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, SUs aim to exploit frequency bands that are not used by PUs in a particular geographic area. This unused portion of the licensed spectrum is known as 'white space' or 'spectrum hole'. Haykin (2005) defines it as, "*a band of frequencies assigned to a primary user but at a particular time and specific geographic location the band is not being utilized by that user*". The special radios that are enablers of OSA or DSA that can use spectrum holes in an opportunistic fashion are known as cognitive radios.

2.7 Cognitive Radio

A cognitive radio is a new paradigm in radio communications that promises an enhanced utilization of the limited radio spectral resource (Simeone *et al*., 2007). According to these authors, the basic idea is to employ a hierarchical model, where both primary and secondary users coexist in the same frequency spectrum. Unlike the conventional radio that is only allowed to operate in a designated spectrum band due to regulatory restrictions, CR has the capability to operate in different spectrum bands. It is a form of wireless communication system in which a transceiver can intelligently detect which communication channels are in use and which are not in use, and instantly move into vacant channels while avoiding occupied ones.

The term 'cognitive radio' was first used in Mitola III and Maguire (1999). It is a term that defines the wireless system that can sense, be aware of, learn from, and adapt to the surrounding environment according to inner and outer stimuli. The radio provides a tempting solution to the spectral crowding problem by introducing the opportunistic usage of frequency bands that are not occupied by their licensed users. The radio concept proposes to furnish the radio system with the abilities to measure and be aware of parameters related to the radio channel characteristics, availability of spectrum and power, interference and noise temperature, available networks, nodes, and infrastructures, as well as local policies and other operating restrictions (Arslan and Şahin, 2007).

Recently, CR has emerged as a prime candidate for exploiting the increasing flexible licensing of wireless spectrum. The flexible licensing of radio spectrum was suggested as the spectrum resources are facing both huge usage and demands with the rapid growth of wireless services and applications in recent decades. This increase in both spectrum usage and demands has led to the belief that scarcity of radio spectrum is due to the emergence of new wireless services and applications. However, this misconception about spectrum scarcity is being tempered by a recent survey by a Spectrum Policy Task Force (SPTF) within FCC. The result of their survey shows that the actual licensed spectrum under the current fixed spectrum allocation policy is largely underutilized in vast temporal and geographic dimensions (FCC, 2002).

As reported by Letaief and Zhang (2007), a field spectrum measurement taken in New York City showed that the maximum total spectrum occupancy is only 13.1% from 30 MHz to 3 GHz. A similar measurement result undertaken in an urban setting, reported by Čabrić and Brodersen (2005), revealed a typical utilization of 0.5% in the 3-4 GHz band. The authors reported that the utilization drop amounted to 0.3% in the 4-5 GHz band. Another related survey's result reported by Song *et al*. (2007) also showed that, on average, there is only about 5.2% of the allocated spectrum below 3 GHz actually in use. These exciting findings shed light on the problem of spectrum scarcity and motive a new direction to solve the paradox between spectrum scarcity and spectrum underutilization.

A remedy to spectrum scarcity as a result of spectrum underutilization is then to improve spectrum utilization by allowing secondary users to access underutilized licensed frequency bands dynamically when and where licensed users are absent. The main enabler of this opportunistic spectrum access, as mentioned above, is cognitive radio.

Based on its abilities to sense and adapt to different radio environments, cognitive radio has been defined in various ways (Haykin, 2005; Akyildiz *et al.*, 2006; Ghozzi *et al.*, 2006; Hamdi *et al.*, 2007). For instance, it was defined in Akyildiz *et al.* (2006) as, "*a radio that can change its transmitter parameters based on interaction with the environment in which it operates*." Similarly, Haykin (2005) defines CR as "*an intelligent wireless communication system that is aware of its surrounding environment (i.e., outside world), and uses the methodology of understanding-by-building to learn from the environment and adapt its internal states to statistical variations in the incoming radio* *frequency (RF) stimuli by making corresponding changes in certain operating parameters (e.g., transmit-power, carrier-frequency, and modulation strategy) in real-time, with two primary objectives in mind:*

• *highly reliable communications whenever and wherever needed; and*

• *efficient utilization of the radio spectrum."*

For CR to operate in an interference-avoidance way, one of most critical components of CR is spectrum sensing. By sensing and adapting to the environment, a CR is able to utilize spectrum holes and serves its users without causing interference to the licensed user. To ensure interference-free communication, different sensing and detection methods have been proposed for detecting the presence of primary or licensed radio signals. These different sensing and detection methods are reviewed in section 2.8.

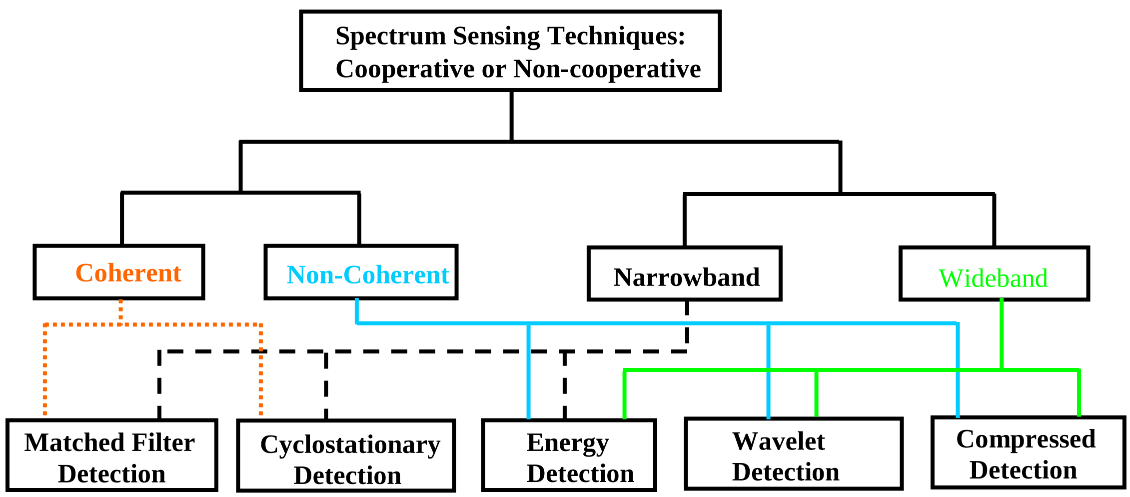
2.8 Spectrum Sensing Techniques

Spectrum sensing is a key element in CR communications, as it should be firstly performed before allowing unlicensed users to access an unused licensed spectrum. The essences of spectrum sensing are two-fold: one to ensure CR or secondary user does not cause interference to a PU and two, to assist CR or secondary user to identify and exploit the spectrum holes for the required quality of service (Popoola and van Olst 2011c). This sensing operation is a binary hypothesis-testing problem. The goal of spectrum sensing is to decide between the following two hypotheses:

$$\begin{aligned} H_0 &: x(t) = n(t) \\ H_1 &: x(t) = s(t) + n(t) \end{aligned} \tag{2.1}$$

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 the spectrum sensing.

Generally, 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 (Akyildz *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 *a priori* 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 2.7.



Source: Akyildz et al., (2011)

Figure 2.7: Classification of Spectrum Sensing Techniques

2.8.1 Non-cooperative Spectrum Sensing Method

An individual CR 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 compare 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, 2008).

2.8.2 Cooperative Spectrum Sensing Method

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:

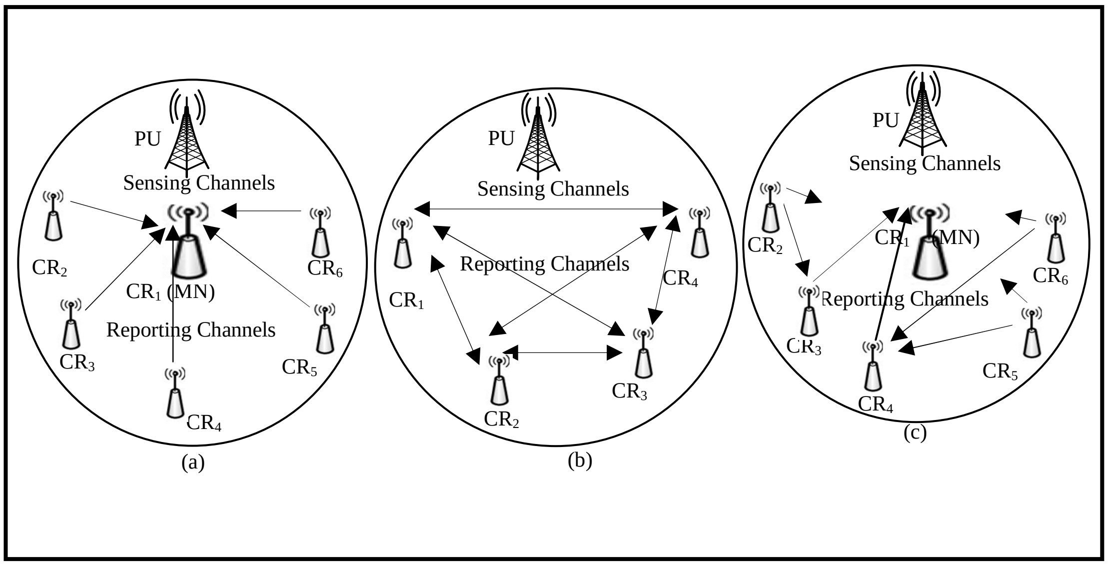
- Step I: Each cognitive radio performs its own local spectrum sensing measurement independently and then makes a binary decision on whether the primary user is present or not.

- Step II: All the cognitive radios forward their decisions to the MN or common receiver.

- Step III: The MN aggregates the cognitive radios binary decisions received using an "OR" logic and finally makes a decision 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 (Akyildz *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 (Akyildz *et al.*, 2011; Popoola and van Olst, 2011a). The classes are namely centralized, distributed and relay-assisted. The three classes of cooperative spectrum sensing illustrated in Figure 2.8 are briefly discussed in the following subsections.



Adapted from: Popoola and van Olst (2011a)

Figure 2.8: Classification of Cooperative Sensing: (a) Centralized, (b) Distributed, and (c) Relay-assisted

2.8.2.1 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 2.8(a), CR_1 is the master node and CR_2-CR_6 are the cooperative cognitive radio users performing local sensing and reporting the results back to CR_1. CR_1 or MN collects sensing information from CR_2-CR_6, identifies unused spectrum and broadcasts the information to CR_2-CR_6.

2.8.2.2 Distributed Cooperative Spectrum Sensing

Unlike centralized cooperative sensing, distributed cooperative sensing, as shown in Figure 2.8(b), does not rely on a MN for making the final cooperative decision. In this cooperative sensing, after local sensing, the cognitive nodes CR_1-CR_4 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 (Akyildz *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.

2.8.2.3 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 experiences a weak sensing channel and a strong reporting channel and a CR 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 2.8(c), CR_2, CR_5 and CR_6 that observe strong primary users' signals will observe a weak reporting channel. CR_3 and CR_4 that have strong reporting channels can serve as relays to the prior CRs and assist them in forwarding their sensing results to MN. In Figure 2.8(c), reporting channels from CR_3 and CR_4 report to MN and are known as relay channels (Akyildz *et al*., 2011).

2.8.3 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. Figure 2.7 shows five of most commonly used detection methods in spectrum sensing in a cognitive radio environment or network. Each detection method is briefly reviewed with emphasis on their merit and demerit, as follows:

2.8.3.1 Matched Filter Detection

Matched filter detection is an optimal detection method (Čabrić *et al*., 2004) normally used in a situation where a secondary user has *a priori* knowledge 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 needs for cognitive radios or secondary users to have receivers for all signal types make matched filter detection method uneconomical to implement (Lataief and Zhang, 2009).

2.8.3.2 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 priori* knowledge concerning the primary signal, it has been proved to be appropriate to use an energy detector in determining the presence of unknown signal (Hamdi and Letaief, 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 priori* knowledge 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 (Akyildz *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.

2.8.3.3 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 *et al*., 2009), or even be intentionally produced to aid channel estimation and synchronization (Ma *et al*., 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 Akyildz *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 (Čabrić 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 (Akyildz *et al*., 2011; Akyildiz *et al*., 2006).

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 the cyclostationary 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 and Letaief, 2007).

2.8.3.4 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). 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 sub-band, but changes abruptly on the border of two neighboring sub-bands (Lataief and Zhang, 2009). 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 priori* knowledge information about the primary user's signal.

2.8.3.5 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 (Candes *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 (Akyildz *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.

2.9 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 signal. 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 CR 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 CR 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 CR or secondary user may be shadowed away from the primary transmitter, but there may be a primary receiver closer to the CR or secondary user that is not shadowed from the primary transmitter. In such a situation, if the CR 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 CR transmission can interfere with the primary user signal as a result of weak signal strength at the CR terminal. Hence, for the general acceptability of application of CR 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 CR by both the spectrum regulatory bodies and the spectrum-licensed owners.

A solution to such challenges is the motivation for this study. In attempting to find a sensing/detection method that can adequately detect all forms of primary radio signals whether they are weak or strong, pre-known or unknown, as well as overcoming the hidden terminal issue in a cognitive radio environment, this research work proposed an alternative spectrum sensing/detection method. The method employed in this study is the usage of an automatic modulation classification or an automatic modulation recognition scheme to detect all forms of modulation signals in the cognitive radio environment. An AMR classifier using an ANN is proposed. This approach is used because all signal transmissions in the spectrum bands are modulated using one form of modulation technique or another.

The detection method is proposed because modulation recognition must be an important feature of a CR and that knowledge of the types of signal modulations on a channel can assist CR deciding to jump either into or out of a spectrum band in a way to prevent interference to and from primary users of the spectrum. Since all wireless devices in the radio environment make use of a specific modulation scheme, the extra spectral awareness provided by AMR will indeed contribute to a safer environment for the primary users and enhances higher CR performance. A detailed literature review on both the AMR and ANN are presented in the Sections 2.11 and 2.12 respectively.

2.10 Basic Modulation Techniques

In a wireless communication system, before a message signal, which is either in analog or digital form, is transmitted through a communication channel, some form of modulation process is typically utilized to produce a signal that can easily be accommodated by the communication channel. A modulation process usually translates an information-bearing signal, also referred to as the message signal, to a new spectral location (Ziemer and Tranter, 1990). Modulation, by definition, is the process by which some parameters of high frequency waveform, called the carrier wave, is varied in accordance with a modulating wave or message signal.

Mathematically, modulation is described as the process of mapping from a message space to a signal space. A fundamental requirement for the generation of the desired type of modulation is the use of a carrier. A carrier must be characterized by some property that makes it distinguishable from other carriers of the same or different class that may be present simultaneously (Baghdady, 1961). For example, a sinusoidal carrier can be distinguished by its amplitude (A_c), frequency (f_c), or its phase (ϕ). The general expression for a sinusoidal carrier is:

$$x_c(t) = A_c \cos(2\pi f_c t + \phi) \tag{2.2}$$

These three parameters, A_c, f_c, and ϕ, may be varied for the purpose of transmitting information, hence giving respectively amplitude, frequency and phase modulation, Table 2.1.

When choosing a modulation format in a wireless systems, the ultimate goal is to transmit with a certain energy as much information as possible over a channel (Molisch, 2005), with a minimum bandwidth, while assuring a certain transmission quality. However, since there is no ideal modulation format for all forms of wireless communications, the modulation format then has to be selected according to the requirement of a specific system and application. The leads to diverse modulation formats in wireless communication.

Generally, as shown in Table 2.1, modulation can be classified into two classes depending on the transmitted signal. If a continuous signal is transmitted, the modulation is referred to as analog modulation. If a discrete signal is transmitted, the modulation is referred to as digital modulation.

Table 2.1: Analog and Digital Modulation Techniques

Modulation Technique	Modulation Scheme	Notation	Types
Analog Modulation Techniques	Amplitude Modulation	AM	Linear
	Frequency Modulation	FM	Non- Linear
	Phase Modulation	PM	Non- Linear
Digital Modulation Techniques	Amplitude Shift Keying	ASK	Linear
	Frequency Shift Keying	FSK	Non- Linear
	Phase Shift Keying	PSK	Linear

2.10.1 Analog Modulation

Traditional wireless communications systems use conventional analog modulation techniques, such as Amplitude Modulation (AM), Frequency Modulation (FM), and Phase Modulation (PM). Analog modulation types are further classified into either linear or non-linear (angle) modulation (Haykin, 2001).

2.10.1.1 Linear Modulation

A linearly modulated carrier is represented by setting the instantaneous phase, ϕ, in (2.2) equal to zero. Thus a linearly modulated carrier is represented as:

$$x_c(t) = A_c \cos 2\pi f_c t \tag{2.3}$$

in which the carrier amplitude A_c varies in one-to-one corresponding with the message signal. The following sub-sections briefly discuss the different types of linear modulation schemes.

Amplitude Modulation

Amplitude Modulation (AM), also known as conventional amplitude modulation, is an example of linear modulation. It is obtained by varying the amplitude of the carrier wave in accordance with the modulating or information-bearing signal. The analytic representation of the amplitude-modulated signal is a sum of the carrier signal and the modulating signal shifted in frequency by the carrier frequency (Hossen *et al*., 2007). The modulation scheme is used in applications such as radio and television broadcasting. Amplitude modulated carrier signal, $x_c(t)$, is represented as:

$$x_c(t) = A_c[1 + bm(t)]\cos 2\pi f_c t \tag{2.4}$$

where $m(t) = A_m \cos 2\pi f_m$ is the normalized message or modulating signal and b is the index of modulation, which is a positive constant between 0 and 1.

During transmission, the transmitted AM signal is contaminated with white Gaussian additive noise, $n(t)$. The expression for the received signal plus the noise is given by:

$$x_r(t) = A_c[1 + bm(t)]\cos 2\pi f_c t + n(t) \tag{2.5}$$

Double-Sideband Amplitude Modulation

According to Ziemer and Tranter (1990), double-sideband (DSB) modulation results when A_c is proportional to the message signal, $m(t)$. Thus the output of a DSB modulator can be represented as:

$$x_c(t) = A_c\, m(t)\cos 2\pi f_c t \tag{2.6}$$

which indicates that DSB modulation is simply the multiplication of a carrier, $A_c \cos 2\pi f_c t$, by the message signal. It follows from the modulation theorem that the spectrum of a DSB signal is given by:

$$X_c(f) = \frac{1}{2} A_c M(f + f_c) + \frac{1}{2} A_c M(f - f_c) \tag{2.7}$$

The spectra $M(f + f_c)$ and $M(f - f_c)$ are simply the message spectrum translated to $f = \pm f_c$. This type of modulation is referred to as amplitude modulation double sideband transmitted carrier (AM-DSB-TC). However if the carrier is suppressed, the modulation type is called amplitude modulation double sideband suppressed carrier (AM-DSB-SC). In many respects, conventional AM is quite similar to DSB amplitude modulation. The only difference is that in conventional AM, $m(t)$ in DSB is substituted with $[1 + bm(t)]$. This substitution makes conventional AM a less economical modulation scheme in terms of power utilization (Proakis *et al.*, 2004).

Single-Sideband Amplitude Modulation

Another type of AM is the single sideband (SSB), in which only one sideband of the spectra $M(f + f_c)$, as in upper sideband (USB) or $M(f - f_c)$, as in lower sideband (LSB) in (2.7) is transmitted. It occupies only half the bandwidth compared to AM-DSB-TC or AM-DSB-SC (Hossen *et al.*, 2007), which makes it an efficient form of AM scheme.

Generally, this family of analog modulation schemes is characterized by a low bandwidth requirement and power inefficiency in comparison to the angle modulation schemes (Proakis *et al.*, 2004). The bandwidth requirement for AM systems varies between W and 2W, where W denotes the bandwidth of the message signal. The AM systems are widely used in broadcasting, as in AM radio and television video broadcasting, point-to-point communication (SSB), and multiplexing applications such as the transmission of many telephone channels over microwave links.

2.10.1.2 Angle Modulation

Angle modulation schemes, which include FM and PM, belong to the class of analog non-linear modulation schemes. These families of analog modulation schemes are characterized by their high bandwidth requirements and good performance in the presence of noise (Proakis *et al.*, 2004). These modulation schemes are visualized as modulation techniques that trade-off bandwidth for power and are, therefore, used where bandwidth is not the major concern, but where high SNR is required.

Frequency modulation is widely used in high fidelity FM broadcasting radio, television audio broadcasting, microwave carrier modulation, and point-to-point communication systems. Frequency modulation and phase modulation differ from the linear amplitude modulation scheme. The major difference is in the instantaneous amplitude, which varies in AM but remains constant in both FM and PM. However, the frequency of the carrier in FM and phase of the carrier in PM varies with respect to the modulating or message signal.

To generate angle modulation, the amplitude of the modulated carrier is held constant and either the phase or the time derivative of the phase of the carrier is varied linearly with the message signal, $m(t)$. Thus, the general angle-modulated signal is given by:

$$x_c(t) = A_c \cos[2\pi f_c t + \phi(t)] \tag{2.8}$$

The instantaneous phase of $x_c(t)$ is defined as:

$$\phi_i(t) = w_c t + \phi(t); \quad w_c = 2\pi f_c \tag{2.9}$$

The instantaneous frequency is defined as:

$$w_i(t) = \frac{d\phi_i}{dt} = w_c + \frac{d\phi}{dt} \quad (2.10)$$

The functions $\phi(t)$ and $d\phi/dt$ are known as the phase deviation and frequency deviation respectively.

PM implies that the phase deviation of the carrier is proportional to the message signal. Thus, for PM:

$$\phi(t) = \kappa_p m(t) \quad (2.11)$$

where κ_p is the deviation constant in radians per unit of $m(t)$. Similarly, frequency modulation implies that the frequency deviation of the carrier is proportional to the modulating signal. This gives:

$$\frac{d\phi}{dt} = k_f m(t) \quad (2.12)$$

2.10.2 Comparative Analysis of Analog Modulation Schemes

Restricting to the domain of analog modulation techniques, a brief overview analysis of different analog modulation schemes were provided in this sub-section. The overview through extensive literature survey in a tabular form, presented in this sub-section establishes the superiority at a glance of specific modulation scheme for a particular application. Generally, according to Glover and Grant (2000), different modulation schemes can be compared on basis of their spectral and power efficiencies. According to these authors, spectral efficiency is defined as a measure of information transmission rate per hertz (Hz) of bandwidth used. On the other hand, the authors defined power efficiency as the ratio of signal energy to noise power spectral density.

Basically, as discussed above, there are three classes of analog modulation techniques, namely AM, FM and PM. These three modulation techniques have in turn lot of class, sub-class or derivatives. For instance, in case of AM shown in Table 2.2, there are several derivatives. These derivatives as shown in Table 2.2 show that AM-SSB-SC has smaller bandwidth and power requirements in contrast with AM-DSB-TC and AM-SSB-FC. Hence, using SSB-SC proves to be better than any other AM schemes.

Similarly, comparative analysis of AM and FM schemes shows a great merit of FM over AM because FM can suppress the effects of noise but at expense of bandwidth. On the other hand, AM is characterized by a low bandwidth requirement and power inefficiency in comparison to FM scheme.

Table 2.2: Performance Analysis of Analog Modulation Scheme

Type of Analog Modulation Scheme	Bandwidth Requirement	Power Requirement	Percentage Power Saving (%)
AM-DSB-TC	$2\omega_m$	$\frac{3}{2}(P_c)$	Standard
AM-DSB-SC	$2\omega_m$	$\frac{5}{4}(P_c)$	66.67
AM-SSB-TC	ω_m	$\frac{1}{2}(P_c)$	16.67
AM-SSB-SC	ω_m	$\frac{1}{4}(P_c)$	83.33
where ω_m *is the modulating frequency and* P_c *the carrier power*			

Adapted from: Sharma et al., (2010)

2.10.3 Digital Modulation

In modern wireless communications systems, traditional communications systems that use conventional analog modulation techniques, such as AM, FM, and PM, are gradually being replaced with digital communications systems that use digital modulation techniques. Digital modulation techniques offer several outstanding advantages over traditional analog modulations techniques. Some of these advantages are:

- better spectral efficiency;
- easier multiplexing of different forms of information, such as voice, video and data;

- better noise and fade-rejecting capability;
- easier implementation of error correction and data encryption; and
- greater noise immunity and robustness to channel impairment.

Like in analog communication systems, in digital communication systems the signal is superimposed onto a sinusoidal carrier in order to achieve modulation. By adjusting a physical characteristic of the sinusoidal carrier, such as the frequency, phase, amplitude or a combination thereof, Frequency Shift Keying (FSK), Phase Shift Keying (PSK), Amplitude Shift Keying (ASK), Quadrature Amplitude Modulation (QAM), are respectively achieved as the different basic digital modulation schemes.

Digital modulation techniques, like analog modulation techniques, can broadly be classified as linear or non-linear depending on how the amplitude of the transmitted signals varies with the modulated waveform. A review of each class is presented in the following sections, along with their corresponding advantages and disadvantages.

2.10.3.1 Linear Digital Modulation Techniques

In linear digital modulation techniques, the amplitude of the transmitted signal varies linearly with the modulation signal. The modulation schemes do not have a constant envelop. The modulation techniques have bandwidth efficiency (Rappaport, 2002), which makes it attractive for use in wireless communication systems where there is an increasing demand for more users within a limited spectrum.

Despite having very good spectral efficiency, the signal to be transmitted using linear digital modulation techniques must use linear RF amplifiers, which have very poor power efficiency since they are continuously switched on. In getting around this disadvantage, complex linear modulation techniques have been developed, but only a few basic techniques are discussed here. Examples of basic linear digital modulation techniques are the ASK scheme and PSK scheme and its variations, which includes Quadrature Phase Shift Keying, (QPSK). These modulation schemes are referred to as linear, because they require linear amplification.

Amplitude Shift Keying

This is the simplest form of digital modulation scheme. In an ASK system, the amplitude of the sine wave to transmit digital data is always varied. Digital data in ASK are represented by variations in amplitude. For instance, binary symbol 1 can be represented by transmitting a sinusoidal carrier wave of amplitude A_c and fixed frequency f_c for the bit duration T_b seconds, while binary 0 is represented by switching off the carrier for T_b seconds. In mathematical terms, ASK wave $s(t)$ is expressed as:

$$s(t) = \begin{cases} A_c \cos(2\pi f_c t), & symbol\,1 \\ 0, & symbol\,0 \end{cases} \tag{2.13}$$

The general analytic expression for the ASK is:

$$s_i(t) = \sqrt{\frac{2E_i(t)}{T}} \cos(2\pi f_c t + \phi); \quad 0 \le t \le T; \quad i = 1, 2, \cdots, M \tag{2.14}$$

where the amplitude term $\sqrt{2E_i(t)/T}$ has M discrete values, and the phase term ϕ is an arbitrary constant. The parameters E_i and T are the symbol energy and time duration respectively.

ASK is the simplest kind of modulation to generate and detect. However, it can only be used when the SNR is very high and does not conserve bandwidth. ASK demonstrates poor performance, as it is heavily affected by noise and interference.

Phase Shift Keying

PSK is an example of linear digital modulation scheme that transmits data by varying the phase of the carrier wave. It is now widely used in military and commercial wireless communications systems. PSK has many representations. A convenient way of representing PSK modulation is by using a signal space diagram known as the constellation diagram (Du and Swamy, 2010). A constellation diagram consists of a group of points representing the different symbols the carrier in a PSK modulated signal can assume. Typical constellation diagrams for Binary Phase Shift Keying (BPSK) and QPSK are shown in Figure 2.9 and Figure 2.10 respectively. The two representations of PSK are described in the following sections.

The general analytic expression for PSK is:

$$s_i(t) = \sqrt{\frac{2E_i(t)}{T}} \cos[2\pi f_c t + \phi(t)]; \quad 0 \le t \le T; \quad i = 1, 2, \cdots, M \tag{2.15}$$

where the phase term, $\phi(t)$, will have M discrete values, typically given by:

$$\phi(t) = \frac{2\pi i}{M} \qquad i = 1, 2, \cdots, M \tag{2.16}$$

Binary phase shift keying

The simplest form of PSK is called the BPSK. In BPSK system, a sinusoidal carrier wave of fixed amplitude A_c and fixed frequency f_c is used to represent both symbols 1 and 0, except that the carrier phase for each symbol differs by $180^0\,(or\,\pi, radian)$. While symbol or logic 1 is sent as a cosine signal with 0^0 phase shift, logic 0 is sent as a cosine signal with 180^0 phase shift. BPSK is thus a binary antipodal ASK (Du and Swamy, 2010). In mathematical terms, BPSK wave $s(t)$ is expressed as:

$$s(t) = \begin{cases} A_c \cos(2\pi f_c t), & symbol\ 1 \\ A_c \cos(2\pi f_c t + \pi), & symbol\ 0 \end{cases} \tag{2.17}$$

In BPSK, where each bit is represented by one symbol, as in either $A_c \cos(2\pi f_c t)$ *or* $A_c \cos(2\pi f_c t - 180^0)$, the constellation diagram consists of two points as shown in Figure 2.9. These two points have the same amplitude, A_c, but are 180^0 apart. This means that a symbol 1 corresponds to $A_c \cos(2\pi f_c t)$ while a symbol 0 corresponds to $A_c \cos(2\pi f_c t - 180^0)$.

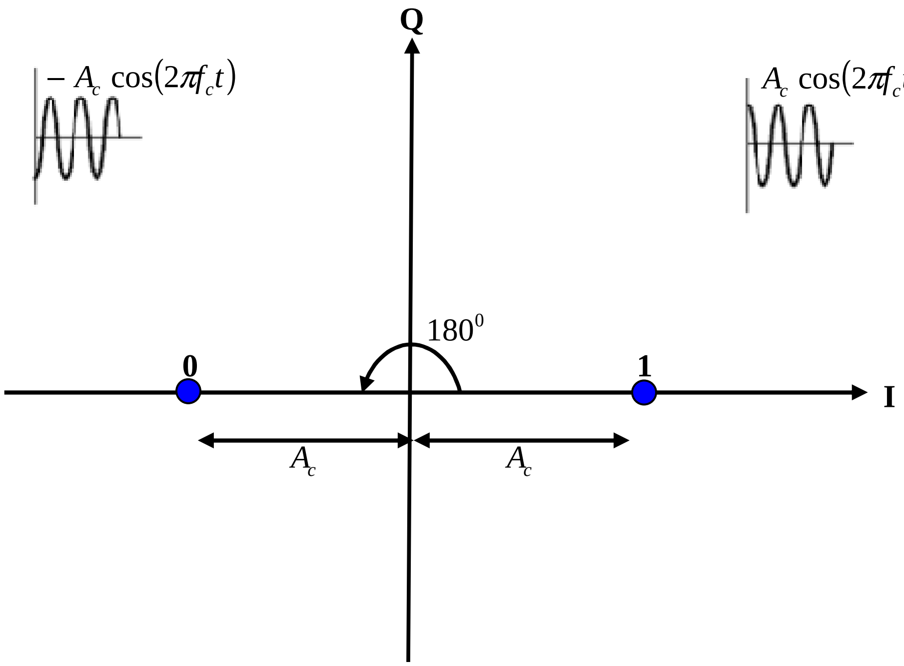


Figure 2.9: BPSK Constellation Diagram

Quadrature Binary Phase Shift Keying

Another common example or representation of PSK is QPSK. QPSK is a higher modulation scheme often used in preference to BPSK when improved spectral efficiency is required. Unlike BPSK, with two define phase states, QPSK uses four possible phases, $45^0\ or\ \left(\pi/4\right)$, $135^0\ or\ \left(3\pi/4\right)$, $225^0\ or\ \left(5\pi/4\right)$, $315^0\ or\ \left(7\pi/4\right)$, for carrier with the same amplitude. With the four phases, QPSK transmits two bits in a single modulation symbol. This accounts for why QPSK has twice the bandwidth efficiency of BPSK (Rappaport, 2002), because as the number of states is increasing, more data bits per symbol can be transmitted. Mathematically, QPSK signal can be represented as:

$$s(t) = A_c \cos\left(2\pi f_c t + (i-1)\pi/2\right) \quad i = 1,2,3,4 \tag{2.18}$$

Using trigonometric identity, $\cos(x+y) = \cos x \cos y - \sin x \sin y$, (2.18) can be re-written as:

$$s(t) = A_c \cos(2\pi f_c t)\cos\left\{(i-1)\pi/2\right\} - A_c \sin(2\pi f_c t)\sin\left\{(i-1)\pi/2\right\} \quad i = 1,2,3,4 \qquad (2.19)$$

which expresses QPSK signal in terms of an in-phase (I) and quadrature (Q) components. Based on this representation, QPSK signal can be illustrated using a two dimensional constellation diagram with four points corresponding to the four phase states of the RF carrier as shown in Figure 2.10.

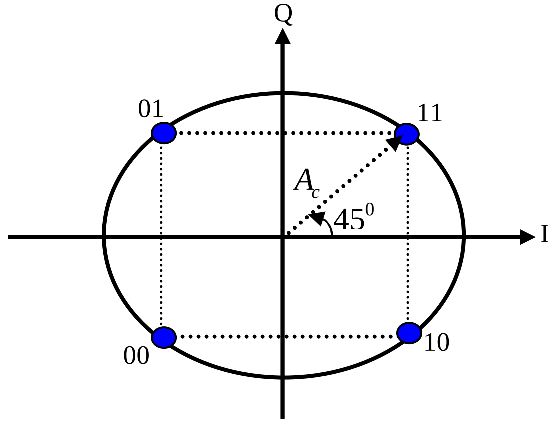


Figure 2.10: QPSK Constellation where Carrier Phases are $45^0, 135^0, 225^0, 315^0$

2.10.3.2 Non-Linear Digital Modulation Techniques

Non-linear modulations techniques have either linear or constant carrier envelopes, unlike linear digital modulation schemes that do not have a constant envelop. This class of non-linear modulation scheme with constant envelop where the amplitude of the carrier is constant regardless of the variation in the modulating signal, are used in mobile communications systems. The schemes permit the use of non-linear amplifiers to improve the power efficiency without degrading the spectrum of the transmitted signal. The major disadvantage of constant envelop modulations is that they occupy a larger bandwidth unlike linear modulation schemes. This makes the schemes well suited to systems where power efficiency is more important than bandwidth efficiency, as in a mobile communication handset. An example of a non-linear constant digital modulation technique is FSK and its variations, namely Binary Frequency Shift Keying, (BFSK), are discussed below.

Frequency Shift Keying

FSK is a relatively simple form of digital modulation. It is a constant envelop modulation technique, appropriate for channels that lack phase stability. FSK has the advantage of being simple to generate and demodulate. It has several advantages over ASK because the carrier has a constant amplitude. Some advantages present in FSK include its immunity to non-linearity; that is the high order harmonics do not superimpose on the fundamental signal (Chen and Tsao, 1998), immunity to rapid fading, immunity to adjacent channel interference and the ability to exchange SNR for bandwidth. The significant disadvantage, however, are the poor spectral efficiency and Bit Error Rate (BER) performance. This preludes its use in the basic form from cellular and even cordless systems.

The general analytic expression for FSK modulation is:

$$\begin{aligned} s_i(t) &= \sqrt{\frac{2E}{T}}\cos(2\pi f_c t + \phi) \\ &= \sqrt{\frac{2E}{T}}\cos(w_i t + \phi); \quad 0 \le t \le T; \quad i = 1, 2, \cdots, M \end{aligned} \tag{2.20}$$

where the frequency w_i has M discrete values and the phase term ϕ is an arbitrary constant.

Depending on how the frequency variations are imparted into the carrier signal, the FSK will either have a discontinuous phase or continuous phase between bits (Rappaport, 2002). The discontinuous phase FSK is normally generated by switching between two independent oscillators according to whether the data bit or message signal is a 0 or a 1. Under this condition, the generated FSK signal normally results in a waveform that is discontinuous at the switching times. Since phase discontinuities pose problems, such as spectral spreading and spurious transmissions, this type of FSK is generally not used in highly regulated wireless communications systems.

On the other hand, continuous phase frequency shift keying is an attractive choice of modulation, because of its well-behaved spectral characteristics and ability to be non-coherently detected (Cheng *et al*., 2007). In addition, while the Power Spectral Density (PSD) ultimately falls off as the inverse fourth power of the frequency offset from the carrier frequency in continuous phase frequency shift keying, the PSD falls off as the inverse square of the spectrum frequency offset from the carrier frequency in discontinuous phase frequency shift keying. This reason also makes continuous phase systems more desirable than discontinuous ones.

Binary Frequency Shift Keying

In binary frequency-shift keying, the instantaneous frequency of the carrier signal is usually shifted between two discrete values, representing symbol 1 and symbol 0. Two sinusoidal carrier waves of the same amplitude, but different frequencies f_1 and f_2 are used to represent binary symbol 1 and 0, respectively. That is, the modulated waveform is $\cos 2\pi f_1 t$ for symbol 1 and $\cos 2\pi f_2 t$ for symbol 0. Therefore, from (2.20) BFSK wave, $s(t)$, can be expressed mathematically as:

$$s(t) = \begin{cases} \sqrt{\frac{2E}{T}}\cos(2\pi f_c + 2\pi\Delta f)t, & symbol\,1 \\ \sqrt{\frac{2E}{T}}\cos(2\pi f_c - 2\pi\Delta f)t, & symbol\,0 \end{cases} \tag{2.21}$$

where $2\pi\Delta f$ is a constant offset from the nominal carrier frequency.

The PSD of a BFSK signal consists of discrete frequency components at f_c *and* $f_c \pm n\Delta f$, where n is an integer. This makes the bandwidth (B_T) of an FM signal to be ideally infinite. However according to Rappaport (2002), for a BFSK signal, the approximate B_T, is provided by Carson's rule as:

$$B_T = 2\Delta f + 2B \tag{2.22}$$

where B is the bandwidth of the digital baseband signal.

2.10.4 Multicarrier Modulation Scheme

2.10.4.1 Orthogonal Frequency Division Multiplexing

Orthogonal Frequency Division Multiplexing (OFDM) is a promising multicarrier modulation system for transmission of a high rate stream with spectral efficiency and fading immunity. As a multicarrier modulation system, OFDM utilizes a parallel processing technique that allows the simultaneous transmission of data on many sub-carriers that are orthogonally closely spaced (Abdullah *et al*., 2009). This multicarrier transmission densely squeezes multiple modulated sub-carriers that are orthogonal to each other together in the frequency domain. The orthogonality of the multiple modulated sub-carriers enhances interference-free communication amongst the multiple modulated sub-carriers and is accomplished by exploiting the properties of the symbol windowing function, as well as by choosing the precise sub-carrier frequencies. The sub-carriers are encoded using different digital modulation techniques such as BPSK, QPSK and QAM.

The primary reason for using OFDM is to increase the robustness against frequency selective fading (Anibal, 2000). Another reason for using OFDM is because it offers good spectral efficiency and efficient elimination of sub-channel and symbol interference using the Fast Fourier Transform (FFT) for modulation and demodulation, which does not require equalization (Djordjevic and Vasic, 2006). Hence, any digital communication system utilizing an OFDM modulation scheme will theoretically use available bandwidth more efficiently than many other modulation schemes. This is because of its ability to break the bandwidth up into smaller sub-channels which enables different sub-carrier modulation schemes to be used, depending on the quality of each section of the bandwidth. This makes OFDM efficient, flexible and adaptable to changing environments.

The establishment of OFDM-based systems as an elegant and popular method for overcoming the frequency selective fading (Ekström *et al*., 2006), aids its usage in different flavours of Broadband Cellular Wireless (BCW) systems (Laroia *et al*., 2004). According to Srikanth *et al*. (2006), the IEEE 802.16d and 802.16e standards, which are more popularly known by the industry forum name Worldwide interoperability for Microwave Access (WiMAX), were first considered for BCW and were the first standards to use the OFDM transmission technique. Likewise, the IEEE 802.11 a/g standards for Wireless Local Area Networks (WLANs) , which are more popularly known as Wi-Fi have used OFDM to achieve speeds of the order of 50 Mbps in an indoor multipath environment. Other systems that use OFDM include digital audio and video broadcasting systems, high-definition television, terrestrial broadcasting and ultra-wideband-based systems for short-range wireless.

2.10.4.2 Quadrature Amplitude Modulation

Due to its high spectral efficiency, Multilevel Quadrature Amplitude Modulation (M-QAM) is an attractive modulation technique for wireless communications (Tang *et al*., 1999). QAM is a combination of ASK and PSK. It is both an analog and a digital modulation scheme that can convey two analog message signals, or two digital bit streams by modulating the amplitudes of two carrier waves using the ASK digital modulation scheme or AM analog modulation scheme. The analog versions of QAM are typically used to allow multiple analog signals to be carried on a single carrier. Likewise, when QAM is used for digital transmission, radio communication applications are able to carry higher data rates than ordinary amplitude modulated schemes and phase modulated schemes.

In QAM, two carrier waves, $(\cos 2\pi f_c t)$ and $(\sin 2\pi f_c t)$, that are out of phase with each other by 90^0 are usually employed, and are thus called quadrature carriers or quadrature components. The modulated waves are algebraically summed, the results of which is a single signal to be transmitted, containing the in-phase (I) and quadrature (Q) information (Hannan *et al*., 2010).

An M-ary Quadrature Amplitude Modulation (M-QAM) signal is defined mathematically as:

$$\begin{aligned} s(t) &= I(t).\cos(2\pi f_c t) + Q(t).\sin(2\pi f_c t) \\ &= A_m^I.g(t).\cos(2\pi f_c t) + A_m^Q.g(t).\sin(2\pi f_c t) \end{aligned} \qquad m = 1,2,3,\cdots,M \tag{2.23}$$

where $I(t)$ and $Q(t)$ are the modulating signals, A_m^I and A_m^Q are the sets of the amplitude levels for the in-phase and quadrature phase respectively, and $g(t)$ is the real valued signal pulse, whose shape influences the spectrum of the transmitted signal.

Digital formats of QAM are often referred to as quantized QAM. In digital M-QAM, two or more bits are usually grouped together to form symbols and one of M possible signals is transmitted during each symbol period. Normally, the number of possible signals is $M = 2^n$, where n is an integer. Hence, possible M-QAMs are: 4-QAM, 8-QAM, 16-QAM, 32-QAM, 64-QAM, as soon on. The number of 4, 8, 16, 32 and 64 is corresponding to 2^2, 2^3, 2^4, 2^5 and 2^6 in which the superscript number 2, 3, 4, 5 or 6 is the bits per symbol respectively.

As with many digital modulation schemes, the constellation diagram of M-QAM provides a graphical representation of the complex envelope of each possible symbol state. Some popular constellation diagrams for M-QAM reported by Pappi *et al*., (2009) are the square QAM (SQAM), the triangular QAM (TQAM) or hexagonal packing, the rectangular-QAM (RQAM), and the circular-QAM (CQAM) while the cross-QAM (C-QAM) was reported in Vitthaladevuni *et al*., (2005).

Although a large variety of QAM constellations can be constructed, studies have shown that some specific constellations attracted special interest due to the low complexity demodulation methods required (Pappi *et al*., 2009). In addition, the authors observed that for a specific value of the SNR, the maximum transmission efficiency achieved by different constellation types varied. In Vitthaladevuni *et al*. (2005), it was established that RQAM is a typically used constellation when the number of bits in a symbol is even, as 4-, 16-, 64-, 256-QAMs, and unsuitable for M-QAM with odd number of bits per symbol.

The first even rectangular QAM usually encounter is 16-QAM. This is because analysis has revealed it that 4-QAM is a typical QPSK. In this study, 16-QAM and 64-QAM are used. Figure 2.11 shows the constellation diagram for 16-QAM with gray coded bit-assignment.

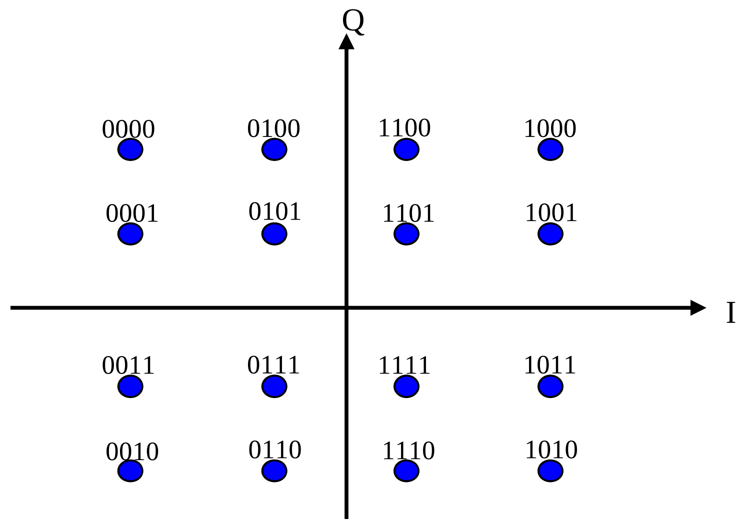


Figure 2.11: Constellation Diagram for Rectangular 16-QAM

The various analog and digital modulation techniques described above are simulated in this study using MATLAB® Software. Similarly, an automatic modulation classifier, using an ANN for both the analog and digital modulation schemes, are developed. The purpose is to use the classifiers in the CRE develop in this study. The simulation details are presented in next chapter. Meanwhile, this chapter further review AMC or AMR and ANN, as it applies in the next chapter.

2.10.5 Comparative Analyses of Digital Modulation Schemes

In this sub-section, brief overview analyses of some of the digital modulation schemes discussed under Sub-section 2.10.3 and Sub-section 2.10.4 and their derivatives were provided. The analyses establish the superiority at a glance of those digital modulation schemes by stating their respective merit(s) and demerit(s). Like the comparative analysis carried out on the analog modulation schemes in Sub-section 2.10.2, the comparative analyses in this sub-section was basis on the schemes spectral and power efficiencies as well as their respective cost and implementation complexity. The comparative result was presented in a tabular form in Table 2.3.

Table 2.3: Comparative Analyses of Some Digital Modulation Schemes

Type of Digital Modulation Scheme	Derived From	Merit	Demerit
2ASK	ASK	Low cost and Simple to implement	Inefficiency bandwidth scheme. It is noise prone. It can only operate in linear region
2FSK	FSK	Low cost and Simple to implement	Received design is complex
BPSK	PSK	Simple to implement. It is robust. It is used mostly for satellite communication. It has about 3 dB power advantage over 2ASK	Inefficient use of bandwidth
QPSK	PSK	It is bandwidth efficient and more spectrally efficient than 2PSK	It requires complex receiver design
QAM	ASK and AM	It is bandwidth efficient and high data rates	Because QAM involves AM, linearity of the transmitter's power amplifiers can cause the system error
OFDM	From multicarrier modulation scheme such as 16-QAM, QPSK, etc	It is robust to Inter-channel interference and inter-symbol interference. It is high spectral efficiency. It be efficiently implemented using FFT. Tuned sub-channel receiver filter is not required.	It is sensitive to Doppler shift. It has inefficient transmitter power consumption since linear power amplifier is required

2.11 Automatic Modulation Recognition

One of the major variables of the radio signals that need to be determined, whenever an unknown radio signal is being monitored, is the modulation scheme or format of the radio signal. The process of determining the modulation scheme of a radio signal without foreknowledge of the signal modulation characteristics is known as modulation recognition. Radio signal modulation recognition can be carried out in two ways, either in an automatic or non-automatic fashion. In a non-automatic fashion, the classification and identification of the modulation signal depends on an operator's interpretation of the measured parameters (Hsue and Soliman, 1990). The approach is unpopular because its success is subjected to the operator's conditions coupled with its slow rate in a hostile environment (Dominguez *et al.*, 1991). For a fast response, automatic modulation recognition techniques are employed (Guldemir and Sengur, 2007).

Automatic modulation recognition of both analog and digital radio communications signals are important signal processing fields of study in communications and its related areas. It is an intermediate step between signal interception and information recovery (Yaqin *et al*., 2003; Azzouz and Nandi, 1996a; Prakasam and Madheswaran, 2008), which automatically identifies the modulation type of the received signal for further demodulation and other tasks (Yaqin *et al.*, 2003) such as signal identification and interference management. It is one of the important characteristics used in signal monitoring and identification (Arulampalam *et al*., 1999). It is an extremely important process in communication intelligent applications for several reasons. It helps in preventing the application of the communication signal to an improper demodulator, as this act may damage the signal information content (Nandi and Azzouz, 1995). Since any damage of the communication signal information content considerably confuses the following deciphering process, which converts the demodulated message from its ciphered, or non-intelligible, form to the deciphered, or intelligible, one. Furthermore, knowing the correct modulation type helps in recognizing threat signal and jamming waveforms (Nandi and Azzouz, 1995).

Automatic modulation type identification generally plays an important role for various applications and purposes. For example, in a military domain, it can be employed for electronic surveillance, electronic warfare and threat analysis. In the civilian domain, its applications include signal confirmation, interference identification and spectrum management (Prakasam and Madheswaran, 2008; Arulampalam *et al*., 1999). Similarly, in communications applications, such as in the surveillance of the radio spectrum, there is a requirement for rapid and automatic identification of the modulation type of a received signal. A receiver continuously scans over the spectrum of interest and when it detects a transmission signal, the output of its IF amplifier is passed on to an identifier. The task of the identifier is to determine the transmission's modulation type, which may be any form of modulation schemes, such as DSB modulation, SSB modulation, FM, PM or FSK.

Numerous modulation recognition methods have been proposed. A significant contribution has been made by E.E. Azzouz and A.K. Nandi, who have proposed an Analog Modulation Recognition Algorithm (AMRA), Digital Modulation Recognition Algorithm (DMRA), and Analog and Digital Modulation Recognition Algorithm (ADMRA) based on the decision-theoretic approach (Azzouz and Nandi, 1997a; Azzouz and Nandi, 1996b) and an artificial neural networks approach (Azzouz and Nandi, 1997b). In another research project of this group in 1998, computer simulations of different types of band-limited analog and digitally modulated signals corrupted by band-limited Gaussian noise sequences were carried out to measure the performance of their algorithms (Nandi and Azzouz, 1998). Likewise, many other authors have made different contributions on the topic of AMR using different methods, such as decision theoretic, neural networks, statistical pattern recognition, wavelet transform and filtering (Prakasam and Madheswaran, 2009; Yaqin *et al*., 2003; Wong and Nandi, 2001; Kavalov, 2001; Zhang, 2000; Lopatka and Pedzisz, 2000; Arulampalam *et al*., 1999; Dubuc *et al*., 1999).

Generally, automatic modulation type identification methods fall into two main categories, decision theoretic (DT) and pattern recognition (PR). DT approaches use probabilistic and hypothesis testing arguments to formulate the recognition problem and to obtain the classification rule (Wei and Mendel, 2000; Panagotiou *et al*., 2000). The approach is based on the likelihood function (Yücek and Arslan, 2004; Zhao and Tao, 2004), where modulation classification is deemed as a multiple-hypothesis test. Once the appropriate likelihood functions are established, either Average Likelihood Ratio Test (ALRT), Generalized Likelihood Ratio Test (GLRT), or Hybrid Likelihood Ratio Test (HLRT) can be adopted as the potential solution.

The merits of DT classifiers developed using Maximum Likelihood (ML) are that they performed optimally. However, one of its demerits is high computational complexity (Zadeh *et al*., 2006). Another drawback of this approach is the fact that is not robust with respect to the model mismatch in the presence of phase or frequency offsets and residual channel effects (Yücek and Arslan, 2004; Zhao and Tao, 2004). Table 2.4 summaries some of the likelihood-based classifiers in literature.

Table 2.4: A Summary of Likelihood-Based Classifiers

Author(s)	Classifier(s) Type	Modulations[1] Used	Channel Used
Kim and Polydoros, (1988)	Quasi-ALRT	BPSK, QPSK	AWGN
Polydoros and Kim, (1990)	Quasi-ALRT	BPSK, QPSK	AWGN
Long *et al*., (1994)	Quasi-ALRT	16PSK, 16QAM, V29[2]	AWGN
Huang and Polydoros, (1995)	Quasi-ALRT	BPSK, QPSK, 8PSK, 16PSK	AWGN
Beidas and Weber, (1995; 1996; 1998)	ALRT and Quasi-ALRT	32FSK, 64FSK	AWGN
Chugg *et al*., (1995)	HLRT	BPSK, QPSK, OQPSK	AWGN
Sapiano and Martin, (1996)	ALRT	BPSK, QPSK, 8PSK	AWGN
Sills, (1999)	ALRT	BPSK, QPSK, 16QAM, V.29, 32QAM, 64QAM	AWGN
Wei and Mendel, (2000)	ALRT	16QAM, V29	AWGN
Panagiotou *et al*., (2000)	GLRT and HLRT	16PSK, 16QAM, V29	AWGN
Hong and Ho, (2002)	HLRT	BPSK, QPSK	AWGN
Hong and Ho, (2003)	ALRT	BPSK, QPSK	AWGN
Abdi *et al.*, (2004)	ALRT and Quasi-ALRT	16QAM, 32QAM, 64QAM	Flat Fading
Li *et al.*, (2005)	Quasi-ALRT	4QAM, 16QAM, 64QAM	AWGN

Source: Dobre et al. (2007)

[1]*These are the modulation schemes used in the original papers.*

[2] *V29 is a special QAM modulation with 16 points in the signal constellation.*

On the other hand, in the PR approach, the modulation classification module is divided into two subsystems, namely the feature extraction subsystem and the classifier subsystem (Zadeh *et al.*, 2006; Dobre *et al.*, 2007; Swami and Sadler, 2000; Mobasseri, 2000; Nandi and Azzouz, 1998). In the first subsystem of this approach, feature extraction keys are extracted from the radio signal. Some of the commonly adopted feature extraction keys are higher-order statistics (HOS), including moments, cumulants, and cyclic cumulants (CC) of the signal (Wu *et al.*, 2008; Zadeh *et al.*, 2006; Dobre *et al.*, 2003; Dobre *et al.*, 2004; Dobre *et al.*, 2005), fuzzy logic (Wei and Mendel, 1999; Lopatka and Pedzisz, 2000), a constellation shape recovery method (Mobasseri, 1999) and usage of information contained in an incoming signal (Nandi and Azzouz, 1995; Nandi and Azzouz, 1998; Azzouz and Nandi, 1996a; Azzouz and Nandi, 1997a; Azzouz and Nandi, 1996b; Guldemir and Sengur, 2007; Arulampalam *et al.*, 1999; Wong and Nandi 2001; Popoola and van Olst, 2011b).

The second subsystem of the PR approach is a pattern recognizer, which processes those feature keys and determines the modulation type of the received signal according to a pre-designed decision rule. Multi-Layer Perceptron Neural Network (MLPNN) is one of the classifiers that are used in modulation identification systems. It has been shown that this type of classifier outperforms other classifiers, such as the K-nearest neighborhood algorithm (Nandi and Azzouz, 1998). Table 2.5 summarizes most of the feature based automatic modulation classifiers in literature, emphasizing the features employed, modulation format classified and channel used.

Table 2.5: A Summary of Feature Based Classifiers

Author(s)	Features	Modulations[1] Used	Channel Used
Nandi and Azzouz, (1988)	Maximum power spectral density (PSD) of normalized centered amplitude, standard deviations of normalized centered amplitude, phase and frequency	AM, FM, DSB, SSB, BPSK, QPSK, 2ASK, 4ASK, 2FSK, 4FSK	AWGN
Arulampalam *et al.*, (1999)	Maximum PSD of normalized centered amplitude, standard deviations of normalized centered amplitude, phase and frequency, standard deviations of direct value of instantaneous amplitude, standard deviations of the normalized instantaneous frequency, evaluated over the non-weak segment of the intercepted signal and maximum PSD of the normalized instantaneous frequency of the intercepted signal	2ASK, 4ASK, MSK, 2FSK, 4FSK, 2PSK, 4PSK	AWGN
Dobre *et al.*, (2003)	Eighth-order cyclic cumulants of the received signal	BPSK, QPSK, 8PSK 4ASK, 8ASK, 16QAM, 64QAM, 256QAM	AWGN
Yu *et al.*, (2003)	Discrete Fourier Transform (DFT) of the received signal	2FSK, 4FSK, 8FSK, 16FSK, 32FSK	AWGN
Dobre *et al.*, (2004)	Eighth-, sixth-, and fourth-order cyclic cumulants of the received signal	4QAM,16QAM	AWGN, impulsive noise
Zadeh *et al.*, (2006)	Normalized eighth-order moments and cumulants of the received signal	4ASK, 8ASK, 2PSK, 4PSK, 8PSK, 16QAM, 32QAM, 64QAM, Star-8QAM[3], V29	AWGN
Guldemir and Sengur, (2007)	Maximum PSD of normalized centered amplitude, standard deviations of normalized centered amplitude, phase and frequency	AM, FM, DSB, SSB (LSB, USB), CW[4]	AWGN
Wu *et al.*, (2008)	Normalized fourth-order cumulants of the received signal	BPSK, QPSK	AWGN and Multipath Fading

Source: Dobre et al.(2007)

[1] *These are the modulation schemes used in the original papers.*
[3] *Star-8QAM is a star shaped M-QAM modulation where $M = 2^n$ (M = 4, 8, 16, etc, n is the number of bits per one symbol).*
[4] *If the signal has no phase information and no amplitude information, it is called a CW signal. In this case, the instantaneous phase is a linear function of time and the instantaneous amplitude is constant, meaning that the CW signal has no useful information; no amplitude and no phase information.*

In contrast to the DT approaches, the PR methods may be non-optimal, but simple to implement and can often achieve the nearly optimal performance, if carefully designed. Furthermore, the PR methods can be robust with respect to the aforementioned model mismatches. In addition, observation from Table 2.4 and Table 2.5 revealed that classifiers developed using feature based PR methods were capable of handling or classifying more modulation schemes when compared with classifiers developed using likelihood-based DT approaches. Also, the high computational complexity involved in likelihood-based DT approaches compared to the feature based PR classifiers does hinder these types of classifiers from handling more modulation schemes. These capabilities of feature-based PR classifiers over the likelihood-based DT approach were considered in this thesis. Thus, the PR approach was used in developing the automatic modulation classifiers for this research work. In this study, the maximum PSD of normalized centered amplitude, standard deviations of normalized centered amplitude, phase and frequency are used as the primary feature extraction keys for the three classifiers developed. In all the three classifiers, an artificial neural network was used for the development of the AMC. Details on the development of the three classifiers for this research work were presented in chapter 3.

2.12 Artificial Neural Networks

Artificial Neural Networks (ANNs) are information-processing systems that have certain performance characteristics in common with biological neural networks. They are computational modeling tools that have recently emerged and found extensive acceptance in many disciplines for modeling complex real-world problems (Liao and Wen, 2007; Basheer and Hajmeer, 2000). They are defined as structures consisting of densely interconnected adaptive simple processing elements called artificial neurons or nodes that are capable of performing massively parallel computations for data processing and knowledge representation (Hecht-Nielsen, 1990; Schalkoff, 1997). The main objective of developing ANN-based computing, like neurocomputing, is to develop mathematical algorithms that will enable ANNs to learn by mimicking information processing and knowledge acquisition in the human brain (Basheer and Hajmeer, 2000).

Though ANNs are drastic abstractions of biological neural network, the idea of ANNs is not to replicate the operation of the biological systems, but simply to make use of what is known about the functionality of the biological neural networks for solving complex problems. According to Basheer and Hajmeer (2000), the attractiveness of ANNs comes from the remarkable information processing characteristics of the biological neural networks, namely non-linearity, high parallelism, robustness, fault and failure tolerance, learning, ability to handle imprecise and fuzzy information and their capability to generalize (Jain *et al*., 1996).

Artificial models possessing these processing characteristics of the biological neural networks are desirable firstly because nonlinearity allows a better fit to the data; secondly because high parallelism implies fast processing and hardware failure tolerance; thirdly because learning and adaptivity allow the system to update or modify its internal structure in response to the changing environment, and lastly because generalization enables application of the model to unlearned data.

The main features of ANNs are that they have the ability to learn complex nonlinear input-output relationships, use sequential training procedures, and adapt themselves to the data. Based on these characteristics, an ANN has emerged as an important tool for classification, which is one of the most frequently encountered decision-making tasks of human activity. Usually, a classification problem occurs when an object needs to be assigned into a predefined group or class based on a number of observed attributes related to that object. Many problems in science, engineering, business and medicine can be treated as classification problems. Common examples include character recognition, speech recognition, quality control, modulation scheme recognition, medical diagnosis, fraud and bankruptcy prediction to mention a few.

Recent research activities in neural classification have established that ANNs or simply neural networks (NNs) are a promising alternative to various conventional classification methods (Zhang, 2000). Its effectiveness as classifier has been empirically tested. Many researchers (Packianather and Drake, 2005; Robert *et al*., 1997; Curram and Mingers, 1994; Huang and Lippmann, 1987) have carried out different performance comparisons between NNs and conventional classifiers. Similarly, several computer experimental evaluations of NNs for classification problems have been conducted under different conditions (Patwo *et al*., 1993; Subramanian *et al*., 1993) confirming the superiority of the NN classifier over other classifiers.

There are three main features that normally characterize an ANN:

(i) The pattern of connectivity among neurons, that is the ANN architecture or structure;

(ii) The method of determining connection strengths i.e. ANN learning or training algorithm; and

(iii) The activation functions of the network neurons.

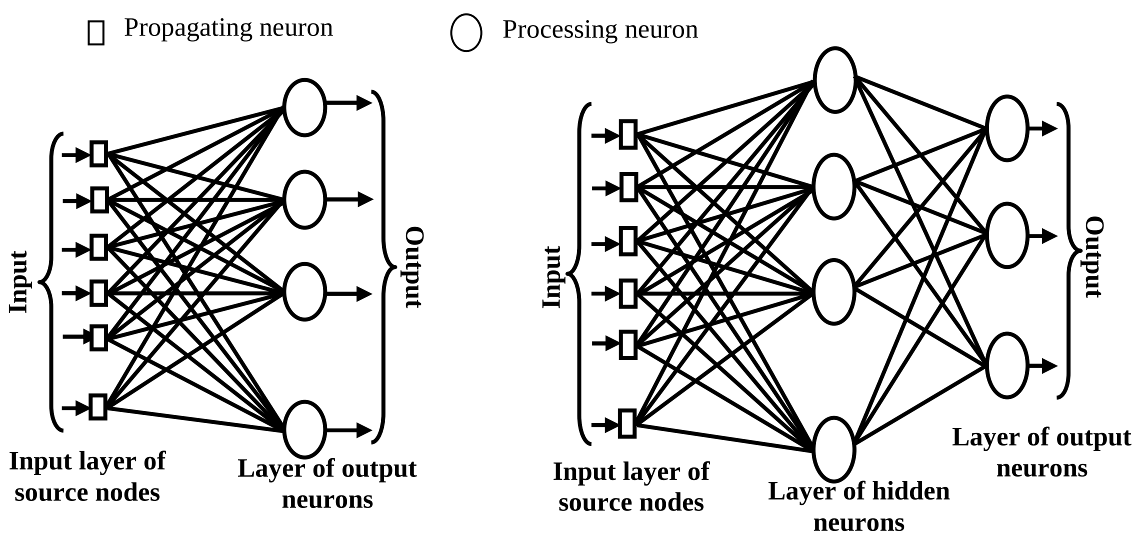
2.12.1 Artificial Neural Network Architecture

ANNs contain a sequence of layers. Each layer consists of set of neurons, also called Processing Elements (PEs). The arrangement of neurons or PEs into layers and the connection patterns within and between layers give rise to the neural network architecture. In neural network architecture, the first and the last layers are called input and output layers (Suryanarayana *et al*., 2008).

To cope with nonlinearly separable problems, additional layer(s) of neurons are usually placed in between the input layer and the output layer to form a Multi-Layer Perceptron (MLP) architecture (Basheer and Hajmeer, 2000). This intermediate layer(s) of neurons, are called hidden layer(s) and the nodes are called hidden nodes, because they do not interact with the external environment. The inclusion of intermediate or hidden layer(s) usually empowers the perceptron by extending its ability to solve nonlinear classification problems. The number of hidden layers is usually not known; hence its number of neurons only depends on the problem considered. Except for purely linear networks, the more neurons used in the hidden layer, the more powerful the network (Demuth and Beale, 2000). The number of both input and output neurons, on the other hand, are usually problem dependent (Aggarwal *et al*., 2005).

In terms of architectural structure, neural networks are classified into two major categories, namely Feed-Forward Neural Networks (FFNNs) and Recurrent Neural Networks (RNNs). In a FFNN, the connections between neurons are in a feed-forward manner. Similarly, the signal's flow is usually from the input layer to the output layer in a forward direction without feedback. The network is usually arranged in the form of layers. The arrangement is such that there is no connection between the neurons within the same layer and no feedback between layers.

A fully connected single layer and multilayer neural network, as shown in Figure 2.12 (a) and (b) respectively are examples of FFNNs. On the other hand, the fully interconnected multilayer neural network shown in Figure 2.13 is an example of RNN. The fundamental feature of RNN is that the network usually contains at least one feedback connection.



(a) Single Layer Network **(b) Multilayer Layer Network**

Figure 2.12: Fully-Connected Multiple Inputs Multiple Output Feed-Forward Neural Networks

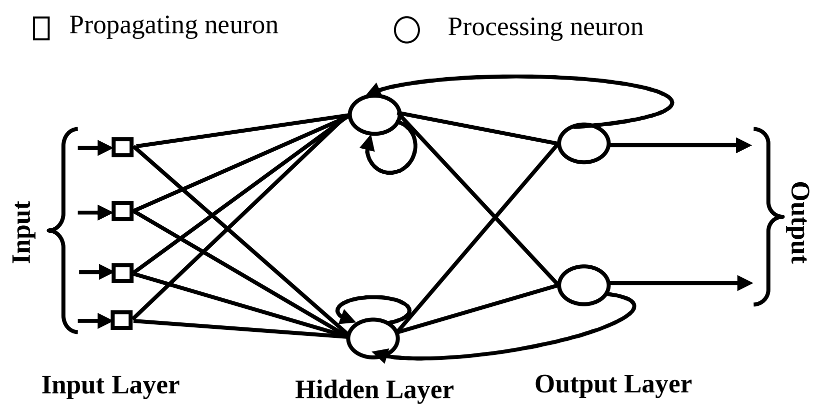


Figure 2.13: Fully-Connected Multiple Inputs Multiple Output Recurrent Neural Networks

2.12.2 Training or Learning Methods

In NNs, learning or training corresponds to the process by which the network's parameters, or weights, are adapted or adjusted through a mechanism of the presentation of an input stimulus. It is an algorithm for finding suitable weights, W, and/or other network parameters. NNs are usually trained by epoch. An epoch is a complete run when all training examples are presented to the network and processed using the learning algorithm only once.

Generally, when NNs are to be used, it is believed that the exact nature of the relationship between inputs and outputs are not known, otherwise the user would have modeled the system directly. Hence for NNs to model the relationship between the inputs and outputs, they need to learn the inputs and outputs relationship through training. There are three types of training used in NNs, with different types of networks using different types of training. These training types are supervised learning, unsupervised learning and reinforcement learning. Supervised learning is the most common and is the training method applied in this research work.

Supervised learning is widely used in problems which involve pattern recognition or classification, approximation, control modeling and identification, signal processing and optimization. Unsupervised learning schemes, on the other hand are mainly used for pattern recognition, clustering, vector quantization, signal coding and data analysis while reinforcement learning is usually used in control. More details about the three types of learning methods in a neural network are presented in following subsections.

2.12.2.1 Supervised Learning

This learning method embeds the concept of a supervisor or teacher, who has the prior-knowledge about the environment in which the network is operating. This prior-knowledge is represented in form of a set of input-output samples or patterns. These input-output samples or patterns are provided in form of input data and desired output or target (Torrecilla *et al.*, 2007). In order words, the desired output or target is the output expected to be received from the given input data.

The input data is propagated forward through the network until activation reaches the output neurons. The output from the network will be compared with the desired output. If the output from the network agrees with the desired output, there will be no need to change the network parameters. However, if the output from the network differs from the desired output then there will be a need to adjust the network parameters to ensure that the network gives the correct answer in the future when it is presented with the same or similar input data. This adjustment of the network parameters is carried out by adjusting a combination of the training pattern set and the corresponding errors between the desired output and the actual network response.

This network parameters adjustment scheme is what is known as supervised learning or learning with a teacher. It is being regarded as a closed-loop feedback system where the error is the feedback signal. It is being done so that the network can emulate the system. A diagrammatic representation of a supervised learning algorithm is shown in Figure 2.14. The environment in Figure 2.14 provides the input patterns to train the network.

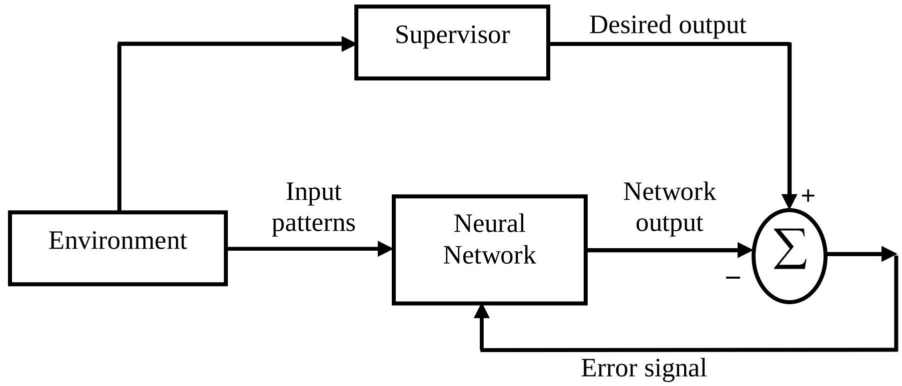


Figure 2.14: Diagrammatic Representation of Supervised Learning Algorithm

In order to control the learning process, a criterion is needed to decide the time for terminating the learning process. In supervised learning, an error measure, which indicates the difference between the network output and the output from the training sample, is normally used to control the learning process. This error measure is obtained by the Mean Squared Error (MSE), which is mathematically expressed as:

$$E_R = \frac{1}{N}\sum_{x=1}^{N} | y_x - \hat{y}_x |^2 \qquad (2.24)$$

where N is the number of the pattern pairs in the sample, y_x is the output part of the xth pattern pair and $\hat{y}_x$ is the network output corresponding to the pattern pair x. The error, E, is calculated afresh after each epoch, while the learning process terminates when E is sufficiently small (Du and Swamy, 2006).

According to Du and Swamy (2006), error E can be made to decrease toward zero by applying a gradient-descent procedure. The gradient-descent method converges to a local minimum in a neighborhood of the initial solution of the network parameters. The least mean square and back-propagation (BP), as reported by the authors, are the two early and most popular supervised learning algorithms. The two of them are derived using the gradient-descent procedure. In this research work, the BP learning algorithm was used in reducing the error.

2.12.2.2 Unsupervised Learning

Unlike supervised learning, the unsupervised or self-organized learning method does not involve a supervisor or target values to evaluate the network performance in relation to the input data set, as shown in Figure 2.15. The network is only provided with the input data to teach itself depending on some structures in the input data. These structures may be some form of redundancy in the input data or clusters in the input data. The learning method is particularly suitable for biological learning, in that it does not rely on a teacher.

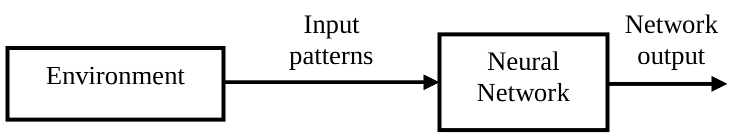


Figure 2.15: Diagrammatic Representation of an Unsupervised Learning Algorithm

Like the supervised learning, an unsupervised learning method needs a criterion to terminate the learning process. This is to prevent the learning process from continuing indefinitely. In this regard, Du and Swamy (2006) reported that, Hebbian learning, competitive learning and Kohonen's self-organization maps are the three mostly used unsupervised learning criteria. Generally unsupervised learning has been observed to be slow to settle into stable conditions.

2.12.2.3 Reinforcement Learning

This learning method is half-way between the supervised and unsupervised learning methods. It is distinguished from the other learning methods as it only relies on learning from direct interaction with the environment, but does not rely on explicit supervision or complete models of the environment as shown in Figure 2.16. In this learning method, the network is provided with the input data. The activation will then be propagated forward with additional information, such as a reinforcement signal, telling the network whether it has produced the desired output or not. If the network produces an output different from the desired output, some adjustment of the network weights will be done so that a desired output is obtained in the future presentation of that particular input. In this learning method, the network's output provides the environment with information about how the neural network is performing.

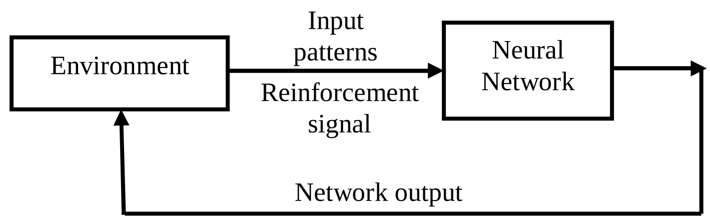


Figure 2. 16: Diagrammatic Representation of Reinforcement Algorithm

In the real sense, reinforcement learning is a special case of supervised learning (Barto *et al*., 1983). It is useful for learning control strategies only from a performance index without any teacher who instructs how to control a system at each moment. It is a learning procedure that rewards the NN for its good output result and punishes it for a bad output result. It is normally used in a situation where the correct output for an input pattern is not available and there is need for developing a certain output. It is a less powerful method when compare with supervised learning and sometimes requires a large amount of time. Reinforcement learning teaches the network structure by trial-and-error and is suitable for online learning (Barto *et al*., 1983; Kaelbling *et al*., 1996).

2.12.3 Transfer Function

An activation or transfer function is a function used to transform the activation level of a neuron into an output signal. It determines how the state of a neuron and its internal activation is going to be modified in order to produce the neuron output. They are monotonically non-decreasing and present non-linearity associated with saturation (De Castro and Timmis, 2002). The most common activation functions employed in artificial neural networks are hard limit, linear, logistic, and log-sigmoid transfer functions.

- The hard limit transfer function usually sets the output of the neuron to zero if the function argument is less than zero, or one if its argument is greater than or equal to zero.

- The linear transfer function usually set its output to its input.

- The log-sigmoid transfer function takes an input that has any value between plus and minus infinity and squashes the output into the range 0 to 1, according to the expression:

$$u = \frac{1}{1+e^{-1}} \tag{2.25}$$

- The log-sigmoid (logsig), tan-sigmoid (tansig) and linear (purelin) transfer functions are commonly used in multilayer networks that are trained using a BP algorithm because these transfer functions are differentiable and also monotonic increasing functions. Meaning that, the output of each function increases with increase in its input value (Demuth and Beale, 2000).

In BP networks, one or more layers of sigmoid neurons are usually used as the hidden layer, followed by an output layer of linear neurons. The multiple layers of sigmoid or non-linear transfer functions allow the network to learn non-linear and linear relationships between input and output vectors. On the other hand, the linear transfer function at the output layer allows the network to produce values outside the range -1 and +1. However, when it is desirable to constrain the outputs of a network to have values between 0 and +1, then a sigmoid or non-linear transfer function, such as logsig, can be used at the output layer. The mathematical definitions of commonly used activation functions are presented in Table 2.6.

Table 2.6: Activation Functions

Function	Definition	Range
Identity	x	$(-\inf, +\inf)$
Logistic	$\frac{1}{1-e^{-1}}$	$(0,+1)$
Hyperbolic	$\frac{e^{x}-e^{-x}}{e^{x}+e^{-x}}$	$(-1,+1)$
Exponential	e^{-x}	$(0,+\inf)$
Softmax	$\frac{e^{x}}{\sum_{i} e^{x_i}}$	$(0,+1)$
Unit sum	$\frac{x}{\sum_{i} x_i}$	$(0,+1)$
Square root	$\sqrt{x}$	$(0,+\inf)$
Sine	$\sin(x)$	$(0,+1)$
Ramp	$\begin{Bmatrix} -1: & x \leq -1 \\ x: & -1 < x < +1 \\ +1: & x \geq +1 \end{Bmatrix}$	$(-1,+1)$
Step	$\begin{Bmatrix} 0: & x < 0 \\ +1: & x \geq 0 \end{Bmatrix}$	$(0,+1)$

2.13 Summary

The focus of this chapter was to present basic background to this thesis, as well as to enlighten all classes of readers on some of the developmental history in radio technology and terms that will be later employed in this thesis. To fulfill these objectives, the chapter has provided an overview of radio evolution, which led to both digital radio realizations and software radio capabilities. The inclusion of software in radio systems has made possible software capable radio that processes radio signals digitally. In the pursuit of flexibility, software programmable radio, which eventually gave birth to the SDR, is currently a standard in the military domain and gradually gaining recognition in the commercial world especially in an academic environment, as reviewed in Section 2.1.

In Sections 2.2 and 2.3, a detailed background on SDR and GNU Radio in the development of CR was reviewed. Section 2.4 presented various AIT associated with CR, while the intelligence systems behind CR or CN are reviewed in section 2.5. Sections 2.6 and 2.7 presented full reviews of CR applications. The sections also provided reviews on the demerits of the current radio spectrum management policy and the suitability of cognitive radio technology as a novel technology in solving spectrum management problems. The DSA application, based on cognitive radio technology to enhance radio spectrum efficiency, was fully reviewed.

Section 2.8 and Section 2.9 of this chapter focused on the analyses of various sensing and detection techniques in the surveyed literature respectively. The review shows that none of the available sensing and detection methods is capable of sensing and detecting all forms of radio signals in the cognitive radio environment. An attempt to address this challenge motivated this research work, which proposes an alternative sensing and detection technique using AMC. The proposed sensing and detection method using AMC was envisioned because all users of the radio spectrum make use of one form of modulation scheme or another. Hence, the ability to accurately detect the modulation schemes of radio signals is sufficient to confirm the presence of radio signal in a cognitive radio environment.

Section 2.10 is therefore devoted to the in-depth reviews of both fundamental analog and digital modulation schemes. In Section 2.11, a comprehensive review of AMC for various fundamental analog and digital modulation schemes used in wireless communications systems and applications was carried out. Section 2.12, concludes the study literature review work with a comprehensive review on ANNs.

Finally, having observed the demerits of the various available spectrum sensing detection methods in the surveyed literature, this research work is embarked upon finding a novel technique for sensing and detecting all forms of radio signals in a cognitive radio environment. The execution of the research work is presented in two phases. The first phase involves the development of the AMR used using MATLAB®. The second phase involves the experimental development of the CRE using an USRP2 coupled with a combined analog and digital AMR classifier developed in the first stage of the study. The diagrammatic representation of the radio environment model for the study is shown in Figure 2.17.

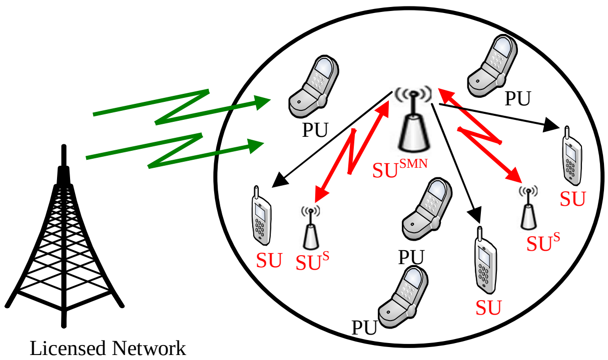


Figure 2.17: Cognitive Radio Environment Model

In order to ensure reliable and effective spectrum sensing, each SU^S (secondary user sensor), in Figure 2.17 will individually perform spectrum sensing and relay its decision to the master node secondary user sensor (SU^{SMN}). The SU^{SMN} will finally broadcast the condition of the spectrum to all the SUs connected to it for dynamic spectrum access. The other function of the SU^{SMN} is to determine the SU terminal or node to access the free spectrum per time, while the SU^S are continuing spectrum sensing. The SU^{SMN} also ensures even distribution of the spectral resources amongst the SUs.

The condition for DSA of licensed spectrum in this research work is based on non-detection of any form of modulation scheme on any channel considered. This condition is fulfilled by the in-built capability of the AMR incorporated into the developed CRE. Therefore, the focus of the next chapter will be on development of automatic modulation classifiers for the research work. The next chapter discusses details on how the feature extraction keys used in developing the AMR classifiers for the research are obtained using simulation. The chapter also provides in-depth information on how the three AMR classifiers were developed using ANNs, as well as their individual performance.

CHAPTER 3

3.0 DEVELOPMENT OF AUTOMATIC MODULATION CLASSIFIERS

This chapter presents details on the development of the three automatic modulation classifiers developed in this study. The developed classifiers are: analog automatic modulation recognition (AAMR), digital automatic modulation recognition (DAMR) and combined analog and digital automatic modulation recognition (ADAMR). The AAMR was developed to discriminate between four of the best-known analog modulation schemes, namely AM, DSB modulation, SSB modulation FM. The developed DAMR was developed to discriminate between eight of the best-known digital modulation schemes, which are:

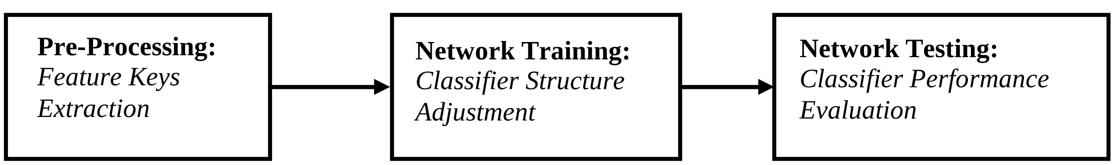
- two symbol amplitude shift keying (2ASK);
- four symbol amplitude shift keying (4ASK);
- two symbol frequency shift keying (2FSK);
- two symbol phase shift keying (BPSK);
- four symbol phase shift keying (QPSK);
- orthogonal frequency division multiplexing (OFDM);
- sixteen symbol quadrature amplitude modulation (16-QAM); and
- sixty-four symbol quadrature amplitude modulation (64-QAM).

The combined ADAMR was developed to discriminate between twelve, four analog and eight digital modulation schemes considered, as well as un-modulated noise. The classifiers are feature based modulation recognition algorithms using statistical features. The classifiers are developed using MATLAB. They are implemented in a hierarchical approach to classify radio signals using the smallest amount of required data, while simultaneously maximizing the reliability of the classifiers. The twelve simulated modulation schemes were realized using MATLAB codes. In addition to the basic MATLAB® software, the Netlab Algorithm for pattern recognition was used in developing the three classifiers.

This chapter's focus, however, is not to develop a new feature extraction key algorithm but simply to develop AMC classifiers that would be employed in developing the spectrum sensing engine for the thesis. Hence, in developing the three developed classifiers for the thesis, earlier existing feature extraction keys algorithms were employed. However, the employed feature extraction keys algorithms were not from a single study but from various studies based on the effectiveness of those feature extraction keys.

3.1 Analog Classifier Development

The development of the three AMR classifiers for this research work involved three different stages as shown in Figure 3.1. For the AAMR classifier, the four analog modulation schemes employed were first simulated using MATLAB codes in the first stage. In addition, in this first stage, the three feature keys that were used as input data sets to the classifier to discriminate between the four analog modulation schemes were extracted using MATLAB codes. The second step involved the development of the classifier, while the third step was on the performance evaluation of the developed classifier. Details on each of the three stages are presented in the following subsections.



Source: Azzouz and Nandi (1996a)

Figure 3.1: Functional Blocks for AMR Development

3.1.1 Pre-Processing Stage

This stage deals with the extraction of the feature keys used in discriminating between the four analog modulation schemes considered. In an automatic modulation identification study, finding the proper feature extraction keys is very important (Zadeh *et al.*, 2006). In the development of the AAMR for this research work, three feature keys were used to discriminate between the four analog modulation schemes of interest. The three key extraction features were derived from the instantaneous amplitude $a(t)$ and phase $\phi(t)$ of the simulated signals.

The first feature extraction key used is $\gamma_{\max}$, which represents the maximum value of the PSD of the normalized instantaneous amplitude of the signal, or, simply put, as the squared Fourier transform of the normalized signal amplitude. It is defined as (Popoola and van Olst, 2011b):

$$\gamma_{\max} = \max \frac{\left|DFT\left(a_{cn}(i)\right)\right|^2}{N} \tag{3.1}$$

where N is the number of samples per segment and $a_{cn}(i)$ is the value of the normalized-centered instantaneous amplitude of the signal at time instants $t = {}^{i}\!/\!_{f_s}$ $(i = 1,2,\cdots,N)$, f_s is the sampling frequency (Hz) and $a_{cn}(i)$ is defined as:

$$a_{cn}(i) = a_n(i) - 1 \tag{3.2}$$

and;

$$a_n(i) = \frac{a(i)}{m_a} \tag{3.3}$$

where m_a is the average value of the instantaneous amplitude evaluated over one segment. It is defined as:

$$m_a = \frac{1}{N}\sum_{i=1}^{N} a(i) \tag{3.4}$$

The feature ($\gamma_{\max}$) was used to measure the envelope variation of the modulated signal and aids in the reliable classification of constant envelope signals from non-constant envelope signals.

The second feature extraction key used is, σ_{dp}, which is the standard deviation of the direct instantaneous phase of the of the simulated signal. It extracts information from the instantaneous phase of the simulated signal. σ_{dp} is defined as (Popoola and van Olst, 2011b):

$$\sigma_{dp} = \sqrt{\frac{1}{C}\left(\sum_{a_n(i)>a_t}\phi_{NL}^2(i)\right) - \left(\frac{1}{C}\sum_{a_n(i)>a_t}\phi_{NL}(i)\right)^2} \tag{3.5}$$

where $\phi_{NL}(i)$ is the value of the non-linear component of the instantaneous phase at time instants t, C is the number of the samples in $\phi_{NL}(i)$, and a_t is the threshold.

The third feature extraction key used is for measuring the spectrum symmetry around the carrier frequency. This feature extraction key is based on the spectral powers for the lower and upper sidebands of the simulated signal. The key is defined as (Popoola and van Olst, 2011b):

$$P = \frac{P_L - P_U}{P_L + P_U} \tag{3.6}$$

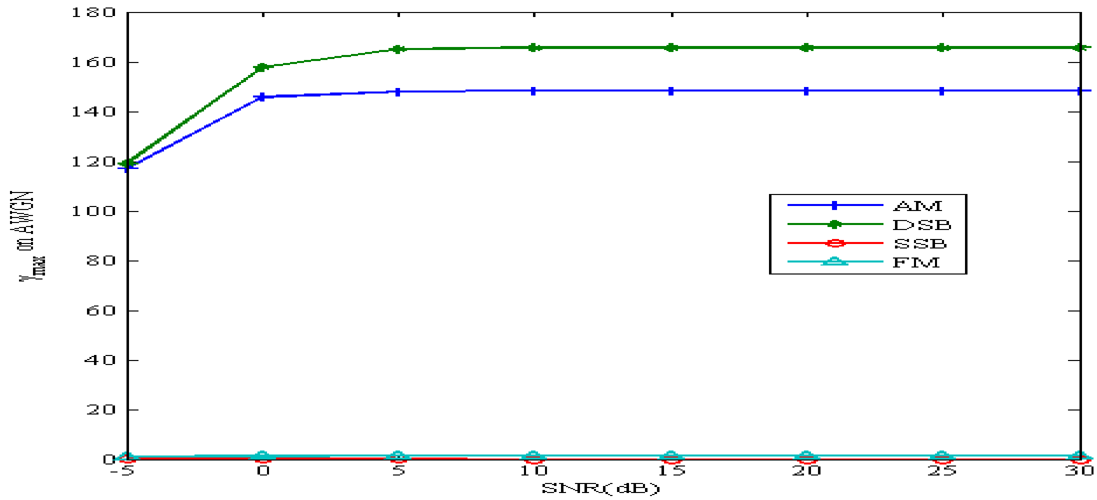
where

$$P_L = \sum_{i=1}^{f_{cn}} \left|X_c(i)\right|^2 \quad \text{and} \quad P_U = \sum_{i=1}^{f_{cn}} \left|X_c(i + f_{cn} + 1)\right|^2 \tag{3.7}$$

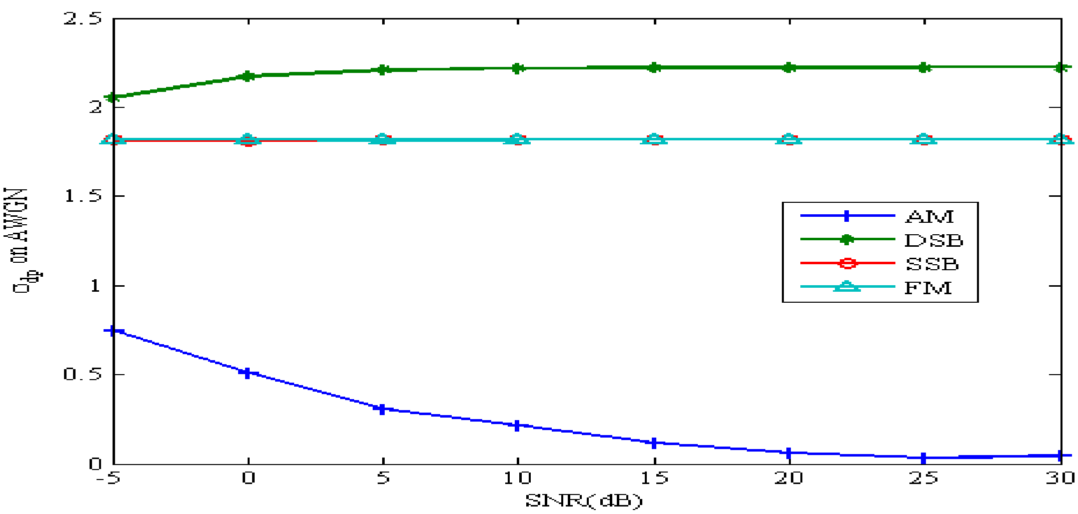
where $X_C(i)$ is the Fourier transform of the intercepted signal, $(f_{cn} + 1)$ is the sample number corresponding to the carrier frequency f_c and f_{cn} is defined as

$$f_{cn} = \frac{f_c N}{f_s} - 1 \tag{3.8}$$

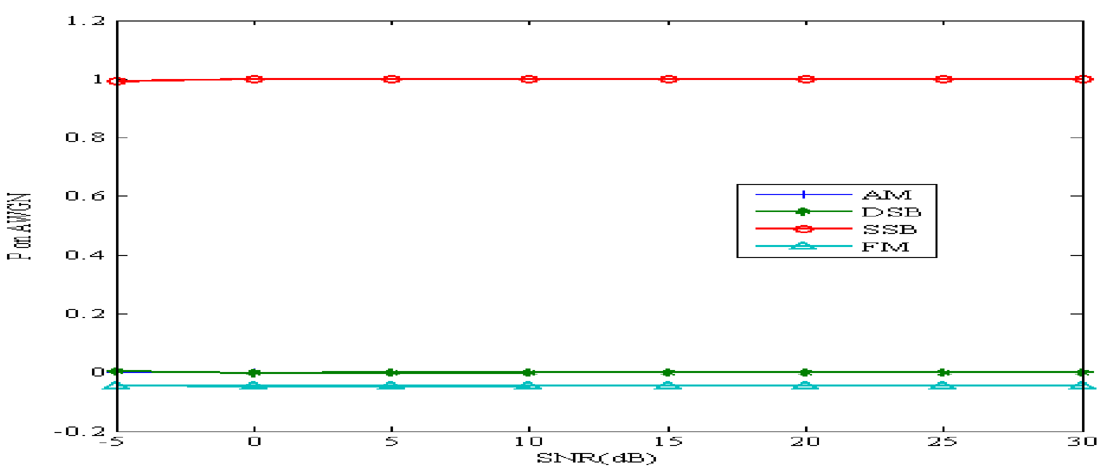
Based on equations (3.1) – (3.8), the graphical model of the three feature extraction keys obtained for the simulated analog modulated signals, on AWGN channel, are shown in Figure 3.2(a) – (c).



(a)



(b)



(c)

Figure 3.2: Graphical Illustration of $\gamma_{\max}$, σ_{dp} and P for Analog Modulated Signals

The choice of $\gamma_{\max}$, σ_{dp} and P as feature keys for the development of the AAMR classifier for this research work is based on the capability of these extracted feature keys to discriminate between the four analog modulation schemes considered. Firstly, σ_{dp} was chosen because it can discriminate between signals that have direct phase information and signal that has no direct phase information. It is, therefore, used to discriminate between AM as a subset and (DSB, SSB and FM) as the second subset. If $t(\sigma_{dp})$ represents the threshold value, σ_{dp} value for AM that has no direct phase information is therefore expected to be less than threshold value $(\sigma_{dp} < t(\sigma_{dp}))$. On the other hand, for the other types of signals (DSB, SSB and FM) that have direct phase information by nature, Azzouz and Nandi (1996a), they have their (σ_{dp}) values greater or equal to ($\sigma_{dp} \geq t(\sigma_{dp})$) . The σ_{dp} values for the four modulation schemes obtained from the simulation result are presented in Figure 3.2(b).

Secondly, P was chosen because it can discriminate between signals that have unity sidebands spectral power and those whose sideband spectral power is less than one. As shown in Figure 3.2(c), the choice of the ratio P is based on its capability to discriminate between (DSB and FM) with their sidebands spectral power less than one as one subset, and SSB as another subset, whose sideband spectral power equals one. The accuracy of the simulation result presented in Figure 3.2 (c) is confirmation of its conformity with the earlier result obtained in Guldermir and Sengur, (2007).

Thirdly, $\gamma_{\max}$ was chosen because of its capability to discriminate between signals that have amplitude information and signals that do not have amplitude information. Hence, it was used to discriminate between DSB with amplitude information as a subset and FM without amplitude information as a second subset. Since $t(\gamma_{\max})$ represents the threshold value, the $\gamma_{\max}$ value for a FM signal without amplitude information is lesser than the threshold value $(\gamma_{\max} < t(\gamma_{\max}))$, as shown in Figure 3.2(a). On the other hand, DSB which possesses amplitude information, has a $\gamma_{\max}$ value greater or equal to the threshold value,

$(\gamma_{\max} \geq t(\gamma_{\max}))$. Hence, $\gamma_{\max}$ was used to discriminate between DSB as one subset and FM as another subset.

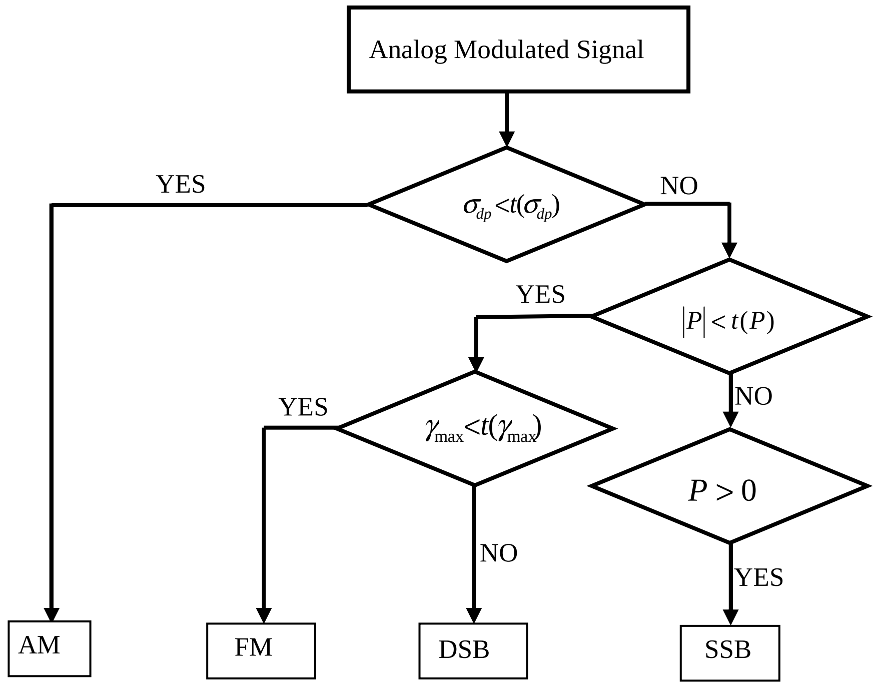


Figure 3.3: Flowchart for the Developed AAMR

Based on these criteria, the algorithm used in this research work to distinguish between the four analog modulated signals considered is shown in Figure 3.3 in form of a flowchart. The optimum feature keys thresholds, $t(\gamma_{\max})$, $t(\sigma_{dp})$ and $t(P)$, in Figure 3.3 are automatically and adaptively chosen at each neuron of the ANN (Azzouz and Nandi, 1996a). This is one of the advantages of the PR approach employed in this research, as opposed to the DT approach, where a suitable threshold for each feature key has to be selected.

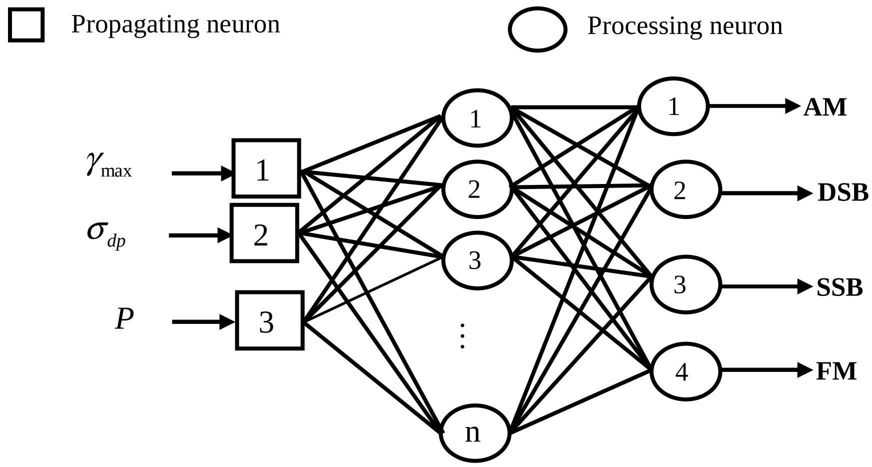


Figure 3.4: The AAMR Architecture

3.1.2 Network Training Stage

This stage involves the actual development and training of the AAMR classifier. The AAMR classifier was developed using an ANN. The ANN architecture that was used for this classification problem is a MLP, which is referred to as a feed-forward backpropagation network, while the training method used is the supervised learning method, discussed in Section 2.12.2. The architecture of the developed classifier is shown in Figure 3.4 having the statistical feature extracted keys discussed above as the input data sets. The MLP consists of one input layer, one hidden or intermediate layer of computational nodes or neurons and one output layer of computational neurons. All the neurons are fully connected as shown in Figure 3.4.

Neurons at the input layer do not perform computations, but only distribute the input features to the computing neurons in the hidden layer. The neurons in the hidden layer, on the other hand, perform computations on the input from the input layer and pass their results to the neurons in the output layer. Three neurons are used at the input layer corresponding to the number of input features, and seven neurons are used at the hidden layer. The network has four neurons at the output layer corresponding to the number of targets. The specifications for the developed AAMR classifier for this research work are shown in Table 3.1.

Table 3.1: Specifications for the Developed AAMR

Item	Parameters	Value
1.	Type of neural network architecture	Feed-forward
2.	No. of neurons in input layer	3
3.	No. of neurons in hidden layer	7
4.	No. of neurons in output layer	4
5.	Coefficient of weight-decay	0.01
6.	Activation function in hidden layer	tanh
7.	Activation function in output layer	logistic
8.	Maximum number of epochs	100
9.	Performance function	MSE
10.	Learning algorithm	SCG

During the training or learning process, input vectors and corresponding target vectors are used to train the network until it can classify the modulation schemes in an appropriate way. Whenever the results of the output neurons differ from the expected or target value, errors are propagated in a backward manner from the output layer to the hidden layer. This backpropagation algorithm (BPA) involves two paths, namely the forward and the backward path.

The forward path involves creating a feed-forward network by initializing weight and training the network. During this path, the initialized weights are fixed when the inputs are propagated through the network layer by layer, as shown in Figure 3.4. The phase ends with the error signal (e_i) computation using the relationship:

$$e_i = t_i - y_i \tag{3.9}$$

where t_i is the target or desired response of, i th input and y_i is the actual output produced by the network in response to the i th input.

The backward path involves a network update by modifying the connection weights to reduce the total error in the network output. The error signal (e_i) generated during the forward path is propagated in a backward direction through the network of Figure 3.4. The backward error signal propagation causes an adjustment in network weights, so as to minimize the error signal in a statistical sense using MSE (E_R):

$$E_R = \frac{1}{N_{ip}} \sum_{i=0}^{N} (t_i - y_i)^2 \tag{3.10}$$

where N_{ip} is the total number of input.

A total of 2000 data elements, with three inputs and four target outputs, were used in developing the AAMR classifier for this research. The procedures followed to train the developed AAMR are highlighted, as follows:

(1) Generated data, consists of input vectors and target vectors, were imported into a MATLAB environment from an excel spreadsheet.

(2) The loaded data were normalized and randomly sorted.

(3) The loaded data were partitioned into training, validation and testing data sets. 50% of the generated total data were used for the network training. The training data set was used to update the weights of the network. The training was done until the MSE, which was used as the performance function, was minimal. 25% of the total data were used to validate that the network was able to generalize and stop training before the network was over fitting. The last 25% of the total data were used as a completely independent test data to test the network generalization; and

(4) The ANN classifier was created. A feed-forward network with non-linearity activation functions of tan-sigmoid (tanh) and logistic (log-sigmoid) were used in the hidden and output layers respectively in order to introduce non-linearity into

the network because without non-linearity, the network will not be more powerful than plain perceptrons. The MLP was trained using the Scaled Conjugate Gradient (SCG), which has been shown to handle large-scale problems effectively (Moller, 1993). As reported in Mohamad, *et al.,* (2010), SCG utilizes second order information from the neural network, but has modest memory requirements with high accuracy and speed due to inexpensive calculation of the gradient information. These findings about SCG were confirmed in Section 3.3.3, where SCG performance is compared with another training algorithm, Conjugate Gradient (CONJGRAD). The CONJGRAD training algorithm was chosen because it is also known to be a fast training algorithm with numerical efficiency and very low memory requirement (Shanthi *et al.,* 2009).

3.1.3 Network Testing Stage

After the development and training of the network or classifier, its performance was evaluated by using 25% of the total generated data as test data. The performance evaluation carried out was investigated on different SNR values of -5, 0, 5, 10, 15 and 20 dB. Table 3.2 lists the success recognition rate for all the SNR values considered when the developed AAMR was run for 100 cycles. The result of the performance evaluation of the developed AAMR shows that the classifier can correctly and accurately recognize the four analog modulation schemes considered, with an average success rate above 99.80%.

Table 3.2: Developed AAMR Success Recognition Rate

Modulation scheme	Percentage of success recognition rate at different SNR value					
	- 5 dB	0 dB	5 dB	10 dB	15 dB	20 dB
AM	99.84	99.89	99.93	99.97	99.98	99.99
DSB	99.87	99.92	99.95	99.97	99.99	99.99
SSB	99.93	99.96	99.97	99.98	99.99	99.98
FM	99.90	99.95	99.97	99.97	99.98	99.99
Overall success rate (%)	**99.89**	**99.93**	**99.96**	**99.97**	**99.99**	**99.99**
Operational time taken (milliseconds)	**1.14**	**1.10**	**1.11**	**1.11**	**1.10**	**1.11**
Average operational time = 1.11 milliseconds						

3.2 Digital Classifier Development

Like the AAMR classifier discussed in section 3.1, the development of the DAMR for this research work follows the same procedures. The message signal was first modulated onto the baseband signal using MATLAB code. Eight of the best known digital modulation schemes were classified: 2ASK, 4ASK, 2FSK, BPSK, QPSK, OFDM, 16-QAM and 64-QAM. The three stages involve in developing the DAMR for this research work are discussed in detail in the following subsections.

3.2.1 Pre-Processing Stage

Feature keys extraction was carrier out, as was done during the development of the AAMR, described in Section 3.1.1. The feature keys extraction was carried out in order to obtain input feature keys for the DAMR classifier. Feature keys that compute a small number of salient features from the raw modulated signals were extracted. The choice of the feature keys is a trade-off between minimizing the number of features to reduce the ANN input size, as well as the computational complexity and including all necessary features for the reliable recognition of the digital modulation schemes. Some previous studies in Arulampalam *et al*., (1999), Azzouz and Nandi, (1996a) have explored this trade-off.

A set of seven feature keys are used in developing the digital classifier for this research work. As for the analog classifier, the seven feature extracted keys are extracted from the instantaneous amplitude, $a(t)$, and the instantaneous phase $\phi(t)$ of the simulated signal. Two out of the seven feature extraction keys, $\gamma_{\max}$ and σ_{dp}, had already been described in section 3.1.1. Their mathematical expressions are given by equations (3.1) and (3.5). Equations (3.1), (3.5) and (3.11) – (3.15) are used to describe and define the seven feature extracted keys used for the development of the DAMR. These feature extracted keys have earlier been employed in Azzouz and Nandi, (1996a), An *et al*. (2010), Dobre *et al*. (2005) and Huang *et al*. (2008), but none of these authors combined the keys as is done in this research work. The sources of each of these feature extracted keys employed are presented in tabular form in Table 3.3.

Table 3.3: DAMR Feature Extraction Keys Sources

Previous Study	Adapted Feature Extracted Key
An et al., (2010)	v_{20}
Dobre et al., (2005)	β
Huang *et al*. (2008)	X
Azzouz and Nandi, (1996a)	$\gamma_{\max}, \sigma_{ap}, \sigma_{dp}$ *and* σ_{aa}

The mathematical expressions and function descriptions of the seven keys used are provided, as follows:

The first feature extraction key employed for the development of the DAMR classifier is v_{20} , which is the combined or mixed order moments. Based on the Joint Power Estimation and Modulation Classification (JPEMC) algorithm, v_{20} is defined mathematically in An *et al*. (2010) as:

$$v_{20} = \frac{M_{4,2}(y)}{M_{2,1}^{2}(y)} = \frac{E\left(\left|y(n)\right|^{4}\right)}{E\left(\left|y(n)\right|^{2}\right)} = \frac{m_{20}\left(S/N\right)^{2} + 4\left(S/N\right) + 2}{\left(S/N\right)^{2} + 2\left(S/N\right) + 1} \tag{3.11}$$

where $m_{20} = \dfrac{M_{4,2}(u)}{M_{2,1}^{2}(u)} = 2k_{20}$ and $k_{20} = \dfrac{M_{4,2}(s)}{M_{2,1}^{2}(s)} = 2k_{20}$ (3.12)

The theoretical values of k_{20} for 16-QAM, 64-QAM and OFDM according to Wang and Ge (2005) are 1.312, 1.378 and 2.0 respectively. This extracted feature was used to discriminate between OFDM, where information is carried in more than one channel and other modulation schemes, where the information is carried in only one channel. Hence, the feature key, v_{20}, was used to distinguish between OFDM as a subset and the rest of the modulation schemes considered as another subset.

The second feature extraction key employed for the development of the DAMR is signal power key denoted as β. This key was used to discriminate between a signal with complex and real signals components. Mathematically, it is defined by Dobre *et al*. (2005) as:

$$\beta = \frac{\int_{-\infty}^{\infty} r_Q^2(t)dt}{\int_{-\infty}^{\infty} r_I^2(t)dt} \tag{3.13}$$

where $r_Q(t)$ and $r_I(t)$ are the quadrature components, while indexes I and Q stand for in-phase and quadrature component respectively. This extracted key was used to discriminate between 16-QAM and 64-QAM as a subset and the rest of the modulation schemes as another subset. Although, by nature, QPSK also has in-phase and quadrature components, but because its β value is lower that the threshold value, $t(\beta)$, it therefore falls among the rest of the modulation schemes.

The third feature extraction key used is the mean value of the amplitude designated as X. It is defined mathematically by Huang *et al*. (2008) as:

$$X = \frac{1}{N}\sum_{n=1}^{N} A_n \tag{3.14}$$

where A_n is the instantaneous amplitude. This key was used to discriminate between 16-QAM as a subset and 64-QAM as the other subset.

The fourth feature extraction key employed for the development of the DAMR for this research work is $\gamma_{\max}$, which is already described Section 3.1.1 for AAMR and defined by the equation (3.1). It is used to distinguish between signals that have amplitude information as a subset and those without amplitude information as another subset. In this research work, $\gamma_{\max}$ was used to distinguish 2FSK without amplitude information as a subset from 2ASK, 4ASK, BPSK and QPSK with amplitude information as the second subset. Since 2FSK has no amplitude information, its $\gamma_{\max}$ value is less than the threshold value, $t(\gamma_{\max})$, while other signals with amplitude information have $\gamma_{\max}$ values greater than the threshold value, $t(\gamma_{\max})$. The BPSK and QPSK have amplitude information because the band limitation imposes amplitude information on them at the transitions between successive symbols (Azzouz and Nandi, 1996a).

The fifth feature key used in developing of the DAMR is σ_{ap}, which is the standard deviation of the absolute value of the non-linear component of the instantaneous phase. It is defined as:

$$\sigma_{ap} = \sqrt{\frac{1}{C}\left(\sum_{a_n(i)>a_t}\phi_{NL}^2(i)\right) - \left(\frac{1}{C}\sum_{a_n(i)>a_t}\left|\phi_{NL}(i)\right|\right)^2} \tag{3.15}$$

where $\phi_{NL}(i)$ is the value of the non-linear component of the instantaneous phase at time instants $t = {}^{i}/_{f_s}$, C is the number of the samples in $\phi_{NL}(i)$, and a_t is the threshold.

This fifth key was used to distinguish between signals that have no absolute phase information and those that have absolute phase information. It is thus used to distinguish between 2ASK, 4ASK and BPSK as a subset and QPSK as the second subset. By their nature, 2ASK and 4ASK have no absolute phase information, while, according to (Azzouz and Nandi, 1996a) BPSK also has no absolute phase information. Hence, their σ_{ap} values are less than $t(\sigma_{ap})$, which is the threshold value. On the other hand, QPSK has absolute information by nature. This makes its σ_{ap} value greater than $t(\sigma_{ap})$. So, σ_{ap} was used to distinguish between 2ASK, 4ASK and BPSK as a subset and QPSK as the second subset.

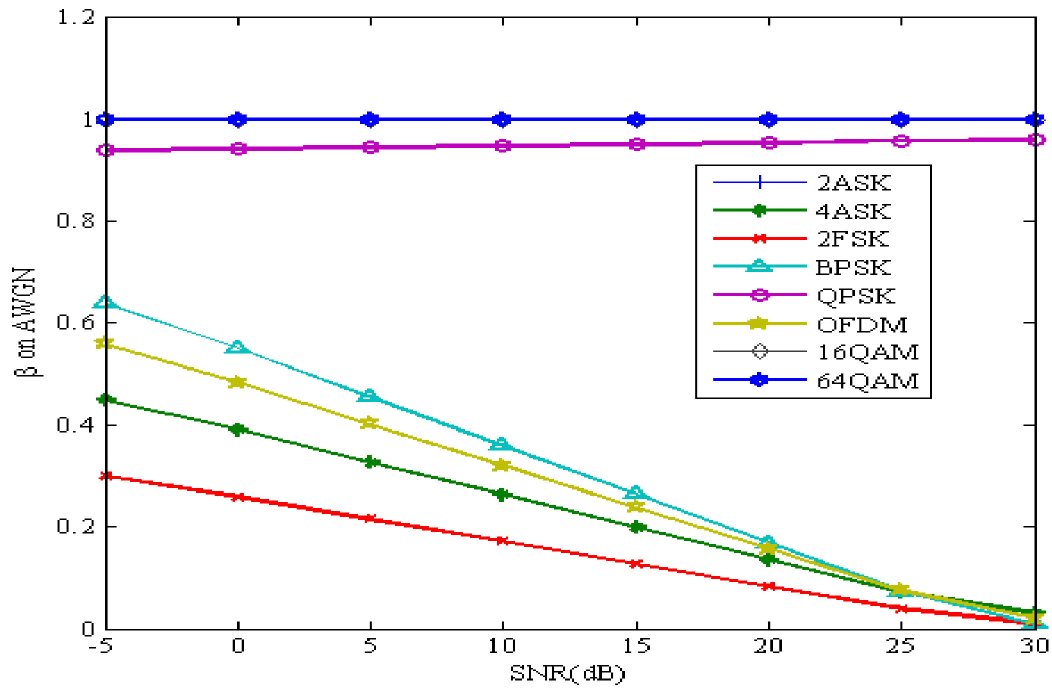
The sixth feature key used is σ_{dp}, which is also used in developing AAMR in Section 3.1.1 and it is defined by the equation (3.5). It is used to distinguish between signals that have direct phase information and those without direct phase information. 2ASK and 4ASK have no direct phase information, while BPSK on the other hand has direct phase information. Hence, while σ_{dp} values for both 2ASK and 4ASK are less than $t(\sigma_{dp})$, which is the threshold value, the σ_{dp} value for BPSK in contrast is greater than or equal to the threshold value. So, σ_{dp} was used to distinguish between 2ASK and 4ASK as a subset and BPSK as the second subset.

The seventh feature extraction key used in developing the DAMR is σ_{aa}. It is the standard deviation of the absolute value of the normalized instantaneous amplitude of the simulated signal. It is defined as:

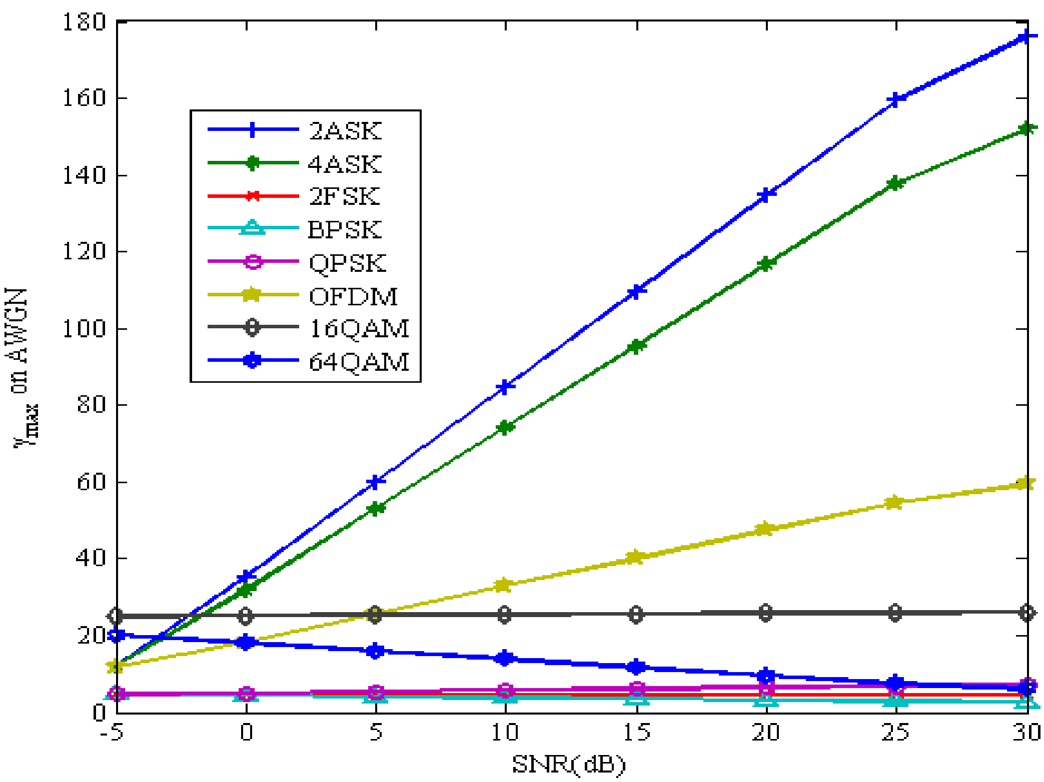
$$\sigma_{aa} = \sqrt{\frac{1}{N}\left(\sum_{i=1}^{N} a_{cn}^{2}(i)\right) - \left(\frac{1}{N}\sum_{i=1}^{N}|a_{cn}(i)|\right)^{2}} \tag{3.16}$$

σ_{aa} was used to distinguish between 2ASK as a subset and 4ASK as the second subset. The discrimination between the two signals is possible because the value of the normalized instantaneous amplitude of 2ASK is constant, so it has no absolute amplitude information. This makes σ_{aa} value for 2ASK to be less than $t(\sigma_{aa})$, being the threshold value. On the other hand, the 4ASK signal has absolute and direct amplitude information by nature, which makes its σ_{aa} value greater than the threshold value, $t(\sigma_{aa})$. So, σ_{aa} is used to distinguish between 2ASK and 4ASK.

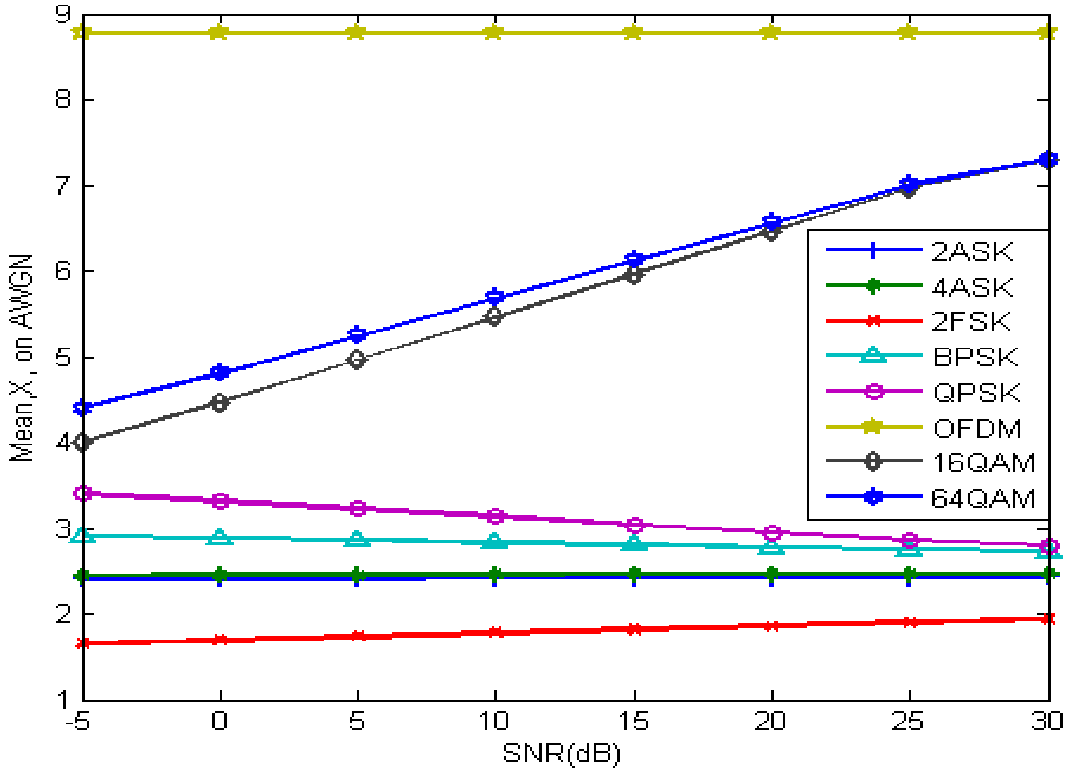
Detailed graphical plots of these feature extracted keys against SNR values are shown in Figure 3.5, while the algorithm used to discriminate between the eight digital modulated signals is shown in Figure 3.6. The optimum feature keys thresholds, $t(\beta)$, $t(\gamma_{\max})$, $t(X)$, $t(\sigma_{aa})$, $t(\sigma_{dp})$, $t(\sigma_{ap})$ and $t(v_{20})$, shown in Figure 3.6, are automatically and adaptively chosen at each neuron of the ANN, which is one of the advantages of PR approach over DT approach where suitable threshold for each feature key has to be chosen (Azzouz and Nandi, 1996a).


1.2
1
0.8
0.6
0.4
0.2
0
β on AWGN
-5
0
5
10
15
20
25
30
SNR(dB)
2ASK
4ASK
2FSK
BPSK
QPSK
OFDM
16QAM
64QAM

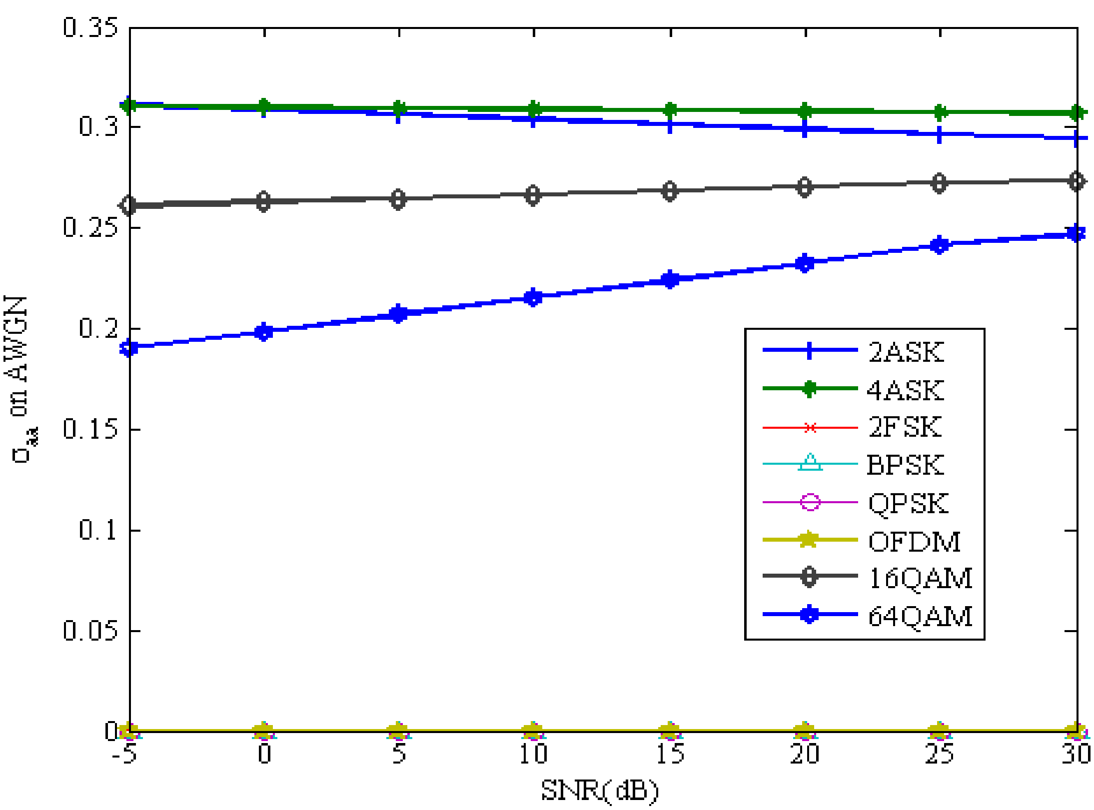
(a)


180
160
140
120
100
80
60
40
20
0
γ_{max} on AWGN
-5
0
5
10
15
20
25
30
SNR(dB)
2ASK
4ASK
2FSK
BPSK
QPSK
OFDM
16QAM
64QAM

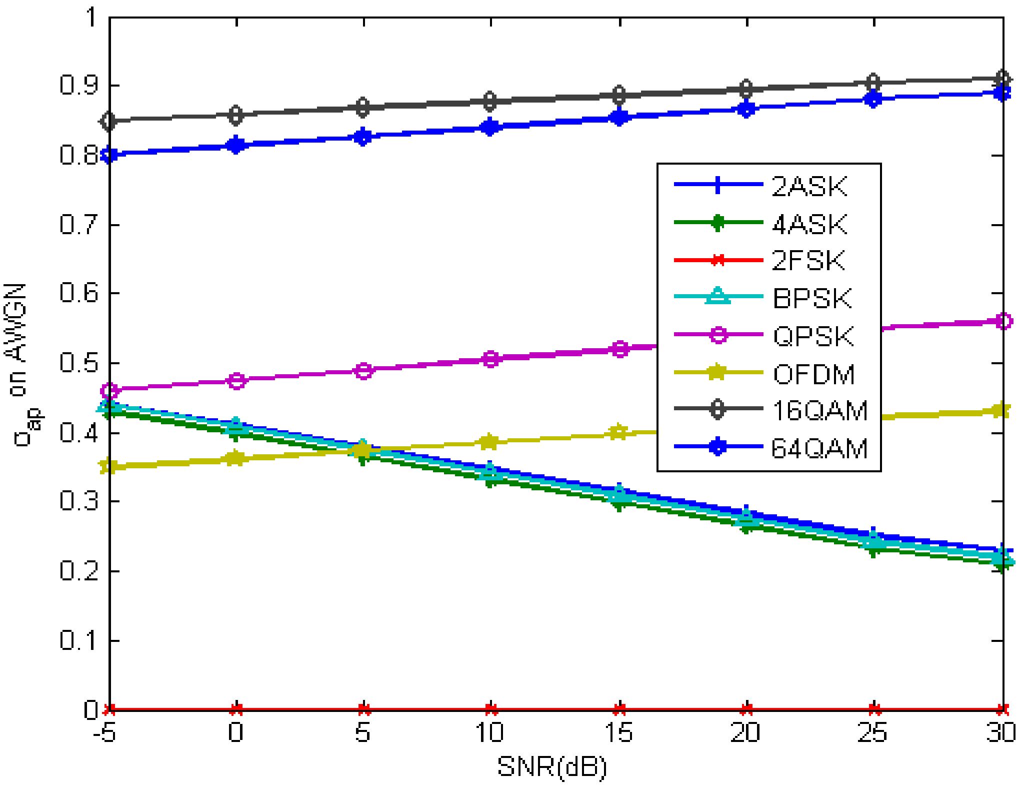
(b)


Mean X, on AWGN
SNR(dB)
2ASK
4ASK
2FSK
BPSK
QPSK
OFDM
16QAM
64QAM

(c)

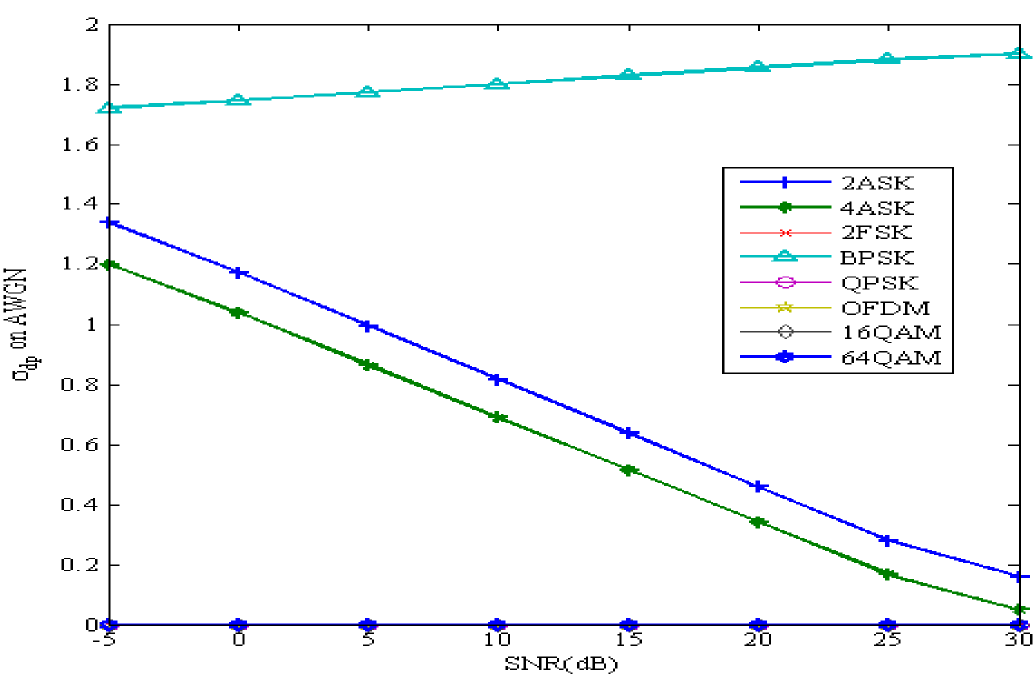

on AWGN
SNR(dB)
2ASK
4ASK
2FSK
BPSK
QPSK
OFDM
16QAM
64QAM

(d)



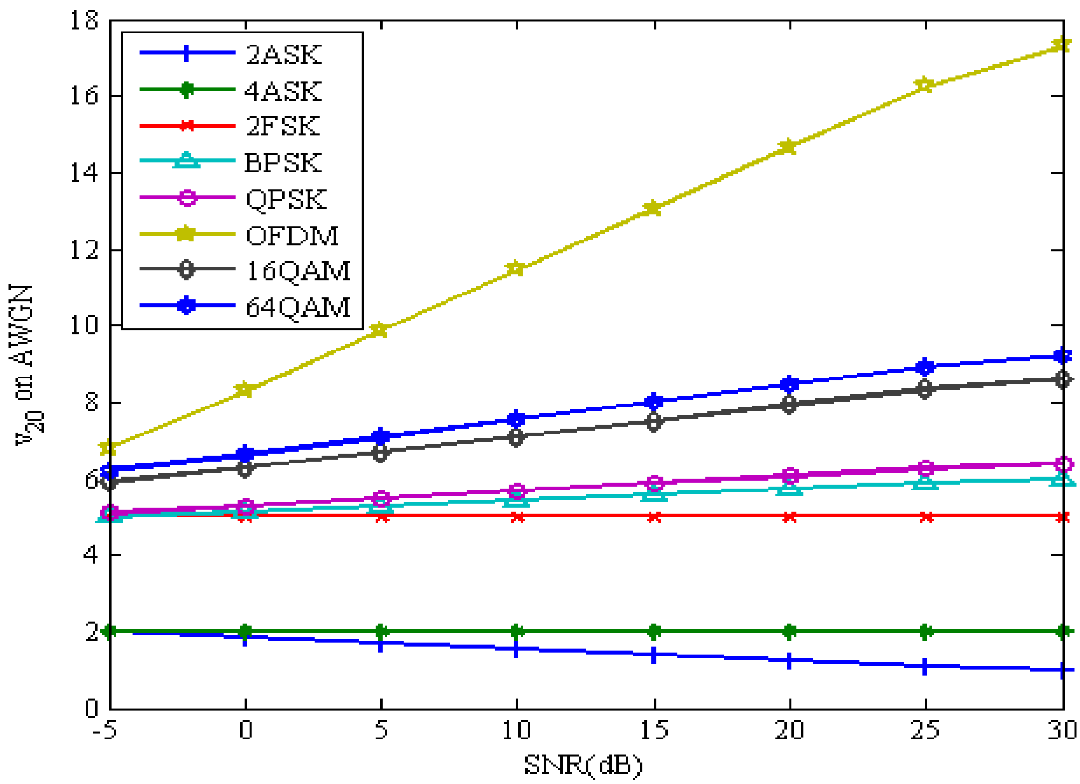
1
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
σ_{ap} on AWGN
-5
0
5
10
15
20
25
30
SNR(dB)
2ASK
4ASK
2FSK
BPSK
QPSK
OFDM
16QAM
64QAM

(e)



2
1.8
1.6
1.4
1.2
1
0.8
0.6
0.4
0.2
0
σ_{dp} on AWGN
-5
0
5
10
15
20
25
30
SNR(dB)
2ASK
4ASK
2FSK
BPSK
QPSK
OFDM
16QAM
64QAM

(f)



(g)

Figure 3.5: Variation of (a) β, (b) γ_{max}, (c) Mean, X, (d) σ_{aa}, (e) σ_{ap}, (f) σ_{dp} and (g) v_{20} with SNR for Digital Modulated Signals

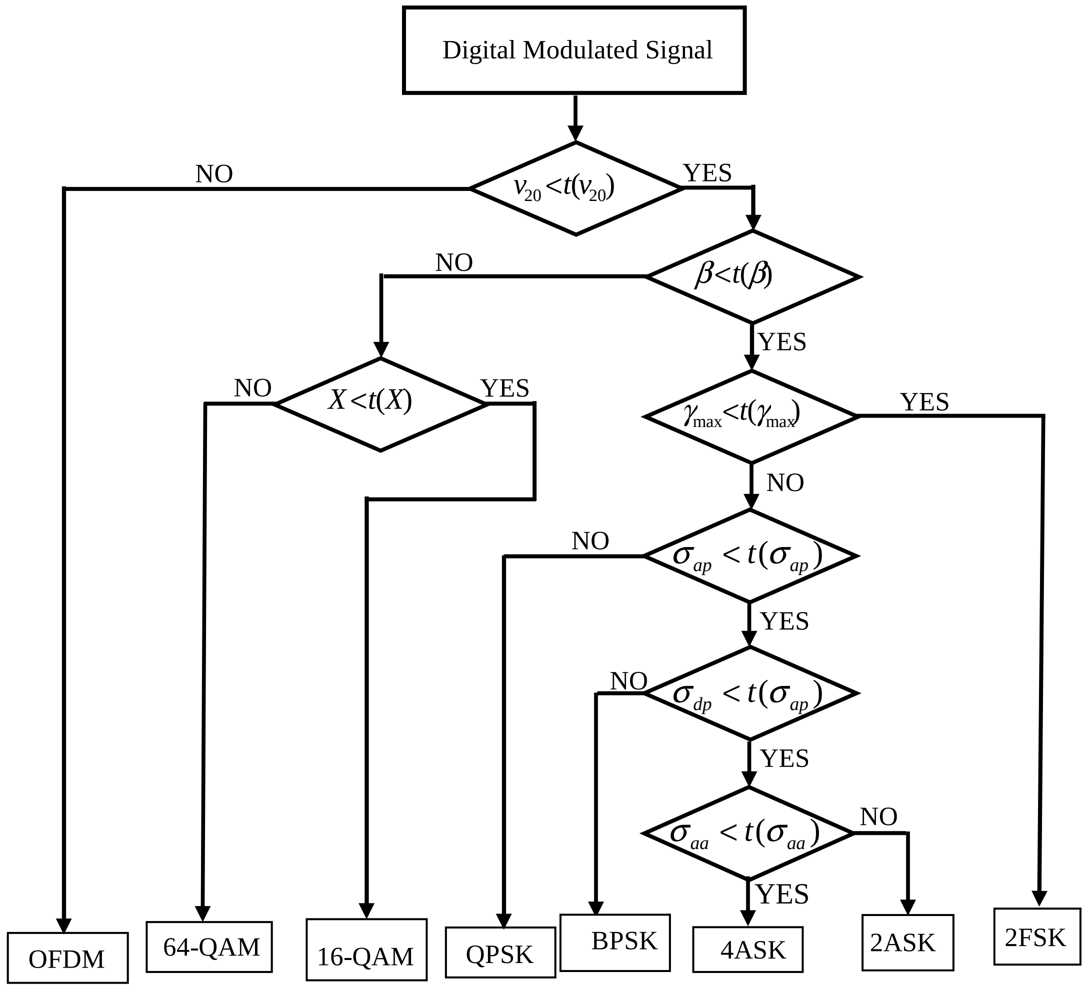


Figure 3.6: Functional Flowchart for Digitally Modulated Signals

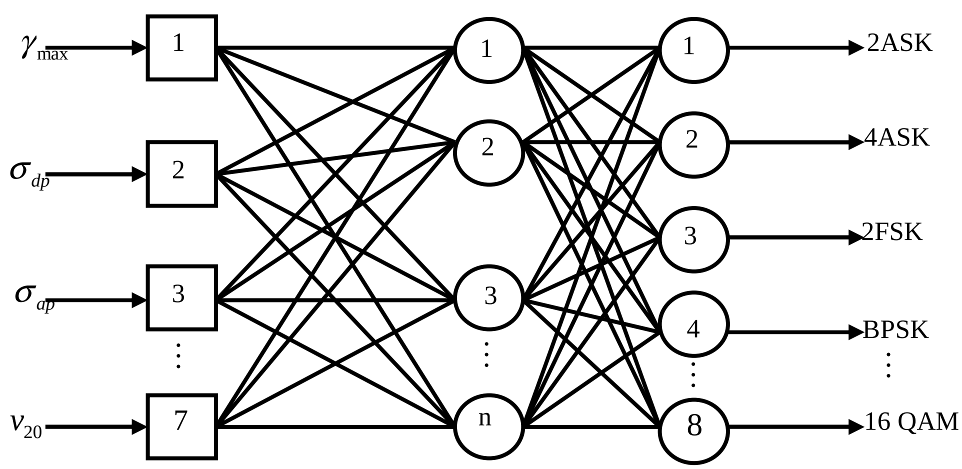


Figure 3.7: Multilayer Feed-forward Network Architecture for the DAMR

3.2.2 Network Training Stage

As in the development of the AAMR in Section 3.1.2, this stage discussed the training and development of the developed DAMR classifier. The DAMR classifier was developed using the ANN. A MLP or feed-forward backpropagation network was also employed in developing the DAMR. The architecture of the developed DAMR classifier is shown in Figure 3.7, as having the statistical feature extracted keys discussed in Section 3.2.1 as the input data sets.

The MLP consists of one input layer, one hidden or intermediate layer of computational nodes or neurons and one output layer of computational neurons. All the neurons are fully connected, as shown in Figure 3.7. Seven neurons are used at the input layer corresponding to the number of input features and seven neurons are used at the hidden layer. The network has eight neurons at the output layer corresponding to the number of targets. The specifications for the ANN employed in this research work for the classification of the digital modulation schemes considered are shown in Table 3.4.

Table 3.4: Specifications for the Developed DAMR

Item	Parameters	Value
1.	Type of neural network architecture	Feed-forward
2.	No. of neurons in input layer	7
3.	No. of neurons in hidden layer	7
4.	No. of neurons in output layer	8
5.	Coefficient of weight-decay	0.01
6.	Activation function in hidden layer	tanh
7.	Activation function in output layer	logistic
8.	Maximum number of epochs	100
9.	Performance function	MSE
10.	Learning algorithm	SCG

The training of the developed DAMR for this research work followed the same procedures described for the developed AAMR in Section 3.1.2. Input vectors and corresponding target vectors are used to train the network until it could classify the modulation schemes in appropriate way. Whenever the results of the output neurons differ from the expected or target value, errors are propagated in a backward manner from the output layer to the hidden layer. This BPA involves two paths as described in Section 3.1.2. A total of 3500 data elements with seven inputs vectors and eight target outputs vectors were used.

3.2.3 Network Testing Stage

After the development and training of the classifier, its performance was evaluated by using 25% of the total generated data as the test data set. The performance evaluation was investigated using six different SNR values of -5, 0, 5, 10 15 and 20 dB. Table 3.5 lists the success recognition rate for all the SNR values considered when the developed DAMR was run for 100 cycles. The result of the performance evaluation of the developed DAMR shows that the classifier can correctly and accurately recognize the eight digital modulation schemes considered, with an average success rate above 99.60% for signals with SNR values from 0 dB upward and above 98.0% for signal at – 5 dB SNR value without a pre-knowledge of the signals parameters.

Table 3.5: Developed DAMR Success Recognition Rate

Modulation scheme	Percentage of success recognition at different SNR vale					
	- 5 dB	0 dB	5 dB	10 dB	15 dB	20 dB
2ASK	98.43	99.29	99.57	99.91	99.94	99.98
4ASK	95.40	99.55	99.76	99.89	99.96	99.99
2FSK	99.79	99.87	99.90	99.92	99.95	99.97
BPSK	99.91	99.94	99.95	99.97	99.99	99.99
QPSK	99.35	99.89	99.92	99.95	99.98	99.99
OFDM	99.71	99.82	99.87	99.94	99.97	99.99
16QAM	98.95	99.64	99.79	99.83	99.92	99.98
64QAM	97.19	99.29	99.57	99.62	99.84	99.95
Overall success rate (%)	**98.59**	**99.66**	**99.79**	**99.88**	**99.94**	**99.98**
Operational time taken (milliseconds)	**0.50**	**0.49**	**0.49**	**0.53**	**0.50**	**0.54**
Average operational time = 0.51 ms						

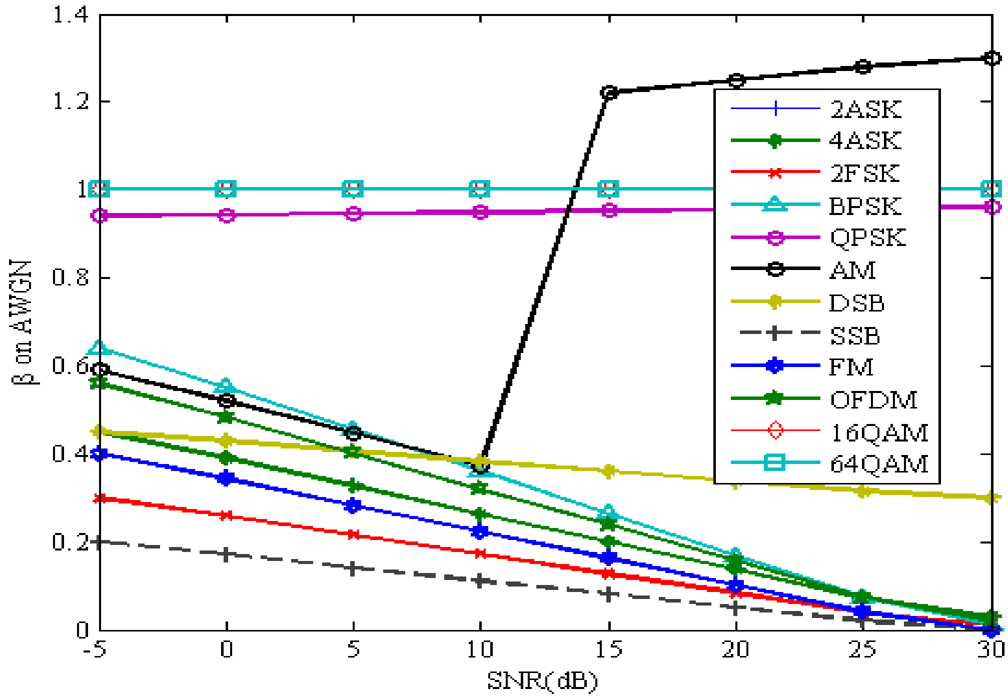
3.3 Combined Analog and Digital Classifier Development

The development of the combined ADAMR for this research work follows the same steps observed in developing both AAMR and DAMR, respectively described in sections 3.1 and 3.2. The development of only the DAMR would have been sufficient alone, because of the increasing usage of digital modulation schemes in radio technologies, such as wireless communication nowadays. However, because analog modulation schemes are still in use in most developing countries, the study also includes the developing of the AAMR. The ADAMR classifier presented in this section is included because in a cognitive radio environment, it is unexpected of the cognitive device or secondary user to know in advance the features of the primary user's signal, including its modulation scheme, whether it is analog modulated or digitally modulated. Therefore, the desire to have a universal AMR that can operate in a blind cognitive radio environment underlines the development of the combined ADAMR presented in this Section.

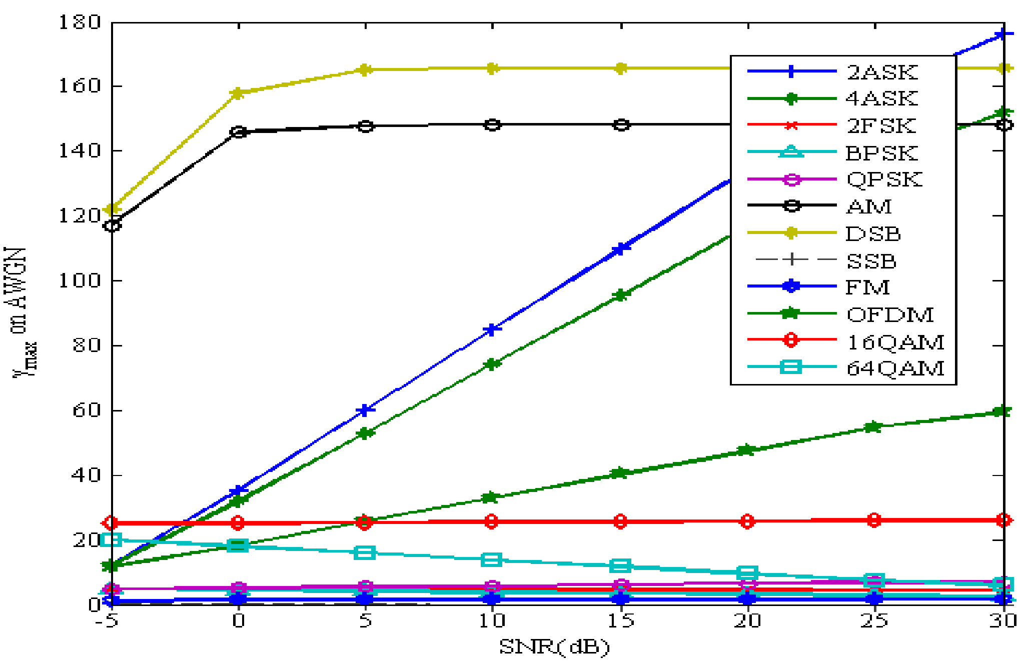
As in the development of both AAMR and DAMR classifiers discussed in Sections 3.1 and 3.2, the development of the ADAMR for the study follows the three functional blocks for AMR development, as shown in Figure 3.1. Thirteen target outputs comprise of twelve-combined analog and digital modulation schemes and un-modulated noise signal were classified. The un-modulated noise or no modulation was added only to this ADAMR classifier to serve as control experiment, which represents absence of a primary radio signal in a cognitive radio environment. The addition of the un-modulated noise to only this classifier is because of the peculiarity of the classifier as the only one later incorporated into the developed CRE for this thesis. The three stages involved, as illustrated in Figure 3.1, are observed as discussed in the following subsections.

3.3.1 Pre-Processing Stage

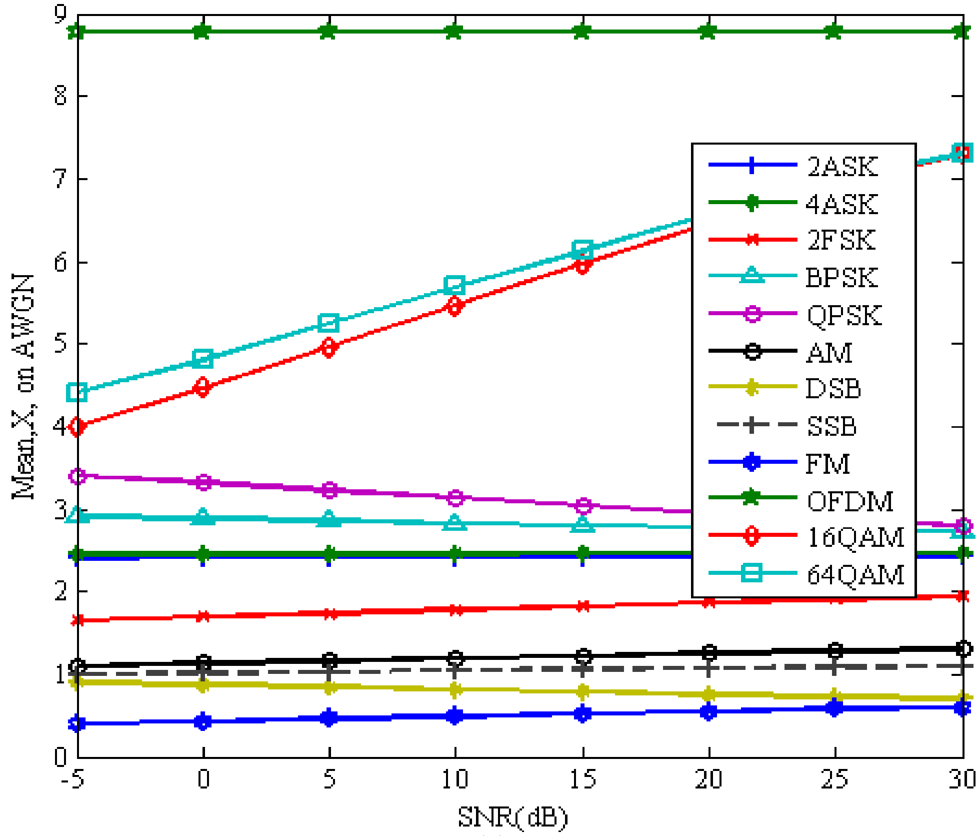
The feature keys extraction process was carrier out, as done for both AAMR and DAMR. A set of eight feature keys were used in developing the combined analog and digital classifier. The eight feature keys were derived from the instantaneous amplitude $a(t)$, and the instantaneous phase $\phi(t)$ of the simulated signal. The eight feature extraction keys employed are: $\gamma_{\max}$, σ_{dp}, P, v_{20}, β, mean X, σ_{ap} and σ_{aa} which have already been described in Sections 3.1.1 and 3.2.1. Their mathematical expressions are given by equations (3.1), (3.5), (3.6), (3.11), (3.13), (3.14), (3.15) and (3.16) respectively. Detailed graphical plots of these extracted feature keys against SNR are shown in Figure 3.8.



(a)

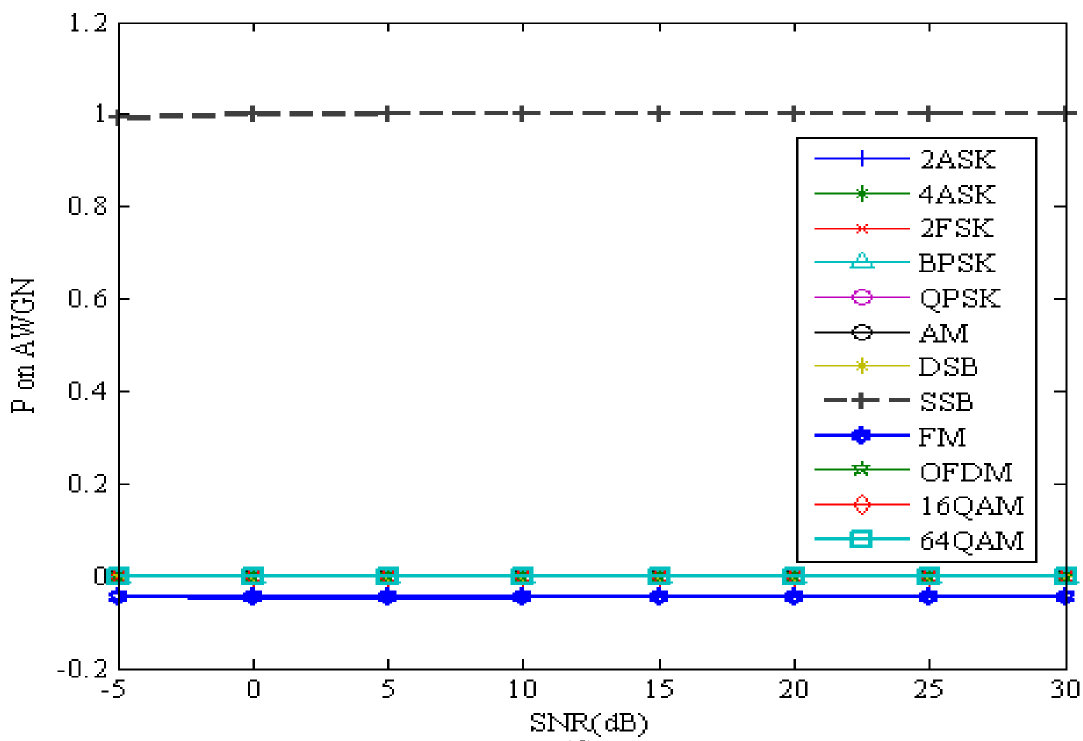


(b)



9
8
7
6
5
4
3
2
1
0
Mean,X, on AWGN
-5
0
5
10
15
20
25
30
SNR(dB)
2ASK
4ASK
2FSK
BPSK
QPSK
AM
DSB
SSB
FM
OFDM
16QAM
64QAM

(c)



1.2
1
0.8
0.6
0.4
0.2
0
-0.2
P on AWGN
-5
0
5
10
15
20
25
30
SNR(dB)
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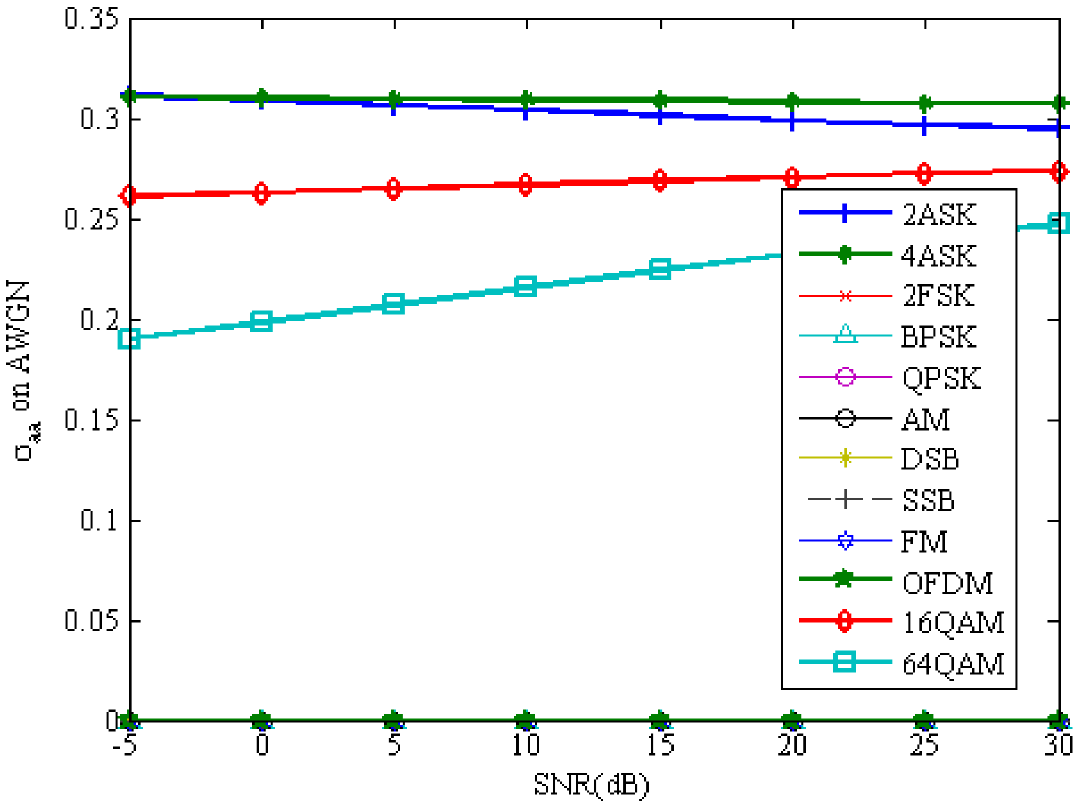
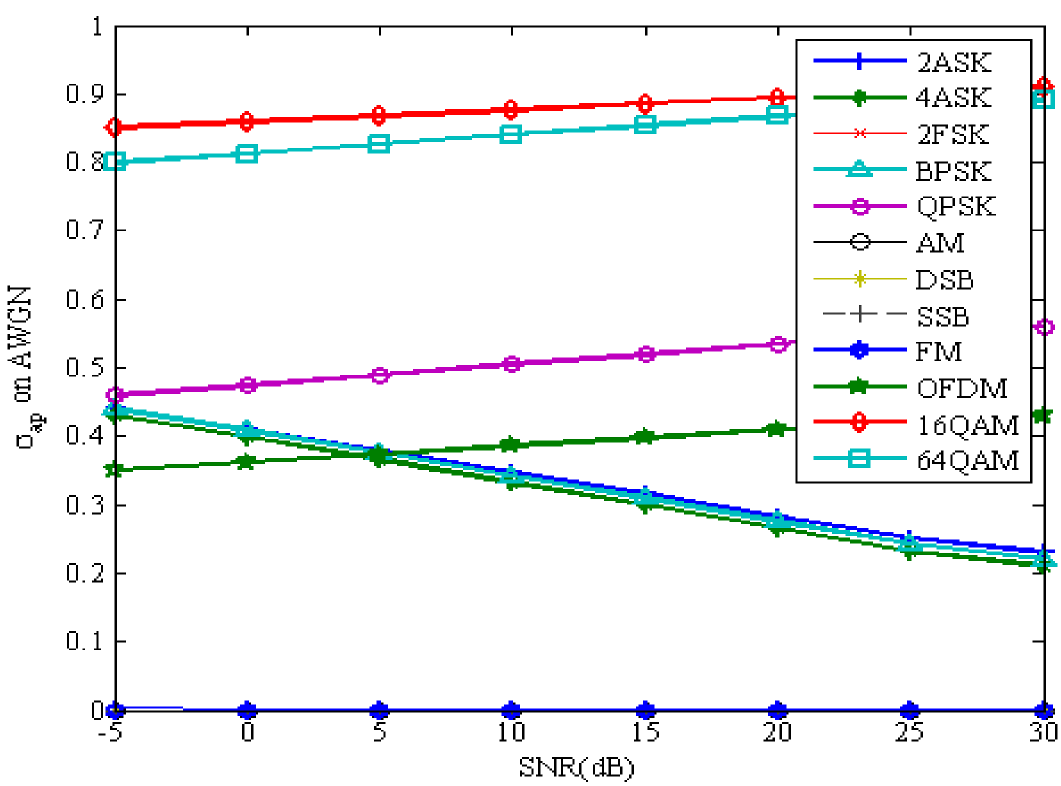
4ASK
2FSK
BPSK
QPSK
AM
DSB
SSB
FM
OFDM
16QAM
64QAM

(d)


0.35
0.3
0.25
0.2
0.15
0.1
0.05
0
-5
0
5
10
15
20
25
30
SNR(dB)
σ_{aa} on AWGN
2ASK
4ASK
2FSK
BPSK
QPSK
AM
DSB
SSB
FM
OFDM
16QAM
64QAM

(e)


1
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
-5
0
5
10
15
20
25
30
SNR(dB)
σ_{ap} on AWGN
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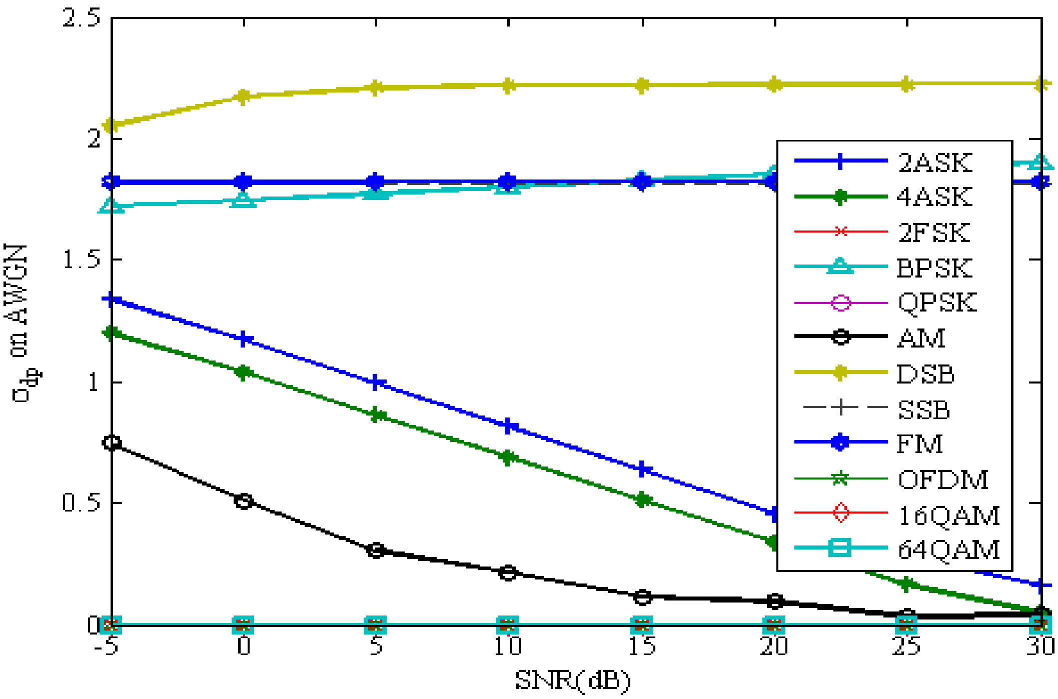
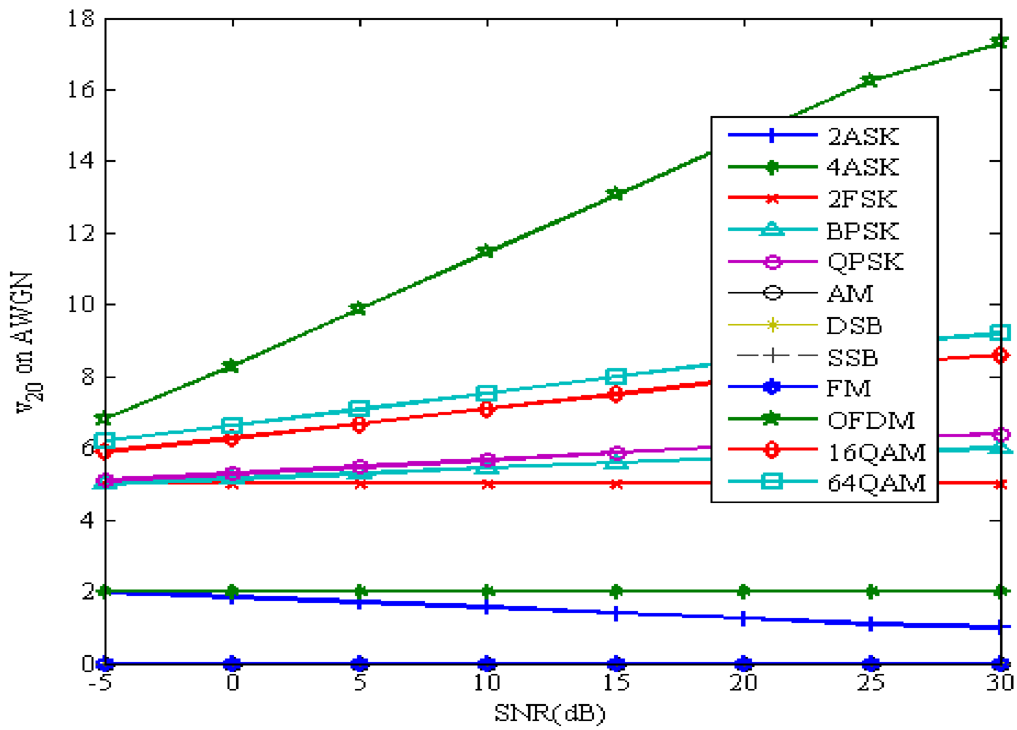
4ASK
2FSK
BPSK
QPSK
AM
DSB
SSB
FM
OFDM
16QAM
64QAM

(f)



(g)



(h)

Figure 3.8: Variation of (a) β, (b) γ_{max}, (c) Mean, X, (d) P, (e) σ_{aa}, (f) σ_{ap} , (g) σ_{dp} and (h) v_{20} with SNR for Digital Modulated Signals

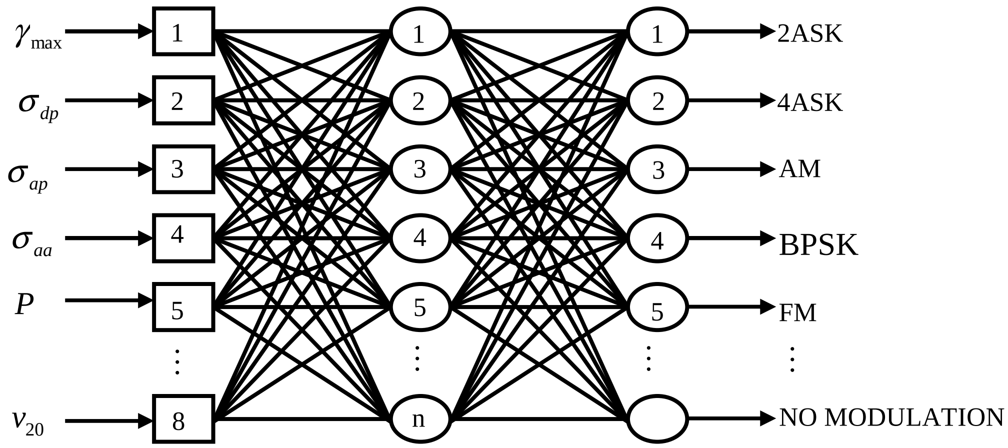


Figure 3.9: Multilayer Feed-Forward Network Architecture for the ADAMR

3.3.2 Network Training Stage

As in the development of both AAMR and DAMR, this stage involves the training of the ADAMR classifier. The ADAMR classifier was developed using an ANN. A MLP or feed-forward backpropagation network was employed in developing the ADAMR for this research work. The developed ADAMR was also trained using the supervised learning method.

The architecture of the developed ADAMR classifier is shown in Figure 3.9 as having the statistical feature extracted keys plotted in Figure 3.8(a)-(h) as the inputs. The MLP consists of one input layer, one hidden or intermediate layer of computational nodes or neurons and one output layer of computational neurons. All the neurons are fully connected, as presented in Figure 3.9. Eight neurons were used at the input layer corresponding to the number of input features, and fifteen neurons were used at the hidden layer. The network has thirteen neurons at the output layer corresponding to the number of targets, thus 12 combined analog and digital modulation schemes and the noise signal or un-modulated signal. The noise signal is included to serve as control experiment for the absence of a primary radio signal. The noise signal or un-modulated signal is, as mentioned above, included in only this classifier because it is the one further used in developing the CRE for the research work. The specifications for the developed ADAMR classifier are shown in Table 3.6.

Table 3.6: Specifications for the Developed ADAMR

Item	Parameters	Value
1.	Type of neural network architecture	Feed-forward
2.	No. of neurons in input layer	8
3.	No. of neurons in hidden layer	15
4.	No. of neurons in output layer	13
5.	Coefficient of weight-decay	0.01
6.	Activation function in hidden layer	tanh
7.	Activation function in output layer	logistic
8.	Maximum number of epochs	150
9.	Performance function	MSE
10.	Learning algorithm	SCG and CONJGRAD

In the training of the developed ADAMR for this research work, input vectors and corresponding target vectors are used to train the network until it could classify the modulated signals and the noise signal in appropriate manner. Whenever the results of the output neurons differ from the expected or target value, errors are propagated in a backward manner from the output layer to the hidden layer, as described in Section 3.1.2. A total of 6500 data elements, with eight feature inputs vector and nine target outputs vectors were used. The procedures followed in training the developed ADAMR are exactly the training procedure described in Section 3.1.2 for the AAMR.

As a result of the sensitivity of this particular classifier, it was trained using two different types of training algorithms. The first algorithm used is the normal SCG used for the other two classifiers. The second and new training algorithm used to train the classifier is CONJGRAD. The essences of using the two training algorithms for only this classifier, i.e. the developed ADAMR, were two-fold. The first reason is because the classifier was the only one used later in developing the CRE for the thesis. The second reason was to determine the effect of different training algorithms on the classifier's performance. Hence, the use of the two training algorithms provided information on the appropriate training algorithms for the thesis. It also helped in eliminating the negative effect the wrong choice of training algorithm might have caused on the classifier's performance and the developed CRE. The choice of the appropriate training algorithm was achieved by comparing the two training algorithms' performances in terms of success detection rate and operational time taken. The obtained success detection rate and operational time taken results were presented in Section 3.3.3.

3.3.3 Network Testing Stage

After the development and training of the developed ADAMR classifier, its performance was evaluated using 25% of the total generated data as a test data set. The performance evaluation was investigated on different SNR values of -5, 0, 5, 10, 15 and 20 dB, using the SCG and the CONJGRAD training algorithms. The success recognition or detection rate and the operational time taken when the combined ADAMR was run for 150 cycles, using the two training algorithms, SCG and CONJGRAD, with the same test input data sets are presented in Table 3.7 and Table 3.8 respectively.

Table 3.7: Developed Combined ADAMR Success Recognition Rate when Trained with SCG

Modulation scheme	Performance of success recognition rate at different SNR value using 15 hidden neurons and 150 training cycles on additive white Gaussian noise (AWGN) channel					
	- 5 dB	0 dB	5 dB	10 dB	15 dB	20 dB
2ASK	97.55	99.46	99.66	99.84	99.91	99.97
4ASK	96.79	97.77	98.68	99.47	99.94	99.98
2FSK	99.22	99.65	99.79	99.84	99.97	99.99
BPSK	99.85	99.89	99.93	99.97	99.98	99.99
QPSK	99.54	99.64	99.88	99.92	99.97	99.98
AM	99.91	99.93	99.94	99.96	99.98	100.00
DSB	99.84	99.87	99.90	99.95	99.97	99.98
SSB	99.91	99.95	99.97	99.98	99.99	99.99
FM	99.93	99.95	99.96	99.97	99.99	99.99
OFDM	99.81	99.89	99.94	99.96	99.97	99.98
16QAM	98.89	99.15	99.88	99.91	99.95	99.99
64QAM	98.75	98.97	99.75	99.89	99.93	99.97
Overall success rate (%)	**99.17**	**99.51**	**99.77**	**99.89**	**99.96**	**99.98**
Absence of modulation scheme	**92.92**	**99.93**	**99.95**	**99.96**	**99.98**	**99.99**
Operational time taken (milliseconds)	**4.15**	**4.04**	**4.07**	**4.06**	**4.04**	**4.08**
Average operational time = 4.07 ms						

Table 3.8: Developed Combined ADAMR Success Recognition Rate when Trained with CONJGRAD

Modulation scheme	Performance of success recognition rate at different SNR value using 15 hidden neurons and 150 training cycles on additive white Gaussian noise (AWGN) channel					
	- 5 dB	0 dB	5 dB	10 dB	15 dB	20 dB
2ASK	87.10	99.91	99.94	99.97	99.99	99.99
4ASK	82.21	99.87	99.91	99.96	99.98	99.99
2FSK	99.56	99.88	99.93	99.95	99.98	99.99
BPSK	99.92	99.95	99.96	99.97	99.99	100.00
QPSK	99.42	99.76	99.84	99.96	99.98	99.99
AM	99.57	99.89	99.94	99.97	99.98	99.99
DSB	97.87	99.82	99.93	99.95	99.97	99.98
SSB	99.90	99.94	99.95	99.97	99.99	100.00
FM	99.93	99.95	99.97	99.98	99.99	99.99
OFDM	99.48	99.91	99.94	99.96	99.98	99.98
16QAM	98.46	99.87	99.84	99.92	99.97	99.98
64QAM	93.66	98.91	99.65	99.87	99.94	99.99
Overall success rate (%)	**96.42**	**99.81**	**99.90**	**99.95**	**99.98**	**99.99**
Absence of modulation scheme	**99.92**	**99.96**	**99.97**	**99.99**	**100.00**	**100.00**
Operational time taken (milliseconds)	**10.17**	**10.00**	**10.49**	**11.03**	**10.18**	**11.97**
Average operational time = 10.64 ms						

The results of the performance evaluation of the developed, combined ADAMR with the two training algorithms shows that the classifier could correctly and accurately recognize the twelve combined analog and digital modulation schemes considered with an average success rate above 99.0% for signals with SNR values from 0 dB upward without a pre-knowledge of the signals parameters. However, for signal at – 5 dB SNR, the performance varies slightly, where SCG outperforms CONJGRAD. The results show a progressive increase in the success recognition as the SNR value increases.

The developed, combined ADAMR is also able to detect the noise signal introduced, which acts as the control experiment for absence of a modulation scheme at over 99.90% success rate using the two training algorithms. The significant difference between the two training algorithms used is their operational time taken. The results show that SCG acts faster than CONJGRAD, with average operational time taken of about 4.0 milliseconds, while that of CONJGRAD is above 10.0 milliseconds. Thus, the developed ADAMR classifier, using SCG training algorithm, is used in development of CRE for this research work, because speed in detecting a primary radio signal is important in a cognitive radio environment.

Furthermore, the pictorial classification output of the developed ADAMR, irrespective of the training algorithm employed, illustrating the classifier accuracy is shown in Figure 3.10. The figure shows the typical output of the classifier when tested using test data sets that are different from the training data sets. The result shows that not only does the classifier perfectly recognize the test data sets, but also does without any error. This shows that the developed ADAMR classifier is capable of recognizing data sets that were different from those used to train it. This indicates how the classifier behaves when incorporated into the developed CRE.

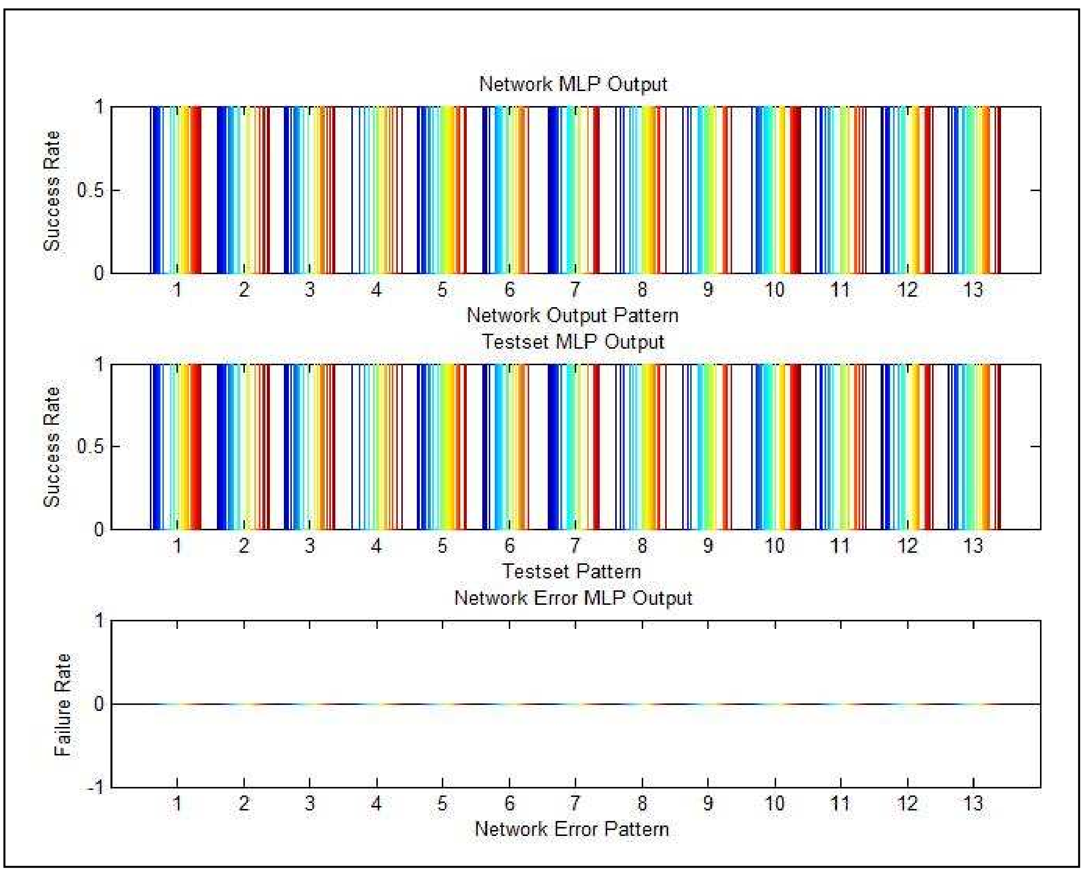


Figure 3.10: Typical Network Output Result of the Developed ADAMR Classifier

The "$t(\ )$" used as a function to determine the threshold value for each of the feature keys is an optimum feature extraction key value. Its value, $t(\gamma_{\max})$, $t(\sigma_{dp})$, $t(P)$, $t(\beta)$, $t(X)$, $t(\sigma_{aa})$, $t(\sigma_{ap})$, and $t(v_{20})$, for each of the feature extracted keys is automatically and adaptively chosen at each neuron of the ANN (Azzouz and Nandi, 1996a). This automatic determination of "$t(\ )$" is one of the advantages of PR approach employed in developing the three classifiers for this thesis, as opposed to the DT approach where a suitable threshold for each feature extracted key has to be selected.

3.4 Summary

The focus of this chapter is on the development of AMR, which can automatically recognize all forms of modulation schemes. The chapter's focus is primarily in meeting one of the objectives of this research work. In fulfilling this objective, three different automatic modulation classifiers were developed, namely AAMR, DAMR and ADAMR. The m-files for the development and the training of the three classifiers are presented in Appendix A. Details on their developments were presented in Section 3.1, Section 3.2 and Section 3.3 respectively.

The performance evaluation studies carried out on the three classifiers show that the initial objective of developing an automatic modulation classifier or recognizer that can automatically classify or recognize modulation schemes without any pre-knowledge about the modulation scheme was achieved. In addition, in this chapter, the two different training algorithms used to train the combined ADAMR especially shows that different training algorithms have different effects on ANN performance. The results obtained using the SCG and CONJGRAD training algorithms show that the SCG training algorithm is faster than the CONJGRAD training algorithm. Similarly, the operational time taken using the SCG training algorithm reveals that the developed DAMR classifier is the fastest, followed directly by AAMR and lastly by ADAMR, with an average operational time taken of 0.51 milliseconds, 1.11 milliseconds and 4.07 milliseconds respectively. These calculated average operational time taken show that the developed

DAMR classifier executes almost twice as fast as the developed AAMR classifier. This is as a result of digital modulation schemes' inherent greater noise immunity and robustness to channel impairment compared with analog modulation schemes. Similarly, the high operational time experienced in the combined ADAMR is as a result of the inherent poor noise immunity the analog modulated signal incorporated into the combined ADAMR introduced to the combined classifier.

However, the only observed limitation that was common to the three developed classifiers is their incorrect prediction of the name(s) of other modulation scheme(s) that were not included in their designed. Although when the three developed classifiers were tested using modulation scheme(s) that were not included in their respective designs, each of them was able to detect the presence of modulation scheme but the modulation name-type given to such modulation scheme(s) were inappropriate. This is because respective classifiers could only correlate those modulation scheme(s) to one of the modulation schemes involved in their designs. However, none of the three classifiers was unable to detect those modulation scheme(s). Likewise, the combined ADAMR classifier, which un-modulated noise was included in its design, did not classify such modulation scheme(s) as un-modulated signal. This shows that the three developed classifiers could reliably detect all forms of modulation schemes, whether included in their designs or not, presented to them except that they could not give those "strange modulation scheme(s)" the appropriate modulation name-type.

CHAPTER 4

4.0 COOPERATIVE SPECTRUM SENSING OPTIMIZATION

Cognitive radio technology introduces the idea of spectrum sharing between the primary or licensed owner of the spectrum, and the unlicensed or secondary user. The aim is to overcome the current underutilization of licensed spectrum. To deploy a CR technology application or DSA, reliable detection of the licensed owner signal, so as to avoid interference between the primary and secondary users, must be guaranteed. This condition makes spectrum sensing to detect the presence of the primary user, as well as identifying the available spectrum holes, a principal requirement in a cognitive radio environment or network.

The cooperative spectrum sensing technique has been identified as an effective spectrum sensing technique, as a result of its spatial diversity scheme. Despite its effectiveness, the cooperative spectrum sensing technique can incur a cooperative overhead, such as extra sensing time, delay, energy and operations devoted to collaborative sensing (Popoola and van Olst 2011c). These cooperative overheads occur as a result of an increasing traffic burden from the series of reports that are needed to be sent over the channel when large numbers of secondary users collaborate.

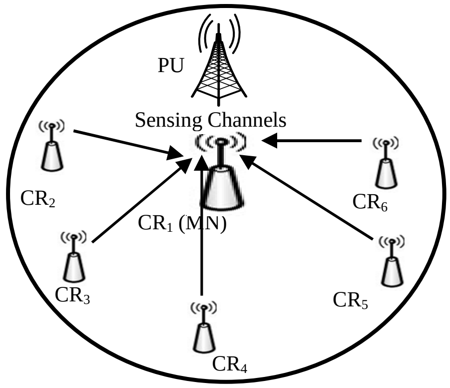
In order to overcome this problem, this chapter emphasizes the development of an effective cooperative spectrum sensing algorithm that can prevent the recurrence of a cooperative overhead. This objective was achieved by developing a sensing time algorithm that can predict spectrum sensing duration. The detailed information on the development and performance of the algorithm is presented in this chapter.

4.1 Cooperative Sensing Time Algorithm Development

In order to optimize the usage of the radio spectrum, the CR or secondary user should be able to detect the presence of the primary user's signal within a very short time frame. Though spending more time in spectrum sensing can aid spectrum sensing accuracy, its excessive duration can cause secondary user interference to a primary user, as well as hinder immediate vacation of the secondary user in cases where the primary user re-appears when the secondary user is transmitting. To prevent this scenario, an algorithm was employed in the cooperative spectrum sensing tool in such a way that the primary user's signal can be detected within a short time period.

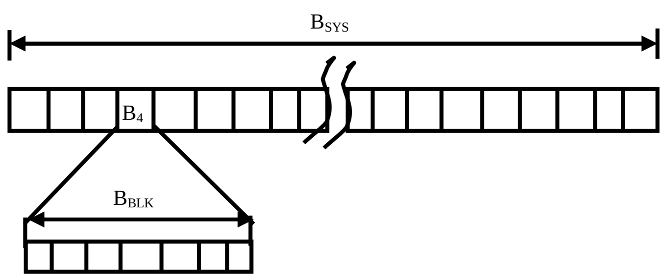
In developing the sensing time algorithm, the expected total time taken to reliably sense the spectrum was divided into two parts. The first part is the time required to quickly sweep over the whole system's bandwidth, B_{SYS}, which is called rough resolution sensing time, T_{RRS}. During this period, the CR user is expected to scan for possible frequency bands or channels with less probability of an active primary user signal. During the rough resolution sensing, the cooperative sensors, CR_1-CR_6 as shown in Figure 4.1, are to detect the presence of any form of modulation scheme in each block or channel that makes up the B_{SYS}, as shown in Figure 4.2.

The second part is the fine resolution sensing time. It is the time required for the cooperative sensors, CR_1-CR_6, to thoroughly scan the detected idle frequency bands or blocks observed during the rough resolution sensing process. At this period, the system bandwidth must be processed in smaller blocks, as shown in Figure 4.2, each having a smaller bandwidth, B_{BLK}. The time taken for carrying out fine resolution sensing is denoted by T_{FRS}.



Adapted from: Popoola and van Olst (2011c)

Figure 4.1: Centralized Cooperative Sensing



Source: Popoola and van Olst (2011c)

Figure 4.2: Channel Model

In Figure 4.1, if M numbers of cooperative sensors or secondary users are cooperating together to sense the spectrum, the total number of rough blocks that must be sensed per secondary user is expressed as:

$$N_{CR} = \frac{B_{SYS}}{MB_{RS}} \tag{4.1}$$

where B_{RS} is the number of channel or blocks constituting the rough sensing bandwidth.

After the completion of the rough scanning of the entire system bandwidth, the smaller bandwidth, B_{BLK}, will be processed or scanned at a fine resolution frequency, F_{RES}. During the fine resolution sensing, all the M cooperative sensors or secondary users are to down-convert the same frequencies and use an FFT to process the single B_{BLK} being considered. According to Neihart *et al*., (2007), an N fast Fourier transform, which converts time-domain signal or continuous signal to discrete frequency-domain data or signal, is required to set up a fine sensing bandwidth, B_{FS}, as well as the minimum sensing fine frequency resolution, F_{RES}. Apart from the time-domain to frequency-domain conversion of the signal, the other usefulness of the N fast Fourier transform is to improve the signal resolution, as increase in N improves the signal resolution. Therefore, the fine sensing bandwidth, B_{FS}, set by an N fast Fourier transform at a minimum fine sensing frequency resolution, F_{RES}, is thus given as:

$$B_{FS} = NF_{RES} \tag{4.2}$$

As shown in Figure 4.2, the same way the overall system bandwidth is divided into frequency bands or blocks of rough sensing bandwidth (B_{RS}), the entire fine sensing bandwidth (B_{BLK}) also was divided into frequency blocks of fine sensing bandwidth (B_{FS}) where B_{RS} is α multiple integer of B_{FS} given as:

$$B_{RS} = \alpha B_{FS} \tag{4.3}$$

where $\alpha = 1,2,3,4,\cdots,$ is the number of fine frequency blocks from a rough block.

Now substituting (4.2) and (4.3) in (4.1), the number of rough sensing blocks that must be sensed by each cooperative sensor or cognitive radio user is given as:

$$N_{CR} = \frac{B_{SYS}}{\alpha MNF_{RES}} \tag{4.4}$$

As reported in Neihart *et al*., (2007) and Zamat and Nataarajan (2009), the total number of real additions and multiplications that need to perform a power-of-two N-point FFT in a practical implementation is given as:

$$4N\log_2(N) - 6N + 8 \tag{4.5}$$

The essence of performing a power-of-two N-point FFT is to reduce the computational complexity of the algorithm. Hence, for optimum running speed of the algorithm, the FFT need the data size to be a power of two, called radix-2 N-point FFT, which reduces the signal or data multiplications to $N/2(\log_2(N))$ and the signal additions to $N(\log_2(N))$. Therefore, if the operating frequency of each CR user or cooperative sensor is F_{CR}, the total time required to perform rough resolution sensing of the entire system bandwidth, B_{SYS}, is given as:

$$T_{RRS} = \frac{B_{SYS}}{\alpha MNF_{RES}F_{CR}}\left[4\frac{N}{M}\log_2\left(\frac{N}{M}\right)-6\left(\frac{N}{M}\right)+8\right] \tag{4.6}$$

When a fine bandwidth of size αB_{FS}, has been detected, the fine resolution sensing will then take place using N points of FFT. Thus, the total duration to perform a fine resolution sensing for α frequency blocks is given as:

$$T_{FRS} = \frac{\alpha}{F_{CR}}\left[4\log_2(N)-6(N)+8\right] \tag{4.7}$$

Therefore, the total sensing time, T_S, to perform the overall spectrum sensing by all the cooperative sensors or secondary users collaborating together is simply the sum of (4.6) and (4.7), which is:

$$T_S = \frac{B_{SYS}}{\alpha MNF_{RES}F_{CR}}\left[4\frac{N}{M}\log_2\left(\frac{N}{M}\right)-6\left(\frac{N}{M}\right)+8\right]+\frac{\alpha}{F_{CR}}\left[4N\log_2(N)-6N+8\right] \tag{4.8}$$

Equation (4.8) is therefore used to develop the cooperative spectrum sensing duration from which various system level trades-offs were considered and their effects upon T_S are examined. The results obtained are used in predicting the possible optimization strategies for maximizing the cooperative gain without incurring a cooperative overhead.

4.2 Cooperative Spectrum Sensing Optimization

A computational implementation of the proposed sensing time algorithm was developed. The computational algorithm was tested with a system bandwidth, B_{SYS}, frequency of 2.5 GHz, which is divided into rough sub-bands bandwidth, B_{RS}, of 25 MHz. The B_{RS} is further sub-divided into 2.5 MHz fine bandwidth, B_{FS}, frequency. The FFT size (N) is chosen as 32. The other fixed parameter used is F_{CR} which equates to 100 kHz, while various values of α, M and F_{RES} are used to evaluate the performance of the computational algorithm developed in achieving the objective of this research work. The value of F_{CR} was fixed at 100 kHz because the lowest frequency band, Table 5.1-5.4, of the four wireless services considered is in this frequency range. The summary of the simulation parameters for analyzing the developed spectrum sensing duration algorithm's performance evaluation is shown in Table 4.1. In developing the algorithm, location of the terminals as well as their spatial ranges apart were assumed to be negligible because of the space constraint of the laboratory setup.

Table 4:1: The Simulation Parameters for the Developed Spectrum Sensing Time Algorithm

Parameter	Value
Operating Frequency of the System (B_{SYS})	0 – 2.5 GHz
Rough Sub-bands Bandwidth (B_{RS})	25 MHz
Fine Sub-bands Bandwidth (B_{BLK})	2.5 MHz
CR User or Cooperative Sensor Operating Frequency (F_{CR})	100 kHz
FFT Size (N)	32
SNR Range	- 5 dB to 30 dB
Channel Condition	AWGN

Equation (4.8) is used to compare the sensing time, depicted as T_S for two or more cognitive radios performing cooperative sensing techniques with a single cognitive radio performing spectrum sensing individually. Various practical trade-offs are explored for achieving optimal cooperative gain with minimal sensing time, such as the number of cognitive radios required in cooperative sensing, and their impact on the number of sub-bands in B_{RS}, as well as the appropriate rough resolution bandwidth frequency settings. The numerical results obtained are presented in graphical form and discussed in the following sub-sections.

4.2.1 Number of Cognitive Radios Collaborating

The parameter in equation (4.8), with its impact on spectrum sensing optimization, which was first considered, is the number of cognitive radio or cooperative sensors, M, that can collaborate together to achieve minimal sensing time with optimal cooperative gain, and without incurring a cooperative overhead. From equation (4.8), it is observed that T_S is inversely proportional to M. Therefore, theoretically, it is possible for as many cooperative sensors as possible to collaborate together in sensing the spectrum without incurring a cooperative overhead. However, in a practical sense, increasing the number of cognitive radios or cooperative sensors without caution will cause a substantial penalty in power consumption due to duplication of transceiver chains. In addition, a large spatial distance will be required to ensure that the received signals between the cognitive radios are uncorrelated. The impractical nature of this large distance in the cognitive radio environment, as well as the power consumption required, places a premium on the number of cognitive radios that can be used.

In order to maintain a balance between distances required, the power consumption, the system performance and effective sensing time, specified numbers of cognitive radios need to collaborate together in spectrum sensing. Numerical results obtained from the simulation carried out show that a maximum of four cognitive radios or cooperative sensors are ideal to collaborate. This can be easily deduced from Figure 4.3, which shows a plot of T_S against a number of cognitive radios M at F_{RES} = 10 kHz and fixed values of B_{SYS}, B_{RS}, B_{FS}, N and F_{CR} stated above.

From Figure 4.3, it is observed that the sensing time (T_S) decreases with increasing number of cognitive radios. However, as the number of cognitive radios collaborating becomes four, a point of diminishing returns is reached. Hence, after M = 4, an increase in the number of cognitive radios is not justified given the small decrease in sensing time achieved. Based on this observation, this research work established that a maximum of four cognitive radios users are ideal for optimal cooperation gain in a cognitive radio environment in order to avoid incurring cooperative overhead.

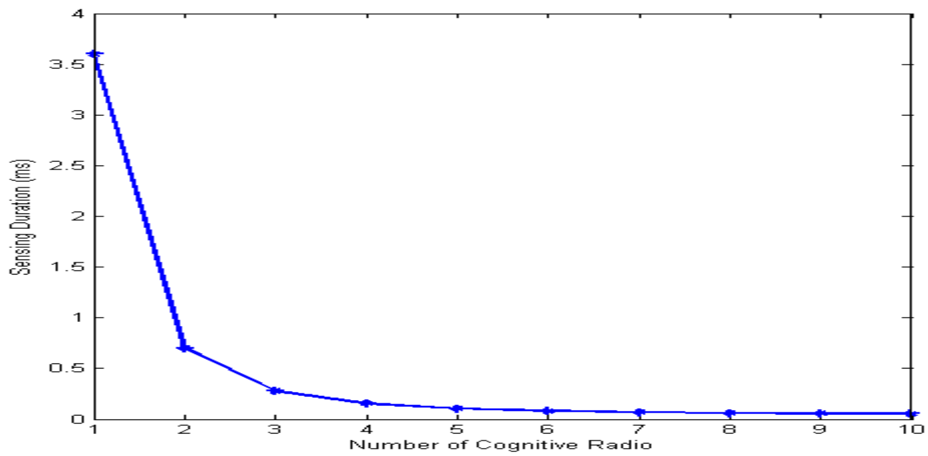


Figure 4.3: Plot of Sensing Time against Number of Cognitive Radios

Careful observation of Figure 4.3 also shows the effectiveness of cooperative spectrum sensing techniques over non-cooperative spectrum sensing techniques. As shown in the figure, while it takes one cognitive radio sensor 3.6 milliseconds to sense the spectrum alone, it takes two cognitive radio sensors collaborating together about 0.7 milliseconds to sense the same portion of the spectrum.

4.2.2 Effect of Fine Frequency Sensing Resolution Selection

The second parameter, as in equation (4.8), with its effect on cooperative gain which was considered, is fine frequency sensing resolution (F_{RES}). F_{RES} is the frequency required to process the smaller bandwidth denoted by B_{BLK}, in Figure 4.2, after the completion of the rough scanning of the entire system's bandwidth, B_{SYS}. Like the number of cognitive radios, F_{RES} is inversely proportional to the sensing time, T_S. Hence, a theoretical assumption that a high value of F_{RES} will improve the cooperative gain without incurring cooperative overhead is impracticable, as shown in Figure 4.4.

From Figure 4.4, it is observed that the T_S decreases with increase in fine frequency sensing resolution until 60 kHz, when a point of diminishing returns is reached. Hence, after this frequency, observations show that an increase in fine frequency sensing resolution does not justify the small decrease in sensing time. This shows that for optimal cooperative gain, an appropriate fine frequency sensing resolution needs to be determined, so as not to incur a cooperative overhead.

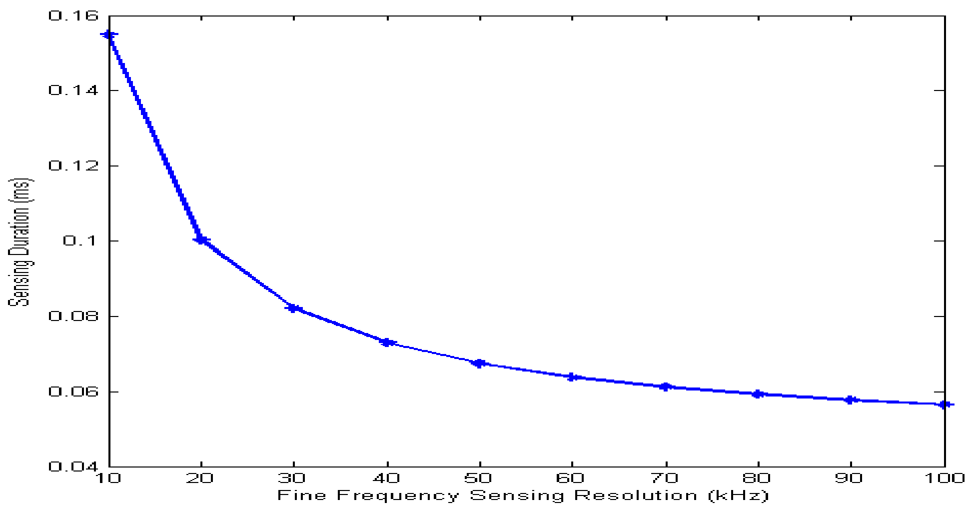


Figure 4.4: Plot of Sensing Time against Fine Frequency Sensing Resolution

4.2.3 Impact of Effect of α value Selection

The third and last parameter in equation (4.8), with its impact which was also considered is α, or the number of fine frequency blocks in a rough block. Considering Figure 4.5, which shows the plot of sensing time against the number of cognitive radios at different values of α, it is noted that for a small number of cognitive radios, for example M = 2, a large value of α gives a minimal sensing time and vice-versa. However, this is not generally true as the number of cognitive radios collaborating for spectrum sensing increase.

For instance, when the four cognitive radios predicted as the appropriate maximum cognitive radios to collaborate for spectrum sensing were considered, the numerical result obtained from the algorithm shows that minimum sensing time was obtained at $\alpha = 30$, rather than at $\alpha = 50$. This shows that, as values of α increase beyond a certain point, it is only adding to the number of blocks to be scanned during the fine sensing process, rather than contributing to a fast sensing rate. Hence, in a practical implementation of cooperative sensing, the appropriate value of α needs to be wisely selected in order to achieve optimal cooperative gain without incurring a cooperative overhead. Based on the fixed parameters used, as well as four maximum numbers of cooperative sensors or cognitive radios suggested for collaborative sensing in this study, the ideal value of α for optimal cooperative gain without incurring a cooperative overhead is 30.

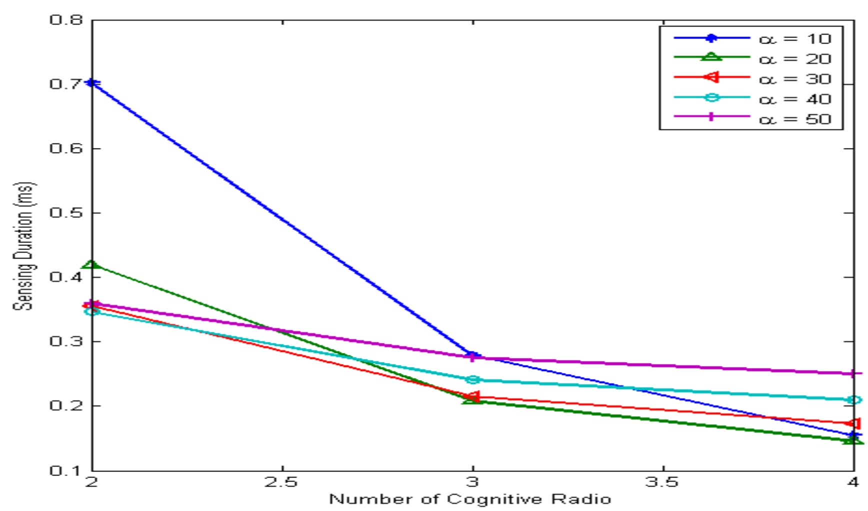
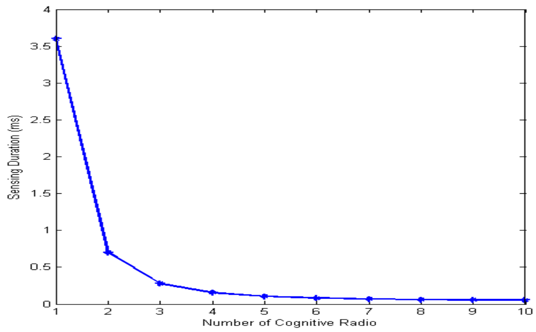


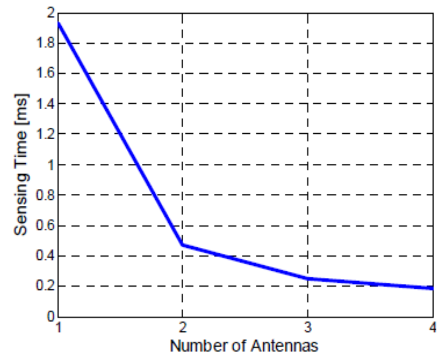
Figure 4.5: Plot of Sensing Time against Number of Cognitive Radios at Different Values of α

4.3 Comparative Analysis of the Developed Sensing Time Algorithm

To further evaluate the accuracy of this thesis spectrum sensing time algorithm, one of its analysis results or graphs shown in Figure 4.3 was compared with a similar graph presented in Neihart *et al*., (2007). The choice of the reference work was based on the fact that the two studies employed the same sensing time algorithm. Though this thesis and the reference work employed different simulation parameters in obtained their respective graphs shown in Figure 4.6(a) and Figure 4.6(b) respectively, observation shows that the two obtained graphs were similar. This similarity in the nature of the two graphs and predictions of equal numbers of secondary users that can collaborate together to obtain optimal cooperation gain without incurring cooperative overhead, show that the simulation result in this thesis is as accurate as that of the reference work. The similarity also indicates that inferences made in this thesis are accurate and that the results obtained from it can perform favourably with the results from the reference work.



(a) Present Work: Popoola (2012) PhD Thesis



(b) Reference Work: Neihart *et al*., (2007) Conference Paper

Figure 4.6: Comparative Analysis of the Simulation Results between this Research Work and Neihart *et al*., (2007)

Furthermore, the peculiarity and improvement this thesis made to the earlier study of Zamat and Nataarajan (2009) on sensing time algorithm development was in replacing the Dedicated Sensing Receiver (DSR) used in that study with SU^{SMN}, which is a transceiver. The improvement, this introduction of the SU^{SMN} added was that it enables the MN or central controller in this thesis to receive sensing results' information from other secondary sensors as well as combining the received sensing results' information to decide the channel condition before broadcasting the final decision it made to other secondary sensors. Although the two-way communication introduced in this thesis consumed more energy, it indeed enhances overall spectrum sensing result when compared with the DSR used in Zamat and Nataarajan (2009).

4.4 Summary

This chapter focused on improving cooperative spectrum sensing reliability for detecting primary radio signals in a cognitive radio environment. This is another major objective of this research work. In addition to the development of a sensing time algorithm for cooperative sensing in a cognitive radio environment, the results of the sensing time algorithm have shown the effectiveness of cooperative sensing techniques over non-cooperative sensing techniques. The simulation result shows that cooperative spectrum sensing outperforms non-cooperative spectrum sensing. The developed sensing time algorithm was optimized by striking a balance between the fast, but less accurate, rough sensing operation and the slow, but more accurate, fine sensing operation. Numerical results from the developed algorithm in this chapter show that cooperative spectrum sensing can work effectively without incurring a cooperative overhead, if the sensing time parameters are carefully selected. The ideal parameters obtained in this chapter are used in chapter 5 for the development of the cognitive radio engine for this research work.

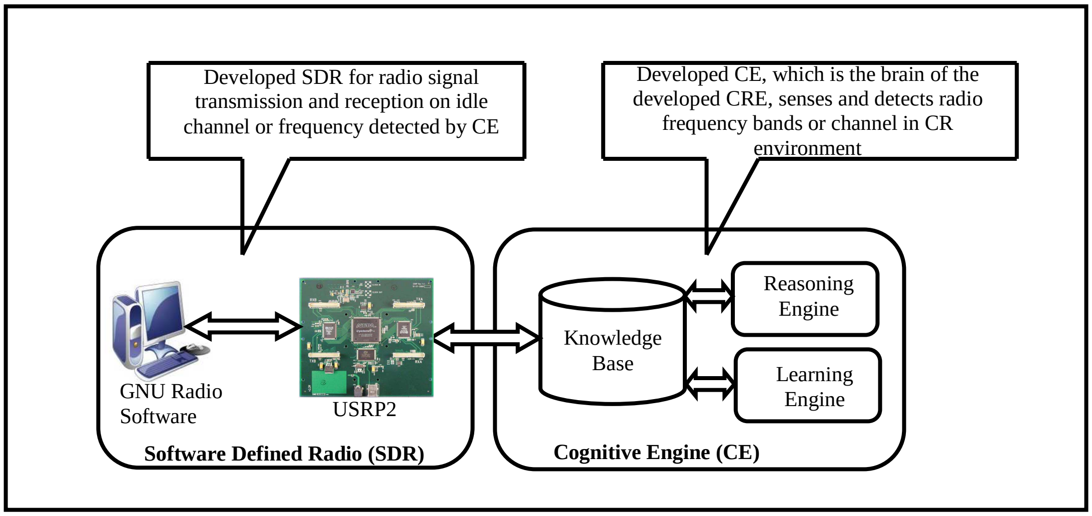
CHAPTER 5

5.0 DEVELOPMENT OF THE STUDY COGNITIVE RADIO ENGINE

This chapter focuses on the development of the CRE for this research work. The CRE development was based on the CR architecture adapted from Clancy *et al*. (2007) shown in Figure 5.1. The development of the CRE was divided into three stages. The first stage centered on the development of an adaptive CE for the research work. In the second stage, the SDR for radio signal transmission and reception was developed. The third stage, which was the last stage for the CRE development, involves the coupling of the developed CE and SDR together. The full description of each stage is presented in Section 5.1, Section 5.2 and Section 5.3 respectively.

5.1 Cognitive Engine Development

Following up on the development of the ADAMR classifier and cooperation spectrum sensing optimization algorithm, as presented in chapter 3 and chapter 4 respectively, an adaptive CE to characterize the primary user's activities is described in this chapter. The CE uses the developed sensing time algorithm and the ADAMR classifier for the spectrum sensing time determination and primary radio signal sensing and detection respectively on the frequency band of interest. At the core of the CE is the ADAMR which was developed for the automatic detection of modulation schemes when monitoring the primary user activities on licensed spectrum.



Adapted from: Clancy et al. (2007)

Figure 5.1: Developed Cognitive Radio Architecture

The CE consists of three components, namely a knowledge base, a learning engine and a reasoning engine, as shown in Figure 5.1. The CE is developed in such a way that it can learn and store these lessons as experience in the knowledge base. This experience can be retrieved to perform similar actions and decisions when needed in the future. Based on past experiences and interactions with information in both the learning engine and the reasoning engine, the knowledge base generates the final decision for the CE.

The reasoning engine in this study serves as action repository system for the CE. The actions stored in the reasoning engine are precondition actions defining the operations the reasoning engine should perform based on the status of the primary user activities. The precondition action the reasoning engine performs is to infer either an idle or occupied spectrum band. The reasoning engine therefore looks at the current status of the spectrum to determine the right actions ideal for that condition. Based on the precondition action taken, the knowledge base evaluates the appropriateness of the reasoning engine action based on its past experience.

The learning engine in this study is the ADAMR classifier described in chapter 3 using an ANN. Its major function is to precisely characterize a primary user's activities by monitoring the modulation scheme on the radio channel in an effort to find a means of optimizing radio spectrum utilization. Therefore, the role of the learning engine in this research work is to provide radio frequency band statistics of “1” and “0”, each denoting an occupied channel or an idle channel respectively. This is intended to predict the probability of secondary frequency usage. The other function of the learning engine is to update both the knowledge base and the reasoning engine with its experience on the channel per time period. As the learning engine learns about different radio frequency bands or channels, it will store these lessons in the knowledge base for future use by the reasoning engine. Other functions of this engine and the two other components of the CE for this research work are provided in section 5.4.

5.2 Software Defined Radio Development

The components of the SDR employed in the development of the CRE for this research work are the GNU Radio and USRP2, as depicted in Figure 5.1. GNU Radio, as described in chapter 2 is an open-source software toolkit, which consists of a signal-processing block library and the glue to tie these blocks together for SR or SDR deployment. With GNU Radio, the SDR is built by creating a graph, which its vertices are signal-processing blocks and the edges represent the data flow between them. The procedures involved in installing the GNU Radio and configuring the USRP2 used in this research work are presented in Appendix B.

5.3 Coupling of the Developed SDR and CE

As shown in Figure 5.1, a CR can be defined as an extension of the SDR by adding an intelligent CE comprising of a knowledge base, a learning engine and a reasoning engine to drive software modifications. For the components to communicate, an application programming interface was developed that enables the components, namely the SDR and CE, to interact or communicate with each other.

5.4 Laboratory Spectrum Sensing Setup

The research laboratory spectrum sensing setup, as shown in Figure 5.2, was implemented using the developed CRE. The laboratory spectrum sensing and detection functionality to detect the status of the channel is the sole responsibility of the CE component of the developed CRE. The spectrum-sensing setup is divided into two stages. The first stage involves the cooperative sensing to monitor the frequency band or channel in order to detect a primary user's radio signal. In this step of the spectrum sensing setup, each of the cognitive radios or secondary user sensors (SU^S) in Figure 5.3 employed the developed ADAMR to perform individual or local spectrum sensing to detect the primary user. The detection observation made by each SU^S is reported to the secondary user's sensor master node (SU^{SMN}) for the final decision on the channel. The developed Spectrum Sensing and Detection Algorithm (SSADA) graphical user interface to demonstrate the operational description of the stage, is presented in section 5.5.

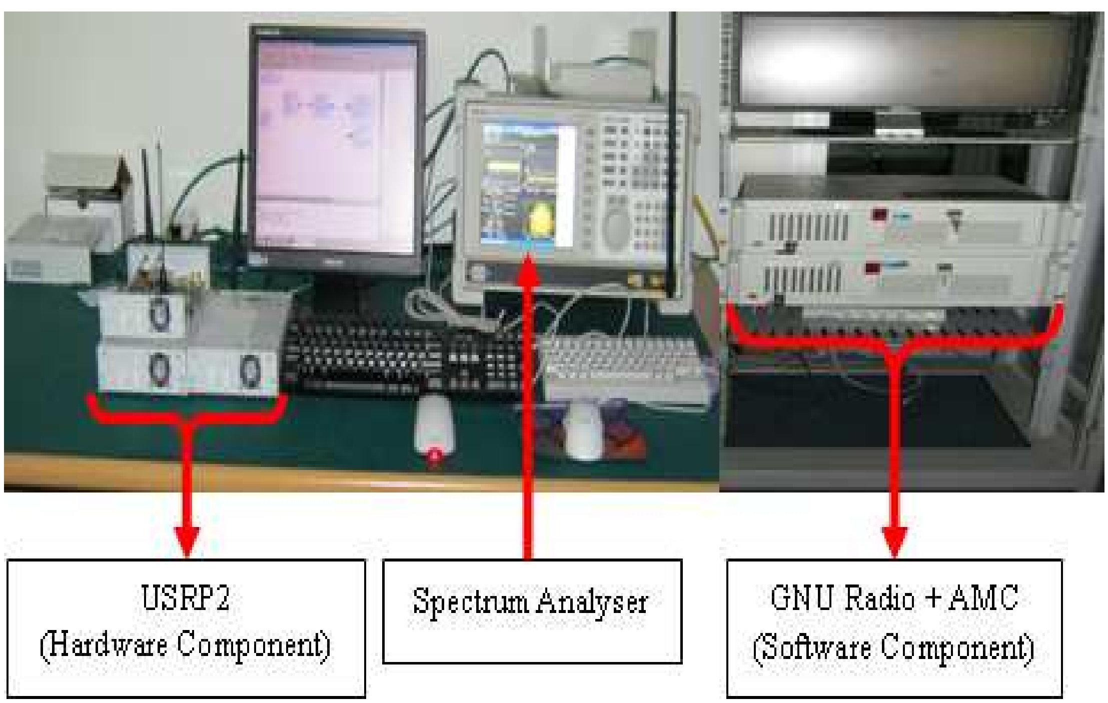


Figure 5.2: Laboratory Setup for the Spectrum Sensing Modulation Identification Method

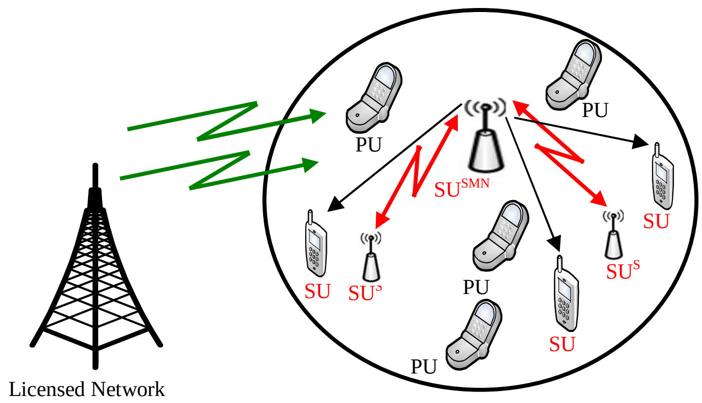


Figure 5.3: Cooperative Sensing Model

The second stage of the research laboratory spectrum-sensing setup is the seizure of the identified or detected idle channel for secondary usage by the cognitive or secondary user (SU) in Figure 5.3. To transmit radio or signal waveform in software form, an extension of GNU Radio called GNU Radio Companion (GRC) was used to facilitate the creation of an appropriate system of GNU Radio blocks with the aid of a visual flow graph. A typical GRC flow graph created is shown in Figure 5.4

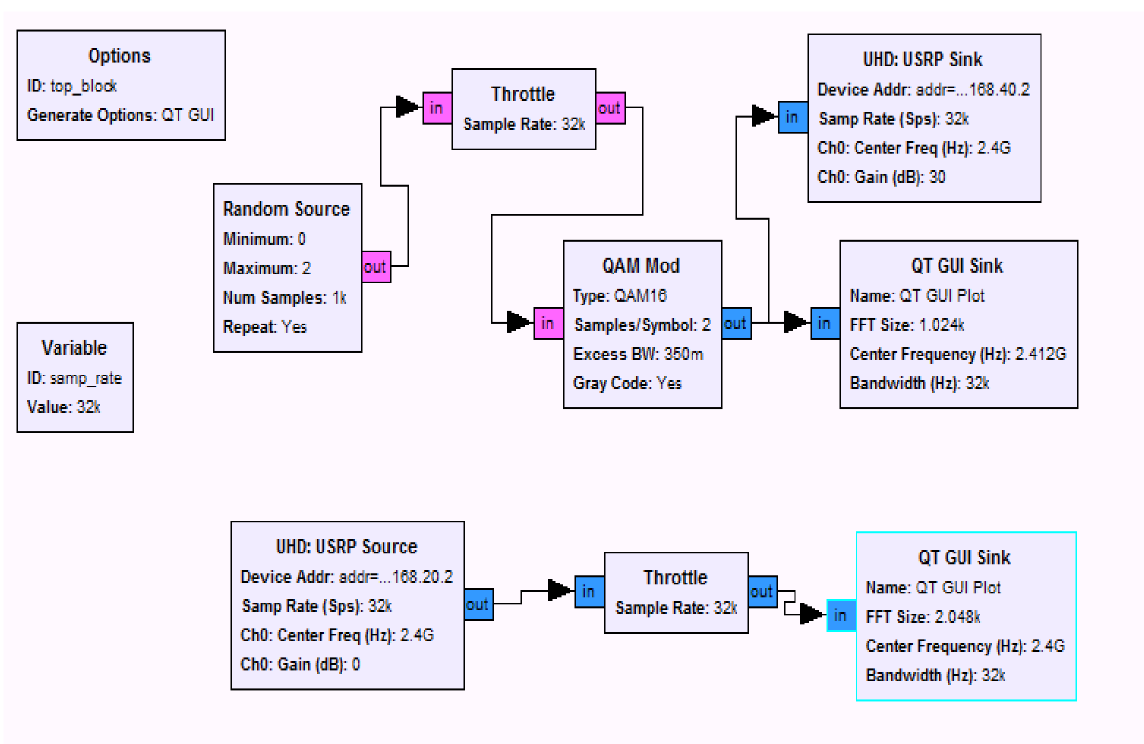


Figure 5.4: Typical GNU Radio Companion Model

At the transmitting end of Figure 5.4, the source block produces the digital stream from the hardware component or USRP2. The digital stream is modulated using different modulation schemes. Figure 5.4 specifically shows 16-QAM, which is one of the modulation schemes used. The modulated data is transmitted using the developed SDR. The designated USRP2 device that was used as the primary transmitter is device D_1, with IP address 192.168.10.2. The modulated signal captured before transmitting is shown in Figure 5.5. The center frequency of the transmitter was set at 2.5 GHz in order to prevent interference to the ISM band employed.

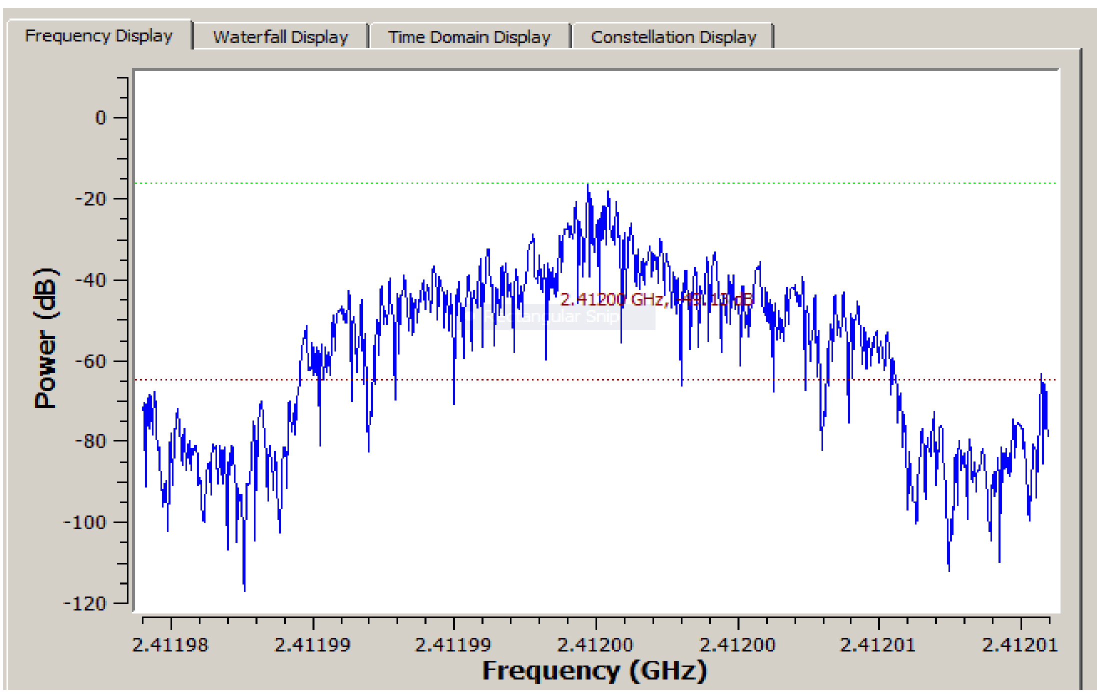


Figure 5.5: Typical Modulated Signal using XCVR2450 Daughterboard

At the receiving end, the center frequency of each SU is set at 2.5 GHz. SU and SU^S in Figure 5.3 are transceiver cognitive radios equipped with the developed ADAMR to enable each to automatically detect the modulation scheme of the primary user's signal from the transmitter. In addition, different designated responsibilities were assigned to SU and SU^S despite the fact that they have the same capabilities. SUs are used only as secondary transmitters, while SU^Ss are used as secondary user sensors to ensure continuous spectrum sensing when one or more SUs is/are transmitting. This is to ensure instantaneous detection of a primary user's re-appearance in a channel when the SU is transmitting. Typical captured waveform at the receiving end is shown in Figure 5.6.

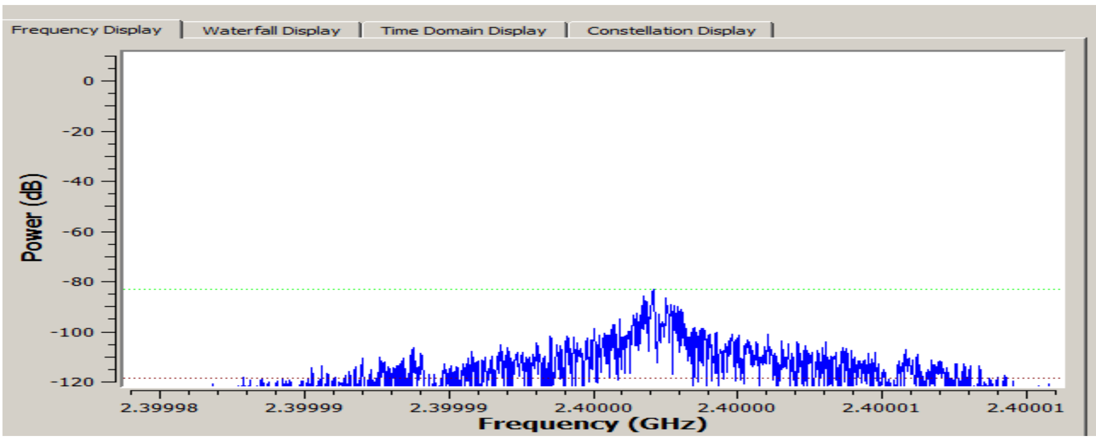


Figure 5.6: Typical Received Signal using XCVR2450 Daughterboard

5.5 Developed Spectrum Sensing and Detection Algorithm Description

The developed SSADA demonstration for the research work is initiated in stage 1 of Figure 5.7, by choosing a wireless service of interest in the developed graphic user interface program. A hypothetical South Africa frequency allocation table was used for the spectrum sensing and detection demonstration activities using four wireless services' frequency bands namely radio broadcasting, television broadcasting, mobile telephone and unlicensed, or ISM frequency bands. The four frequency bands were stored in the knowledge base, as demonstrated in Figure 5.1, which serves as the database for the developed CRE. In addition, the latitude and longitude of the six main cities in South Africa, namely Bloemfontein, Cape Town, Durban, Johannesburg, Port Elizabeth and Pretoria, used as the test sites, were stored in the database to provide information about the location of each of the cities. After providing the preference service and location, the reasoning engine in Figure 5.1 was updated with this data and the developed SSADA commences rough spectrum sensing by scanning over the entire system bandwidth (B_{SYS}), as described in chapter 4.

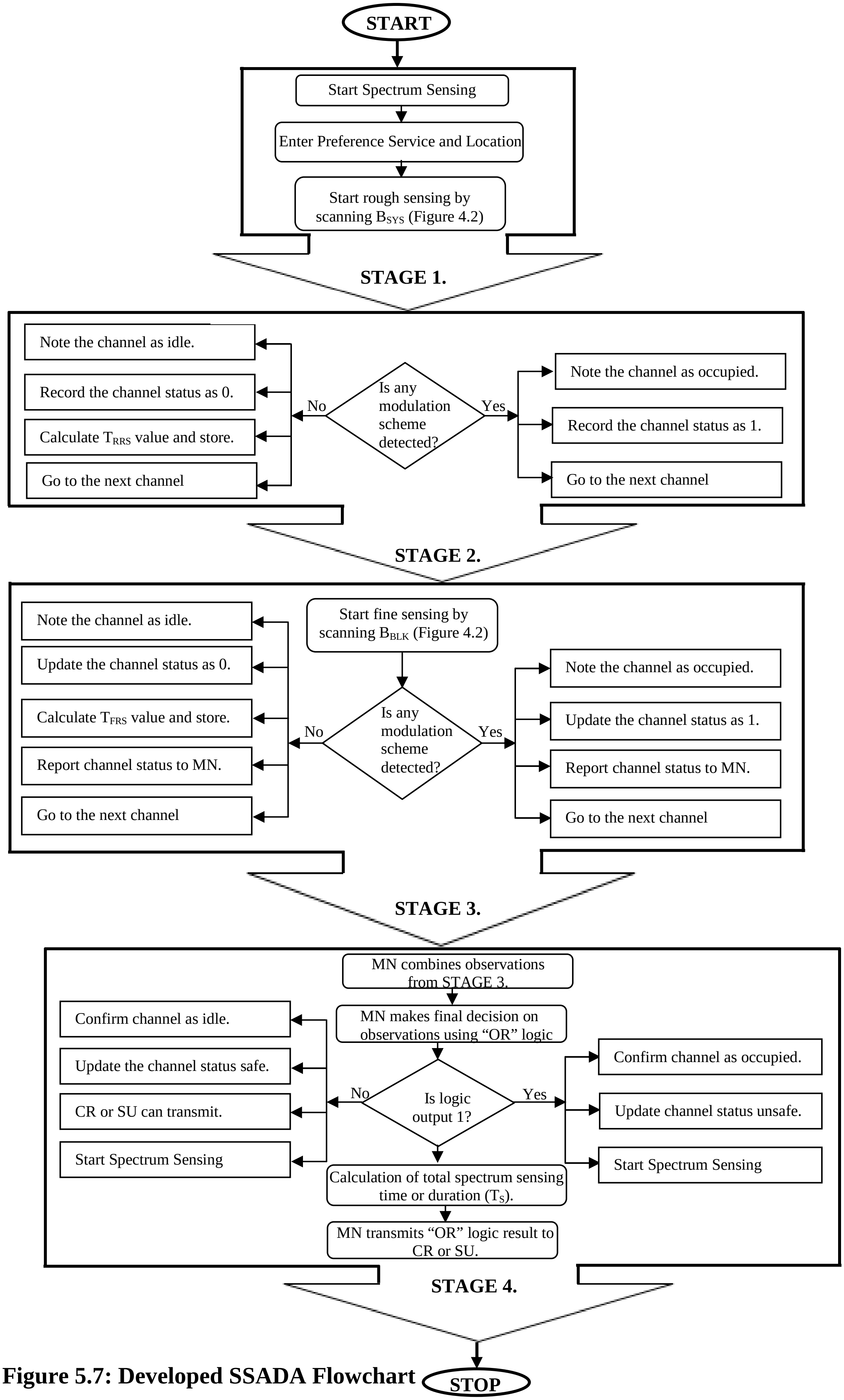


Figure 5.7: Developed SSADA Flowchart

Stage 2 of the SSADA, as demonstrated in Figure 5.7, performs the rough sensing by sweeping over the frequency bands or channels to detect presence of a modulation scheme. The hypothetical frequency bands tables designed for each of the services is shown in Tables 5.1 – 5.4. If any of the modulation schemes is detected, the algorithm notes the channel as occupied and record the channel status as “1” in the learning engine. On the other hand, if no modulation scheme is detected, the algorithm notes the channel as idle and “0”, is recorded against the channel in the learning engine. For idle channels, the algorithm also calculates the time taken to carry out the rough spectrum sensing, T_{RRS}, using equation (4.6) and stores the value obtained in the learning engine.

Table 5.1: Table of FM broadcasting Frequency Bands

System Bandwidth (B_{SYS})/MHz							Band Allocation
87.00	87.23	87.46	87.69	87.92	88.15	88.40	**Band 1**
88.50	88.73	88.96	89.19	89.42	89.65	89.90	**Band 2**
90.00	90.23	90.46	90.69	90.92	91.15	91.40	**Band 3**
91.50	91.73	91.96	92.19	92.42	92.65	92.90	**Band 4**
93.00	93.23	93.46	93.69	93.92	94.15	94.40	**Band 5**
94.50	94.73	94.96	95.19	95.42	95.65	95.90	**Band 6**
96.00	96. 23	96.46	96.69	96.92	97.15	97.40	**Band 7**
97.50	97.73	97.96	98.19	98.42	98.65	98.90	**Band 8**
99.00	99.23	99.46	99.69	99.92	100.15	100.40	**Band 9**
100.50	100.73	100.96	101.19	101.42	101.65	101.90	**Band 10**
102.00	102.23	102.46	102.69	102.92	103.15	103.40	**Band 11**
103.50	103.73	103.96	104.19	104.42	104.65	104.90	**Band 12**
105.00	105.23	105.46	105.69	105.92	106.15	106.40	**Band 13**
106.50	106.73	106.96	107.19	107.42	107.65	107.90	**Band 14**
108.00	108.23	108.46	108.69	108.92	109.15	109.40	**Band 15**

Table 5.2: Table of ISM Frequency Bands

System Bandwidth (B_{SYS})/MHz							Band Allocation
2400.00	2401.17	2402.34	2403.51	2404.68	2405.85	2407.04	**Band 1**
2407.14	2408.31	2409.48	2410.65	2411.82	2412.99	2414.18	**Band 2**
2414.28	2415.45	2416.62	2417.79	2418.96	2420.18	2421.32	**Band 3**
2421.42	2422.59	2423.76	2424.93	2426.10	2427.27	2428.46	**Band 4**
2428.56	2429.73	2430.90	2432.07	2433.24	2434.41	2435.60	**Band 5**
2435.70	2436.87	2438.04	2439.21	2440.38	2441.55	2442.74	**Band 6**
2442.84	2444.01	2445.18	2446.35	2447.52	2448.69	2449.88	**Band 7**
2449.98	2451.15	2452.32	2453.49	2454.66	2455.83	2457.02	**Band 8**
2457.12	2458.29	2459.46	2460.63	2461.80	2462.97	2464.16	**Band 9**
2464.26	2465.43	2466.60	2467.77	2468.94	2470.11	2471.30	**Band 10**
2471.40	2472.57	2473.74	2474.91	2476.08	2477.25	2478.44	**Band 11**
2478.54	2479.71	2480.88	2482.05	2483.22	2484.39	2485.58	**Band 12**
2485.68	2486.85	2488.02	2489.19	2490.36	2491.53	2492.72	**Band 13**
2492.82	2494.00	2495.18	2496.36	2497.54	2498.72	2499.90	**Band 14**
2500.00	2501.17	2502.34	2503.51	2504.68	2505.85	2507.04	**Band 15**

Table 5.3: Table of Television Broadcasting Frequency Bands

System Bandwidth (B_{SYS})/MHz														Band Allocation
174.00	174.25	174.50	174.75	175.00	175.25	175.50	175.75	176.00	176.25	176.50	176.75	177.00	177.27	**Band 1**
177.37	177.62	177.37	178.12	178.37	178.62	178.87	179.12	179.37	179.62	179.87	180.12	180.37	180.64	**Band 2**
180.74	180.99	181.24	181.49	181.74	181.99	182.24	182.49	182.74	182.99	183.24	183.49	183.74	184.01	**Band 3**
184.11	184.36	184.61	184.86	185.11	185.36	185.61	185.86	186.11	186.36	186.61	186.86	187.11	187.38	**Band 4**
187.48	187.73	187.98	188.23	188.48	188.73	188.98	189.23	189.48	189.73	189.98	190.23	190.48	190.75	**Band 5**
190.85	191.10	191.35	191.60	191.85	192.10	192.35	192.60	192.85	193.10	193.35	193.60	193.85	194.12	**Band 6**
194.22	194.47	194.72	194.97	195.22	195.47	195.72	195.97	196.22	196.47	196.72	196.97	197.22	197.49	**Band 7**
197.59	197.84	198.09	198.34	198.59	198.84	199.09	199.34	199.59	199.84	200.09	200.34	200.59	200.86	**Band 8**
200.96	201.21	201.46	201.71	201.96	202.21	202.46	202.71	202.96	203.21	203.46	203.71	203.96	204.23	**Band 9**
204.33	204.58	204.83	205.08	205.33	205.58	205.83	206.08	206.33	206.58	206.83	207.08	207.33	207.60	**Band 10**
207.70	207.95	208.20	208.45	208.70	208.95	209.20	209.45	209.70	209.95	210.20	210.45	210.70	210.97	**Band 11**
211.07	211.32	211.57	211.82	212.07	212.32	212.57	212.82	213.07	213.32	213.57	213.82	214.07	214.34	**Band 12**
214.44	214.69	214.94	215.19	215.44	215.69	215.94	216.19	216.44	216.69	216.94	217.19	217.44	217.71	**Band 13**
217.81	218.06	218.31	218.56	218.81	219.06	219.31	219.56	219.81	220.06	220.31	220.56	220.81	221.08	**Band 14**
221.18	221.43	221.68	221.93	222.18	222.43	222.68	222.93	223.18	223.43	223.68	223.93	224.18	224.45	**Band 15**
224.55	224.80	225.05	225.30	225.55	225.80	226.05	226.30	226.55	226.80	227.05	227.30	227.55	227.82	**Band 16**
227.92	228.17	228.42	228.67	228.92	229.17	229.42	229.67	229.92	230.17	230.42	230.67	230.92	231.19	**Band 17**
231.29	231.54	231.79	232.04	232.29	232.54	232.79	233.04	233.29	233.54	233.79	234.04	234.29	234.56	**Band 18**
234.66	234.91	235.16	235.41	235.66	235.91	236.16	236.41	236.66	236.91	237.16	237.41	237.66	237.90	**Band 19**
238.00	238.61	239.22	239.83	240.44	241.05	241.66	242.27	242.88	243.49	244.10	244.71	245.32	245.90	**Band 20**
246.00	246.06	246.12	246.18	246.24	246.30	246.36	246.42	246.48	246.54	246.60	246.66	246.72	246.79	**Band 21**
246.89	246.95	247.01	247.07	247.13	247.19	247.25	247.31	247.37	247.43	247.49	247.55	247.61	247.68	**Band 22**
247.78	247.84	247.90	247.96	248.02	248.08	248.14	248.20	248.26	248.32	248.38	248.44	248.50	248.57	**Band 23**
248.67	248.73	248.79	248.85	248.91	248.97	249.03	249.09	249.15	249.21	249.27	249.33	249.39	249.46	**Band 24**
249.56	249.62	249.68	249.74	249.80	249.86	249.92	249.98	250.04	250.10	250.16	250.22	250.28	250.35	**Band 25**
250.45	250.51	250.57	250.63	250.69	250.75	250.81	250.87	250.93	250.99	251.05	251.11	251.17	251.24	**Band 26**
251.34	251.40	251.46	251.52	251.58	251.64	251.70	251.76	251.82	251.88	251.94	252.00	252.06	252.13	**Band 27**
252.23	252.29	252.35	252.41	252.47	252.53	252.59	252.65	252.71	252.77	252.83	252.89	252.95	253.02	**Band 27**
253.12	253.18	253.24	253.30	253.36	253.42	253.48	253.54	253.60	253.66	253.72	253.78	253.84	253.90	**Band 29**
254.00	254.06	254.12	254.18	254.24	254.30	254.36	254.42	254.48	254.54	254.60	254.66	254.72	254.79	**Band 30**

Table 5.4: Table of Mobile Phone Frequency Bands

System Bandwidth (B_{SYS})/MHz														Band Allocation
890.00	890.28	890.56	890.84	891.12	891.40	891.68	891.96	892.24	892.52	892.80	893.08	893.36	893.58	**Band 1**
893.68	893.96	894.24	894.52	894.80	895.08	895.36	895.64	895.92	896.20	896.48	896.76	897.04	897.26	**Band 2**
897.36	897.64	897.92	898.20	898.48	898.76	899.04	899.32	899.60	899.88	900.16	900.44	900.72	900.94	**Band 3**
901.04	901.32	901.60	901.88	902.16	902.44	902.72	903.00	903.28	903.56	903.84	904.12	904.40	904.62	**Band 4**
904.72	905.00	905.28	905.56	905.84	906.12	906.40	906.68	906.96	907.24	907.52	907.80	908.08	908.30	**Band 5**
908.40	908.68	908.96	909.24	909.52	909.80	910.08	910.36	910.64	910.92	911.20	911.48	911.76	911.98	**Band 6**
912.08	912.36	912.64	912.92	913.20	913.48	913.76	914.04	914.32	914.60	914.88	915.16	915.44	915.66	**Band 7**
915.76	916.04	916.32	916.60	916.88	917.16	917.44	917.72	918.00	918.28	918.56	918.84	919.12	919.34	**Band 8**
919.44	919.72	920.00	920.28	920.56	920.84	921.12	921.40	921.68	921.96	922.24	922.52	922.80	923.02	**Band 9**
923.12	923.40	923.68	923.96	924.24	924.52	924.80	925.08	925.36	925.64	925.92	926.20	926.48	926.70	**Band 10**
926.80	927.08	927.36	927.64	927.92	928.20	928.48	928.76	929.04	929.32	929.60	929.88	930.16	930.38	**Band 11**
930.48	930.76	931.04	931.32	931.60	931.88	932.16	932.44	932.72	933.00	933.28	933.56	933.84	934.06	**Band 12**
934.16	934.44	934.72	935.00	935.28	935.56	935.84	936.12	936.40	936.68	936.96	937.24	937.52	937.74	**Band 13**
937.84	938.12	938.40	938.68	938.96	939.24	939.52	939.80	940.08	940.36	940.64	940.92	941.20	941.42	**Band 14**
941.52	941.80	942.08	942.36	942.64	942.92	943.20	943.48	943.76	944.04	944.32	944.60	944.88	945.10	**Band 15**
945.20	945.48	945.76	946.04	946.32	946.60	946.88	947.16	947.44	947.72	948.00	948.28	948.56	948.78	**Band 16**
948.88	949.16	949.44	949.72	950.00	950.28	950.56	950.84	951.12	951.40	951.68	951.96	952.24	952.46	**Band 17**
952.56	952.84	953.12	953.40	953.68	953.96	954.24	954.52	954.80	955.08	955.36	955.64	955.92	956.14	**Band 18**
956.24	956.52	956.80	957.08	957.36	957.64	957.92	958.20	958.48	958.76	959.04	959.32	959.60	959.90	**Band 19**
960.00	1028.45	1096.90	1165.35	1233.80	1302.25	1370.70	1439.15	1507.60	1576.05	1712.95	1644.50	1781.40	1849.90	**Band 20**
1850.00	1851.19	1852.38	1853.57	1854.76	1855.95	1857.14	1858.33	1859.52	1860.71	1861.90	1863.09	1864.28	1865.46	**Band 21**
1865.56	1866.75	1867.94	1869.13	1870.32	1871.51	1872.70	1873.89	1875.08	1876.27	1877.46	1878.65	1879.84	1881.02	**Band 22**
1881.12	1882.31	1883.50	1884.69	1885.88	1887.07	1888.26	1889.45	1890.64	1891.83	1893.02	1894.21	1895.40	1896.58	**Band 23**
1896.68	1897.87	1899.06	1900.25	1901.44	1902.63	1903.82	1905.01	1906.20	1907.39	1908.58	1909.77	1910.96	1912.14	**Band 24**
1912.24	1913.43	1914.62	1915.81	1917.00	1918.19	1919.38	1920.57	1921.76	1922.95	1924.14	1925.33	1926.52	1927.70	**Band 25**
1927.80	1928.99	1930.18	1931.37	1932.56	1933.75	1934.94	1936.13	1937.32	1938.51	1939.70	1940.89	1942.08	1943.26	**Band 26**
1943.36	1944.55	1945.74	1946.93	1948.12	1949.31	1950.50	1951.69	1952.88	1954.07	1955.26	1956.45	1957.64	1958.82	**Band 27**
1958.92	1960.11	1961.30	1962.49	1963.68	1964.87	1966.06	1967.25	1968.44	1969.63	1970.82	1972.01	1973.20	1974.38	**Band 27**
1974.48	1975.67	1976.86	1978.05	1979.24	1980.43	1981.62	1982.81	1984.00	1985.19	1986.38	1987.57	1988.76	1989.90	**Band 29**
1990.00	1991.19	1992.38	1993.57	1994.76	1995.95	1997.14	1998.33	1999.52	2000.71	2001.90	2003.09	2004.28	2005.46	**Band 30**

To ascertain the particular modulation detected by the algorithm, the developed ADAMR was designed in a matrix form called a table of Modulation Scheme Detection Matrix (MSDM), as shown in Figure 5.8. The position of “1”, in each row of the table indicates the presence of the corresponding modulation scheme in the channel. This table of MSDM, Figure 5.8, is used in stages 2 and 3 of the algorithm to detect the presence of the modulation scheme in the channel.

$$MSDM = \begin{bmatrix} 0&0&0&0&0&0&0&0&0&0&0&0&1 \\ 0&0&0&0&0&0&0&0&0&0&0&1&0 \\ 0&0&0&0&0&0&0&0&0&0&1&0&0 \\ 0&0&0&0&0&0&0&0&0&1&0&0&0 \\ 0&0&0&0&0&0&0&0&1&0&0&0&0 \\ 0&0&0&0&0&0&0&1&0&0&0&0&0 \\ 0&0&0&0&0&0&1&0&0&0&0&0&0 \\ 0&0&0&0&0&1&0&0&0&0&0&0&0 \\ 0&0&0&0&1&0&0&0&0&0&0&0&0 \\ 0&0&0&1&0&0&0&0&0&0&0&0&0 \\ 0&0&1&0&0&0&0&0&0&0&0&0&0 \\ 0&1&0&0&0&0&0&0&0&0&0&0&0 \\ 1&0&0&0&0&0&0&0&0&0&0&0&0 \end{bmatrix} \begin{bmatrix} 2ASK \\ 4ASK \\ 2FSK \\ BPSK \\ QPSK \\ AM \\ DSB \\ SSB \\ FM \\ OFDM \\ 16QAM \\ 64QAM \\ NONE \end{bmatrix}$$

Figure 5.8: Modulation Scheme Detection Matrix

In stage 3, a fine spectrum-sensing operation is executed. The algorithm searches for the presence of any modulation scheme by scanning through the B_{BLK} as previously described and demonstrated in Figure 4.2 of chapter 4. If any of the modulation schemes are detected, the channel is noted as occupied and finally the status of the channel during this local sensing process is updated as “1”, in the learning engine. However, if there is no modulation scheme in the channel, the channel is noted as idle and its status is updated as “0”, in the learning engine. These binary observations of “1” and “0”, for occupied and idle channels respectively, are the results of the local spectrum sensing that are reported to the SU^{SMN} by SU^{S}s. This local sensing reporting procedure is illustrated in Figure 5.9. Also, at this stage, the time taken to carry out the fine sensing (T_{FRS}) is calculated using equation (4.7). The calculated T_{FRS} value is stored in the learning engine.

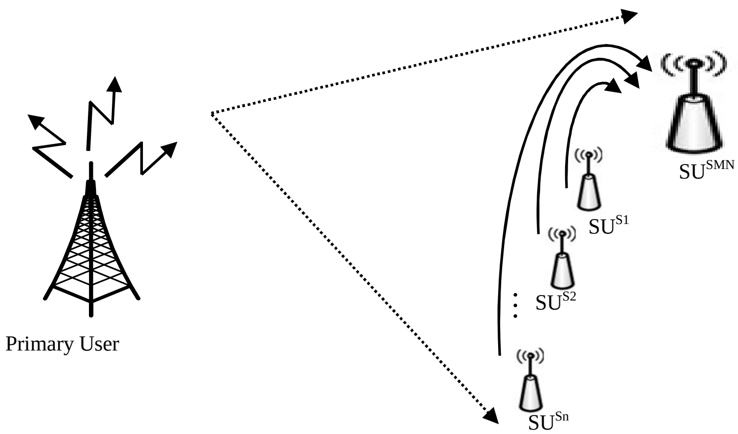


Figure 5.9: Local Cooperative Sensing Reporting Model

In stage 4, depicted in Figure 5.7, which is the last stage of the algorithm, terminates one complete cycle. In the stage, the SU^{SMN} combines all the binary observations from the third stage using “OR” logic, as illustrated in Table 5.5. The “OR” logic was used to prevent both false and miss detection rate probabilities. Furthermore, in this stage, the “OR” logic result is tested. If the “OR” logic result is “1”, the channel is confirmed as occupied and unsafe for secondary transmission by SU.

However, if the “OR” logic result testing is “0”, the channel is confirmed as idle and safe for secondary or opportunistic usage. The result of the “OR” logic test provides the final decision on the channel. A typical result of the spectrum scanning exercise by the algorithm is shown in Figure 6.4. When the final decision is made like this, the SU^{SMN}, also known as MN, transmits the final decision for opportunistic secondary transmission possibility to the CR or SU as illustrated in Figure 5.3. The algorithm finally determines the total time (T_S) taken to carry out the overall spectrum-sensing using equation (4.8).

Table 5.5: Table of “OR” logic

SU^S	SU^S	SU^{SMN}
0	0	0
0	1	1
10	0	1
1	1	1

After a complete cycle like this, the spectrum sensing by the SU^S starts all over again while SU is transmitting on the detected idle channel. As mentioned earlier, the proposed sensing and detection method uses separate devices as the spectrum sensor and secondary transmitter. This approach enables continued sensing of the cognitive radio environment, even when the secondary transmitter is transmitting opportunistically in a licensed spectrum. The approach therefore assists in preventing secondary user interference to a primary owner in a situation where the primary user re-appears while the secondary transmission is in progress. The evaluation of the developed SSADA, described above, in achieving the desired objective of the study is presented in the next chapter.

5.6 Summary

The objective of developing a CRE that can automatically sense and detect radio signals in the cognitive radio environment without having *a priori* information about the signals characteristics was achieved in this chapter using the developed SDR and CE. The performance evaluations of the developed CRE and SSADA, also known as CE, are presented in chapter 6.

CHAPTER 6

6.0 THE DEVELOPED COGNITIVE RADIO ENGINE EVALUATION

This chapter presents detailed information on the performance evaluation tests carried out on the CRE as developed. The tests are classified under two main headings, namely laboratory/experimental setup and SSADA proof of concept evaluation. The performance of the CRE for spectrum sensing and detection is analyzed and verified through the numerical results obtained.

6.1 Experimental Evaluation of the Developed Cognitive Radio Engine

Experiments were conducted to evaluate the performance of the developed CRE setup in the previous chapter. Three main performance criteria or metrics were employed. The designated USRP2 primary transmitter was used to transmit modulated signals generated in the host PC. The results obtained for each of the performance evaluation metrics are presented and discussed in the following sub-sections.

6.1.1 Detection States

From equation (2.1), it can be deduced that the spectrum sensing output can fall into any of these three detection states, namely:

- correct detection;
- miss detection; and
- false detection.

These three detection states are defined, as follows:

- Occupied spectrum or channel detected as occupied and/or unoccupied spectrum or channel detected as unoccupied (i.e. correct detection);

- Occupied spectrum or channel detected as unoccupied (i.e. miss detection); and
- Unoccupied spectrum or channel detected as occupied (i.e. false detection).

Considering the three detection states, it is obvious that while both correct and false detection states would cause no interference to the primary user in a cognitive radio environment, miss detection would certainly cause a secondary user to interfere with the primary user's transmission. Hence, if interference avoidance to the primary user is the only parameter considered in determining both the effectiveness and efficiency of the developed CRE, high correct detection and high false detection with low miss detection would have been the expected result from the developed CRE. However with high false detection, one of the disadvantages is that the spectrum would not be efficiently utilized, since idle spectrum is being classified as busy spectrum. Another disadvantage of high false detection is that it would introduce a high cooperative overhead to the spectrum sensing in terms of additional energy and sensing time.

Therefore, in assessing both the effectiveness and efficiency of the developed CRE for this research work, its detection accuracy with pre-known modulation schemes, denoting an occupied channel, and non-modulated noise, denoting an unoccupied channel, were examined. The average, overall detection accuracy results obtained are shown in Figure 6.1. From Figure 6.1, it is evident that both the miss and false detection states of the developed CRE are negligible. The result shows that the correct detection state is the highest, which is an indication of both high interference-free and high spectrum utilization efficiency.

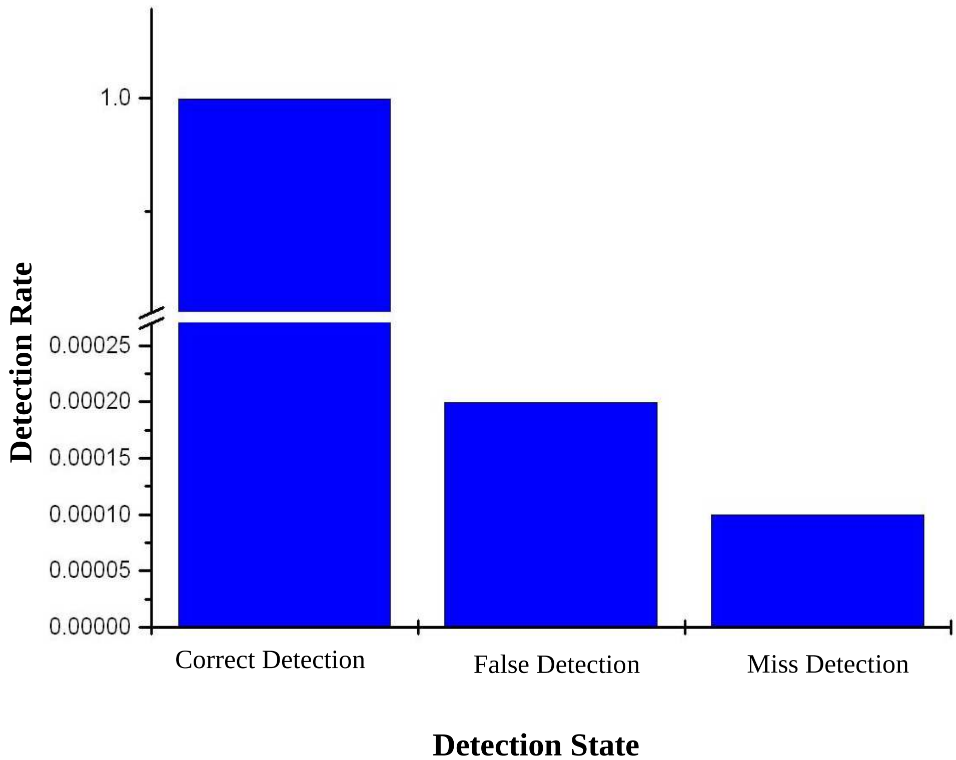


Figure 6.1: The Developed CRE Detection State

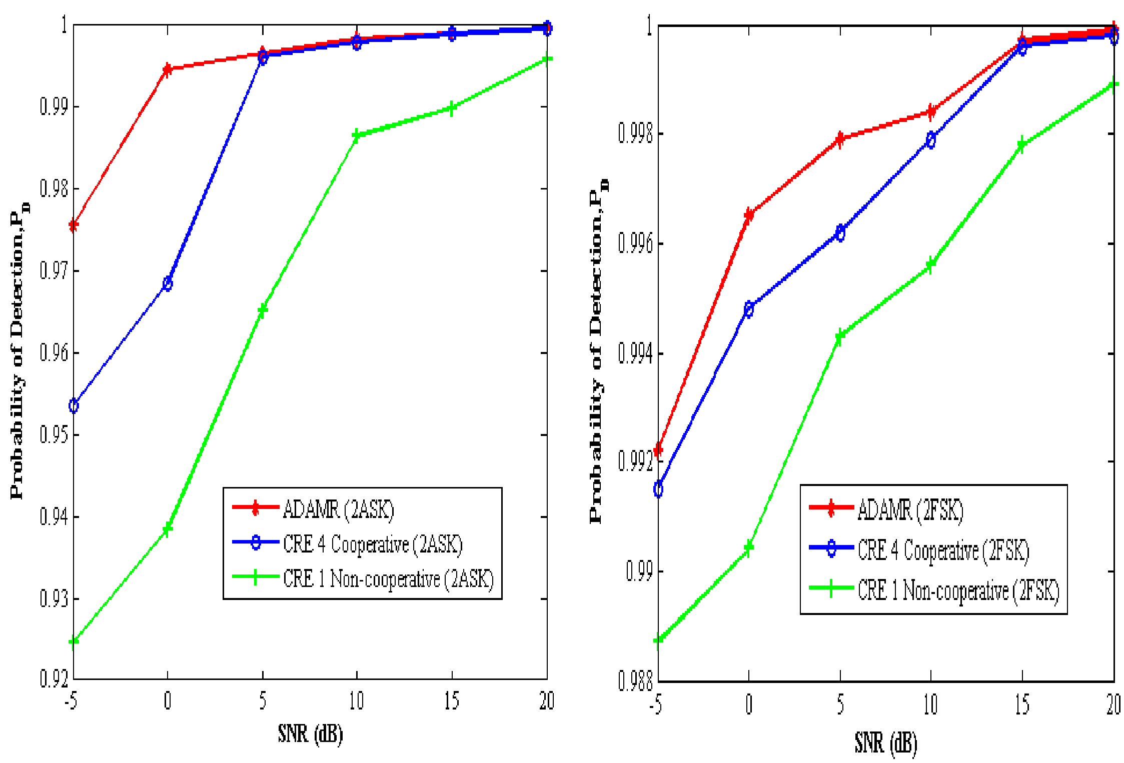
6.1.2 Probability of Detection

The sequel to the negligible false and miss detection states obtained when the developed CRE's overall signal-detection capability was tested was further evaluated. The additional performance evaluation test carried out on the developed CRE was its spectrum-sensing probability of detection (P_D). The metric, P_D, was used to determine the CRE level of interference protection provided to the primary user. The metric was determined for each of the modulation schemes employed at various SNR values. The numerical results obtained are presented in graphical form in Figure 6.2(a-h).

The P_D was measured for SNR levels ranging from – 5 dB to 20 dB. The measurements were repeated 50 times for each SNR value in order to accurately measure the P_D values obtained. The average P_D values plotted against the various SNR are shown in Figure 6.2(a-h) for eight out of the twelve modulation schemes considered. The P_D obtained at each SNR value for each of these eight modulation schemes is compared with the corresponding detection rate of the developed ADAMR presented in Table 3.6. Figure

6.2(a-h), shows that the P_D for the developed CRE was less compared with corresponding P_D values for the developed ADAMR at low SNR values of – 5 dB and 0 dB. However, as the SNR values increase, for instance from 5 dB upward, the CRE's P_D performance increases comparably with that of the ADAMR.

Figure 6.2(a-h), also shows that the developed CRE level of interference protection to the primary user is favourable at all the SNR values considered with the average P_D value above 0.9. The metric value also shows that the developed CRE is not biased towards either of the modulation schemes employed or any of the SNR values. It was also evident from these figures that the performance of this detection method is directly proportional to that of the developed ADAMR used. The implication of this observation is that the sensitivity of the automatic classifier employed has a direct impact on the P_D of the developed CRE. Hence, if the detection ability of the classifier employed is low, the P_D ability of the CRE will also be low.



(a) (b)

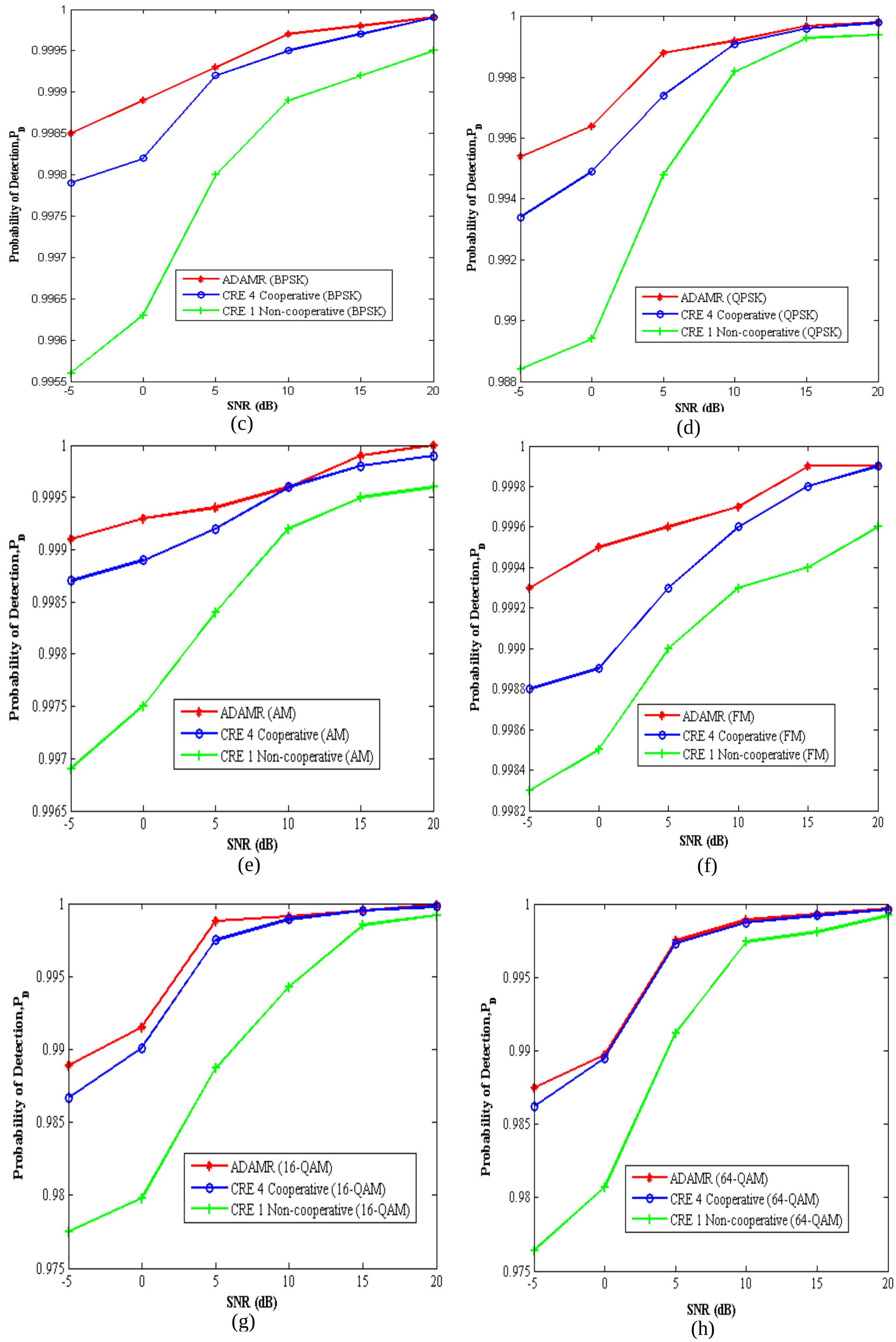


Figure 6.2: The Developed ADAMR and CRE Detection Probability

Further consideration of Figure 6.2(a-h) shows the better performance of the cooperative nodes over the non-cooperative or single node individually performing the spectrum sensing operation. A careful observation of each of the eight plots (a) to (h) in Figure 6.2 shows that the corresponding values of P_D for cooperative nodes are higher than that of non-cooperative nodes. The plots also reveal that the P_D values of the cooperative nodes are favourable with that of the ADAMR compared with those of corresponding non-cooperative nodes. This again shows the advantage of cooperative spectrum sensing over the non-cooperative spectrum sensing in term of performance index. In addition, the analysis shows that cooperative spectrum sensing application guarantees high interference protection to the primary user than non-cooperative sensing method.

6.1.3 Detection Response Time

The third performance evaluation metric that was used to evaluate the performance of the developed CRE for this research work is the time taken to detect different modulation schemes. This detection response time is different from the calculated average recognition time for the AAMR, DAMR and combined ADAMR classifiers presented in Table 3.2, Table 3.5, and Table 3.7 respectively. The classifier recognition time taken or duration presented in those Tables on page 89, 101 and 109 respectively are the respective classifier's recognition time. But the response time considered in this section is the time taken for the developed CRE to recognize modulation schemes used to test its response rate.

As mentioned earlier, out of these three classifiers, only the combined ADAMR classifier was employed in the CRE developed for this study. Hence, when this test was carried out, the response time obtained was the CRE response time for the different modulation schemes transmitted. Analog, digital and combined analog and digital modulation schemes were transmitted from the designated USRP2 transmitter at random. The duration of detecting the modulation schemes was observed.

The detection response time, presented graphically in Figure 6.3, reveals that the detection response time for the modulated signals varies considerably from one modulated type to another. The numerical results presented in Figure 6.3 shows that the developed CRE response time for the digitally modulated signal is the fastest, while its response time to detect a combined analog and digital modulated signal was the slowest. The detection response time for the analog modulated signal falls somewhere in between.

Although the CRE's response time or observation time for the modulated signals varies from one modulated type to another, the overall short time, in the ranges of milliseconds that the CRE uses to detect all the modulation schemes considered coupled with its non-complexity in nature, makes the implementation of the proposed sensing and detection method practically feasible.

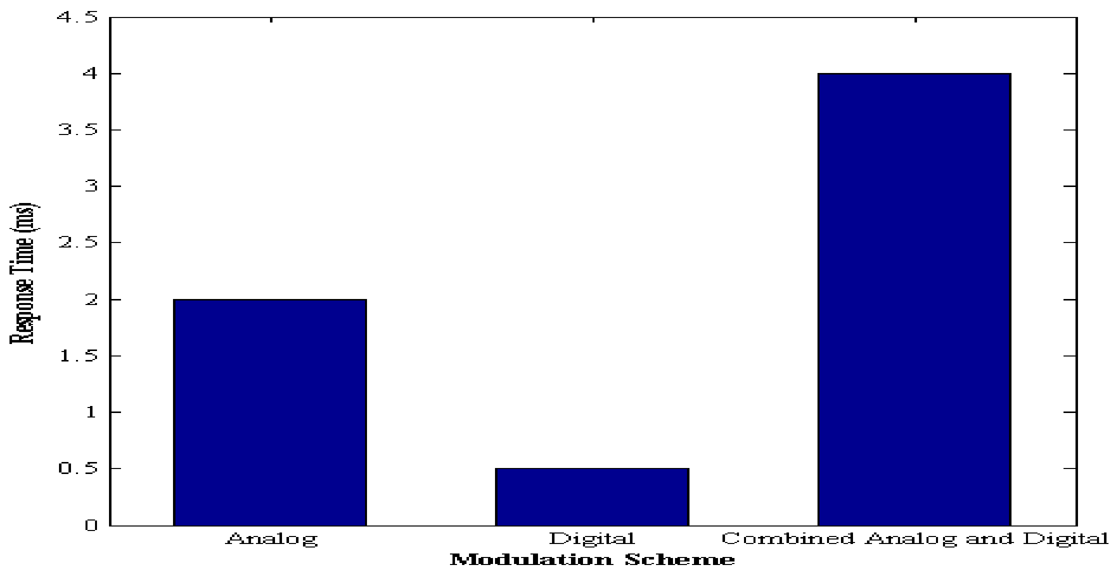


Figure 6.3: Detection Response Time for FM, 16-QAM and Combined Modulated Signals

6.2 Comparative Analysis

To further evaluate the performance of the CRE, results obtained from it were compared with a recent study on another spectrum sensing and detection method. The choice of the reference study, Haniz *et al*., (2010), was characterized by:

- usage of both GNU Radio and USRP;
- usage of the same ranges of SNR;
- application of mixed or combined analog and digital modulation schemes;
- usage of same AWGN channel condition; and
- usage of the same USRP daughterboard (XCVR 2450).

However, two differences are observed between this research work and the reference study in Haniz *et al*., (2010). The first is the SNR ranges employed. While this research work used SNR values ranges from – 5 to 20 dB, the reference study used SNR values ranges from – 20 to 10 dB. Hence, for the comparative analysis, only the limited SNR ranges of – 5 dB to 10 dB, common to the two studies were considered. The second observed difference between this research work and study presented in Haniz *et al*., (2010), is the detection method employed. While the reference work used the energy detection method, which is currently acclaimed the best detection method (Akyildiz *et al*., 2011) in literature, this study employed the automatic modulation recognition technique.

However, the authors of the reference study used both AM and BPSK modulated signals, which are parts of the modulation schemes considered in this research work, to test their spectrum sensing performance. The two modulation schemes used to evaluate their spectrum sensing system as well as the best acclaimed detection method used in the reference study makes it the most appropriate study to further evaluate the performance of the developed CRE and the detection method proposed in this research work. The obtained comparison result is presented in Table 6.1.

The result shows that this research work produced better P_D results at a low SNR value of – 5 dB for the two modulation schemes considered. The poor performance of the reference work at this low SNR value indicates that the reference work detection of weak primary radio signal is relatively low compared with this thesis. Therefore, the outperformance of this research work at this low SNR value shows that the developed CRE in this research work can reliably detect weak primary radio signal in a CR environment better than the reference work. Hence, application of the detection method developed in this thesis does guarantee interference free in a CR environment when compared with the reference work. In addition, the better P_D results of this research work at a low SNR value over the reference work makes this research work more relevant in CR environment than the reference work. This is because the ability of the developed CRE in this research work to reliably detect weak primary radio signal has provided another milestone toward solving the problem of weak signal detection in CR environment, which is one of the challenging issues in CR environment.

The reference work, however, outperforms this research work in the other three SNR values but with only a close margin. The overall analysis of the comparative study presented in Table 6.1 shows that this research work performs favourably well with previous work in the literature. The analysis result also confirms that the automatic modulation identification's detection method proposed in this research work can compare favourably well with the energy detection method which is the current generally acclaimed best detection method.

Table 6:1: Probability of Detection Values' Comparison between this Research Work and Haniz *et al*., (2010)

SNR (dB)	Doctoral Thesis (Popoola, 2011)				Conference Proceedings (Haniz *et al*., (2010) *			
	P_D Value for AM Signal		P_D Value for BPSK Signal		P_D Value for AM Signal		P_D Value for BPSK Signal	
	Single Node	Cooperative Nodes	Single Node	Cooperative Nodes	Single Node	Cooperative Nodes	Single Node	Cooperative Nodes
- 5	0.996	0.998	0.995	0.997	0.500	0.900	0.550	0.930
0	0.997	0.998	0.996	0.998	0.950	1.000	0.990	1.000
5	0.998	0.999	0.998	0.999	1.000	1.000	1.000	1.000
10	0.998	0.999	0.998	0.999	1.000	1.000	1.000	1.000

*: Data's second decimal points are approximate values extracted from graphs.

6.3 SSADA Proof of Concept Evaluation

Due to limitations of the USRP2 daughterboards availability, the tests results presented above were carried out using an XCVR2450 daughterboard operating in an ISM frequency band. Therefore, in order to extend the testing, as well as showcase the practicability of the proposed spectrum sensing and detection method in other usable frequency bands, the CE, which is the brain of the developed CRE, was further developed in a graphical user interface called SSADA. The SSADA's development was fully described in chapter 5, while its performance is briefly examined in this chapter. Additional information on the performance evaluation of SSADA is presented in Appendix C. Meanwhile, its performance evaluation in a hypothetical television frequency allocation table is presented below using two of its features. The two features demonstrated are its spectrum scanning and cooperative gain optimization prediction's capabilities presented in section 6.3.1 and 6.3.2 respectively.

6.3.1 SSADA Spectrum Scanning Capability Test

A typical spectrum scanning result by the developed SSADA is presented here. Based on the current radio spectrum allocation policy, the Television (TV) frequency bands shown in Table 5.4 are randomly allocated among the six cities used. The frequency bands' random allocation was carried out to conform to the current frequency allocation policy. Figure 6.4 shows typical cooperative spectrum sensing for the hypothetical TV frequency band. The algorithm scans each frequency band to detect spectrum holes in each band before proceeding to the next band. The result shows that the developed SSADA functions well, with a high capability of detecting occupied bands and spectrum holes respectively in the TV frequency bands used to illustrate it capability.

: Represent some cut off parts of the scanning result's screen

Figure 6.4: A Section of Typical TV Frequency Bands Scanning Result

Careful observation of the developed SSADA shows that, irrespective of the allocated frequency bands for each of the locations, the developed SSADA is designed to scan the overall frequency bands for each wireless service. This approach enables OSA or DSA deployment in all the locations as the overall scanning of the spectrum provides information on primary user activity on each channel per time period, and therefore enhances overall optimal spectrum utilization. Further evaluations of the SSADA are presented in Appendix C.

6.3.2 Sensing Time versus FFT size

The second evaluation test carried out on the developed SSADA is its capability of predicting the appropriate setting of the FFT size (N), so as not to incur a cooperative overhead. The parameter, N, was not considered in chapter 4, however, observation shows that its indiscriminate selection can affect the sensing time and increase the cooperative overhead. Considering Figure 6.5, which shows the plot of the sensing time against N obtained from the developed SSADA, with value of N varying from 16 to 1024; the figure shows that the sensing time increases with increase in N. This is expected since processing gain is proportional to FFT size N and observation or sensing time (Čabrić *et al.*, 2004). However, Figure 6.5 shows that indiscriminate choice of N will increase the sensing time and cooperative overhead rather than increasing the sensing accuracy. Thus, in this research work, FFT size of 32 was employed. The FFT size of 32 was chosen because values of FFT sizes above 32 only cause a sporadic increase in Ts. This shows that the increase in N's value above 32 only increases the sensing or observation time, Ts, without enhancing the detection probability.

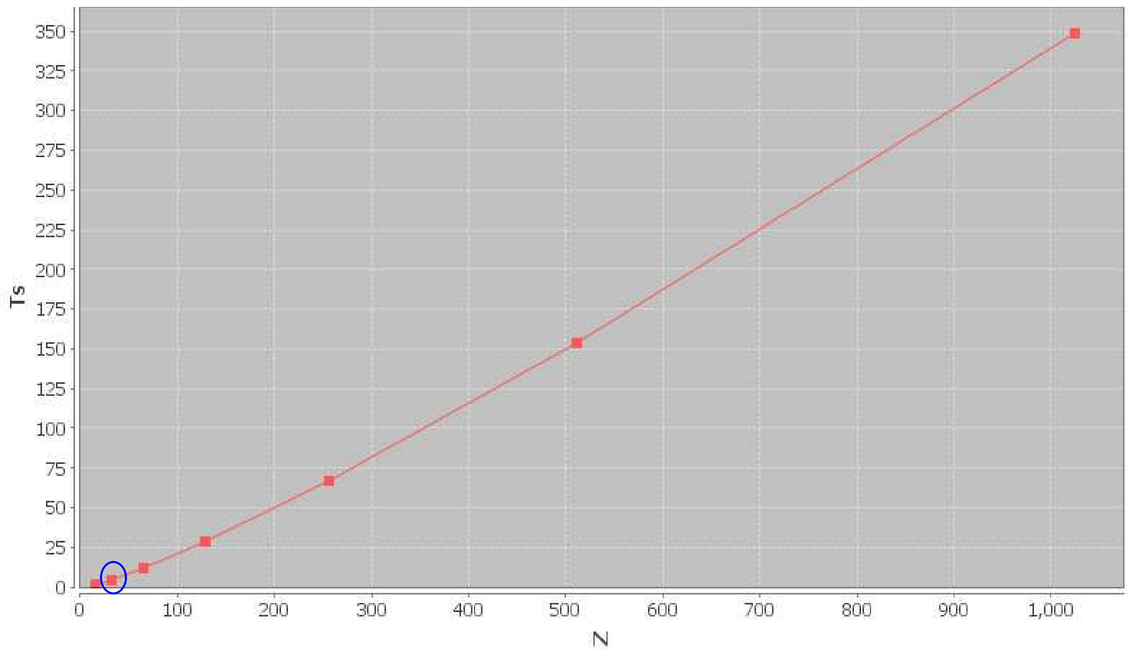


Figure 6.5: SSADA Sensing Time against FFT size N

6.4 Summary

In this chapter, the focus is on performance evaluation of the developed CRE for this research work. The laboratory setup to evaluate the performance of the developed CRE by determining its detection states and detection probabilities using various modulation schemes at different SNR shows that primary aim and objectives of the research had been achieved. Though the sensing time required for this sensing and detection method varies from one modulation type to another, its high correct detection state with negligible false and miss detection states is one of the significant advantages of the proposed method. Its other advantage is its high average P_D values that cut across all the SNR values for all the modulation schemes considered.

In addition, the capability of the developed SSADA that could scan all the hypothetical allocated frequency bands for the four wireless services within the country is an indication that the CRE as developed, which incorporates implemented CE as its core, can enhance OSA or DSA deployment in any part of the country. Similarly, since the hypothetical allocated frequency bands can be replaced by any frequency bands of any country, makes the developed CRE's deployment applicable to any part of the world.

CHAPTER 7

7.0 RESEARCH SUMMARY AND CONCLUSION

This chapter concludes this thesis with a brief summary of the thesis and the contributions of the work to the field of primary radios' signals sensing and detection in a cognitive radio environment. The chapter ends with recommendations on the adoption of DSA as an alternative spectrum access strategy in mitigating the current challenge of spectrum underutilization and enhancing the continued availability of radio spectrum for future wireless devices.

7.1 Thesis Summary

The world as a whole is approaching the limits of the availability of useable radio frequency for wireless communication, while at the same time the demand for and use of radio spectrum for wireless services and applications are greatly increasing. Observations have also shown that, as the demand for and use of the radio spectrum is increasing, so do the challenges to the successful management of the radio spectrum using the current fixed allocation policy. In light of this, there is a need to adopt an alternative radio spectrum access strategy and management policy that would enhance both the management and usage of radio spectrum in order to enhance radio spectrum availability for future wireless devices. The aim of this research work, as stated in chapter 1, is to develop a CRE that can sense and detect all forms of primary radio signals in a cognitive radio environment. This is because the development of this type of radio engine that generates little or no interference to primary users in a cognitive radio environment, such a radio engine is one solution that can guarantee the general acceptance of cognitive radio technology, which is a promising solution for overcoming radio spectrum scarcity and underutilization currently experiencing worldwide.

In achieving this aim, a comprehensive literature review on conventional primary radio detection methods in a cognitive radio environment was carried out in chapter 2. It was during the literature survey that factors responsible for failure of most of these conventional spectrum sensing and detection methods was discovered, as most of these methods were developed based on features that are limited to certain types of radio signals, instead of employing a feature that is common to all primary radio signals. This shortfall was accounted for in this research work, by using an automatic modulation identification methodology to develop this research work's spectrum sensing and detection method. The methodology was used because all radios using the radio spectrum make use of one modulation or another.

Chapter 3 discussed in full the procedures involved in developing the Automatic Modulation Recognition (AMR) classifier used for the research. The starting point for the AMR classifiers' development, which is the feature keys extraction process, was presented in chapter 3. The chapter also contains detailed information on the development and evaluation of the three AMR classifiers developed. In chapter 4, the sensing time algorithm for enhancing cooperative spectrum sensing performance was developed.

Chapter 5 of this thesis was devoted to one of the major components of this research work, which is on the development of a CRE to sense and detect a primary radio signal in a cognitive radio environment. The importance of CRE in cognitive radio technology was reviewed in section 2.5. Different AI schemes employed in developing previous CREs were also reviewed in that section. The review of these schemes revealed their limitations, such as non-resistance to noise, which was adequately taken care of in the ANN employed for the development of the CRE in this research work.

The other major component of this research is the development of an SSADA or CE using the JAVA programming language. The user-friendly interface program was developed to provide a proof of concept evaluation of the developed CRE, where the developed SSADA is its core brain. The SSADA incorporates the following three modules:

- Preferred service and location for radio spectrum scanning and random table of frequency allocation per geographical location;

- The plotting section, where the sensing time parameters selection for optimizing cooperative spectrum sensing gain can be done; and
- The manual calculations section for calculating the spectrum sensing time (Ts).

The three modules incorporated in the developed SSADA are shown in Figure C.1 in Appendix C.

Testing of the developed CRE and SSADA using different performance criteria and metrics was undertaken. Although the proposed sensing and detection method's response time varies with the modulation schemes, the overall results revealed that the developed CRE and SSADA were versatile. In addition, the favouarble comparative analysis result obtained when the results of the proposed sensing and detection method in this research work was compared with the generally acclaimed best detection method in the literature provides a good assessment of the proposed sensing and detection method in this research.

7.2 Conclusion and Recommendation

The dynamic spectrum access, which is one of the applications of cognitive radio technology, has been observed as a promising solution to the problem of radio spectrum scarcity and underutilization by introducing the opportunistic usage of licensed frequency bands that are not efficiently utilized by licensed owners. Following the general belief that spectrum sensing is the key functionality to enable DSA, this research work focused on issues of spectrum sensing. The thesis discussed merits and demerits of most of the current detection methods or algorithms presented in literature. After a careful, neutral and constructive analysis of most of the current detection methods in literature, it showed that none of the methods can adequately and reliably detect all forms of primary radio signals in a cognitive radio environment. This leads to the novel detection method proposed in this research work using an automatic modulation recognition method.

The implementation of this study's detection method using both hardware and software components has been fully discussed. Also the results obtained in this study, when compared with other conventional detection methods, showed high reliability of the proposed detection method in detecting all forms of primary radio signals in a cognitive radio environment. Although the proposed sensing and detection method's observation time or sensing time varies with modulation schemes, the numerical result from the study shows the significant performance of the proposed detection method, even at a low SNR values, where the conventional detection methods usually perform poorly.

In addition to these, another significant contribution of this research work is the practical implementation of the proposed detection method using practical and available components. This study has shown that the practical development of a reliable detection method is possible and attainable using AMR. The AMR, which is the core identification feature employed in this detection method, has confirmed the preliminary investigated discovery during the literature survey that most conventional detection methods in literature perform poorly because the features used were not features common to all radio signals like the modulation identification scheme employed in this study. The proposed detection method in this research shows a favourable comparison with the energy detection method, whereby signal energy content, which is also a feature common to all radio signals, shows that a single spectrum sensing and detection method can only be achieved when a feature common to all radio signals is employed in its development rather than using features that are limited to certain signal types.

Another significant factor or contribution of this research work is the bedrock information it has provided on how to improve cooperative spectrum sensing gain without incurring a cooperative overhead. Numerical results from the study have shown that not only does the detection method perform well, but that the overall objectives of the research work have been achieved.

Based on the results obtained from this research work and the performance of the novel spectrum sensing detection method proposed in this study, it is hereby recommended that the adoption of an opportunistic spectrum access, also known as DSA, as an alternative spectrum access strategy be adopted. The access strategy is proposed because it will not only solve the current problem of radio spectrum underutilization, but will equally reduce the current problem of radio spectrum scarcity. Furthermore, because the proposed detection method in this thesis guarantees no interference amongst users of the spectrum, which is the primary objective of the traditional fixed spectrum allocation policy, thus the adoption of DSA will not compromise the performance of existing radio systems that will continue to adopt the traditional radio spectrum regulation system with the implementation of the novel detection method devised in this research work.

7.3 Future Work Recommendations

With the success recorded in this research work, there is guarantee now that the perceived danger of interference due to DSA radio operation has been solved and the adoption of DSA using CR technology for radio spectrum management and access is gradually becoming a reality. However, some research work still needs to be done. The recommended work is actually outside the scope of this research project but it is recommended for future work so as to enhance the CRE developed in this research as well as accelerating the immediate adoption of DSA. The future work recommended is as follows:

- Firstly, future work needs to be carried out on how to incorporate an efficient and adaptive channel access scheme that can support both dynamic channel selection and power allocation in a cognitive radio environment to the CRE developed. To achieve this, instead of the random allocation of the radio spectrum band by MN in this study, game theory for spectral resources, such as power and spectrum bands, allocation can be incorporated into the CRE developed. The use of game theory was specified because of its inherent capability to check users that behave in a selfish manner by seeking a performance advantage over other users at the cost of overall network performance.

- Secondly, future work needs to be carried out on the developed ADAMR classifier incorporated in the developed CRE in this thesis. This is to improve the classifier operational time and the developed CRE detection time. Another alternative work to this is to replace the ADAMR classifier employed in the development of the CRE for this thesis with DAMR with better operational time performance especially now that most systems and nations are shifting from analog communication system to digital communication system. Furthermore, the number of the modulation schemes can be increased to accommodate more modulation schemes.

- Thirdly, comparative future work analysis on this thesis algorithm complexity and that of energy method needs to be carried. This future work is essential as it will provide basis for comparing the two spectrum sensing and detection methods on their respective complexity, which is different from the comparative P_D performance analysis carried out in this thesis.

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APPENDIX A: M-FILE FOR THE THREE CLASSIFIERS

APPENDIX A1: ANALOG CLASSIFIER M-FILE

```
% ===================================================================
% Author: J.J. Popoola
% Date: 17/02/2011
% -------------------------------------------------------------------
% Script for preparing the Analog generated data for Automatic
% Modulation Classification (AMC)
% The 3 feature extracted keys generated form the inputs to the
% classifier
% The classifier has 4 outputs corresponding to the four modulation
% schemes (AM, DSB, SSB and FM) intended to classify or identify
% Inputs features and output target are combined in matrix form
% Database is split into training data, validation data and test data
% Prepare_Features(traindata,validdata,testdata)
% ===================================================================
% Load the generated feature extracted data imported to MATLAB
% environment from excel called data already in input-output matrix
% form

load data

% -------------------------------------------------------------------
% Normalize each column of the 400 x 7 data matrix

[r,c] =size(data);
Max = repmat(max(data), [r 1]);
Min = repmat(min(data), [r 1]);
output1 = (data - Min)./(Max - Min);

% -------------------------------------------------------------------
% Randomizing the normalized data matrix each column of the 400 x 7 data
matrix

output2 = output1(randperm(size(output1,1)),:);
% -------------------------------------------------------------------

% Now split the randomized data i.e. output2 into trainingset,
validationset and testset data sets in 50%, 25% and 25% respectively

% Save the divided data sets as Prepared_Features.mat

trainingset = output2([1:200],:);
trainingsetinput = trainingset(:,[1:3]);
trainingsetoutput = trainingset(:,[4:7]);
X_trn = [trainingsetinput,trainingsetoutput];
save trn_data X_trn;

validationset = output2([201:300],:);
validationsetinput = validationset(:,[1:3]);
validationsetoutput = validationset(:,[4:7]);
X_valid = [trainingsetinput,trainingsetoutput];
save valid_data X_valid;

testset = output2([301:400],:);
testsetinput = testset(:,[1:3]);
testsetoutput = testset(:,[4:7]);
X_test = [testsetinput,testsetoutput];
```

```
save test_data X_test;

save('Prepared_Features.mat', 'testsetinput', 'testsetoutput',
'validationsetinput', 'validationsetoutput', 'trainingsetinput',
'trainingsetoutput')

% start stopwatch timer for the "operation" using tic, which save the
% current time

tic

% Load features

load Prepared_Features.mat

% classifying the input-output size

no_input = size(validationsetinput,2);
no_out = size(validationsetoutput,2);

% ----------------------------------------------------------------------
% Set up Network Parameters

% net = mlp(nin,nhidden,nout,outfunc,alpha)

nin = no_input;         % Number of inputs.
nhidden = 7;            % Number of hidden units or neurones.
nout = no_out;          % Number of outputs.
alpha = 0.01;           % Coefficient of weight-decay prior.
outfunc = 'logistic';   % String describing the output unit activation
                          function

% Create and initialize network weight vector.

net = mlp(nin,nhidden,nout,outfunc,alpha);

% Training the network



% ----------------------------------------------------------------------

% Set up vector of options for the optimiser

options = zeros(1,18);
options(1) = 1;      % This provides display of error values
options(14) = 100;   % Number of training cycles observed

% Train using scaled conjugate gradients.
[net, options] = netopt(net, options, trainingsetinput,…
trainingsetoutput, 'scg');


% Test the Network
```

```
% ----------------------------------------------------------------------

Output_Ts_mlp = mlpfwd(net, testsetinput);
Output_Ts_mlp = round(Output_Ts_mlp);
error = Output_Ts_mlp - testsetoutput;

% ----------------------------------------------------------------------

% Script for displaying the network training output

figure,
subplot(3, 1, 1);
imagesc(Output_Ts_mlp');
xlabel('Network  Output  Pattern'),ylabel('Success  Rate'),title('Network
MLP Output');
subplot(3, 1, 2);
imagesc(testsetoutput');
xlabel('Testset   Pattern'),ylabel('Success   Rate'),title('Testset   MLP
Output');
subplot(3,1,3), hold on;
imagesc(error');
xlabel('Network  Error  Pattern'),ylabel('Failure  Rate'),title('Network
Error MLP Output');


figure,
subplot(3, 1, 1);
bar(Output_Ts_mlp');
xlabel('Network  Output  Pattern'),ylabel('Success  Rate'),title('Network
MLP Output');
subplot(3, 1, 2);
bar(testsetoutput');
xlabel('Testset   Pattern'),ylabel('Success   Rate'),title('Testset   MLP
Output');
subplot(3,1,3);
bar(error');
xlabel('Network  Error  Pattern'),ylabel('Failure  Rate'),title('Network
Error MLP Output');



% ----------------------------------------------------------------------

% Save the AANN classifier

save ('AANN_Model.mat', 'net');

% Loading of the ('AANN_Model.mat','net') at Command Window can be used
% to evaluate the developed AANN classifier; thus:
% ----------------------------------------------------------------------

% load ('AANN_Model.mat','net')

mlpfwd(net,[training/validation/test data set]);

roundedValues = round(mlpfw(net,[training/validation/test data set]));
```

```
for i=1:4
    if i==1 && roundedValues(i,1)==1
        disp 'AM';
    end
    if i==2 && roundedValues(i,2)==1
        disp 'DSB';
    end
    if i==3 && roundedValues(i,3)==1
        disp 'SSB';
    end
    if i==4 && roundedValues(i,4)==1
        disp 'FM';
    end

end

%toc at the end of the "operation" measures the elapsed time for the
"operation"


toc

% round(mlpfw(net,[training/validation/test data set])); rounding up
% not necessary in order to give actual percentage of classification of
% each modulation scheme
% ---------------------------------------------------------------------
```

APPENDIX A2: DIGITAL CLASSIFIER M-FILE

```
% =====================================================================
% Author: J.J. Popoola
% Date: 17/02/2011
% ---------------------------------------------------------------------
% Script for preparing the Digital generated data for the Digital
% Automatic Modulation Recognition (DAMR)
% The 7 feature extracted keys generated form the inputs to the
% classifier
% The classifier has 8 outputs corresponding to the 8 modulation
% schemes (2ASK, 4ASK, 2FSK, BPSK, QPSK, OFDM, 16-QAM and 64-QAM)
% intended to classify or identify
% Inputs features and output target are combined in matrix form
% Database is split into training data, validation data and test data

% Prepare_Features_Digital_new(traindatasetdn,validdatasetdn,…
%  testdatasetdn)

% =====================================================================

% Load the generated feature extracted data imported to MATLAB
% environment from excel called newdigitaldata already in input-output
% matrix form

load newdigitaldata

% ---------------------------------------------------------------------

% Normalize each column of the 800 x 15 data matrix

[r,c] = size(newdigitaldata);
Max = repmat(max(newdigitaldata), [r 1]);
Min = repmat(min(newdigitaldata), [r 1]);
outputdd1 = (newdigitaldata - Min)./(Max - Min);
% ---------------------------------------------------------------------

% Randomizing the normalized data matrix each column of the 500 x 9
% data matrix

outputdd2 = outputdd1(randperm(size(outputdd1,1)),:);

% ---------------------------------------------------------------------

% Now split the randomized data i.e. outputd2 into trainingsetdn,
% validationsetdn and testsetdn data sets in 50%, 25% and 25%
% respectively

% Save the divided data sets as Prepared_Features_Digital.mat

trainingsetdn = outputdd2([1:400],:);
trainingsetinputdn = trainingsetdn(:,[1:7]);
trainingsetoutputdn = trainingsetdn(:,[8:15]);
X_trndn = [trainingsetinputdn,trainingsetoutputdn];
save trndn_data X_trndn;
```

```
validationsetdn = outputdd2([401:600],:);
validationsetinputdn = validationsetdn(:,[1:7]);
validationsetoutputdn = validationsetdn(:,[8:15]);
X_validdn = [trainingsetinputdn,trainingsetoutputdn];
save validdn_data X_validdn;

testsetdn = outputdd2([601:800],:);
testsetinputdn = testsetdn(:,[1:7]);
testsetoutputdn = testsetdn(:,[8:15]);
X_testdn = [testsetinputdn,testsetoutputdn];
save testdn_data X_testdn;

save('Prepared_Features_Digital_new.mat',              'testsetinputdn',
'testsetoutputdn',   'validationsetinputdn',   'validationsetoutputdn',
'trainingsetinputdn', 'trainingsetoutputdn')

% start stopwatch timer for the "operation" using tic, which save the
% current time

tic

% Load features

load Prepared_Features_Digital_new.mat

% classifying the input-output size

no_input = size(validationsetinputdn,2);
no_out = size(validationsetoutputdn,2);

% -----------------------------------------------------------------------
% Set up Network Parameters

% net = mlp(nin,nhidden,nout,outfunc,alpha)

nin = no_input;         % Number of inputs.
nhidden = 7;           % Number of hidden units or neurones.
nout = no_out;          % Number of outputs.
alpha = 0.01;           % Coefficient of weight-decay prior.
outfunc = 'logistic';   % String describing the output unit activation
                          function

% Create and initialize network weight vector.

net = mlp(nin,nhidden,nout,outfunc,alpha);

% Training the network

% -----------------------------------------------------------------------

% Set up vector of options for the optimiser

options = zeros(1,18);
options(1) = 1;     % This provides display of error values
options(14) = 100;   % Number of training cycles observed
```

```
 % Train using scaled conjugate gradients.

[net, options] = netopt(net, options, trainingsetinputdn,…
trainingsetoutputdn, 'scg');

% Test the Network
% ----------------------------------------------------------------------

Output_Ts_mlpdn = mlpfwd(net, testsetinputdn);
Output_Ts_mlpdn = round(Output_Ts_mlpdn);
Error = Output_Ts_mlpdn - testsetoutputdn;
% ----------------------------------------------------------------------

% Script for displaying the network training output

figure,
subplot(3, 1, 1);
imagesc(Output_Ts_mlpadnoise');
xlabel('Network Output Pattern'),ylabel('Success Rate'),title('Network
MLP Output');
subplot(3, 1, 2);
imagesc(testsetoutputadnoise');
xlabel('Testset Pattern'),ylabel('Success Rate'),title('Testset MLP
Output');
subplot(3,1,3), hold on;
imagesc(error');
xlabel('Network Error Pattern'),ylabel('Failure Rate'),title('Network
Error MLP Output');


figure,
subplot(3, 1, 1);
bar(Output_Ts_mlpadnoise');
xlabel('Network Output Pattern'),ylabel('Success Rate'),title('Network
MLP Output');
subplot(3, 1, 2);
bar(testsetoutputadnoise');
xlabel('Testset Pattern'),ylabel('Success Rate'),title('Testset MLP
Output');
subplot(3,1,3);
bar(error');
xlabel('Network Error Pattern'),ylabel('Failure Rate'),title('Network
Error MLP Output');
% ----------------------------------------------------------------------

% Save the DAMR classifier

save ('DAMRn_Model.mat', 'net');

% Loading of the 'DAMRn_Model.mat' at Command Window can be used to
% evaluate
% the developed DAMR classiifer; thus:
% ----------------------------------------------------------------------

% load ('DAMRn_Model.mat', 'net')
mlpfwd(net,[training/validation/test data set]);
roundedValues = round(mlpfw(net,[training/validation/test data set]));
```

```
for i=1:8
    if i==1 && roundedValues(i,8)==1
        disp '2ASK';
    end
    if i==2 && roundedValues(i,7)==1
        disp '4ASK';
    end
    if i==3 && roundedValues(i,6)==1
        disp '2FSK';
    end
    if i==4 && roundedValues(i,5)==1
        disp 'BPSK';
    end
    if i==5 && roundedValues(i,4)==1
        disp 'QPSK';
    end
    if i==6 && roundedValues(i,3)==1
        disp 'OFDM';
    end
    if i==7 && roundedValues(i,2)==1
        disp '16-QAM';
    end
    if i==8 && roundedValues(i,1)==1
        disp '64-QAM';
    end

end

%toc at the end of the "operation" measures the elapsed time for the
"operation"

toc

% round(mlpfwd(net,[trainingd/validationd/test datad set])); rounding
% up not necessary in order to give actual percentage of classification
% of each modulation scheme
% ---------------------------------------------------------------------
```

APPENDIX A3: COMBINED ANALOG AND DIGITAL CLASSIFIER M-FILE

```
% ======================================================================
% Author: J.J. Popoola
% Date: 17/02/2011
% ----------------------------------------------------------------------
% Script for preparing the Combined Analog-Digital generated data with
% Noise for the Combined Analog-Digital Automatic Modulation
% Modulation Recognition (ADAMR)
% The 8 feature extracted keys generated form the inputs to the
% classifier
% The classifier has 13 outputs corresponding to the 12 combined
% analog and digital modulation schemes (2ASK, 4ASK, 2FSK, BPSK, QPSK,
% AM, DSB, SSB, FM, OFDM, 16-QAM, 64-QAM and Noise) intended to
% classify or identify
% Inputs features and output target are combined in matrix form
% Database is split into training data, validation data and test data
% Prepare_Features_ADcn(traindatasetadnoise,validdatasetadnoise,…
% testdatasetadnoise)
% ======================================================================

% Load the generated feature extracted data imported to MATLAB
% environment from excel called adnoisedata already in input-output
matrix
% form

load adnoisedata

% ----------------------------------------------------------------------
% Normalize each column of the 1300 x 21 data matrix

[r,c] = size(adnoisedata);
Max = repmat(max(adnoisedata), [r 1]);
Min = repmat(min(adnoisedata), [r 1]);
outputadnoise1 = (adnoisedata - Min)./(Max - Min);
% ----------------------------------------------------------------------
% Randomizing the normalized data matrix each column of the 1300 x 21
% data matrix

outputadnoise2 = outputadnoise1(randperm(size(outputadnoise1,1)),:);

% ---------------------------------------------------------------------

% Now split the randomized data i.e. outputdnoise2 into
% trainingsetadnoise, validationsetadnoise and testsetadnoise data sets
% in 50%, 25% and 25% respectively
% Save the divided data sets as Prepared_Features_ADNOISE.mat

trainingsetadnoise = outputadnoise2([1:650],:);
trainingsetinputadnoise = trainingsetadnoise(:,[1:8]);
trainingsetoutputadnoise = trainingsetadnoise(:,[9:21]);
X_trnadnoise = [trainingsetinputadnoise,trainingsetoutputadnoise];
save trnadnoise_data X_trnadnoise;
```

```
validationsetadnoise = outputadnoise2([651:975],:);
validationsetinputadnoise = validationsetadnoise(:,[1:8]);
validationsetoutputadnoise = validationsetadnoise(:,[9:21]);
X_validadnoise = [trainingsetinputadnoise,trainingsetoutputadnoise];
save validadnoise_data X_validadnoise;

testsetadnoise = outputadnoise2([976:1300],:);
testsetinputadnoise = testsetadnoise(:,[1:8]);
testsetoutputadnoise = testsetadnoise(:,[9:21])
X_testadnoise = [testsetinputadnoise,testsetoutputadnoise];
save testadnoise_data X_testadnoise;

save('Prepared_Features_ADNOISE.mat','testsetinputadnoise',
'testsetoutputadnoise','validationsetinputadnoise',
'validationsetoutputadnoise',                 'trainingsetinputadnoise',
'trainingsetoutputadnoise')

% start stopwatch timer for the "operation" using tic, which save the
% current time

tic

% Load features

load Prepared_Features_ADNOISE.mat

% classifying the input-output size

no_input = size(validationsetinputadnoise,2);
no_out = size(validationsetoutputadnoise,2);

% ----------------------------------------------------------------------
% Set up Network Parameters

% net = mlp(nin,nhidden,nout,outfunc,alpha)

nin = no_input;          % Number of inputs.
nhidden = 15;            % Number of hidden units or neurones.
nout = no_out;           % Number of outputs.
alpha = 0.01;            % Coefficient of weight-decay prior.
outfunc = 'logistic';    % String describing the output unit activation
                           function

% Create and initialize network weight vector.

net = mlp(nin,nhidden,nout,outfunc,alpha);

% Training the network


% ----------------------------------------------------------------------

% Set up vector of options for the optimiser


options = zeros(1,18);
```

```
options(1) = 1;         % This provides display of error values
options(14) = 150;      % Number of training cycles observed

% Train using scaled conjugate gradients.

[net,  options]  =  netopt(net,  options,  trainingsetinputadnoise,…
trainingsetoutputadnoise, 'scg');

% Test the Network
% ----------------------------------------------------------------------

Output_Ts_mlpadnoise = mlpfwd(net, testsetinputadnoise);
Output_Ts_mlpadnoise = round(Output_Ts_mlpadnoise);
ErroR = Output_Ts_mlpadnoise - testsetoutputadnoise;

% ----------------------------------------------------------------------

% Script for displaying the network training output

figure,
subplot(3, 1, 1);
imagesc(Output_Ts_mlp');
xlabel('Network  Output  Pattern'),ylabel('Success  Rate'),title('Network
MLP Output');
subplot(3, 1, 2);
imagesc(testsetoutput');
xlabel('Testset   Pattern'),ylabel('Success   Rate'),title('Testset   MLP
Output');
subplot(3,1,3), hold on;
imagesc(error');
xlabel('Network  Error  Pattern'),ylabel('Failure  Rate'),title('Network
Error MLP Output');

figure,
subplot(3, 1, 1);
bar(Output_Ts_mlp');
xlabel('Network  Output  Pattern'),ylabel('Success  Rate'),title('Network
MLP Output');
subplot(3, 1, 2);
bar(testsetoutput');
xlabel('Testset   Pattern'),ylabel('Success   Rate'),title('Testset   MLP
Output');
subplot(3,1,3);
bar(error');
xlabel('Network  Error  Pattern'),ylabel('Failure  Rate'),title('Network
Error MLP Output');

% ----------------------------------------------------------------------

% Save the ADNAMR classifier

save ('ADNAMR_Model.mat', 'net');
% Loading of the 'ADNAMR_Model.mat' at Command Window can be used to
% evaluate the developed DAMR classifier; thus:
% ----------------------------------------------------------------------
% load ('ADNAMR_Model.mat', 'net')
```

```
mlpfwd(net,[training/validation/test data set]);
roundedValues = round(mlpfw(net,[training/validation/test data set]));


for i=1:13
    if i==1 && roundedValues(i,13)==1
        disp '2ASK';
    end
    if i==2 && roundedValues(i,12)==1
        disp '4ASK';
    end
    if i==3 && roundedValues(i,11)==1
        disp '2FSK';
    end
    if i==4 && roundedValues(i,10)==1
        disp 'BPSK';
    end
    if i==5 && roundedValues(i,9)==1
        disp 'QPSK';
    end
    if i==6 && roundedValues(i,8)==1
        disp 'AM';
    end
    if i==7 && roundedValues(i,7)==1
        disp 'DSB';
    end
    if i==8 && roundedValues(i,6)==1
        disp 'SSB';
    end
    if i==9 && roundedValues(i,5)==1
        disp 'FM';
    end
    if i==10 && roundedValues(i,4)==1
        disp 'OFDM';
    end
    if i==11 && roundedValues(i,3)==1
        disp '16-QAM';
    end
    if i==12 && roundedValues(i,2)==1
        disp '64-QAM';
    end
    if i==13 && roundedValues(i,1)==1
        disp 'NO MODULATION';
    end

end

%toc at the end of the "operation" measures the elapsed time for the
"operation"

toc

% round(mlpfwd(net,[trainingd/validationd/test data sets])); rounding
% up not necessary in order to give actual percentage of classification
% of each modulation scheme
% ----------------------------------------------------------------------
```

APPENDIX B: GNU RADIO INSTALLATION AND USRP2 CONFIGURATION

B.1 GNU Radio Installation

GNU Radio runs in virtually all the operating systems or platforms. However, some installations are easier than others. In order to ensure a complete installation of GNU Radio, the software must be compiled from source, and all the dependencies have to be included. The Ubuntu operating system is an ideal platform for a GNU Radio installation, because all the dependencies can be easily accommodated. The installer simply needs to select the correct check boxes and select “install”.

However, installing GNU Radio is somewhat more tedious in other platforms. For this research work, GNU Radio was installed on a Microsoft Windows Operating System (OS) using Cygwin, which is a Linux emulation environment. The steps involve in GNU Radio installation on Microsoft Windows OS in this research work is highlighted as follows:

Step I: Downloading and installation of Universal Hardware Driver (UHD). The latest UDH installer driver was downloaded and installed from http://code.ettus.com/redmine/ettus/projects/uhd/wiki. The goal of a UHD is to provide a host driver and Application Programming Interface (API) for current and future Ettus Research products.

Step II: Downloading and the installation of the latest GNU Radio installer. This was downloaded and installed from http://www.ettus.com/downloads/gnuradio/.

Step III: Downloading and the installation of the PYTHONPATH environment variable for the GNU Radio installation using the syntax: “c:\program files (x86)\gnuradio\lib\site-packages”.

Step IV: Installation of the Microsoft Visual C++ (MSVC) 2010 redistributable package (x86) from http://www.microsoft.com/downloads/en/details.aspx?FamilyID=a7b7a05e-6de6-4d3a-a423-37bf0912db84

Step V: Finally, at the last step, the installer for the dependencies was downloaded and installed from http://www.ettus.com/downloads/gnuradio/other_deps_with_installers/. The command window (cmd.exe) was opened and "c:\program files (x86)\gnuradio\bin\gnuradio-companion.py" was entered. By pressing the enter key, the GNU Radio Companion (GRC) page was opened, showing that the installation was comprehensive and completed. The online installation procedure followed is available on http://www.joshknows.com/gnuradio.

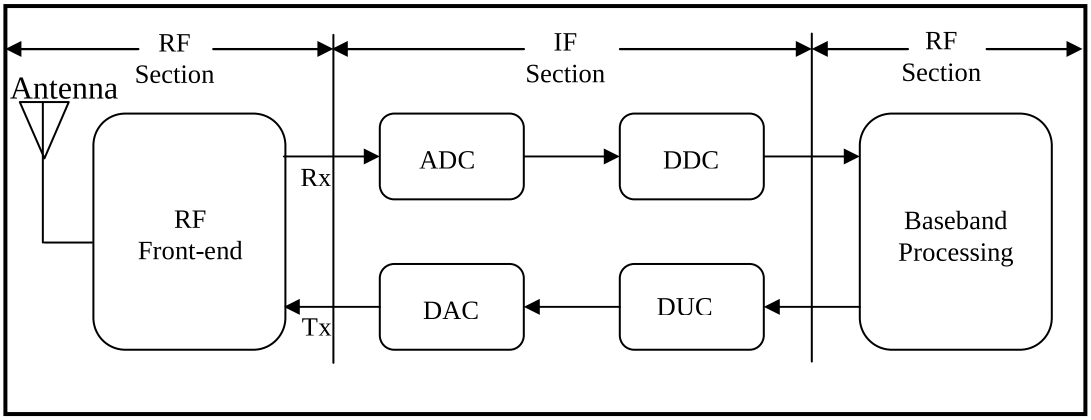
B.2 USRP2 Components Description and Configuration

The hardware component employed in the development of the SDR for the CRE in this research work is the USRP2. The USRP2 is an upgraded version of its earlier release, USRP1. The four USRP2s used were purchased from Ettus Research LLC, Mountain View, California, USA.

B.2.1 USRP2 Component Description

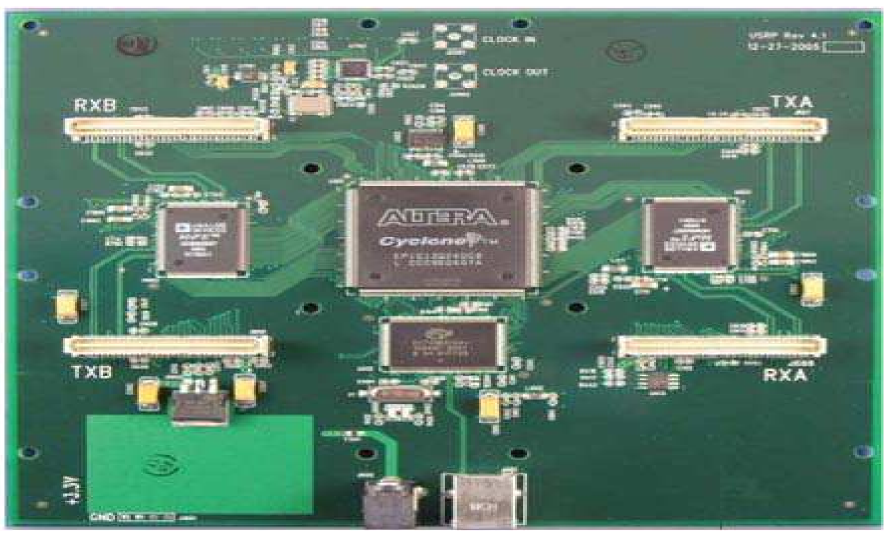
The USRP2 employed consists of two main boards, namely the motherboard and the daughterboard. The motherboard has four 14-bit 100 MS/s ADC, four 16-bit 400 MS/s DAC, two digital down converter (DDC) and two digital up converter (DUC) with programmable interpolation rates. The four input and output channels of the ADCs and DACs are connected to Xilinx Spartan 3 200 FPGA. The FPGA, in turn, connects to a Gigabit Ethernet (1000 MBits/s) interface chip and on to the host PC.

In the USRP2, high sampling rate processing takes place in the FPGA, while the low sampling rate processing takes place in the host PC. The two DDCs mix, filter and decimate incoming signals in the FPGA. The two DUCs interpolate baseband signals to 100 MS/s before translating them to the selected output frequency. This process is illustrated in Figure B.1, while Figure B.2 shows a picture of a typical USRP2 motherboard.



Source: Zhao et al. (2010)

Figure B.1: USRP2 Flow Graph



Source: Zhao et al. (2010)

Figure B.2: USRP2 Motherboard

The second main board of USRP2 is the daughterboard, which acts as the RF FEs of the SDR. Therefore, for the USRP2 to function as a SDR in conjunction with GNU Radio, the daughterboard needs to be connected to the four RF FEs slots on the motherboard. The four FEs slots are TXA, RXA, TXB and RXB, as shown in Figure 5.3. Two of the four slots labeled TXA and TXB are meant for signal transmission via the daughterboard, while the other two slots labeled RXA and RXB are for signal reception.

A wide variety of available daughterboards permit usage of different frequencies for a broad range of applications. In this research work, the XCVR2450 daughterboard was employed. This daughterboard is a dual-band transceiver operating at 2.4 GHz and 5 GHz. It transmits and/or receives signals around the ISM band, namely between 2.4 GHz and 2.5 GHz.

B.2.2 USRP2 Configuration

For the host PC, where the GNU Radio software was installed to recognize USRP2, the USRP2 needs to be configured and to interface with it. The host interface is setup by connecting the USRP2 to the host PC using the Gigabit Ethernet cable with a RJ-45 jack at both ends. The USRP2 communicates at the user datagram protocol/internet protocol (UDP/IP) layer over the Gigabit Ethernet. The default IP address of the USRP2 is 192.168.10.2. Hence, the host Ethernet interface was configured with a static IP address to enable communication. An address of 192.168.10.1 and a subnet mask of 255.255.255.0 were used in the interface setup.

The multiple USRP2 devices were connected via a Gigabit Ethernet switch. In such cases, each Ethernet interface has its own subnet, and the corresponding USRP2 device was assigned an address in that subnet. Therefore, for the four USRP2 devices used, the USRP2s were configured as follows:

Configuration for USRP2 device D_1:

- Ethernet interface IPv4 address: 192.168.10.1
- Ethernet interface subnet mask: 255.255.255.0
- USRP2 device IPv4 address: 192.168.10.2

Configuration for USRP2 device D_2:

- Ethernet interface IPv4 address: 192.168.20.1
- Ethernet interface subnet mask: 255.255.255.0
- USRP2 device IPv4 address: 192.168.20.2

Configuration for USRP2 device D_3:

- Ethernet interface IPv4 address: 192.168.30.1
- Ethernet interface subnet mask: 255.255.255.0
- USRP2 device IPv4 address: 192.168.30.2

Configuration for USRP2 device D_4:

- Ethernet interface IPv4 address: 192.168.40.1
- Ethernet interface subnet mask: 255.255.255.0
- USRP2 device IPv4 address: 192.168.40.2

After connecting the USRP2 with GNU Radio and bringing it to an up-and-running condition to form SDR, a GNU Radio Companion (GRC) was then executed. The GNU Radio and USRP2 are utilized to implement the spectrum sensing system. The sensing system was developed to detect a primary user's signal modulation scheme for spectrum monitoring. The specifications of the host PC used are presented in Table B.1.

Table B.1: Host Computer Specifications

Component	Specifications
Processor	Intel(R) Core (TM) CPU 930 @ 2.80 GHz
RAM	6. 00 GB
Operating System	64-bit, 5.4 Windows 2010
Programs	Python, JAVA, C++ and MATLAB.

APPENDIX C: USER MANUAL FOR SPECTRUM SENSING AND DETECTION ALGORITHM

C.1 Introduction

The spectrum sensing and detection algorithm employed as the core brain of the developed CRE in this thesis was further implemented in a user friendly program called SSADA. SSADA is an acronym for Spectrum Sensing and Detection Algorithm. It is a software algorithm developed to demonstrate spectrum sensing procedures, as well as series of measures to ensure optimal cooperative gain without incurring cooperative overhead.

C.2 SSADA Manual Purpose and Target User

The essence of this manual is to provide fundamental information about the operation of SSADA, as well as to provide a general overview of the basic functions and editing conventions each of the program modules performs. It is assumed that user(s) of SSADA has/have some background knowledge of wireless communication systems, as well as being familiar with the Microsoft Windows OS. The assumption was made because the information in the manual is not sufficient enough to serve as a tutorial for novices in either wireless communication system or Microsoft Window system. The main application of SSADA is to demonstrate spectrum sensing and primary radio signal detection activities in a cognitive radio environment or network.

C.3 SSADA System Requirements

SSADA was written using the Java programming language. It does require a compatible Microsoft Windows 98 or later version with JAVA® . It requires at least a 32-bit operating system with a minimum random access memory (RAM) of 256 MB and about 1.8 GHz processor. Its size on disk is about 1.80 MB.

C.4 SSADA working Environment

The SSADA working environment is shown in Figure C.1. It consists of three modules and is capable of performing three basic functions. The first module is the preferred service and location, which enables SSADA to scan the overall preferred service allocated frequency band in South Africa. The location included enables SSADA to decide upon an appropriate idle channel to claim opportunistically using DSA so as not to cause co-channel interference to a primary user resulting from a re-used frequency.

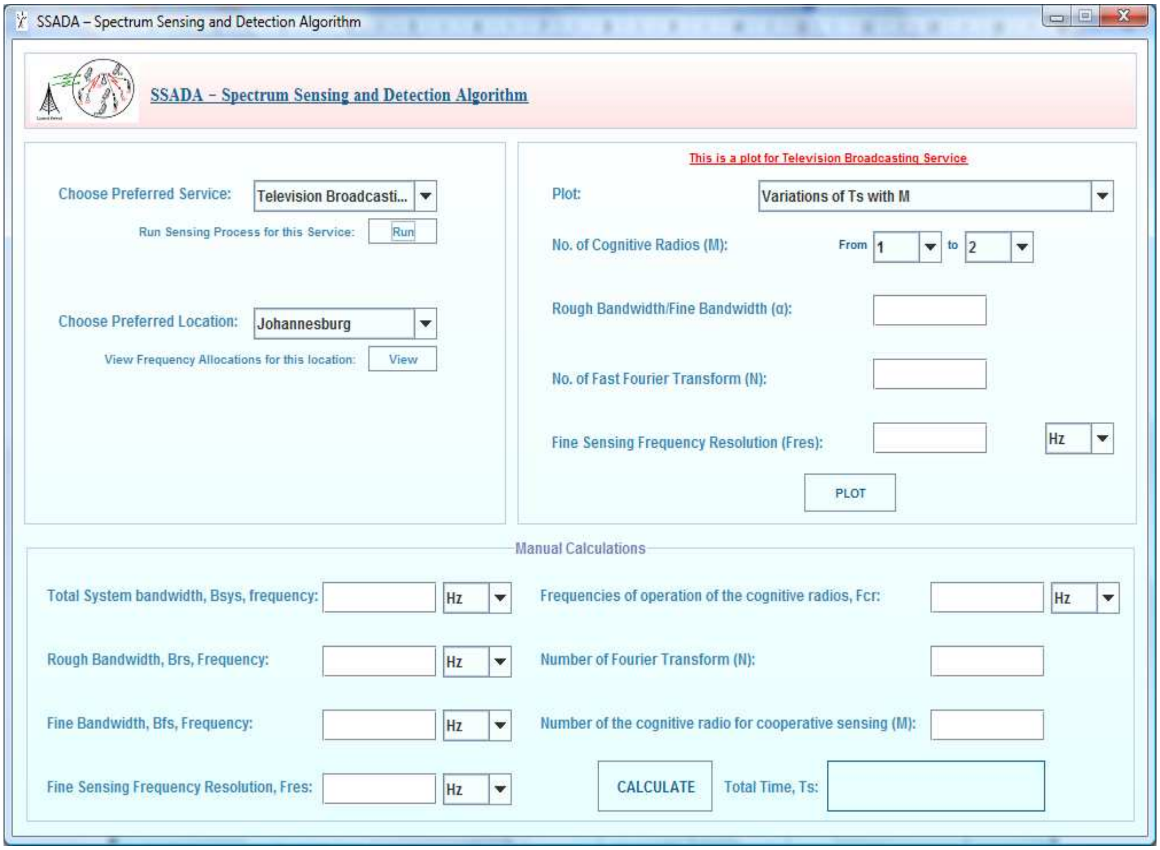


Figure C.1: The Developed SSADA Attributes

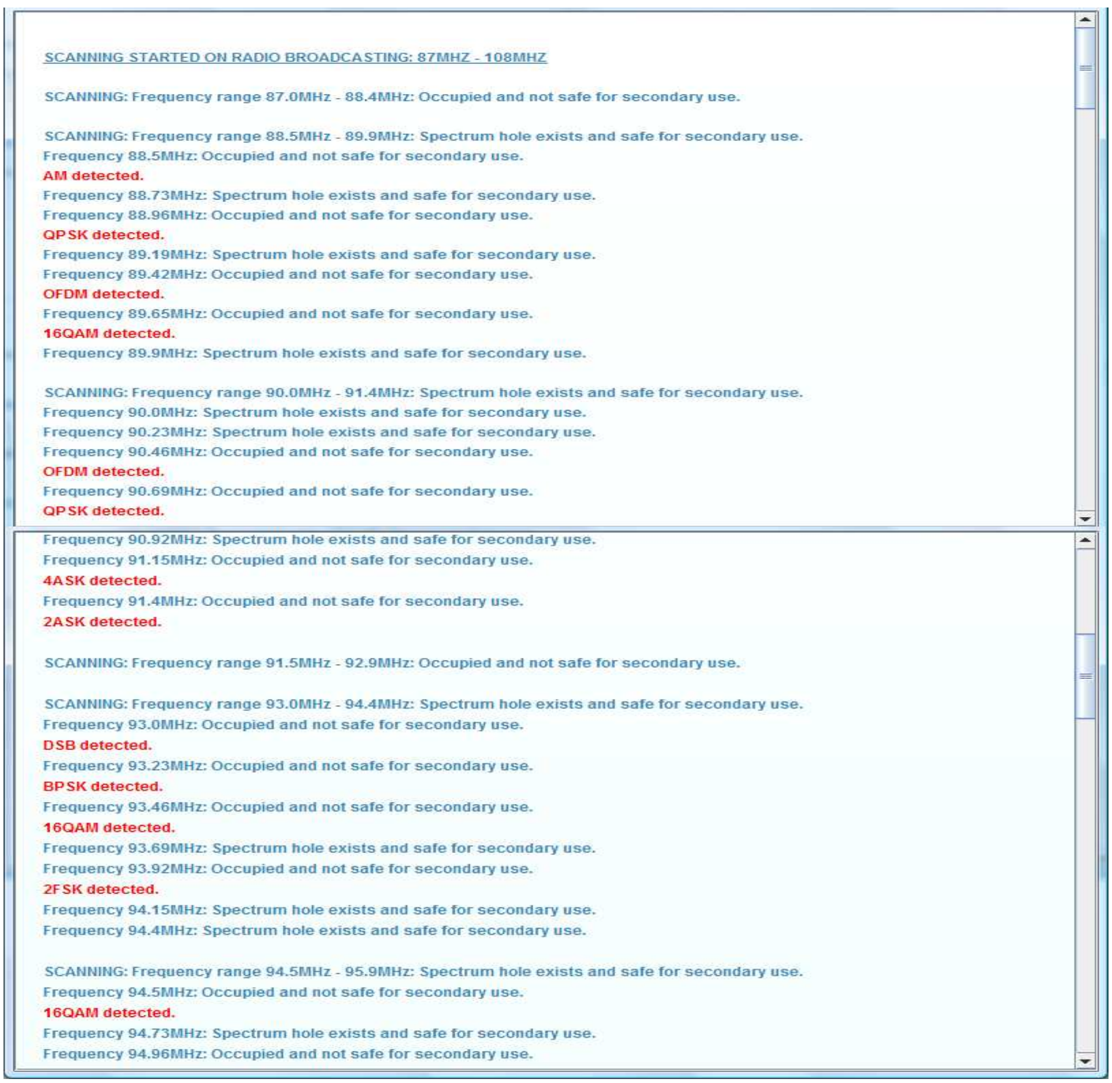
The second module on an SSADA working environment is the plotting section, where the sensing time parameters selection for optimizing cooperative spectrum sensing gain can be derived. The third module in an SSADA working environment is the manual calculations section, for determining sensing time (Ts). The basic different between this module and the second module is that it presents its results in numerals, while the second module presents its results in a graphical form.

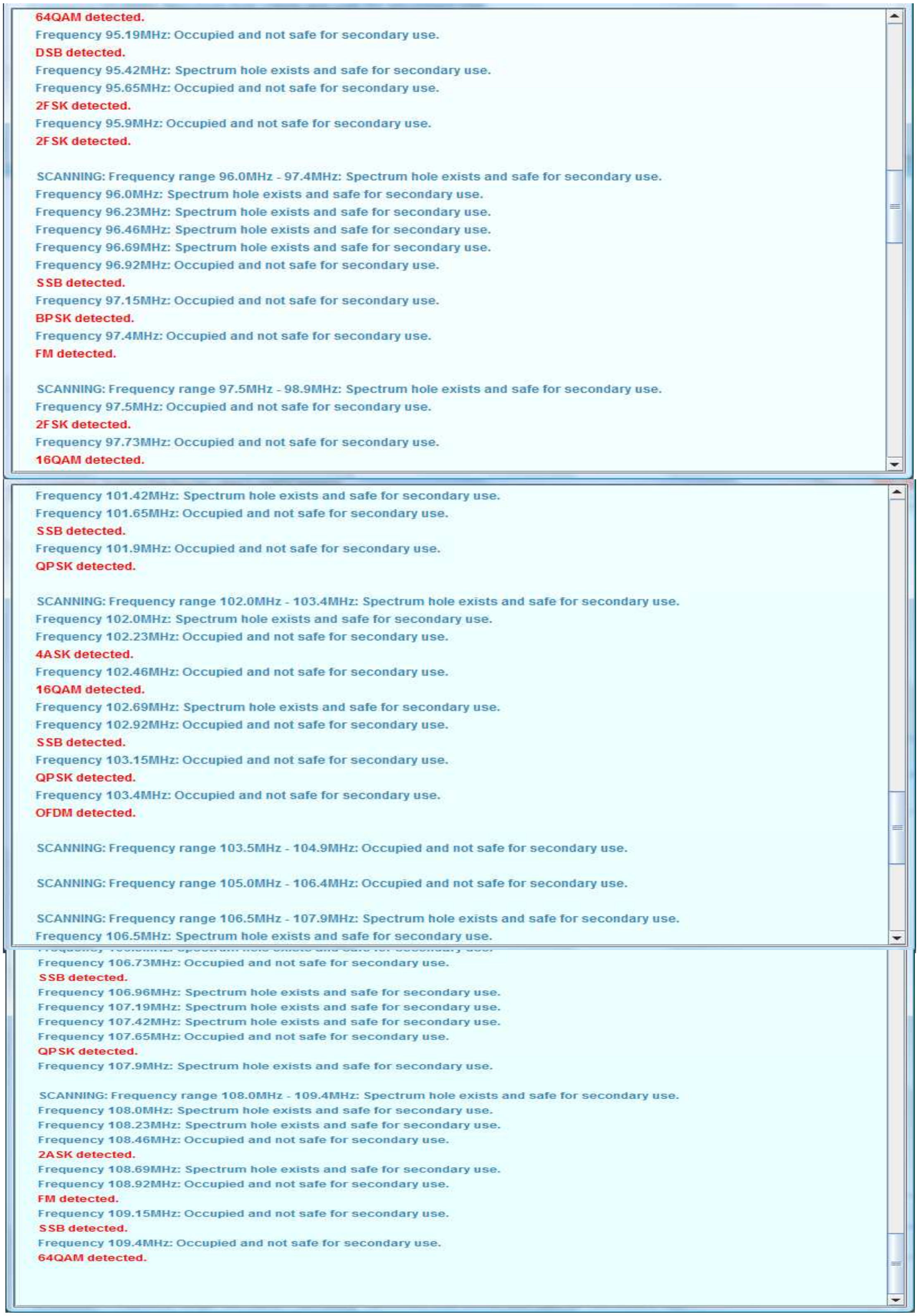
C.4. SSADA Applications

This section of this manual is devoted to showcase some of the capabilities of SSADA. The three modules on SSADA are demonstrated using the four wireless services employed. Detailed activities of each module are showcased with examples in section C.4.1 to section C.4.3.

C.4.1 SSADA Spectrum Scanning Module Application

This section presents the application of the first module of SSADA. In using the module, the user needs to choose the preferred services. The preferred service is chosen by selecting either the block or the drop down arrow (∇) beside it. This will bring down a dialog box that contains the four services, namely radio broadcasting, television broadcasting, mobile telephone and ISM. The user then selects the preferred one. The user can subsequently run the program by selecting ‘run-block’. Selecting this option activates the program to carry out overall spectrum sensing or scanning for the selected or preferred wireless service. A typical result of such an overall radio broadcasting system scanning exercise is shown in Figure C.2.





64QAM detected.
Frequency 95.19MHz: Occupied and not safe for secondary use.
DSB detected.
Frequency 95.42MHz: Spectrum hole exists and safe for secondary use.
Frequency 95.65MHz: Occupied and not safe for secondary use.
2FSK detected.
Frequency 95.9MHz: Occupied and not safe for secondary use.
2FSK detected.

SCANNING: Frequency range 96.0MHz - 97.4MHz: Spectrum hole exists and safe for secondary use.
Frequency 96.0MHz: Spectrum hole exists and safe for secondary use.
Frequency 96.23MHz: Spectrum hole exists and safe for secondary use.
Frequency 96.46MHz: Spectrum hole exists and safe for secondary use.
Frequency 96.69MHz: Spectrum hole exists and safe for secondary use.
Frequency 96.92MHz: Occupied and not safe for secondary use.
SSB detected.
Frequency 97.15MHz: Occupied and not safe for secondary use.
BPSK detected.
Frequency 97.4MHz: Occupied and not safe for secondary use.
FM detected.

SCANNING: Frequency range 97.5MHz - 98.9MHz: Spectrum hole exists and safe for secondary use.
Frequency 97.5MHz: Occupied and not safe for secondary use.
2FSK detected.
Frequency 97.73MHz: Occupied and not safe for secondary use.
16QAM detected.

Frequency 101.42MHz: Spectrum hole exists and safe for secondary use.
Frequency 101.65MHz: Occupied and not safe for secondary use.
SSB detected.
Frequency 101.9MHz: Occupied and not safe for secondary use.
QPSK detected.

SCANNING: Frequency range 102.0MHz - 103.4MHz: Spectrum hole exists and safe for secondary use.
Frequency 102.0MHz: Spectrum hole exists and safe for secondary use.
Frequency 102.23MHz: Occupied and not safe for secondary use.
4ASK detected.
Frequency 102.46MHz: Occupied and not safe for secondary use.
16QAM detected.
Frequency 102.69MHz: Spectrum hole exists and safe for secondary use.
Frequency 102.92MHz: Occupied and not safe for secondary use.
SSB detected.
Frequency 103.15MHz: Occupied and not safe for secondary use.
QPSK detected.
Frequency 103.4MHz: Occupied and not safe for secondary use.
OFDM detected.

SCANNING: Frequency range 103.5MHz - 104.9MHz: Occupied and not safe for secondary use.

SCANNING: Frequency range 105.0MHz - 106.4MHz: Occupied and not safe for secondary use.

SCANNING: Frequency range 106.5MHz - 107.9MHz: Spectrum hole exists and safe for secondary use.
Frequency 106.5MHz: Spectrum hole exists and safe for secondary use.

Frequency 106.73MHz: Occupied and not safe for secondary use.
SSB detected.
Frequency 106.96MHz: Spectrum hole exists and safe for secondary use.
Frequency 107.19MHz: Spectrum hole exists and safe for secondary use.
Frequency 107.42MHz: Spectrum hole exists and safe for secondary use.
Frequency 107.65MHz: Occupied and not safe for secondary use.
QPSK detected.
Frequency 107.9MHz: Spectrum hole exists and safe for secondary use.

SCANNING: Frequency range 108.0MHz - 109.4MHz: Spectrum hole exists and safe for secondary use.
Frequency 108.0MHz: Spectrum hole exists and safe for secondary use.
Frequency 108.23MHz: Spectrum hole exists and safe for secondary use.
Frequency 108.46MHz: Occupied and not safe for secondary use.
2ASK detected.
Frequency 108.69MHz: Spectrum hole exists and safe for secondary use.
Frequency 108.92MHz: Occupied and not safe for secondary use.
FM detected.
Frequency 109.15MHz: Occupied and not safe for secondary use.
SSB detected.
Frequency 109.4MHz: Occupied and not safe for secondary use.
64QAM detected.

Figure C.2: Typical SSADA Spectrum Sensing Result for Radio Broadcasting

The user likewise needs to select the preferred location by selecting either the location block or the drop down arrow (∇) beside it. This will also bring down a dialog box that contains the lists of all the six location or cities, namely Johannesburg, Cape Town, Durban, Port Elizabeth, Bloemfontein and Pretoria. The user then selects the preferred location. After selecting the appropriate or preferred location, the user needs to select the 'view-block' to view the drop down box contains the list of all the allocated frequency tables for that location and the four services. Figure C.3 shows a typical result for Bloemfontein. The scanning result presented in Figure C.3, for instance, enables an SSADA to predict the appropriate idle channel to use in each location per time, so as not to cause co-channel interference, as explained earlier. The copying of the spectrum sensing and location results from the SSADA working environment was done by pressing 'Ctrl + Alt + Print Scrn' keys together to copy the screen and paste the copied results on a Microsoft Word environment using 'paste' command.

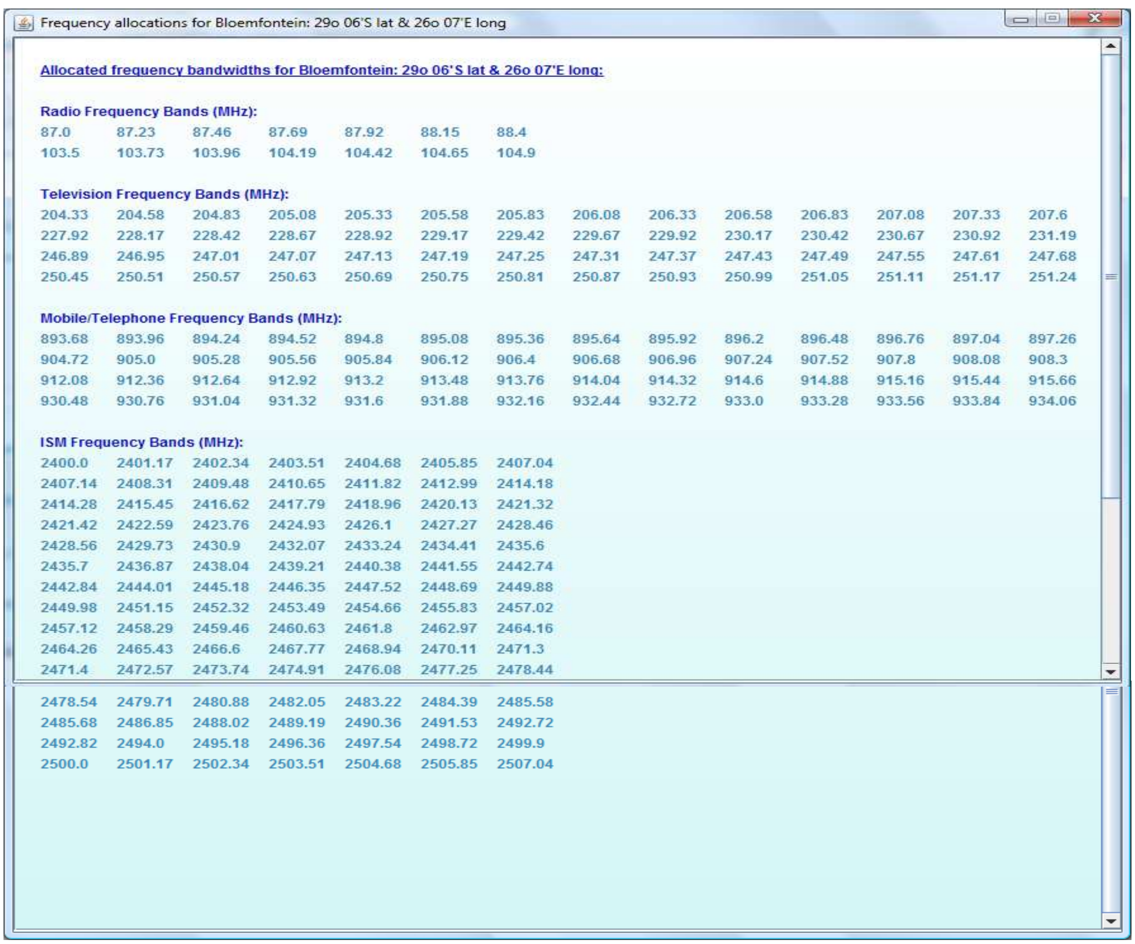


Figure C.3: SSADA Overall Table of Frequency Allocation for Bloemfontein

C.4.2 SSADA Sensing Time (Ts) Plots Module Application

This section is devoted to demonstration of the second module of the developed SSADA. The module was developed to generate four different plots for determining ideal sensing time parameters settings for optimal cooperative gain, without incurring a cooperative overhead. In this module, the user needs to first select the type of service parameter to use its table of allocation. The second step is to select the type of plot to be generated by selecting either the plot block or the drop down arrow (∇) beside it and a dialog box that contains the four plots, namely variation of Ts with M, variation of Ts with F_{RES}, variation of Ts with M at different values of alpha (α) and the variation of Ts with N, will drop down for the user to select the preferred plot type. The next step is to input the values of α, the FFT size (N) and the fine resolution frequency (F_{RES}). The user does not need to input the system's bandwidth (B_{SYS}) value because the SSADA plot's module takes the value directly from the table of frequency allocation.

C.4.2.1 Sensing Time (Ts) Plot against Number of Cognitive Radio (M)

In demonstrating the usage of this module, the four wireless services were used. The plot of the variation of Ts with M was demonstrated using the TV broadcasting frequency band for Cape Town as the preferred location. The resulted plot, as shown in Figure C.4, when compared with Figure 4.3, looks exactly alike in nature. The difference in values of Ts is as a result of differences in value of B_{SYS} employed though the values of α, N and F_{RES} are equal. For plot shown in Figure 4.3, B_{SYS} value is 2.5 GHz, while the value of B_{SYS} was automatically selected by SSADA from the frequency of allocation for Cape Town's TV broadcasting system. The SSADA design system enable automatically generation of the system bandwidth (B_{SYS}) values for the plot module.

A comparison between the two figures, as demonstrated in Figure 4.3 and Figure C.4, shows that they are identical in nature. The similarity in these figures shows that the sensing time algorithm developed using MATLAB in chapter 4, which was used in developing the CRE for this research, and the SSADA used to showcase the research work proof of concept are accurately developed and perfectly executed.

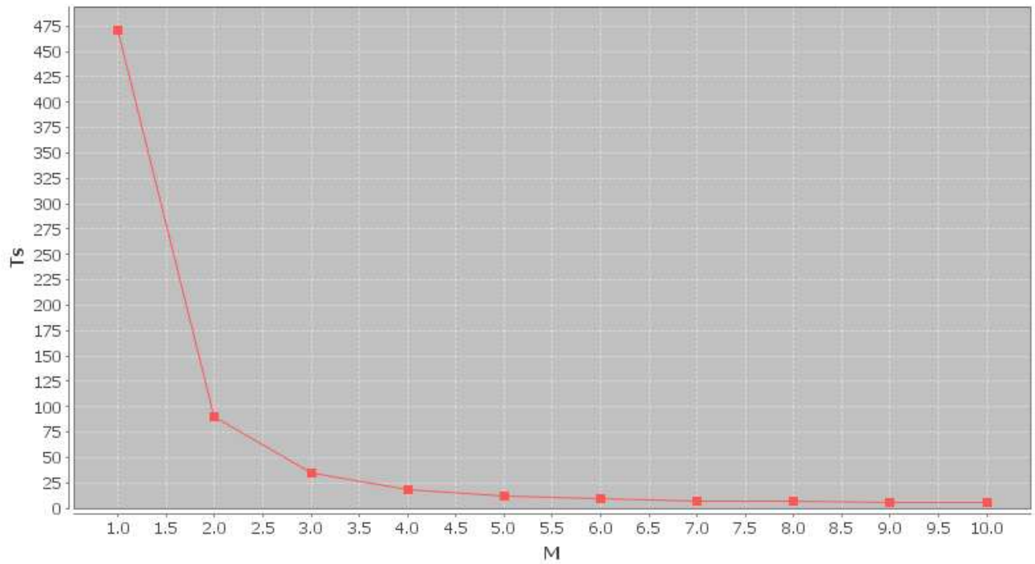


Figure C.4: SSADA Generated Ts Plot against Number of Cognitive Radios (M)

C.4.2.2 Sensing Time (Ts) Plot against F_{RES}

This second SSADA plotting module application follows the same step described in section C.4.2.1. In demonstrating this plot, the mobile phone parameters for Johannesburg were used. The system bandwidth (B_{SYS}) was automatically selected by SSADA with constant values of α = 10 and N = 32 while F_{RES} was varied from 10 kHz to 100 kHz. The result obtained is shown in Figure C.5. When comparing Figure 4.4 with Figure C.5, the two graphs look alike in nature, except their Ts values that differ as a result of the difference in B_{SYS} values employed.

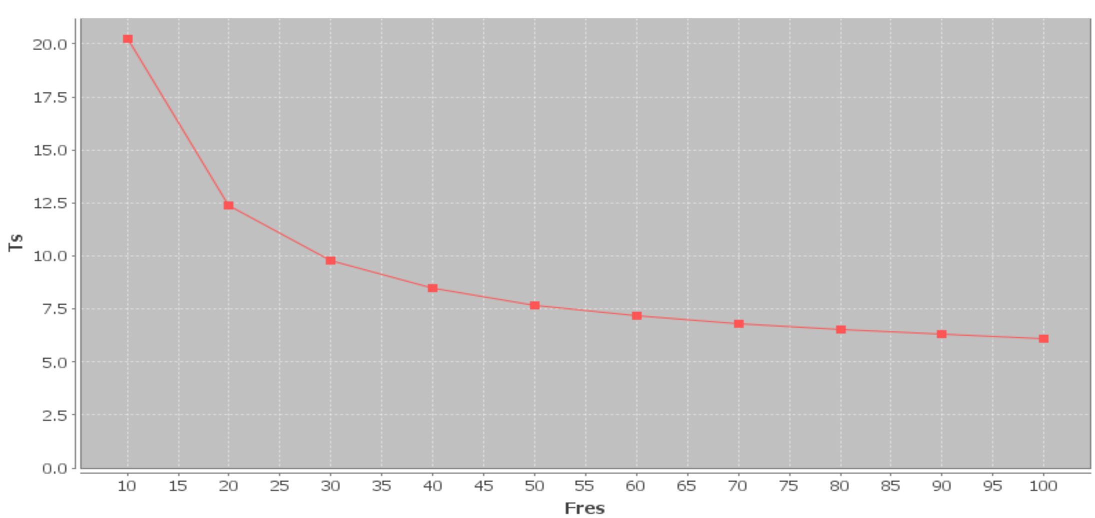


Figure C.5: SSADA Generated Ts Plot against F_{RES}

C.4.2.3 Sensing Time (Ts) Plot against M at Different Values of α

This SSADA module application also follows the same steps described in section C.4.2.1. In demonstrating this plot, the TV broadcasting parameters were used with Durban as the preferred location or test site. The B_{SYS} was automatically selected by SSADA. The values of M were varied from 2 to 4, while the values of alpha (α) were also varied from 10 to 50 with constant values of N = 32 and F_{RES} = 10 Hz respectively. The plot obtained is shown in Figure C.6. When comparing Figure 4.5 with Figure C.6, the two graphs look alike in nature except their Ts values that differ as a result of difference in B_{SYS} values employed. This is an indication of high accuracy in developing both the MATLAB form of the algorithm in chapter 4 and the developed SSADA, being evaluating here.

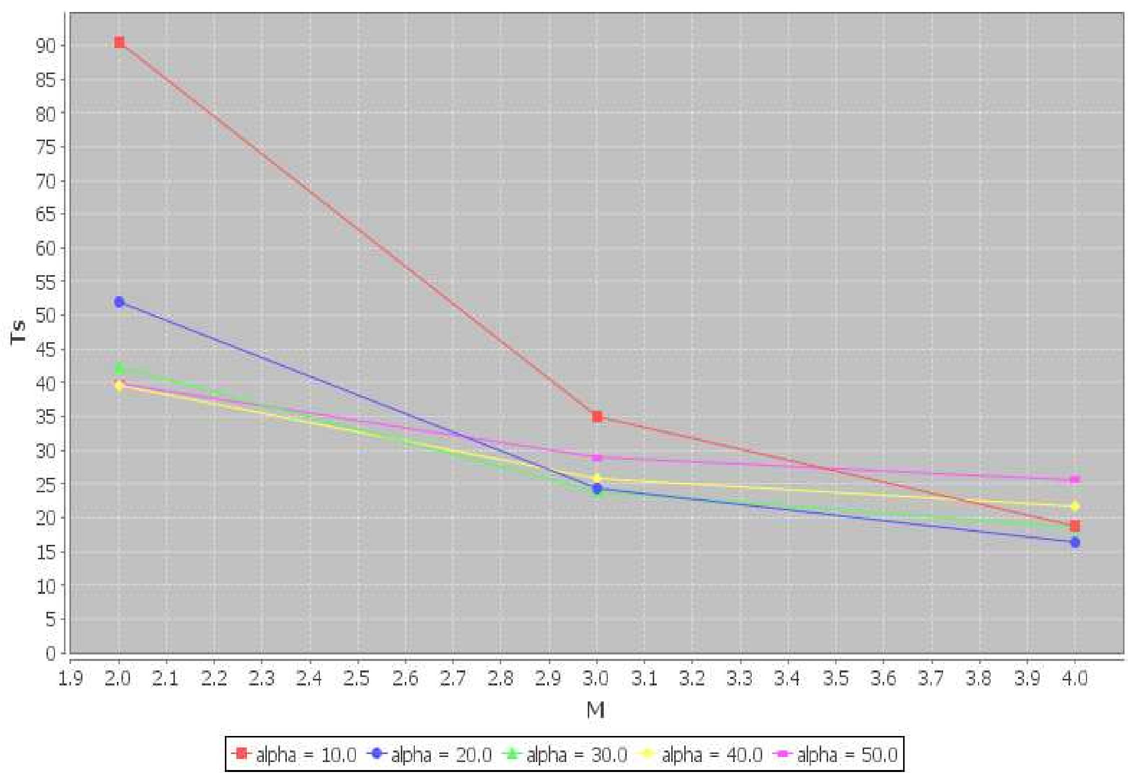


Figure C.6: SSADA Generated Ts Plot against M at Different Values of α

C.4.2.4 Sensing Time (Ts) Plot against FFT size (N)

This SSADA module demonstration was carried out using the radio broadcasting frequency table. Pretoria was chosen as the preferred location or test site. The B_{SYS} was automatically selected by SSADA. The values of N were varied from 16 to 1024 with constant values of M = 4, α = 10 and F_{RES} = 10 Hz respectively. The plot obtained is shown in Figure C.7.

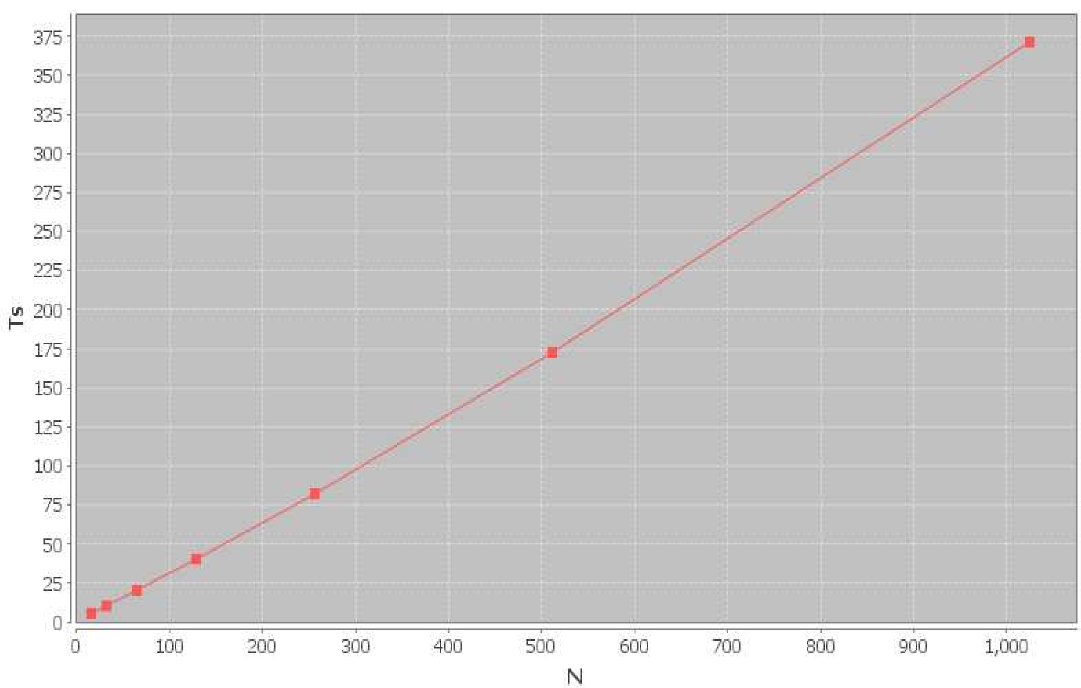


Figure C.7: SSADA Generated Ts Plot against FFT Size (N)

C.4.3 SSADA Plot Module Editing Environment

In SSADA plot module, copying of the plots can be done in two ways. The first is by following the process for the first module whereby the 'Ctrl + Alt + Print Scrn' keys are pressed together to copy the screen and paste the plots on Microsoft Word. The second approach is by right-clicking the mouse on the plot environment to bring down the inbuilt editing feature incorporated in this second module, as shown in Figure C.8. Apart from copying the plot, other editing can be done on the plots.

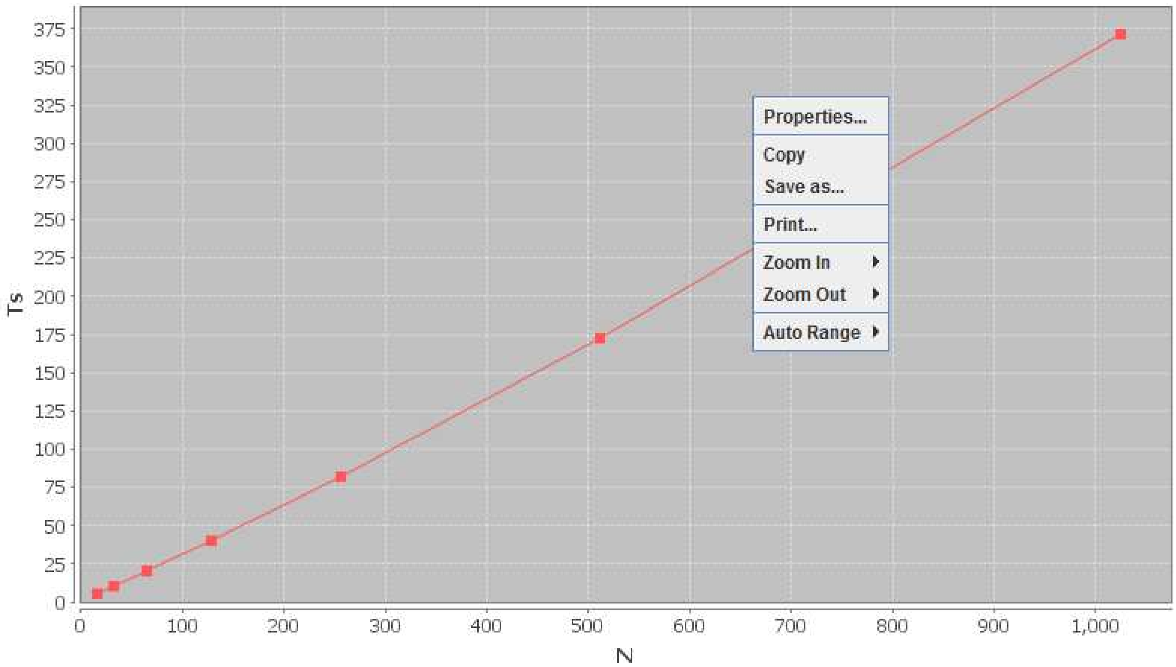


Figure C.8: In-built Editing Capability for SSADA Plot Module

C.4.4 SSADA Manual Calculations

The manual calculation module is the third working module on the developed SSADA working environment. Unlike the two other modules, the B_{SYS} value is not automatically selected. The user has to input all the required values on the keyboard for SSADA manual calculations' module to work. Copying of the manual calculations' module result follows the same procedure as the first module, whereby the 'Ctrl + Alt + Print Scrn' keys are pressed together to copy the screen and paste the results on Microsoft Word using the paste command. A typical example of its usage is presented in Figure C.9 using the ISM parameter employed in chapter 4.

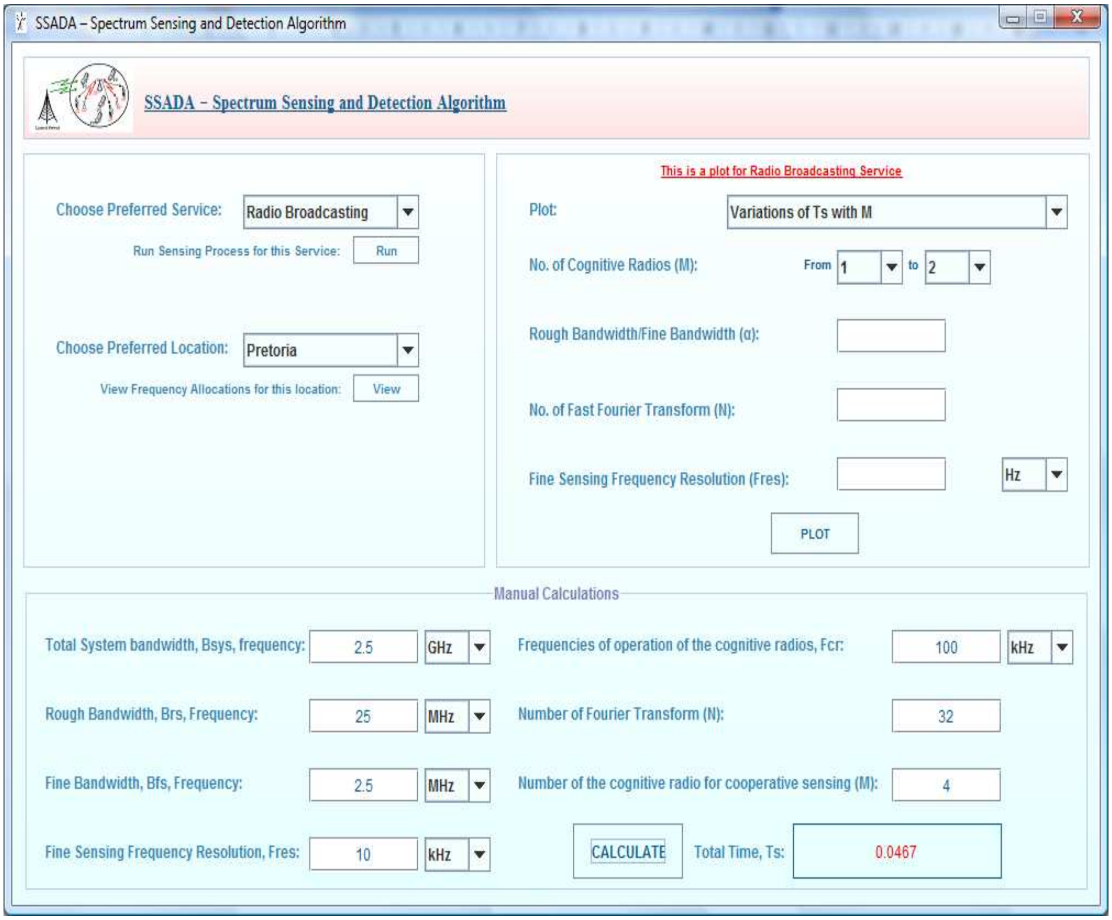


Figure C.9: Typical SSADA Manual Calculation Demonstration